THE UNIVERSITY OF CHICAGO

HEXAGONS, SCENES, ART, AND JOBS: THE NEW URBAN GEOGRAPHY OF CULTURAL ENTERPRISES AND EMPLOYMENT OPPORTUNITY

A DISSERTATION SUBMITTED TO

THE FACULTY OF THE DIVISION OF THE SOCIAL SCIENCES

IN CANDIDACY FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

DEPARTMENT OF SOCIOLOGY

BY

CRISTINA YUMI SAKAMOTO

CHICAGO, ILLINOIS

JUNE 2021

DEDICATION

I would like to express gratitude and dedicate this dissertation to my parents, Luiz Sakamoto and Sumiko Sakamoto, my brother Aurélio Sakamoto, and my grandmother Kyoko Inaba, for their love, support, and encouragement throughout my life.

I would also like to dedicate this dissertation to my husband, Steve Anderson, who joined me in this adventure, endured its challenges, reassured me through difficulties, and celebrated good moments.

And I dedicate this dissertation to artists everywhere, who make our cities interesting and exciting.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

This dissertation explores the reciprocal relationship between the arts and employment. This relationship is characterized by a combination of a "multiplier effect" in which one additional arts job attracts many jobs in other industries, and an "audience effect" in which several jobs in other industries are necessary in order to form an audience large enough to attract additional artists. Using the County Business Patterns dataset from the US Census Bureau, this dissertation explores how employment in the arts affects the nonßß-arts industries and vice versa in 481 urban areas from 1998 to 2016. The main statistical methods used in this research are cross-lagged regressions, followed by fixed-effect meta-analysis. When comparing the arts to non-arts industries in general, results indicate that in both the short and long terms, the multiplier/audience effects hold. When comparing the arts to business services and high-tech industries individually, results showed a much stronger relationship between the arts and business services than for arts and high-tech. As a relatively young industry, high-tech does not yet present an arts multiplier, but it does present higher audience effects than the business services industries, indicating that while artists are not yet attracting high-tech jobs, high-tech jobs are strongly attracting the arts. In all three analyses, the multiplier/audience effects hold better for larger urban areas than for medium, followed by smaller sized urban areas. In addition, this dissertation proposes data selection and transformation methods by overlapping the urban areas and ZIP code maps in order to make the official data units into geographically and time consistent hexagons.

Datasets: US Census Bureau County Business Pattern (yearly from 1998 to 2016); 2000 and 2010 US Census Decennial Population data; 2010 Census Urban Area Reference map; and the 2009 and 2018 ZIP Code maps.

Methodologies: cross-lagged regression, ordinary least squares, sampling methods, fixed effects meta-analysis, hexagonal tessellation, GIS, and mapping.

ACKNOWLEDGMENTS

I would like to thank my advisor, Prof. Terry N. Clark, for giving me the opportunity to be his student, providing interesting and challenging research, and for his friendship all of these years. This project was only made possible with his support and trust in me.

I also would like to thank Prof. Ross Stolzenberg for recommending methodologies and for his reassurance on my research project, and Prof. Karin Knorr-Cetina and Prof. John Levi Martin for their comments, suggestions, and great participation on my committee.

I am also grateful to the Department of Sociology at the University of Chicago, and Linnea Martin, whose support was imperative in getting through all the administrative and academic matters. I also thank the University of Chicago, CAPES-Brasil, and the Dissertation Completion Fellowship for their financial support from the start of the PhD program to its completion.

CHAPTER 1

INTRODUCTION AND THE CURRENT STATE OF THE FIELDS OF THE ARTS AND ECONOMIC DEVELOPMENT

1.1 Introduction

The arts industry exerts powerful influence in economic growth despite its relatively small size. This dissertation aims to understand the symbiotic relationship between the arts and industry development in the United States. On the one hand, people still decide where to live based on job opportunities, but on the other hand, people may also choose where to live based on what a city offers. Therefore, that symbiotic relationship is marked in two ways: (1) people move for employment, and as the local market grows, arts and entertainment establishments follow, and (2) people move for arts and entertainment, prompting other industries to move to cities to employ its human capital. We may frame the central research questions as: Do people follow jobs that then are followed by the arts? Or do people follow arts that are then followed by jobs?

Employment is not always everyone's top concern, and people may prioritize a city's dynamics, leisure, landscape, and arts, which we call "amenities," meaning any area where the local activities contribute value to the day-to-day life of residents. Amenities include buildings (e.g., opera houses), events (e.g., music festivals), or even scenic locations, such as mountains and the sea (Clark 2011). At a macroscopic level, these decisions are reflected in growth patterns within cities, where job growth can encourage growth in amenities and amenities can in turn encourage job growth in a reciprocal manner. This bidirectional relationship between growth in jobs and amenities is what we call the "chicken and egg" problem.

When deciding where to live, decisions may encompass more than employment considerations, such as whether the location provides the desired amenities needed for a full and satisfying life. In addition to employment, safety, and basic services, individuals also need opportunities to form their social networks, enjoy leisure and recreation, dedicate time to their hobbies and interests, and promote their own well-being. Individuals may search for places according to the availability of jobs as well as lifestyle amenities based on their taste, personality, and stage in life—things that allow them to feel accomplished and fulfilled. At the same time, city governments and private entities understand the benefits of attracting talented workers and make efforts to promote amenities in their cities to also attract high revenue industries.

Therefore, a cycle follows: amenities help revitalize neighborhoods, attracting new inhabitants, creating a favorable environment for businesses to hire new employees, which then attracts even more inhabitants to work in these businesses, resulting in even more arts and amenities, and therefore more businesses, more people, more amenities, and so on. This is the cycle that we refer to as the chicken and egg problem: What drives urban growth? Jobs or city amenities? Do jobs attract amenities to the city, or do amenities attract companies (and their jobs) to the city? In between work and life, jobs and the arts, how does one decide where to live while taking into account work-life balance? As individual level decisions result in waves of migrants into cities, were those decisions made primarily based on the search for jobs or life-style amenities?

Both sides of this cycle happen concurrently, and they simply cannot be detached from each other: people move, businesses are created, and amenities are developed all at the same time. For a sociological study, they should all be observed together across time. In this research, we analyze the development of arts amenities and jobs in the US and aim to understand the dynamics of the two over a span of sixteen years.

This research suggests that indeed individuals consider all factors simultaneously when choosing where to work and live. To be sure, individuals have different tastes and seek different options. For example, people may choose between the option of a job in a remote and small city with higher wages and a low cost of living and a job in a cosmopolitan city with lower wages and a high cost of living. Unless there is a strong personal preference for remote places or a particular economic need, most people choose to move into the bigger cities where they can also find more diverse types of amenities and opportunities for work and entertainment (Rosen 1979; Roback 1982). The simple fact that urban population has increased steadily in the past several decades is evidence of this movement.

In this chapter, I introduce the current sociological literature that informs this study. In some parts, I explore beyond the theoretical limits of the empirical section, as the literature in this field of study is wide and generous. This chapter is divided into four main sections. I start by citing important works on migration and preferences, and follow this with views of arts districts as an urban development strategy. We then move to the production and consumption of the arts, and finally, the relationship between arts to business services and high-tech industries.

1.2 Migration and Preferences: The Underlying Forces of Economic Growth

This dissertation examines the interrelations between artistic activities and economic development in urban areas. People choose where to live and work, and places offer unique combinations of amenities that attract people. The underlying force is migration, as migration propels cities to grow in both population and economic activity. In this section, I discuss some of the literature regarding the role of migration in economic growth in the classical, human capital and amenities perspectives.

In the classical view, people moved to cities to escape poverty and work in new manufacturing industries. Adam Smith argued in the *Wealth of Nations* that poverty and unemployment were major push factors that led people to leave rural areas in favor of employment in nascent industries (Smith 1786; Rauhut 2010). Thus, in post-industrial revolution countries, jobs were created first, and then people followed. The relatively free mobility of labor allowed for a speedy balance between labor force and production demands. Thus, factories were built in cities, creating employment and attracting people from rural areas for those jobs in manufacturing.

About two hundred years after Smith's *Wealth of Nations*, Muth's (1971) chicken and egg analysis suggested that "migration not only affects but is affected by employment growth" (Muth 1971, 298), indicating for the first time the reciprocal effect between migration and employment. People migrate to areas that offer employment opportunities, and at the same time, employment grows in areas where people migrate to, in a chicken and egg pattern. Just like Adam Smith argued, Muth pointed to the reciprocal relationship between migration and employment, with employment still being the main reason for migration rather than human capital or amenities.

It is important to point out that Muth's analysis is based on the 1950s, a decade when (1) manufacturing was still the fastest growing industry; (2) migration was a phenomenon happening primarily from rural to urban areas or from urban to suburban areas, but not so much among urban areas as migration after the 1990s; and (3) arts, entertainment, and tourism did not yet have central roles in the urban planning and development strategies of cities. In 1971, when the article was written, the major focus of Muth's academic analysis involved traditional variables such as employment numbers, industry growth, unemployment rates and income. It did not yet consider lifestyle choices, tastes, preferences, nor the arts and cultural industries. In other words, studies still concluded that people moved from rural areas to post-war industrial cities seeking first and foremost employment in manufacturing. But at this time, migration was seen as affecting where new industry jobs were created. Thus, in the classical view, employment comes first and people follow.

The arts started being applied as an urban development tool in the mid-1960s as a strategy to revitalize declining city centers and run-down neighborhoods in urban areas. This was an effort to attract and keep a population that was steadily moving to the suburbs. The establishment of the National Endowments for the Arts (NEA) together with the rise of federal and corporate support for the arts led to bigger efforts for "arts-centered" urban strategies to be put in place in order to spur growth and development in central areas (Markusen and Gadwa 2010; Goody 1984). Since then, the arts started gaining importance as a driver of population and economic growth rather than just employment itself (Perloff 1981; Whitt 1987; Frost-Krumpf 1998; Galligan 2008; Shkuda 2015).

In an article from 1987, Whitt (1987) noted that "the performing arts are becoming an important part of the urban growth machine, a development not yet recognized by social scientists" (15). In other words, it was only in the late 1980s that the social sciences started considering the role of the arts sector in urban development, two to three decades after the initial investment and growth of the arts in urban revitalization. Instead of moving to cities to escape poverty and seek better wages (Kundu and Sarangi 2007), people were able to choose to move to locations that better fit their lifestyle and personal interests. This was a strong indicator of a country that managed to improve the quality of life for many people in its population.

Over the past three decades, scholars have been arguing that people move for reasons other than just employment, but that lifestyles, recreation, and personal preferences play a role in individuals' decision making when moving from one urban area to another. Simultaneously, the human capital centered perspective argues that firms operate from urban areas that provide the best labor force and talent for their businesses. Hence, in the human capital approach, people move first and employment follows the labor force (Currid 2009; Fullerton and Villemez 2011; Gabe and Abel 2011).

However, if people decide to move to cities, what attracts them to one city instead of another? A large body of literature from the past thirty years presents a consensus that arts and cultural activities are important factors in attracting talented and highly educated people to urban areas. Many scholars have come to similar conclusions through different analyses, but with subtle differences.

In an article from 1993, Treyz et al. (1993) suggest that migration is significantly related to "amenity differentials, relative employment opportunities, relative real wages, and industry composition" (Treyz et al. 1993, 209). In other words, migration is linked to the presence of a combination of amenities and economic opportunities that make a city more attractive for new migrants. Even though Treyz et al. (1993) consider in their analysis the components that are central to this dissertation (i.e., amenities, industry composition, and employment), they mainly analyzed correlations. However, they did not specify exactly what kind of amenities, or the type of employment opportunities and industries, or where this phenomenon happens.

In a study about the occupational consequences of migration for white and black men from 1995 to 2000, Flippen (2014) suggests that "migration boosts occupational attainment for both black and white men regardless of the regional direction of the move and net of personal socioeconomic characteristics" (Flippen 2014, 56). She also suggests that we take a careful look at the context of the receiving and sending locations. For example, places with more arts activities attract more residents, but did the urban area of origin offer as much art as the destination? In this dissertation, I do not focus directly on the origin or direction of each migration event, but instead, I use the growth of both arts and economic activities in the final destination as an indicator of that migration. For example, the growth of arts in a city is determined by an increase in the number of those employed in the arts industry, regardless of the origin of the new artists, whether from a nearby town or from another region in the country.

Chen and Rosenthal (2008) and Gabriel and Rosenthal (2004) suggest that young and older adults prefer different types of places: workers and firms tend to be attracted to denser and growing cities with thicker job markets, while households in retirement ages prefer to move to non-metropolitan coastal locations that offer more natural amenities illustrating that "households seek to maximize utility while firms seek to maximize profits" (520). In addition, young college graduates move towards cities favorable to businesses and career advancements where they increase their chances of finding a field-specific job and a broader networking community.

Rappaport (2007) argues that people move to areas that would improve their quality of life, whether that improvement comes in the form of amenities (such as beautiful landscapes, low pollution, and warmer weather) or better economic opportunities. Quality of life improvements may be so significant for some individuals that they may be willing to indirectly pay to enjoy a certain location in the form of higher costs of living, higher taxes, and a decrease in relative income (Rappaport 2009, 2007).

The migration described thus far seems to be more easily realized by the highly educated, professional class as costs of moving are high, which may lead us to believe that people from lower classes are not able to migrate based on amenities or lifestyles. Thus, they suffer from more constraints when moving and remain tied to their residence or place of origin (Logan and Molotch 1987). While this may be the case for many individuals, foreign immigrants who are trying to escape poverty in their own country may find employment and housing more easily in areas where they are able to find ethnic communities, even under financial constraints, although this may be considered a racial and ethnic segregation issue (Havekes, Bader, and Krysan 2016; Ellis, Wright, and Parks 2004).

Ethnic neighborhoods in major urban areas are the destinations for migrants who chose a place that provides them with preferred and familiar amenities—for example, things related to their heritage, culture, and community, thus allowing them to feel more at home. This is evident in many Chinatown neighborhoods in many cities in the US, as well as Indian neighborhoods in Canada and England, and Latin American communities in New York and Chicago. Therefore, choosing where to live based on preference is achievable to individuals in many segments of the population and not just the high and creative classes.

In summary, there are many reasons why people migrate, and it is not just limited to employment. The main reasons for moving besides economic opportunity discussed in this section include a nicer climate, quality of schools, housing availability, community, and arts and cultural amenities. Each person has their own personal preference for one type of place over another. And as cities compete for human capital, employment, and industry, the dynamics taking place affect the overall outlook of urban development.

1.3 The Arts and Cultural Districts as an Urban Development Strategy

The importance of the arts in society is indisputable, as the arts provide enjoyment, empowers creation and self-expression, displays the local culture, documents history, and serves many other purposes. The arts are especially important for the central city as it helps revitalize neighborhoods, connects communities, contributes to the charm of a place, and provides employment in the arts and other industries (Markusen and Gadwa 2010; Perloff 1981; Kay 2000). There are many mechanisms that contribute to the growing importance of the arts, but in this research project, we focus on a more general outlook on the places where the arts are created, shared, and enjoyed, as well as how the presence of the arts in those places attracts and are attracted by other industries.

One way cities implement their arts-centered revitalization strategies is by increasing investment in their arts or cultural districts. The cultural or arts district in a city is "a well-recognized, labeled, mixed-use area of a city in which a high concentration of cultural facilities serves as the anchor of attraction" (Frost-Krumpf 1998, 10). In other words, cultural districts are geographically defined areas where a variety of arts and entertainment institutions can be found. Cultural districts are generally located in city centers, easily accessible by public transportation, and places where large gatherings attend "specialized landscapes that typically feature high culture or fine arts" (Frost-Krumpf 1998, 11). They feature concert halls, theaters, galleries, and art museums. However, other types of establishments that largely contribute to the artistic environment are historical museums, educational institutions, libraries, restaurants, nightclubs, and popular entertainment, such as music venues.

Cultural districts usually attract a mix of office, retail, and residential space. In addition, other city amenities, such as historical features, convention spaces, and natural amenities, are often found far away from the cultural district, but still contribute to the cultural environment of the city. All these elements contribute to a sense of place (Galligan 2008) by expressing and defining the local culture, reflecting the city's unique environment, history, and cultural development (Frost-Krumpf 1998).

There are many types of cultural districts that can be identified in American cities, according to Frost-Krumpf (1998). "Cultural compounds" are areas removed from the business districts, surrounded by parks and/or housing, and with high concentrations of museums, world-class performing halls, and theaters, such as the National Mall in Washington, DC. Cultural districts with a "major arts institutions focus" aggregate both large and smaller arts institutions in a particular cultural genre located near the business district, such as Times Square in New York City. Cultural districts with "arts and entertainment focus" look to the younger population and offer a bohemian atmosphere, with smaller and privately owned arts establishments, such as the Gaslamp Quarter in San Diego, CA. Cultural districts with a "downtown focus" are located in the business district and include major arts institutions, historical landmarks, and cultural establishments such as restaurants, parks, and music venues, as in the Loop in Chicago, IL. And cultural districts with a "cultural production focus" are clusters of arts production establishments, such as music, television and movie production studios, as in Culver City, in the Los Angeles metropolitan area.

The type of cultural district may be defined organically or planned, depending on the cultural environment and strategy of the city. Therefore, Grodach et al. (2014) point out that arts policies need to be place-specific. Thus, cultural districts in the largest urban areas may look more similar to each other compared to cultural districts in smaller urban areas, which may offer more local experiences. This is because the mix of cultural institutions in larger urban areas tend to focus more on world-class orchestras, opera houses, and art museums while the mix of cultural institutions in smaller urban areas tend to be more location specific, according to the local amenities, history, and cultural environment.

Seifert and Stern (2005) point out that investing in existing clusters is more cost effective than starting a cluster from scratch, especially if the cultural clusters identified present different types of institutions and are undergoing demographic and cultural changes. The ideal areas for cultural districts are those where both production and consumption of the arts may happen at the same time; this argument is further detailed in section 1.4.

As a strategy to promote cities, cultural districts may be permanent or temporary, depending on the city's strategic goals (Seifert and Stern 2005; Galligan 2008). Some goals of cultural districts are to (1) revitalize a particular area of the city, (2) offer evening activities, (3) make an area safe and attractive, (4) provide arts facilities, (5) provide employment and housing for artists, and (6) connect the arts with the community (Frost-Krumpf 1998; Phillips 2004).

Blau (1989) argues that investment in the arts are safe investments for cities that want to attract other industries. In other words, cities that invest in museums and an opera house attract new residents and visitors, corporate headquarters, and the establishment of new companies, creating more jobs for the region at low risk. Blau (1989) also emphasizes that while the high arts investments are often associated with large metropolitan areas, the top cities in development of high culture are not the biggest cities, but smaller cities throughout the US. These cities invested in the arts with the goal of attracting companies and industries, which would then create new jobs for the local population. Thus, if smaller cities are also receiving arts investments aimed at increasing the number of jobs in all of their industries, then it makes sense to do an analysis of the development of arts in the entire US and not only for the largest metropolitan areas.

Cultural districts are demographically more diverse, specifically regarding ethnicity, national origin, and a young, college-educated population. However, cultural districts also require financial and long-term commitments from local individuals and governments in order to develop. Also, cultural districts require infrastructures in place in order to be established and sustained, such as safety, street traffic, and easy connection to other parts of the city through public transportation, allowing participants to easily visit the area (Stern and Seifert 2010; Perloff 1981; Seifert and Stern 2005; Brooks and Kushner 2001).

Arguably, the arts districts are the most distinct areas of a city as they are natural destinations for both visitors and locals alike. However, as people, goods, and ideas commute around the urban area, the benefits of the arts may leak to neighboring areas. An art enthusiast may choose to move to a neighborhood next to the cultural district and equally enjoy both areas of the city. Similarly, different urban amenities are distributed in different areas of the city: while the layout of cultural districts make them accessible by foot, parks and historical monuments may be located where space is more abundant.

However, in some cases, systematic investments in the arts and amenities for revitalization of specific areas might result in what some researchers point to as *gentrification*. As a generic and loose example, an artist moves to a loft in a neglected building in a run-down but central neighborhood in a major city. This artist then assumes the role of not only resident but also of investor and architect, remodeling and changing the look of the building. As many artists move to the same area and do the same for different buildings, a community is formed. The local changes function as indicators of future development, attracting real estate developers and investors, increasing rent prices that can only be afforded by the upper-middle and high classes, eventually driving out the artistic community that first established and changed that neighborhood (Shkuda 2015; Galligan 2008). This type of gentrification is the result of accelerated growth and development rather than displacement and class tensions, as indicated in a well-studied case of Soho in New York City by Currid and Williams (2010) and Mathews (2010).

Gentrification is a double-edged sword that rehabilitates deteriorated parts of the city through the construction of new amenities, preservation and restoration of historic buildings, and execution of new commercial and residential projects. On the other hand, the consequences of gentrification may be the displacement of the existing population—especially the lower classes—through increased rent and property taxes, and the standardization of central areas by economic institutions and policies (Zukin 1987).

The arts as an urban planning strategy brings many benefits, such as more employment and population, revitalization of neighborhoods, and economic and social prosperity. At the same time, there are some negative consequences that need to be taken into consideration, characterized by the displacement of the population and loss of housing.

1.4 Production and Consumption of the Arts

The romanticized version of the starving artist who produces art despite poverty and a lack of resources is nothing but a myth, as poverty deprives artists of time, energy, and equipment (Baumol and Bowen 1965). In the same way that Van Gogh needed his brother Theo as his sponsor for living costs and painting materials, artists also need the resources required to create and produce their artistic products. As in any other industry, the arts materialize through production, to be ready for consumption. Also as in any other industry, the arts need input to generate output, but in the case of the arts, artists create in creative, unique, and innovative ways each time. Thus, in the arts industries, the artists are the producers and the public is its consumer.

In this dissertation, arts and culture are materialized and counted as any goods and services that produce or are consumed for the purposes of the arts, entertainment, and recreation. They are taste-driven, in the highbrow, lowbrow, and omnivore senses (Currid and Williams 2010; Bordieu 1984; Peterson and Kern 1996). Scott (2004) describes cultural-product industries as those industries from which outputs are focused on entertainment, edification, and information, which includes motion pictures, music studios, publishers, and print media.[1] He also points to the manufacturing of products for self-affirmation and individuality as cultural-product industries, but in this study, these industries are aggregated into the manufacturing categories as they are harder to identify and isolate.

The production of art is realized by artists with equipment, raw materials, and time. The consumption of art may happen simultaneously during its production (i.e., live and in front of an audience, such as in the performing arts), or posterior to production, as in cultural products such as books, recorded music, and movies (Scott 2004; Throsby 1994; Blau, Blau, and Golden 1985). The experience of the performing arts is also more collective, while cultural products may be

[1] "Cultural-products industries can thus be identified in concrete terms as an ensemble of sectors offering (1) service outputs that focus on entertainment, edification, and information (e.g., motion pictures, recorded music, print media, or museums), and (2) manufactured products through which consumers construct distinct forms of individuality, self-affirmation, and social display (e.g., fashion clothing or jewelry)" (Scott 2004, 462).

consumed in more intimate settings. Similarly, performing artists need to live where their audiences are, while non-performing artists may live anywhere they please.

Bordieu (1984) separates individual taste distinctions according to different levels of appreciation of the type of art, such as classical music and paintings. The individuals who appreciate art that is not their primary type, according to Bourdieu's expected classification, are considered cultural omnivores, in an analogy to the biological concept. Peterson and Kern (1996) also define different levels of cultural consumers as highbrow, middlebrow, and lowbrow. They proceed to explain that "among highbrows, the snob is one who does not participate in any lowbrow or middlebrow activity, while the omnivore is at least open to appreciate them all" (Peterson and Kern 1996, 901).

The rigor of the traditional arts (for example, classical music, opera, European paintings) in form, expectation, and conformity makes the investment in the type of art safer, as the traditional forms have a general format to be followed and even known costs and return on investments. Thus, traditional arts are safer to implement and maintain than, for example, alternative and new art forms (new bands, pop music composers, new artists), which require the spontaneous and daring creativity of local artists. This also depends on the local Zeitgeist to be executed and is thus more variable in terms of continuity and investment. Hence, if a city government invests in a classical music orchestra, the enthusiasts of this type of music will have a certain expectation of the performance of that art, and upon succeeding in delivering the performance, the orchestra can be said to be a success. However, the expectation is not the same for the alternative arts as it is hard to anticipate. Although the alternative arts may be equally or even more influential in attracting young, talented people to the city who search for a type of entertainment that differs from traditional forms often sought after by older generations. The point here is that in order to attract young, talented people, a city should not only invest in traditional art forms, but they also need to set the artistic ground for contemporary types of art to flourish. Thus, individuals might feel compelled to accept other forms of art other than high culture if they are offered different options. This choice-option structure allows one to combine different interests that form individuals' personality and networks, providing them with the right amount of stimuli to act blasé, indifferent to whatever is not of their personal interest (Simmel, 1994a, 1994b). At the same time, they learn to tolerate the presence of things that are not of their interest or that might be strange to them, but that will compose an overall diverse urban environment. Eventually, they may even get interested in a type of amenity that they were not interested in before.

An arts system includes not only the artists but also the arts-supporting institutions and the community (Perloff 1981). The production and consumption of the arts are interrelated: the arts are produced and consumed in higher intensity in cities, where a variety of supporting services for the production of the arts are available. For example, an orchestra may be seen mainly as a group of musicians and a maestro performing classical music before an audience. However, an entire behind-the-scenes crew is necessary to produce a classical music concert in its entirety, from the box office attendants to marketing managers, musical instrument specialists and tuners, stage managers, and accounting and legal services. This division of labor in the production of the arts is well detailed in Becker's book (2008), in which an "art world" is constituted by "all the people whose activities are necessary to the production of the characteristic works which that world, and perhaps others as well, define as art" (Becker 2008, 34).

The occupations supporting the arts differ in their connection to the main arts occupations as they either work with the arts directly from within the same organization or from outside of it. Stage managers and box office attendants might be directly employed by the orchestra hall, but the marketing campaign might be done by an outside advertising and press agency, as do the specialists who take care of the orchestra's musical instruments, who might work in their own shops and offer services to the orchestra. Therefore, not only are the artists involved in the production of art, but also several other types of occupations and organizations are involved in that production. Caves (2003) describes well the relationships among artists and other agents in the arts industries by detailing the contract deals between musicians and their music studios, actors and their agents, and so on, and how these different agents are legally and operationally bound to each other.

For Clark and Ferguson (1983), production and consumption of the arts co-constitute each other, and in the simultaneous choice of workplace and lifestyle, the work becomes more similar to one's lifestyles, especially for the self-employed and highly skilled professionals. Thus, "people select a location for many reasons, including amenities, and once they are there, they contribute to the character of the place, including its scenes" (Silver and Clark 2016, 64). Regardless of the industry in which an arts-enthusiast or hobbyist works, they are more likely to choose a place to live where they are able to pursue their interests in order to maintain a lifestyle that includes arts and culture establishments as options.

The production of art is also part of the consumption of the arts in two ways: first, production is essential for services such as live performances and curating art exhibitions; second, arts-producing industries are employers of people who are inclined to be interested in the arts. Therefore, locations that have a high concentration of arts-producing establishments also have a population that is more likely to consume more art (Markusen and Schrock 2006). For example, consider now a recording studio that employs music specialists who enjoy music and perhaps other types of arts. As these specialists most likely live in the city where they also work, during their free time, they are very likely to take time to appreciate local art for the convenience of going to amenities closer to their homes. Thus, they would appreciate the easy access to concert halls, art galleries, local coffee shops, and bars. The presence of people who are interested in the arts as producers increases the number of people who frequent arts and cultural amenities as consumers.

These differences account for the different arts categories analyzed in this study: The performing arts and other entertainment that is time-consuming and have a direct relation to their consumer are considered as *arts amenities*; the industries that produce cultural products are considered *arts producers*; and the industries that supply participatory and physical activities are considered *recreation*. This is detailed further in chapter 3.

1.5 The Arts, Business and High-Tech Industries

In Marshall's agglomeration theory, firms aggregate around each other to benefit from the local exchange of goods (i.e., supply linkages, and I add here producer services), people (i.e., local labor market), and ideas (i.e., knowledge spillovers) (Marshall 1890; Ellison, Glaeser, and Kerr 2010; Potter and Watts 2011). Therefore, even in the era of telecommuting, geography still matters (Pratt 2000). Industry clusters help to better match workers to firms, facilitating job mobility between and within industries and improving both performance and wages. Wages are higher in places with local labor market agglomerations that attract high levels of human capital (Fullerton and Villemez 2011).

Larger urban areas benefit from a more diverse combination of professionals and occupations, as service jobs concentrate in larger cities while manufacturing and non-service jobs are in less concentrated areas (Desmet and Fafchamps 2005; Glaeser and Resseger 2010). A high concentration of service jobs and skilled labor in larger urban areas leads to human capital agglomerations in both quantity and quality. This environment leads to knowledge spillovers, in which knowledge and ideas are passed through a network of interrelated actors helping in the development and growth of industries. Thus, high-technology companies present a special case of knowledge spillovers as it benefits from geographical agglomeration more than other industries. As a nascent industry, stronger networking and knowledge exchanges between high-tech workers advances the industry further than if they were set far apart (Markusen 1983).

Industries that benefit from sharing information in person, building a professional network, and quickly exchanging ideas are more dependent on the geographically located network than industries from which knowledge is shared from more centralized systems (such as the medical field, which obtains the latest research through centralized systems rather than networks and word of mouth) (Gabe and Abel 2011). Another example of industry that highly benefits from knowledge spillover is the movie production industry as a tightly knit network of people exchange ideas and talent for new movies and shows more rapidly if they are closer together than if they were far apart. In some cases, geography is critical for knowledge exchange, especially in the high-tech and movie industries. Then the industries themselves may be a sufficient reason for people to move to where these companies are located. In other words, people may move to San Francisco and San Jose to work in high-tech, or to Los Angeles to work in movie production as the primary reason, while urban amenities become their secondary reason (Feldman and Audretsch 1999; Simon and Nardinelli 2002; Glaeser et al. 1992; Moretti 2010, 2012).

I mention above the benefits of geographical agglomeration for the movie industry, but the same rationale may be applied to the other artistic industries. Currid and Williams (2010) argue that the consumption of arts and culture is not spatially random, and that the status of a cultural place is reinforced by iconic sites, buzz, and cultural goods. Therefore, as places become known as cultural clusters, they tend to grow their reputation even further as a cultural cluster, increasing ΩΩΩeven more the arts concentration in the cluster.

Considering the industry dynamic outlined above, we establish that firms in both the arts and non-arts industries aggregate around each other to benefit from supply linkages, local labor markets, and knowledge spillover. But how can we understand the impact of the arts industry on the non-arts industries and vice versa?

Two concepts help us quantitatively understand the impact of the arts on employment. The first concept is the *artistic dividend*, or the income stream for having arts activities in a host community, usually measured in dollars. One example of the artistic dividend is the dollar estimate of income to a region if a festival or event took place. In other words, the artistic dividend would estimate how much visitors spend not only on the event itself but also on food, hotels, transportation, and other supplemental costs. The second concept is *arts multiplier*, or the number of non-arts-related employment that one arts job helped create. One example of the arts multiplier is the number of jobs created in hotels, restaurants, and transportation if an additional arts venue or park were added to a location (Markusen and Schrock 2006). In the empirical chapters, I use the concept of arts multiplier to interpret the regression results, and do not use the concept of artistic dividend in this project.

Many studies attempt to answer these questions, but in specific and different contexts than the study I present in this dissertation, which I summarize below.

Moretti (2012) focuses on the multiplier effect of the high-tech industry in Silicon Valley, in which one high-tech employee generates a multiplier effect of five times in other occupations, such as baristas, doctors, and taxi drivers; in other words, one high-tech job would generate up to five jobs in these other occupations. He also argues that the high-tech industry has a multiplier effect of three times on manufacturing. Moretti's study, while groundbreaking and valuable, focused on the benefits of the growth of the high-tech sector on other service industries that cater to the lifestyle of high-tech workers in general, and not so much on the arts themselves.

In a study focused on Canadian cities, Polèse (2012) could not detect a relationship between arts and jobs, with the exception of the two largest Canadian cities, Toronto and Montreal. He indicated that except for the largest cities in Canada, the arts are not important in generating jobs and vice versa. Similarly, Whitt (1987) argues that the arts promote competition among cities, and that elite cities (i.e., richer cities that can invest more heavily in the arts) fare better.

Also in Canada, Ferguson et al. (2007) compared amenities in rural and urban areas and found that both amenities and economic factors are important to attracting highly skilled workers to urban areas, while only economic factors were significant in attracting population to rural areas. On the other hand, Deller et al. (2001) found that amenities are important to attracting more people to American rural areas.

Gapinski (1981) found that attendance at arts events is related to income, age, and education level, intersecting with the creative class. The creative class occupations consist mostly of artists, entertainers, writers, engineers, and other professionals. (Florida 2002) The creative class encompasses those whose work is related to generating innovative ideas, technologies, and creative content. The creative class's talents are desired in many different places, especially on locations of high specialization, such as Silicon Valley, Hollywood, and Wall Street (Storper and Scott 2009; Storper 2013).

In addition, Flippen (2014) also argues that "migrants are more likely to work in high-skilled and professional occupations and have occupations with higher prestige than comparable individuals who did not migrate, even net of human capital characteristics and selection into migration" (55). For example, Hart and Acs (2011) argue that in 16 percent of high-tech companies, there is at least one foreign-born founding member. Thus, as we count the employment numbers by industry in the empirical chapters, we implicitly include foreign immigrants that work in those industries, especially because these special cases are not detectable from the census dataset.

A more educated and wealthier population leads to the increasing importance of high-end and innovative city amenities, especially those that require a large population base in order to support their fixed costs. These include world-class museums, aquariums, concert halls, and so on, as well as smaller establishments such as coffee houses, underground theaters, and dance studios (Glaeser 2009; Storper and Scott 2009; Moretti 2012). Not only are these workers patrons of the arts and entertainment establishments, but they also work for the corporations that donate to art institutions.

In the past twenty years, customers have become interested not only in the products and services a firm provides, but also in their ethical core values. Some businesses respond to their consumers by financially supporting initiatives outside their industry and different from their main mission in order to show corporate social responsibility. One common approach is the support of arts and cultural organizations, which may be considered by some as strategic philanthropy (Kirchberg 1995; Withers 1980; Epstein 1989; Stead 1985). Regardless of the altruistic nature of the patronage, this strategic approach brings the arts and businesses together, from sponsorship to marketing strategies to more involved partnerships—so much so that the arts are said to have three main sources of funding: government (30%), foundations (34%), and corporate (36%) (Goody 1984). In other words, businesses are not only sponsoring the arts by creating a positive association with artistic and cultural organizations, but they are also forming close partnerships with arts and culture organizations as a strategic indicator of their values by financially supporting the arts significantly (McNicholas 2004; Leclair and Gordon 2000).

However, the relationship between businesses and arts go beyond philanthropy and charity to the urban synergy that surrounds and attaches both industries together. In major cities, the cultural and business districts are often geographically located near each other. In Chicago, for example, the Loop houses both cultural and business districts together, where financial operations coming from the city happen near the Art Institute of Chicago and the Lyric Opera. To be sure, other neighborhoods also have banks and retail shops near theaters and music halls, but the magnitude of the artistic operation and business conducted in the Loop are of global proportions and much higher relative to the business conducted in other neighborhoods in the same city.

While both local and global business are an important part of the life and economy of a city, corporate arts support is higher where more capital to be donated is available, which also coincides with areas where the population is highly educated, where the local service sector generates more income, and where the local manufacturing sector generates less income. On the other hand, the arts depend financially on corporate and government giving, so when the revenue of other industries that support the arts drops, donations to the arts also drop, increasing the risk of a loss of financial support for the arts (Kirchberg 1995).

In conclusion, the arts, business services, and high-tech industries have a strong synergy as they share the same areas, communities, and interests. In the empirical section of this dissertation, I differentiate between the business services and high-tech industries from the non-arts industries in general in order to understand more specifically their symbiotic relationship to the arts.

1.6 Plan of the Dissertation

Following this discussion on the current state of the field, this dissertation has two methodological chapters, two empirical chapters, and a conclusion. The outline below summarizes the topics addressed in the next five chapters.

Chapter 2 discusses the geographical transformation of the data, from ZIP codes irregular in shape, size, and change, to evenly distributed hexagons. Topics presented in this chapter are:

- Types and characteristics of the official boundaries in the US, mainly urban areas, and ZIP codes;
- The processes of geographical transformations including overlapping, rearranging, and dividing urban areas and ZIP codes into a hexagonal grid, producing *slivers*;
- The changes in the relational descriptive statistics between ZIP code and hexagons;
- The process of calculating the weights of slivers for application on the dataset;
- And methods of quality control.

Chapter 3 presents the data sources, algorithms, and methodologies used to transform the raw data from the US Census Bureau into industry variables used in the empirical chapters, including:

- Descriptions of the US Census County Business Patterns and NAICS codes;
- Time series consistency issues due to changes in the industry classification system;

- Classification of industries for the purposes of this dissertation;
- Transformation of the raw data by combining the total employment and the detailed establishment datasets to estimate the employment number by industry and ZIP code;
- The process of applying the weights of slivers to calculate the employment numbers by industry and hexagon;
- Description of the statistical methods used in chapters 4 and 5, such as cross-lagged regressions and fixed-effects meta-analysis.

Chapter 4 analyzes the reciprocal relationship between arts and non-arts jobs in their highest level of classification. This chapter aims to understand the relationship between the two types of jobs by:

- Analyzing the shape of datasets, their correlations and outliers;
- Analyzing cross-lagged regression results in a nineteen-year period using only the first and last years in the dataset to establish a baseline model;
- Analyzing cross-lagged regression results in one- and ten-year periods, and changes between two years for a general understanding of the impact of time on the variables;
- Analyzing cross-lagged regression results by urban area using first difference models and the difference in results by urban area size;
- Analyzing cross-lagged regression results where the arts variable is replaced by its subcategories “arts amenities,” “arts producers,” and “recreation.”

The main research questions in chapter 4 are:

- Do people move to cities for jobs and the arts follow? Or do people move for arts and amenities and the jobs follow?
- What comes first, arts activities or employment?
- How, when, and where do the arts attract jobs? And how, when, and where do jobs attract arts?
- What is the impact of the arts on jobs and jobs on the arts?

Chapter 5 presents the same statistical analyses and methods as in chapter 4, but replacing the non-arts jobs variables by the business services or high-technology industry variables. In addition, this topic discusses the trajectory of industry growth in the US from 1998 to 2016 and the correlations among industries. The research questions explored in this chapter are:

- How do business services and high-tech industries differ from the general non-arts jobs analyses in relation to the arts?
- What is the relationship between business services and high-tech to the arts?
- Are the arts more influential on business services and high-tech? And vice versa?

Chapter 6 summarizes chapters 1 through 5, integrating the data transformation processes into the empirical results by combining the findings on the general non-arts jobs to the industry specific results for business services and high-tech.

CHAPTER 2

GEOGRAPHICAL DATA TRANSFORMATION: FROM ZIP CODES AND URBAN AREAS TO HEXAGONS

The biggest challenge in comparing secondary data across different regions in the country is the definition of the unit of analysis. The goal of this chapter is to redefine the sampling method to compare different areas in cities, while transforming the unit of analysis provided by the census. The analyses in this research depend on the local differences, such as the differences between downtown and neighborhoods in a city and between cities; the differences among commercial, industrial, and residential areas; and differences between growing and declining areas. Therefore, it is crucial to consider the connection between datasets and their geography to understand how industries interact with each other. To that end, I present in this section the sampling method used to create a correspondence table among different geographical entities into more comparable units of analysis. The shape selected for this task is the hexagon, as they tessellate without any loss of area. The main official geographical entities used in this study are the urban areas and ZIP codes, as urban areas and ZIP codes link data to location.

The US Census provides data based on standard territorial divisions that are built into a hierarchical structure of geographic entities. Due to non-disclosure guidelines, the census consolidates individual data into these units to prevent the identification of individuals or businesses at any level. The US Census also adds noise in this effort to avoid individual disclosure (Census 2019). As both urban areas and ZIP codes are defined under the same criteria in all states, these entities can be said to be comparable at the *national level*.

The final product of this chapter is a *"geographic correspondence table"* that connects each geographic piece to its corresponding urban areas, ZIP code, and hexagons that is then used to convert ZIP code data into hexagon data. The computational process of this chapter is summarized the flowchart in figure 2.1 and is expanded upon later in the chapter. We start the process with four maps: (1) the continental State boundary map, (2) the urban areas map, and (3) the ZIP code map for 2009, and (4) the ZIP code map for 2018, as available by the Census Bureau (Census 2009; Census 2018a). The first step is to produce a tessellation grid of hexagons over the entire country. Second, through a series of selections, we select the hexagons that intersect with urban areas and the zip codes that also intersect with urban areas. And third, we merge or intersect all the boundaries to find the smaller geographic unit among all units, which I call *slivers*. All areas are measured in *square kilometers*, and the final hexagons measure five square kilometers in area.

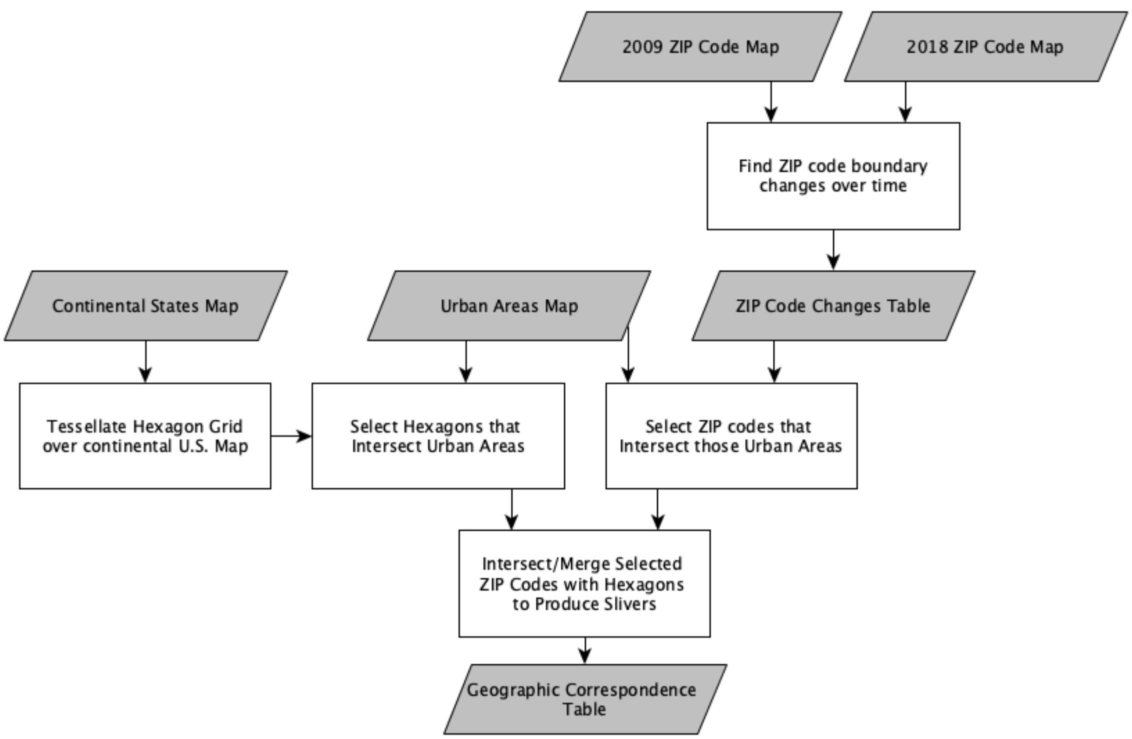

Figure 2.1: Workflow for the mapping process to transform ZIP codes into hexagons

A few GIS concepts should be outlined for this chapter:

- A **feature** is a point, line, or polygon that represents an object in space, to which variables and data can be assigned. For example, if we add a city as a point, its name, population size, and any other data may be linked to a feature.
- A **point** is a discrete location with specific x-y coordinates that locate them in space—for example, location of a business establishment.
- A **line** is a representation of objects that are too narrow to be represented as an area, such as a road.
- A **polygon** is the representation of areas, shapes, and locations of entities of data—for example, the boundaries of a country. A feature polygon can also be represented as a combination of smaller polygons but that share the same characteristic (e.g., an archipelago in the same ZIP code).
- A **centroid** is the center of gravity of a polygon, calculated as the intersection of all sides of the polygon.
- A **shapefile** is a set of files that store information about a map. Shapefiles require special software to open.
- **ESRI ArcMap** is the mapping software used in this project.
- A **map document** is a file that contains one or more layers of a working project.
- A **layer** is a single map in a map document. A layer can have the format of points, lines, or polygons.
- An **attribute table** is the data frame with information (columns) about each feature (rows) in a map (i.e., a table within the mapping software shows the relationship between features and data).
- A **projection system** is the method of representing a 3-D object into a 2-D plane; in this case, projection systems are methods of representing the earth onto a flat surface.

Before proceeding, I should briefly point out the importance of properly selecting a projection system, as each projection system is bound to cause some type of distortion, be it of shape, distance, direction, or area. Because the census dataset is fixed on their geographical entities, such as ZIP codes, counties, metropolitan areas, and urban areas, the projection system must prioritize area, with minimal area and shape distortions so that the sampling probability is preserved regardless of location (White, Kimerling, and Overton 1992). For the conterminous US, the projection system chosen is the *US National Atlas Equal Area* that uses the *Lambert Azimuthal Equal Area* projection method (EPSG:2163). This projection system preserves area with minimal shape distortion in the conterminous states. Due to higher radial distortions away from the center of the conterminous US, Puerto Rico, Alaska, and Hawaii are excluded from the analysis. The process of setting a project system to the maps is described in appendix A.2.

The data analysis in this dissertation involves dealing with several moving parts: geographic units, industry categories, types of variables, and statistical methods. These parts are built over US census data, which are freely available to the public for download. Over the years, I became familiarized with the data and maps required for this study. At first, the amount of information can be overwhelming; however, with detailed documentation and a lot of patience, it is possible to join the pieces together to produce a coherent and robust dataset to start answering the questions posed by this and future studies. When relevant, I indicate the commands used on ArcMap briefly in the footnotes and in the appendix for clarity and reproducibility.

In the first section of this chapter, I discuss how we produce the "geographic correspondence table," which is a table that connects identification numbers and characteristics of urban areas, ZIP codes, and hexagons as a reference for the dataset. In the second section of the chapter, I discuss the definitions of industry categories based on the North American Industry Classification System (NAICS) code structure. In the third section, I describe the main data source for this project, the US Census Bureau's County Business Patterns (CBP) datasets, which provides us with the number of jobs by industry data required in the other chapters. In the fourth section, I discuss the algorithm in R that transforms the census's raw data into hexagon format. Finally, in the fifth section, I discuss the statistical methods chosen for the analysis in the next chapters.

2.1 Urban Areas

One of the geographical units we use to link space to data is the US Census Bureau's *urban areas* (Census 2012). *Urban areas* are defined as the "continuously built-up area with a population of 50,000 or more" (U. S. Department of Commerce and Statistics Administration 1994, 12–11); *urban clusters* are those areas that account for between 2,500 to 50,000 people, and all other areas that are neither urban areas nor clusters are considered *rural* (Census 2017). The census delimits urban areas by tracking continuously built-up blocks that amount to at least one thousand people per square mile, and a minimum total of 50,000 people. Urban areas are more appropriate as the selection criteria for areas of study rather than metropolitan area boundaries because urban areas provide a more accurate location of urban activities as they take into account population density and continuity of built-up blocks. Metropolitan areas (CBSAs, or core based statistical areas) are defined as combinations of county boundaries, and therefore, also include small towns and rural zones without specific delimitation. Even though I focus the sampling on areas, the Census Bureau's delimitation of urban areas takes into account the population density from the 2010 decennial census, and therefore, urban areas also normalize for population.

From the 2010 US census urban areas map, we consider 481 out of a total 497 urban areas for analysis. The selection criteria for these urban areas were: (1) being an "urban area" (as opposed to "urban cluster" or "rural area"),[1] (2) being located in the continental US (thus, excluding Puerto Rico, Alaska, and Hawaii),[2] and (3) intersecting with the 2009 ZIP code boundaries.[3] These criteria were used to select urban areas from the census's urban area map using "selection by attribute" and "selection by location" commands on ESRI ArcMap.

The sizes and characteristics of the 481 urban areas vary greatly. Table 2.1 shows the descriptive statistics of the number of ZIP codes and hexagons associated with each urban area. On average, each urban area is associated with twenty-four to twenty-five ZIP codes and 181

---

[1] On the ESRI ArcMap, Selection > Select by Attributes > "UATYP10" == "U."
[2] Selected with the "select features" tool, and then saved as another layer.
[3] Selection > Select by Location > Select features from the 2009 ZIP code boundary map that intersect with urban areas.

hexagons, but half of the urban areas are associated with fewer than ten ZIP codes and fewer than ninety-six hexagons. This shows how strongly the top half of the urban areas stretches the distribution as seen in the histogram.

	N	Mean	Median	S.D.	Skewness	S.E.
Number of ZIP Codes	481	24.5	10.0	54.1	8.9	2.5
Number of Hexagons	481	181.4	96.0	262.2	4.8	12.0

Table 2.1: Descriptive statistics of the number of ZIP codes and hexagons per urban area

The histogram in figure 2.2 shows the distribution of urban areas by territory. The distribution is skewed to the left, showing that half of the urban areas have areas under 194km^2 with a spottier size distribution on the top half. In order to make the histogram easier to visualize, all urban areas with areas above 2000 km^2 are aggregated in one bar to the right side of the graph.

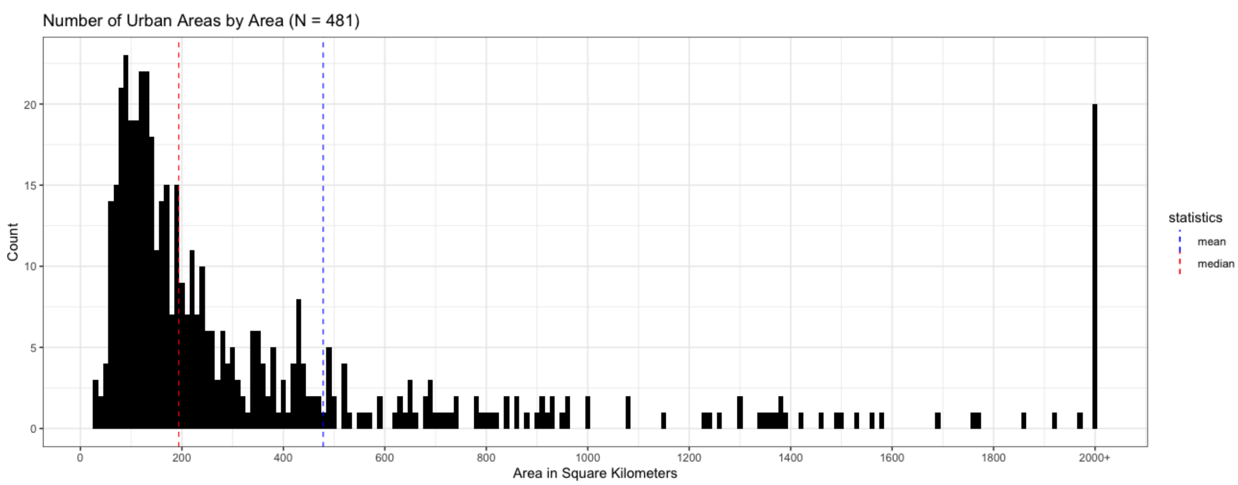

Figure 2.2: Histogram of the distribution of urban area sizes (in sq km)

The twenty urban areas with areas larger than 2000km^2 are listed in table 2.2, and ordered by area from larger to smaller. It is no surprise that the New York metropolitan area leads the list, with 9457km^2 and 841 ZIP codes. It is interesting to note that cities like Atlanta, GA, Dallas, TX, and Houston, TX, for example, have a large area but fewer ZIP codes in comparison to other cities due to the relative dispersion of those cities. We should note from table 2.2 that the number of ZIP codes does not increase evenly with the area of the urban areas as hexagons do. For example, Atlanta is the second largest urban area in area size but has only 158 ZIP codes, followed by Chicago, which is third in area but with 304 ZIP codes. ZIP codes account for population density in their areas; however, people interact with businesses beyond their ZIP codes, but according to the space and travel time to destinations. This is the main reason for this exercise of recalculating the data to fit hexagons rather than keeping the data in ZIP codes.

Urban Area	Area (sqkm)	Number of ZIP Codes	Number of Hexagons
New York--Newark, NY--NJ--CT	9457	841	2730
Atlanta, GA	6947	158	2001
Chicago, IL--IN	6423	304	1729
Philadelphia, PA--NJ--DE--MD	5254	320	1612
Boston, MA--NH--RI	5047	270	1716
Dallas--Fort Worth--Arlington, TX	4705	194	1373
Los Angeles--Long Beach--Anaheim, CA	4559	344	1220
Houston, TX	4393	163	1284
Detroit, MI	3549	180	1068
Washington, DC--VA--MD	3491	201	1054
Miami, FL	3407	178	879
Phoenix--Mesa, AZ	2983	117	850
Minneapolis--St. Paul, MN--WI	2872	143	772
Seattle, WA	2781	137	830
Tampa--St. Petersburg, FL	2693	113	887
St. Louis, MO--IL	2420	114	718
Pittsburgh, PA	2384	200	883
Cincinnati, OH--KY--IN	2063	102	623
Cleveland, OH	2013	88	694
Charlotte, NC--SC	2012	57	701

Table 2.2: Area, number of ZIP codes, and number of hexagons for the twenty largest urban areas

We should note that the number of hexagons is more highly correlated with the size of the urban area than with the number of ZIP codes, supporting the argument that hexagons help standardize the number of units of analysis associated with an area, neutralizing the fact that ZIP codes vary by density of mailing addresses, mostly regardless of distance. Table 2.3 shows the correlations among the three variables of table 2.2. When we isolate the twenty largest urban areas, we observe that the correlation between area and number of hexagons improves even more than for the overall urban area.

Variable 1	Variable 2	Correlation (All Urban Areas)	Correlation (Largest 20)
Number of Hexagons	Area	0.99	0.98
Number of ZIP Codes	Number of Hexagons	0.92	0.84
Area	Number of ZIP Codes	0.92	0.83

Table 2.3: Correlation between the number of hexagons to area and ZIP code

Urban areas are the base of the discussion in this dissertation, as the analyses are interpreted by urban areas after regressions are performed at the hexagon level. In the next section, I discuss ZIP codes and how we handle them.

2.2 ZIP Codes

The smallest unit in which the data is available is the *ZIP code* level. However, ZIP codes were created to define mail delivery routes by volume of mail and density of addresses rather than for urban analysis. In a way, ZIP codes standardize the data in the sense that areas with a higher density of addresses, businesses, or people are smaller than lower density areas. However, this does not reflect the way people move around in cities as we are not constricted by ZIP codes but by how far one is willing to travel.

For example, figure 2.3 shows the configuration of ZIP code boundaries in Midtown Manhattan, where many buildings have their own ZIP codes. Keeping count of businesses and employments within each building as presented by ZIP codes is assuming that all of those economic activities happen within the area of the building. However, this is a highly walkable area, where people circulate through many ZIP codes without noticing. Businesses and people, especially in places like Midtown Manhattan, flow over ZIP code boundaries to at least the nearby areas, if not the rest of the country or the world. Therefore, the decision to re-aggregate data from ZIP codes to hexagons is based on the distances people are able to travel.

To be sure, hexagons could have many configurations: hexagons could be bigger or smaller, and hexagon grids could have been placed over the continental US map using different coordinates and positioning. In order to simplify the interpretation of results, here I use hexagons of five square kilometers in area (about 1.93 square miles), and one single hexagon grid placement based on the continental US boundaries for all analyses.

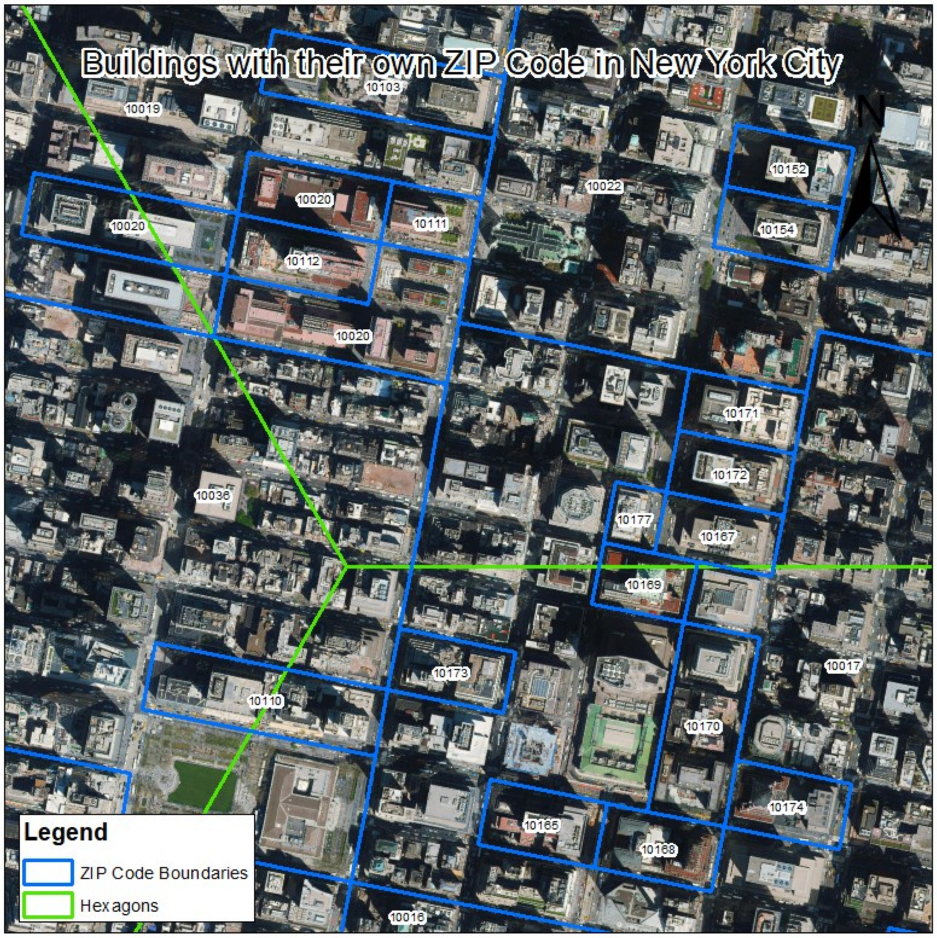

Figure 2.3: Example of ZIP code boundaries in high density urban area - Manhattan, NY

In this project, we focus on two types of ZIP codes: (1) *standard* ZIP codes, which refer to geographical areas where mail is delivered and to which businesses are registered and operate in, and (2) *unique* ZIP codes, which are assigned to large businesses, buildings, universities, and government agencies, or any address that handles high volumes of mail. New York City presents the highest concentration of unique ZIP codes, as is seen in figure 2.3. The Chrysler (ZIP code 10174) and the MetLife (ZIP code 10169) buildings are examples of unique ZIP codes in New York City. The ZIP codes related to post office boxes and military ZIP codes are not included here.

As noted in the previous section, urban areas are strictly defined by the census as boundaries of built-up areas that amount to 50,000 people or more. In order to reduce the data to the urbanized areas, we proceed to select ZIP codes that overlap with the census's urban areas. The intersect method retains ZIP codes that make contact with urban areas, regardless of the extent of the contact, to prevent loss of data at this stage.[4] Therefore, after the selection process by location and type of ZIP code, 11,200 out of 32,657 ZIP codes were selected by this method for this study, as shown in figure in appendix A.1, also available for interactive viewing through the ArcMap link.[5]

Figure 2.4 shows the histogram of the number of ZIP codes by area. The top histogram shows the counts for areas for all ZIP codes in the US, and the bottom histogram shows the counts for the urban ZIP codes selected for this study. The tail is longer for all ZIP codes as we observe a high count of very large ZIP codes. On the other hand, for the urban ZIP codes, the areas are much smaller with just a few being larger than 500 square kilometers. For all ZIP codes, half are smaller than 105 km^2, but for urban ZIP codes, half are smaller than 33 km^2.

---

[4] Selection > Select by Location > Select ZIP codes with source layer in the urban areas > method: "intersect the source layer feature" on ESRI ArcMap.
[5] See https://crissakamoto.com/maps.html for interactive maps.

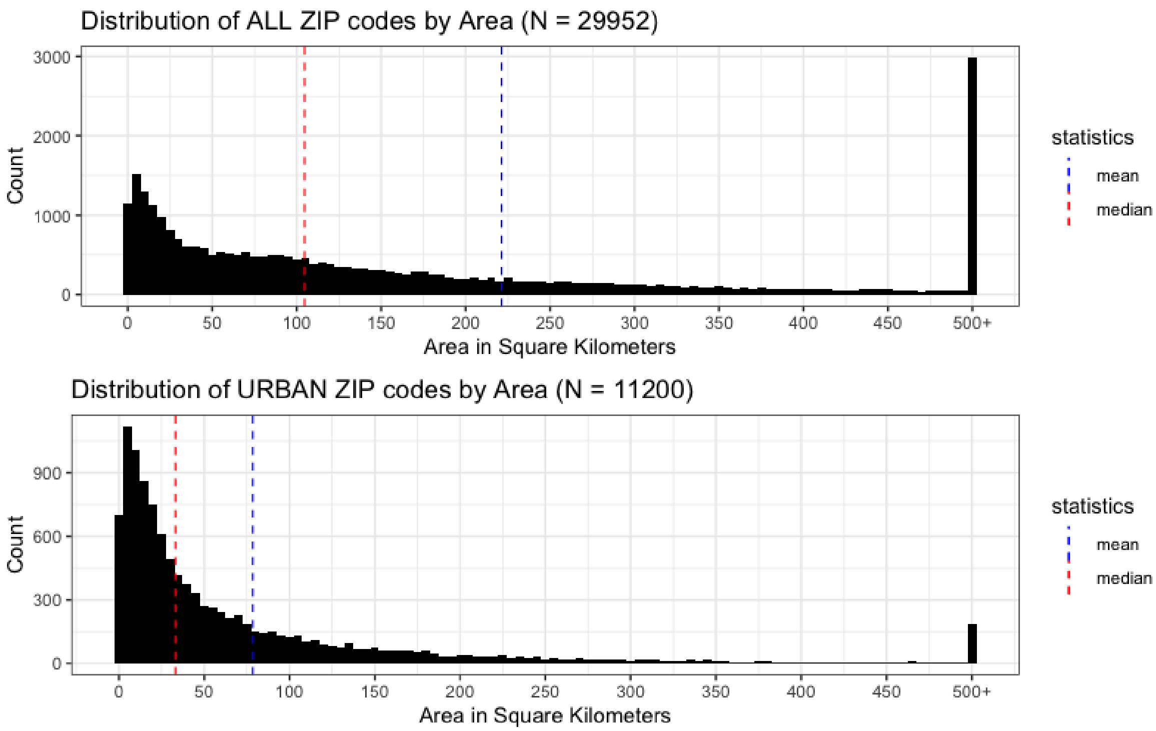

Figure 2.4: Histograms of the distribution of all ZIP codes and urban ZIP codes by area

Table 2.4 shows the descriptive statistics of the ZIP code sizes for both urban ZIP codes and all ZIP codes in the US. Urban ZIP codes are much smaller than ZIP codes in general, with a mean of $78km^2$ and a median of $33km^2$ as opposed to the average $221km^2$ and median of $105km^2$ for the general ZIP code. The variability of urban ZIP codes is also much smaller than for ZIP codes in general, both in standard deviation and standard error, even though the skewness is similar for both. These differences point to the fact that it would be harder to compare all ZIP codes at once and that making specific decisions on how we analyze them may improve the quality of the interpretations and results.

Comparing ZIP Code Area Descriptive Statistics						
Area in sqkm	**N**	**Mean**	**S.D.**	**Median**	**Skew**	**S.E.**
All ZIP codes	29952	221	431	105	8.131	2.5
Urban ZIP Codes	11200	78	145	33	8.48	1.4

Table 2.4: Descriptive statistics of ZIP code area sizes comparing all to urban ZIP codes

In this section, I presented ways in which considering the right ZIP codes improves the focus on this study. As the economic activities considered here are mostly urban, we select ZIP codes that intersect urban areas as defined in the previous section. In the next section, I present how changes in ZIP code boundaries may affect the dataset.

2.3 ZIP Codes Change All the Time

After a long time looking for urban ZIP codes and considering how to select them, I started running into issues of consistency in the time series data, especially because some ZIP codes would have data in later years but zeros in the first years. While most ZIP codes have kept their boundaries over the last two decades, a few ZIP codes had boundaries changed, and even a series of ZIP codes within cities changed their 5-digit codes over time. In this section, I discuss how ZIP codes change all the time and propose a simple solution to fix this issue between the 2009 and 2018 ZIP code maps. While some cities advertise major changes to let its citizens know when they happen, ZIP codes change at the discretion of the postal service, at different rates, times, and places. Thus, these changes do not happen in a scheduled or predictable manner. Accessing the 2018 ZIP code map was easier than the 2009 ZIP code map, but with both in hand, we were able to compare changes in ZIP codes over time.

ZIP codes are the smallest unit of many datasets provided by the US Census Bureau, and therefore, it is essential to identify and reconcile as many ZIP code changes as possible. In this study, we use data from 1998 to 2016, so the many changes that have happened during this period may affect the continuity of the data over time. Therefore, if we do not use caution with these changes, we may have consistency issues in the data even with the transformations into hexagons as the connection from ZIP code to hexagon may be broken in some years.

The main approach to connecting changes in ZIP codes is through mapping. Unfortunately, ZIP code maps are not expected or consistently published; therefore, the conversion was performed using two ZIP codes maps available on the TIGER/Line Census Website (Census 2009; Census 2018a). An ideal scenario would be to have nationwide ZIP code maps for the years required by our data to compare maps from specific years. However, lacking that kind of resource, the baseline map we use in this research was published in 2009, and we compare with changes in the ZIP code map published in 2018, two years from the last date of the data, 2016. However, I believe most changes are reflected in between these two maps. There are many reasons for ZIP codes to change, including:

- A ZIP code becomes so populated that it needs to be broken down in smaller areas to make mail delivery manageable again—for example, the 10021 ZIP code in Manhattan (see below).
- An area previously without a ZIP code (forests, deserts, parks, federal land, etc.) now requires a ZIP code because it was opened for development or has acquired population and addresses.
- Changes in boundaries—for example, the exclusion of a body of water. The 2018 ZIP codes include more areas of bodies of water, whereas the 2009 version were more tightly gripped to land boundaries, excluding water.
- Changes in boundaries by including a road or a row of blocks, which I consider a minor change here that does not necessarily require significant changes.

Table 2.5 shows the number of ZIP code changes from 2009 to 2018 for both urban and all ZIP codes. From 2009 to 2018, we have 1,089 urban ZIP codes that have changed. These changes (10 percent of ZIP codes) could definitely affect a research project if using time series data at the

ZIP code level, leading to missing data points. The urban ZIP codes also changed more than ZIP codes in general, with new ZIP codes being generated in urban areas more often than in other areas. Most changes seem to have occurred by the addition of new ZIP codes (97.5 percent for urban areas), while only 2.5 percent were results of code changes. A cluster of ZIP codes around Phoenix, AZ, had their numbers changed all at once.

Comparing ZIP code changes between 2009 and 2018

	All ZIP Codes	**Urban ZIP Codes**
Number of ZIP Codes in 2018	32657	11964
Number of ZIP Codes in 2009	29952	10902
- ZIP Codes that Didn't Change	29836 (91%)	10875 (90%)
- ZIP Codes that Did Change	2821 (9%)	1089 (10%)
-- New ZIP Code Number	2705 (95.9%)	1062 (97.5%)
-- Code Changes	116 (4.1%)	27 (2.5%)

Table 2.5: Number of ZIP codes and changes from 2009 to 2018

Figure 2.5 shows how ZIP code changes, if left as they are, could affect the data. The graph shows the progression of number of jobs by year from 1998 to 2016 for the ZIP code 10021 in New York City. This ZIP code was broken down around 2006–2007 into three ZIP codes. As we can see, if we keep the three ZIP codes separate, we would have two main issues when analyzing this data as a time series: (a) for the two new ZIP codes, 10065 and 10075, half the data would be seen as missing or zeros, when in reality, they have just been counted differently; and (b) there would be a decline in the number of jobs for the 10021 ZIP code, which is also not accurate for the same reason. The red line shows the sum of all three ZIP codes, which correspond to roughly the same area, as seen in figure 2.6. Therefore, we note an upward trend in the number of jobs in that ZIP code, which is consistent with the USPS decision of breaking down the 10021 due to higher population density in this period. This is the type of issue we try to avoid by carefully considering ZIP code changes in a time series analysis.

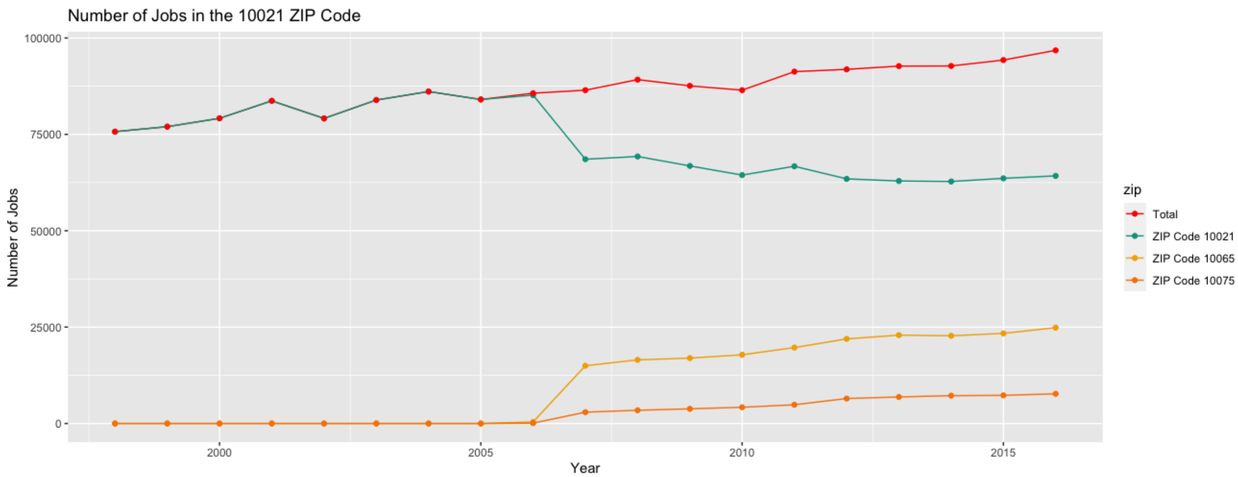

Figure 2.5: Example of the number of jobs as a ZIP code changed in New York City, when a ZIP code was broken down into three parts

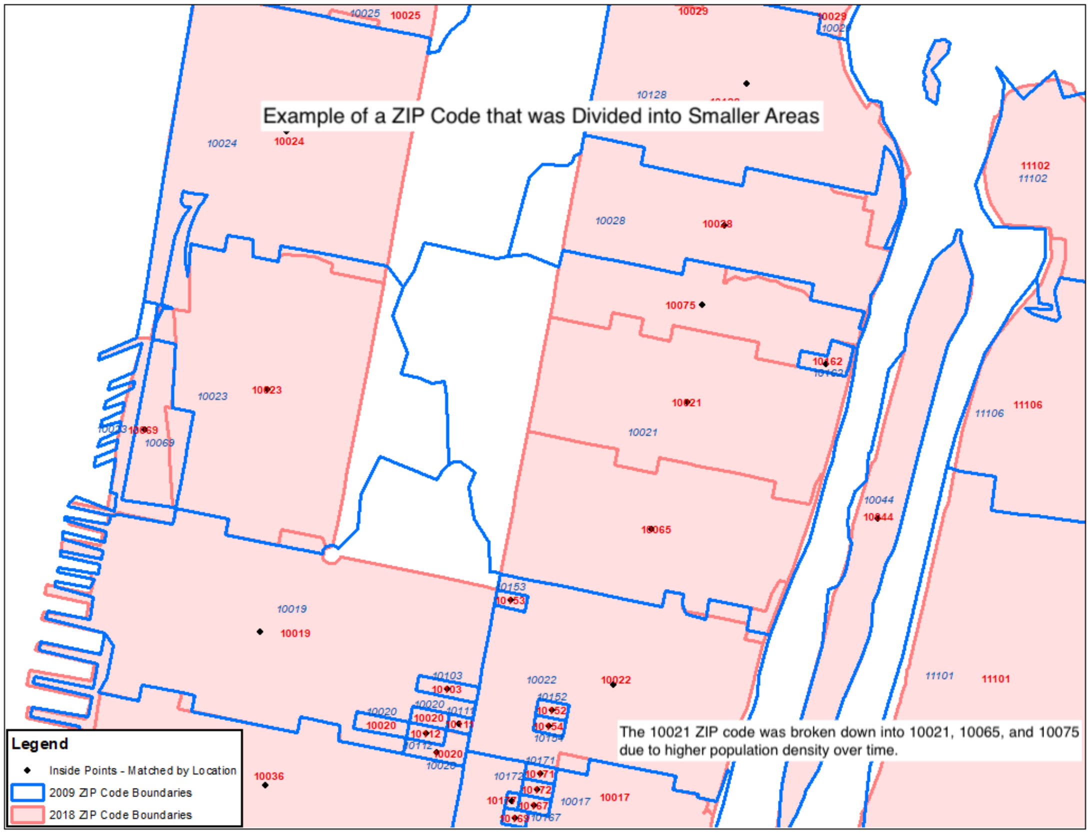

Figure 2.6: Example of a high-density ZIP code that had its area broken down into smaller ZIP code boundaries

In order to avoid geographical issues, we use GIS to look at the ZIP codes. Thus, we have now two options: one is to convert the 2018 ZIP codes into the 2009 geographic area, and the second is to convert 2009 into 2018. Table 2.6 shows that there are more new ZIP codes in 2018 than in 2009, and because the current representation of ZIP codes will not be required in the next chapters, we may take the simpler route of converting 2018 ZIP codes to 2009. Recalculating the data in the direction from 2018 to 2009 requires aggregation of data, which is easier and more accurate to do than if we were to use the direction of 2009 to 2018, which would require proportioning data from earlier years into smaller area units. In an attempt to avoid introducing more errors, we adopt here the simplest solution. In the New York 10021 example, it is simpler for us to add the three ZIP codes rather than find out how much of 10021 should be allocated to 10065 and 10075 for all the data for the years prior to 2009. This reverse process is possible and doable; however, as the final transformation into hexagons won't reflect the particular changes in ZIP codes, using the 2009 ZIP code boundaries is acceptable.

Next, I describe the steps to pair ZIP code polygons and numbers from the 2018 map to the 2009 map. This is a multi-step approach because of the many different ways in which ZIP codes changed between the two years. In this approach, I start with an automated pairing of ZIP codes and try to minimize manually linking them; however, we still need to perform some manual pairings. The steps taken to pair the 2018 and 2009 ZIP code maps are described below.

1. Search both ZIP code shapefiles on the Census Bureau's website, for 2009 and 2018, and add them both to ArcMap (Census 2009; Census 2018a).
2. Verify the number of ZIP codes in each and the direction in which we should aggregate the data. We have decided to aggregate the ZIP codes from 2018 into the 2009 boundaries.
3. For each 2018 ZIP code, we compute the centroid of the polygon, i.e., its center of gravity.[6] The centroid is a simple method and the one most likely to fall within the correct polygons without "activating" too many neighbors or relating to more than one ZIP code at a time.
4. Overlap the 2018 centroids map onto the 2009 ZIP code map and perform a spatial join by connecting each centroid to their corresponding 2009 ZIP code map polygons.[7] The result should be a new points layer, in which the attribute table also presents the data from the 2009 polygons.
5. Some points will fall outside corresponding polygons; most points fall inside a 2009 polygon, but a few have fallen out of any polygon. This happens because of the shape of some ZIP codes: some are archipelagos, other are shaped like arcs or have a gap in the middle, or include bodies of water in 2018 but not in 2009, for example. In this case,

[6] On ArcMap > ArcToolbox > Data Management Tools > Features > Features to Point > Check the "Inside" option. The result is a new layer that has a point for the center of each polygon. You may check by adding the new layer to the map and looking closely at the polygons.
[7] On ArcMap > ArcToolBox > Analysis Tools > Overlay > Spatial Join > add the centroids layer as target features, the polygons layer as the join features, change the join operation to "one to many."

we need to *select and save the points that have fallen outside the polygons from the inside points*.[8]

6. Now, the inside points have had their 2018 ZIP code paired with their 2009 ZIP codes. But we need to solve the outside points disparity. In this step, we join by attributes the 2018 points to the 2009 polygons by ZIP code number.[9] As a result, all the "outside points" that found a ZIP code match will be highlighted, and we can create a layer for the "outside points that have been matched" and another layer for "problem points."
7. The problem points are those that have fallen outside the polygons in the first stage and were not matched by ZIP code number on the second stage. Now, we must check them manually to relocate them into the nearest 2009 ZIP code.[10] Figure 2.7 shows how a few of these problem points were relocated. Two simple reallocation criteria are outlined here:
   a. If the point is located near a boundary, move the point to the other side of that closest boundary.
   b. If a point is located exactly in the middle of two or more polygons, then check the 2018 map to see which of the polygons that point should fall in to, and relocate the point to that ZIP code. The points just need to be relocated to inside a 2009 polygon, rather than requiring a specific location because the point carries the 2018 information and connects to a 2009 polygon by either manual input of the 2009 ZIP code number to its field or by spatial join of the problem points to the 2009 polygons, as in step 6.

8. Merge the layers for all three types of points: inside points (32,052 points), matched outside points (569 points), and problem points (36 points) to obtain the final conversion between 2009 and 2018. This process was done for all ZIP codes.
9. Export the attribute table for the points to polygon layer into R to start converting the 2018 ZIP code number to their 2009 correspondents.

---

[8] On ArcMap, open the attribute table for the spatial join layer and sort the points by 2009 ZIP code. Select all the points that have a corresponding 2018 and 2009 ZIP code and save as the "inside points" layer; then, reverse selection and save the remainder points as the "outside points" layer.

[9] Right-click on the 2018 points layer > Join and Relates > Join > Select "join attributes from a table;" choose the ZIP code field, then select the "outside points" layer from the drop down menu, and the 2009 ZIP code field.

[10] Click on Editor > Start Editing. With the attribute table open, select each point and zoom to it. Then use the outlined criteria to reallocate points.

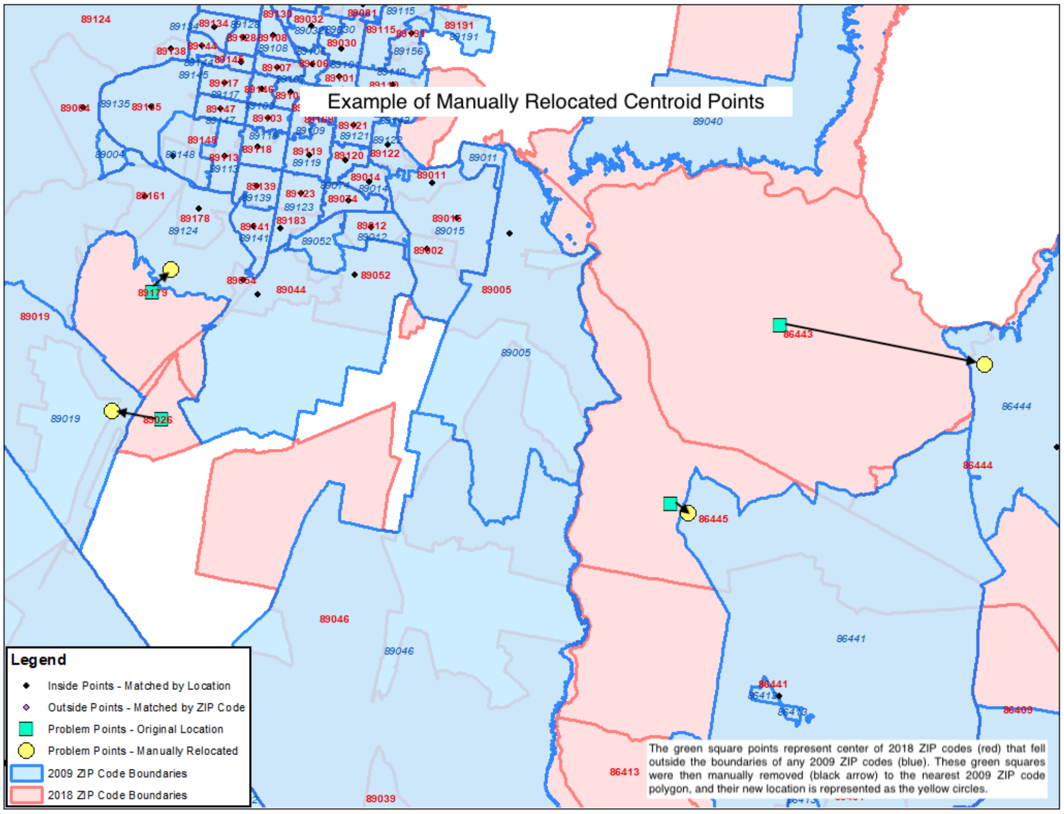

Figure 2.7: Example of manual relocation of centroid points from outside to inside ZIP code boundaries

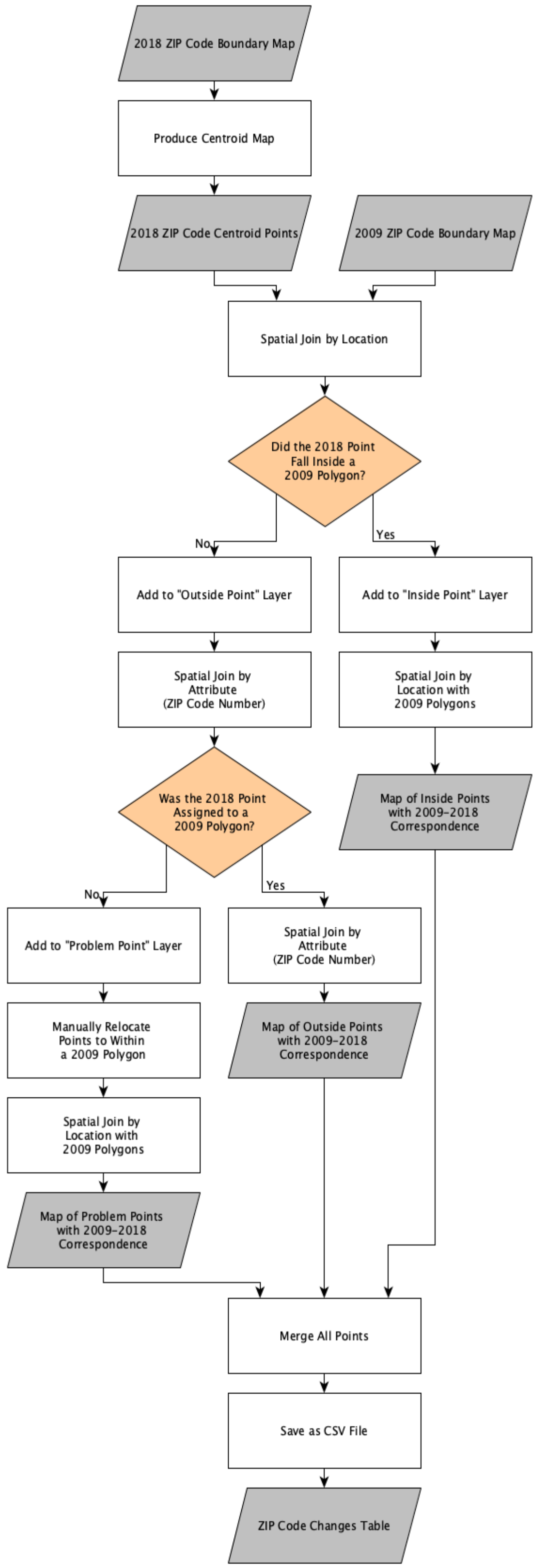

Figure 2.8: Workflow for placing, correcting, and associating ZIP codes from the 2018 map onto the 2009 map

The total number of points should be the same as the total number of ZIP code polygons in 2018, and because there are fewer ZIP codes in 2009, some 2009 ZIP codes will be related to more than one ZIP in 2018.

Table 2.6 shows how many new ZIP codes were added to the 2018 map when compared to the same positions in the 2009 map. This table was calculated by counting the number of centroids from the 2018 map that fell inside each 2009 polygon. While 92 percent of the ZIP codes were not broken down into smaller ZIP codes, 7 percent of them were broken down in two, and up to ten new ZIP codes in 2018, as happened to one ZIP code.

Number of 2018 points per 2009 polygon	Count	%
1	27570	92.047%
2	2121	7.081%
3	218	0.728%
4	34	0.114%
5	5	0.017%
6	2	0.007%
8	1	0.003%
10	1	0.003%

Table 2.6: Number of 2009 ZIP codes that were divided in 2018

The ZIP code conversion table from the 2018 points to the 2009 polygons will be used in the algorithm presented in chapter 3, which estimates the number of jobs and establishments by ZIP code. For each dataset, we convert the ZIP codes to their corresponding year in 2009. For example, ZIP codes in 2016 will be converted to the 2009 ZIP codes and aggregated where necessary, while the 2009 dataset remains unchanged. In the next section, I connect how ZIP codes and urban areas are translated into hexagons.

2.4 Hexagons

Both urban areas and ZIP codes are inadequate units of analysis because they are highly irregular in shape and area as they were defined by the Census Bureau and the Postal Service according to population density, built-up areas, and mailing volumes, which vary greatly from city to city. They were not made for data analysis. For that reason, the geographical entities need to be transformed to a neutral and uniform unit that can incorporate area and quantities well, without loss.

The hexagon can solve this issue by redistributing the data. The origin of the hexagonal grid is unknown (Carr, Olsen, and White 1992), but this method has been used by scholars in many fields for spatial sampling and data visualization with great success. Most frequently, ecologists have used hexagon tessellations to standardize forestry areas and count the number of trees (Birch, Oom, and Beecham 2007) to observe wildfire areas (Senici et al. 2010) and to study the diversity of birds (Johnson and Patil 1995).

Tessellations are transformations of a surface area into units of the same shape without loss, such as squares, triangles, or hexagons. These geometric shapes "tessellate" because they do not leave gaps or overlaps. The hexagon grid is created in an ESRI ArcMap, with the tessellation function over the entire continental US,[11] using the continental ZIP codes map on the USA National Atlas Equal Area projection system as the definition of extent.

[11] On ESRI ArcMap: ArcToolbox > Data Management Tools > Sampling > Generate Tessellation.

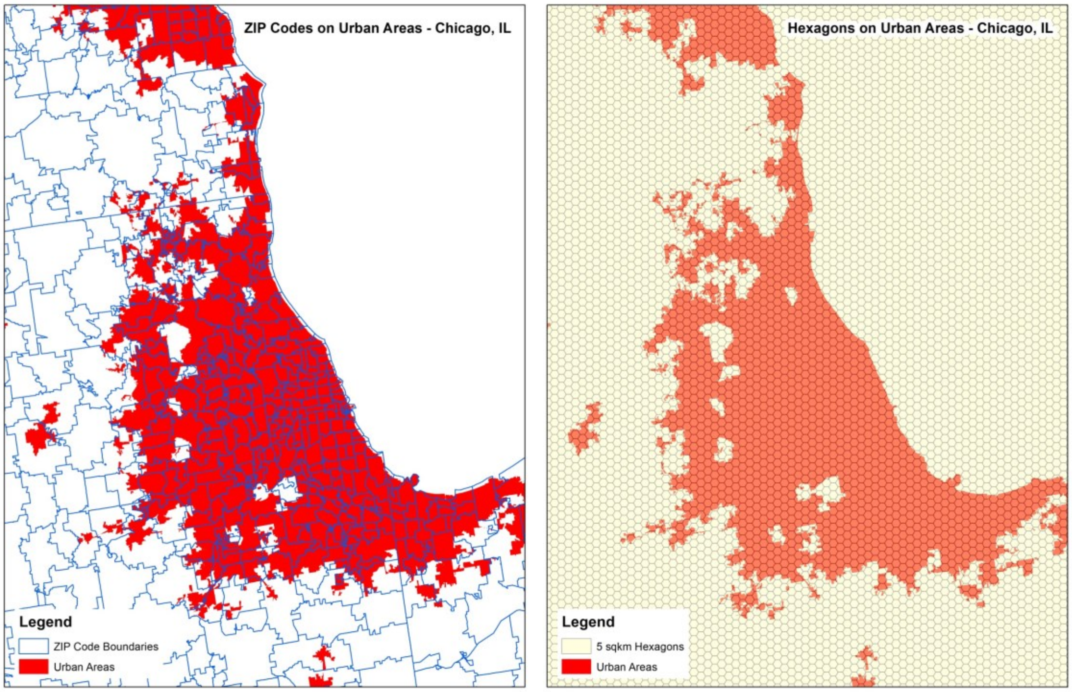

Figure 2.9: Differences in ZIP code and hexagon boundaries over the city of Chicago

Figure 2.9 shows the irregularity of ZIP code boundaries, while the hexagon grid is more uniform. ZIP codes in downtown Chicago are much smaller than the ones on the edges of the urban area. This pattern repeats throughout the country, potentially adding a lot of noise to the analysis due to the differences in size and how data points are counted within each boundary. The hexagon map shows a more even structure for distances and neighbors. After also testing for 3, 10, and 20 square kilometers, the 5 square kilometer area was chosen as it offers walkable areas and distances, but they are still significant to preserve diversity and interaction among its neighbors without collapsing the data too much or being too small for statistical significance. Neither boundaries of ZIP codes nor hexagons exactly match the boundaries of the urban area (in red), causing some hexagons to not have their total areas covered.

Advantages	Disadvantages
Uniform sizes and shapes: Solves irregular administrative unit issues	Not intuitive: It is hard to place the hexagon geographically without consulting the map.
Less orientation bias: All six neighbors are equally distant, smallest average distance between center to sides	Join accuracy issues: Need to preserve hexagons map to secure geographic accuracy
Adjustable: Hexagon areas can be adjusted to preserve diversity of data points	Compositional issue: Hexagons cannot be subdivided or joined as well as squares
Reduces bias: Data has equal probability of being selected	Creates more rows: 11000 ZIP codes are transformed in to 73000 hexagons, requiring more processing power
Visually appealing: Patterns are seen more easily, no horizontal and vertical lines	Out of boundaries: Hexagons require quality control in boundaries and edges
Aggregates small units: Small ZIP codes are aggregated to their surrounding area	May increase skewness: More hexagons may result in more skewed data than it already was by concentrating industries

Table 2.7: Advantages and disadvantages of using the hexagonal tessellation for recalculating data

There are many advantages and disadvantages in using the hexagons, as table 2.7 summarizes. First, hexagons solve the issues of administrative units presenting varying sizes and shapes because they have simpler, more uniform, and more symmetric shapes. Also, the average distance from the center of a hexagon to its sides is smaller and more uniform than in triangles and squares. In other words, hexagons are the closest shape to a circle that can provide tessellations without overlaps or gaps between polygons (Robinson, Lindberg, and Brinkman 1961; Poorthuis and Zook 2015). Second, the relationships between neighboring hexagons are easier to identify because hexagons have six neighbors sharing the sides of the same length, as opposed to squares, which have four sides and four corners sharing neighbors. The hexagon neighboring relationship optimizes movement paths between hexagons and also simplifies Euclidean distances and nearest-neighbor calculations (Haworth and Vincent 1976; Poorthuis and Zook 2015; Birch, Oom, and

Beecham 2007). This is significant for some forms of analysis, such as the geographical weighted regressions. Third, hexagons can be adjusted according to the phenomena being observed. In this study, each hexagon covers a five square kilometer area, which in most cases, aggregate parts of several neighboring ZIP codes. But other sizes could be used for different types of studies. Fourth, the hexagonal grid is required to be randomly positioned so that the data have an equal probability of being selected, which should fix any bias created by other units (White, Kimerling, and Overton 1992; Carr, Olsen, and White 1992). Therefore, hexagons can be used to aggregate and normalize data points without the bias of other types of units. Fifth, hexagons are more visually appealing than the square grid, and patterns are more easily observed (Poorthuis and Zook 2015; Carr, Olsen, and White 1992). And sixth, building-size or small ZIP codes are aggregated to their surrounding areas, incorporating them into a larger environment rather than being kept isolated when in reality they are not.

On the other hand, there are also disadvantages to using hexagons. First, hexagons are harder to be identified geographically because the software creates its own identification system (GRID_ID). The GRID_ID identification variable codes hexagons by two or three letters followed by three numbers, separated by a dash—for example, “GG-744” or “BDK-415.” Second, due to the particular GRID_ID system, we need to be careful in preserving and backing up the map that will match the hexagon ID to the correct geographical area. Third, aggregating hexagons causes compositional issues, making it hard to analyze hexagons hierarchically as hexagons do not aggregate as well as squares. Fourth, hexagons expand the dataset by dividing ZIP codes into several rows; for example, the 11,200 ZIP codes in this study were broken down to 63,166 hexagons, making this analysis more computationally expensive. Fifth, hexagons require quality control to ensure that only relevant hexagons are kept in the analysis and that noise is not being added by including areas that should not be included in the study. And sixth, hexagons might worsen the skewness of some data as the concentration or dispersion of some industries or areas may become more exacerbated than if it was kept at the ZIP code level.

After consideration of all reasons, the advantages of using hexagons still outweigh the disadvantages as the latter refer mostly to computational rather than theoretical issues.

2.5 Process and Metadata

The goal of this section is to lay out the process of obtaining the "geographic correspondence table," which is the attribute table of the final map after urban areas, ZIP codes, and hexagons were intersected, combined, and merged.

Figure 2.10 shows the workflow detailed in this section. Each step of this workflow was performed on ESRI ArcMap.

This process starts with three maps: (1) US states boundary map, (2) 2009 ZIP code map, and (3) urban areas map.[12] All maps should be projected to the *US National Atlas Equal Area* projection system that uses the *Lambert Azimuthal Equal Area* method and should also be reduced down to the conterminous US states to reduce distortions in areas further from the country's center.

[12] Available on https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html.

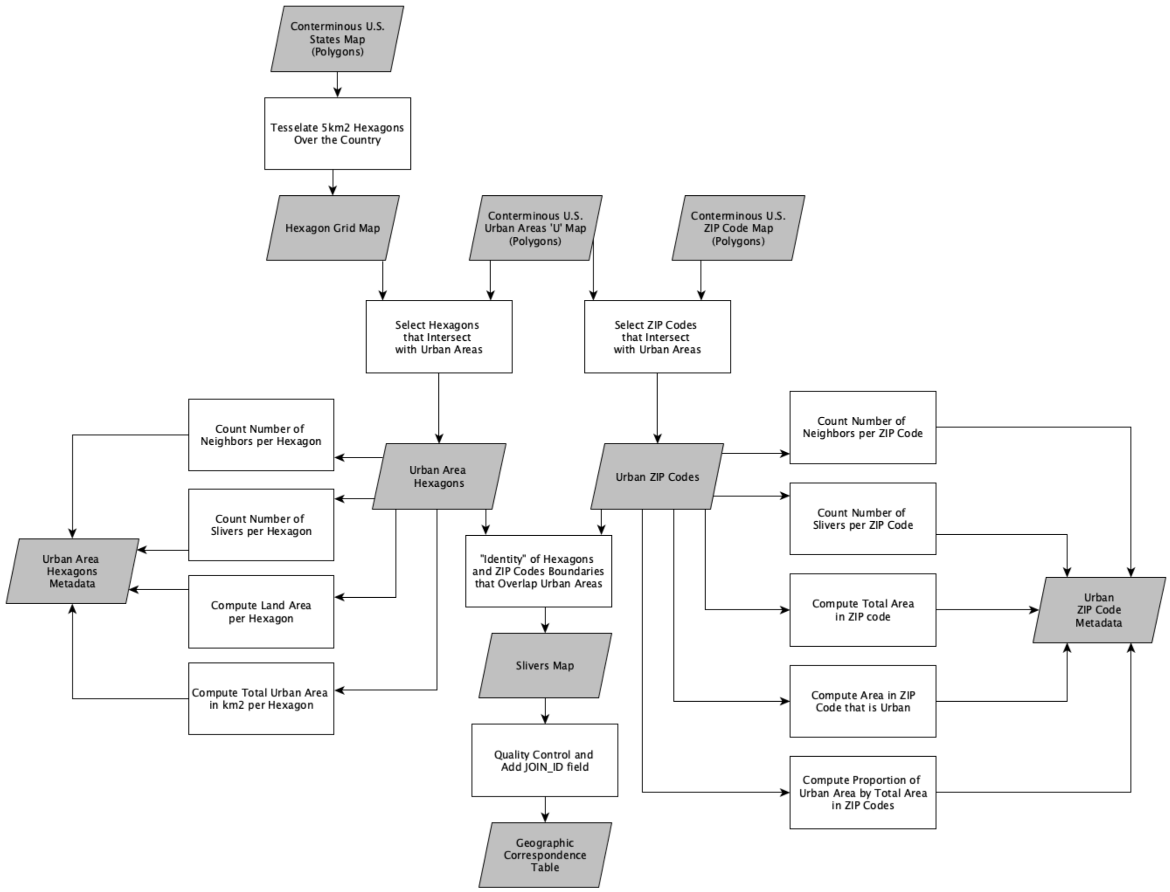

Figure 2.10: Workflow of the process of intersecting urban areas, ZIP codes and hexagons

We start by using the *conterminous US States Map* as a foundation to generate a general hexagon tessellation grid over all contiguous states, called the *hexagon grid map* (technical details in appendix A.2). The tessellation map covers the map of the entire country with hexagons of $5km^2$ of area. Then, we use the *urban areas "u" map* to select hexagons that intersect urban areas, generating the *urban area hexagons* map. We also select the 2009 ZIP codes that intersect urban areas, generating the *urban ZIP codes* map. By selecting intersecting areas, we reduce the number of polygons in the layers, which also helps with the computational processes.

Then, we merge the boundaries between ZIP codes and hexagons with a function called *identity* (technical details in appendix A.2). This function merges all boundaries from both ZIP code and hexagon maps, creating the *slivers map*. Each sliver is unique and represents the area of intersection between one ZIP code and one hexagon, a sample of which can be seen in figure 2.11. Therefore, each sliver is the intersection between the ZIP code boundaries (blue) and hexagon (red) boundaries. Each sliver has a unique combination of ZIP code, hexagon, and urban area.

The final step is to export or extract the attribute table from the slivers map as the *geographic correspondence table*. Four hundred eighty-one urban areas intersect with 11,200 ZIP codes of urban activity, which were then intersected with and rearranged into 63,166 hexagons and 156,769 slivers. Each sliver represents a small part of both geographic units, and in order to preserve their unique IDs, I added a new ID column that appends the 5-digits ZIP code to the GRID_ID, called JOIN_ID—for example, "60637-BDM-423." Thus, it is required that all slivers have both the correspondence among urban areas, ZIP codes, and hexagons to be included in the data; otherwise, if any of this information is missing, it would be hard to recalculate the data and the slivers and hexagons should be excluded. The correspondence table should also contain the area for the original ZIP code, total area of hexagons, and areas of slivers.

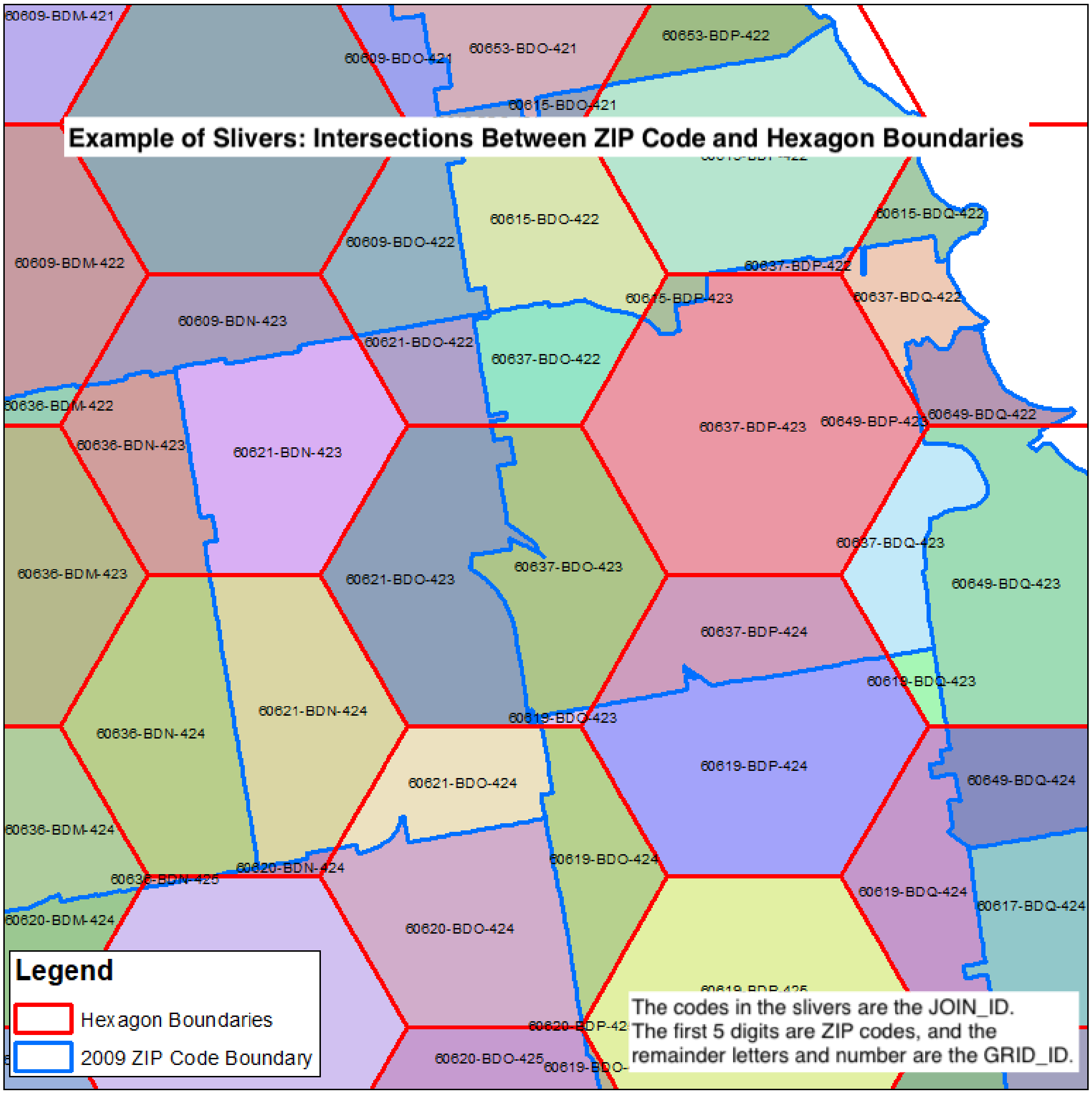

Figure 2.11: Example of slivers: The intersections between hexagons and ZIP code boundaries

Now that we have a grasp of how hexagons and slivers look, we should compare the metadata from ZIP codes and hexagons to compare how these two units differ in the analysis to justify this choice. First, we should compare the number of neighbors ZIP codes and hexagon polygons have. Figure 2.12 shows the histograms for number of neighbors in both units. The top histogram shows the distribution of ZIP codes by number of neighbors that have an average of 4.7

neighbors, while hexagons have on average 5.5 neighbors, as the maximum number of neighbors for hexagons is six. Sixty-nine percent of hexagons have six neighbors. Thus, we see a wider variety in the number of neighbors for the ZIP codes than for hexagons. This type of irregularity may affect some types of analysis, such as the geographically weighted regressions, which is not included in the empirical sections but reserved for later research projects.

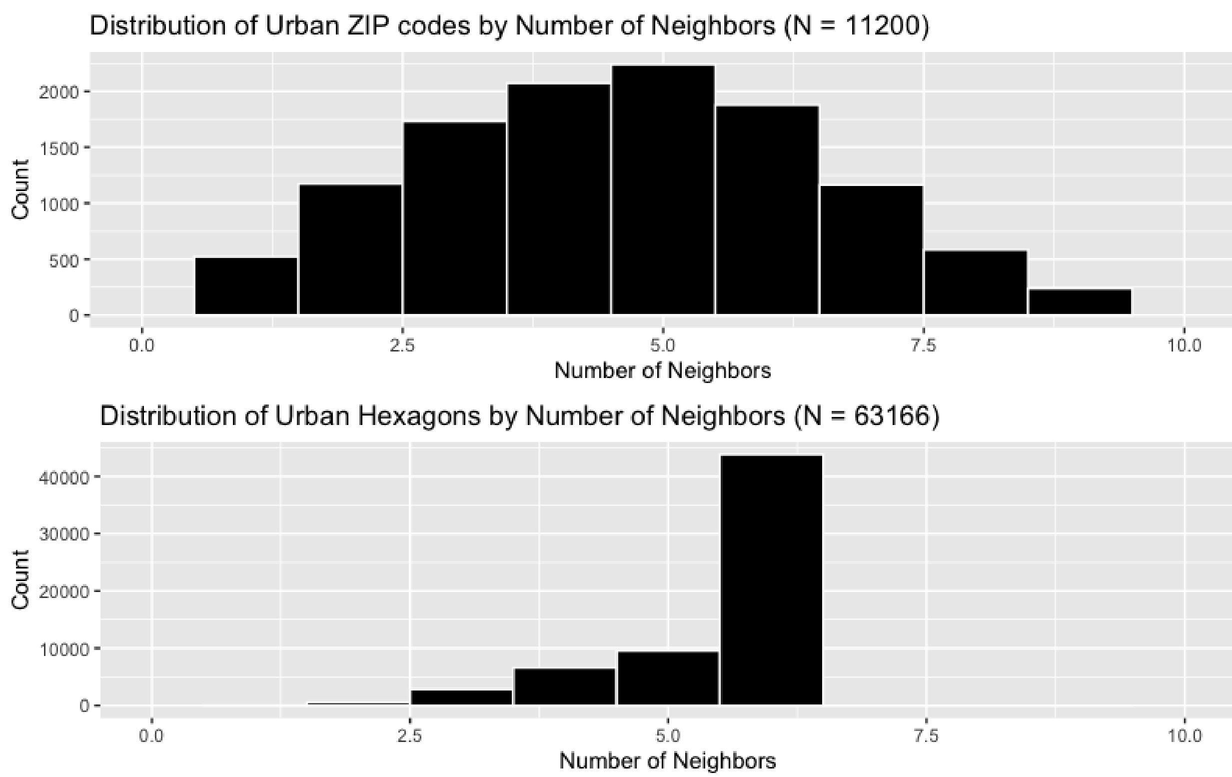

Figure 2.12: Distribution of the number of neighbors by ZIP code and hexagon

Figure 2.13 shows the histograms for number of slivers within each ZIP code and hexagon polygon. The top histogram shows that there are ZIP codes that contain up to seventy-eight slivers within its boundaries, but most ZIP codes contain up to twenty slivers. On the other hand, the maximum number of slivers per hexagon is twenty, with the highest number of slivers per hexagon located in Manhattan, where buildings have their own ZIP codes (as discussed in previous sections). Here again, we see that the distribution of pieces of data per hexagon is much more compact or concentrated than the number of pieces of data per ZIP code.

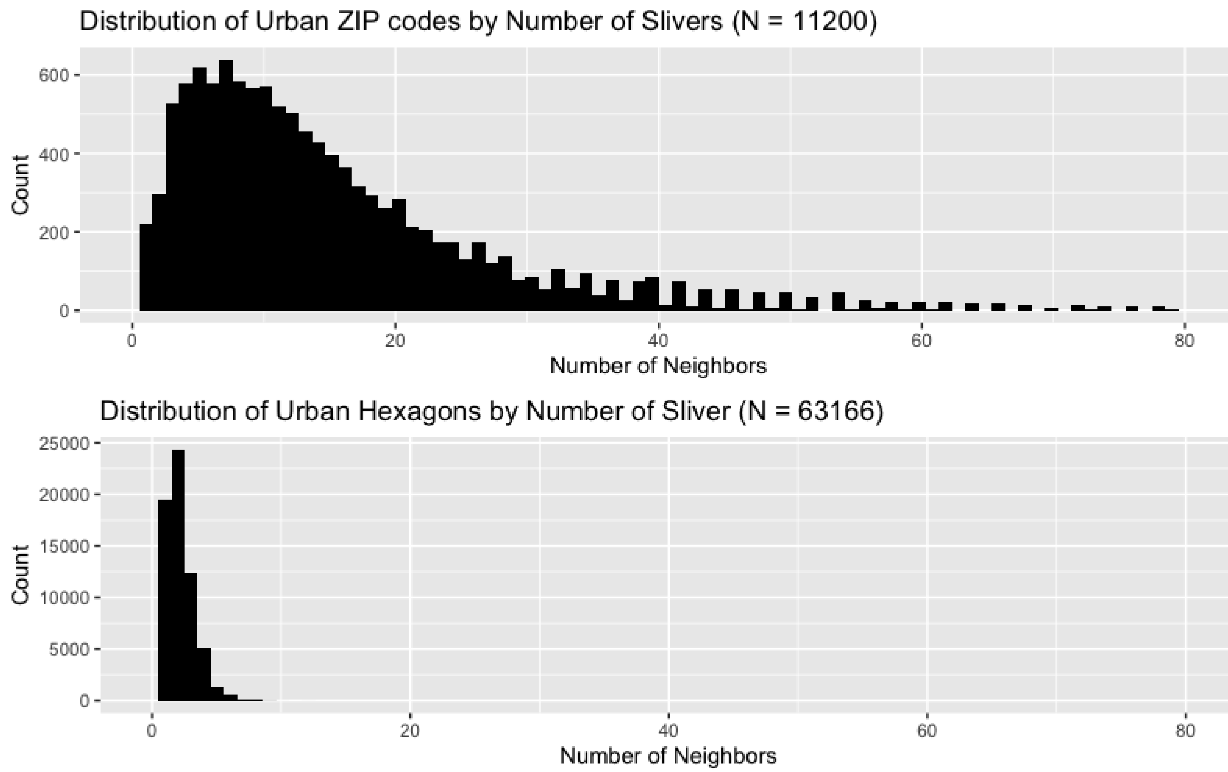

Figure 2.13: Distribution of urban ZIP codes and urban hexagons by number of slivers

Finally, we compare the average area for ZIP codes and hexagons, as shown in figure 2.14. Here, we compute the amount of land that intersect both ZIP code or hexagon with urban areas to find how much of the total area would show urban activity. Even though we define the area of hexagons as five square kilometers, some hexagons may fall over bodies or water or intersect with other types of boundaries that would make them smaller than 5km^2. Again, we see a larger disparity between ZIP code areas and hexagon areas.

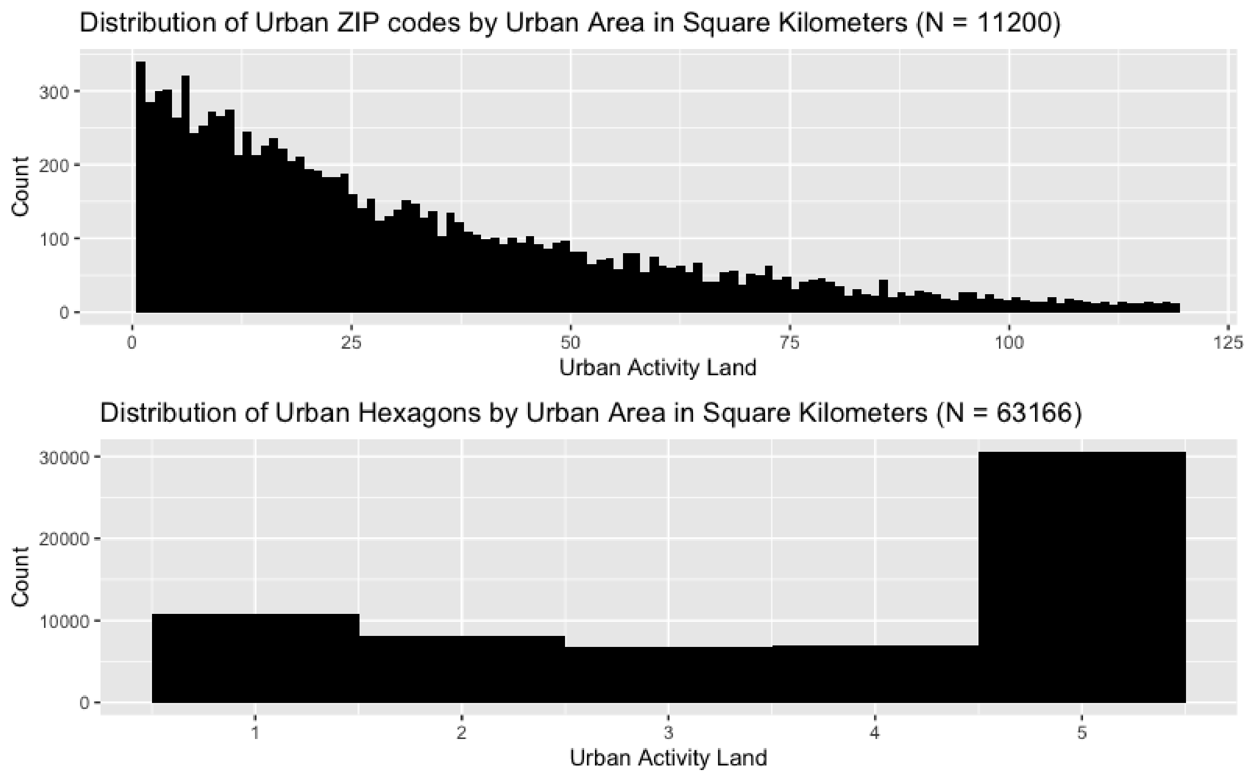

Figure 2.14: Distribution of ZIP code and hexagons by area in square kilometers

In this section, I discussed the method of overlapping different geographical units to create slivers to help us recalculate ZIP code level data into hexagons. Then, we analyzed some metadata, which showed that hexagons present more similar number of areas, neighbors and land than ZIP codes. Next, I discuss how to recalculate the data itself, from ZIP code to hexagon.

2.6 Sliver Weights to Recalculating Data

After defining the slivers and the geographic correspondence table, we calculate the area within each sliver as we use the area of slivers as the parameter to redistribute data points.[13] Then we calculate the proportion of the ZIP code that belongs in each sliver by calculating the slivers' area divided by the total area of the corresponding ZIP code, as in equation 1, which I call the *sliver weight*.

$$Weight_{sliver} = \frac{Area_{sliver}}{Area_{ZIPCode}}$$

Next, we aggregate the data values per sliver by hexagon and total the final count of data inside each hexagon. To recalculate the data, we multiply the sliver weight by the ZIP code level data to find the proportional count of any variable. Suppose a ZIP code has a total area of $10km^2$, and a sliver is completely contained in that ZIP code with an area of $5km^2$. Then, this sliver's weight is 0.5. If the dataset shows that there are 200 jobs in that ZIP code, the sliver will account for 100 of those jobs. This calculation process is outlined in the workflow in figure 2.15.

[13] ArcMap > Attribute Table > Calculate Geometry.

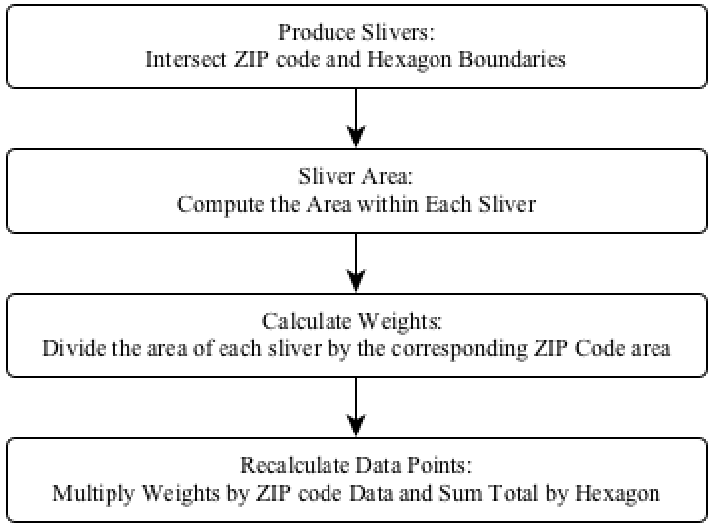

Figure 2.15: Process of transforming slivers into weights to recalculate data points

Even though the process of generating slivers from ZIP codes and hexagons seems straightforward for most urban areas, upon closer look, issues surface in smaller urban areas. The maps of New York and Chicago in figure 2.16 show cases where ZIP codes are completely divided into hexagons, with all their trimmings accounted for. Therefore, hypothetically, if a ZIP code is perfectly split into two parts, half of it joins one hexagon, and the other half joins the other hexagon. This type of area requires simple calculations as the ZIP code variables are mostly proportioned among neighboring hexagons. However, in cities such as Mills, WY, and Sioux Falls, SD, the ZIP codes are much larger than their corresponding urban areas; in other words, the ZIP codes include both urban and rural areas. This impacts the proportioning of the data because in some cases, the non-urban areas are taken into account when they should not be, causing loss of some data points.

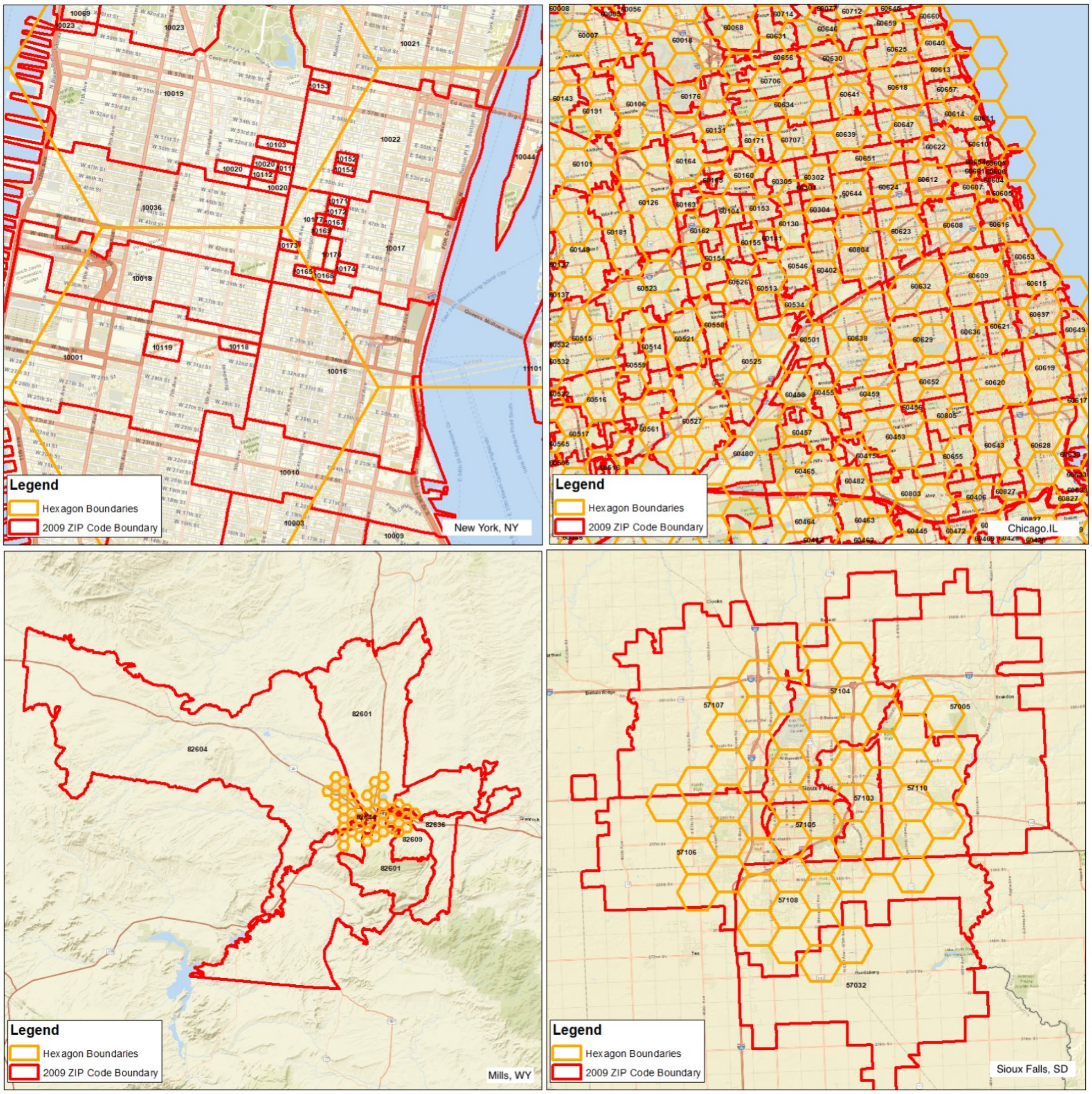

Figure 2.16: Differences between hexagons overlapping in large and small urban ZIP codes

ZIP codes that include rural areas present issues because calculating the weight as suggested above would leave many data points unaccounted for as area weights distribute data points evenly across the entire ZIP code, not only over urbanized areas covered by hexagons; in fact, most jobs concentrate in the built-up urban areas with higher concentrations of people within those ZIP codes. Thus, when summarizing the data by hexagons, some data points would not be included if we consider the entire area of these ZIP codes, leading to an inaccurate account of the data points. In addition, if those data points are not counted, then lower density ZIP codes will skew the data to the right even more, leading to more cases with values nearing zero in the dataset.

Figure 2.17 shows an example with a satellite view of the ZIP code 59105 in Billings, MT. The urban area boundaries (red) delineate the continuously built-up areas as defined by the census, while the ZIP codes (light blue) include mail delivery routes at the discretion of the United States Postal Service. The satellite image shows streets and buildings in the areas inside urban areas, while most of the ZIP codes are made of rural zones, with farms and natural areas. Hypothetically, if this ZIP code had 100 jobs but the areas under the hexagon occupied about 30 percent of the total ZIP code area, then only thirty of the 100 jobs would be accounted for when dividing the jobs among all hexagons. However, most of those jobs would be found within the urban area; thus, it is more accurate to place the 100 jobs within the hexagon-covered areas than the entire ZIP code. In conclusion, before calculating the weight of the ZIP codes, we should first reduce the total ZIP code area to the area under hexagons and recalculate the new ZIP code area as the *sum of the areas of all slivers* within a ZIP code. Then, we use this new urban ZIP code area to calculate the sliver weights. And to verify, the weights of all slivers within each ZIP code must total one.

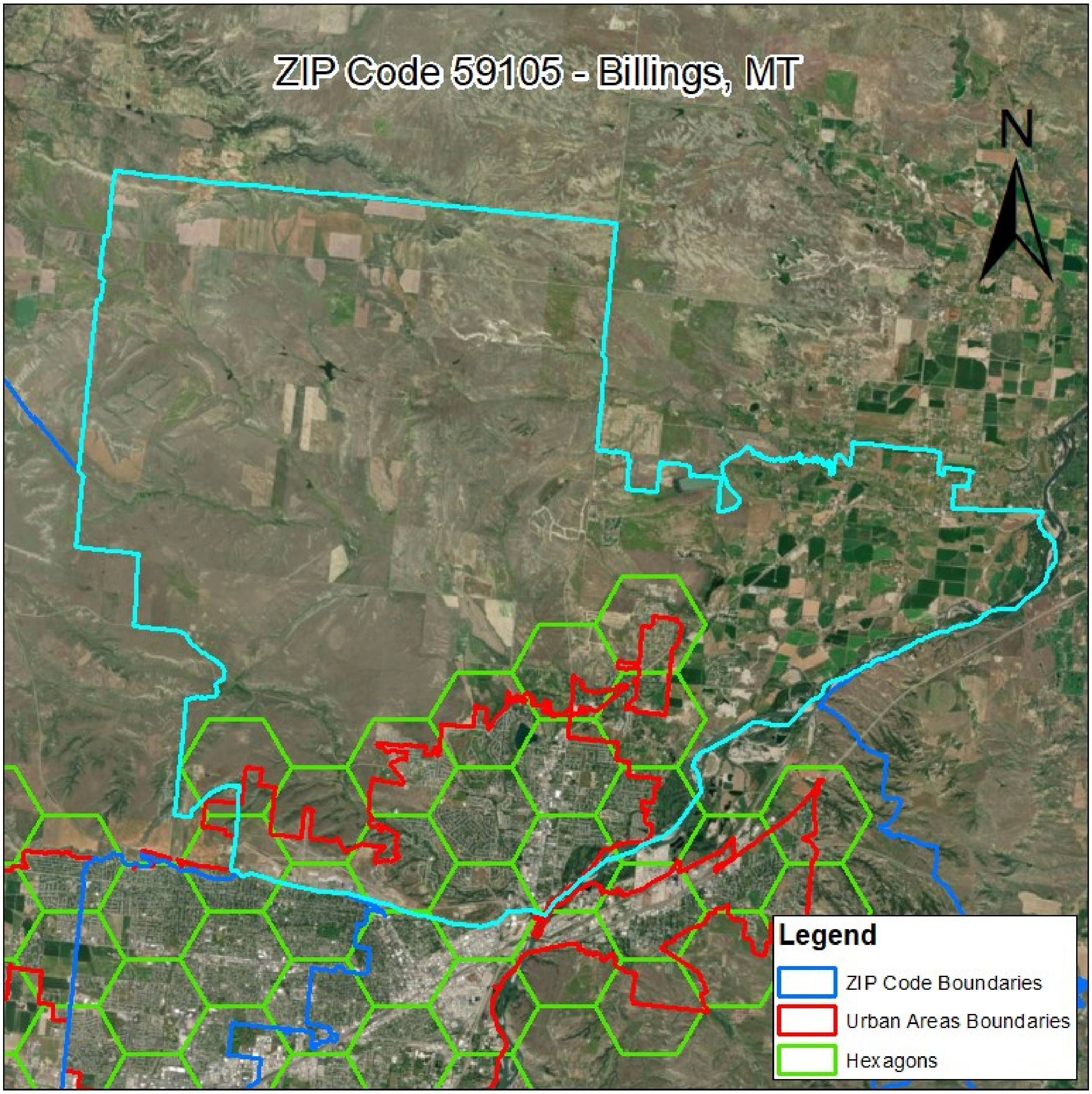

Figure 2.17: Example of a rural ZIP code that intersects with an urban area, and placement of hexagons over the urbanized area

Figure 2.18 includes the additional steps taken to compute the weights for the slivers in all ZIP codes. With this additional step, we have two ZIP code areas: the official ZIP code area and the new urban ZIP code area.

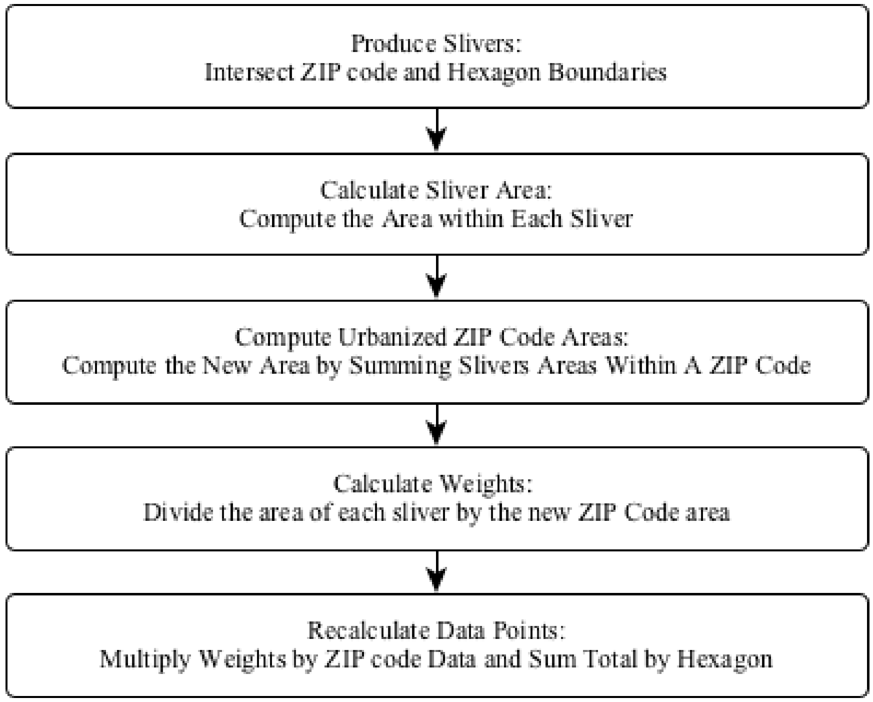

Figure 2.18: Adding one step to the workflow where the ZIP code area is compressed into the urbanized area within the ZIP code

The difference between the total area and the urban zone areas show the amount of rural lands that are being removed to recalculate the dataset. In table 2.8, we see that 55.5 percent of the ZIP codes have less than $1km^2$ difference between the total area and the urban zone area. Thirty-one percent of ZIP codes had an area change of between 1 and 100 km^2, and 13.4 percent had area differences of over 100km^2, as in the case of ZIP code 59105 shown above. These high numbers show the importance of adjusting the urban area size before weighting the data to recalculate hexagon data.

Area Differences of Total Area of ZIP Code Minus Urban Zones		
ZIP Code Area Sizes (in sqkm)	**N**	**%**
Area under 1 sqkm	6231	55.6%
Area between 1 and 100 sqkm	3470	31.0%
Area over 100 sqkm	1499	13.4%

Table 2.8: Changes in the ZIP codes areas to accommodate urban zones

Table 2.9 shows the descriptive statistics comparing the total area of ZIP codes after calculating the urban zones used as a base for calculating data weights. The average area considered for calculating weights went from 78.5 km^2 to 32.4 km^2, meaning that for many ZIP codes, the weights of urban areas increased after eliminating rural areas from the calculation.

Descriptive Statistics of Total Area and Urban Zones per ZIP Code							
	N	**Mean**	**S.D.**	**Median**	**Min.**	**Max.**	**Skewness**
Total Area of ZIP Code	11200	78.5	145.2	33.1	0.0	4003.4	8.5
Area of Urban Zone	11200	32.4	31.5	22.5	0.0	329.4	1.8

Table 2.9: Descriptive statistics comparing the total original area to the urban zone area of ZIP codes

Besides the adjustment presented in this section, there are other alternative methods to proportion ZIP codes areas into hexagons. First, we may consider the area of urban areas within each ZIP code instead of the area of slivers. This method would require intersecting urban areas according to ZIP code boundaries and calculating the area of the urban area polygons within each hexagon to find the proportion of the urban area within each sliver divided by the area of the urban area in a ZIP code, adding many more steps to the process. Second, we may consider the number of neighbors for each hexagon.[14] Hexagons with six neighbors should receive proportionately more

[14] How to calculate number of neighbors: ArcMap > ArcToolbox > Analysis Tools > Polygon Neighbors.

data points than hexagons with five, four, or three neighbors, decreasing gradually. However, this method can create bias against certain industries that operate outside city centers.

Even though we can be creative in finding new ways of proportioning ZIP code data into hexagons, the method I described in the flowchart is the one selected for this dissertation. There are several advantages to this approach: (1) all data points are aggregated within hexagons without loss, (2) all data points are aggregated within urban zones of higher economic and urban activities, and (3) the weights are based on both the population density (from the definition of urban areas) and area (from hexagons).

2.7 Quality Control

Some quality control is required after overlaying a hexagonal grid over the ZIP code and urban area maps. Not all polygons that were programmatically selected should remain in the dataset because some hexagons may skew the data even further and not only not contribute to the analysis, but they may make it worse. Quality control is important at this point due to the particular geographical characteristics of coastlines, boundaries, and administrative units. Selecting units computationally is effective, but it still requires a human eye to identify areas where the rules do not apply accurately, or where noise is added. Therefore, we create some rules to ensure data quality and that extra bias is not introduced.

By looking at the map closely,[15] we start to identify problem areas in which hexagons are placed in relation to the urban areas and ZIP codes. Some hexagons are not placed over an urban area and a ZIP code at the same time—for example, if they are mostly over water. Other hexagons

[15] See https://crissakamoto.com/maps.html for interactive maps.

narrowly touch an urban area, making us reconsider whether that hexagon should be kept as part of the analysis. Based on close observations such as these, the criteria used to keep or remove hexagons from the data are the following: (1) hexagons must have a correspondence between ZIP code, urban area, and sliver concomitantly (i.e., correspondence criteria); (2) the area of a hexagon should cover a minimum of one and a maximum of five square kilometers of land area (i.e., land area criteria); and (3) hexagons should intersect at least $0.5km^2$ of an urban area (i.e., urban area criteria).

The *correspondence criteria* refer to the correct aggregation of data based on the transformation between units. Some hexagons are placed either outside an urban area or a ZIP code, and those cases can result in one of two outcomes: (1) the hexagons may not have a corresponding ZIP code, making them not useful for aggregating data, or (2) the hexagons might aggregate parts of large external ZIP codes that wouldn't be included in the data otherwise. We remove hexagons from the first case but keep the ones in the second case. Therefore, only those hexagons that have correspondence to a ZIP code are kept for aggregating data, satisfying the correspondence criteria.

The *land area criteria* refer to the minimum area covered by the hexagon. Most of the hexagons that cover less than five square kilometers are over water and useful for the analysis as many establishments and businesses operate in or near coasts and shorelines in many cities. We must remove those hexagons that are "hanging by a thread" to a ZIP code or urban area or cover less than one square kilometer in total because these hexagons remained in the selection by a computational rule. However, they would proportion the data to very small numbers, adding rows of data with values close to zero without properly reflecting the economic activity in the area.

Of the 63,138 hexagons selected, 51,836 hexagons cover five square kilometers (counted as area larger than 4.999), and 11,537 hexagons aggregate less land area. The distribution of areas of the hexagons within the $1km^2$ to $4.999km^2$ range is shown in figure 2.19, after the removal of hexagons with less than $1km^2$.

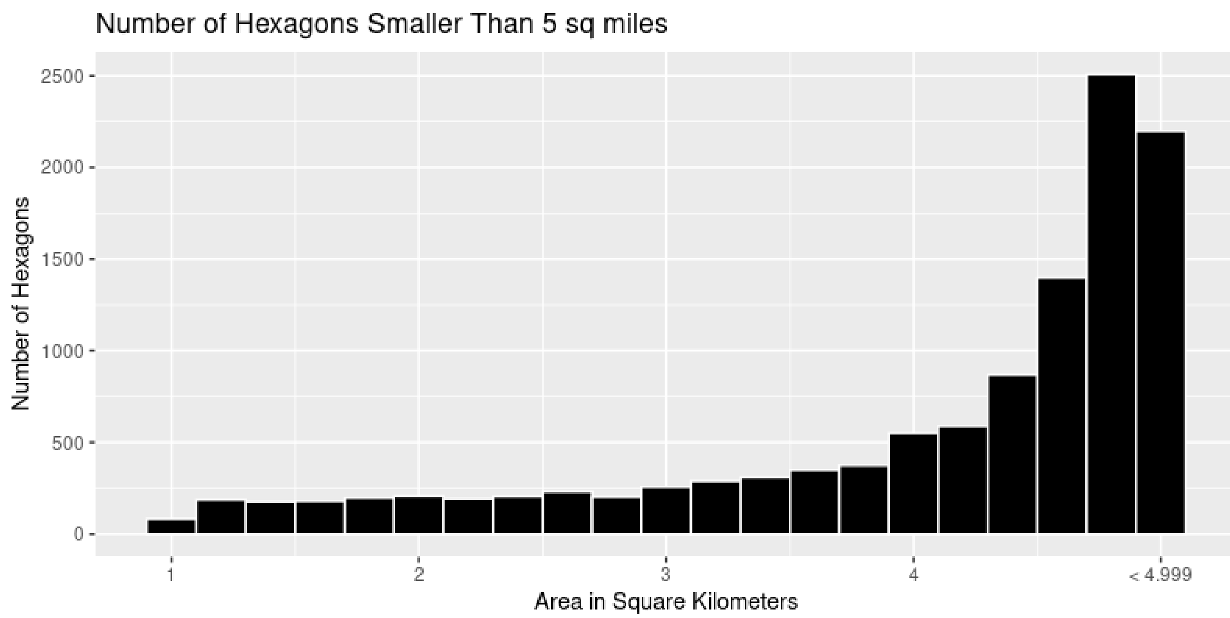

Figure 2.19: Histogram of the distribution of hexagons with areas under five square kilometers

The *urban area criteria* is very similar to the land area criteria, except for determining that the urban area within each hexagon should be at least $0.5km^2$. Some urban areas merely touch a hexagon; however, that is enough to keep it in the dataset when they are covering rural areas. These are the types of hexagons that this rule removes. For the last two criteria, hexagons should be at least 10 percent urban and have 20 percent of its area on land.

Figure 2.20 shows examples of hexagons removed on the coast of Baltimore, MD.[16] The labels show how much of either the urban area or ZIP code areas were computed inside the hexagon in square kilometer. As we can see, a hexagon requires a minimum of land area or urban area coverage in order for it to aggregate and represent data properly.

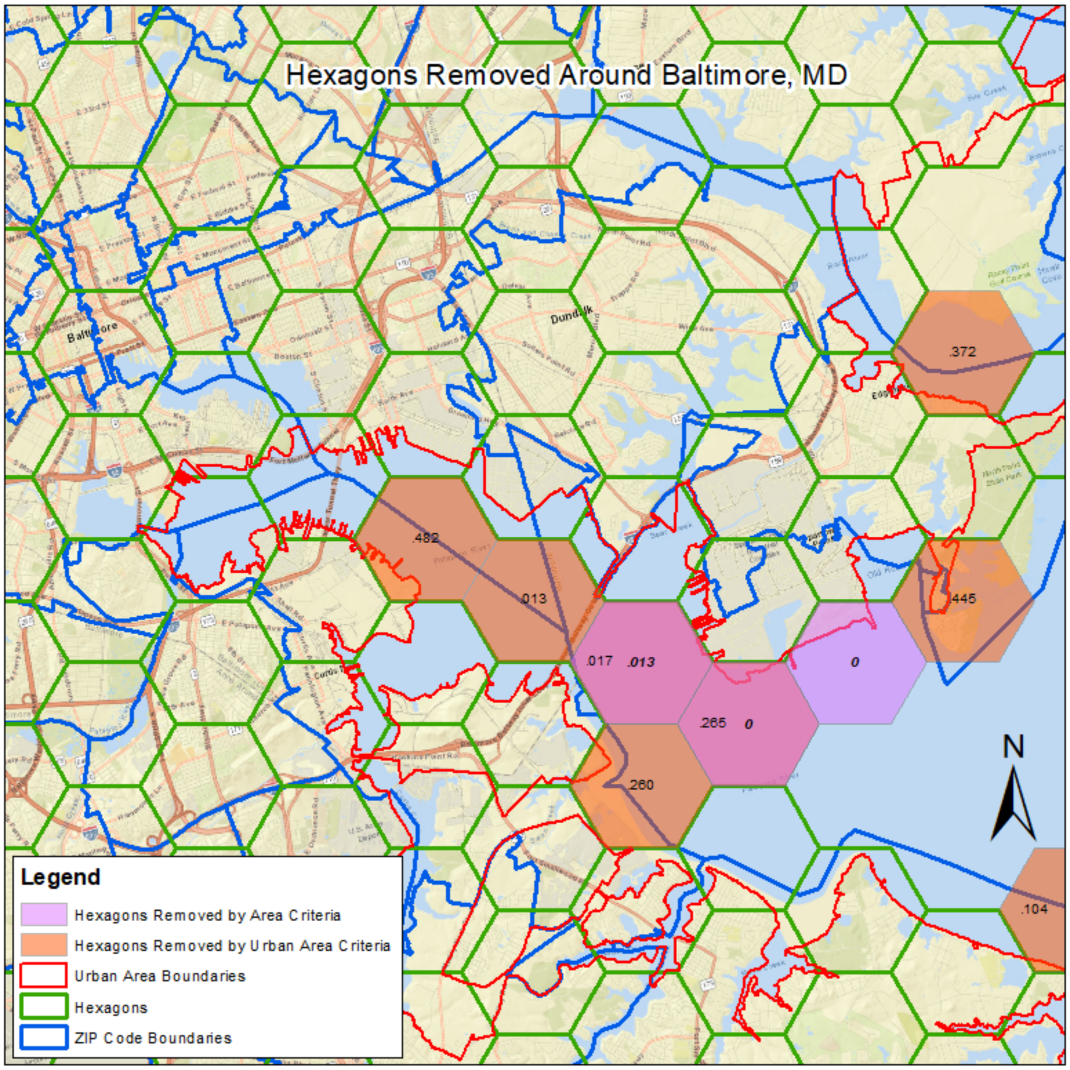

Figure 2.20: Example of hexagons removed for lack of land area coverage

[16] See https://crissakamoto.com/maps.html for interactive maps.

Based on all the criteria discussed, 12,894 hexagons have been removed, leaving 63,166 hexagons remaining in the analysis to represent 11,200 ZIP codes in 481 urban areas.

2.8 Descriptive Statistics

Urban areas and ZIP codes were transformed into hexagons to reduce the variation in size, neighbors, and boundary shapes. Table 2.10 shows the descriptive statistics of the areas of the three geographic units analyzed in this section. Urban areas are single polygons that delineate cities as long as there are continuously built-up structures; thus, urban areas contain several ZIP codes and hexagons. In this study we analyze 481 urban areas of different sizes, with an average size of $478km^2$, the smallest being $26km^2$ (Delano, CA), and the largest being $9{,}457km^2$, the New York metropolitan area.

Descriptive Statistics of Area Units

Geography	N	Mean	Median	S.D.	Min	Max
Urban Areas	481	478	194	897	26	9457
Total ZIP Code Area	11098	78	33	145	0.01	4003
Urban ZIP Code Area	11098	33	23	32	0.01	329
Hexagons	63166	4.8	5	0.57	1	5

Table 2.10: Descriptive statistics of urban areas, original and modified ZIP code areas, and hexagons

Table 2.11 shows the descriptive statistics of the 63,166 hexagons. The average area of the hexagons is 4.9, with very little variation. This average is not a round $5km^2$ because of bodies of water within hexagons. The minimum area is $1km^2$, as defined. The average area of the urban area within each hexagon is $3.6km^2$, with a minimum of $0.5km^2$ as specified. Hexagons have an average of 5.5 neighboring hexagons; however, most of them have six neighbors. Hexagons have on average 2 slivers within them, with upwards of 21 slivers.

Variable	Mean	SD	Median	Min	Max	Skew
Area	4.9	0.41	5	1	5	-6.44
Urban Area Within Hexagon	3.6	1.59	4.4	0.5	5	-0.62
Number of Neighbors	5.5	0.93	6	1	6	-1.73
Number of Slivers	2	0.98	2	1	21	1.32

Table 2.11: Descriptive statistics of hexagons

2.9 Conclusion

In this chapter, I discussed the issues with using unstandardized units to compute the number of establishments and employment for studies like this one and offered one method to recalculate and standardize the units of the data using spatial techniques. ZIP codes are the smallest unit in which the US Census Bureau provides datasets. However, their irregular shape may not represent phenomena on the ground for a sociological study. In order to adjust the dataset into more regular areas, we overlap maps of ZIP codes, urban areas, and a hexagonal grid in order to find the smallest areas to calculate weights to be assigned to the original dataset.

In summary, the general process to transform the geographies used in this study is as follows:

1. Create a hexagon grid based on the ZIP code map in the US National Atlas Equal Area projection system;
2. Select urban areas from the census shapefile;
3. Select ZIP codes that intersect urban areas;
4. Merge geographic features based on the boundaries of ZIP codes and hexagons to produce slivers;
5. Calculate areas of urban zones within the ZIP codes;
6. Calculate weights based on the new total urban area by ZIP code.

From this point, we proceed to chapter 3, where I discuss how to calculate the dataset, as we move on from the maps. To be sure, the same methods could be used to other geographic units, such as the county or metropolitan areas. Most of the data in this study is available on the ZIP code level. This transformation is necessary to standardize the geographic units in this study. Now, we proceed to the next section on data, where we combine hexagons and data for the analysis.

CHAPTER 3

DATA SOURCES AND METHODOLOGY

In this chapter, I present and discuss the dataset and the algorithm used for data transformation from official units into hexagons. The main dataset used in this study is the US Census Bureau's County Business Patterns (CBP), which is available online by the US Census from the year 1986.[1] However, due to industry classification consistency issues (discussed further in section 3.2.2), we focus on the data for the years 1998 to 2016.

The CBP is the main data source for this study, but the Census Bureau also indicates that this data is adequate for studying local economic activities and many other applications. The CBP data originates from the Business Register and uses the North American Industry Classification System (NAICS - see section 3.2) for its industry classification. The data is available in several levels of geographies such as state, county, metropolitan area, ZIP Code (as used in this study), and congressional district levels.

In this chapter, I present the data sources and methodologies. In the first section, I discuss the CBP dataset in more detail; in the second section, I discuss the industry classification system (NAICS); in the third section, I present the algorithm used to compute the hexagon data based on the ZIP code data; and in the fourth section, I discuss the statistical methods utilized in the empirical chapters of this dissertation.

[1] See https://www.census.gov/programs-surveys/cbp/data/datasets.html.

3.1 US Census County Business Patterns (CBP)

The County Business Patterns (CBP) are yearly economic data released by the US Census Bureau since 1964. The data are administrative records extracted from the Business Register, a single- and multi-establishment employers database that is updated every economic census in years ending with 2 and 7. It also includes annual surveys called "Report of Organization." Each dataset in the series includes the number of establishments by size and industry, employment during the week of March 12, first quarter payroll, and annual payroll. The data are released at the national, state, CBSA (metropolitan area), county, congressional district, and the ZIP code levels, including all fifty states, Puerto Rico, and the American islands. The CBP covers most NAICS industries except agriculture, rail transportation, private households, and establishments that report government employees.[2] The Census adds noise to data to protect individual establishments from disclosure (Census 2018b).[3]

The Census Bureau's definition of an establishment is "a single physical location at which business is conducted or services or industrial operations are performed" (Census 2019). In other words, establishments are physical permanent structures where business is conducted and operates, and where employees are hired and compensated. Establishments may be classified as single or multi-unit companies. Single-unit companies reference one single establishment while multi-unit

---

[2] "County Business Patterns covers most NAICS industries excluding crop and animal production (NAICS 111,112), rail transportation (NAICS 482), Postal Service (NAICS 491), pension, health, welfare, and vacation funds (NAICS 525110, 525120, 525190), trusts, estates, and agency accounts (NAICS 525920), private households (NAICS 814), and public administration (NAICS 92)" (Census 2019).

[3] In accordance with US Code, Title 13, Section 9, "no data are published that would disclose the operations of an individual employer" (Census 2019).

companies consist of at least two establishments, but each establishment is identified by their geographical location, and not registration location. The Census recognizes the importance of large corporations to local economies and makes efforts to provide proper coverage in payroll and employment data based on location, rather than as a corporate unit.

For the purposes of this study, I focus on two CBP ZIP code level datasets: (1) the "ZIP Code Totals File," which provides the total number of employees per ZIP code without identifying industries (henceforth *employment data*); and (2) the "ZIP Code Industry Detail File," which provides the number of establishments (not the number of employees) by size and industry (henceforth *establishment data*).

The CBP dataset tries to capture the universe of establishments, and therefore, the data is subject to non-sampling errors. In other words, the most common errors in this data set are the "inability to identify all cases that should be in the universe; definition and classification difficulties; errors in recording or coding the data obtained; and other errors of coverage, processing, and estimation for missing or misreported data" (Census 2019).

In this dissertation, the preferred method of verifying if a missing value is zero or actually missing is to check the total number of employees for a ZIP code and compare it to the number of establishments reported. If the ZIP code presents a total number of employment and/or establishments, then we consider that a particular industry had zero jobs. On the other hand, if neither the employment nor establishment numbers are present, then we may consider the report to be missing, which accounts for about 6.5 percent of ZIP codes.

The structure of the establishment data is presented in table 3.1. Rather than presenting the total number of employees, we obtain the number of establishments in nine ranges of number of employees. Since the census does not disclose the number of employees per ZIP code and per industry concomitantly due to disclosure issues, these two datasets together can provide a reasonable estimate, as is calculated with the algorithm presented in section 3.3.

Data Dictionary for CBP Data

Name	Description
ZIP	ZIP Code
NAICS	Industry Code - 6-digit NAICS code.
EST	Total Number of Establishments
N1_4	Number of Establishments: 1-4 Employee Size Class
N5_9	Number of Establishments: 5-9 Employee Size Class
N10_19	Number of Establishments: 10-19 Employee Size Class
N20_49	Number of Establishments: 20-49 Employee Size Class
N50_99	Number of Establishments: 50-99 Employee Size Class
N100_249	Number of Establishments: 100-249 Employee Size Class
N250_499	Number of Establishments: 250-499 Employee Size Class
N500_999	Number of Establishments: 500-999 Employee Size Class
N1000	Number of Establishments: 1000 or More Employee Size Class

Source: U.S. Census Bureau

Table 3.1: Variables in the raw data as downloaded from the US Census Bureau's website

A simple sum of the number of establishments may not reflect a city's total job market because it is not reasonable to suggest that a small company of four is similar to a large company of two thousand. However, if we combine the data on total employment numbers from the employment data with the number of establishments by number of employees from the establishment data, we are able to estimate the number of employees per industry. By combining both employment data and establishment data, I aim to obtain a dataset that better indicates the employment numbers by industry in each ZIP code, and subsequently, in each hexagon.

In the next section, I present the industry classification system and how industries are classified in this study.

3.2 The NAICS Codes

The North American Industry Classification System (NAICS) classifies the industries of business establishments according to their main production outputs, activities, and/or processes. This classification is used in datasets by federal agencies in the United States, Canada, and Mexico. The NAICS started to be developed in the 1990s, but was first released in 1997 by the Office for Management and Budget (OMB) to replace the SIC (Standard Industrial Classification), established in the 1930s. Along with the US census, other American federal agencies also use the NAICS, such as the Federal Reserve Board, the Bureau of Economic Analysis, and the Bureau of Labor Statistics (Murphy and Burgess 1998; Parker 2003; Hiles 2001). For the purposes of this study, the NAICS is used in conjunction with the CBP as a tool to identify industries of business establishments in the dataset.

In the 1990s, the NAICS was updated to increase the level of detail of services industries, especially to reflect the emergence of high-technology industries. The 1987 final SIC revision accurately covered the manufacturing industries, while most of services and high-technology industries were only presented in the highest level of identification, which later warranted thorough revision of the classification system (US Census 2017; Murphy and Burgess 1998; Russel, Tack, and Usher 2004).

In the revised NAICS, most of the high-technology industries were detailed under the "51 - Information" category—establishments that, in the SIC system, were spread out into categories such as manufacturing, communication, and others, without any clear identification.

Another major change from the SIC to the NAICS was the separation of *auxiliary establishments*—such as personnel management, research and development, data processing, centralized management, and administrative support—from manufacturing industries. In the SIC, auxiliary establishments were classified according to the industry they served that in many cases were manufacturing industries, and thus classified as such. But under the NAICS, the auxiliary establishments are classified by the type of service the establishment provides. Instead of being counted as manufacturing establishments, management and corporation headquarter jobs gained their own category, the "55 - Management of Companies and Establishments" category (Murphy and Burgess 1998; Parker 2003; Russel, Tack, and Usher 2004; Hiles 2001).

Hiles (2001) suggests a separation of the industries into two major domains: the "goods-producing" industries, such as industries related to natural resources and mining, construction, and manufacturing; and the "service-providing" industries, such as trade, transportation, utilities, information, financial activities, professional and business services, education, health services, leisure, hospitality, other services, and unclassified (Hiles 2001). I use Hiles's characterization to aggregate different industries into more comprehensive but yet specific industries.

Although the NAICS still maintains a detailed and high number of manufacturing industries with 364 codes, the service sectors combined add up to 525 industries. This high level of industry detailing allows us to count those industries that are most relevant for this study. Next, I discuss the hierarchical structure of the codes, the issues and challenges posed by this classification system, and the solution I implemented in this dissertation.

3.2.1 NAICS Structure

NAICS codes are organized in a hierarchy of codes, ranging from two- to six-digits, in five levels of detail. The two-digit NAICS codes represent industries in very broad terms, such as "Retail Trade," "Educational Services," and "Arts, Entertainment, and Recreation"—in other words, their highest level of aggregation. Each additional digit breaks down the parent category: three digits refer to subsectors, four digits refer to industry groups, five digits refer to the international industry level, and six digits refer to the national detail, as table 3.2 summarizes (Murphy and Burgess 1998; Parker 2003). Codes in the US should match those of Mexico and Canada up to the five-digits level.

Hierarchy of NAICS Codes

Number of Digits	Level
Two	Highest Level of Aggregation
Three	Subsector
Four	Industry Group
Five	International Industry Level
Six	National Detail

Source: Murphy and Burgess, 1998.

Table 3.2: Hierarchy of industry codes by number of digits

Table 3.3 illustrates this hierarchical structure with the "72 - Accommodation and Food Services" industries as an example. Dashes and slashes represent place holders in the 6-digit codes. The subsectors in this category are "721 - Accommodation" and "722 - Food Services and Drinking Places." Therefore, the 72 category is a "parent" category to 721 and 722, and the latter two are the former's "children."

The first subsector, "721 – Accommodation," is broken down into three industry groups: "7211 - Traveler Accommodation," "7212 - RV Parks and Recreational Camps," and "7213 - Rooming and Boarding Houses." In the first industry group, we find three 5-digit levels, which correspond to the international industry level because it should match datasets in Mexico and Canada at least up to this level. The first two of these groups, "72111 - Hotels (except Casino Hotels) and Motels" have only one category in its national detail, which is "721110 - Hotels (except Casino Hotels) and Motels," of the same title. Codes that end with zero mean that they are the only one in that group. On the other hand, the category "72119 - Other Traveler Accommodation" contains two subcategories, "721191 - Bed-and-Breakfast Inns" and "721199 - All Other Traveler Accommodation," none of which end in zero. This pattern repeats for each industry category, with differing degrees of complexity, according to the level of detail represented.

Example of Data Structure Within Industry

NAICS	DESCRIPTION
72----	Accommodation and Food Services
721///	Accommodation
7211//	Traveler Accommodation
72111/	Hotels (except Casino Hotels) and Motels
721110	Hotels (except Casino Hotels) and Motels
72112/	Casino Hotels
721120	Casino Hotels
72119/	Other Traveler Accommodation
721191	Bed-and-Breakfast Inns
721199	All Other Traveler Accommodation
7212//	RV (Recreational Vehicle) Parks and Recreational Camps
72121/	RV (Recreational Vehicle) Parks and Recreational Camps
721211	RV (Recreational Vehicle) Parks and Campgrounds
721214	Recreational and Vacation Camps (except Campgrounds)
7213//	Rooming and Boarding Houses
72131/	Rooming and Boarding Houses
721310	Rooming and Boarding Houses
722///	Food Services and Drinking Places

Source: U.S. Census Bureau, 2012 NAICS Definition

Table 3.3: Example of industry classification structure in the "accommodation and food services" industry

Each category should count most of the accommodation establishments in the industry. However, the "Other" or "All Other" categories allow for counting the establishments that do not directly fit into the description of the main categories, but that are too small to have a major category as their own. In consulting the NAICS website,[4] we see that examples of the "other accommodations" are guest houses, tourist homes, housekeeping cabins and cottages, and youth hostels. In each NAICS national detail level, there is a similarly structured "other" or "all other" category.

This is the structure used by the US Census to release establishment data at the ZIP code level, and the method used to identify which categories are relevant for the variables used in this study. At any level, any "parent" category should equal the sum of its "child" categories. Therefore, if we know the number of establishments of the "child" categories, we are able to calculate the number of establishments in the parent category, but the inverse is not true, unless there is a single subcategory. This setup will lead to the decisions for the final job count for each industry presented in the last subsection.

3.2.2 Time Series Consistency Issues

After many years trying and with the advice of experts in the field,[5] it was established that the transition between the SIC and NAICS codes is not seamless over time. The NAICS Association offers an identification tool on their website,[6] where we can find crossovers between SIC and different editions of NAICS, as well as more detail about each category and information about the largest companies in each industry. While there are corresponding SIC to NAICS categories and vice-versa, these crossovers do not constitute continuous time series data as SIC categories were organized very differently compared to the NAICS categories. Therefore, for some

---

[4] See https://www.naics.com/naics-code-description/?code=721199, accessed July 06, 2019.
[5] Murphy and Burgess (1998), Russel, Tack, and Usher (2004), Hiles (2001), and a very helpful clerk at the National Archives in Washington, DC.
[6] See https://www.naics.com/search/.

categories, estimating the number of jobs may be very hard even at the highest level of aggregation. These irregular changes also occur among different NAICS releases, creating industry code conversion issues, which is taken into consideration in this section.

The NAICS codes were released in 1997 and first implemented on the 1998 County Business Patterns dataset. The NAICS codes are updated every five years. The first three releases of the NAICS codes were implemented to classify business in the county business patterns data in the following year,[7] while the 2012 NAICS codes were implemented in that same year (Census 2019). Table 3.4 shows the correspondence of the NAICS code update year to the CBP datasets release years.

Years of NAICS Codes Implementation

CBP Data Years	SIC/NAICS Year
1974 - 1987	SIC 1972
1988 - 1997	SIC 1987
1998 - 2002	NAICS 1997
2003 - 2007	NAICS 2002
2008 - 2012	NAICS 2007
2012 - 2016	NAICS 2012

Source: U.S. Census Bureau

Table 3.4: Years of SIC/NAICS industry classification list and implementation years

Table 3.5 shows that since the release of the 1997 NAICS there hasn't been a great increase in the number of industries; in fact, there has been a decline in the number of 6-digit codes. However, the codes should reflect changes in the industries from one release to another. Some of these changes might be as simple as new numbers—for example, from 513120 in 1997 to 515120

[7] Prior to 2012, County Business Patterns lagged by one year in the adoption of the classification system employed in the Economic Census. Starting in 2012, the classification system was changed in the same year (Census 2019).

in 2002, both referring to "Television Broadcasting." However, trickier changes involve new categories that are the result of a breakdown of old categories, making it difficult to estimate the number of jobs in some industries as the codes split. Due to these ruptures, data comparisons across years require attention and some degree of generalization to higher levels of codes; otherwise, some industries might be lost from or duplicated in the data.

Number of Categories by NAICS Edition and Industry Title

Code	Industry Title	Number of Categories in 1997	Number of Categories in 2002	Number of Categories in 2007	Number of Categories in 2012
11	Agriculture, Forestry, Fishing and Hunting	64	64	64	64
21	Mining	29	31	29	29
22	Utilities	10	10	10	14
23	Construction	28	31	31	31
31	Manufacturing	110	110	110	73
32	Manufacturing	127	127	127	97
33	Manufacturing	236	238	235	194
42	Wholesale Trade	69	71	71	71
44	Retail Trade	48	48	48	44
45	Retail Trade	24	27	27	25
48	Transportation and Warehousing	50	50	50	50
49	Transportation and Warehousing	7	7	7	7
51	Information	33	36	32	32
52	Finance and Insurance	42	42	41	41
53	Real Estate Rental and Leasing	24	25	24	24
54	Professional, Scientific, and Technical Services	47	47	48	48
55	Management of Companies and Enterprises	3	3	3	3
56	Administrative and Support and Waste Management and Remediation Services	43	45	44	44
61	Educational Services	17	17	17	17
62	Health Care and Social Assistance	39	39	39	39
71	Arts, Entertainment, and Recreation	25	25	25	25
72	Accommodation and Food Services	15	15	15	15
81	Other Services (except Public Administration)	49	49	49	49
92	Public Administration	29	29	29	29
Total		1168	1186	1175	1065

Table 3.5: Number of categories by year of NAICS release in the highest level of industry aggregation

In order to identify NAICS codes changes, I use the US Census's concordance tables from 2012 to 2007, 2007 to 2002, and 2002 to 1997, as the first year of data is 1998 and the last is 2016.[8] The 2016 NAICS have already been released, but since data after 2016 is not included in this study, that concordance table was not included here. After connecting the four concordance tables

[8] All concordance tables can be found on:
https://www.census.gov/eos/www/naics/concordances/concordances.html, accessed on 2019-08-12.

programmatically, I manually checked the correspondences in order to identify how these changes can affect the time series data.

Number of Code Changes Across Years

Category	Number of Code Changes
Manufacturing	561
Wholesale	68
High-Tech	55
Retail	35
Construction	24
Producer Services	12
Arts Producers	11
Utilities	5
Agriculture	4
Food	4
Arts Amenities	1
Total	780

Table 3.6: Number of industry code changes across all four NAICS releases

Table 3.6 shows that most of the changes were in the manufacturing industries. However, there are many changes that should be considered in high technology, producer services, arts producers, and recreation categories.

One notable change is the revision of "516100 - Internet Publishing and Broadcasting" (table 3.7), where the 1997 code for "511110 - Newspaper Publishers" was broken down in 2002 into "511110 - Newspaper Publishers" and a portion into "516110 - Internet Publishing and Broadcasting." This partition would not present aggregation problems if the code 516110 wasn't also constituted of parts from "Periodical Publishers," "Book Publishers," "Directory and Mailing List Publishers," and "Greeting Card Publishers," all of which also have a 2002 category of their own. Therefore, each one of these single categories in 1997 were broken down into its own category in 2002, plus an unknown portion into "516110 - Internet Publishing and Broadcasting."

In this case, we may assume that when the Census aggregated these establishments, the ones that were related to an online presence were separated from the original category into the 516110 category.

At the same time, the “511119 - All Other Publishers” and “514199 - All Other Information Services” 1997 category were also broken down into three parts each and incorporated into other categories in 2002. Estimating how these categories were broken down by dividing by the number of parts can be tricky as we cannot be sure how that division actually occurred; therefore, I decided against it. The categories mentioned are relevant here as they affect the categories that include arts and high-technology industries, which are singled out in this study. Thus, these classification differences might pose issues when analyzing high-tech and arts industries.

Changes to Information (51) Industry Codes from 1997 to 2002 NAICS

1997 NAICS		2002 NAICS	
Code	**Title**	**Code**	**Title**
511110	Newspaper Publishers	511110	Newspaper Publishers
511110	Newspaper Publishers	516110	Internet Publishing and Broadcasting (pt.)
511120	Periodical Publishers	511120	Periodical Publishers
511120	Periodical Publishers	516110	Internet Publishing and Broadcasting (pt.)
511130	Book Publishers	511130	Book Publishers
511130	Book Publishers	516110	Internet Publishing and Broadcasting (pt.)
511140	Database and Directory Publishers	511140	Directory and Mailing List Publishers
511140	Database and Directory Publishers	516110	Internet Publishing and Broadcasting (pt.)
511191	Greeting Card Publishers	516110	Internet Publishing and Broadcasting (pt.)
511199	All Other Publishers	511130	Book Publishers
511199	All Other Publishers	511199	All Other Publishers
511199	All Other Publishers	516110	Internet Publishing and Broadcasting (pt.)
514199	All Other Information Services	516110	Internet Publishing and Broadcasting (pt.)
514199	All Other Information Services	518112	Web Search Portals
514199	All Other Information Services	519190	All Other Information Services

Table 3.7: Example of changes in industry classification in the Information industry

In this section, I pointed to some issues in the time series consistencies while trying to connect datasets from different years, even though the source is the same. Some of these issues do occur in the industries of interest; however, not many. Many of the issues for this study belong to the “51 - Information” category, while the majority of the codes for other industries remained the same, as discussed in the next section.

3.2.3 Simplifying NAICS Codes

Informed by the issues and challenges of industry aggregation methods above, I propose a simplification of the NAICS industries classification system according to past literature and the goals of this study. This dissertation focuses on the arts, recreation, business services, and high-technology industries. Each one of the industry variables analyzed in chapters 4 and 5 are constituted of a combination of industries identified by the NAICS codes. Therefore, industries such as agriculture, construction, manufacturing, mining, retail, transportation, utilities, and wholesale can be kept in their 2-digit codes, their highest level of aggregation, thus eliminating time consistency issues. Then, we re-aggregate the industries of interest, such as high-tech, arts and entertainment, and business services from the 6-digit level into larger and more comprehensive subcategories.

This re-aggregation procedure redefines more relevant industry variables by combining 6-digit industries in different approaches than the official classification. For example, in the beginning of this project, we separated arts industries from non-arts industries, thus having one arts category. But as different characteristics within the arts industries became clearer, we divided the arts into three arts categories. Therefore, in order to compute NAICS industries, we should also consider how much aggregation is acceptable (1) to summarize industries into fewer variables, (2) to keep relevant distinctions among industries, and (3) to minimize the time-series inconsistency issues discussed above. One solution that I propose here is to still create the arts and non-arts separation, but then to include two levels of categories and subcategories in each industry type.

Table 3.8 shows the categories and subcategories in “arts” and “jobs” (our shorthand for non-arts related employment). Chapter 4 analyzes the more comprehensive relationship between “arts” and “jobs,” while chapter 5 discusses a narrower relationship between “arts” (and their subcategories) with business services and high-tech industries separately.

Type	Category Codes	Category Title	Subcategory Code	Subcategory Title
arts	amn	Arts Amenities	aa1	Museums
		Arts Amenities	aa2	Performing Arts
		Arts Amenities	aa3	Spectator Sports
	apr	Arts Producers	ap1	Broadcasting
		Arts Producers	ap2	Motion Pictures
		Arts Producers	ap3	Publishers
		Arts Producers	ap4	Sound
		Arts Producers	ap5	Writers
	rcr	Recreation	rec1	Gambling
		Recreation	rec2	Parks
		Recreation	rec3	Sports
		Recreation	rec4	Tourism
jobs	bs	Business Services	bs1	Accountants
		Business Services	bs2	Advertising
		Business Services	bs3	Business Support
		Business Services	bs4	Consulting
		Business Services	bs5	Finance
		Business Services	bs6	Insurance
		Business Services	bs7	Law
		Business Services	bs8	Real Estate
	edu	Education	edu	Education
	foo	Food	foo	Food
	hlth	Health	hlth	Health
	is	Infra-Structure	trsp	Transportation
		Infra-Structure	util	Utilities
		Infra-Structure	whsl	Wholesale
	gp	Goods-Producing	agr	Agriculture
		Goods-Producing	cntr	Construction
		Goods-Producing	mfct	Manufacturing
		Goods-Producing	min	Mining
	ht	High-Tech	ht1	Design
		High-Tech	ht2	HT Bio
		High-Tech	ht3	HT Manufacturing
		High-Tech	ht4	Internet
		High-Tech	ht5	Research
		High-Tech	ht6	Telecom
	oth	Other	oth	Other
	rtl	Retail	retl	Retail

Table 3.8: Industry categories and subcategories used to aggregate the data in this dissertation

While I do not address each individual category and subcategory presented here, these are classifications that were worked on for a long time during the development phases of this project.

The initial plan for this dissertation included latent variable models that would require more detailed individual industries as variables. Thus, the subcategories would be the constructs for the categories, which would then in turn be part of either arts or jobs. However, these then became future projects to follow this dissertation.

The tables in appendix B.2 show the NAICS codes and industry names included in each category and subcategory in more details as seen in table 3.8. The codes are from the 2012 NAICS edition, and for brevity, I have removed the "other" and "all other" categories; however, please keep in mind that the "other" and "all other" categories do exist for most industries presented, which can always be consulted on the NAICS website.[9]

3.2.4 Arts, Business Services, and High-Tech Categories

In this section, I present with greater detail elements in each of the categories that are more closely analyzed in this dissertation: the arts, business services, and high-tech industries.

The *arts and entertainment* (or "arts") industries are divided into three categories: arts amenities, arts producers, and recreation. Each of these arts categories are aggregations of 6-digit NAICS codes into subcategories, as show in table 3.8. Table 3.9 shows further details within the arts subcategories.

In the *arts amenities* category are those industries that include establishments in which the consumer is part of an audience or a patron of the arts, who watch performances or sports events. The arts amenities category is subdivided into: (1) museums and libraries, (2) performing arts (theaters, musical groups), and (3) spectator sports (sports teams and their promoters). This

[9] https://www.naics.com/search/.

category reflects the employment that produces art directly to the consumer mostly live, and thus the location of these industries is relevant to where it is consumed.

The *arts producer* category includes those establishments that produce products for the arts but that do not provide their final product directly to the consumer, but through a third mean. The location of these establishments do not necessarily need to be in the same locations as the consumers, and their products can be transported and distributed further than where they are produced. The arts producers category is subdivided into (1) broadcasting (radio and television stations), (2) motion picture production and distribution, (3) publishers (newspapers, books, etc.), (4) sound (such as music producers), and (5) writers.

The *recreation* category includes industries in which the consumers participate in the activities rather than being just an observer. These industries may offer recreation services to the consumers that are not necessarily artistic in nature but that provide entertainment value and related services. Similar to arts amenities, recreation establishments offer their services directly to the consumers and in the same location. The recreation category is subdivided into: (1) gambling establishments, (2) parks, (3) sports, and (4) tourism.

Arts Categories Details

	Code	Subcategory Name	Title
Arts Amenities (amn)	**aa1**	Museums	Libraries and Archives Museums and Historical Sites
	aa2	Performing Arts	Theater Companies and Dinner Theaters, Dance Companies Musical Groups and Artists Other Performing Arts Companies
	aa3	Spectator Sports	Sports Teams and Clubs, Racetracks, Other Spectator Sports Promoters of Performing Arts, Sports, and Similar Events with and without Facilities Agents and Managers for Artists, Athletes, Entertainers, and Other Public Figures
Arts Producers (apr)	**ap1**	Broadcasting	Radio Networks and Stations Television Broadcasting Cable and Other Subscription Programming
	ap2	Motion Pictures	Motion Picture and Video: Production, Distribution, Theaters, Drive-Ins Teleproduction and Other Postproduction Services
	ap3	Publishers	Publishers: Newspaper, Periodicals, Books, Directory, Mailing List, Greeting Cards All Other Publishers
	ap4	Sound	Software and Other Prerecorded Compact Disc, Tape, and Record Reproducing Blank Magnetic and Optical Recording Media Manufacturing Record Production, Distribution Music Publishers, Sound Recording Studios
	ap5	Writers	News Syndicates Independent Artists, Writers, and Performers
Recreation (rcr)	**rec1**	Gambling	Casinos (except Casino Hotels) Other Gambling Industries
	rec2	Parks	Zoos and Botanical Gardens Nature Parks and Other Similar Institutions Amusement and Theme Parks Amusement Arcades
	rec3	Sports	Sports and Recreation Instruction Golf Courses and Country Clubs, Skiing Facilities, Marinas Fitness and Recreational Sports Centers Bowling Centers All Other Amusement and Recreation Industries
	rec4	Tourism	Scenic and Sightseeing Transportation, Land, Water, Other Travel Agencies, Tour Operators Convention and Visitors Bureaus Hotels and Motels, Casino Hotels, Bed-and-Breakfast Inns, Traveler Accommodations RV (Recreational Vehicle) Parks and Campgrounds, Camps

Table 3.9: Industries included in the arts categories and subcategories

The *high-tech* industries are analyzed in chapter 5, and its construct is based on Moretti's (2012) and Hecker's (2005) concepts. Hecker (2005) defines high technology as industries that operate with (1) high-proportion of scientists, engineers, and technicians; (2) high-proportions of research and development; (3) production of advanced-technology products; and (4) advanced production methods, including high-tech goods and services in production (Hecker 2005, 58). High-tech industries are also seen as attractive by local governments as they create well-paying, high-level jobs that also require a highly educated workforce, increasing productivity, competitiveness, and economic growth. Hecker calculates the growth and proportion of technology-oriented occupations in forty-six four-digit 2002 NAICS codes, separating the high-tech industries into three levels. His industry lists include oil refineries, chemical manufacturing, and others that will not be considered in this study as high tech. While it is true that some manufacturing industries employ engineers and scientists, when we talk about high-technology industries, the concept that comes to mind are the internet and computer industries as in Moretti's definition of high tech, rather than petroleum and chemicals. Therefore, we consider Hecker's description of high-tech industries, but follow Moretti's conception of high-tech industries to calculate this variable.

Table 3.10 shows the subcategories for high tech but in only one level. Initially, I planned on analyzing the high-tech industry as a latent variable of the six subcategories, but in this dissertation, I maintain the high-tech industry as one category, but take a closer look into the internet industry. The high-tech category is subdivided into: (1) design, (2) biotechnology, (3) manufacturing of high-tech products, (4) internet, (5) research and development, and (6) telecommunications.

High-Tech Categories Details

	Code	Subcategory Names	Category Descriptions
High-Tech (ht)	**ht1**	Design	Architectural, Landscape, Engineering, Drafting, Building Inspection Services Geophysical Surveying and Mapping Services Testing Laboratories Interior Design, Industrial Design, Graphic Design, Other Specialized Design Services
	ht2	Bio	Medicinal and Botanical Manufacturing Pharmaceutical Preparation Manufacturing In-Vitro Diagnostic Substance Manufacturing Biological Product (except Diagnostic) Manufacturing
	ht3	Manufacturing and Repair	Manufacturing: Electronic Computer Computer Storage Device, Computer Terminal, Communication Equipment, Audio and Video Equipment, Electronic Components, Electromedical and Eletrotherapeutic Apparatus, Navigation Systems, Environmental Control Equipment, Measuring Instruments, Guided Missile and Space Vehicle Aircraft Manufacturing, Aircraft Engine and Engine Parts Manufacturing, Other Aircraft Parts and Auxiliary Repair and Maintenance: Consumer Electronics, Computer and Office, Communication Equipment, Commercial and Industrial Equipment Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing
	ht4	Internet	Software Publishers, Internet Publishing and Broadcasting and Web Search Portals Computer Programming Services, Computer Systems Design Services, Computer Facilities Management Services
	ht5	Research	Research and Development in the Social Sciences and Humanities Professional, Scientific, and Technical Services Research and Development in Biotechnology Research and Development in the Physical, Engineering, and Life Sciences (except Biotechnology)
	ht6	Telecom	Wired Telecommunications Carriers Wireless Telecommunications Carriers (except Satellite) Telecommunications Resellers Satellite Telecommunications Data Processing, Hosting, and Related Services

Table 3.10: Subcategories for high-tech industries

The *business services* categories include “insurance, banking, financial services, real estate, legal services, accounting, and professional associations” (Sassen 2001, 90), based on Sassen’s (2001) concept of the services aimed at private sector firms that serve as anchors in global cities. In other words, the more and better mix of producer services a city offers, the more it can be connected globally to other cities, serving as headquarters to large corporations. The business services category is subdivided into (1) accounting services, (2) advertising services, (3) business support, (4) consulting, (5) finance, (6) insurance, (7) law, and (8) real estate.

Business Services Categories Details

	Code	Subcategory Names	Category Descriptions
Business Services	**ps1**	Accountants	Accountants, Tax Preparation Services, Other Accounting Services Payroll Services
	ps2	Advertising	Advertising Agencies, Public Relations Agencies, Media Buying Agencies, Media Representatives Outdoor Advertising, Direct Mail Advertising, Advertising Material Distribution Services Marketing Research and Public Opinion Polling Photography Studios, Portrait, Commercial Photography
	ps3	Business Support	Offices of Bank Holding Companies, Corporate, Subsidiary, and Regional Managing Offices Office Administrative Services, Facilities Support Services Employment Placement Agencies, Temporary Help Services, Professional Employer Organizations Document Preparation Services, Other Business Service Centers (including Copy Shops) Telephone Answering Services, Telemarketing Bureaus, Private Mail Centers, Packaging and Labeling Services Collection Agencies, Credit Bureaus, Repossession Services, Court Reporting and Stenotype Services Convention and Trade Show Organizers Human Resources Consulting Services, Executive Search Services
	ps4	Consulting	Administrative Management and General Management Consulting Services Marketing Consulting Services Process, Physical Distribution, and Logistics Consulting Services Environmental Consulting Services, Other Scientific and Technical Consulting Services Human Resources Consulting Services
	ps5	Finance	Monetary Authorities-Central Bank, Commercial Banking, Savings Institutions, Credit Unions, Credit Card Issuing, Sales Financing, Consumer Lending, International Trade Mortgage and Nonmortgage Loan Brokers, Real Estate Credit, Financial Transactions Processing, Reserve, and Clearinghouse Activities Investment Banking and Securities Dealing, Securities Brokerage, Commodity Contracts Dealing and Brokerage Portfolio Management; Investment Advice; Trust, Fiduciary, and Custody Activities Pension Funds, Health and Welfare Funds, Insurance Funds, Open-End Investment Trusts, Estates, and Agency Accounts
	ps6	Insurance	Life Insurance Carriers; Health and Medical Insurance Carriers; Property and Casualty Insurance Carriers Insurance Agencies and Brokerages, Claims Adjusting Third Party Administration of Insurance and Pension Funds
	ps7	Law	Offices of Lawyers, Offices of Notaries Title Abstract and Settlement Offices
	ps8	Real Estate	Lessors of Residential Buildings and Dwellings, of Miniwarehouses and Self-Storage Units, of Other Real Estate Property Offices of Real Estate Agents and Brokers Residential Property Managers, Nonresidential Property Managers Offices of Real Estate Appraisers, Other Activities Related to Real Estate

Table 3.11: Industries included in the business services categories and subcategories

In this section, I presented the NAICS codes re-aggregation method for the variables relevant for the empirical section of this study. Most industries will remain in their highest level of aggregation, but the arts, high tech, and business services industries were subdivided into subcategories. The main NAICS codes per subcategory of the categories mentioned here can be found in appendix B.2.

3.3 Algorithm to Compute Variables

In this section, I explain in detail the algorithm used to transform the Census CBP raw data into *estimated number of jobs by hexagon*. This calculation is performed in several steps because we distribute the total number of jobs per ZIP code from the employment data proportionately to the count of establishments by number of employees and industry from the establishment data. We then transform the final product of this first transformation into hexagon data. The calculations are done for all 11,200 ZIP codes and fifty-seven industry categories at once. I discuss the ideas of the algorithm in general, but I do not provide the full code in R here because of its length.

The flowchart in figure 3.1 shows a summary and sequence of steps taken to produce the final dataset of estimated number of jobs by industry and hexagon. We merge four different datasets: the CBP *employment data* (for total employment numbers), the CBP *establishment data* (for industry size), the *NAICS codes* (for the corresponding subcategories), and the *geographic correspondence table* (for the ZIP code to hexagon conversion).

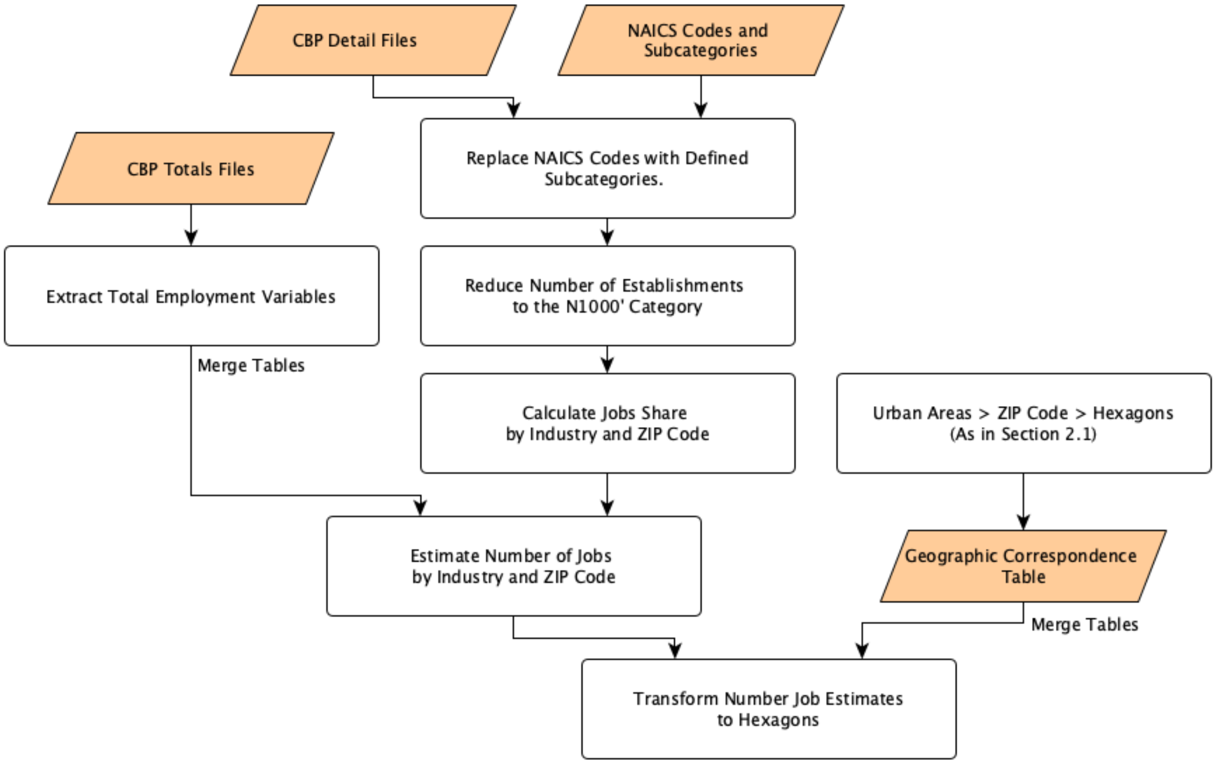

Figure 3.1: Workflow of the data transformation from ZIP code to hexagon

In the next section, I discuss the procedures to recalculate the data from ZIP codes into hexagons.

3.3.1 The Employment and Establishment Data

The CBP ZIP Code Totals File provides generalized data for all industries combined at the ZIP code level. The main variables in this dataset are total number of employees, first quarter payroll, total annual payroll, and number of establishments, regardless of industry type. The Census releases these files annually, but here we use the files from 1998 to 2016, or nineteen years of data.

The variable of interest for this study is the *total number of employees (emp)* as this variable guides us in estimating the number of jobs by industry and ZIP code. Thus, with each year's employment data, we read the dataset, extract the zip and emp variables, and filter the urban ZIP codes found in the correspondence file. Then, we merge[10] all years of total employment data into one dataset.[11]

The CBP ZIP code establishment data is released annually together with the employment data. The establishment data is significantly larger than the employment data as it discloses the number of establishments by ZIP code and industry based on the NAICS. All variables from the establishment data are used as released by the Census Bureau.

The steps presented below redistributes the total number of employees from the employment data based on the number of establishments and industries from the establishment data to estimate the number of employees by industry in each hexagon. Since we aggregate the total employment by hexagons, we are still protecting the employment numbers for individual establishments.

The following items explain the different steps in the algorithm to estimate the number of employees per industry as described above.

1. Replace the NAICS codes with the subcategories names. As discussed in section 3.2, the changes in each release of the NAICS codes complicates the time continuity of the dataset. Instead of keeping each 6-digit NAICS code separate, I aggregated codes that fit into the subcategories of industries as defined in that section. A complete list of the NAICS codes aggregated by subcategory can be found in appendix B.2.

---

[10] Function full_join from package tidy verse.
[11] File “data/total_emp_zip.csv.”

2. Aggregate the number of establishments for the subcategories. Since we replaced the NAICS codes with the subcategories, the dataset now contains rows with the same industry and ZIP code; therefore, we aggregate by sum all the rows of the same ZIP code and subcategory, which decreases the number of rows to one row per industry by ZIP code. This computation is done column-wise for each column reflecting number of establishments, grouping ZIP codes and subcategories concomitantly. The end result is a new table of ZIP codes, subcategories, and nine columns of establishments by number of employees.

3. Reduce the establishments' size variables. In this step, we need to equate the different establishment sizes and reduce them to one single establishment variable. We know the exact range of the first eight ranges of establishment size: the first range counts the number of establishments that employ between one and four people, the second range shows the number of establishments that employ between five and nine people, and so on. However, the ninth range has the maximum value undefined, making it harder to estimate the number of employees in that variable from the total that could be assigned to that range.

As a solution, I propose equating the first eight ranges as if all establishments were made up of establishments that employ over one thousand employees as in the N1000 range. We use the *median* between the minimum and maximum values of each range to define how much each establishment in the first eight ranges would add to the N1000+ category by multiplying the number of establishments in each range by the constants in table 3.12.

Multipliers for Estimating Number of Jobs				
Range	**Bottom**	**Top**	**Median**	**Constant**
N1-4	1	4	2.5	0.0025
N5-9	5	9	7	0.007
N10-19	10	19	14.5	0.0145
N20-49	20	49	34.5	0.0345
N50-99	50	99	74.5	0.0745
N100-249	100	249	174.5	0.1745
N250-499	250	499	374.5	0.3745
N500-999	500	999	749.5	0.7495
N1000	1000	Inf	?	1

Table 3.12: Multipliers for the allocation of the estimated number of jobs from ZIP code to hexagons

In other words, one company that employs from one to four people would add 2.5 more employees to the N1000+ category on average; one company of five to nine people would add seven more employees on average to the N1000+ category, and so on. The median is a better alternative as it offsets companies that are closer to the bottom or top of the range by averaging the establishments. After these calculations, however, we still don't know how many employees are in the N1000+ category, but only the number of establishments. Therefore, taking into consideration the value available in the N1000 category, we divide the medians by 1,000 to define constants. In other words, these constants indicate how much more each establishment in the smaller ranges would accrue to a hypothetical N1000 unit if they were to add up to a total of 1,000 employees to that category. The constant for N1000 is 1, as there should be no changes in the number of establishments in that category.

Thus, we multiply the number of establishments in the first eight ranges by the corresponding constant as if these smaller establishments were adding equivalent establishments to the N1000+ category, as N1000' (prime). After this multiplication, we sum all values to find the total estimate. This computation is done row-wise.

Equation X summarizes the aforementioned transformation of all establishment size variables into the N1000' estimate,

$$n1000'_{i,j} = n_{1-4} * .0025 + n_{5-9} * .0070 + n_{10-19} * .0145 + n_{20-49} * .0345 + n_{50-99} * .0745 + n_{100-249} * .1745 + n_{250-499} * .3745 + n_{500-999} * .7495 + n_{1000+} * 1$$

where i is any given ZIP code and j is any given industry.

Again, the N1000' estimates the number of establishments that employ over 1,000 employees if establishments of all sizes were transformed into the N1000 category, using the constants presented above as guide.

4. Calculate the *employment share* of each industry. To distribute the total number of employment by ZIP code among the industries, first we must find the proportion of employment retained by each industry. Using the estimated number of N1000' establishments calculated above, we compute the job share of each industry by dividing the number of N1000' of one industry by the sum of N1000' of all industries in each ZIP code. This equation gives us a picture of how the industries are distributed within ZIP codes if all establishments were the same size, and thus, N1000’ can be used to proportion the total number of jobs in an industry. The composition of industries in each ZIP code may vary as not all ZIP codes have all or the same set of industries; therefore, each ZIP code may have a different number of rows in the dataset.

$$JobsShare_{i,j} = \frac{n1000'}{\sum n1000'}$$

where i is any given ZIP code and j is any industry.

We can verify if the computation was done correctly if the sum of all jobs shares in each ZIP code is equal to one.

$$\sum JobsShare_i = 1$$

where i is any given ZIP code.

5. Estimate number of jobs for each industry. In this step, we estimate the total number of jobs using the jobs share calculated above. First, we must isolate the total employment variable from the totals file, and join it to the other variables. Then, we estimate the number of jobs by multiplying jobs share by the corresponding total employment emp.

$$Jobs_{i,j} = JobsShare * emp$$

At this point, we merge the results from all years into one data frame. The contents of the final data frame for the jobs are zip, subcategory, and 19 columns of jobs_ variables from 1998 to 2016.

3.3.2 Merging the Geographic Correspondence Files

Now that the number of jobs has been estimated by industry for each urban ZIP code and year, we merge the employment estimates with the geographic correspondence data to transform the data from ZIP code format to hexagons. As discussed previously, slivers are pieces that are results of the intersection between a ZIP code and a hexagon. The crucial information from each sliver is its *area*, as the areas are used to estimate the proportion of jobs that should be transferred from one ZIP code to a hexagon. In other words, the areas of the sliver are also the weight of the proportion of jobs from each ZIP code into a hexagon. Thus, to calculate the number of jobs by hexagon, we must sum all the data for the slivers that belong to each hexagon.

$$jobs_{hj} = \sum slivers_{ij}$$

Where h represents each given hexagon, j represents each given industry, and i represents number of jobs by ZIP code in each sliver. What follows are the steps to generate a new dataset.

1. Create a summarized correspondence table. First, we isolate only the geographic correspondence variables of interest:

- JOIN_ID: slivers ID (combination of ZIP and GRID_ID) (N = 128804)
- zip: 5-digits ZIP code (N = 11658)
- GRID_ID: hexagon ID (N = 63555)
- NAME10: the name of the urban area (N = 479)
- weight_area: the proportion of ZIP code in the hexagon

We use these variables to identify locations and weights to aggregate the data from ZIP codes to hexagons.

2. Merge geographic with jobs data. Second, we merge the geographic data with the jobs data by ZIP code. This duplicates rows of data so long as ZIP codes repeat, and for each industry in the ZIP code. For example, if a ZIP code is divided into ten pieces and has five industries, this process will create fifty rows of data for this ZIP code. The new dataset has *5,933,630 rows* of slivers.

3. Estimate number of jobs by sliver. Third, we multiply the ZIP code number of jobs by the area weight corresponding to each sliver. This proportions the estimated number of jobs by ZIP code into its slivers.

4. Estimate number of jobs by hexagon. Fourth, we aggregate slivers by their hexagon GRID_ID and sum sliver values to find the total number of jobs by hexagon and industry. There are a total of *2,560,606 rows* of hexagons.

The result from the steps described in this section generates a new dataset where we have estimated the employment numbers by hexagon for each year from 1998 and 2016, and for each industry subcategory. To find the employment numbers for any category, we must add the total jobs in all of its subcategories.

In the next section, I discuss the methods used in chapters 4 and 5 on the types of variables, cross-lagged regressions, effect sizes, and meta-analysis to understand the relationship between arts and non-arts jobs.

3.4 Methodology to Analyze the Relationship Between Arts and Industry Categories

In this section, I discuss the methodologies used in the empirical chapters to analyze the relationship between arts activities and non-arts employment. Linear regressions are the basis of this study. However, there are many ways in which the data can be analyzed, and after years searching for the most appropriate methods, I chose to combine multiple methods: cross-lagged regressions, first difference regressions, and meta-analysis.

3.4.1 Variable Transformation: Log-Transformation and First Differences

When counting the number of jobs in different urban areas, the distribution of every single variable was extremely skewed. Histograms in figures 3.2 and 3.3 show the skewness of the data in the original metric for the number of jobs per industry type. In this section, the “arts” variables are the sum of “arts amenities,” “arts producers,” and “recreation” as characterized in chapter 3, and the “jobs” variables are the sum of all other variables except the ones in the “arts” variables.

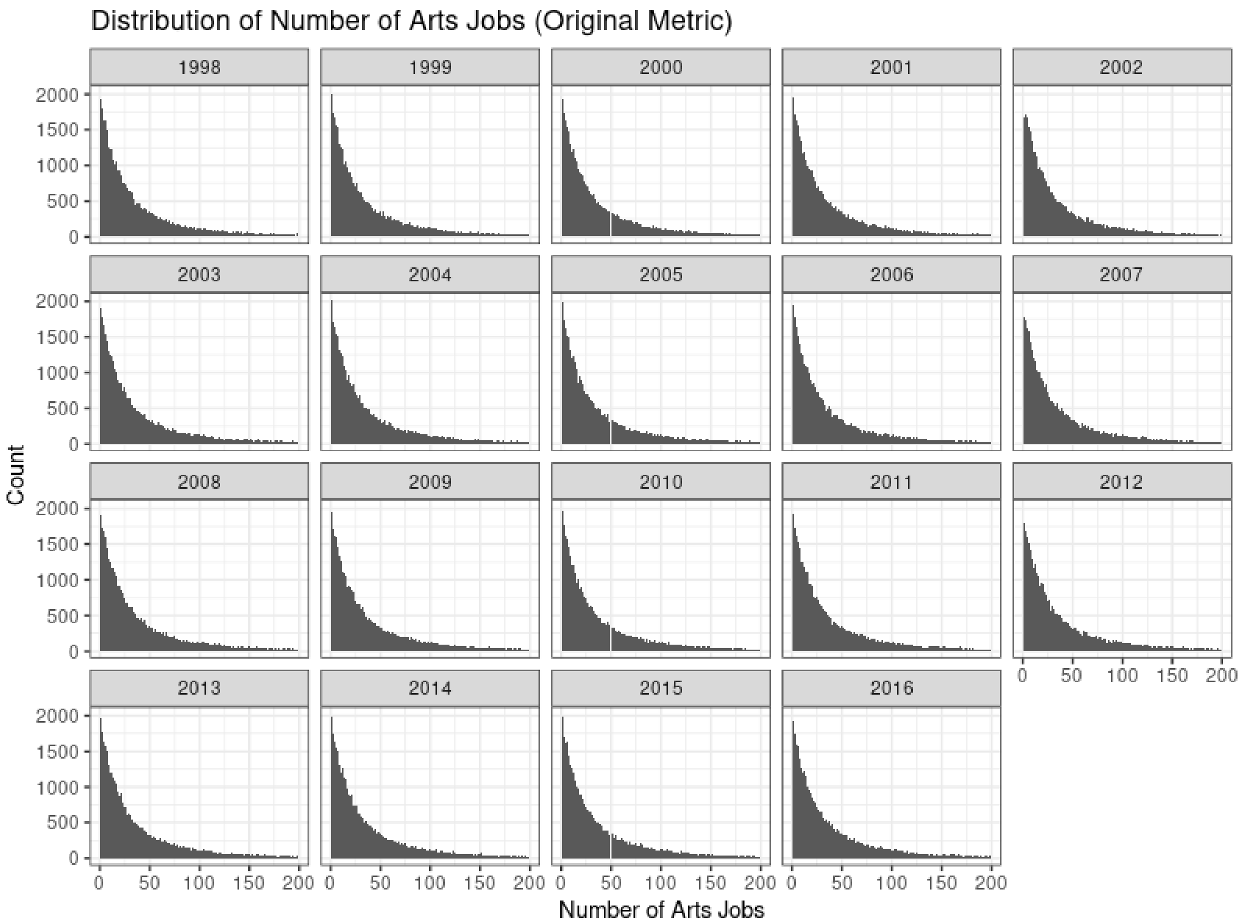

Figure 3.2: Distribution of arts jobs by year in the original metric after data transformation from ZIP code to hexagons

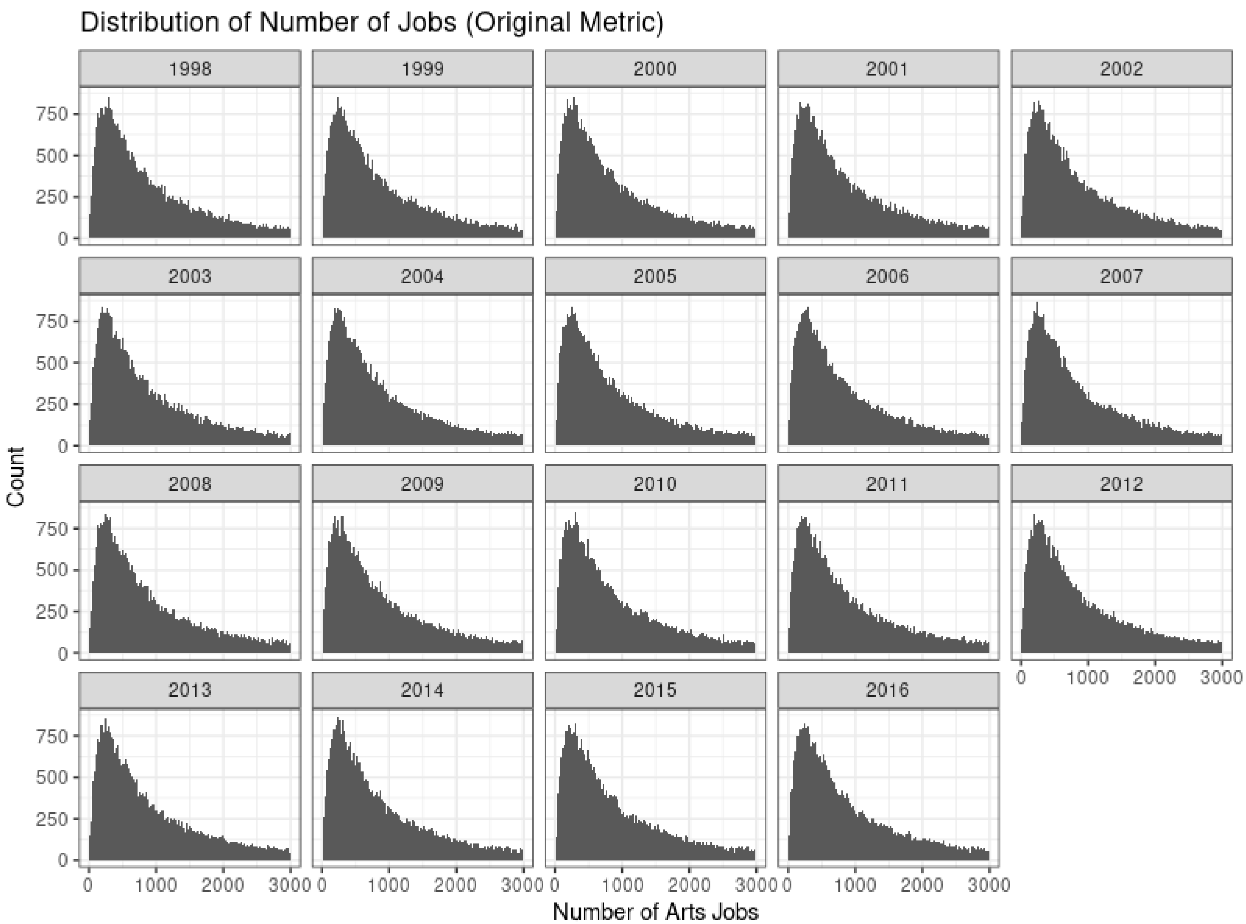

Figure 3.3: Distribution of non-arts jobs by year in the original metric after data transformation from ZIP code to hexagons

The data reflects that there are fewer high density city centers with a high volume of establishments and jobs, like Manhattan in New York and downtown Chicago, than lower density areas, such as suburban residential areas. Therefore, the arts and jobs variables as well as their subcategories are extremely skewed to the right in general. As linear regressions are the main method of analysis, we can simplify the interpretation of results by transforming the variables in two ways: *log-transformation* and *first differences*.

A simple method to correct the skewness is by calculating the log of each variable. In order to avoid infinite as result of $log(0)$, I add .001 to each value (Bellégo and Pape 2019). Histograms in figures 3.4 and 3.5 show that the previously skewed variables present a normal distribution after the log-transformation. The data is extremely skewed in the original metric because even if we select only urban areas, there are still many more hexagons that account for smaller employment numbers than an extraordinary number of jobs per hexagon. Therefore, the histograms focus on the job counts from 0 to 200 jobs to observe the distribution better, but around four thousand cases (the long tail) have been excluded from each histogram for being extreme outliers.

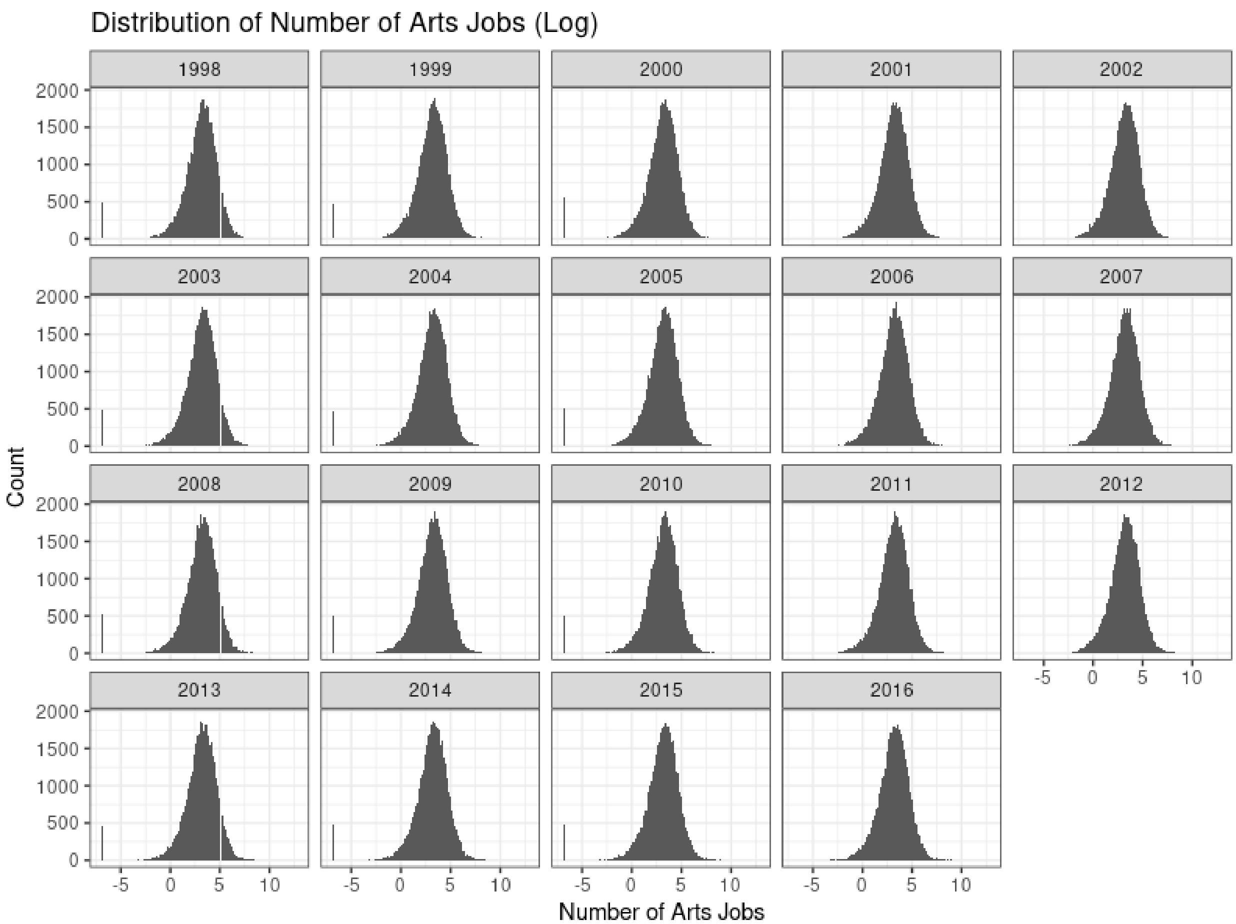

Figure 3.4: Distribution of arts jobs by year and log-transformed after data transformation from ZIP code to hexagons

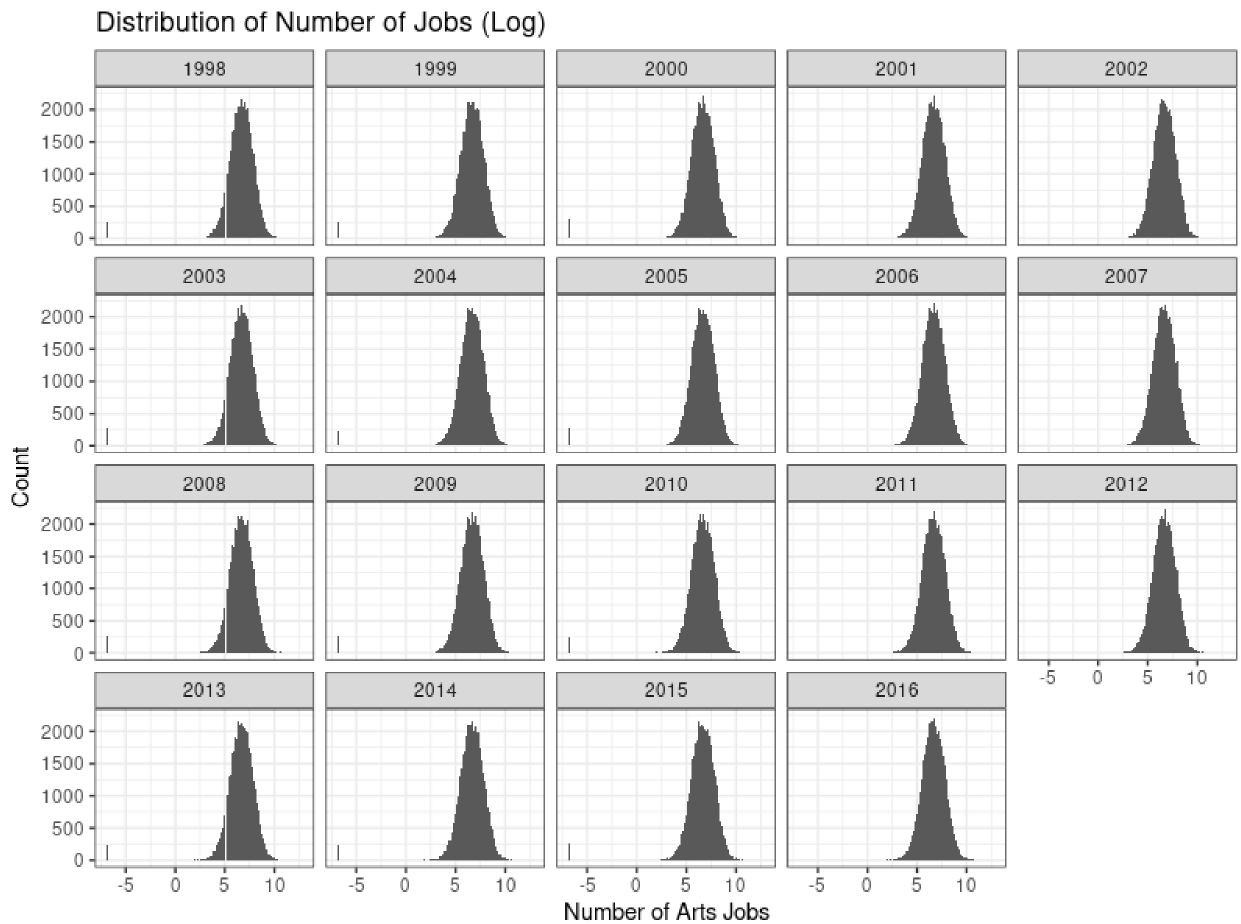

Figure 3.5: Distribution of non-arts jobs by year and log-transformed after data transformation from ZIP code to hexagons

Log-transformation of the variables serves two purposes: (1) it reduces the skewness of the distribution, normalizing it, as shown below; and (2) it simplifies the interpretation of the coefficients. The variables in the original metric were already comparable because they all indicate the *count* of the number of jobs per hexagon; thus, the scale was not an issue in the regressions. Therefore, when we regress one jobs count variable on another jobs count variable, the interpretation is such that "one increase of x-jobs lead to β increase in y-jobs," where β is the regression coefficient for the X independent variable. However, when log-transforming count variables such that both dependent and independent variables are logged, the regression coefficients can be interpreted as *elasticities* from their log-log regressions. As elasticities, the coefficients can be interpreted as percentages, such that "for 1% change in x-jobs, we have β% change in y-jobs."

The second type of transformation used in this study is first differences. The first difference variables are calculated as the changes in number of jobs in each industry from one year to the next, resulting in both positive and negative values, with many values close to zero and high kurtosis. Histograms in figure 3.6a and 3.7 show the distribution of the changes year by year for both arts and jobs variables.

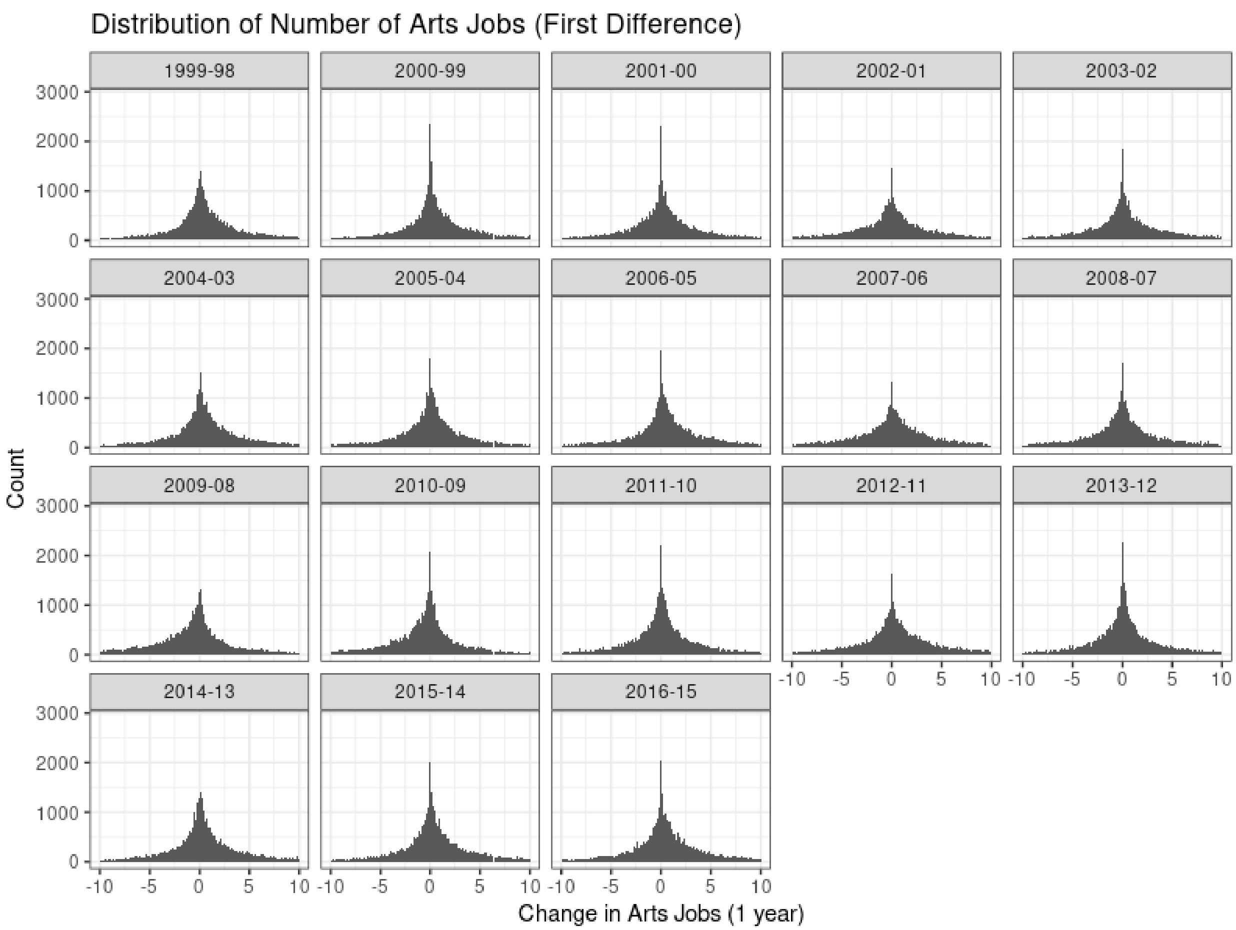

Figure 3.6: Distribution of arts jobs by year and first differences after data transformation from ZIP code to hexagons (part one)

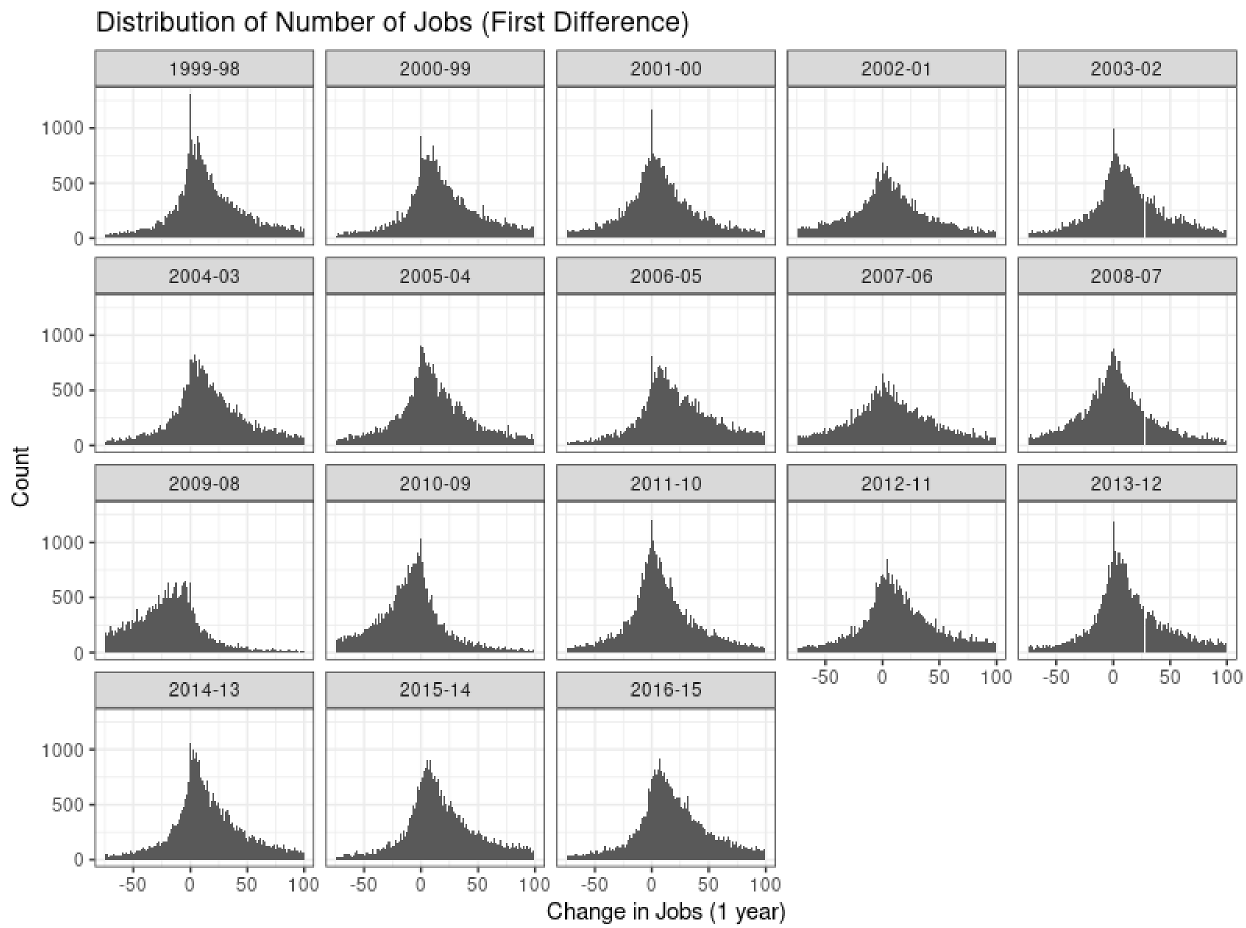

Figure 3.7: Distribution of non-arts jobs by year and first differences after data transformation from ZIP code to hexagons (part 2)

In the case of these count variables, log-transformations and first differences of variables are necessary as these methods improve the quality of the analysis by adjusting skewness, kurtosis, and scales of measurement. Analyses in the original metric could be possible, but rather than linear regressions, other general linear models could be more appropriate, such as binomial or Poisson regressions.

Appendix B.3 shows the descriptive statistics for the variables in the original metric, log-transformations, and first differences for comparison. In the histograms and descriptive statistics we observe that the range of values in each variable has narrowed. Therefore, variable transformations not only reduce the variability in the data, but will also improve the interpretation of regression results.

3.4.2 Regression Methods: Time Lags and First Differences

The industry analysis in chapters 4 and 5 are structured with five different models: a base model, one-year lag, ten-year lag, first differences, and first difference regressions nested by urban area. In this section, I describe each model and how they are applied in the next chapters.

The initial method proposed applying cross-lagged regressions, which combines linear regressions and time. Generally, regressions are performed in cross-sectional data (data for a single time period), but cross-lagged regressions compare two variables in two time periods, where the independent variable is one variable in the prior period, and the dependent variable is another variable in the later year. Using this method, we are able to check how one variable affected another in time, and vice-versa, as we can also compare the effects of each variable on the other.

The main research question in this dissertation is: Do arts activities attract employment, or does employment attract arts activities? In other words, do arts activities in time 1 attract employment in time 2? Or does employment in time 1 attract arts activities in time 2? The path diagram on figure 3.8 reflects the two hypotheses posed in this chapter.

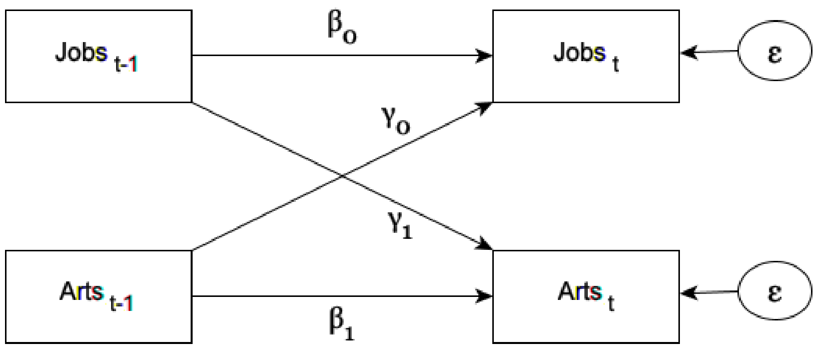

Figure 3.8: Path diagram showing variables and coefficients for each pair of cross-lagged regression model

Where t is the second time period, β represents the lagged coefficients, and γ represents the crossed coefficients. Thus, each variable in the later period is not only regressed on the opposing variable but also on its own lagged value in the earlier period (Berrington, Smith, and Sturgis 2006).

This method maintains that *what happens first, comes first* in the analysis, as independent variables, while what happens later also comes later, as dependent variables. These two regression models include the time component into an otherwise cross-sectional methodology. Then, we compare the results from both regressions to decide which direction is stronger in the time period considered—i.e., whether arts attracted employment or employment attracted arts.

Each regression analysis requires two regressions in two time periods. One set of one straight and one diagonal arrow arriving in a later year variable is one regression equation. As we analyze different pairs of regressions for different pairs of years, we may find a *reciprocal effect* in which for one time period, one of the coefficients is larger than the other, but in the next period, it may be the reverse. The following equations are the mathematical representation of the two regression equations in the path diagram above:

Hypothesis 0, or the hypothesis where jobs attract arts:

$$Arts_{it} = \alpha_0 + \beta_0 * Arts_{i,t-1} + \gamma_0 * Jobs_{i,t-1} + \epsilon$$

Hypothesis 1, or the hypothesis where arts attract jobs:

$$Jobs_{it} = \alpha_1 + \beta_1 * Jobs_{i,t-1} + \gamma_1 * Arts_{i,t-1} + \epsilon$$

Where i is each hexagon, t is the time period, α is the intercept, β is the lagged coefficient (the coefficient of the same variable across the two time periods), γ is the crossed coefficient (the coefficient of the opposing variable across the two time periods), and ϵ is the error term.

From the path diagram, the coefficients β_0 and γ_0 refer to the coefficients in the regression corresponding to the first hypothesis. Both arts and jobs in $t-1$ lead to the value of jobs in t, as both arts and jobs in the previous period have impacts on the next period. The same applies to the coefficients β_1 and γ_1. However, we are mostly interested in the values of both γ coefficients, as their comparison will determine which crossed coefficient is stronger. Then, we compare which γ coefficient is larger, which then determines which direction, if (1) arts on jobs or (2) jobs on arts, are stronger between any two time periods. Therefore, the variables in time *t-1* have an impact on the variables in time *t*, where t is any year from 1999 to 2016. A third possibility is that *neither arts nor jobs have a significant impact on the other*. This is determined when neither crossed regression coefficients is significant at 95 percent confidence level. However, there are many possible ways to analyze the same data: Should we include the entire data or just the year by year changes? How long should the lag between dependent and independent variables be? What kind of transformations should the data receive? Would results change if regressions were run by urban area instead of the entire country at once?

Chapter 4 compares arts with non-arts jobs, and chapter 5 compares arts with business services industries, and arts and high-technology industries. The analyses described below is performed similarly for each pair of variables, but I use the term “jobs” as a shortcut to either non-arts jobs, business services jobs, or high-tech jobs.

The first regression type is the *base model*, in which we perform the regressions for the first and last years of data, 1998 and 2016, as the independent and dependent variables, respectively. This model shows the results in the longest term possible in the data and may serve as a benchmark for the other methods.

The second regression type is the *one-year lag analysis*, in which the independent variable is one year prior to the dependent variable. We also need to include the same variable in the previous year as an independent variable.

The third regression type is the *ten-year lag analysis*, identical to the one-year lag analysis, but the time lag between independent and dependent variables is ten years. In this case, we analyze the effects of the variables in longer terms. Due to the odd number of years of data, the first dependent variable is 2008 and the last independent variable is 2006; the variables for 2007 are not included in any pair of regressions.

The fourth type is the *first difference regression*, different from the three methods above as both the independent and dependent variables are the changes between two years rather than different variables by year:

$$(Arts_t - Arts_{t-1}) = \alpha_0 + \gamma_0 * (Jobs_t - Jobs_{t-1}) + \epsilon$$

or also:

$$\Delta Arts_{t-(t-1)} = \alpha_0 + \gamma_0 * \Delta Jobs_{t-(t-1)}$$

Conversely, when analyzing the effects of jobs on arts, we reverse the position of the variables:

$$\Delta Jobs_{t-(t-1)} = \alpha_1 + \gamma_1 * \Delta Arts_{t-(t-1)}$$

where t is the later year and t-1 is the previous year of analysis. In first differences analysis, I analyze the effects of changes from one year to another for both variables. Thus, the analyses focus on the effects of the changes of either arts or non-arts employment on the other variable for the same time period.

The fifth type of analysis is the *first difference regressions nested by urban area*, in which hexagon data are grouped by urban area, within which we perform the same pairs of regressions as in the first differences analysis described above. This process takes longer to run, even in the supercomputer, but this type of analysis allows us to see differences among cities.

By combining different types of analysis, I hope to be more comprehensive in the ways we understand the different mechanisms between arts and economic activities. The three types of cross-lagged regressions provide us with an overview of how industries as a whole react to each other in different lengths of time, i.e., how industries as indicated by their employment size, for both old and new jobs, attract more of the other industries' employment. On the other hand, first differences regressions show us how the yearly changes in industries interact; in other words, how much change in one year to the next for one industry affects the yearly changes for another industry.

3.4.3 Effect sizes and meta-analysis

The five methods presented in the previous section are effective ways to analyze our data. However, the amount of data and number of years generate a vast number of results which complicates interpretation. Surely, we could select only one pair of years for the analysis, interpret it, and claim it satisfactory. However, if we have nineteen years of data, the appropriate course is to attempt to use them all. Other methods could include all years at once, such as the *growth curve model* or *latent growth modeling*, which assesses growth of longitudinal data, a method that I plan to apply in future research. But for now, I apply each method mentioned above for each possible pair among the nineteen years of data and run meta-analysis to combine the results.

Meta-analysis is generally used to compare results from different studies. For example, several medical studies about a drug or a procedure report their own results. Then, other researchers perform meta-analysis with the results of these different studies looking for a global result instead of performing the same experiment with another group of test subjects themselves. In this dissertation, I have a similar case in which we obtain different results for each pair of years and combination of variables. Thus, after each type of regression analysis and combination of variables, we must also perform meta-analysis to find a more global result based on the individual results (Borenstein et al. 2009).

In the medical study example above, the subjects in each study are likely very different from each other: from different places, age groups, health conditions, and so on. For that type of study, meta-analysis random effect methods are recommended. However, in this study, all regression results refer to exactly the same sample and units; therefore, the fixed effect method is simpler and more appropriate, which is a rare situation as most meta-analysis studies use random effects.

The fixed-effect model assumes that all studies share a common effect size. Because all the studies that are synthesized are similar, a fixed-effect model is adequate for assessing the effect size of the studies. What changes are the start and end years from each regression analysis, but the variables and the sample are same. In the fixed-effect meta-analysis, we compute the joint effect sizes of several studies, giving higher weight to more precise studies (lower standard error). The random-effects model takes into account more variation among studies so it is assumed that the true effect size is normally distributed.

I use the meta package in R to perform meta-analysis. The function metagen is a more general meta-analysis method that accepts coefficients and standard errors as inputs, and the outputs are results for both fixed- and random-effect methods (Schwarzer 2007).

In summary, for each type of regression and pair of arts and non-arts variables, I calculate the regressions for every possible combination of years given the type of variable and time lags. Then, I perform meta-analysis on all regression results to find the standardized mean difference (SMD) and confidence interval.

In each empirical chapter, the results for the one-year and ten-year cross-lagged regressions and first difference regressions are reported with line graphs showing the coefficients per year and the confidence interval for each coefficient. When the confidence interval includes zero, the coefficient is deemed not statistically significant at 95 percent confidence.

For the first difference regressions nested by urban area, I also perform fixed effect meta-analysis for each urban area separately. This results in high volumes of output; however, I add them in the appendix for each chapter.

3.4.4 Workflow for Nested Data

Figure 3.9 shows the workflow used to calculate the coefficients and statistics. The raw data was cleaned, treated, and transformed in a long algorithm in chapter 2. From the chapter 2 data, I calculated the total number of arts and jobs, as explained in section 4.2.1, as a first step. The second step was to partition, nest, or divide the data rows (in the GRID_ID unit) by their corresponding urban areas into list elements. Then, using a series of steps, calculations, and "for loops," I ran the regression commands for each set of data for each urban area while saving the outputs into a new table. This results table provided the estimates, standard errors, p-values, and all the information needed to perform the meta-analysis. With another set of "for loops," I ran the meta-analysis for each set of regression results by urban area, as a fourth step. The final product was a table containing only overall effects for each urban area, where I also compared the arts and jobs coefficients to draw one of the three conclusions by the criteria described below. The "NA" conclusion was defined by the software as the regression fails for some urban areas.

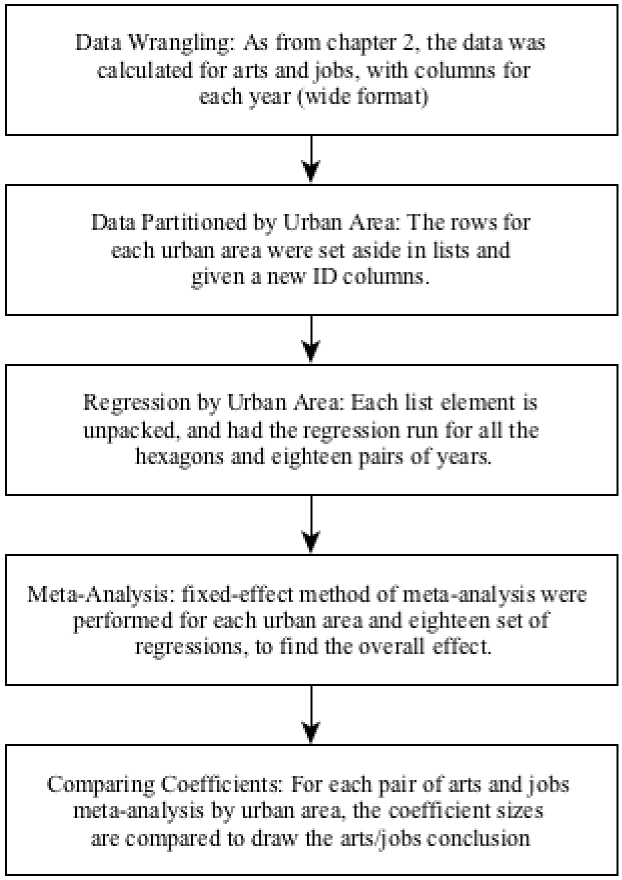

Figure 3.9: Workflow of the statistical analysis performed in chapters 4 and 5

For the general analysis and the analyses for each individual urban area, three results are possible:

1. If $\gamma_0 > \gamma_1$, then the conclusion is that "jobs attract arts" in that urban area;
2. If $\gamma_0 < \gamma_1$, then the conclusion is that "arts attract jobs" in that urban area;
3. If both γ_0 and γ_1 present a p-value greater than .05, or zero within its confidence interval for both γs or the greater γ, then the conclusion is "not significant" for that urban area.

Both the general analyses and analyses by urban areas rely on these three interpretations on chapters 4 and 5.

3.5 Conclusion

In this chapter, I delineate the datasets and methodology that are empirically applied in chapters 4 and 5. I describe in detail the raw data as downloaded from the US Census Bureau's website, their original structures, and the algorithm used to transform numbers of establishment data at the ZIP code level into number of employment at the hexagon level. These steps standardized the data into common areas while strengthening the representation of different populations and market sizes in American urban areas. With these changes implemented, we are then able to analyze the mutual relationships between the impact of arts activities and employment.

CHAPTER 4

THE RECIPROCAL RELATIONSHIPS BETWEEN ARTS ACTIVITIES AND EMPLOYMENT

The main question in this research is centered on a chicken and egg dilemma: Do people move to cities for jobs and the arts follow? Or do people move for arts and amenities and the jobs follow? What comes first, arts activities or employment? On the one hand, people move to cities in search of employment, and as a sizable market for the amenities is formed, more amenities are established in that location. On the other hand, people move to cities looking for a lifestyle, quality of life, and entertainment, and as a workforce aggregates, more companies are established, creating more employment in that location.

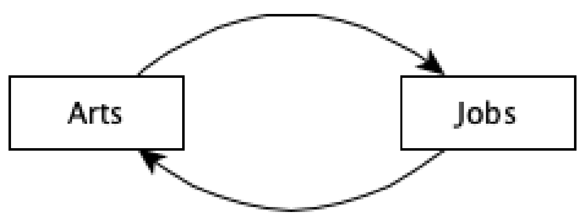

Figure 4.1: Path diagram showing the direction between arts and jobs

This chapter aims to explore the reciprocal relationship between arts and non-arts jobs in their highest level of classification. The "arts jobs" variables indicate not only type and location of the artistic job market, but also the size of the arts scene in cities. In other words, the presence of arts jobs, and therefore, the presence of artists, indicates how artistic an urban area is. Conversely, "non-arts jobs" variables indicate jobs in industries excluding the arts. For both types of variables, we are counting their specific job positions, excluding the aggregated population that comes with them as we are not counting as non-arts jobs the families that move together with a new hire who moves to another urban area. Therefore, in this chapter, when we discuss number of jobs in either arts or non-arts, we should keep in mind that more people are implicitly linked to the number of jobs counted by the census.

In the following sections, we analyze how this reciprocal dynamic takes place using several methods, and we find that answers to the research questions lead us to local contexts and time. In section 4.1, I discuss the data types, the correlations among the variables, and how outliers are important for this analysis as they represent industries in the denser cities in the US. In section 4.2, I discuss the baseline model as we compare the variables from 1998 to the variables in 2016, ignoring the years in between. This discussion uses three types of variables: natural employment numbers, log-transformed, and first differences. The baseline model serves as a basis for comparison as we move on to more detailed analyses. In section 4.3, we use the log-transformed variables to analyze the impact between arts and jobs in one-year and ten-year lags. In section 4.4, we use first differences to analyze the impact of the changes between two years. In section 4.5, we analyze the effects of arts and jobs in each urban area. And in section 4.6, we break down the arts category into its three subcategories (arts amenities, arts producers, and recreation) to find the effects of each arts subcategories on the non-arts and vice versa.

4.1 Data

The relationships between arts and employment are analyzed in this chapter using the data processed in chapters 2 and 3. The data format reflects the estimated number of jobs by industry category and subcategory as defined in chapter 3, at the hexagon level as detailed in chapter 2, by year from 1998 to 2016. However, in this chapter, I aggregate all the industry categories related to the arts under the umbrella variable “arts” and all industry categories *not* related to the arts under the umbrella variable “jobs.” A complete list of the categories and subcategories in arts and jobs are shown in appendix B.2. The sum of arts and jobs should equal the total number of jobs released in the Census Bureau’s CBP *total* number of employment dataset. As discussed in section 3.4 of chapter 3, the “arts” and “jobs” variables are extremely skewed, and therefore, these variables have been log-transformed.

In this chapter, the arts and jobs variables are analyzed at the highest level of classification for a more general understanding of the effects between arts and jobs, as we explore the question: How do the arts affect employment in other non-arts industries and vice versa? By exploring this most general relationship, we seek to understand the overall impact of one industry on the other, understand the mechanism of the analysis, and obtain the baseline results to compare to subsequent analyses as well.

Another variable included in this chapter is population size, used to classify the sizes of urban areas and compare their results. The population size variable is from the 2010 Centennial Census, originally provided at the urban area level, and was joined to the number of employment table to define three tiers of urban areas. The first tier includes urban areas with over one million people, the second tier includes urban areas of populations between 300,000 to one million people, and the third tier includes urban areas of populations of less than 300,000 people. By comparing the results based on the size of the urban area, we aim to notice differences in the impact of arts and jobs.

Time lag is another variable intrinsic to the analysis, which is controlled by changing the pairs of years in each cross-lagged regression model. The dependent variable (Y) should always be from a year later than the independent variable (X) as the cause should come before the effect. As such, by manipulating the years for X and Y, we are able to include different time lags; in this case, one-year gaps for short-term analysis (e.g., 1998 in X and 1999 in Y, 1999 in X and 2000 in Y, and so on) and ten-year gaps for the long-term analysis (e.g., 1998 in X and 2008 in Y, 1999 in X and 2009 in Y, and so on). This method results in a great volume of regression results for each pair of two years in the short and long terms, multiplied by two, as the arts and jobs variables switch places as X and Y in each pair of years.

In summary, there are four main types of variables in this chapter: estimated number of arts, estimated number of jobs, population size tiers, and time lengths.

4.1.1 Correlation Matrices

Before presenting the regression results, we should observe the correlations between the arts and jobs variables for two reasons: even though it would be straightforward to assume that places with more jobs would also have more arts in quantity and vice versa, we should still look at the distribution of the number of arts and jobs and how they relate to each other in the data.

In this section, we observe the correlations between arts and jobs in 1998 and 2016 to the original metric and as log-transformed variables to illustrate the variable distributions and correlations. This is due to space as most pairs of years showed similar results. Appendix C.1 shows the correlations for every pairs of years, for correlations between arts-arts, jobs-jobs, and arts-jobs.

The diagonal of figure 4.2 shows the histograms for the natural variables for number of arts and jobs. The extreme skewness of each variable—a single bar to the left and scattered points to the right—illustrate that only a few hexagons or ZIP codes have an extremely high number of arts and jobs, while most places are concentrated in similar amounts of both arts and jobs. Similarly, the scatterplots on the bottom triangle of figure 4.2 show a concentration of data points on the lower left corner of each plot, with a few points spread out on the diagonal and top right of the plot, indicating that a high number of arts are where there are high number of jobs and vice versa. Thus, these variables present high correlations within themselves, with the jobs-jobs pair showing the highest correlation at .96. This is followed by the arts-arts pair with a correlation of .94, and the arts-jobs correlations vary from .77 to .84. Note that the ranges in the y- and x-axis also show different scales. For the arts, the axis show a range from zero to 50,000 jobs, while for the jobs variables, the axis show a range of zero to 500,000 jobs. Thus, the correlation is higher between the years for the same variable than the correlations between the two variables in the same or different years.

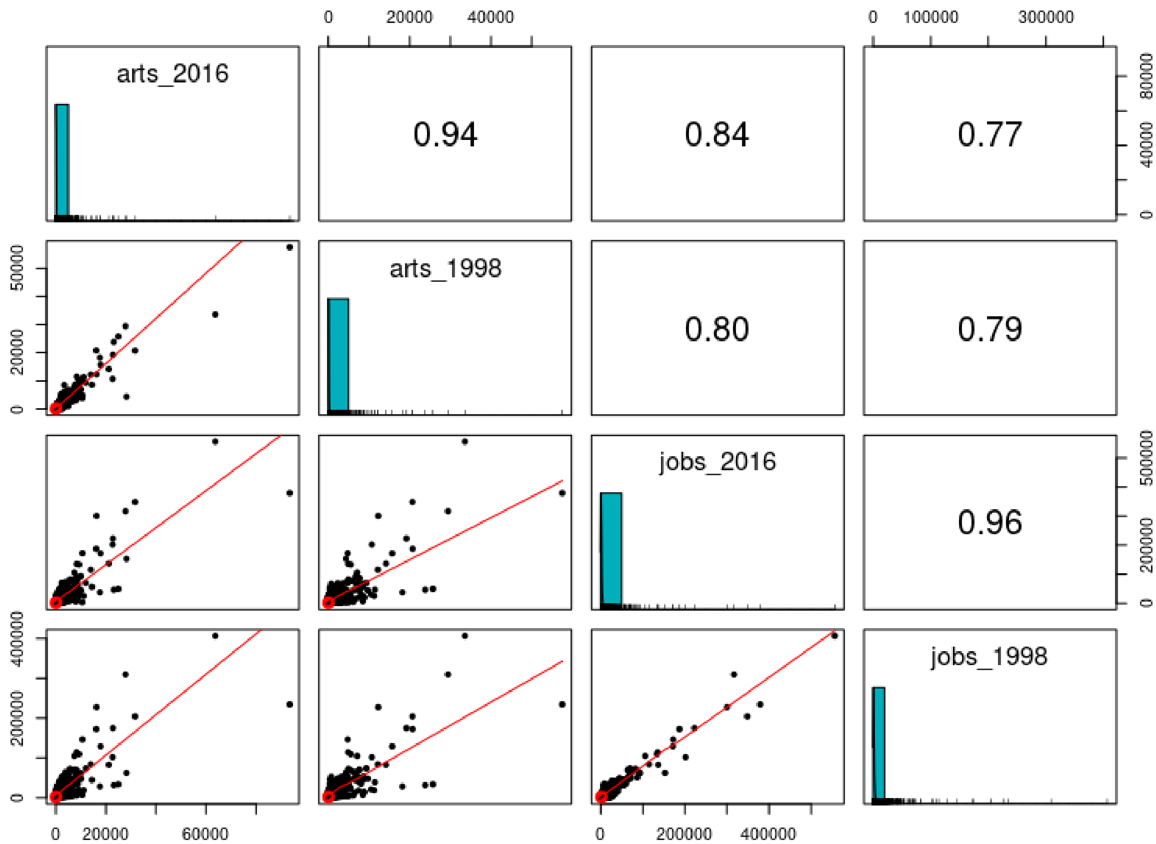

Figure 4.2: Correlations between arts and jobs in 1998 and 2016 in the original metric as an illustration of the skewness of the data

Due to the high skewness, I chose to normalize the data by log-transformation. For each value that was log-transformed, I added .001 to avoid logs of zero resulting in infinite values. Figure 4.3 shows a similar correlation matrix but with the variables after the log-transformation. The main diagonal shows how the distribution in the histograms are normalized. The range of data points for both variable types are in the same scale for both arts and jobs, with values varying between -6.9 and 13. The scatterplots on the bottom triangle show a more spread out and positive correlation across the plot, as well as a linear relationship among variables. However, the correlations are smaller than in the previous graph, with the arts-arts correlation at .65, the jobs-

jobs correlation at .56, and the arts-jobs correlations varying between .44 (for arts in 2016 and jobs in 1998) and .85 (for jobs and arts in 1998). The decreased correlations indicate that the variables are not as dependent on their past. We also observe that the shape of the scatterplots shows a wider variation in the relation over time and between variables than before the log-transformation. Thus, the log-transformed variables are more independent from their past and each other than the natural variables.

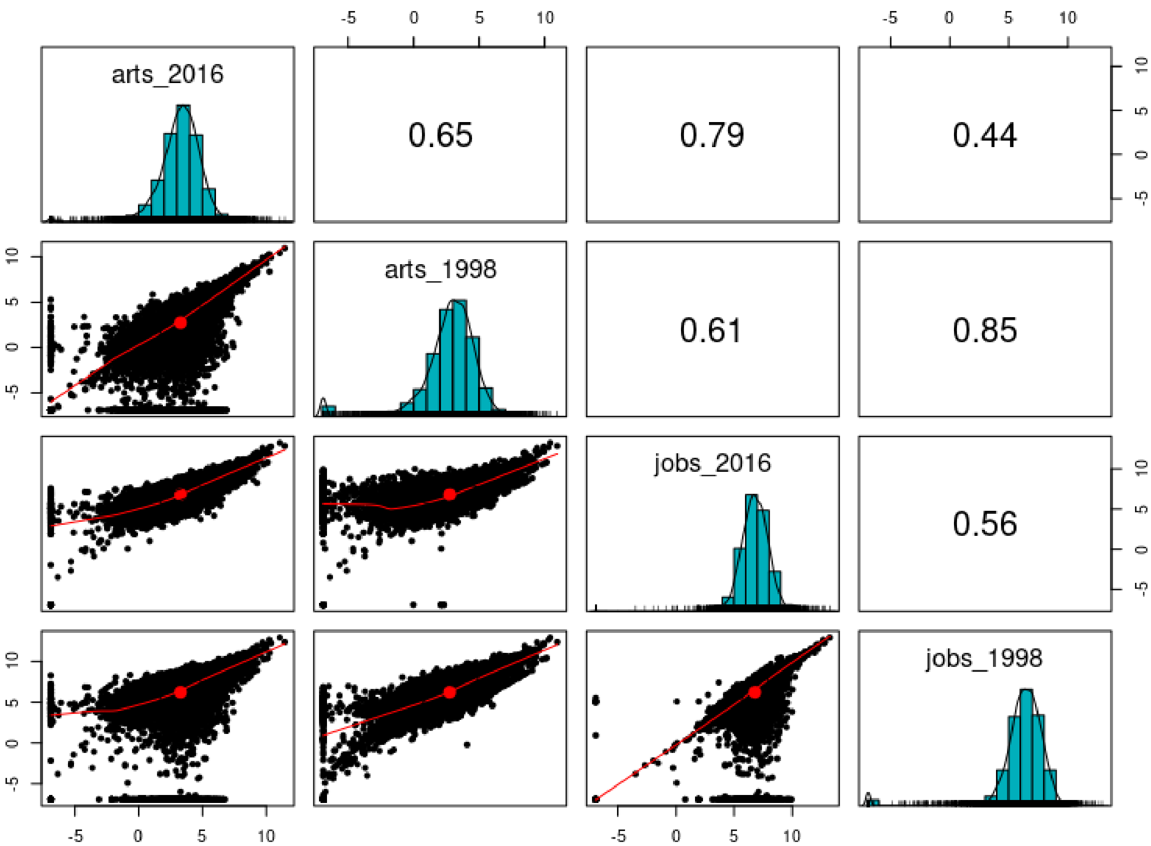

Figure 4.3: Correlations between arts and jobs in 1998 and 2016 as an illustration of the normalization of the data after log-transformation

Figure 4.4 shows the correlations and distributions between the first difference variables, as the changes in number of arts and jobs from 1998 to 1999, and from 2015 to 2016. In this case, we consider only the changes between the years rather than the total number of employment. Thus, there is a larger number of zeros in the dataset.

It stands out that the correlations among the different years are zero or are close to zero, indicating that the changes between two years is independent from the changes when compared to another year, be it for the same variable or opposing variables. For example, the changes in arts between 1998–99 are independent from the changes in jobs between 2015–16. At the same time, we see that the changes for the same two years between arts and jobs are much higher for both the 1998–99 as well as the 2015–16 variables. In other words, the changes that occur in the same year for arts are more related to the changes in jobs for that same year rather than to the arts in the other year. Therefore, the first difference variables between years are more independent of each other in this case than in the log-transformed cases (in figure 4.3) and even more so than the natural case, in figure 4.2.

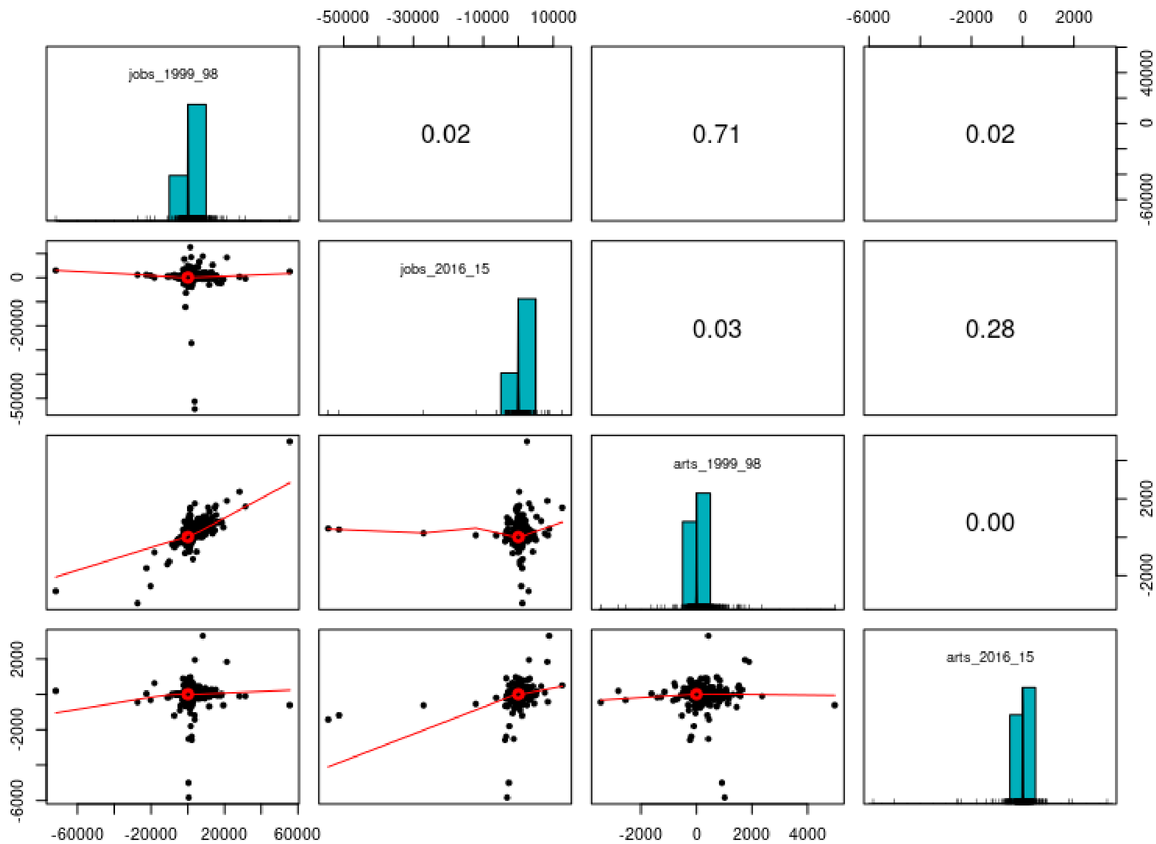

Figure 4.4: Correlations between arts and jobs in 1998 and 2016 as an illustration of the normalization of the data in first differences

Appendix C.1 shows the correlation tables for arts-arts, jobs-jobs, and arts-jobs for the log-transformed variables and first difference variables, respectively.

4.1.2 Outliers

In the previous section, we observed the distributions and correlations between arts and jobs variables in different years, in which the vast majority of hexagons have a small number for employment, while only a few hexagons have large amounts of employment in both arts and non-arts industries. Equally important as the main body of the distribution seen in the previous section are the outliers, as these outliers were the inspiration for this project. Cities like New York, Los

Angeles, and Chicago and their vast arts and entertainment industries seem to attract larger and more global corporations than smaller urban areas. Therefore, in this section, we focus on the descriptive statistics of these outliers, which are highly populated hexagons with numbers of arts and jobs that extraordinarily exceed the average.

The boxplots on figure 4.5 show the natural number of arts and jobs in each year. As in the histogram and scatterplots, there is an extremely skewed distribution that flattens the box of the boxplot into a thin line at the bottom of the graph. For each year, the arts boxplot is on the left, and the jobs boxplot is on the right, and we see that the distribution of the arts is much more compact than the distribution of the non-arts industries.

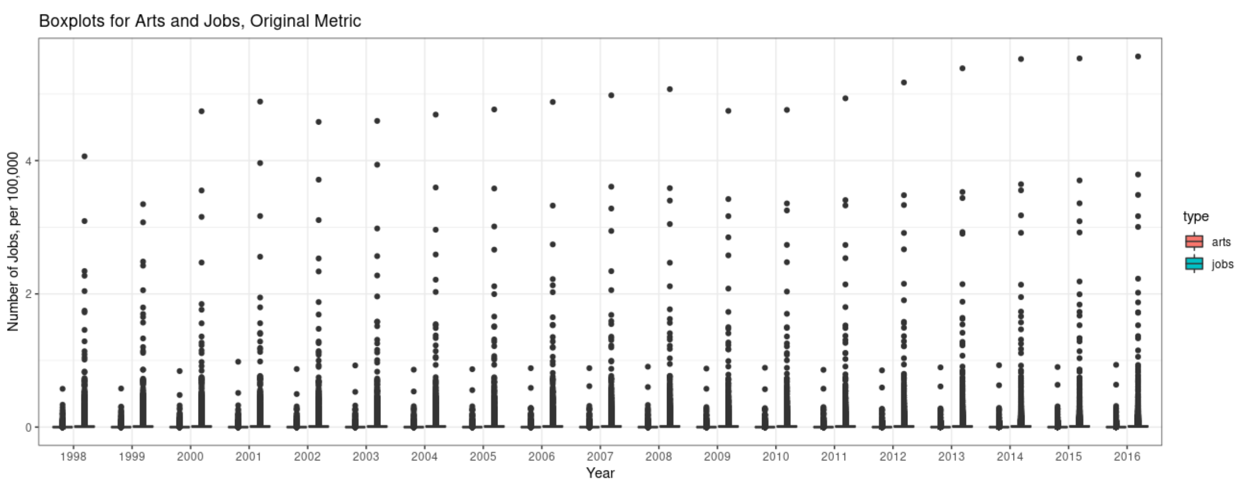

Figure 4.5: Boxplots of the arts and jobs original metric variables highlighting outliers

Table 4.1 shows the cut-off values per year that make the hexagon a suspected outlier. The top table shows the cut-off values for the arts, and the bottom table shows the cut-off values for jobs. The mean of the cut-off value for the arts is 146 jobs as the cut-off point for arts, 3,773 for jobs. For example, for the arts in 2016, out of the 63,072 data points, 6,085 hexagons are above the cut-off point of 161 that year. For jobs also in 2016, 5,070 hexagons are above the cut-off point of 4,081 for that year. The highest value for arts jobs in 2016 is 93,488 for a hexagon in Manhattan; a neighboring hexagon has the highest value for jobs in 2016 of 556,369 jobs. Therefore, we see that the outliers have much higher numbers of both arts and jobs compared to the bulk of hexagons.

Outlier Minimum per Year for Arts Jobs, Original Metric

1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
128	135	139	141	136	143	147	147	151	152	154	148	144	144	145	148	153	157	161

Outlier Minimum per Year for Jobs, Original Metric

1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
3367	3568	3632	3693	3611	3713	3790	3833	3947	3940	3939	3733	3647	3695	3745	3823	3902	4020	4081

Table 4.1: Minimum and maximum outlier values by year

This is an important observation because when topics such as the impact of arts on employment are mentioned, they are mostly discussed in terms of the largest urban areas and exceptional places where the number of arts and jobs are prominent.

Figure 4.6 shows the same boxplots as above but for the log-transformed variables. These boxplots scale both variables, making them easier to visualize. However, there are now outliers both in the positive and negative values. Hexagons with zero arts or zero jobs are counted as -6.9.[1]

[1] $(\ln(0 + .001) = -6.9)$.

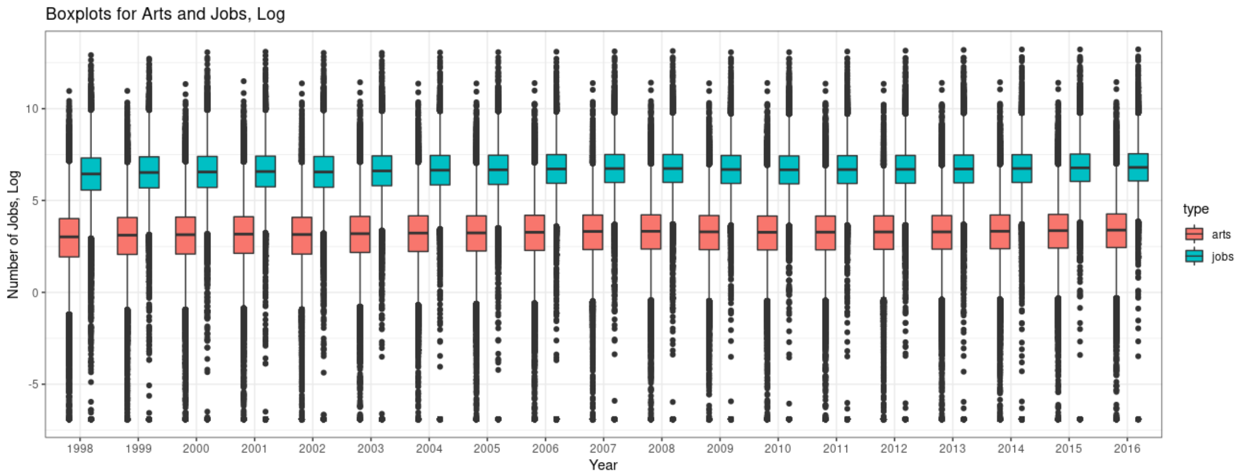

Figure 4.6: Boxplots of the log-transformed arts and jobs variables highlighting outliers

So far, we've seen that working with outliers in this type of analysis is inevitable: the largest urban areas in the US present exceptionally in their quantity and variety of arts and non-arts industries and have much larger populations and job markets. Figure 4.7 identifies changes over time in the top ten urban areas ranked by number of arts jobs after considering only urban areas with populations of over one million people.

New York is at the top, with a gain of 200,000 arts jobs between 1998 and 2016. The trend shows a stronger gain until 2001, and a milder upward trend from 2002 onward. Los Angeles comes in second, with most gains between 2013 and 2015, which followed a long decline from 2008. In 1998, Chicago had the third largest arts market, but was surpassed by Las Vegas, Orlando, and Washington DC by a small difference among these cities. Washington DC had a decline between 1999 to 2001, recovering quickly until 2003, keeping a steady but still fluctuating number of arts jobs. In addition, Miami, Boston, Philadelphia, and San Francisco alternate positions from year to year, indicating similar trajectories over time.

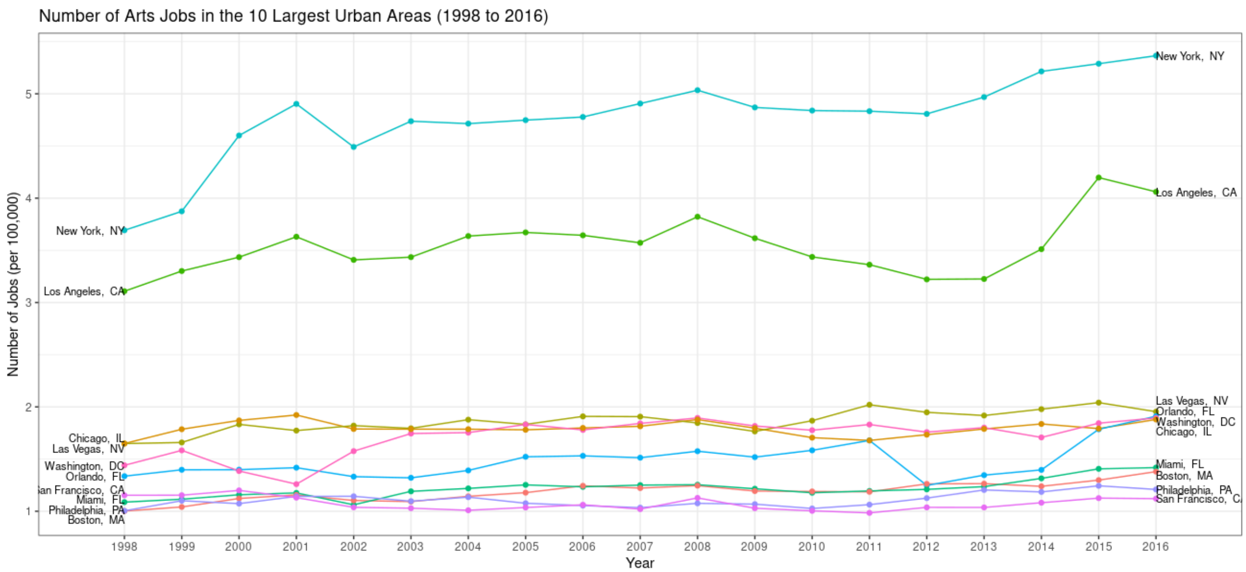

Figure 4.7: Number of arts jobs in the largest urban areas

Figure 4.8 shows the changes in non-arts employment between 1998 and 2016 for the ten urban areas with the most jobs and with populations over one million people. Again, New York leads in the number of non-arts employment, followed by Los Angeles. Different from the previous figure, Chicago's non-arts jobs is much larger when compared to cities with comparable arts industries in numbers that place Chicago distinctly in third place. In this non-arts employment graph, we also see that cities like Atlanta and Detroit are now placed among the top ten urban areas, whereas for arts employment, Las Vegas and Orlando were in the top ten position. Washington DC, Boston, Philadelphia, Atlanta, San Francisco, Miami, and Detroit all have job markets of similar sizes for both arts and non-arts industries.

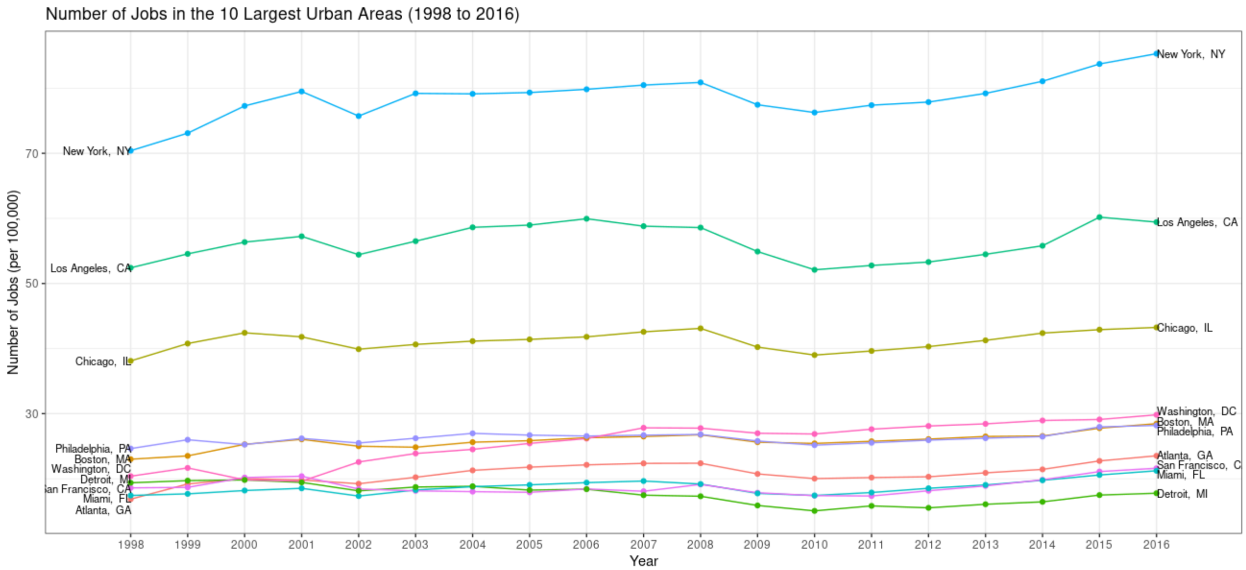

Figure 4.8: Number of non-arts jobs in the largest urban areas

Based on the correlation analysis from the previous section together with the graphs in this section, we note that as number of jobs increase or decrease year by year in each urban area, these values are not strongly correlated over time for the same variable. In other words, the number of non-arts jobs in one year is not as strongly correlated to the number of non-arts jobs in another year as they are to the number of arts in the same year, and vice versa. This indicates that the number of arts and non-arts jobs in the same year explain each other more than the same type of jobs in two different years.

Thus, we see that from 1998 to 2016, most cities did not present a monotonic growth in the number of arts and non-arts employment, as systemic and local factors affect the trajectory of industries in different urban areas. In both graphs, there is a slight trend upwards, but some bumps over the years nullify previous growth, requiring recovery time.

4.1.3 Employment Locations Within Urban Areas

Hexagons with denser numbers of arts and jobs are found in central areas of the city, and employment numbers by hexagon decrease as we go further away from the city center. Figure 4.9 shows areas of higher density in number of arts and non-arts employment in dark red, in a color gradation to fewer number of jobs (yellow, then blue). Areas with a high number of arts often coincide with a high number of jobs; however, not all locations with a high number of jobs present a high number of arts. Due to space, I did not include the same map for all urban areas, as this type of analysis could be a study in and of itself. However, we should keep in mind that areas in the city center are denser in number of jobs than areas further away.

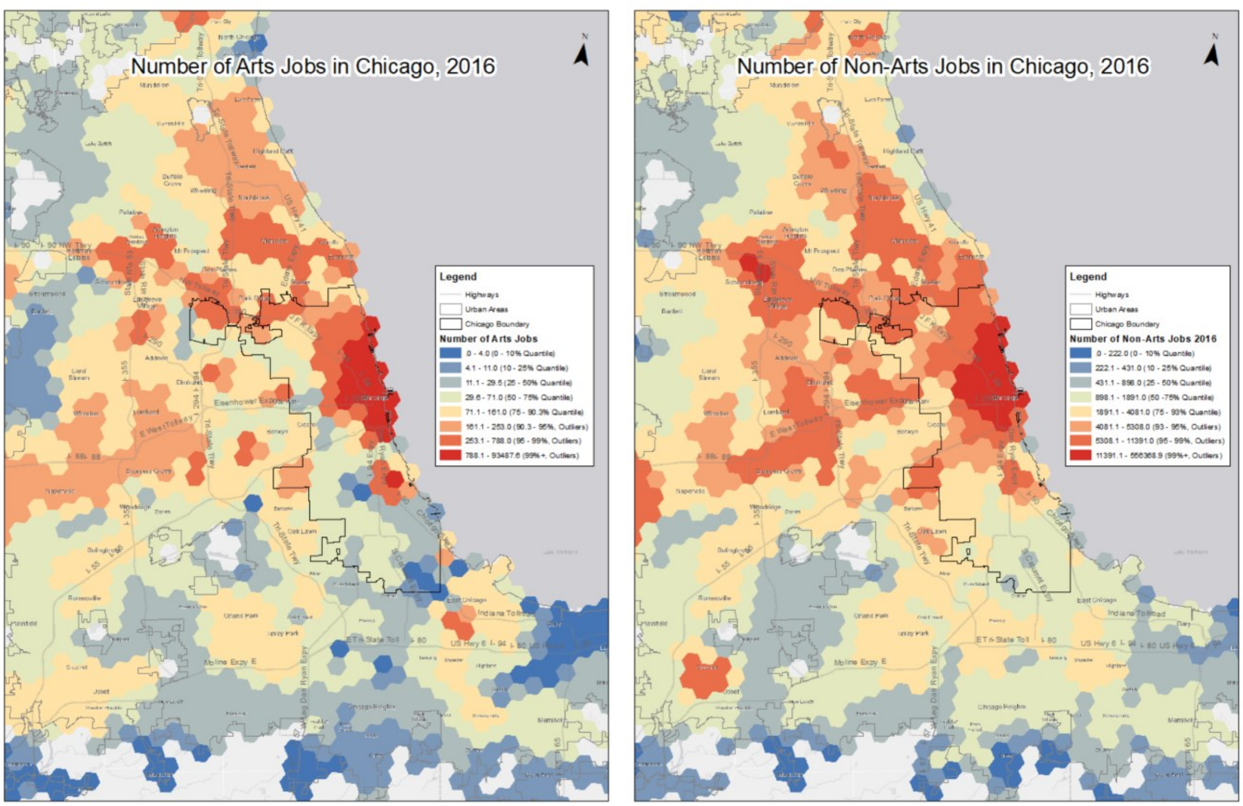

Figure 4.9: Number of arts and non-arts jobs by hexagon in Chicago

Beyond the number of arts and jobs, we should also understand the proportion of number of arts to non-arts jobs. Figure 4.10 shows the top ten urban areas with populations larger than one million people that have the highest proportion of arts to total jobs by year. On the top cluster, we find Washington DC, Miami, Los Angeles, and New York varying among each other over time, with at least 5 percent of arts jobs. On the same graph, we see a bottom cluster: Boston, Atlanta, Chicago, Philadelphia, Dallas, and Houston have similar proportions, from 3.5 percent to 4.7 percent of the total jobs in the arts industries.

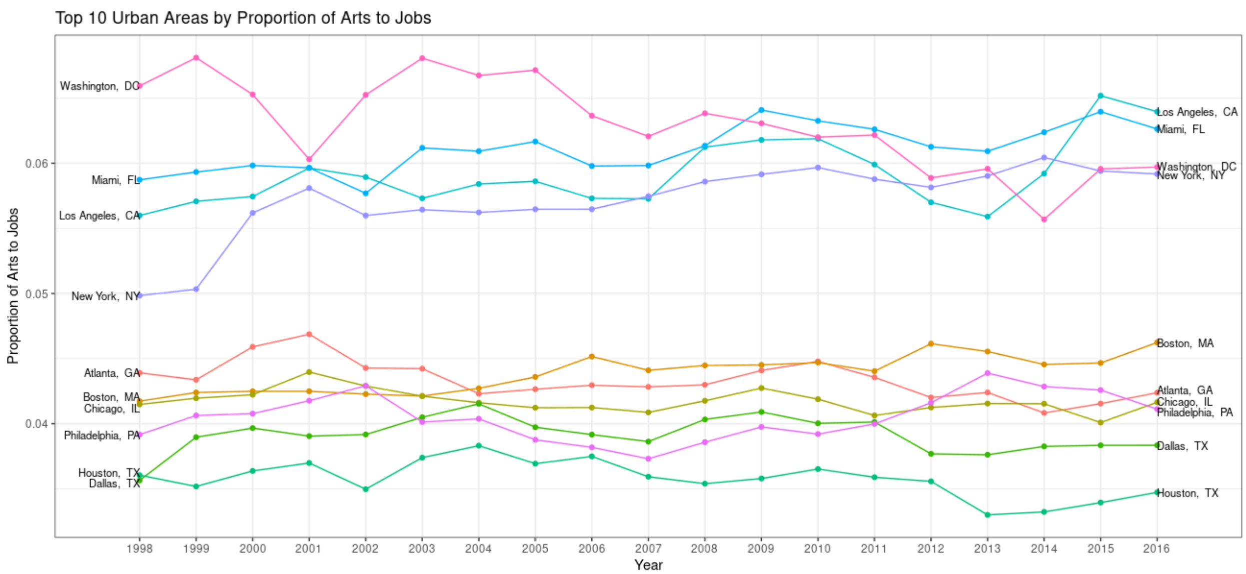

Figure 4.10: Proportion of arts to non-arts jobs in the largest urban areas

Figure 4.10 shows the highest proportions of arts to jobs for the largest urban areas; however, smaller cities show even higher proportions of arts to jobs. Figure 4.11 show the ten highest proportions of arts to jobs for all urban areas. In this case, we see that Atlantic City had a 27 percent proportion of arts to jobs in 1998, and Kissimmee, FL—home of the Walt Disney World—leads with a 20 percent proportion of arts in 2016. Besides Las Vegas, the other cities in figure 4.11 have populations of less than 900,000 people.

One peculiar example in figure 4.11 is the urban area of Gulfport, MS, which has been a historic and tourist destination with many jobs in casinos and the hospitality industries. In 2006, there was a significant dip in the proportion of arts to jobs as a result of Hurricane Katrina, which devastated many buildings along the coast, requiring reconstruction. However, the arts to jobs proportion rebounded rather quickly—it took one year to recover, and another year to surpass the 2005 levels.

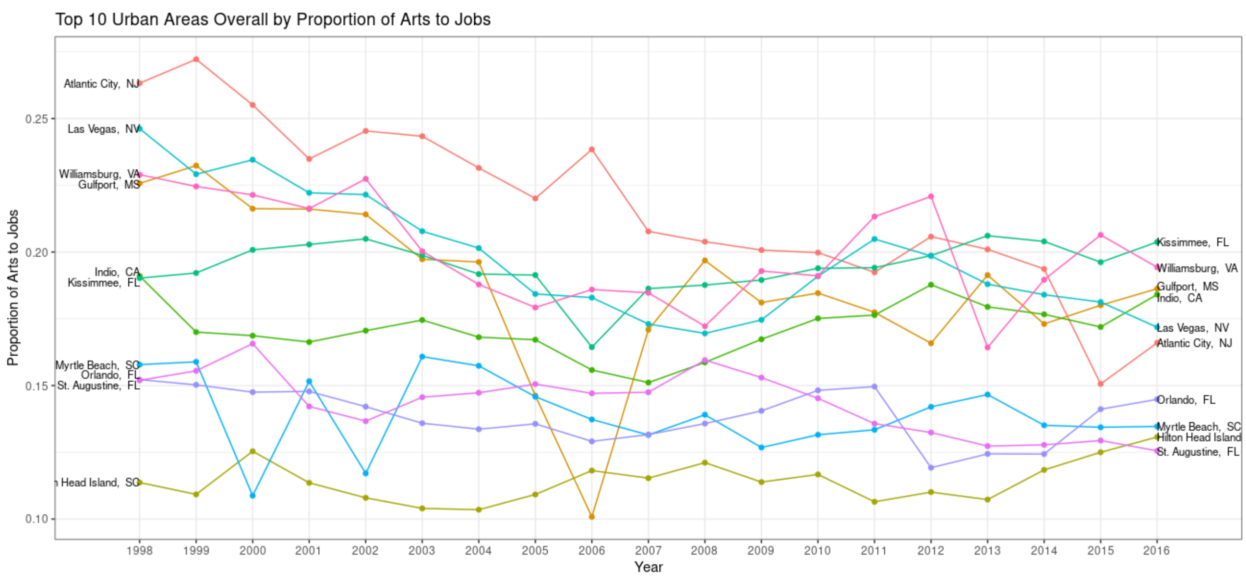

Figure 4.11: Proportion of arts to non-arts jobs in all urban areas, showing smaller urban areas having higher proportions than the largest urban areas

On the other hand, Las Vegas had a much higher proportion of arts to jobs in the late 1990s, with almost 25 percent of jobs in the arts industry to less than 15 percent of jobs in the arts industry in 2016. In figure 4.11, we see that the number of arts jobs in Las Vegas increased from 1998 to 2016, which leads us to understand that the dip in the proportion of arts in jobs is due to an increase in non-arts industries in Las Vegas, lowering the arts to jobs proportions. In this case, the arts industries in that city have attracted more non-arts industries as hypothesized in this dissertation. A similar analysis could be done for many of the urban areas presented above, but as we're analyzing 481 urban areas at once, it is very hard to specify how each urban area developed over time, which could also be a project on its own.

In conclusion, places with a higher number of arts also tend to have higher numbers of jobs but the inverse is not true. The correlations between arts and jobs are high, including for outliers for the same year, but independent for correlations of different years. At the same time, the high volume of jobs in larger cities decrease the relative proportions of the arts, leaving some smaller urban areas with larger proportions of their jobs in the arts industries. Therefore, even though larger urban areas have larger arts economies, we should not underestimate the power of the arts in smaller urban areas.

4.2 Regressions for the Relationship Between Arts Activities and Employment

In this section, I present the analysis of the relationships between arts and jobs. For brevity, I call the sum of estimated number of jobs of arts amenities, arts producers, and recreation as *arts*, and the sum of all non-arts industries, as *jobs*, as discussed in chapter 3.

In the remainder of this chapter, we explore the impact of arts and non-arts jobs over time and vice versa. In other words, do arts come first and the jobs follow, or do jobs come first and the arts follow? This analysis starts with a baseline model, followed by analyses in one-year and ten-year lags, in one-year changes (first differences), by population size, and by arts category.

The classic economic view suggests that people move for jobs. Thus, as people move to urban areas, a critical mass of consumers forms a market for arts and entertainment, attracting arts establishments. For example, the cities in Silicon Valley started off as suburbs where many high-tech firms were launched. As these firms grew, the region started attracting highly educated and talented workers who moved to those cities for the high-tech jobs and networking opportunities. As more people moved into the area, the need for leisure activities also grew, bringing in more cafes, yoga centers, music venues, and museums to serve the growing local population (Moretti 2012). Thus, in cases like this, we seek to understand how *jobs attract arts*, represented by the equation:

$$Arts_t = \alpha_0 + \beta_0 * Arts_{t-x} + \gamma_0 * Jobs_{t-x} + \epsilon_0$$

where t is the later period, x is a time lag, α is the intercept, β is the lagged coefficient, γ is the crossed coefficient, and ϵ is the error term. This equation represents the null hypothesis.

On the other hand, cities like New York and Chicago offer a large variety of world-class arts and entertainment such as museums, parks, concert halls, stadiums, operas, different types of bars and restaurants, and so on, that attract highly educated and talented workers who have an interest in those activities in their free time. As these highly qualified workers move in, businesses that are interested in their talent also move to these cities in order to employ these workers, and in turn, growing the job market, the urban area, and its economy. In this case, we may say that *arts attract jobs*, a hypothesis that is represented by the equation:

$$Jobs_t = \alpha_1 + \beta_1 * Jobs_{t-x} + \gamma_1 * Arts_{t-x} + \epsilon_1$$

where t is the later period, x is the time lag, α is the intercept, β is the lagged coefficient, γ is the crossed coefficient, and ϵ is the error term. This equation is the alternative hypothesis in this study, as this is the hypothesis we try to support.

For each pair of years in the analysis, we regress both equations and compare the results in a method called cross-lagged regression. Then, we compare the γ_0 and γ_1 coefficients from both equations, and the larger coefficient indicates in which direction (arts to jobs or jobs to arts) we have a larger impact, suggesting which type of industry attracted more of the other. Thus,

if $\gamma_0 > \gamma_1$, then jobs attract arts, and

if $\gamma_0 < \gamma_1$, then arts attract jobs;

given that the coefficients are statistically significant at 95 percent confidence level.

There are many ways in which this analysis can be performed. In the remainder of this chapter, I start the analysis using a broader analysis as a baseline model for arts and jobs for all hexagons in all urban areas for the first and last year of data (1998 and 2016), and then partition the data into more localized variables and areas, using all years of data.

4.2.1 Baseline Models

The baseline model is the simplest pair of cross-lagged regressions that can be performed using this dataset, which could show results for all urban areas combined, with 1998 as the first year of data in the independent variable, and 2016 as the last year of data in the dependent variable. The variables included in the baseline model are the aggregated arts and jobs variables. In other words, here we look at how much did jobs grow in 2016 for each additional unit of arts in 1998, and vice versa?

Thus, the equations described in the previous section can be rewritten as:

$$Arts_{2016} = \alpha_0 + \beta_0 * Arts_{1998} + \gamma_0 * Arts_{1998} + \epsilon_0$$

for the hypothesis that *jobs attract arts*, and

$$Jobs_{2016} = \alpha_1 + \beta_1 * Jobs_{1998} + \gamma_1 * Arts_{1998} + \epsilon_1$$

for the hypothesis that *arts attract jobs*, where α_0 and α_1 are the respective intercepts, β_0 and β_1 are the lagged coefficients, γ_0 and γ_1 are the crossed coefficient, and ϵ_0 and ϵ_1 are the error terms. After obtaining the results for both regressions, we compare the two crossed coefficients, γ_0 and γ_1 to find whether arts or jobs had a stronger impact on the other.

Even with the model laid out, we still come across many ways to run this model due to the different data types that can be used in the analysis. Thus, in this section, we look at three types of baseline regressions where the variables are (1) in the natural number of jobs as computed in chapter 3, (2) the log-transformed arts and jobs variables to pull back outliers, and (3) first difference variables that are computed as yearly changes. This baseline model serves as our guide to understand the relationship between arts and jobs in different types of units and serve as a benchmark as we break down the analyses into smaller pieces and details later on.

4.2.1.1 Reciprocal Impact of Arts and Jobs in Natural Employment Numbers

In this first baseline model, we apply the pair of regressions above on the count data, or the natural number of jobs data, in which the unit of variables is employment numbers. In this case, there are no negative values, where zero is the minimum value that either arts or jobs values can take. The jobs and arts variables in 2016 are each regressed according to the equations above. The results are shown in table 4.2.

Cross-Lagged Regressions Results for Original Metric Variables

	Arts Attract Jobs Hypothesis	**Jobs Attract Arts Hypothesis**
Dependent Variable	**Jobs 2016**	**Arts 2016**
Intercept	97.56 ***	-16.92 ***
	(1.25)	(.925)
Arts 1998	**1.25 *** **	1.2 ***
	(.019)	(.003)
Jobs 1998	1.11 ***	**.0145 *** **
	(.002)	(.00036)
Residual S.E.	1340	215
R-Squared	**0.926**	**0.883**
Adjusted R-Squared	0.926	0.883
N	63046	63046

Note: *** p<0.01

Gamma coefficients are highlighted in bold.

Table 4.2: Regression results for the baseline model using number of jobs as unit

The results for the "jobs attract arts" hypothesis are significant, with ($F(2, 63046) = 397000$, $p < 0.000$) with a R^2 of 0.926, and the results for the "arts attract jobs" hypothesis are also significant with ($F(2, 63046) = 239000$, $p < 0.000$) with an R^2 of 0.883. As the units are "number of jobs," the interpretation for the first hypothesis is that each additional unit of arts in 1998 increased jobs by 1.25 in 2016. In other words, each artist who moved into any urban area in 1998 helped increase the number of jobs by 1.25 on average in hexagons in all urban areas in the US in the nineteen-year period.

On the other hand, each additional job in 1998 increased arts by .0145 in 2016, a very small effect, close to zero. One interpretation for this result is that many non-arts jobs (approximately 69, in this case) are necessary in order to make an urban area worthwhile for one additional artist to move in. This can also be interpreted as about sixty-nine workers interested in the arts but who are not artists themselves would have to move into a city, together with their families, in that period in order for one extra artist to join and participate in the arts community of that urban area. We should mention here that the variables compare the count for the number of arts and jobs and not the total population that moved for one industry or another. Therefore, for each additional count in this analysis, the effects may actually impact many more people than what the coefficient suggests. While estimating the number of people accompanying non-arts workers would be interesting, it is out of the scope of this study.

In conclusion, this simple model indicates that even when we consider all hexagons in all urban areas at the same time, the arts have a strong impact on jobs, while jobs constitute the audiences necessary for the arts to flourish.

4.2.1.2 Reciprocal Impact of Arts and Jobs in Log-Transformed Employment Numbers

This second baseline model is similar to the previous model but with log-transformed variables for both dependent and independent variables. Thus, we have a pair of log-log regressions for each two time periods, meaning that the results should be interpreted in terms of percentages rather than natural numbers of jobs. The results for both regressions are shown in table 4.3. The results for the null hypothesis are significant with ($F(2, 63046) = 26800$, $p < 0.000$) with an R^2 of 0.459, and the results for the alternative hypothesis are also significant with ($F(2, 63046) = 18800$, $p < 0.000$) with a R^2 of 0.374.

Cross-Lagged Regressions Results for Log Variables

	Arts Attract Jobs Hypothesis	Jobs Attract Arts Hypothesis
Dependent Variable	**Jobs 2016**	**Arts 2016**
Intercept	5.6 ***	3.14 ***
	(.014)	(.018)
Arts 1998	**.25 *** **	.72 ***
	(.003)	(.004)
Jobs 1998	.08 ***	**-.295*** **
	(.003)	(.004)
Residual S.E.	0.9	1.2
R-Squared	0.374	0.459
Adjusted R-Squared	0.374	0.459
N	63046	63046

Note: *** $p<0.01$
Gamma coefficients are highlighter in bold.

Table 4.3: Regression results for the baseline model using log number of jobs as unit

The R-squared for the log-transformed regressions are much smaller than the R-squared for the natural numbers regressions because, as seen in figures 4.2 and 4.3, the distribution of points for the log data is much more spread out than the distribution of points for the number of jobs data.

This model also compares the independent variables in 1998 to the dependent variables in 2016, according to each regression equation. The interpretations for these log-log regressions are done in percentages. Therefore, for the *arts attract jobs* hypothesis, a one percent increase in the arts in 1998 indicates a gain of .246 percent jobs in 2016, keeping everything else constant. At the same time, a 1 percent increase in jobs in 1998 may indicate a decrease of .295 percent of arts in 2016. This negative number, however, does not necessarily mean that jobs destroy the arts, but as the size of urban areas increase, the number of both arts and jobs also increase, but the proportions of arts to jobs decrease, as discussed in section 4.1.2.

The results of this log-log model are not straightforward enough to understand even though the model is simple. In this case, we should consider that the higher the numbers of jobs, the smaller the proportion of arts to jobs, which may be influencing the negative crossed coefficient in this baseline model. Nonetheless, this is one interpretation that needs to be verified with more details in the models presented next.

4.2.1.3 Reciprocal Impact of Arts and Jobs in Changes of Employment Numbers

The third baseline model analyzes the changes in the number of arts and jobs from 1998 to 2016, or the number of jobs in 2016 minus the number of jobs in 1998. The cross-lagged regression equations for the change variables are shown below:

$$(Arts_t - Arts_{t-1}) = \alpha_0 + \gamma_0 * (Jobs_t - Jobs_{t-1}) + \epsilon_0$$

or also:

$$\Delta Arts_{t-(t-1)} = \alpha_0 + \gamma_0 * \Delta Jobs_{t-(t-1)} + \epsilon_0$$

for the “jobs attract arts” hypothesis; and

$$(Jobs_t - Jobs_{t-1}) = \alpha_1 + \gamma_1 * (Arts_t - Arts_{t-1}) + \epsilon_1$$

or also:

$$\Delta Jobs_{t-(t-1)} = \alpha_1 + \gamma_1 * \Delta Arts_{t-(t-1)} + \epsilon_1$$

for the “arts attract jobs” hypothesis, where t is the later year.

For the “arts attract jobs” hypothesis, again the interpretation depends in the comparisons between γ_0 and γ_1 coefficients.

In this model, we compare only the changes in each variable between two years. In other words, we are observing the employment sections that increase or decrease in a period in relation to each other while excluding the fixed portion of jobs. The results for the two regressions are shown in table 4.4, and the regressions results for the “jobs attract arts” hypothesis are also significant with ($F(1, 63047) = 42200$, $p < 0.000$) with an R^2 of 0.401, and the results for “arts attract jobs” hypothesis are significant with ($F(1, 63047) = 60300$, $p < 0.000$) with a R^2 of 0.489.

Cross-Lagged Regressions Results for Change Between 1998 and 2016

	Arts Attract Jobs Hypothesis	**Jobs Attract Arts Hypothesis**
Dependent Variable	**ΔJobs**	**ΔArts**
Intercept	179.84 ***	-39.17 ***
	(4.72)	(.033)
ΔArts	**1.824 *****	-
	(.00743)	
ΔJobs	-	**.033 *****
		(.00016)
Residual S.E.	1170	198
R-Squared	0.489	0.401
Adjusted R-Squared	0.489	0.401
N	63047	63047

Note: *** p<0.01

Table 4.4: Regression results for the baseline model using first difference changes as unit

The units of measurement for these variables are the natural number of jobs, as no transformations were done after calculating the differences. For one additional arts job between 1998 and 2016, there was an increase in 1.824 jobs, while an increase of one non-arts job would increase arts jobs by .033. Therefore, when we consider only the changes that occurred in that period, the arts again had a much stronger impact on jobs than the inverse. Similar to the interpretation in the first model, one additional arts job almost doubled its number in non-arts job, while about thirty non-arts jobs workers would have to move in (not counting their families) to add one additional artist.

In the three baseline models shown in this section, we took into consideration all hexagons from all urban areas together, and we have already seen that the arts had a larger impact on jobs than vice versa, even though more attention is needed for the log-transformed variables. This is a general analysis that may guide the interpretation of the rest of this dissertation.

4.3 The Effects of Arts and Jobs in the Short and Long Terms

The baseline models discussed in the previous section provides a glimpse in a general analysis for two years of data nineteen years apart, 1998 and 2016; however, data for each year in between are also available. In using cross-lagged regression models, we compare two years of data repeatedly, producing for each pair of regressions different results. This procedure would result in hundreds of coefficients to be examined individually at a volume in which the results become data by themselves. We use fixed-effects meta-analysis after obtaining the coefficients for the regressions for each pair of data in order to summarize the results and simplify interpretation. The fixed-effects method is appropriate here as the sample and variables for each one of the separate models are the same. This process is detailed in section 3.4 of chapter 3.

Observing the impact of arts and jobs in each pair of years can reduce systemic and local random events for any particular period that could have disturbed the economic course in one urban area or another. Systemic causes affect most, if not all, urban areas more or less equally, such as in the case of the 2007 financial crisis or the COVID-19 pandemic. Local causes affect particular areas, such as in the case of major natural disasters—for example, Hurricane Katrina or the wildfires in California. As these events strongly impact the markets, I try to neutralize them by comparing all possible combinations of years in the same cross-lagged regression models with the meta-analysis.

In this section, I explore the impact of arts and jobs when we consider different time lags between the dependent and independent variables. For example, how do the relationships between arts and jobs change when the time lag between the dependent and independent variables are one year apart or ten years apart? Next, I present three models: one-year time lag, ten-year time lag, and first difference change analysis by adapting the cross-lagged regression models with different time lags and variables.

The one-year lag models show shorter term effects, and the ten-year models show longer term effects, but the time lags could have been of any number of years. I chose ten-year lags to represent longer term effects as ten-year lags would allow for multiple combinations of years (1998 and 2008, 1999 and 2009, …, 2006 and 2016) in the model—in this case, nine combinations. Longer time lags decrease the possible combinations of years, and thus, produce fewer models.

Both time lag models use the log-transformed data and not the natural number of jobs. For the first difference analysis, we compute the changes in the natural number of jobs from one year to the next without any transformations. In addition, I compare the results for regressions for all hexagons to the results for the hexagons in the top ten urban areas, based on population size. The top ten urban areas are shown in table 4.5, and the population data by urban area is sourced from the US Census Bureau's Decennial Census. The top ten largest urban areas have gained population between 2000 and 2010 in different degrees, with Houston, TX with the highest population gain of 1.1 million people, while Boston, MA had gained 160,000 people in the same period.

Top 10 Urban Areas by Population

Urban Area	Pop. 2000	Pop. 2010	Growth
New York, NY	18,218,797	18,779,040	560,243
Los Angeles, CA	12,238,824	12,689,306	450,482
Chicago, IL	8,672,523	8,980,718	308,195
Philadelphia, PA	5,586,709	5,851,504	264,795
Dallas, TX	4,682,596	5,710,855	1,028,259
Miami, FL	4,994,903	5,556,025	561,122
Houston, TX	4,123,681	5,288,255	1,164,574
Atlanta, GA	4,099,396	5,112,741	1,013,345
Washington, DC	4,267,239	4,925,961	658,722
Boston, MA	4,539,614	4,699,794	160,180

Data Source: U.S. Census Bureau, Decennial Census, 2000 and 2010

Table 4.5: Ten largest urban areas by population, showing population size in 2000, 2010, and growth

As discussed in chapter 3, each cross-lagged regression analysis contains two separate regression equations, which, in general terms, are written as:

$$Arts_{i,t} = \alpha_0 + \beta_0 * Arts_{i,t-x} + \gamma_0 * Jobs_{i,t-x} + \epsilon_0$$

and,

$$Jobs_{i,t} = \alpha_1 + \beta_1 * Jobs_{i,t-x} + \gamma_1 * Arts_{i,t-x} + \epsilon_1$$

where i represents each hexagon case, t is the year of the dependent variable, x is the length of the time lag, α is the intercept, β is the lagged coefficient, γ is the crossed coefficient, and ϵ is the error term. The γ is the value of most interest from both equations as it compares the effects of one variable on the other. When γ_0 is larger than γ_1, we have that "jobs attract arts," and when γ_1 is larger than γ_0, we have that "arts attract jobs."

4.3.1 The Effects of Arts and Jobs in One Year

The cross-lagged regressions for the one-year lag are those in which the dependent variable is one-year apart from the independent variable. In the one-year lag, we have eighteen pairs of regressions, from which I represent the γ coefficients in the graphs below. The x-axis shows the year of the independent variable, and the y-axis shows the value of the coefficients. The red line connects the coefficient values for arts, and the blue line connects the coefficient values for jobs. Each coefficient also presents its confidence interval calculated by their standard error. The horizontal red and blue dashed lines are the standardized mean difference (SMD) for all the arts coefficients as calculated by the meta-analysis, respectively for arts and jobs.

Figure 4.12 shows the results for the one-year lags for all hexagons. We see that the SMD for arts is larger than the SMD for jobs, indicating that the arts have a higher impact on jobs. The jobs SMD is negative, which may be due to the fact that many hexagons do not have a high number of arts and have not attracted the arts in this short period.

In years when the red and blue line cross each other, we see an inversion from "arts attract jobs" to "jobs attract arts" or vice versa. Therefore, in 2005, 2007, 2010, and 2015, jobs attracted arts, and arts attracted jobs in the other fourteen periods. The interchanging positions of jobs and arts with stronger impacts in some years but not others justify the need to analyze all possible combinations of years to get a more complete understanding.

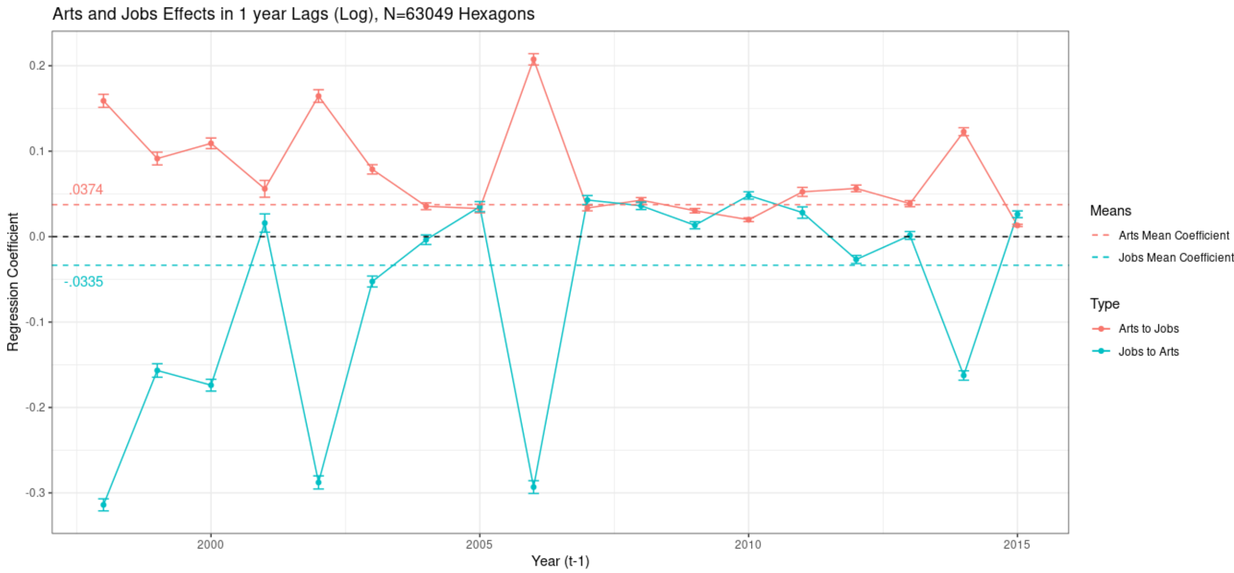

Figure 4.12: Crossed coefficients for one-year lag regressions for all urban areas

The arts coefficients are overall greater than the jobs coefficient. On average, a 1 percent increase in the arts would increase jobs by .0374 percent, while 1 percent increase in jobs would decrease arts by -.0335 percent. These values may seem small, but from 2006 to 2007, a 1 percent increase in the arts would increase jobs by .21 percent, indicating that these were two years when arts attracted jobs the most, while jobs did *not* attract arts just as much.

The negative jobs coefficient may be explained by the inequality in the number of arts among the hexagons, with a few hexagons having a lot more arts than most, and where not all employment gains are justifiable by the arts, at least on a yearly basis. Another possible explanation relates to the critical mass effect that indicates that for the arts to grow, the number of jobs need to grow significantly more to increase the local audience, or reach a critical mass to make the work of more artists viable. Throughout this dissertation, the multiplier effects of the arts and the critical mass effect of jobs work hand in hand, as both are mechanisms that feed the other.

Figure 4.13 shows the one-year-lag crossed-coefficients for the top ten urban areas listed above. The overall arts coefficient is larger than the jobs coefficient (which is not statistically significant, p-value = .4).[2] In all hexagons, the arts seem to have generally a stronger effect than in the top ten urban areas. This effects swap between arts and jobs for the top ten urban areas indicates a stronger reciprocal effect of arts and jobs on each other in larger urban areas, and a balance tilted towards the arts when considering all hexagons.

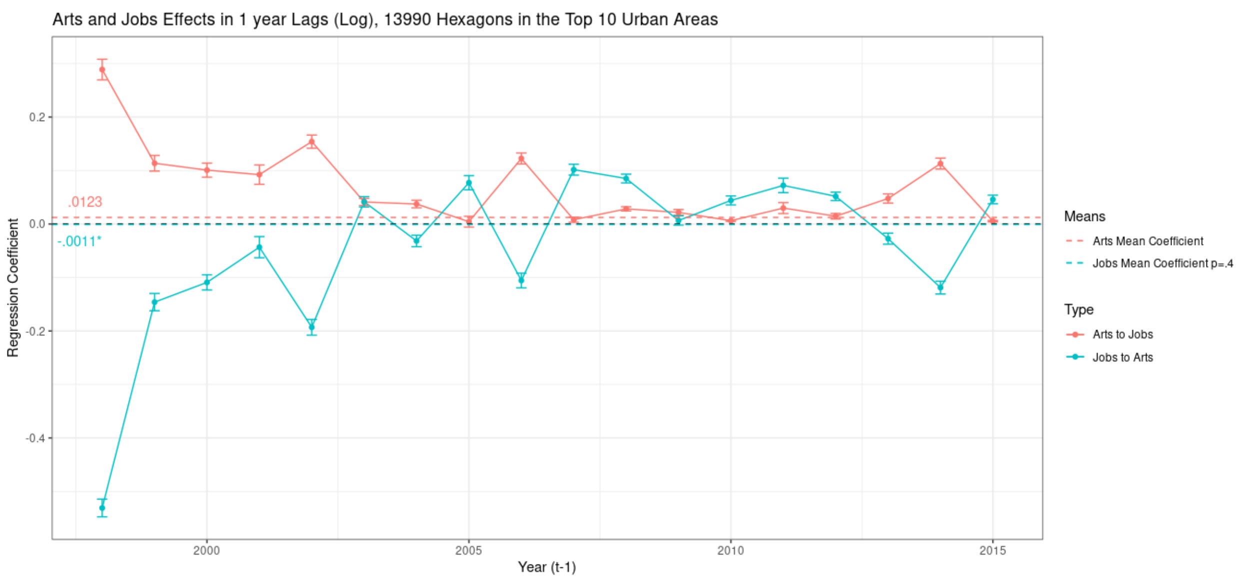

Figure 4.13: Crossed coefficients for one-year lag regressions for the ten largest urban areas

The ten largest urban areas showed a stronger arts impact in ten periods as opposed to the fifteen years in all urban areas. The balance between arts and jobs in the largest cities indicates that due to the more dynamic economies, arts and arts institutions find larger urban areas more attractive as a result of the large non-arts industries in those places. In the average American urban

---

[2] While the meta-analysis SMD was not statistically significant, individual coefficients for each model were statistically significant at 95 percent confidence levels.

area, the arts are succeeding as urban planning strategies to promote cities and attract more businesses.

When we include the intermediate years in the analysis, we see more nuance from year to year, and that both arts and jobs take turns attracting each other, rather than this being a relationship with one single direction. We also see that there is a better balance to the effects in larger urban areas.

4.3.2 The Effects of Arts and Jobs in Ten Years

In this section, I discuss the findings for the ten-year lag models, in which the dependent variable is ten years apart from the independent variable. In figure 4.14, the x-axis shows the year of the independent variable, starting in 1998 (for a dependent variable in 2008), and ending in 2006 (for a dependent variable in 2016). The year 2007 was left out of this analysis as the 2017 data is not included in this study. As opposed to the results for the one-year lags, we see that the red and blue lines never touch, indicating that in the long term, the arts have a much higher and consistent impact on jobs than the contrary. For a 1 percent change in arts, jobs increase by .1931 percent. On the other hand, for a 1 percent change in jobs, there's a decrease in arts of -.1587 percent. This negative coefficient may be due to similar reasons discussed in the previous section: an uneven proportion of arts to jobs in smaller urban areas and the critical mass effect. Therefore, the effects in percentages from the log-log regressions go negative, even though the variables have positive correlations.

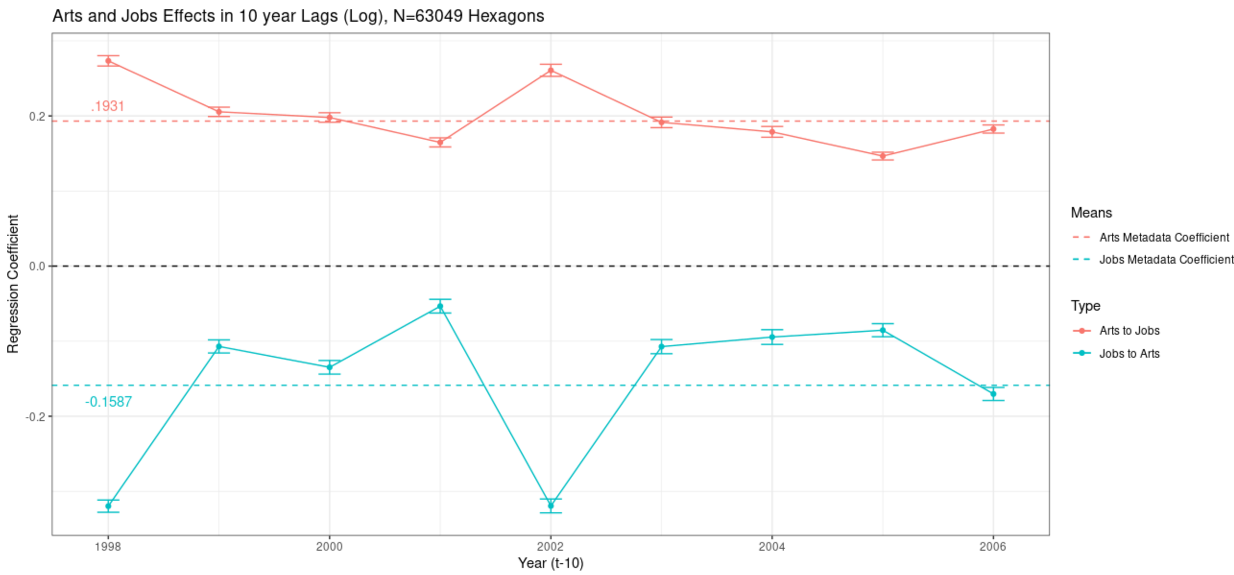

Figure 4.14: Crossed coefficients for ten-year lag regressions for all urban areas

This finding may reinforce the idea that the arts are long-term investments, as argued by Blau (1989). At the same time, non-arts industries are not as impactful in attracting the arts, on average. This result may be a symptom of high investment in the arts in each urban area, where the arts make those places attractive to other industries, but just the presence of the other industries is not sufficient to attract artists at the same pace.

When we compare the overall results to the ten largest urban areas, we see again a better balance between the two types of industries. Figure 4.15 shows that until the period between 2002 and 2012, the arts had a stronger impact, but after 2003, non-arts industries had a larger role attracting the arts to these larger cities. The relationship is again reversed in 2006 to 2016, but there is not enough data to verify if this reversal is due to a cycle or systemic conditions.

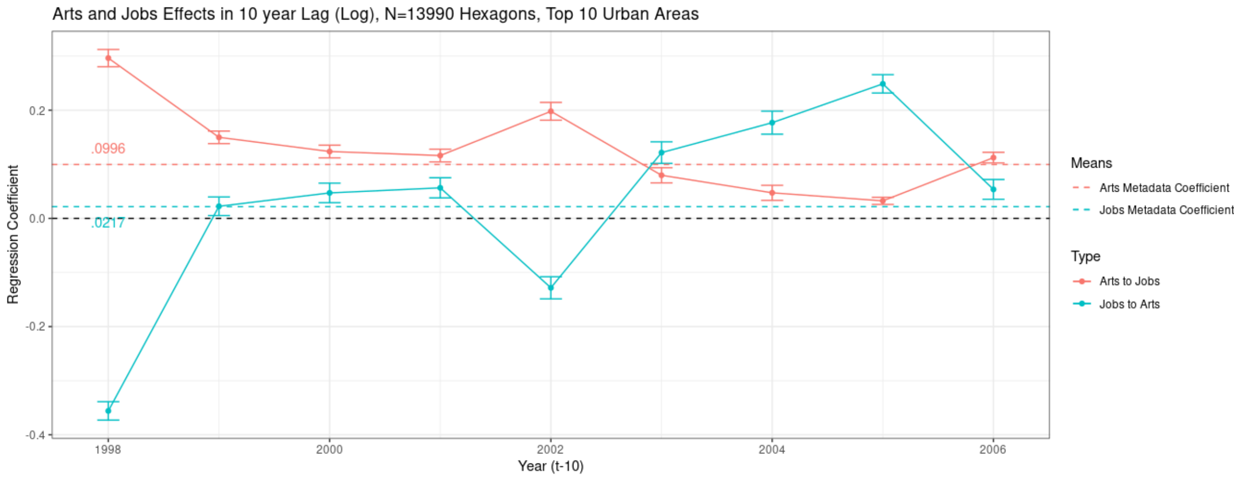

Figure 4.15: Crossed coefficients for ten-year lag regressions for the ten largest urban areas

In the 1990s, in larger cities, communities of artists transformed run-down neighborhoods into desirable and thriving areas to live and work. These neighborhoods were then overtaken by workers in higher wage occupations as rising rent prices drove the artists out of the neighborhoods they helped revitalize. As a swarm of wealthy workers in non-arts industries moved to the cities, they brought together not only money to spend, but also a great interest in the arts, increasing the audience for the arts. At first, arts attracted jobs, but then the roles reversed, and non-arts industries attracted more artists to the largest urban areas (Shkuda 2015; Galligan 2008).

The two time-lag analyses above show that the arts have an even stronger effect on jobs in the longer term than in the shorter term. There are also indications that in both the short and long terms, the relationship between arts and jobs is more balanced in larger urban areas than in all urban areas.

4.4 The Effects of Changes in Arts and Jobs

In this section, we analyze the regression using first differences, and we remove trends from the variables by computing the differences from one year to the next. The cross-lagged regression equations are similar to the ones presented in the beginning of the section, but for first differences, we do not include the lagged variable as the independent variable. Thus, in this case, we compare the changes in each industry between the same two years, and we should interpret the coefficients in terms of number of jobs. The equations for the first difference models are:

$$(Arts_t - Arts_{t-1}) = \gamma_0 * (Jobs_t - Jobs_{t-1}) + v_t$$

and,

$$(Jobs_t - Jobs_{t-1}) = \gamma_1 * (Arts_t - Arts_{t-1}) + v_t$$

where the t is the year of the dependent variable, γ_0 and γ_1 are the crossed coefficients, and v_t is the error term. Again, we compare the γ coefficients from both equations to determine which direction had a larger effect.

Based on the equations presented above, we run the first differences regressions for every pair of years in one-year lags. Figure 4.16 shows the coefficients for the first difference regressions. The overall arts coefficient is much larger than the overall jobs coefficient. The jobs coefficients are nearing zero, while the arts coefficient is 3.53. Therefore, for each arts job, there's an arts multiplier effect that increases non-arts jobs by 3.5 on average. The arts effects were much larger until 2008, after which the effects decreased but were still much larger. On the other hand, for each job increase, there's an increase of .07 arts jobs, or an additional fourteen non-arts jobs are required to increase one arts job. This again points to the critical mass effect, in which a certain number of people, workers, audience members, and patrons are required to increase the production of arts.

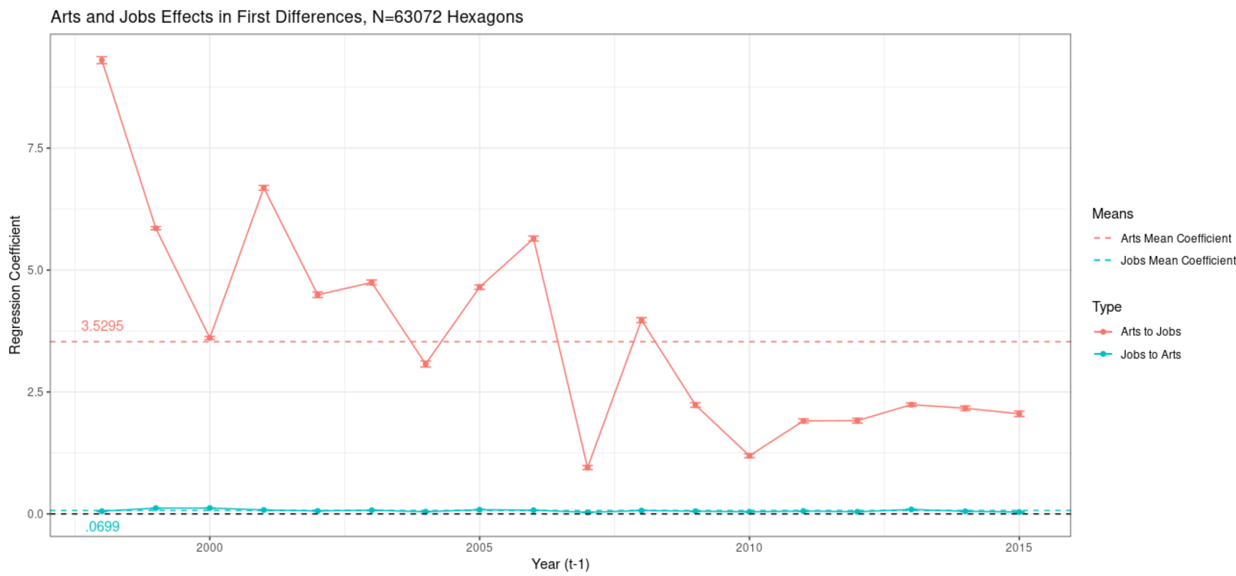

Figure 4.16: Crossed coefficients for first difference regressions for all urban areas

In the first difference analyses focused on the top ten urban areas, we see a similar pattern, with higher coefficients than in the general analyses. In both, we see that one increase in arts increased jobs by almost four, whereas a jobs increase of about fourteen is necessary to attract one more artist.

Figure 4.17: Crossed coefficients for first difference regressions for the ten largest urban areas

For the first difference analyses, we see that the arts have a stronger and more direct impact on jobs, regardless of the urban area size. When analyzing only the year-by-year changes for arts and jobs, results show a significant multiplying effect of one art to four jobs. On the other hand, about thirteen non-arts workers (and their families) should move into an urban area in order to attract one additional artist, on average.

From all three analyses in this section, the critical mass theory indicates that the arts flourish more where there are growing audiences, but that places on average greatly benefit from the arts to grow their economies.

4.5 The Effects of Arts and Jobs by Urban Area

The analyses thus far have shown results for all urban areas combined. In this section, I present the results for the same analyses with the urban area data partitioned based on population size. Table 4.6 shows the general contexts of population and location of hexagons in urban areas.

The top fifty largest urban areas contain about half the hexagons in the data, while the middle and bottom tiers contain one quarter of the total number of hexagons each, even though these two tiers account for 90 percent of the urban areas. This distribution is a reflection of the area sizes and density of cities: the largest urban areas cover larger built-on areas, and thus have more hexagons within their boundaries than urban areas in the middle and bottom tiers, which have fewer hexagons covering urbanized city centers, as discussed in chapter 2. For the exact number of hexagons contained in each urban area, please refer to the table of results in appendix E.

Number of Cases by Urban Area Population Size

	Top 50	**Middle Tier**	**Bottom Tier**	**Total**
	More than 1M people	Between 300k and 1M people	Less than 300k people	
Number of Hexagons	30151	16780	16141	63072
Number of Urban Areas	50	111	320	481
Average Hexagon per Urban Area	603.0	151.2	50.4	131.1

Table 4.6: Number of hexagons in each urban area size tier: half of the hexagons are inside the fifty largest urban areas

Table 4.6 shows that fifty urban areas contain 30,151 hexagons, with an average of 603 hexagons per urban area, while the 111 middle-tier urban areas contain almost 16,780 hexagons with an average of 151 hexagons per urban area, and the 320 urban areas in the bottom tier contain 16,141 hexagons with an average of fifty hexagons per urban area. These discrepancies should lead us to look for differences in the results based on population size.

To be sure, the population, jobs, and establishments in each urban area are not equally distributed among all hexagons. As we look for differences in economic and arts activities, therefore, larger urban areas are more likely to have higher numbers of hexagons with significant arts activities, while the few hexagons in smaller cities may present very few or no arts activities.

The map on figure 4.18 shows conclusions for each urban area after comparing the two γ coefficients from the cross-lagged regression models using first differences data. Urban areas in *orange* show stronger arts effects on jobs in 294 cases; urban areas in *blue* show stronger jobs effects on arts in 131 cases; green areas had neither coefficient significant at 95 percent confidence level in thirty-five cases,[3] and twenty-one urban areas did not have enough data to produce the regressions results in either equation.

Table 4.7 summarizes the findings in the map according to the three population tiers. Ninety-four percent of the top fifty largest urban areas show stronger arts effects on jobs, while 70.3 percent of the cities in the middle tier show stronger arts effects, and 56.5 percent of the cities in the bottom tier show the same type of effect. This gradation shows that as city size decreases, fewer urban areas present stronger arts impact on jobs. Or, larger urban areas are in fact more likely to have stronger arts effects. However, we should note that still more than half of the smaller urban areas show stronger arts effects on jobs, indicating that even though the arts seem to favor larger urban areas, smaller urban areas also benefit from their presence.

[3] In a few cases, the larger γ coefficient was not significant, but the smaller could have been.

Where the Arts Attract Jobs and Jobs Attract Arts

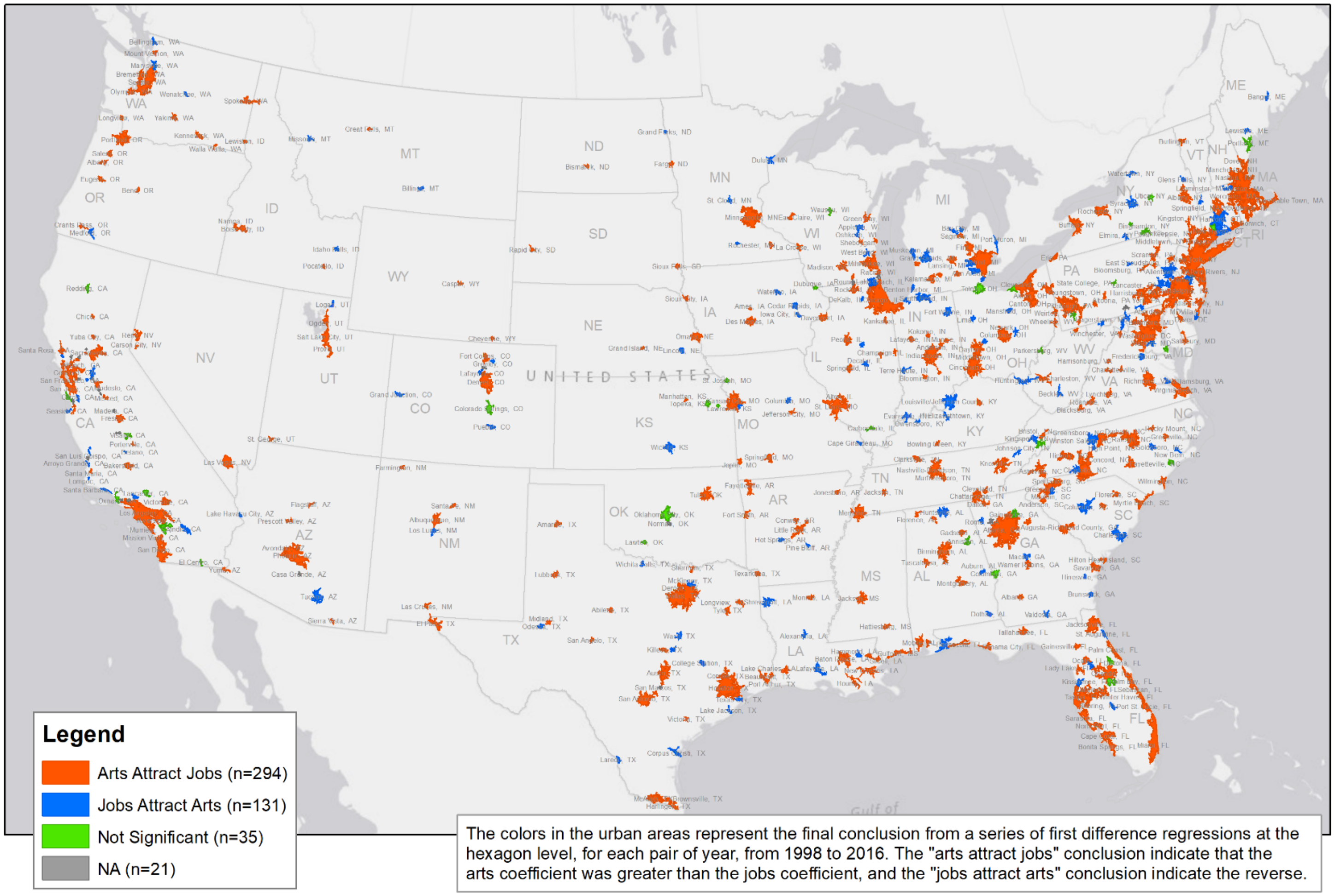

Figure 4.18: Map showing the stronger path direction by urban area

On the other hand, we see that only two of the largest urban areas (Hartford, CT, and Louisville, KY) had a stronger jobs effects on arts, followed by middle-tier urban areas with 22.5 percent and the bottom-tier urban areas with 34.8 percent. In table 4.7, smaller cities indicate stronger jobs effects on arts with more frequency than larger cities, or in other words, non-arts industries are more likely to attract businesses and workers in smaller urban areas. Appendix E shows details of the regression results for each urban area.

Number of Urban Areas by Regression Results and Population Size: Arts and Jobs Variables

	Top 50 Urban Areas	Middle Tier (1)	Bottom Tier (2)	Total
Arts Attract Jobs	47 (94%)	78 (70.3%)	169(56.5%)	294(63.9%)
Jobs Attract Arts	2 (4%)	25 (22.5%)	104 (34.8%)	131 (28.5%)
Not Significant	1 (2%)	8 (7.2%)	26 (8.7%)	35 (7.6%)
Total	50	111	299	460*

* The total number of cases is 460 urban areas because 21 urban areas did not show any results
(1) Middle tier urban areas are those between 300 thousand to 1 million people
(2) Bottom tier urban areas are those with less than 300 thousand people

Table 4.7: Proportions of each direction by urban area size tier

Each urban area shows unique conclusions based on their contexts. While it is hard to discuss each urban area in this text as there are 481 being considered here, in the remainder of this section, I discuss three general cases that found the most in the results table: cities where arts attract jobs, cities where jobs attract arts, and some special cases, as well as the interaction effects with population sizes. These cases are discussed in general terms, but closer discussion on each urban area should be done on another occasion.

4.5.1 Urban Areas Where Arts Attract Jobs

Most urban areas in all three tiers indicate that the arts attract jobs; this is the case for 94 percent of the urban areas in the top tier, 70.3 percent in the middle tier, and 56.5 percent in the bottom tier. For a closer look, table 4.8 show the results for the twenty largest urban areas in the dataset. The estimates in this table are the coefficients and respective statistics from the fixed-effect meta-analyses performed for the eighteen pairs of regressions of each urban area using first differences data. Most studies that use this meta-analysis (or the analysis of the analyses) method prefer the random-effects method over the fixed-effects method. However, the fixed-effect meta-analysis is adequate here because the data collected refer to the same set of individuals and samples but in different time periods.

Arts and Jobs Coefficients for the Top 20 Urban Areas by Population Size

		Arts					Jobs				
City	N	Estimate	S.E.	p-value	Lower C. I.	Upper C. I.	Estimate	S.E.	p-value	Lower C. I.	Upper C. I.
Chicago, IL	1592	4.601	0.051	0.000	4.501	4.701	0.038	0.000	0.000	0.037	0.039
New York, NY	2399	4.168	0.018	0.000	4.132	4.203	0.084	0.000	0.000	0.083	0.085
Seattle, WA	724	3.934	0.072	0.000	3.793	4.075	0.028	0.000	0.000	0.027	0.029
Philadelphia, PA	1430	3.870	0.034	0.000	3.804	3.936	0.046	0.000	0.000	0.045	0.046
San Francisco, CA	423	3.843	0.084	0.000	3.678	4.007	0.036	0.001	0.000	0.035	0.038
Tampa, FL	743	3.210	0.075	0.000	3.063	3.357	0.033	0.001	0.000	0.032	0.034
Washington, DC	934	2.803	0.030	0.000	2.744	2.863	0.065	0.000	0.000	0.064	0.066
Baltimore, MD	456	2.658	0.055	0.000	2.549	2.766	0.050	0.001	0.000	0.049	0.051
Houston, TX	1143	2.216	0.046	0.000	2.126	2.306	0.036	0.001	0.000	0.035	0.037
Phoenix, AZ	757	2.206	0.055	0.000	2.098	2.314	0.037	0.001	0.000	0.035	0.039
Boston, MA	1536	2.129	0.032	0.000	2.066	2.193	0.043	0.001	0.000	0.042	0.044
Los Angeles, CA	1127	1.757	0.024	0.000	1.710	1.803	0.071	0.001	0.000	0.069	0.073
Dallas, TX	1234	1.667	0.047	0.000	1.574	1.760	0.035	0.001	0.000	0.034	0.036
Detroit, MI	954	1.543	0.040	0.000	1.465	1.622	0.037	0.001	0.000	0.036	0.038
Denver, CO	459	1.442	0.061	0.000	1.322	1.561	0.030	0.001	0.000	0.028	0.032
Miami, FL	781	1.407	0.044	0.000	1.319	1.494	0.046	0.001	0.000	0.044	0.049
Minneapolis, MN	698	1.337	0.050	0.000	1.239	1.436	0.040	0.001	0.000	0.038	0.042
Atlanta, GA	1814	0.905	0.023	0.000	0.859	0.950	0.048	0.000	0.000	0.047	0.049
San Diego, CA	500	0.720	0.045	0.000	0.632	0.807	0.037	0.001	0.000	0.034	0.039
St. Louis, MO	633	0.447	0.033	0.000	0.381	0.512	0.040	0.001	0.000	0.039	0.042

Table 4.8: Arts and jobs coefficients and statistics for the twenty largest urban areas

Chicago presents the largest arts to jobs coefficient, as one arts job attracts between 4 to 5 non-arts jobs, but one non-arts job attracts .04 of arts jobs. This goes along with the critical mass effect as multiple non-arts jobs are necessary to make up an audience to invite for one additional artist. In other words, the arts attract jobs in the long run, bringing in people and their families to the city; on the other hand, those jobs support the arts by providing the artists and cultural amenities with audiences, crowds, patrons, and fans. On average in Chicago, twenty-six additional non-arts jobs are required to attract one more artist to Chicago. These new employees move to Chicago with their families, adding up to great numbers able to participate in the arts activities and cultural amenities that the city provides. The cities in this table suggest the same conclusion but to different degrees: arts attract jobs, but non-arts jobs make up audiences for more arts.

The jobs to arts coefficients for New York and Los Angeles are much higher than for the other cities on the table. This indicates that for these two cities, fewer new audience members are required in order to attract one additional artist. This is due to the larger arts job market in these two cities, at levels that allow marginal reductions in audience gains. While most cities require twenty to thirty non-arts jobs for one additional arts job, New York requires eleven, and Los Angeles requires fourteen non-arts job per arts job.

Figure 4.19 shows the individual coefficients for Chicago, New York, and Los Angeles. The arts coefficients (circles on dashed lines) are much larger and fluctuate greatly, while the jobs coefficients (triangles on dashed lines) are much smaller, fluctuating around zero. This figure brings to attention the yearly variations in the three cities. The reasons behind such variations go beyond the scope of this study, as the reasons may be systemic, such as the financial crisis or economic motivations, or local, such as cultural policies put into place. However, with a few exceptions, the arts to jobs coefficients are mostly larger than the jobs to arts coefficients over time and for all three cities.

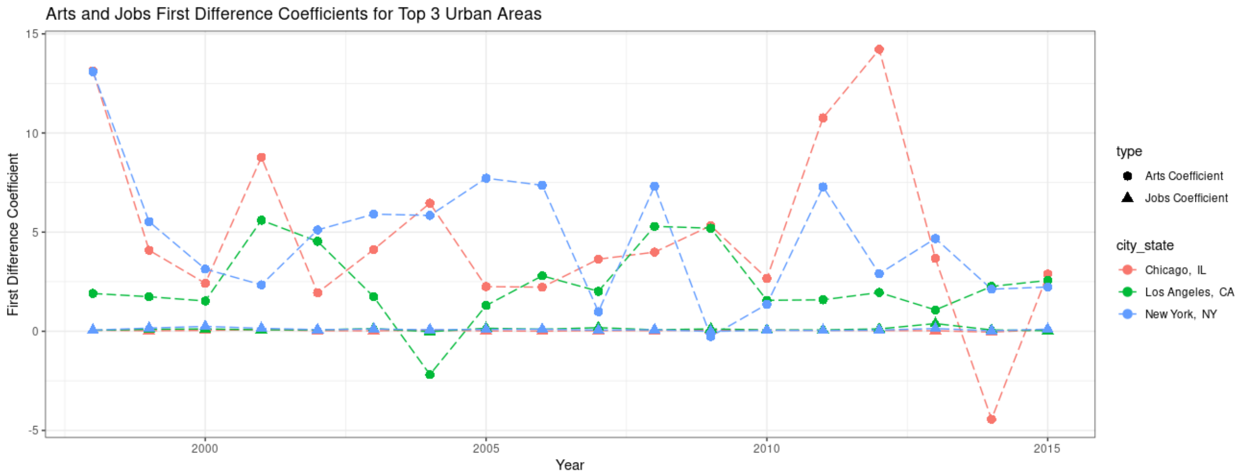

Figure 4.19: First differences coefficients for New York, Los Angeles and Chicago

Figure 4.19 illustrates the amount of variation that the meta-analyses are summarizing as we look at the results on table 4.8 and Appendix E. As the analyses consider the data for two years in one-year differences, each year should present its own type of effect. The meta-analyses also combine different context and types of variations not directly included in the regression equations smoothing out the systemic or periodic effects. For example, from 2012 to 2013, Chicago had a larger growth in the effect of arts on jobs, while New York had that effect decrease and Los Angeles remained stable in the same year. This is not to say that the arts were not as relevant in NY and LA, but that the effects of the arts in attracting new non-arts jobs were stronger in Chicago that year in particular. As the points and lines shift positions in this figure, we see that the effects do not grow monotonically, but rather irregularly.

4.5.2 Urban Areas Where Jobs Attract Arts and Special Cases

Even though the majority of the urban areas showed results favoring the multiplier effect of the arts, many cities are still cases where jobs attract arts, meaning that in these cities, people and businesses move for jobs and the arts industries followed. Table 4.9 shows the largest urban areas where *jobs attract arts*. For many urban areas with this type of conclusion, the arts coefficients are negative, and even some jobs coefficients are negative. These urban areas have lower numbers of hexagons, and as seen above, are mostly in the middle or bottom tiers.

In this study, negative coefficients are harder to decipher than positive coefficients. Positive coefficients are easier to interpret because we understand economic growth more easily than economic decline. For example, it is easier to understand that in Chicago, one additional arts job has the potential to attract 4.6 non-arts jobs, as seen above. The same goes for the positive jobs coefficient, even when they are smaller than one. For example, in Chicago, one additional non-arts job has the potential to attract 0.038 arts jobs, which then leads us to understand that in order for non-arts jobs to make up for one whole arts job, 26 non-arts jobs are necessary (or 1 divided by .038). But in cases where one or both the coefficients are negative, the interpretation is more complex as the reasons for economic decline are more specific to the context of each urban area and not expected, as is economic growth.

In urban areas where the jobs coefficient is positive but the arts coefficient is negative, the interpretation may indicate a nascent arts industry where jobs are still not plentiful enough to attract arts that would then attract jobs; in other words, urban areas with negative arts-coefficient may be great cities to invest in the arts in order to promote economic growth as there are already some arts effects on jobs, but not much growth from year to year in other industries. For example, Santa Barbara, CA, is well-known for its climate, natural landscape, and cultural activities, but the arts effects coefficient is negative (-0.588), showing that one additional arts job leads to fewer non-arts jobs. At the same time, the jobs effects on arts have a positive coefficient (.022), a value that even if it is small, it is statistically significant and close to the values in larger urban areas. Thus, in Santa Barbara, non-arts jobs are attracting arts jobs at similar rates than in larger urban areas, but the arts themselves are not yet attracting non-arts jobs. This may be due to a high concentration of the arts in central areas or stagnant growth of the arts in the period studied. There are sixty-five urban areas in this situation, including the two top-tier urban areas, Hartford, CT, and Louisville, KY. Understanding the mechanisms of the urban areas where the jobs coefficients are positive but arts coefficients are negative would require a closer interpretation of the urban areas where this happens, which goes beyond the scope of this dissertation.

Arts and Jobs Coefficients for the Top 10 Urban Areas by Jobs Estimate

		Arts					Jobs				
City	**N**	**Estimate**	**S.E.**	**p-value**	**Lower C. I.**	**Upper C. I.**	**Estimate**	**S.E.**	**p-value**	**Lower C. I.**	**Upper C. I.**
Charleston, SC	226	-0.132	0.050	0.009	-0.230	-0.034	0.028	0.001	0.000	0.025	0.030
Allentown, PA	287	-0.033	0.065	0.613	-0.160	0.094	0.026	0.001	0.000	0.024	0.029
New Haven, CT	151	-1.081	0.057	0.000	-1.194	-0.969	0.024	0.001	0.000	0.022	0.026
Winston-Salem, NC	272	-0.080	0.067	0.231	-0.212	0.051	0.024	0.001	0.000	0.022	0.027
Wichita, KS	147	-0.416	0.084	0.000	-0.580	-0.251	0.018	0.002	0.000	0.015	0.022
Hartford, CT	499	-0.132	0.055	0.017	-0.239	-0.024	0.016	0.001	0.000	0.014	0.018
Louisville/Jefferson (	326	-0.033	0.048	0.497	-0.127	0.062	0.013	0.001	0.000	0.010	0.015
Tucson, AZ	240	-0.019	0.066	0.769	-0.149	0.110	0.005	0.002	0.025	0.001	0.009
Grand Rapids, MI	205	-0.172	0.104	0.098	-0.377	0.032	0.004	0.002	0.006	0.001	0.007
Columbia, SC	269	-0.426	0.044	0.000	-0.513	-0.340	0.004	0.001	0.000	0.003	0.005

Table 4.9: Largest urban areas where the jobs to arts coefficient was stronger

The interpretation for the urban areas where both arts and jobs coefficients are negative is even more complex and may require even more scrutiny. However, the average number of hexagons associated with these urban areas is forty-three; thus, they may be urban areas lacking enough data for better understanding. In order to avoid over interpretation, I will leave this case aside for now.

4.5.3 Interaction Effects of City Size on Arts and Jobs

As we delve into differences among urban areas by population size, we notice that larger urban areas are the biggest beneficiaries of the arts in attracting other types of industries. But at the same time, we see that medium- and small-sized urban areas also benefit from the arts but in lesser degrees. In the first difference regression analyses, we observe a multiplier effect of the arts in attracting non-arts jobs while many non-arts jobs are required to attract one additional arts job, in the critical mass effect. In order to test this further, we include a categorical variable for "city tier" (as top, middle, or bottom) as an interaction term in the cross-lagged regression model using the log-transformed data.

The top graph in figure 4.20 plots the marginal effect of city size on the arts effects on jobs, where the top and bottom tiers have the same coefficient at .25, and the middle tier has a coefficient of .2. The positive coefficients indicate that the more arts jobs there are in 1998, the more non-arts jobs there would be in 2016. In other words, places with more arts jobs in the previous year show more non-arts jobs in the later year.

On the other hand, the bottom graph, also in figure 4.20, shows that the three lines have negative coefficients. Even though the values among the three lines are somewhat close, we see that the bottom-tier urban areas have a steeper decline than the top and middle tiers. Diametrical to the analysis above, the more non-arts jobs in 1998, the fewer arts jobs there were in 2016. In other words, places with more non-arts jobs in the previous year required more workers to move in so as to gain additional arts jobs. These lines suggest that the critical mass effect in smaller urban areas is proportionally more demanding to attract the arts than in larger urban areas.

For example,[3] Brownsville, TX, a city of 175,000 people, has an arts multiplier effect of four, but a jobs coefficient of .042, indicating that twenty-three non-arts jobs are necessary to attract one additional arts job. The audience effect of Brownsville is double that of New York City,

[3] Based on the first difference analysis, so the units are in number of jobs.

where the jobs coefficient is .084, or twelve non-arts jobs for one arts job, and that also has a similar arts multiplier effect of four. As the population and industries are much larger in NYC, it needs a smaller audience in order to grow its arts industry while a small town like Brownsville needs a larger number of residents than NYC in order to grow its arts; therefore, the bottom tier coefficient is slightly steeper than the top tier coefficient.

Figure 4.20: Regression results for the effect of arts on jobs (top) and the effect of jobs on arts (bottom) as log-transformed variables and their interaction with urban area size

The results presented in figure 4.20 allow for the interpretation above in the general sense, as all urban areas are mixed in this analysis without differentiation. However, as seen in section 4.5.1, many urban areas showed stronger arts multiplier and smaller audience effects than many of the larger urban areas.

Equations X and Y below show the coefficients and interactions for each graph in figure 4.20.

$$Jobs_{2016} = 5.7 + .25 * Arts_{1998} + .03 * Jobs_{1998} - 1.14 * Middle - .47 * Top - .05 * (Arts_{1998} * Middle) -.005^{*} * (Arts_{1998} * Top) + .22 * (Jobs_{1998} * Middle) + .15 * (Jobs_{1998} * Top)$$

where F(8, 156625) = 19300, p < 0.000 with an adjusted R-square of .497.

$$Arts_{2016-15} = 3.3 - .37 * Jobs_{1998} + .77 Arts_{1998} - 1.005 * Middle - .19 * Top +.21^{*} * (Jobs_{1998} * Middle) + .11 * (Jobs_{1998} * Top) - .07 * (Arts_{1998} * Middle) -.004^{*} * (Arts_{1998} * Top)$$

where F(8, 156625) = 22500, p < 0.000 with an adjusted R-square of .535.

The coefficients marked with an asterisk were not significant at 95 percent confidence levels but are presented for interpretation.

For comparison, I also ran first differences cross-lagged regression models with changes in employment numbers between 1998 and 1999 as an independent variable, and changes between 2015 and 2016 as the year of the dependent variable, for both arts and jobs. The interaction variable is also city tier, which is a three-level factor variable that is then turned into a dummy variable by R. The analysis using first differences presented R-squares close to zero (.027 and .01), but in any case, I present the results here.

The top graph in figure 4.21 shows the results of the interaction effects model for the effects of arts on jobs. The top fifty largest urban areas category shows positive coefficients, while the middle- and bottom-tier urban areas show negative coefficients. The bottom-tier coefficient for the arts is not significant; therefore, any differences to be considered here are between the middle and top tiers. The top-tier urban areas show that for each additional arts job, non-arts jobs increase by 1.53. However, for each additional arts job in middle-tier urban areas, there is a decrease of .65 non-arts job, and the effect is even smaller in bottom-tier urban areas, at .22 non-arts jobs per arts job, but this coefficient was not significant at 95 percent confidence (p-value = 0.0662).

The bottom graph on figure 4.21 shows the effect of jobs on arts with city tier interaction. The coefficient for all three groups is close to zero, at -.003 arts job for each additional non-arts job. The interaction terms were not significant for the crossed-coefficients at 95 percent confidence level. Therefore, city size does not change the strength of the change effects of jobs on arts.

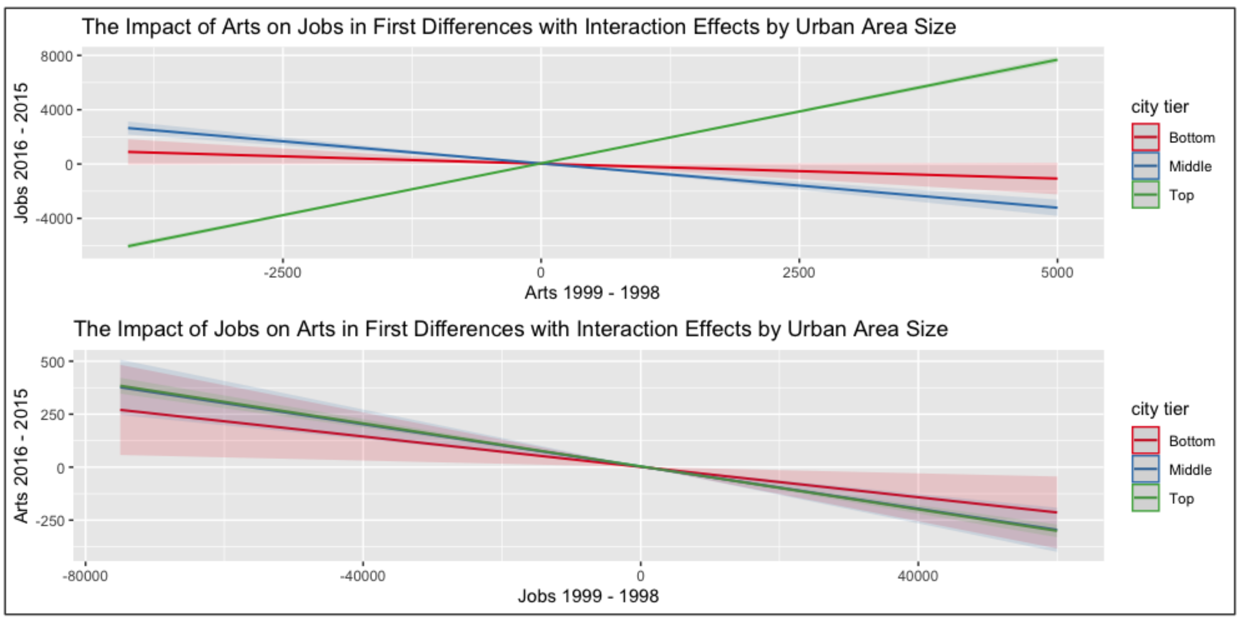

Figure 4.21: Regression results for the effect of arts on jobs (top) and the effect of jobs on arts (bottom) in first difference variables and their interaction with urban area size

The equations below show the coefficients on the top and bottom graphs of figure 4.21.

$$Jobs_{2016-15} = 19.1 -.21^{*} * Arts_{1999-98} + .02 * Jobs_{1999-98} + 15.7 * Middle +$$

$$+ 41.3 * Top - .43 * (Arts_{1999-98} * Middle) + 1.75 * (Arts_{1999-98} * Top) +$$

$$+ .05 * (Jobs_{1999-98} * Middle) - .1(Jobs_{1999-98} * Top)$$

where F(74, 156625) = 276, p < 0.000 with an adjusted R-square of .028.

$$Arts_{2016-15} = .86 - .004 * Jobs_{1999-98} + .09Arts_{1999-98} + 1.2 * Middle +$$

$$+ 2.16 * Top +.001^{*} * (Jobs_{1999-98} * Middle) -.0001^{*} * (Jobs_{1999-98} * Top) +$$

$$+ .11(Arts_{1999-98} * Middle) + .04(Arts_{1999-98} * Top)$$

where, F(74, 156625) = 276, p < 0.000 with an adjusted R-square of .0138.

By adding city tier to the cross-lagged regression models with log-transformed data and first differences, we are able to observe in a general sense that the multiplier effects of the arts grow in places with more non-arts jobs in previous years and in larger cities, and that the critical mass effect hits bottom-tier urban areas where its harder to attract the arts than in top-tier urban areas. Of course, each urban area has their own context and characteristics that adds more variation to this pattern, as this analysis was performed by aggregating every urban area in the US.

4.6 The Effects of Changes in Jobs by Arts Category

The arts variable is composed of three arts categories: arts amenities, arts producers, and recreation. Each one of these categories are indicative of people's preferences for the type of arts they would like to participate in, and therefore, each category plays a unique role in attracting people and businesses. Individuals may value one type of arts more than others, and other individuals may prefer a balanced assortment of entertainment options, but their options are fulfilled based on the availability of establishments in the place they decide to move to.

Splitting the arts variable into categories allows us to better understand nuances in the differences between places that offers a more balanced combination of different types of arts from places that offer a lot of one single type of arts. New York City is a classic example of a city that offers a wide variety of arts and entertainment and also where a variety of industries operate. Thus, as New York offers different types of arts and entertainment to satisfy different tastes, people in different careers and industries are attracted to the city, as they might find something that is of their interest, as illustrated by New York's arts multiplier effect of four non-arts jobs per arts job. On the other hand, places like Orlando, FL, have tourism and theme parks as its prominent industry. Therefore, the types of jobs it attracts is lower and more limited, as illustrated by Orlando's arts multiplier of 1.28 non-arts jobs per arts job. At the same time, Orlando needs the smaller audience growth of four non-arts jobs in order to attract one more arts job (mostly concentrated in the theme parks industry in this case) than New York, which requires twelve non-arts jobs to attract one more arts job, as both the arts and non-arts jobs are spread out in different industries.

In this section, I explore the impact of each of the three arts categories on non-arts jobs and vice versa. To answer this question, I keep the non-arts jobs variable unchanged, but breakdown the arts into each category instead of the composite arts variable, applying the same regression models as in sections 4.2.3 and 4.2.4.

First, we regress jobs on the arts amenities, arts producers, and recreation variables using the first difference variables as in the equation:

$$\Delta Jobs_{t-(t-1)} = \alpha + \gamma_1 * \Delta Amenities_{t-(t-1)} +$$

$$\gamma_2 * \Delta Producers_{t-(t-1)} + \gamma_3 * \Delta Recreation_{t-(t-1)} + \epsilon$$

Figure 4.22 shows the resulting coefficients for each arts categories effect on jobs for each pair of years, as well as the standardized mean difference (SMD) measures as a result of fixed-effects meta-analysis.

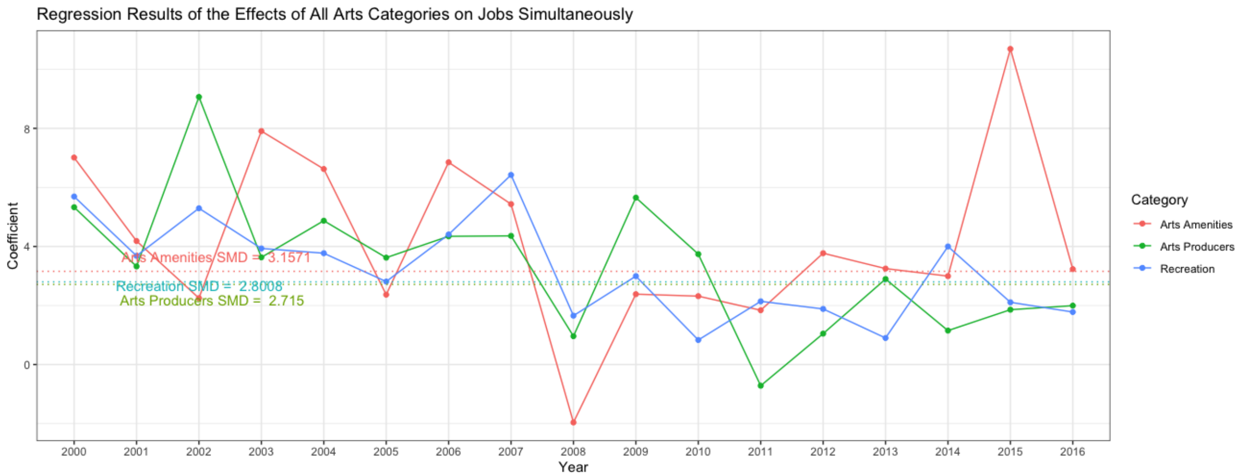

Figure 4.22: Coefficients from the regression with all three arts variables as independent variable in a single equation with non-arts jobs as dependent variable

Arts amenities show the highest SMD, followed by recreation, and then arts producers. However, year by year, the different arts categories seem to have differing levels of impact on non-arts jobs, with arts amenities showing the highest impact in nine years, and arts producers and recreation showing the highest impact in four years each. Thus, the results in figure 4.22 suggests that the arts amenities are a larger attractor of non-arts jobs than the other two industries; however, in 2008, the coefficients for the three arts categories declined, but the arts amenities category was the only one to convert the coefficient to a negative value, indicating that during the economic crisis, arts amenities establishments suffered not only the biggest decline but also the biggest loss out of all three types of arts.

The regression models are done in pairs, with two variables exchanging positions as dependent and independent variable. The equation above featured three independent variables, making it hard to simply exchange the position of the three variables into the dependent variable position in one single equation. So, in order to observe the opposite effect—and also for a more complete analysis—I ran each arts category in their own pair of cross-lagged regressions with non-arts jobs, and the results are shown in figure 4.23.

Figure 4.23 shows the resulting γ coefficients for each pair of cross-lagged regressions using the first difference data. The standard mean differences (SMD) for the arts are much higher than the SMD for jobs. On average, each additional arts job increased non-arts jobs by 3.8, while each additional non-arts job increases arts jobs by .07; in other words, an increase of 14.3 non-arts jobs is required in order to increase one arts job, on average.

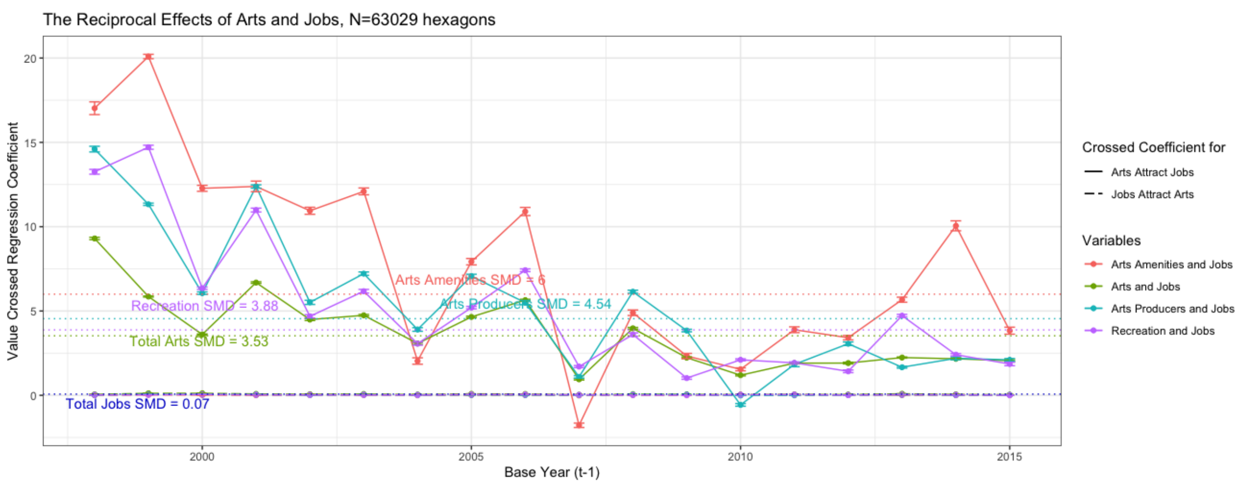

Figure 4.23: Coefficients for the three first differences cross-lagged regression models with arts categories as independent variable

The green line shows the aggregate of all arts as presented in section 4.4. Similar to the aggregate model in figure 4.23, the arts amenities show higher coefficients in thirteen out of the eighteen years of analysis, while arts producers had the lead in three years, and recreation was on top for two years. This indicates that arts amenities have a stronger pull for non-arts jobs than the other two categories even though they all show positive effects. In other words, when the economy runs its growth course, the arts amenities are the biggest attractors of non-arts jobs. On the other hand, during the 2007–08 financial crisis, we see that the only category that dipped below zero was also arts amenities. This shows that in prosperous periods, arts amenities are important attractors of non-arts jobs, but it declines the most during periods of crisis. As Kirchberg (1995) argues, when the revenue in other industries drop, so does donations to the arts, especially arts amenities, which is coherent with my findings.

This analysis also supports the critical mass hypothesis, in which a minimum number of people is required in an urban area in order to develop the arts, as a single variable but also as individual arts industries. Figure 4.24 isolates the “jobs attract arts” lines that are muddled in the bottom of figure 4.23. The green line corresponds jobs to the aggregated arts variable just as discussed in section 4.4 and the other three lines represent each individual industry. The coefficients in this graph are close to zero; however, they are statistically significant at 95 percent confidence and important to our understanding of the relationship between arts and jobs.

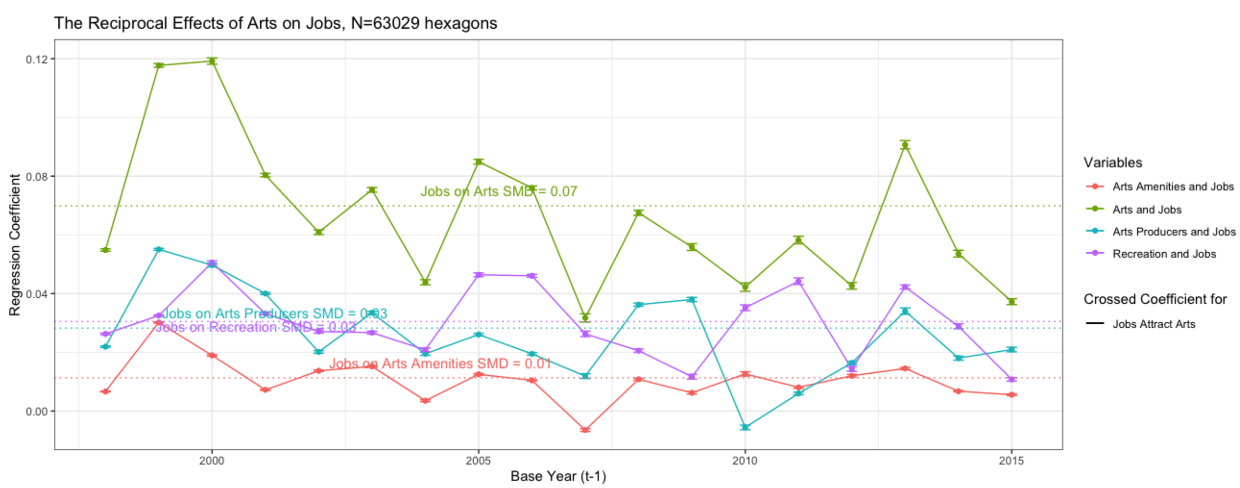

Figure 4.24: Coefficients for the effects of jobs on arts for the three first differences cross-lagged regression models with arts categories as independent variable

Non-arts jobs had a stronger pull for recreation in eleven of the eighteen years in the study, and arts producers for the other seven years. This finding aligns with the nature of the types of establishments in arts producers and recreation as they are made mostly of private companies. For example, arts producers have a high concentration of arts-oriented workers, and of the three arts categories, should follow more closely the structures of non-arts jobs.

Here, the effects from non-arts jobs to any category of arts are small, with even smaller effects for arts amenities. The smaller effects from jobs to arts amenities indicate that the arts amenities establishment require even more people, more patrons, to form larger audiences to support them than arts producers and recreation. Therefore, the arts amenities are more susceptible to decline and need more support from non-arts industries, but they are also the most attractive of the arts industries.

In this section, we discuss findings for the effects of each individual category for arts on non-arts jobs. By dissecting the arts variable into its three categories, the analysis shows that of the three types of arts, arts amenities attract most non-arts jobs, and they also needs the greatest number of non-arts workers to form their audiences in order to grow.

4.7 Conclusion

In this chapter, I analyzed arts and jobs as two aggregate variables in different time lags, the effects in the short and long terms, as well as the changes year by year in first difference analysis. I also analyzed the first differences for each urban area individually, by population size, the interaction effects of arts and jobs with urban area size, and by arts categories.

In the general analysis, the models consistently indicate a multiplier effect of the arts and a critical mass effect of jobs on the arts. These two theories work hand in hand to explain that while the arts attract multiple jobs, many non-arts jobs are required in order to form a large enough audience to attract one additional artist. Still, some urban areas present with stronger jobs coefficients than arts coefficient, counteracting the multiplier/critical mass effect theories. These urban areas are about 28 percent of the total urban area analyzed and require future closer analyses, as it is puzzling why many cities where jobs attract arts have a positive jobs coefficient but negative arts coefficient.

When we break down the analysis for each urban area, we see that most urban areas, regardless of size, still benefit from the arts, while less than half of the urban areas have jobs attracting the arts or are other special cases.

One of the most important conclusions in this chapter is that arts amenities seem to be the industry that most attract jobs, but that also suffer the biggest decline when the economy is not on its growth trajectory. As an industry that depends on patronage, donations, and government financing, it is important that those who can try to keep the arts amenities establishments afloat as they are important in keeping the liveliness of the city. This was seen not only in the tables and figures in this chapter, but also during the COVID-19 pandemic, when the arts amenities establishments were the first ones to cancel all events and shut down and will reportedly be the last ones to open. Without financial support, these establishments could be permanently lost, diminishing the charm and excitement of urban life.

CHAPTER 5

THE RECIPROCAL RELATIONSHIP BETWEEN ARTS ACTIVITIES AND EMPLOYMENT IN BUSINESS SERVICES AND HIGH-TECHNOLOGY INDUSTRIES

In this empirical chapter, we analyze the effects of the arts on non-arts jobs in two major industries: business services and high tech. Many studies refer to these two industries as very synergistic with the arts and entertainment industries. These industries have been singled out for individual analysis as researchers investigate their influence on the American economy as a whole. First, we start with the descriptive statistics, followed by an analysis of the base model, which is then broken down into more specific categories, with which we perform similar analyses as was done in chapter 4 but with the two jobs categories mentioned.

In chapter 5, we explore the relationships between the arts with business services and high-tech industries, as shown in the path diagram on figure 5.1. In chapter 4, the analysis was between arts and jobs in general. However, by breaking this down into smaller categories, we aim to observe the differences between the general analysis with industry-specific analysis.

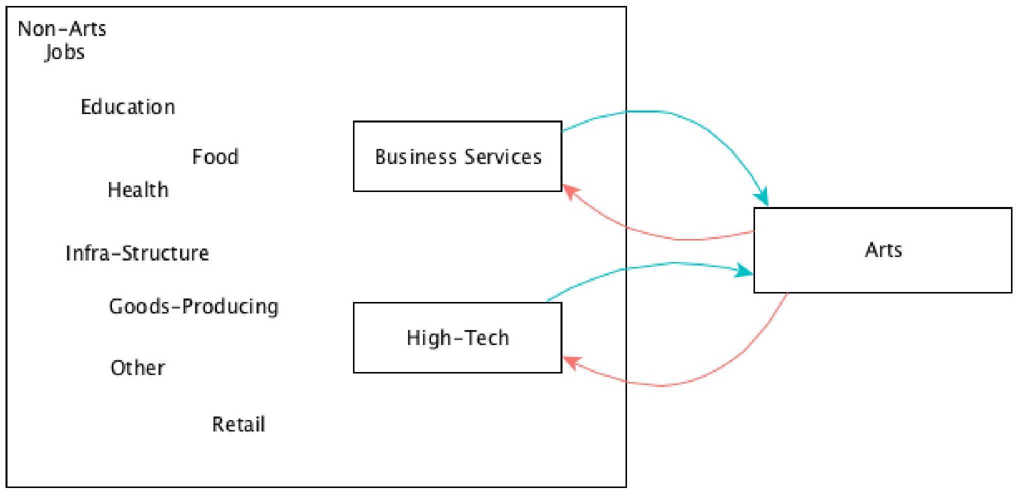

Figure 5.1: Path Diagram of the Relationship Between the Arts and Business Services, High Tech

5.1 Data

The data analyzed in this chapter are a product of the algorithm presented in chapter 3, centered in the employment number by industry category and hexagon. The data source is the US Census County Business Patterns from 1998 to 2016, and we have adapted the NAICS industry classification to match the classification used on the year of release. The estimated employment numbers by industry are in columns, and each row refers to hexagons and urban areas. The methodologies in this chapter are similar to chapter 4, but here we compare business services and high-tech employment as non-arts jobs to the arts industries—both individually as arts amenities, arts producers, and recreation, and their aggregate as arts jobs.

Figure 5.2 shows the distribution of the average size of these industries' job markets. There are in total 63,166 hexagon. The red line on each histogram shows the mean of all the cases. The data distribution for most variables are very skewed, with business services showing the flattest distribution. None of the variables present normal distributions.

Arts amenities, arts producers, recreation, and high tech are very skewed to the right as most hexagons have smaller job markets for these industries, while the larger job markets are concentrated in just a few hexagons. For example, there are many more urban areas with few local theatrical productions compared to a theatrical market on Broadway in New York.

The business services histogram shows a longer tail and a more even distribution of size of company, as these services are more widespread throughout the country than the other four industries discussed here. Thus, business services are more spread out across the country compared to the arts and high-tech industries.

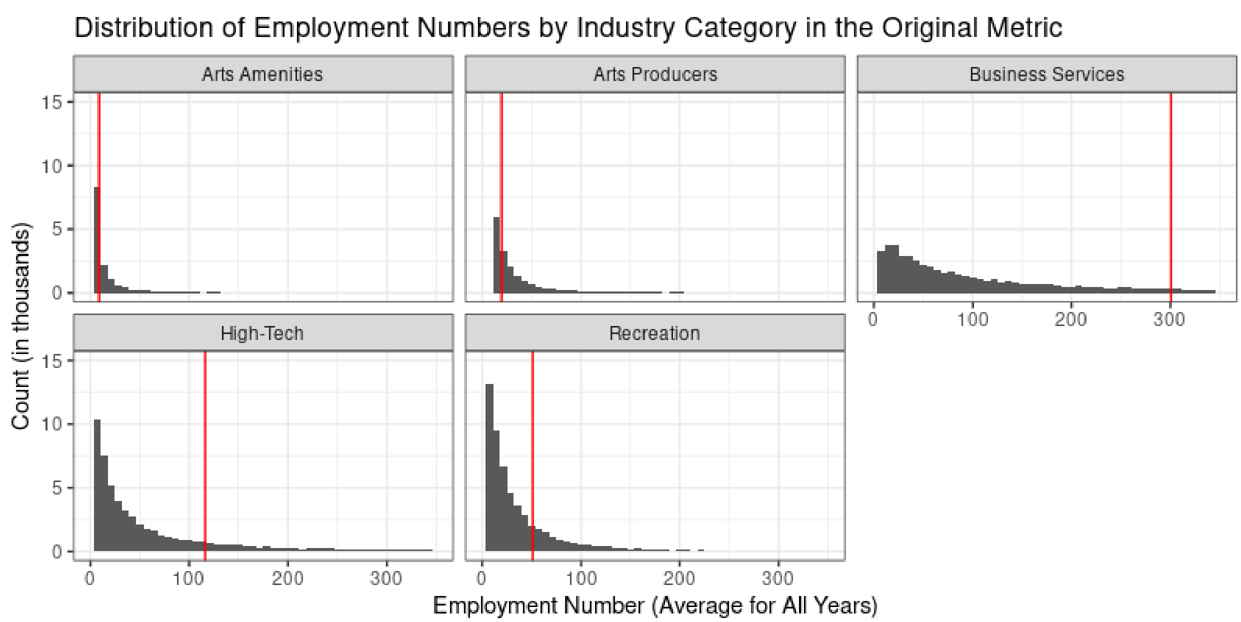

Figure 5.2: Distribution of the time average of variables in the original metric

In order to improve skewness, I log-transformed each variable maintaining their reference year and industry. The advantage of log-transforming variables,[1] where x is the employment number in any given cell, is that distribution become normalized. I also added .001 to each value to avoid calculating logs of zero. Figure 5.3 shows the new distributions for the same variables shown in the figure above.

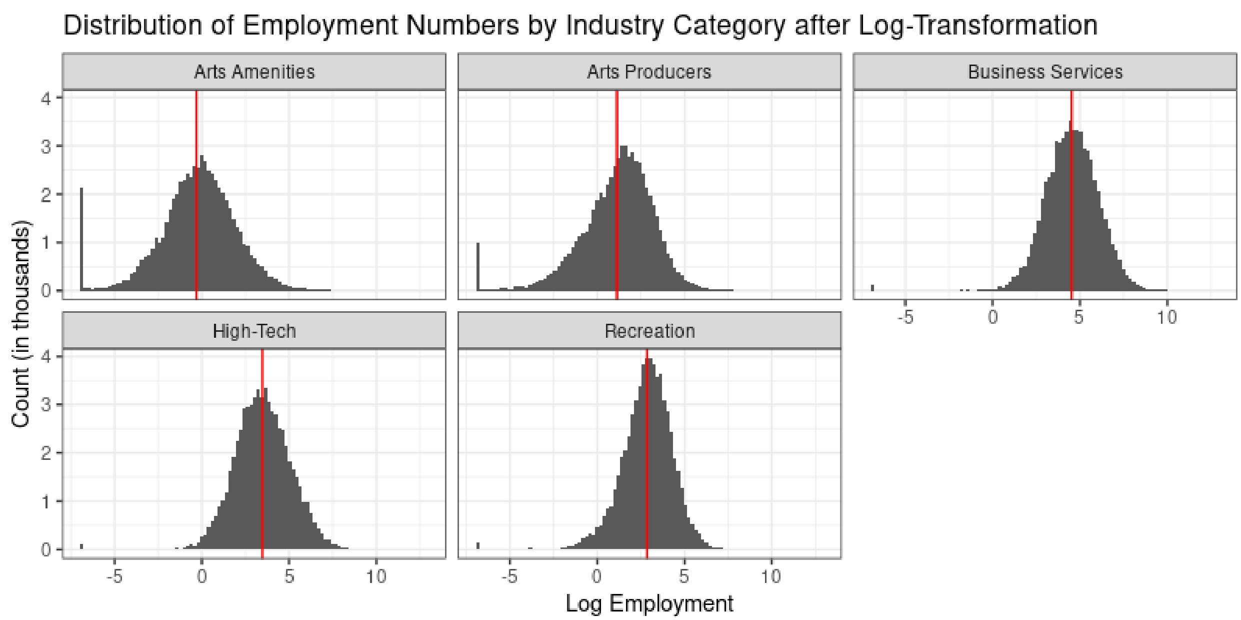

Figure 5.3: Distribution of the time average of variables after log-transformation

For regressions that include log-transformed variables in both sides of the equation, we interpret their coefficients in terms of percentage changed rather than as number of jobs. Thus, for a 1 percent change in the independent variable, there is an x percent change in the dependent variable, where x is the regression coefficient.

[1] log(x + .001).

In the next section, I extend the overview of the variables to include time, and how these industries have evolved in the time period.

5.1.1 Industry Growth

Industries grow at different rates and take different courses. During the period of study, 1998 to 2016, some industries have grown more, such as health and business services, while others have declined, such as manufacturing. Some industries have had little change over time, while others had a more fluctuating path over the years. Some industries have suffered major impacts from the 2008 financial crisis while others have suffered much smaller impacts from that time period.

In this section, I review the growth path of the different industries as characterized in chapter 3. This is an important step as we should be aware of the growth of each industry as it may affect the analysis results as we compare how the industries affect each other later in the chapter. For example, in some analyses that include the years 2007, 2008, or 2009, the effect of the crisis may be more visible for some pairs of industries than for others. I include all categories of data here for more context and illustration purposes even though not all will be examined with the same detail later on.

Figure 5.4 shows the employment numbers from 1998 to 2016 for each industry category. The largest category is "business services," which has kept a leading position through the entire period. From 1998 to 2008, the "goods" category (which includes manufacturing and construction) takes second place, but after 2008, goods-producing employment fell to fourth place, surpassed by health and retail. Health presented a constant growth without the setbacks other industries experienced during this period. Infra-structure and "others" (details in Appendix B.2) had steadier growth until 2008, with a large decline and slow recovery. The food industry presented great growth in this period and remained in the middle with slow and steady growth, with declines that accompany the declines of other industries. The arts category is the second to last largest industry, followed by education as the smallest category in this study.

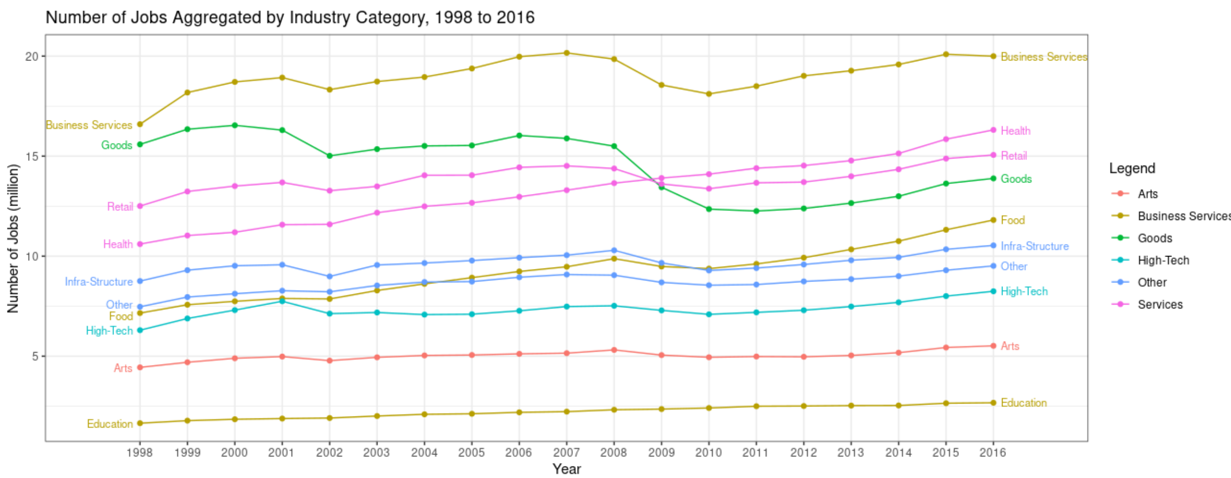

Figure 5.4: Industry trajectory in the period of study by category

More commentary is necessary for the industries in focus, especially the high tech and the arts industries as these categories need to be broken down to be understood more deeply. Figure 5.5 compares the evolution of the arts and high-tech subcategories. The sum of subcategories in figure 5.5 by category is equal to the employment numbers in figure 5.4.

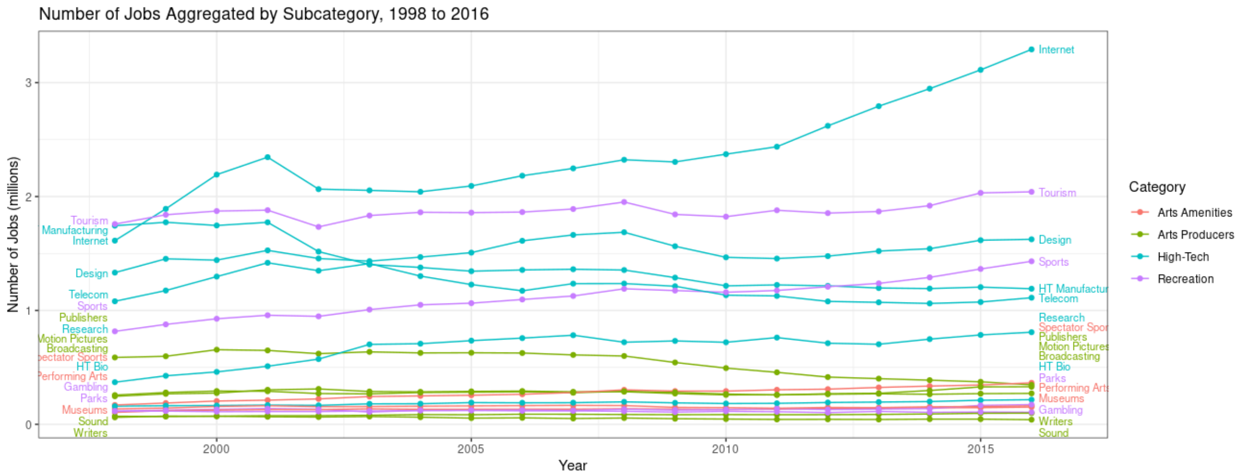

Figure 5.5: Industry trajectory in the period of study by arts and high-tech subcategories

In figure 5.4, the high-tech industry seemed to have experienced much smaller growth than reported by the media. However, in figure 5.5, as we break down the high-tech industry into its subcategories (blue lines), we see that, in fact, the internet industry has grown a great deal during this period. But, because high-technology manufacturing employment declined in that same period, the high-tech sector as a whole seemed to have remained stagnant.

In 1998, the internet industry had about 1.6 million jobs, but that number more than doubled to 3.2 million jobs, with faster growth increases starting in 2007. Similar to other manufacturing jobs, high-tech manufacturing fell from about 1.8 million jobs to 1.2 million jobs.

The arts category in figure 5.4 is also broken down into its subcategories. The purple lines refer to the recreation subcategories, with tourism at the top at around two million jobs in 2016. This is followed by sports, parks, and gambling. The green lines refer to the arts producers, ranked in 2016 with publishers in first place, followed by motion picture studios, broadcasting studios, writers, and sound studios. In 1998, the order for arts producers was the same but with sound studios and writers flipped around. Then, the red lines represent the arts amenities jobs, with spectator sports employing the most people, followed by performing arts and museums.

At the least, it is interesting to observe the size and progression of these industries over time. At best, this data will help us understand the impact that the smaller arts industries have over the others, discussed later in the chapter. For example, I demonstrate in the next sections that although arts amenities are the smallest of the arts industries, arts amenities have a great impact on both business services and high-tech industries.

Figure 5.6 shows the growth of each arts category in the ten most populated urban areas. New York is found on the top of all three categories, followed by Los Angeles. That these two cities dominate the arts markets is nothing new, but these two cities give us perspective on the arts market size in the other eight urban areas.

The growth path for each category varies by urban area and fluctuates throughout the years. Arts amenities are bigger in New York, followed by Los Angeles, while the other eight urban areas are found within similar ranges. In their turn, the arts producers categories show an even greater discrepancy between New York and Los Angeles and the other eight urban areas. This difference indicates that arts amenities may be more evenly distributed among large urban areas than previously thought; while arts producers concentrate in New York and Los Angeles, the other urban areas have much smaller arts producers markets but of similar sizes. Therefore, we confirm here that New York and Los Angeles have denser and more dynamic arts producers activities than in any other urban area.

The recreation categories have more varied sizes in each urban area. New York still has more recreation activities, followed by Los Angeles, with Chicago and Washington DC coming in third and fourth. These figures show that in these urban areas, recreation is the largest category overall, followed by arts producers, and then arts amenities. The difference between arts amenities and recreation lies in the public partaking in activities rather than being spectators. Therefore, more recreation activities are required than for arts amenities (which are supplied for one audience at a time) and arts producers (which are mostly comprised of private companies). In other words, larger urban areas offer activities in larger volumes and varieties than smaller cities, which is reflected in figure 5.6.

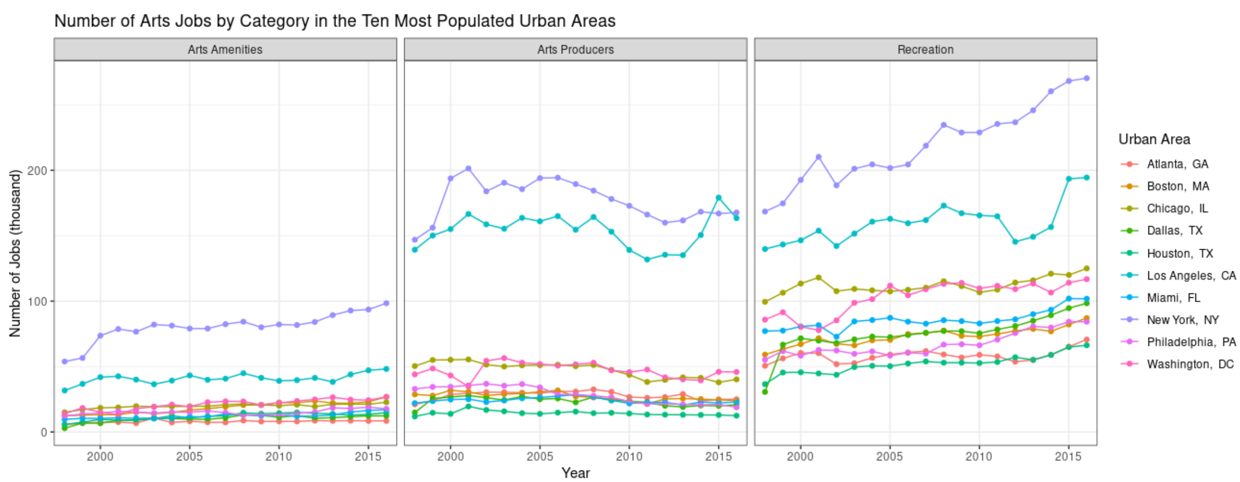

Figure 5.6: Size of arts industries in the ten largest urban areas

In figure 5.7, we break down the business services, goods-producing, and infra-structure categories. The "other" category is in second place in 1998,[2] but moves up to first in 2016, showing a growth in personal, household, and organizational services in the 2000s. Manufacturing employment fell from first to third place in that period, with a loss of one-fourth of the employment in the period.

[2] Refer to appendix B.2 in chapter 3 for detailed table.

The business services categories are shown in red lines with the category explicit in labels. Industries related to business supports (e.g., corporate offices, holdings, employer organizations, trade show organizers, and others as described in appendix B.2 in chapter 3) are the biggest employers, wavering at around 7.5 million jobs throughout the entire period. Finance is the second largest business services industry at around two million jobs, followed by insurance, real estate, consulting, law, accounting, and advertising agencies.

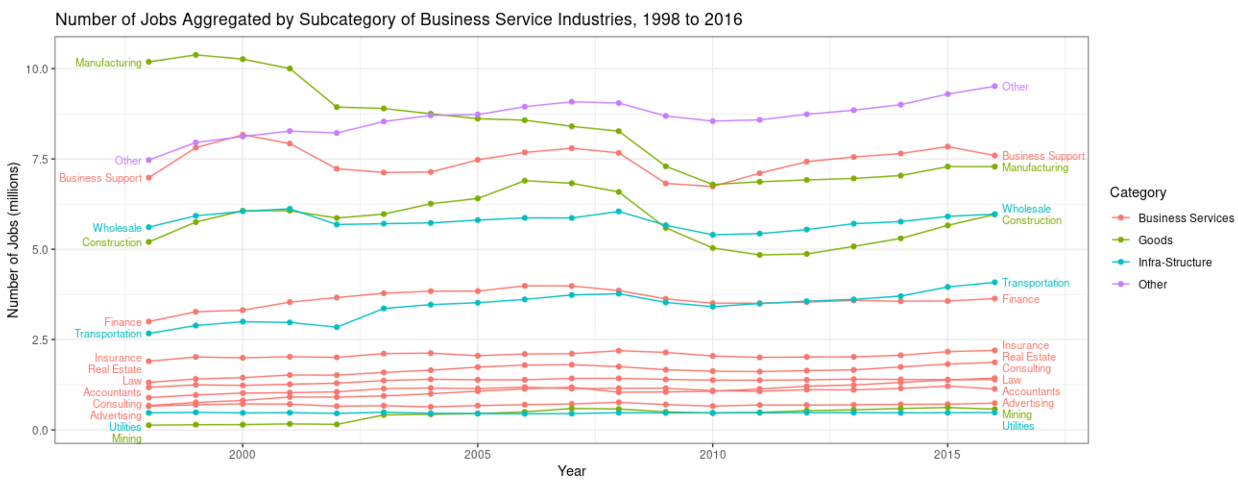

Figure 5.7: Industry trajectory in the period of study for business services, goods-producing, infra-structure, and other industries

Even though we see some industries growing rapidly over time, many industries have hovered around the same numbers when others declined. Therefore, "growth" here is not observed as a monotonic progression at a constant rate, but rather fluctuating paths that are affected by external influences, such as economic crisis, globalization, and changes in technology.

5.1.2 Correlations Among Industries

Some industries are more correlated with particular categories than with others. In this section, we discuss the correlations among industry categories. The correlations are calculated based on the mean of all years by hexagon rather than year by year in an attempt to make results manageable. The correlations combine pairs of industries and are computed at the hexagon level, with N=63166.

Table 5.1 presents the correlations for each pair of industry category, where number of jobs in one industry is compared to the numbers of jobs in another industry for each hexagon. High correlation means that most hexagons had high or similar values for both industries simultaneously. The upper triangle shows the correlations among the log-transformed variables, and the bottom triangle shows the correlations among the variables in the original metric, employment numbers. The full correlation list sorted by correlations in the original metric can be found on Appendix D.2.

Focusing on the bottom triangle, we see that some of the highest correlations are between food and retail (.868), food and others (.847), and food and recreation (.812), which are types of businesses that usually are offered around each other. Another high correlation is between arts amenities and arts producers (.865) as places that offer art to consumers will also require art supplies and arts-related services. Business services and “others” (.83) also show a high correlation, as “other” is made up of personal services, rentals, and repair and maintenance, which tend to cater to the consumption needs of the population, alongside with restaurants.

These high correlations indicate that where one industry is located, the other industry tends to be present in the same area; at the same time, places where one industry is less present, the other also has a low presence. In other words, these industries are not necessarily equally spread throughout the urban areas, but in places where one industry is in high or lower numbers, the other industry is also in that same location in high or lower numbers, respectively. For example, the food and retail industries are widespread throughout the country; therefore, it is straightforward to understand that these two types of businesses are in the same location. For example, arts amenities and arts producers are the two most scarce industries, as seen in figure 5.2. Therefore, the high correlations show that these two industries tend to be present in the same hexagons and not present in the same hexagons as the other. This is important to note because a high correlation may give the impression that the industries are equally spread, which is not the case. In conclusion, high correlation between industries shows a powerful attraction among these industries towards each other in American cities; lower correlations show a weaker attraction among industries as they may or may not necessarily coexist everywhere equally.

Correlations of Number of Jobs for Each Pair of Industry Category, Recorded as the Mean Number of Jobs 1998-2016

This table shows the correlation of number of jobs for each pair of industries in two ways: on the natural metric (on the lower triangle) and the log-transformed variable (on the upper triangle). All correlations are significant at 95%. N=63166 for all pairs.

Upper triangle: correlations among log-transformed mean variables

	Arts Amenities	Arts Producers	Business Services	Education	Food	Goods Producing	Health	High-Tech	Infra-Structure	Others	Recreation	Retail
Arts Amenities	*1*	0.628	0.647	0.591	0.620	0.486	0.603	0.590	0.517	0.629	0.638	0.585
Arts Producers	0.865	*1*	0.780	0.678	0.744	0.583	0.727	0.713	0.611	0.731	0.722	0.735
Business Services	0.722	0.773	*1*	0.769	0.888	0.732	0.853	0.882	0.791	0.907	0.834	0.868
Education	0.636	0.547	0.619	*1*	0.739	0.560	0.759	0.710	0.610	0.756	0.688	0.714
Food	0.783	0.752	0.789	0.750	*1*	0.716	0.859	0.785	0.725	0.896	0.836	0.939
Goods Producing	0.410	0.442	0.494	0.389	0.537	*1*	0.678	0.708	0.860	0.807	0.607	0.743
Health	0.579	0.505	0.580	0.793	0.741	0.495	*1*	0.742	0.689	0.853	0.747	0.856
High-Tech	0.572	0.610	0.805	0.593	0.726	0.573	0.573	*1*	0.767	0.838	0.758	0.766
Infra-Structure	0.584	0.633	0.653	0.459	0.634	0.799	0.513	0.687	*1*	0.818	0.648	0.741
Others	0.701	0.739	0.830	0.742	0.847	0.562	0.722	0.751	0.676	*1*	0.805	0.889
Recreation	0.638	0.605	0.654	0.502	0.812	0.358	0.486	0.537	0.462	0.661	*1*	0.797
Retail	0.621	0.648	0.662	0.658	0.868	0.614	0.739	0.649	0.649	0.747	0.651	*1*

Lower triangle: correlations among raw data mean variables

Table 5.1: Correlations of the average size of industry in the original metric and log-transformed

This point is adjusted on the upper triangle, in which the correlations among log-transformed variables are further heightened. The range of correlations is higher than in the bottom triangle, from .49 to .94. Some correlations have changed substantially. For example, the strong relationship we noted between arts amenities and arts producers decreased from .865 in the original metric correlations to .628, in the log-transformed correlations. On the other hand, the correlation between food and retail increased from .868 in the bottom triangle to .94 in the upper triangle. The correlations among business services, high tech, others, and retail seems to be even stronger than in the original metric. Correlations that are widespread throughout more hexagons tend to be higher for the log-transformed dataset.

Table 5.2 shows the differences between the correlations in the original metric and log-transformed side-by-side for the variables that are analyzed later in the chapter.

Industry Correlations for Original Metric and Log-Transformed Variables. Sorted by Original Metric Correlations.

Category 1	Category 2	Original Metric Correlations	Log-Transformed Correlations
Arts Amenities	Arts Producers	0.865	0.628
Business Services	High-Tech	0.805	0.882
Arts Producers	Business Services	0.773	0.780
Arts Amenities	Business Services	0.722	0.647
Business Services	Recreation	0.654	0.834
Arts Amenities	Recreation	0.638	0.638
Arts Producers	High-Tech	0.610	0.713
Arts Producers	Recreation	0.605	0.722
Arts Amenities	High-Tech	0.572	0.590
High-Tech	Recreation	0.537	0.758

Table 5.2: Correlations among the arts, business services, and high-tech industries

Figure 5.8 shows the relationships between arts (x-axis) with business services and high-tech industries (y-axis) in the original metric of the data, i.e., the average total number of jobs in each category. As discussed in chapter 4, there are many more smaller hexagons than massive job markets, which are restricted to the largest cities in the country. Therefore, in these plots, the points are concentrated in the lower left corner with a few outlying points to the right, which is still the same for both the general picture and the categories depicted here. The x-axis have the same value for all three plots; thus, the points are found on the same horizontal axis, but varying vertically as the number of jobs in the other industry varies.

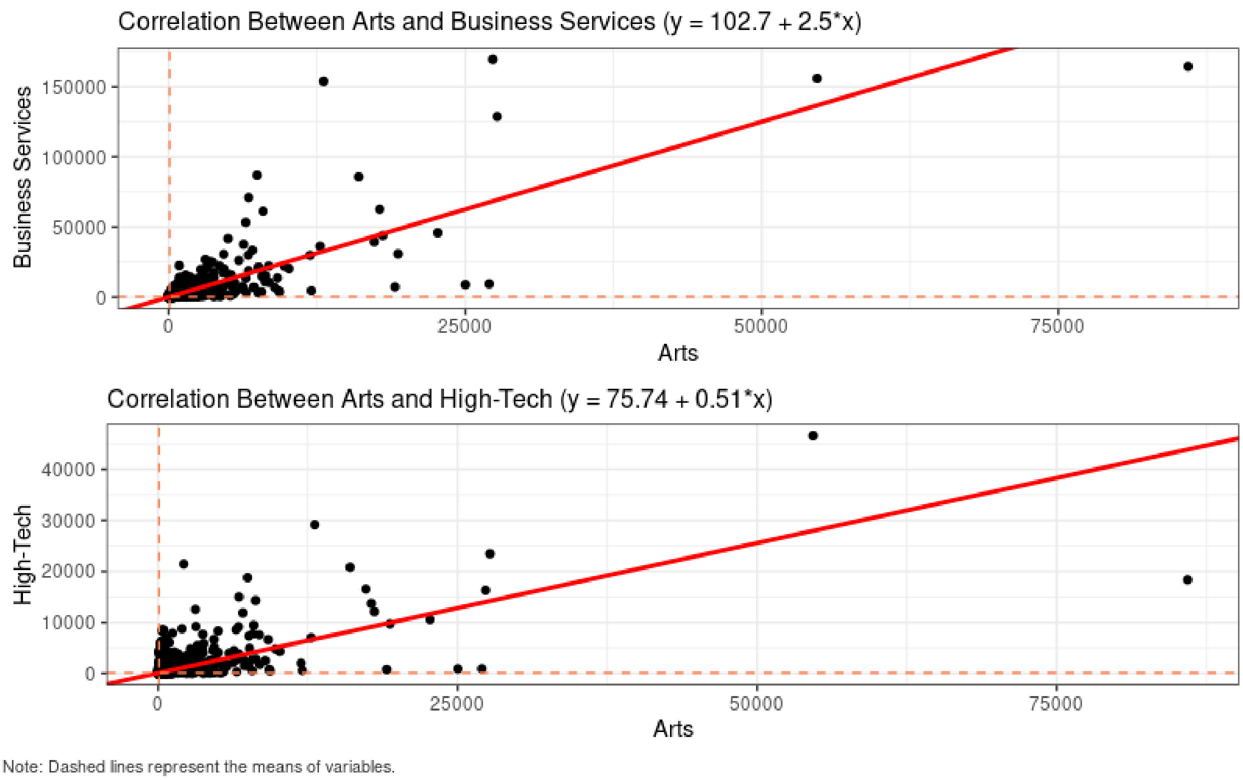

Figure 5.8: Scatterplot between business services and high tech to the arts in the original metric

To correct for the skewness presented in the figure above, figure 5.9 shows the relationship between the log of the average for each category and hexagon. Log-transforming the variables brought the points into a more even distribution on both sides instead of just one side, as seen previously.

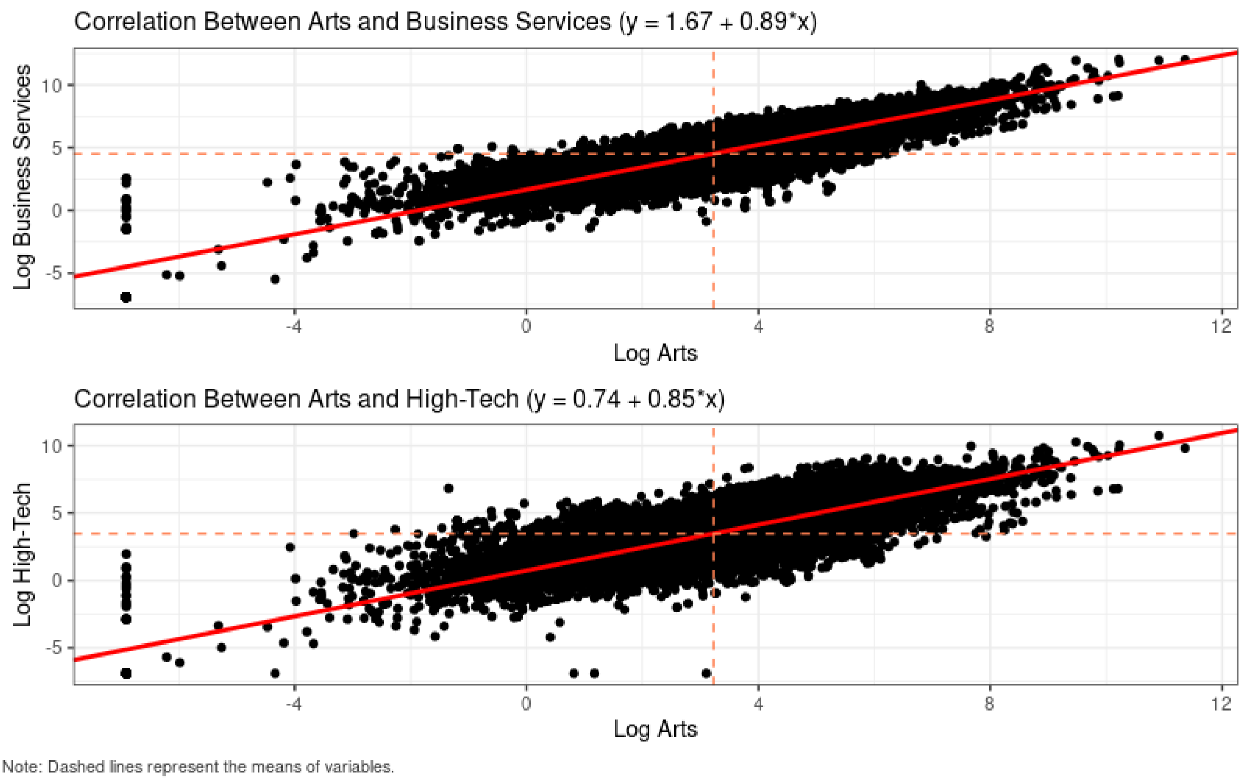

Figure 5.9: Scatterplot between business services and high tech to the arts after log-transformation

The relationships between the arts and the two other industries are positive for both the original metric and the log-transformed data. The correlation between arts and high-technology jobs is .64 for the original metric and .65 for the log-transformed variables. The correlation between arts and business services jobs is .8 for the original metric and .79 for the log-transformed variables, the highest correlation of the three. And the correlation between arts and goods-producing jobs is .45 for the original metric and .65 for the log-transformed variables. These are strong correlations, meaning that each pair of industry occur in the same locations, or that each pair doesn't occur at the same locations.

These correlations point to differences among hexagons in industry size and how much the analyses in the next section may affect an area or not as much. This point will become clearer in the next section.

5.2 The Reciprocal Relationship between the Arts and Business Services

Business services are classic examples of industries that are closely related to the arts. The business services categories include occupations in accounting, advertising, consulting, finance, insurance, law, and real estate. Also included in this category are business supporting industries, which accounts for holding companies, corporate offices, administrative services, telemarketing companies, collection agencies, trade show organizers, and translators, as described in detail in chapter 3. Business services industries require highly educated workers with college-level degrees or higher. Although these industries are somewhat ubiquitous, more complex forms of their organization tend to take place in city centers, where population density is higher.

The arts and business services industries are in geographical proximity, as demonstrated in the previous section. For example, it is common to find theaters and museums next to a corporation’s headquarters. The people who work in business services also are patron of the arts, and some corporations are major sponsors of the arts, with 36 percent of arts revenues coming from corporate donors (Goody 1984). However, the relationship is not clear: Did the theater come after the businesses or did the businesses move to artistic and recreative areas?

In this section, I follow the same analyses structure as in chapter 4. First, we observe the reciprocal effects in the longest time period possible; then, we move on to analyze in the short and long terms, in first differences, by urban area, and by arts categories. Similar to chapter 4, each cross-lagged regression model applied for any two years can be represented in the equations below:

$$Arts_{2016} = \alpha_0 + \beta_0 * Arts_{1998} + \gamma_0 * BusinessServices_{1998} + \epsilon_0$$

for the hypothesis that *jobs attract arts*, and

$$BusinessServices_{2016} = \alpha_1 + \beta_1 * BusinessServices_{1998} + \gamma_1 * Arts_{1998} + \epsilon_1$$

for the hypothesis that *arts attract jobs*, where α_0 and α_1 are the respective intercepts, β_0 and β_1 are the lagged coefficients, γ_0 and γ_1 are the crossed coefficient, and ϵ_0 and ϵ_1 are the error terms.

The equations for the first difference models are:

$$(Arts_t - Arts_{t-1}) = \alpha_0 + \gamma_0 * (BusinessServices_t - BusinessServices_{t-1}) + \epsilon_0$$

or also:

$$\Delta Arts_{t-(t-1)} = \alpha_0 + \gamma_0 * \Delta BusinessServices_{t-(t-1)} + \epsilon_0$$

for the "business services attract arts" hypothesis; and

$$(BusinessServices_t - BusinessServices_{t-1}) = \alpha_1 + \gamma_1 * (Arts_t - Arts_{t-1}) + \epsilon_1$$

or also:

$$\Delta BusinessServices_{t-(t-1)} = \alpha_1 + \gamma_1 * \Delta Arts_{t-(t-1)} + \epsilon_1$$

for the "arts attract business services" hypothesis, where t is the later year.

After obtaining the results for both regressions, we compare the two crossed coefficients, γ_0 and γ_1 to find whether arts or jobs had a stronger impact on the other. If $\gamma_0 > \gamma_1$, then we have that jobs attract the arts, and if $\gamma_0 < \gamma_1$, we have that the arts attract jobs. Using this basic principle, we are able to determine the direction of the relationship as indicated by the path diagram in figure 5.10.

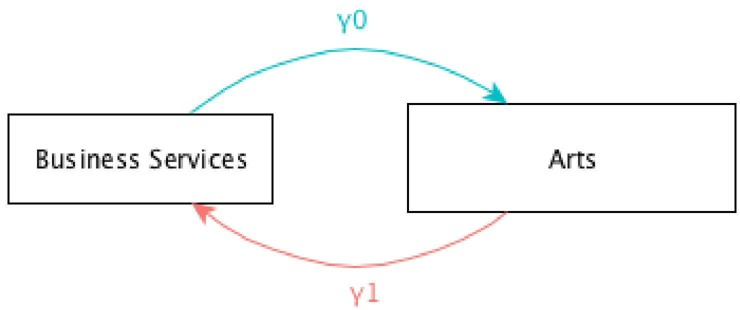

Figure 5.10: Path diagram showing the coefficients of the model analyzing the relationship between arts and business services

As we narrow down the employment numbers from the total non-arts jobs to only business services-related categories, we see smaller coefficients throughout the analyses; therefore, the impact of the arts is directed to a smaller section of the economy rather than to the larger economy as a whole. Thus, coefficients from arts to jobs are now smaller than one, but that does not mean that the multiplier effect is not existent anymore. Rather, that impact is restricted to that subsection of the economy.

5.2.1 The Reciprocal Relationship Between the Arts and Business Services in Baseline Models

In this analysis, we compare the arts and business services industries with the independent variable in the first year of data (1998) and the dependent variable in the last year of data (2016) in two separate regressions: one with arts as the dependent variable (for the business services attract arts hypothesis) and another with business services as the dependent variable (for the arts attract business services hypothesis).

The analyses are performed using three types of data units: the natural employment number by category, the log of the employment number by category, and the first difference variables (one-year changes). Each type of variable produces results that have different interpretations. Table 5.3

shows the results for both equations in each one of the three models. The values corresponding to the γ coefficients are highlighted in light gray on the table, as those are the values of most interest.

Regression results for the base model where the independent variable is in 1998 and the dependent variable in 2016. Results reflect the pair of cross-lagged regression models using three different types of data, in their natural employment numbers, log-transformed and first difference variables.

	Natural Employment Numbers		Log-Transformed		First Differences	
	Business Services Attract Arts	Arts Attract Business Services	Business Services Attract Arts	Arts Attract Business Services	Business Services Attract Arts	Arts Attract Business Services
Dependent Variable	Arts 2016	Jobs 2016	Arts 2016	Jobs 2016	Arts 2016	Jobs 2016
Intercept	-4.91 ***	9.81 ***	1.95 ***	2.87 ***	1.18 ***	-.833 *
	(.87)	(.002)	(.01)	(.009)	(.2)	(1.16)
Arts 1998	.1.25 ***	.54 ***	.465 ***	.06 ***	-.028 ***	.074 ***
	(.0008)	(.007)	(.004)	(.004)	(.005)	(.028)
Jobs 1998	.0149 ***	1.022 ***	.011 ***	.389 ***	.01 ***	-.04 ***
	(.0028)	(.002)	(.004)	(.004)	(.001)	(.006)
Residual S.E.	217	546	1.2	1.1	50	290
R-Squared	.881	.922	.417	.448	.00151	.0007
Adjusted R-Squared	.881	.922	.417	.448	.00148	.00067
N	63046	63046	63046	63046	63046	63046

Table 5.3: Cross-lagged regression results for the baseline model using original metric, log-transformed variables, and first differences

In each of the three models, we see that the arts γ coefficient are higher than the business services γ coefficient, indicating that in general, the arts attract business services jobs more than the opposite. However, the models' fit require some attention as they show differences in the validity of the results.

In the first model using the natural employment numbers, the R^2 is .881, which is a good fit for the model. The unit is the number of either arts or business services jobs, which is also easier to interpret. Therefore, from 1998 to 2016, places with one additional arts job in 1998 added .54 business services jobs in 2016 over places without that additional arts job. On the other hand, one additional business services job in 1998 added .015 arts job in 2016, which does not seem to be a lot; however, both coefficients are statistically significant at 95 percent confidence. Thus, a place with arts attracted half as many business services jobs, while business services still need many additional jobs in order to attract the arts, still following the multiplier and audience effects as seen in chapter 4.

The R^2 of the log-transformed data declines to .417, and here, the coefficients should be interpreted as percentages as the regression equations are of the log-log type. For additional one percent arts job in 1998 there are additional .06 percent business services jobs in 2016, but the additional one percent in business services jobs in 1998 could result in .01 percent of arts jobs in 2016. These coefficients still follow the multiplier and audience effects hypotheses; however, their relationship is much weaker than the previous model.

When we analyze only the changes from 1998 to 1999 as an antecedent to the changes from 2015 to 2016, we have an R^2 close to zero, as the first difference variables are not well correlated across the years as they are in the same year, as discussed in the correlation section of chapter 4. Thus, the changes from 1998 to 1999 have little relation to the changes from 2015 and 2016.

In conclusion, observing the results from the models using the first and last year provides us with a basic insight, but it is not very informative. In order to have a better understanding of the relationships between arts and business services, we must include all the years in between, in more comprehensive analyses, as discussed in the remainder of this section.

5.2.2 The Reciprocal Relationship Between the Arts and Business Services Over Time

In this section, we analyze the data for all the years between 1998 and 2016 to improve our understanding of the relationship between the arts and business services from the previous section. We analyze the log-transformed data in one-year lags, followed by ten-year lags, and then in first differences. In each section, we first analyze all urban areas combined, and then we isolate the hexagons for the ten largest urban areas in the country.

Table 5.4 summarizes the standard mean differences (SMD) and statistical fit measures from the three models discussed in more detail below.

Results for regression models using different types of data and time lag, analyzing the impact between the arts and business services industries.

	Log-Transformed, 1 Year Apart		Log-Transformed, 10 Years Apart		First Differences	
	Business Services Attract Arts	Arts Attract Business Services	Business Services Attract Arts	Arts Attract Business Services	Business Services Attract Arts	Arts Attract Business Services
Fixed Effect SMD	0.029	0.0229	0.093	0.073	0.1331	1.3554
Confidence Interval (95%)	[0.0279; 0.0301]	[0.0220; 0.0238]	[0.0906; 0.0960]	[0.0706; 0.0754]	[0.1327; 0.1336]	[1.3506; 1.3602]
z	51.8	50.53	67.2	59.8	588.02	552.81
p-value	0	0	0	0	0	0
tau^2	0.0015 [0.0011; 0.0048]	0.0001 [0.0001; 0.0004]	0.0028 [0.0013; 0.0110]	0.0001 [0.0000; 0.0005]	0.0038 [0.0022; 0.0093]	0.7094 [0.4084; 1.7024]
I^2	99.6% [99.6%; 99.7%]	96.4% [95.4%; 97.2%]	99.4% [99.2%; 99.5%]	89.7% [82.8%; 93.9%]	100%	100%
Q	4326.22	475.39	1303.41	77.96	69197.58	109364.99

Table 5.4: Fixed-effect meta-analyses results for the relationship between arts and business services for the short and long term, and first differences for all urban areas

At first glance, we notice that the two models using log-transformed data result in the business services attracting arts, and the third model, considering only yearly changes, results in the arts attracting business services. Why do we see such differences in results, as we compare the same industry categories? The statistical measures for all three models are satisfactory; however, the main differences lay in the numbers being measured: the first two models measure the arts and business services job markets as a whole, while the third model considers only the changes. In other words, when we include the well-established section of business services, we see that they are influential in bringing in the arts, but when we consider only the dynamic sector of both arts and business services, we see that the arts have a stronger impact on business services. This difference in perspectives indicates a strong relationship between the two industries.

Figure 5.11 shows regression coefficient results for the one-year lag cross-lagged regression models for all urban areas combined, with the x-axis referencing the year of the independent variable. The horizontal dashed lines represent the respective SMD after performing fixed effects meta-analysis for each type of regression over time. These first results show that on average, the effect of jobs on arts is higher than the effects of arts on jobs, but the two SMD values are very close. When we look at the results for each year, the two effects trade places through the years, indicating that both industries have a stronger pull on the other at different times when considering shorter term analysis. The arts effects had stronger results in five periods, while the jobs effects were stronger in eleven periods, and two periods were not significant to either side. The business services effects on arts range between -.11 to .078, and the effects of the arts range between -.02 and .04. Thus, the effects of business services on arts vary much more than the effects of arts on business services.

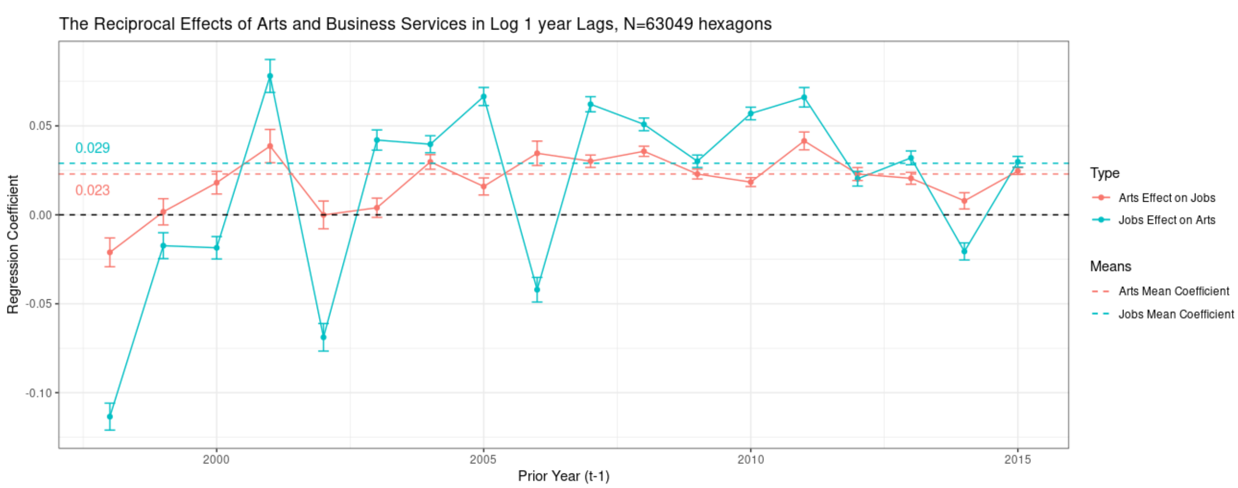

Figure 5.11: Coefficients for the 1-year lag regression models for both directions in the relationship between the arts and business services by year for all urban areas

Figure 5.12 shows the same analysis but for hexagons belonging only to the top ten largest urban areas. Again, the average jobs effects on arts is higher than the arts effects on jobs, but this time, the SMDs are further apart, indicating that in the largest urban areas, business services jobs have a much stronger pull on the arts than in the general analysis. Both industries also exchange positions of highest coefficient year by year, showing that each is important to the other.

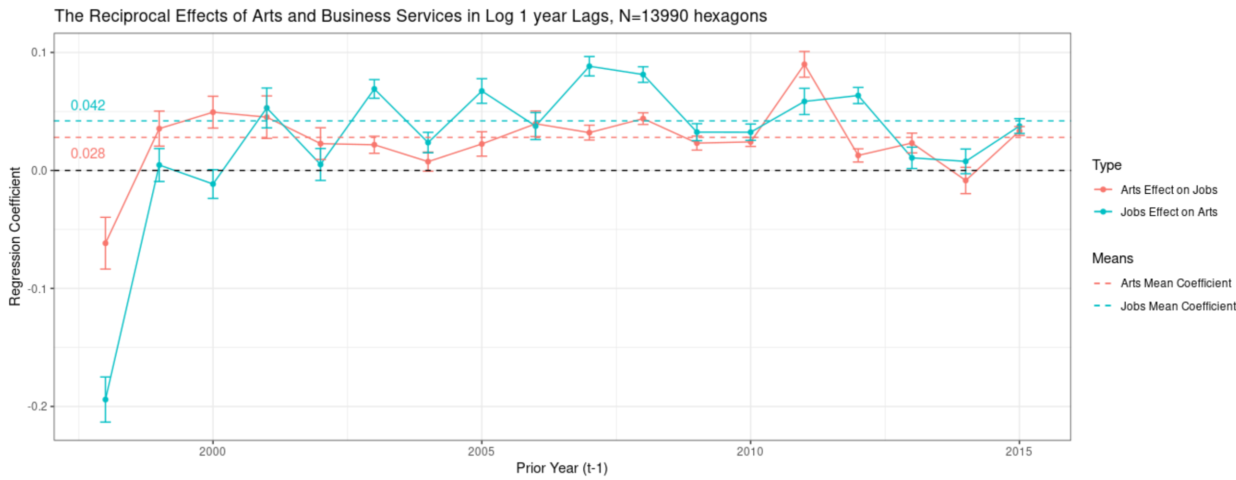

Figure 5.12: Coefficients for the 1-year lag regression models for both directions in the relationship between the arts and business services by year for the ten largest urban areas

The one-year lag analysis indicates that arts and business services industries are significant in attracting each other, but when we consider the entire period, the jobs effects on arts are stronger; even though, the arts effects on business services are partially stronger.

The ten-year lag analysis compares an independent variable from ten years before the dependent variable. In this case, the graph presents fewer points, and the year 2007 has not been included in any analysis as it does not pair with another year. Figure 5.13 shows the coefficients for each pair of analysis with a ten-year lag between dependent and independent variables. The coefficients are larger in the ten-year lag than for the one-year lag analysis due to larger effects observed in longer term analyses. Again, we see that the average jobs effects (.093) is larger than the arts effects (.073). For two years, the arts effects were stronger, while the jobs effects were higher for seven years.

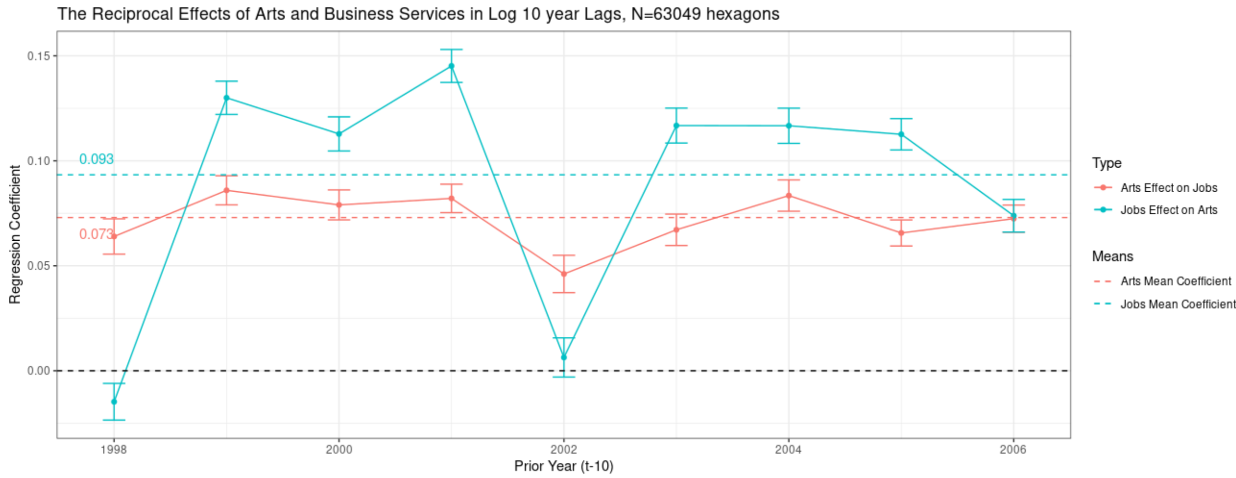

Figure 5.13: Coefficients for the 10-year lag regression models for both directions in the relationship between the arts and business services by year for all urban areas

Figure 5.14 shows the results for the same regressions but only considering the top ten largest urban areas. For the largest urban areas, the jobs effects were much larger (.176, on average) in eight years of analysis. However, the arts effects were also higher than in the general analysis, but more consistently lower than the business jobs effects.

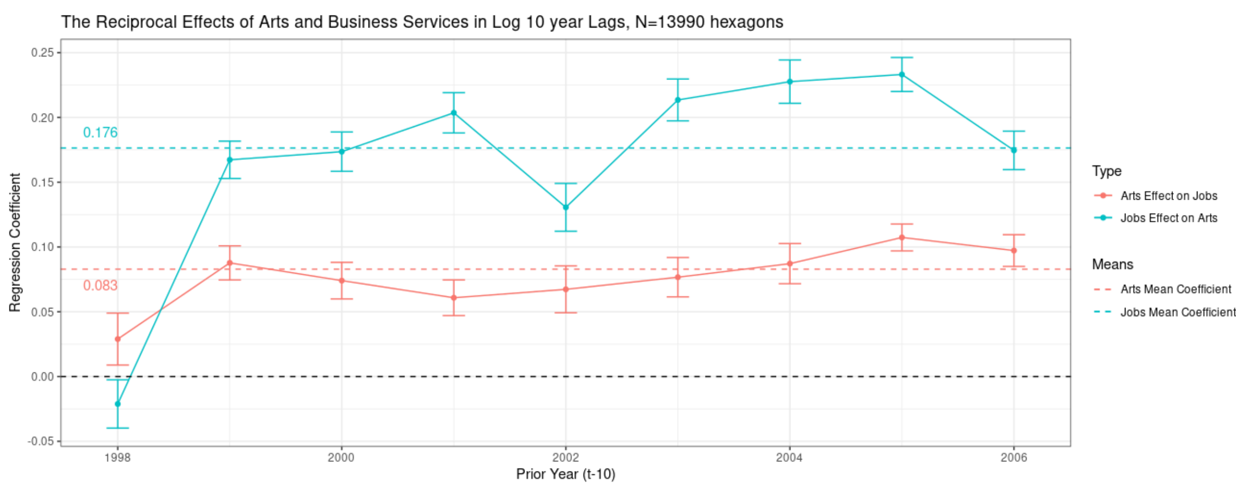

Figure 5.14: Coefficients for the 10-year lag regression models for both directions in the relationship between the arts and business services by year for the ten largest urban areas

In the four analyses presented so far, the jobs SMD is higher than the arts SMD, indicating that business services attract the arts more than the contrary. In this case, the multiplier and audience effects cannot explain this phenomenon; however, we must keep in mind the special synergy between the arts and business services, in which the business services industries sponsor and gravitate around the arts.

On the other hand, the first differences analyses take into consideration only the year-by-year changes in each hexagon and category. Therefore, here we compare how much the yearly change in one industry relates to the other industries. For both industries, we account only for the changes, i.e., any increase or decrease in employment numbers.

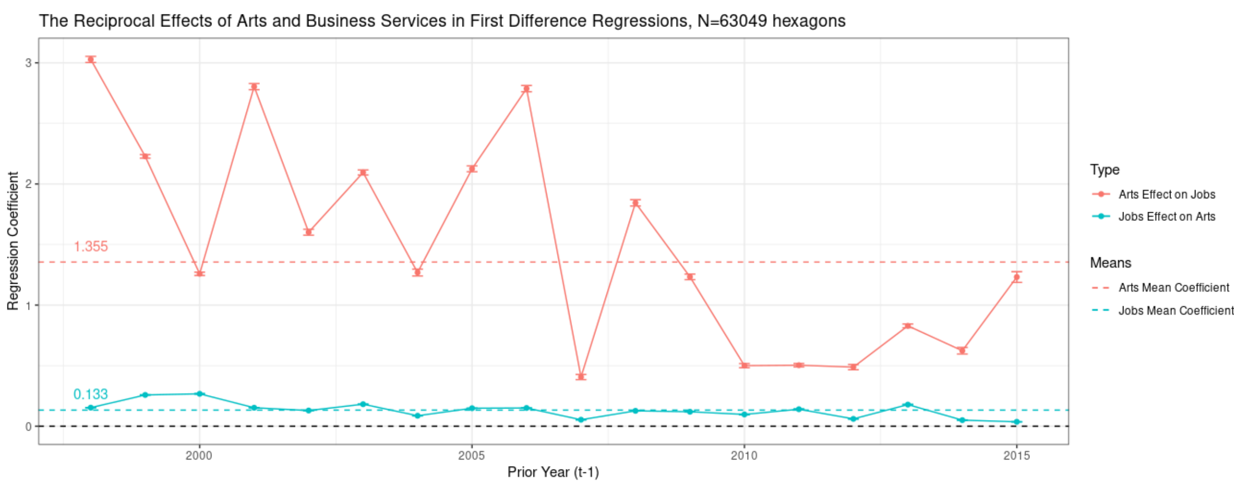

Figure 5.15: Coefficients for the first differences regression models for both directions in the relationship between the arts and business services industry by year for all urban areas

In figure 5.14, the red line of the arts effects on business services shows that all coefficients are much larger than the business services effects on the arts (blue line), bringing back the multiplier and audience effects hypothesis. An increase of one in arts jobs increases business services jobs by 1.355 on average (based on the weighted fixed effects meta-analysis), with the highest effect in 1998–99 with 3.03 new jobs per arts job, and a lower impact of 0.41 of new jobs per arts job in 2007–2008, following the financial crisis. On the other hand, the increase of one business services job increased arts jobs by .0133 on average, with that impact ranging from 0.037 in 2015–16 to 0.268 in 2000–2001. Thus, when we consider one-year changes, the multiplier and audience effects are more prominent.

Similar results are found for the top ten largest urban areas, as shown in figure 5.15. In the largest urban areas, one arts job increased business services jobs by 1.543 on average, ranging from 0.56 in 2007–2008 to 3.51 in 2006–2007. The weighted average and range values for the largest urban areas are larger than all urban areas combined. This confirms slightly higher arts and business services activities in larger urban areas, as the arts effects is eleven times higher than the jobs effects.

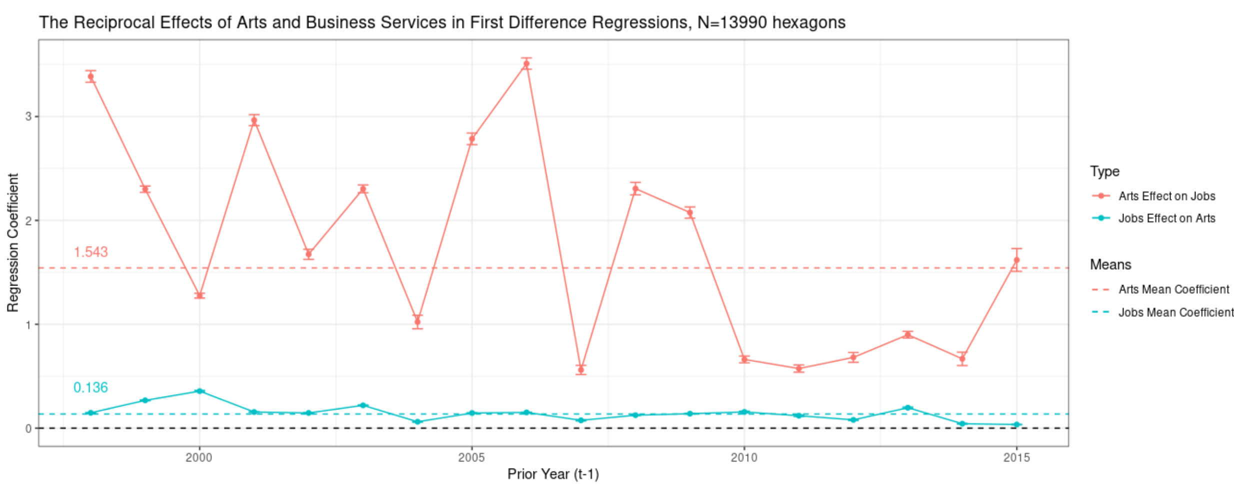

Figure 5.16: Coefficients for the first differences regression models for both directions in the relationship between the arts and business services industry by year for the ten largest urban areas

In both the general and the top ten analyses, the coefficients for the arts effects on business services have more accentuated spikes followed by lower values, while the coefficients for the business services effects on arts were more consistent over time. These differences may be due in part to the “critical mass” effect as discussed in chapter 4. However, in chapter 4, the arts effect was fifty times higher than the jobs effects, while here, the arts effects is ten to eleven times higher than the jobs effects, while the jobs effects on the arts is about double for the business services than for non-arts jobs in general. These findings may indicate that the business services attract more arts than general non-arts jobs, but the arts attract fewer business services than general non-arts jobs.

In comparing the one- and ten-year lag analyses with the first differences analyses, we may notice that when we include both long-established jobs and new jobs into the analysis, the jobs effects will seem higher than the arts. However, the yearly changes in cities show that the arts are more dynamic in attracting jobs.

5.2.3 The Reciprocal Relationship Between the Arts and Business Services by Urban Area

In this section, we analyze the relationship between arts and business services industries for each individual urban area using the first differences model shown at the top of the section, but performed for each urban area separately for each pair of years. Most urban areas have enough cases to generate significant results, but twenty-four urban areas (5 percent) did not have enough cases. Then, we performed meta-analysis for the eighteen regression coefficients, finding a weighted average based on standard error for each urban area.

The map in figure 5.16 shows which effect—whether the arts attract jobs or jobs attract arts—was larger in each urban area. At first glance, we see that the biggest cities show that the arts effects on jobs are stronger, while in a few smaller urban areas the jobs effects are stronger. Cities classified as NA indicate urban areas that did not have enough data points to generate a result, and the cities classified as "not significant" indicate that neither arts effects nor jobs effects coefficients was statistically significant at 95 percent confidence.

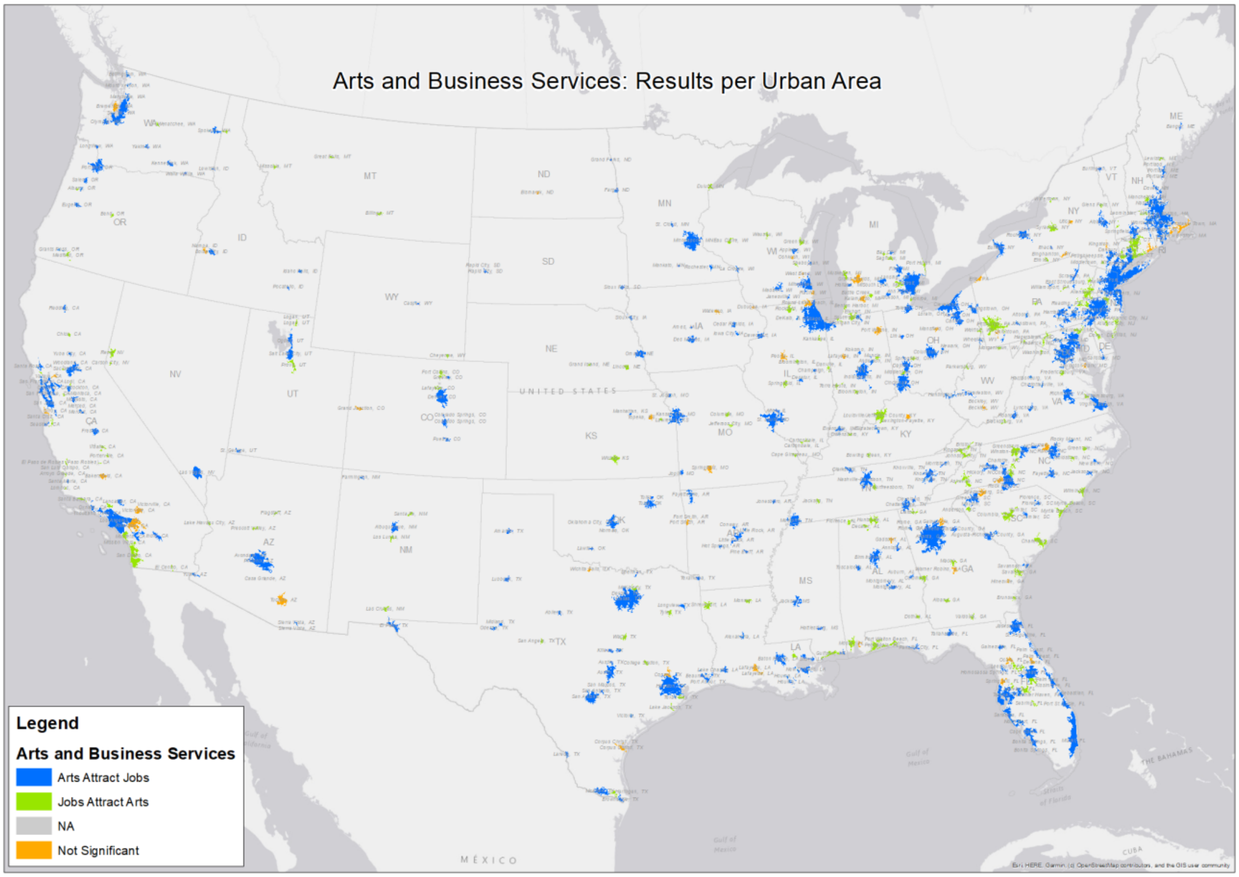

Figure 5.17: Map showing which direction (arts attract business services or business services attract arts) showed stronger coefficients in each urban area

This map suggests that the arts take place in larger cities where there is a large enough critical mass of people for audiences and a large enough population of artists to create a propitious arts environment to attract qualified workers to work in the business services industries in that city. This hint comes from the fact that the larger cities uniformly show stronger arts effects, and small cities show most of the stronger jobs effects or not significant results cases.

While it is impossible to discuss the results for each of the 481 urban areas individually in detail, table 5.5 presents results for the top fifteen largest urban areas and the overall top arts and jobs coefficients for smaller urban areas. The full table can be found in Appendix E.

The largest city with highest arts effects on business service industries is Chicago where each arts job attracts 1.9 business services jobs and each job attracts .074 arts job. We see here another example of the multiplier and audience effects synergy, in which each arts job attracts more than their own numbers in business services, while an additional audience of 13.5 business services jobs are required to attract one extra artist. In Porterville, CA, each arts job attracts 6.58 business services jobs, showing a stronger multiplying effect of the arts in that city, an example of how smaller urban areas may also present a strong arts multiplier effect.

However, there are also special cases—for example in Santa Fe, NM, where each additional business services job attracts 1.018 arts jobs while each arts job attracts .23 business services jobs. This may be an urban area where the population working in business services is ready for more artists to come in.

Arts and Business Services by Urban Area

	City	N	Arts (IV) to Jobs (DV) Estimate	S.E.	p-value	Jobs (IV) to Arts (DV) Estimate	S.E.	p-value	Conclusion
Top 15 Urban Areas (Sorted by Arts Coefficient)	Chicago, IL	1570	1.909	0.025	0.000	0.074	0.001	0.000	Arts Attract Jobs
	New York, NY	2383	1.722	0.007	0.000	0.223	0.001	0.000	Arts Attract Jobs
	Houston, TX	1089	1.502	0.023	0.000	0.072	0.001	0.000	Arts Attract Jobs
	Philadelphia, PA	1388	1.260	0.016	0.000	0.097	0.001	0.000	Arts Attract Jobs
	Seattle, WA	703	1.060	0.022	0.000	0.116	0.002	0.000	Arts Attract Jobs
	Phoenix, AZ	756	1.034	0.025	0.000	0.081	0.002	0.000	Arts Attract Jobs
	Detroit, MI	909	0.921	0.023	0.000	0.061	0.001	0.000	Arts Attract Jobs
	Washington, DC	914	0.869	0.014	0.000	0.114	0.001	0.000	Arts Attract Jobs
	Tampa, FL	720	0.844	0.037	0.000	0.039	0.001	0.000	Arts Attract Jobs
	Dallas, TX	1189	0.570	0.022	0.000	0.063	0.001	0.000	Arts Attract Jobs
	Boston, MA	1501	0.510	0.014	0.000	0.055	0.001	0.000	Arts Attract Jobs
	Miami, FL	781	0.474	0.018	0.000	0.111	0.003	0.000	Arts Attract Jobs
	Los Angeles, CA	1127	0.469	0.011	0.000	0.104	0.002	0.000	Arts Attract Jobs
	Atlanta, GA	1781	0.201	0.012	0.000	0.096	0.002	0.000	Arts Attract Jobs
	Pittsburgh, PA	708	-0.137	0.013	0.000	0.025	0.003	0.000	Jobs Attract Arts
Top Arts Coefficients Overall	Porterville, CA	21	6.584	0.090	0.000	0.011	0.000	0.000	Arts Attract Jobs
	Little Rock, AR	195	4.717	0.031	0.000	0.126	0.001	0.000	Arts Attract Jobs
	Salem, OR	55	3.992	0.026	0.000	0.185	0.001	0.000	Arts Attract Jobs
	Salisbury, MD	63	3.803	0.021	0.000	0.194	0.001	0.000	Arts Attract Jobs
	Sioux Falls, SD	44	3.502	0.066	0.000	0.081	0.002	0.000	Arts Attract Jobs
Top Jobs Coefficients Overall	Santa Fe, NM	41	0.230	0.002	0.000	1.018	0.015	0.000	Jobs Attract Arts
	Myrtle Beach, SC	141	0.578	0.006	0.000	0.718	0.010	0.000	Jobs Attract Arts
	Lewiston, ID	27	1.540	0.005	0.000	0.392	0.001	0.000	Arts Attract Jobs
	East Stroudsburg, PA	30	0.213	0.003	0.000	0.299	0.008	0.000	Jobs Attract Arts
	Lake Havasu City, AZ	22	0.078	0.003	0.000	0.293	0.004	0.000	Jobs Attract Arts

Table 5.5: Regression results for the relationship between the arts and business services jobs by urban area size, and the top five urban areas with the highest arts and jobs coefficients

Table 5.6 summarizes the number of urban areas by size according to the results found in the regressions. The top fifty urban areas have a population of over one million people, the middle-tier urban areas have populations between 300,000 and one million people, and the bottom-tier urban areas have populations of under 300,000 people. Ninety percent of the largest urban areas have a stronger arts impact on business services, which declines to 59 percent for the middle-tier urban areas, and down to 47 percent for the bottom-tier urban areas. On the other hand, we see increases in the business services impacts on the arts as cities become smaller, with only 8 percent of the largest urban areas showing that business services attract arts compared to 26 percent in the middle-tier urban areas, and 41 percent of the smaller urban areas.

Number of Urban Areas by Regression Results and Population Size: Arts and Business Services

	Top 50 Urban Areas	Middle Tier (1)	Bottom Tier (2)	Total
Arts Attract Business	45 (90%)	66 (59%)	142 (47%)	253 (55%)
Business Attract Arts	4 (8%)	29 (26%)	123 (41%)	156 (33.9%)
Not Significant	1 (2%)	16 (14%)	34 (11%)	51 (11.1%)
Total	50	111	299	460*

* The total number of cases is 460 urban areas because 21 urban areas did not show any results
(1) Middle tier urban areas are those between 300 thousand to 1 million people
(2) Bottom tier urban areas are those with less than 300 thousand people

Table 5.6: Proportion of results by urban area size

In the next section, we analyze how the relationship between arts and business services changes as we break down the arts industries into its three arts categories.

5.2.4 The Reciprocal Relationship Between Business Services and the Arts Categories

So far, we compared the business services industries to the arts as a whole; however, how do each of the three arts categories affect business services? In this section, I break down the arts category into arts amenities, arts producers, and recreation to compare the growth of each arts category to the growth of business services jobs using the first difference models described in the beginning of section 5.2. Each model is run for each arts category individually rather than the three categories combined, as the alternative hypothesis equation can only take one dependent variable and not three.

Figure 5.17 shows the results for the first difference analysis for four models, with different arts variables: arts amenities, arts producers, recreation, and the arts as a whole for comparison.

The solid lines show the arts effects on jobs, while the dashed lines show the jobs effects on arts. In eleven out of eighteen periods, when the arts categories present a positive or increasing effect on jobs, we see that arts amenities have the highest coefficients, attracting even more jobs than the other two subcategories. At the same time, in periods when the arts present a negative or declining effect on jobs, the arts amenities also present the lowest coefficients of all three categories. This indicates that of the three arts categories, arts amenities are more susceptible to positive or negative effects than the other two categories. For example, we notice that between 2007 and 2008, arts amenities had the deepest drop with the only negative coefficient in this analysis.

In five periods, arts producers presented the highest coefficients out of the three arts categories, while recreation was highest in only one period. This shows that arts amenities are more volatile to the systemic conditions in each period compared to the other two types of arts industries.

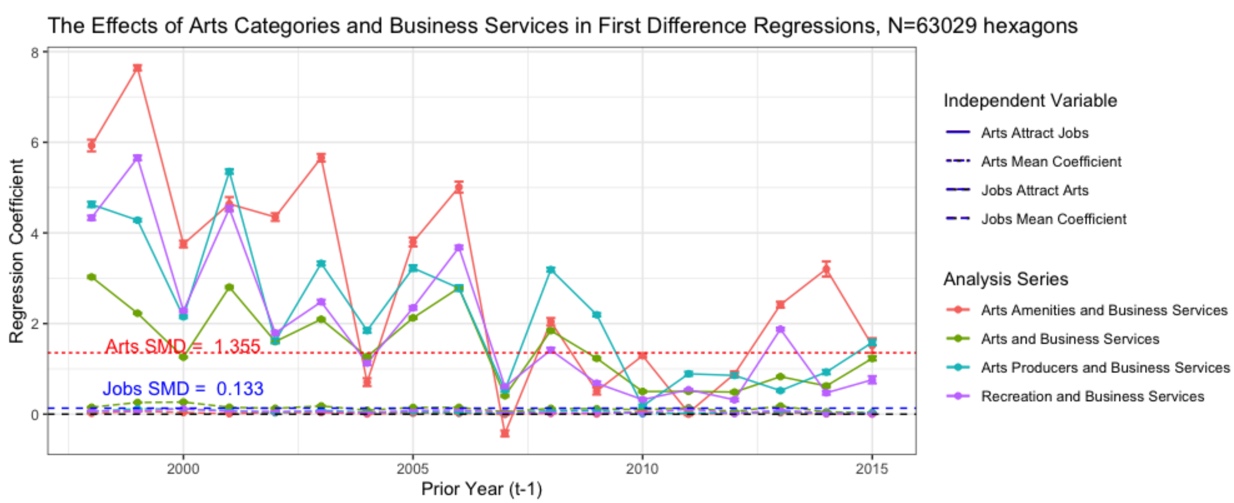

Figure 5.18: The reciprocal relationship between arts categories and business services

Figure 5.18 shows a close-up to the bottom lines on figure 5.17 for easier visualization. The arts amenities (red dashed line) category show the lowest coefficients throughout the entire period, while arts producers (blue dashed line) and recreation (purple dashed line) have interspersed coefficients. This indicates that arts amenities are the ones that require larger audiences from business services in order to grow, compared to the other two arts categories.

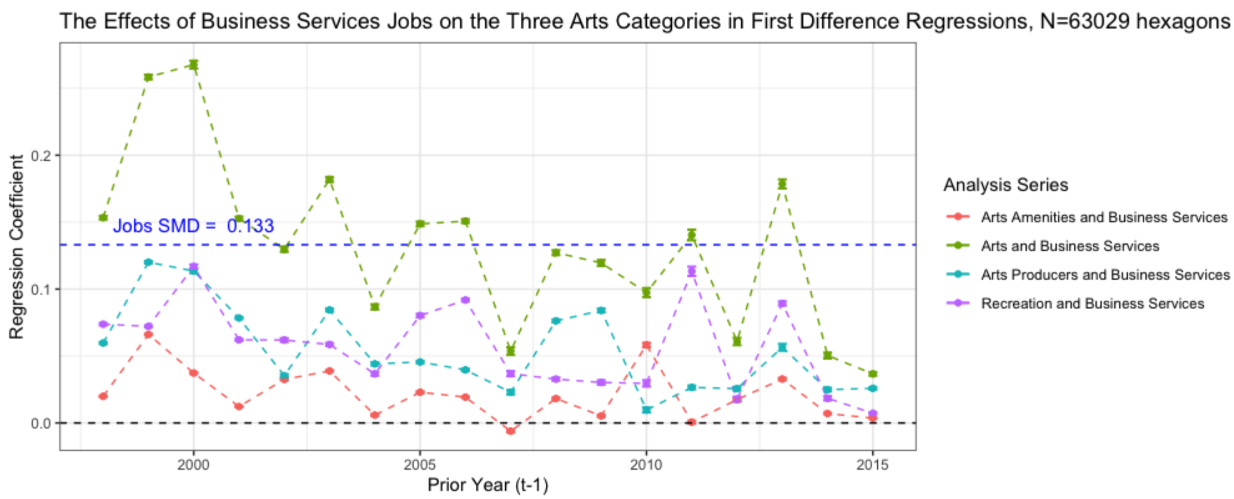

Figure 5.19: Close-up to the business services to arts categories coefficients from figure 5.18

Table 5.7 shows the fixed effect meta-analysis standard mean difference (SMD) coefficients for all periods of industries-pairs effects presented in figures 5.17 and 5.18. Arts amenities had the highest multiplier effects on business services jobs, in which one additional arts job could result in 2.34 new business services jobs. Each additional arts producer job had a multiplier effect of almost two, while recreation had the lowest multiplier effect at 1.4 business services job for each additional recreation job. On the other hand, we see that business services jobs have the lowest multiplier effects for arts amenities, with an additional .02 arts job, while business services had similar multiplier effects on arts producers and recreation, at .06. In other words, in order for the arts amenities industries to grow, it requires an additional audience of fifty workers in business services, while the arts producers and recreation industries require an additional 16.7 additional workers in business services.

Coefficient Means after Meta-Analysis for Arts Subcategories and Business Services

	Arts Effect on Jobs	Jobs Effect on Arts
Arts Amenities	2.34	0.02
Arts Producers	1.93	0.06
Recreation	1.40	0.06
Arts (Combined)	1.36	0.13

Table 5.7: Fixed-effect meta-analysis coefficients for the relationship between arts and business services

The combined multiplier effect of the arts on business services jobs is 1.36, while the business services jobs have a total multiplier effect of .13, which conforms with the multiplier and audience effects discussed in chapter 4 of this dissertation. Individually, the arts amenities seem to attract the business services industries the most out of all arts categories. However, the arts amenities are also the most volatile industries compared to arts producers and recreation. Thus, due to the particular and contingent funding means of the arts amenities, they may require more attention in difficult times in order for them to persist and stimulate the economy in times of prosperity. But we should not ignore the other two arts categories as when combined, the audience required to increase the arts as a whole is of only 7.7 additional business services workers.

5.3 The Reciprocal Relationship of the Arts and High-Tech Industries

According to Hecker (2005), high-tech industries are those industries that employ a "high proportion of scientists, engineers, and technicians," produce high-tech products, and/or have high-tech production methods (Hecker 2005, 58). High-tech industries focus on innovative and leadingedge areas, such as biotechnology, electronics, information, communication, aerospace, weapons, and nuclear technology, and in order to be productive in these fields,

> workers in these occupations need an in-depth knowledge of the theories and principles of science, engineering, and mathematics underlying technology, a knowledge generally acquired through specialized post-high school education in some field of technology leading up to an award ranging from a vocational certificate or an associate's degree to a doctorate. (Hecker 2005, p. 58)

In order to attract and retain highly qualified workers, high-tech companies—especially in the internet industry—are famous for providing amenities, services, and aesthetic qualities to their workplace, such as well-designed and decorated campuses and buildings, common areas for worker's recreation, and sophisticated levels of food service. This is aimed at increasing worker engagement, creativity, and productivity. Internet company workers are highly educated and attuned to culture (e.g., arts and cultural activities), physical fitness (e.g., yoga classes and sports), and the environment (e.g., nature, parks and recreation), making it important to offer these types of amenities wherever they work and live. As both internet companies and internet workers seem to have concerns about aesthetics and quality of life, the analysis in this section observes the relationship between high-tech jobs and arts and entertainment. Therefore, the high-tech industry calls for focused interest and attention when analyzing the impact of the arts, entertainment, and recreation.

The high-tech categories analyzed in this section are comprised of six major components: (1) design (e.g., architecture, engineering, graphic design), (2) high tech bio (e.g., pharmaceutical, medicinal manufacturing), (3) high-tech manufacturing (e.g., manufacturing of electronic components, audio and video equipment, etc.), (4) the internet (e.g., software, web portals, computer facilities), (5) research, and (6) telecom (e.g., wired and wireless communications, satellites). Further details of this category can be found in chapter 3.

As discussed in section 5.1, during the decline of high-tech manufacturing due to the migration of production of technology products overseas, the growth of internet companies (such as Google, Facebook, and others) have soared, especially after 2007. This analysis is especially interesting because the high-tech industry was small and very different from what we know today for the first ten years of data, from 1998 to 2007. From 2008 to 2016, we see a greater growth of the internet industry, with further expansion away from Silicon Valley into many urban areas. Thus, it is possible to observe the evolution of arts and high tech in a pseudo-experimental analysis, as the high-tech industry evolved from manufacturing to a more services-oriented industry in this time period. The fairly recent history of both industries may provide insights harder to obtain with more traditional industries, as the arts have really boomed since the 1960s, as did the high-tech industry as we know them in the 2000s.

To better understand the relationship between the arts and high-tech industries, I follow the same format as the business services section. First, we observe the reciprocal effects in the longest time period possible; then, we move on to analyses in the short and long terms, in first differences, by urban area, and by arts categories. Each cross-lagged regression model applied for any two years can be represented as the equations below:

$$Arts_{2016} = \alpha_0 + \beta_0 * Arts_{1998} + \gamma_0 * HighTech_{1998} + \epsilon_0$$

for the hypothesis that *jobs attract arts*, and

$$HighTech_{2016} = \alpha_1 + \beta_1 * HighTech_{1998} + \gamma_1 * Arts_{1998} + \epsilon_1$$

for the hypothesis that *arts attract jobs*, where α_0 and α_1 are the respective intercepts, β_0 and β_1 are the lagged coefficients, γ_0 and γ_1 are the crossed coefficient, and ϵ_0 and ϵ_1 are the error terms.

The equations for the first difference models are:

$$(Arts_t - Arts_{t-1}) = \alpha_0 + \gamma_0 * (HighTech_t - HighTech_{t-1}) + \epsilon_0$$

or also:

$$\Delta Arts_{t-(t-1)} = \alpha_0 + \gamma_0 * \Delta HighTech_{t-(t-1)} + \epsilon_0$$

for the "business services attract arts" hypothesis; and

$$(HighTech_t - HighTech_{t-1}) = \alpha_1 + \gamma_1 * (Arts_t - Arts_{t-1}) + \epsilon_1$$

or also:

$$\Delta HighTech_{t-(t-1)} = \alpha_1 + \gamma_1 * \Delta Arts_{t-(t-1)} + \epsilon_1$$

for the "arts attract business services" hypothesis, where t is the later year.

After obtaining the results for both regressions, we compare the two crossed coefficients, γ_0 and γ_1, to find whether arts or jobs had a stronger impact on the other. If $\gamma_0 > \gamma_1$, then we have that high-tech jobs attract the arts, and if $\gamma_0 < \gamma_1$, we have that the arts attract high-tech jobs. Using this basic principle, we are able to determine the direction of the relationship as indicated by the path diagram in figure 5.19.

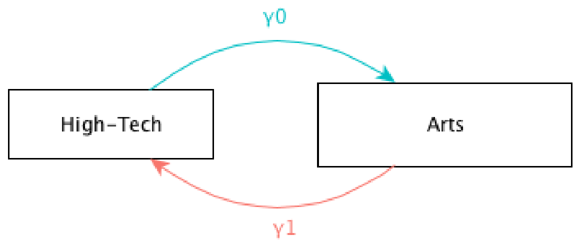

Figure 5.20: Path diagram showing the coefficients of the model analyzing the relationship between arts and high tech

5.3.1 The Reciprocal Relationship Between the Arts and High-Tech Industries in Baseline Models

In this baseline model analysis, we start by considering only the two general variables—high-tech and arts categories—in the most extreme years of the data, 1998 and 2016. This exercise provides us with a base with which to compare more specific subsequent analyses later in this section. In this case, we look for the results if the only existing data were for the years 1998 and 2016.

We run the models using three units of variables: the natural employment numbers, the log-transformed employment numbers, and first differences, at the hexagon level. Table 5.8 shows the regression results for the pair of regressions from each model, along with some statistical measures.

Regression results for the base model where the independent variable is in 1998 and the dependent variable in 2016. Results reflect the pair of cross-lagged regression models using three different types of data, in their natural employment numbers, log-transformed and first difference variables.

	Natural Employment Numbers		Log-Transformed		First Differences	
	High-Tech Attract Arts	Arts Attract High-Tech	High-Tech Attract Arts	Arts Attract High-Tech	High-Tech Attract Arts	Arts Attract High-Tech
Dependent Variable	**Arts 2016**	**Jobs 2016**	**Arts 2016**	**Jobs 2016**	**Arts 2016**	**Jobs 2016**
Intercept	-6.5 ***	-15.8 ***	1.93 ***	2.07 ***	1.12 ***	2.57 ***
	(.89)	(1.11)	(.008)	(.008)	(.035)	(.21)
Arts 1998	1.28 ***	.165 ***	.44 ***	-.017 ***	-.03 ***	-.048 ***
	(.002)	(.003)	(.004)	(.004)	(.004)	(.004)
Jobs 1998	.04 ***	1.35 ***	.046 ***	.505 ***	.035 ***	.15 ***
	(.003)	(.004)	(.004)	(.004)	(.002)	(.003)
Residual S.E.	217	270	1.2	1.2	50	53
R-Squared	.881	.801	.419	.441	.003	.054
Adjusted R-Squared	.881	.801	.419	.441	.003	.054
N	63042	63042	63042	63042	63042	63042

Table 5.8: Cross-lagged regression results for the baseline model using original metric, log-transformed variables and first differences

The relationship between high tech and the arts presents a very special case as the high-tech industry evolved significantly in the period studied. In the first model, using the natural employment numbers, we see that the arts coefficient is higher than the high-tech jobs coefficient, which is a result similar to what was found in the business services section. Even though the arts coefficient is less than 1, and therefore, does not present a multiplier effect, we must consider that this part of the study has narrowed down the number of jobs relating to the arts, dropping the value of the coefficient. The R^2 is .881 and .801, indicating a good fit for the model.

In the log-transformed and first difference models, we see that the R^2 of the log model dropped to .419 and .441, and the R^2 for the first differences model is close to zero, showing a poor fit of the model. However, we observe an unusual phenomenon, in which the arts coefficient is negative and the high-tech coefficient is positive and seems to be in a similar range as the other jobs coefficients in this study. Could this indicate that the high-tech industries attracted the arts, but the arts are still not caught up with the high-tech industry?

The baseline models show a general but incomplete picture of the relationship between the arts and high-tech industries. In the remainder of this section, I analyze more closely the relationship between the two industries using data for every year between 1998 and 2016, in the short and long terms, first differences, by urban area, and by arts category.

5.3.2 The Reciprocal Relationship Between the Arts and High Tech Over Time

In this section, we analyze the relationship between the arts and high-tech industries by applying the cross-lagged regression models in all the years between 1998 and 2016, using the log-transformed data. First, we observe the results for each model when the time lag between the first and last year is one year, followed by the fixed effects meta-analysis on the coefficients to find the standard mean differences (SMD) that allow us to determine whether the arts or high tech had a stronger effect on the other. The second model follows the same sequence, but with a time lag of ten years for a more long-term analysis. And the third model uses the first difference equations for one-year changes in the employment number of each category.

Results for regression models using different types of data and time lag, analyzing the impact between the arts and high-tech industries.

	Log-Transformed, 1 Year Apart		Log-Transformed, 10 Years Apart		First Differences	
	High-Tech Attract Arts	Arts Attract High-Tech	High-Tech Attract Arts	Arts Attract High-Tech	High-Tech Attract Arts	Arts Attract High-Tech
Fixed Effect SMD	0.0228	0.0139	0.0912	0.0266	0.2524	0.3563
Confidence Interval (95%)	[0.0219; 0.0236]	[0.0131; 0.0148]	[0.0890; 0.0935]	[0.0243; 0.0289]	[0.2510; 0.2539]	[0.3545; 0.3581]
z	51.43	30.99	80.08	22.85	345.45	380.9
p-value	0	< 0.0001	0	< 0.0001	0	0
tau^2	0.0004 [0.0003; 0.0014]	0.0007 [0.0005; 0.0022]	0.0010 [0.0005; 0.0037]	0.0008 [0.0004; 0.0033]	0.0421 [0.0243; 0.0991]	0.0454 [0.0255; 0.1064]
I^2	99.1% [99.0%; 99.3%]	99.4% [99.3%; 99.5%]	98.8% [98.4%; 99.1%]	98.5% [98.0%; 98.9%]	100%	100%
Q	1972.68	3011.86	668.37	531.43	73634.99	47885.54

Table 5.9: Fixed-effect meta-analyses results for the relationship between arts and high tech for the short and long term, and first differences for all urban areas

Table 5.9 shows the SMDs and statistical measures for the three models discussed in this section. The two log models show that high-tech jobs had a stronger effect on the arts, while the first differences model show that the arts had a stronger impact on high tech rather than the reverse. These results compare to the similar analysis done on the business services section: when considering the entirety of the high-tech industry, it shows a stronger influence on the arts, but when we consider only the yearly changes in the employment numbers, the arts seem to have a stronger pull on high tech. In other words, in the analyses that maintain the well-established sectors of the industries, we see that high tech attracts the arts. But by looking at the most dynamic sectors of the industries in the form of their yearly changes, we see that the arts have the stronger pull to bring in new high-tech jobs.

Figure 5.20 shows the results for each pair of one-year, lag cross-lagged regression results. The meta-analysis results show that if we consider the entire period, high-tech jobs affect the arts (.023) more than the arts affect high-tech jobs (.014). However, we need to observe closely the yearly results looking for short-term patterns. From 1998 until 2007, the coefficients for the jobs effects were consistently higher than the arts, but after 2008 and 2009, the two industries started to exchange the place of higher coefficient, looking more similar to the pattern observed for business services. In other words, in the beginning of the high-tech industry, jobs attracted people, which then attracted the arts, but as the industry grew, the arts also gained importance in attracting more highly qualified workers, shown by how the two coefficients exchange significance year after year.

From 1998 to 2007, the jobs effects was higher than the arts, indicating that jobs came first, and the arts followed. After 2008, the two industries present interspersed coefficients, indicating that after 2008, the arts became more relevant in attracting high tech, which was not seen before 2007.

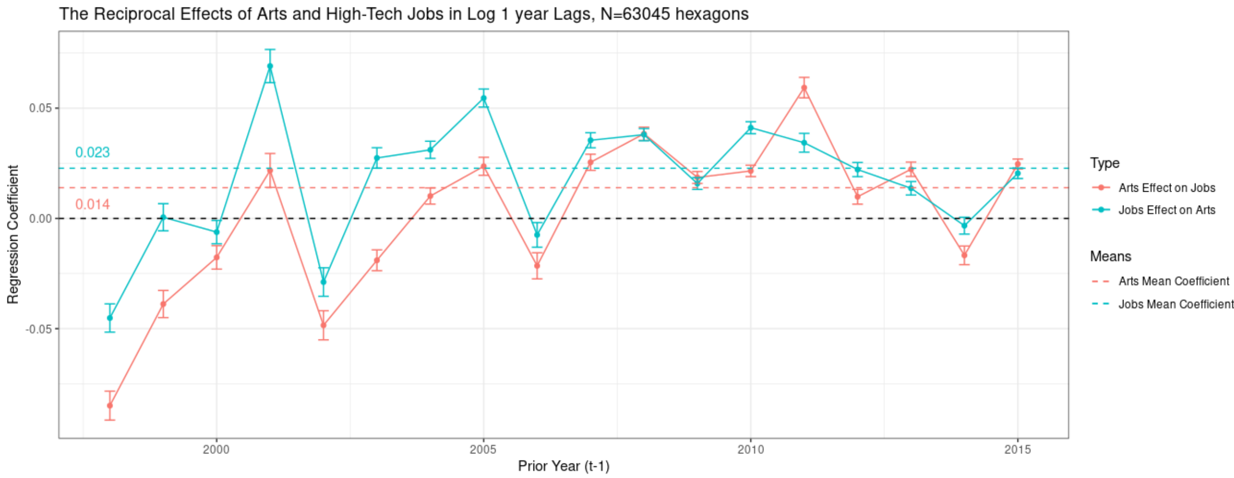

Figure 5.21: Coefficients for the 1-year lag regression models for both directions in the relationship between the arts and high tech by year for all urban areas

Figure 5.21 shows the coefficients for the same model but applied only to the ten largest urban areas. The SMD for both coefficients are similar to the SMDs for the general analysis. However, we see that between 2001 and 2002, the arts had a stronger impact on high-tech jobs, indicating that it is possible that before 2007, larger urban areas already experienced a positive influence from the arts in attracting high-tech jobs.

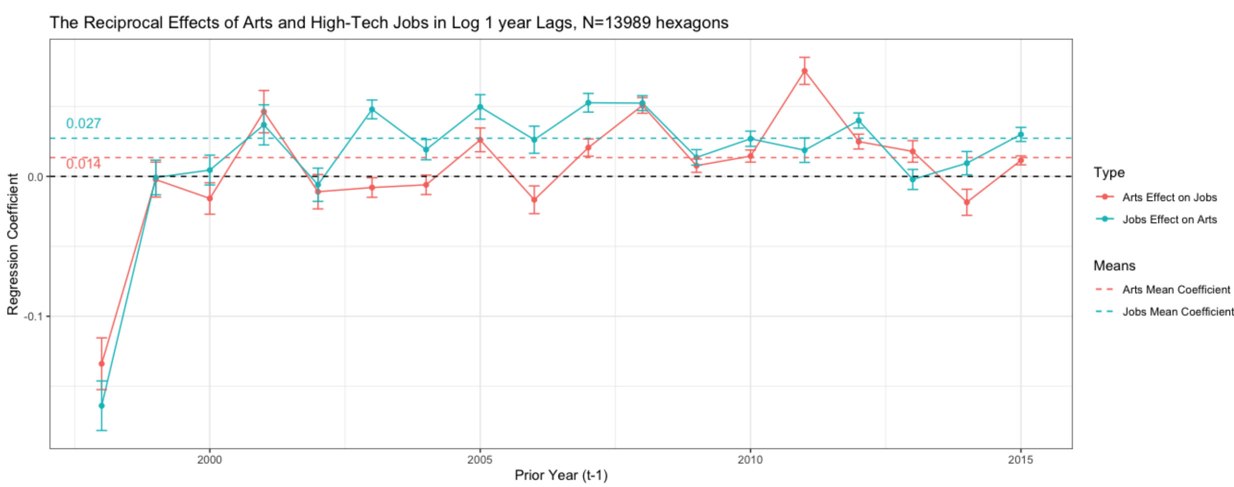

Figure 5.22: Coefficients for the 1-year lag regression models for both directions in the relationship between the arts and high tech by year for the ten largest urban areas

To be sure, the high-tech industry was already in development before 1998 in some of its subcategories, such as telecommunications and manufacturing, as seen in section 5.1.1. But in the 2000s, the sectors emblematic of the high-tech industry started developing into the industry we know today, with large software and internet industries developing from the young and daring small technology companies into global corporations employing thousands of workers. Therefore, here we can examine the relationship between arts and jobs in a growing industry with a great proportion of highly-qualified workers.

Figure 5.22 shows results for the same analysis but isolating the employment numbers in the internet industry. Even though the meta-analysis averages are very small and close to zero, there are still some coefficients throughout the years worthy of insight. Of the eighteen analyses, the arts had larger effects in nine, high tech had larger effects in eight, and one year presented not-significant results. We also see that both arts and internet exchange positions from year to year, but the internet industry has a much wider range of coefficient values (positive as well as negative) than the arts coefficients, which fluctuate closer to zero.

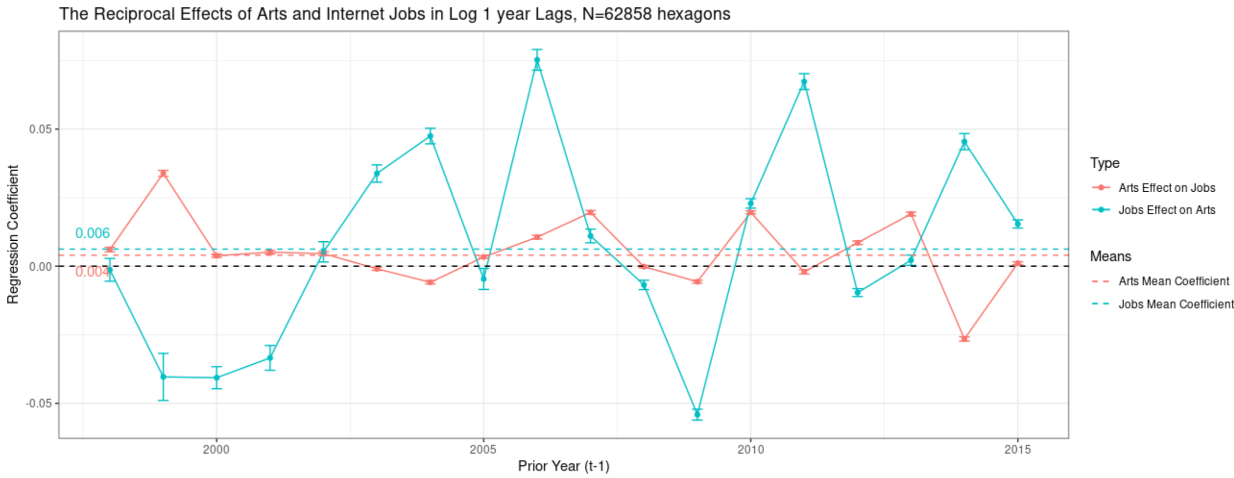

Figure 5.23: Coefficients for the 1-year lag regression models for both directions in the relationship between the arts and internet industry by year for all urban areas

Figure 5.23 shows the same analysis but for the ten largest urban areas in the dataset. In this case, we observe an arts SMD higher than the high-tech jobs SMD, and the arts seem to attract internet jobs in twelve out of eighteen years, more so than in the previous graphs in this section. Thus, in the ten largest urban areas, the arts and internet industries had a closer relationship than in the average urban area.

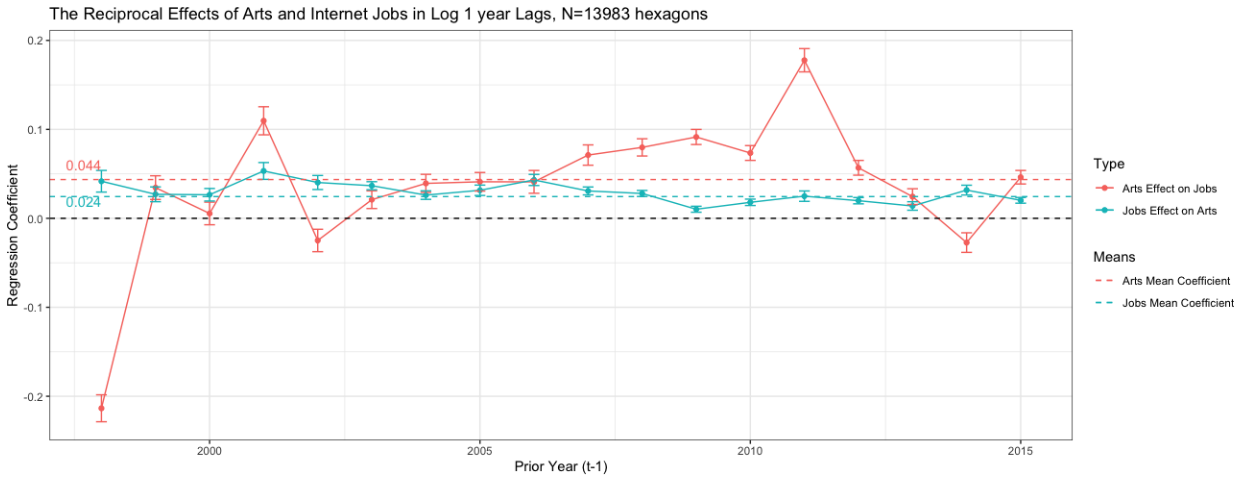

Figure 5.24: Coefficients for the 1-year lag regression models for both directions in the relationship between the arts and internet industry by year for the ten largest urban areas

The ten-year lag analysis helps us grasp a longer-term relationship between the arts and high tech. Due to the uneven number of data points, the year 2007 was not included in any long-term regression analysis. When considered in ten year periods, high-tech jobs are the major force in attracting arts, as the jobs effects coefficients are consistently larger than the arts effects coefficients. The average for the ten-year lag analysis is much larger than the one-year lag analysis, which went from close to zero percent change to .091 percent change in arts for an additional one percent increase in high-tech employment, and to .027 percent change in high-tech employment for each additional one percent increase in arts employment. Therefore, both the one-year and ten-year lag analyses indicate that high-tech employment comes first and the arts follow.

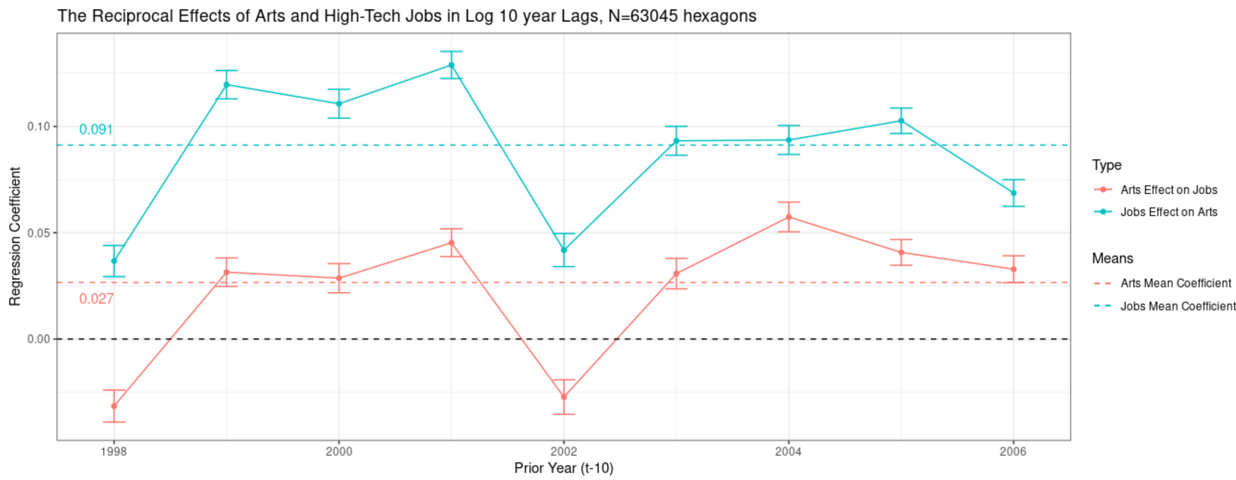

Figure 5.25: Coefficients for the 10-year lag regression models for both directions in the relationship between the arts and high tech by year for all urban areas

The long-term analysis for the ten largest urban areas shows similar results than for all urban areas, with high-tech jobs attracting the arts more than the reverse.

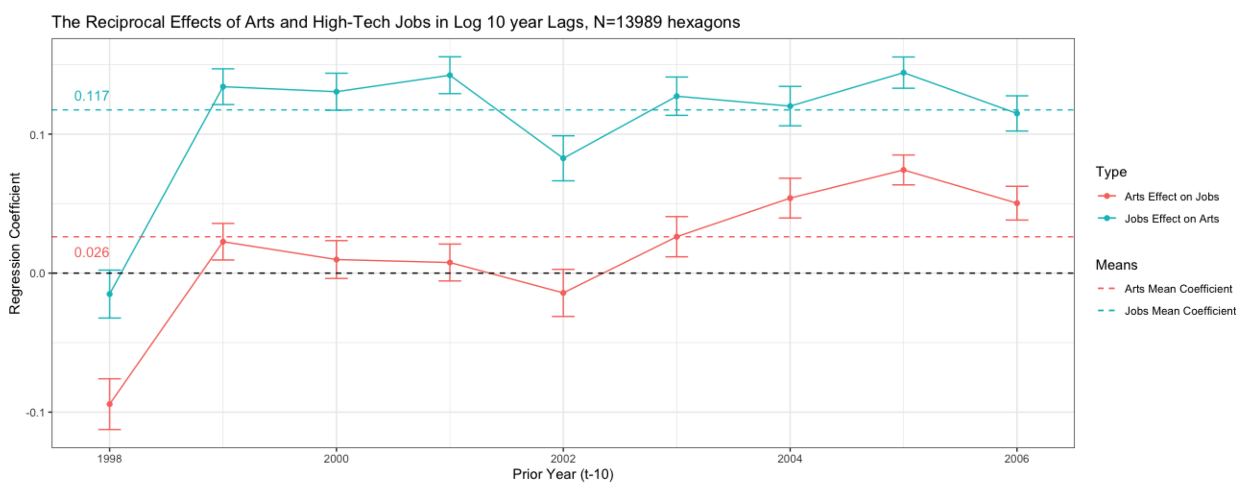

Figure 5.26: Coefficients for the 10-year lag regression models for both directions in the relationship between the arts and high tech by year for the ten largest urban areas

On the other hand, in the long term, the arts seem to attract internet jobs to urban areas in general, as seen in figure 5.26, with six out of nine years showing a higher arts coefficient than internet jobs. However, from this figure, we should also note that the arts coefficients vary much more than the internet jobs coefficient.

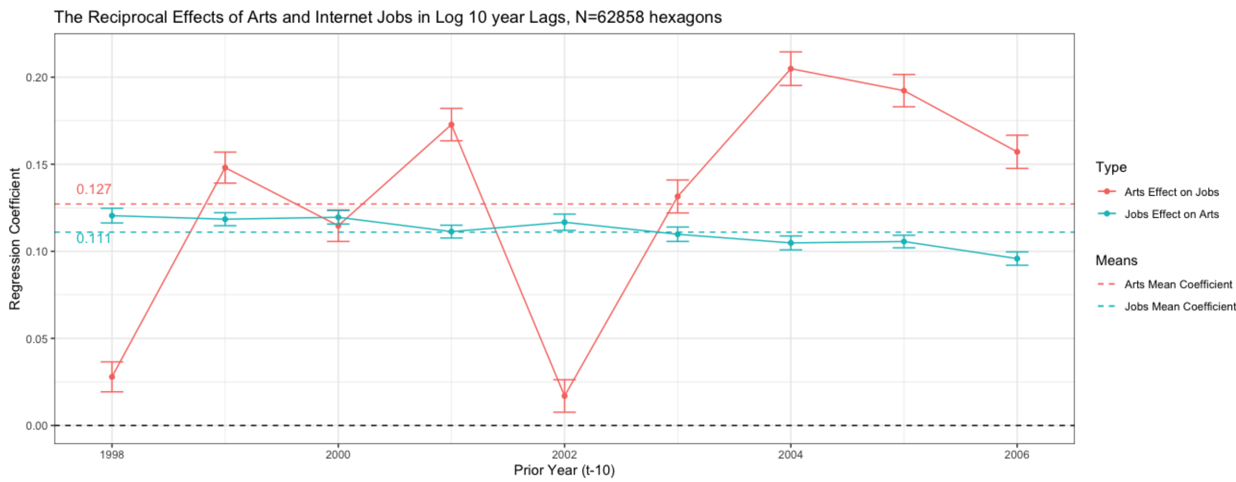

Figure 5.27: Coefficients for the 10-year lag regression models for both directions in the relationship between the arts and internet by year for all urban areas

However, in another interesting and conflicting situation, the internet SMD is higher than the arts SMD in the long term for the ten largest urban areas. This analysis shows that until the 2002–12 period, internet jobs seemed to be the largest driver of the arts, while after the 2003–13 period, the arts attracted internet jobs.

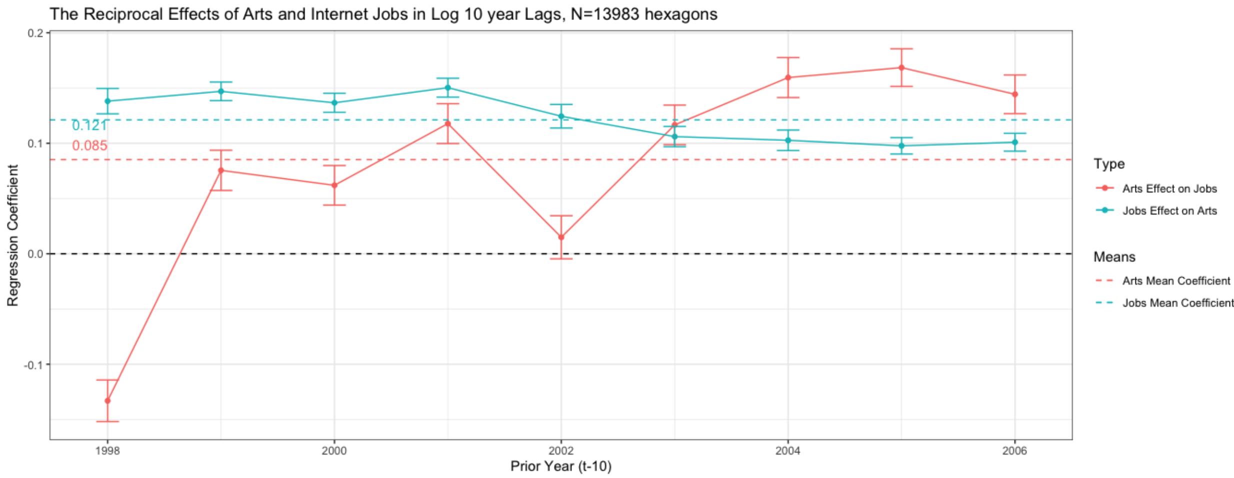

Figure 5.28: Coefficients for the 10-year lag regression models for both directions in the relationship between the arts and internet by year for the ten largest urban areas

In other words, in the largest urban areas, the arts are major drivers of internet jobs in the largest urban areas, but in the long run, the internet jobs were the drivers of the arts. Perhaps more data points might reverse the SMDs and indicate that the arts attracted internet jobs in more years of analysis.

The first difference analysis computes regression coefficients for the changes between the same two years in both the dependent and independent variables, as seen in figure 5.28. For each pair of years from 1998 to 2016, we run the same pair of regressions described in section 5.2. The results for the first difference regression analysis between arts and high-tech industries are shown in figure 5.28. The SMD for the arts is larger than for high tech, which indicates that in that period, the arts attracted more high-tech jobs than the reverse. However, at a closer look, we see that in a few years the jobs coefficient was larger than the arts coefficient, as coefficients are interspersed, year after year.

From 1998 to 2002, we see a larger coefficient for both arts and jobs than for the rest of the analysis. This may be due to different NAICS categorizations, which has been controlled for, but also to the relative size of the high-tech industry, which was smaller in 1998 than in 2016. Thus, the difference between 1998 and 1999 was more significant in the regression analysis than the difference between 2015 and 2016. The gains before 2002 would mean higher coefficients than after 2002. The only year in which both coefficients were negative was the one for the 2007–2008 analysis, indicating that both arts and high-tech industries had suffered negative impacts due to the 2008 financial crisis.

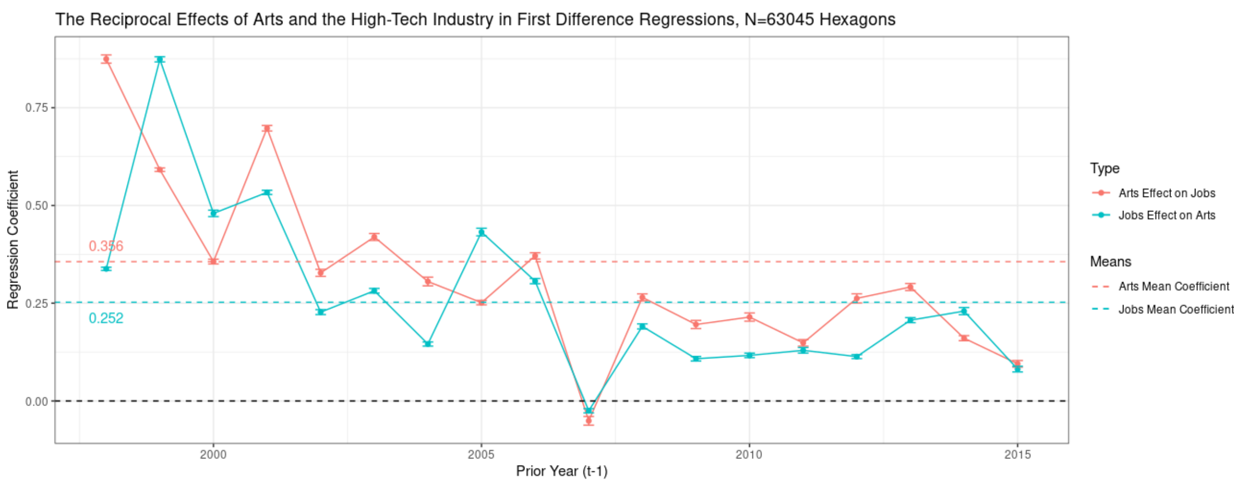

Figure 5.29: Coefficients for the first differences regression models for both directions in the relationship between the arts and high-tech industry by year for all urban areas

Figure 5.29 shows the first difference results for the ten largest urban areas. The arts SMD is slightly higher than the high-tech SMD, showing a stronger impact of the arts on high tech, but not as different than for the overall analysis above. In general, the arts seem to have a higher impact on high-tech jobs when we focus our analysis on one-year changes rather than the entire industries.

Figure 5.30: Coefficients for the first differences regression models for both directions in the relationship between the arts and high-tech industry by year for the ten largest urban areas

Figure 5.30 shows that in the first nine years, high-tech jobs have a much bigger influence on the arts. However, after 2007, both coefficients are interspersed and with similar dimensions.

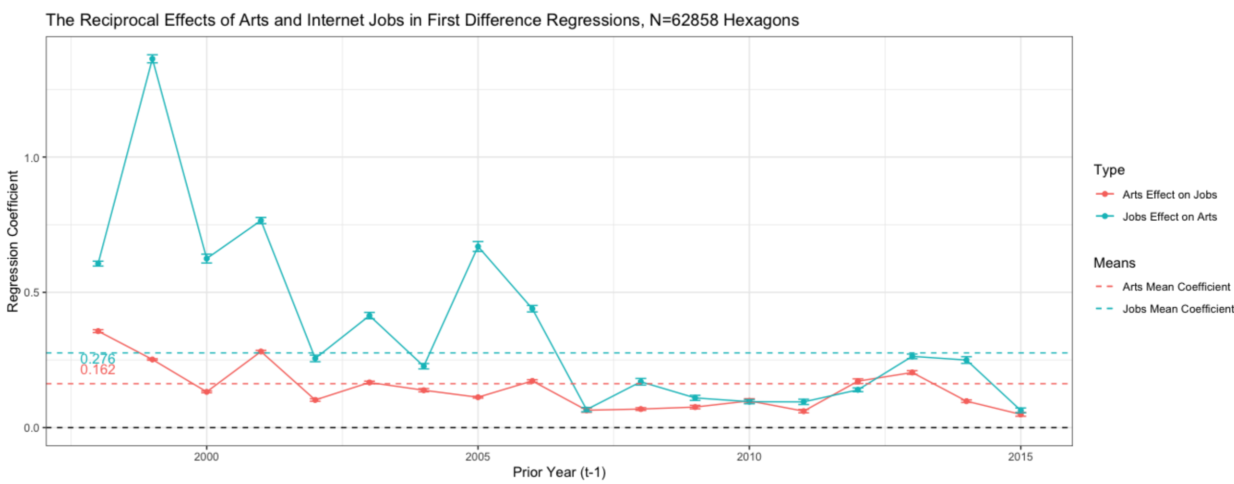

Figure 5.31: Coefficients for the first differences regression models for both directions in the relationship between the arts and the internet industry by year for all urban areas

In another reversal, when we observe only the yearly changes for the internet industry in the ten largest urban areas, the internet SMD shows consistent and persistent higher coefficients over the arts, as seen in figure 5.31. This indicates the opposite of the discussion so far: when we observe the yearly changes, the internet industry is the driver for the arts in large cities. In other words, the presence of internet companies in large cities makes them attractive for new artists to move in. More research would be needed for a fuller understanding of this process and the connection between internet industries and artists in large cities.

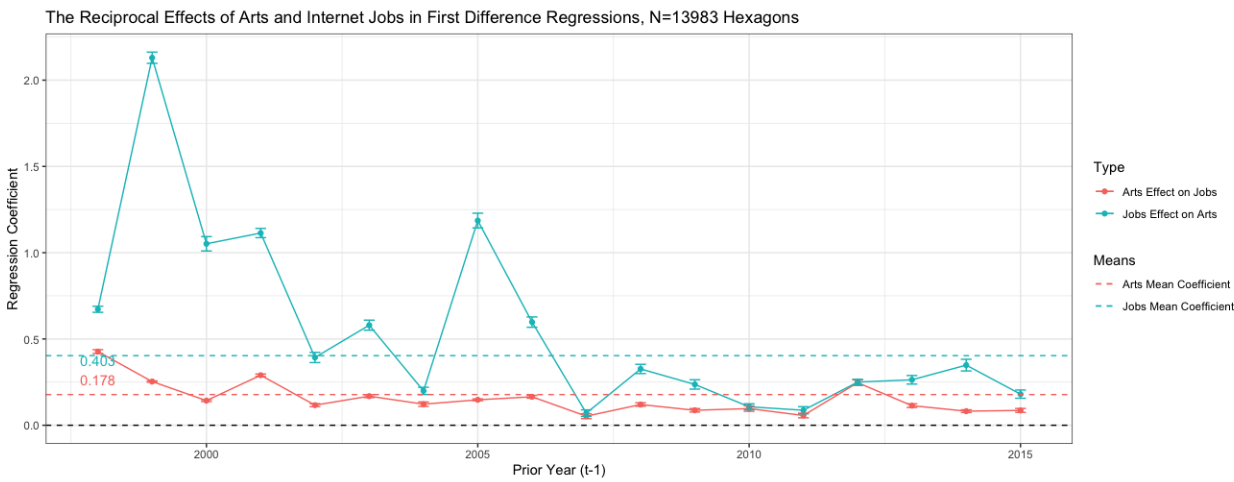

Figure 5.32: Coefficients for the first differences regression models for both directions in the relationship between the arts and the internet industry by year for the ten largest urban areas

In conclusion, the analyses in this section show a strong synergy between the internet industry and the arts as they have developed together over the years. In the beginning, as the internet industry was not yet established, the arts did not offer a strong pull; rather, people would move for the internet jobs. With the rapid acceleration of the internet industry, artistic elements were introduced by the companies and the cities where they are located to attract more workers, thus leading to more similar coefficients from both sides. However, the phenomenon of the internet industries and the arts in large cities warrant more investigation.

5.3.3 The Reciprocal Relationship Between the Arts and High Tech by Urban Area

In this section, I discuss the relationship between the arts and high-tech industries by urban area. While I do not discuss each urban area individually, I present the results of the regressions for the first differences for each urban area, as laid out in the previous section.

The map in figure 5.32 shows in which urban areas we have stronger arts effects or high-tech effects after comparing the standardized mean differences from the fixed effects meta-analysis. The arts effects is stronger in many of the larger urban areas, with the exception of New York and Los Angeles. In these cities, the high-tech effects proved to be stronger, thus attracting qualified workers, and the arts followed. On the other hand, in cities like San Francisco, Seattle, and Chicago, we see a stronger arts effect.

Cities classified as NA indicate those that did not have enough data points to generate a result, and the cities classified as “not significant” indicate that neither arts effects nor jobs effects coefficients was statistically significant at 95 percent confidence.

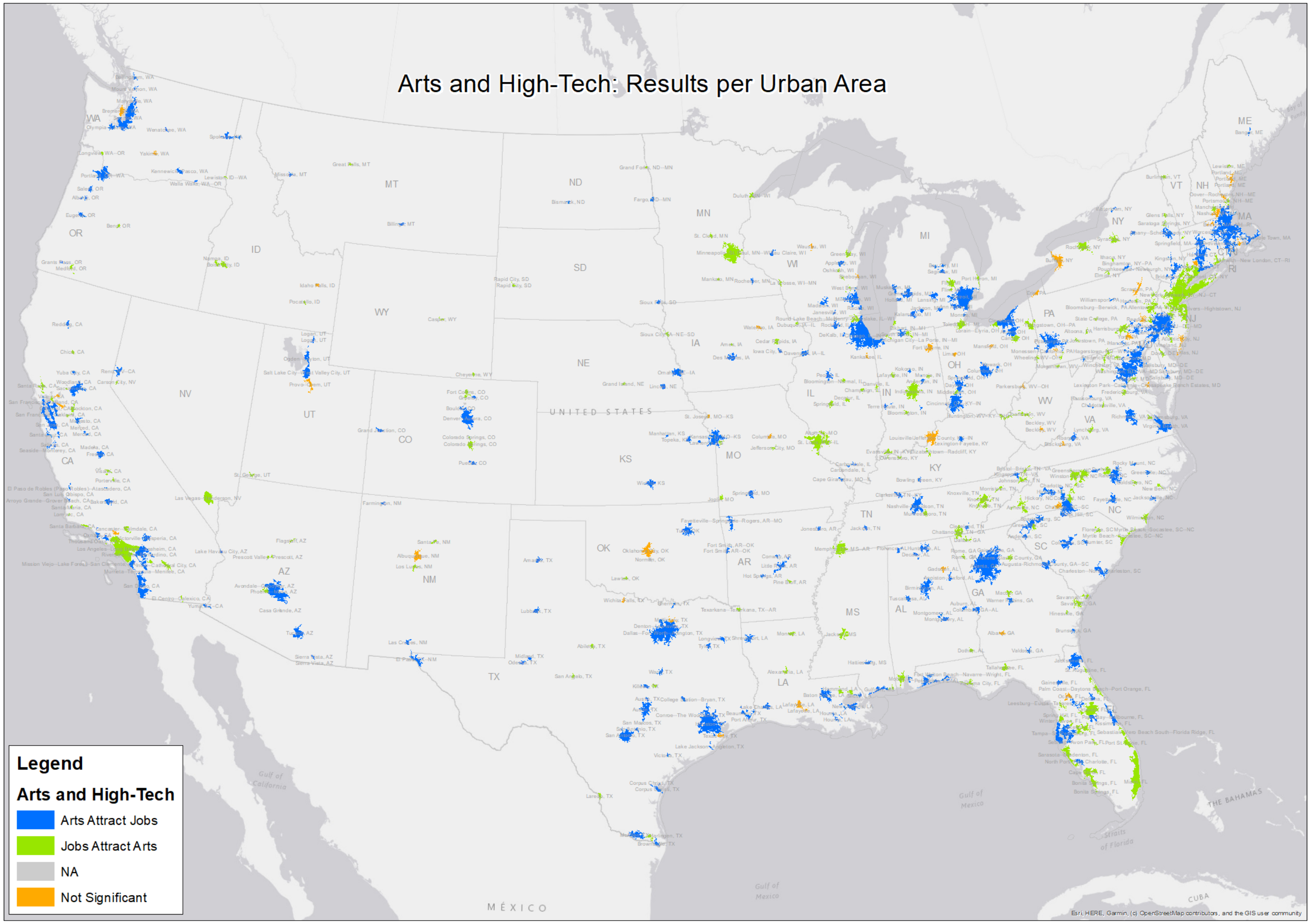

Figure 5.33: Map showing which direction (arts attract high tech or high tech attracts arts) showed stronger coefficients in each urban area

Table 5.10 shows the coefficient values and results for the top fifteen largest urban areas, sorted by the arts effects estimates. Chicago has the highest coefficient for the effect of arts on high-tech jobs over the period, followed by Seattle, Washington DC, and Boston, cities that have invested heavily in their arts scene and are major destinations for recent college graduates. Even though New York was classified as a jobs effects city, the difference between the two coefficients is .034; thus, we may consider New York as strong in both arts and high tech, and not just high tech.

Nonetheless, the largest urban areas do not present the highest coefficients, but smaller urban areas do. In the top arts coefficients we see that Delano, CA, had an arts effects of 1.9, meaning that for each new arts job, the city would gain almost two high-tech jobs. However, this urban area had only twelve cases in the analysis, and even though the results are statistically significant, we must be careful when appraising results for smaller urban areas. The complete table with all urban areas can be found in Appendix E.

Arts and High-Tech Jobs by Urban Area

	City	N	Arts (IV) to Jobs (DV) Estimate	S.E.	p-value	Jobs (IV) to Arts (DV) Estimate	S.E.	p-value	Conclusion
Top 15 Urban Areas (Sorted by Arts Coefficient)	Chicago, IL	1570	0.804	0.010	0.000	0.175	0.002	0.000	Arts Attract Jobs
	Seattle, WA	703	0.507	0.016	0.000	0.116	0.003	0.000	Arts Attract Jobs
	Washington, DC	914	0.474	0.007	0.000	0.179	0.004	0.000	Arts Attract Jobs
	Boston, MA	1501	0.456	0.009	0.000	0.144	0.003	0.000	Arts Attract Jobs
	New York, NY	2383	0.425	0.003	0.000	0.459	0.004	0.000	Jobs Attract Arts
	Philadelphia, PA	1388	0.402	0.005	0.000	0.296	0.004	0.000	Arts Attract Jobs
	Tampa, FL	720	0.399	0.014	0.000	0.098	0.004	0.000	Arts Attract Jobs
	Houston, TX	1089	0.382	0.009	0.000	0.093	0.003	0.000	Arts Attract Jobs
	Dallas, TX	1189	0.312	0.010	0.000	0.113	0.003	0.000	Arts Attract Jobs
	Pittsburgh, PA	708	0.232	0.006	0.000	0.094	0.006	0.000	Arts Attract Jobs
	Detroit, MI	909	0.230	0.008	0.000	0.114	0.004	0.000	Arts Attract Jobs
	Phoenix, AZ	756	0.191	0.010	0.000	0.114	0.006	0.000	Arts Attract Jobs
	Miami, FL	781	0.174	0.006	0.000	0.256	0.009	0.000	Jobs Attract Arts
	Atlanta, GA	1781	0.157	0.005	0.000	0.114	0.003	0.000	Arts Attract Jobs
	Los Angeles, CA	1127	0.132	0.004	0.000	0.337	0.008	0.000	Jobs Attract Arts
Top Arts Coefficients Overall	Delano, CA	12	1.912	0.007	0.000	0.175	0.000	0.000	Arts Attract Jobs
	Rock Hill, SC	62	1.655	0.001	0.000	0.295	0.000	0.000	Arts Attract Jobs
	Salisbury, MD	63	1.542	0.012	0.000	0.294	0.002	0.000	Arts Attract Jobs
	Corvallis, OR	25	1.446	0.026	0.000	0.053	0.001	0.000	Arts Attract Jobs
	Sierra Vista, AZ	22	1.435	0.021	0.000	0.017	0.002	0.000	Arts Attract Jobs
Top Jobs Coefficients Overall	Grand Forks, ND	20	0.264	0.000	0.000	3.777	0.001	0.000	Jobs Attract Arts
	Myrtle Beach, SC	141	0.119	0.001	0.000	3.063	0.027	0.000	Jobs Attract Arts
	Hilton Head Island, SC	50	0.074	0.002	0.000	1.780	0.024	0.000	Jobs Attract Arts
	Wheeling, WV	44	0.361	0.003	0.000	1.377	0.012	0.000	Jobs Attract Arts
	Joplin, MO	49	0.566	0.002	0.000	1.206	0.004	0.000	Jobs Attract Arts

Table 5.10: Regression results for the relationship between the arts and high-tech jobs by urban area size, and the top five urban areas with highest arts and jobs coefficients

We must keep in mind that each city has a unique structure and different plans to develop their local economies, which make their relationship between the arts and high tech unique within their economies. While it is at least interesting to have a general overview of what is happening in American cities, these results may lead us to understand the lessons from different policies throughout the country.

Table 5.11 shows the proportions of industry effects by city size. The top fifty urban areas have populations of over one million people, the middle-tier urban areas have populations between 300,000 and one million people, and the bottom-tier urban areas have populations of under 300,000 people.

Number of Urban Areas by Regression Results and Population Size: Arts and High-Tech

	Top 50 Urban Areas	Middle Tier (1)	Bottom Tier (2)	Total
Arts Attract High-Tech	37 (74%)	59 (53%)	139 (46%)	235 (51%)
High-Tech Attract Arts	10 (20%)	40 (36%)	130 (43%)	180 (39%)
Not Significant	3 (6%)	12 (11%)	30 (10%)	45 (10%)
Total	50	111	299	460*

* The total number of cases is 460 urban areas because 21 urban areas did not show any results
(1) Middle tier urban areas are those between 300 thousand to 1 million people
(2) Bottom tier urban areas are those with less than 300 thousand people

Table 5.11: Proportion of results by urban area size

Seventy-four percent of the top fifty urban areas show a stronger arts effect on jobs, and 20 percent of them show a strong high-tech jobs coefficient, a higher proportion than seen in the business services and the overall analysis in chapter 4. Fifty-three percent of the middle tier and 46 percent of the bottom-tier urban areas show a strong arts effect on high tech, while 36 percent of the middle tier and 43 percent of the bottom tier show a stronger high-tech effect on the arts. These numbers indicate that for the relationship between arts and high tech, the middle- and bottom-tier urban areas start to look more similar to each other.

5.3.4 The Reciprocal Relationship Between High Tech and the Arts Categories

Thus far, we have observed the relationship between high-tech industries and the arts as a whole; however, how would these relationships change if we break down the arts into its three categories? Figure 5.33 shows the coefficients for the first difference regressions as in section 5.3.2, but with the results for each arts subcategory added separately. As the cross-lagged regression models demand the exchange between the independent to the dependent variable, each arts category had their own model run instead of running a regression with three dependent variables, as in the case of the effects of high tech on the arts.

The green line shows the combined effects of all arts on high-tech jobs, and the red, purple, and blue lines show the individual effects of the arts subcategories on high-tech employment. The solid lines show the effect of arts on jobs, while the dashed lines show the effects of jobs on arts.

After meta-analysis results, we have an arts SMD that is higher than the high-tech SMD, indicating that on average, the arts had a stronger impact on high tech than the reverse. These SMDs pertain to the overall analysis, as seen before, and serve as a benchmark here as we are more interested in the breakdown of the arts categories.

The arts amenities category is the one that most consistently attracted high-tech jobs, as their coefficient tops thirteen out of eighteen years of data. This is followed by the arts producers and recreation, which tops two years each, and the year 2007 shows coefficients close to zero.

As with the previous analyses, the coefficients from arts to high-tech jobs is much larger before 2005, as the size of the coefficients decline after 2005. The decline in the size of the coefficient is not necessarily bad news, as high tech and arts better equated with each other in the later years.

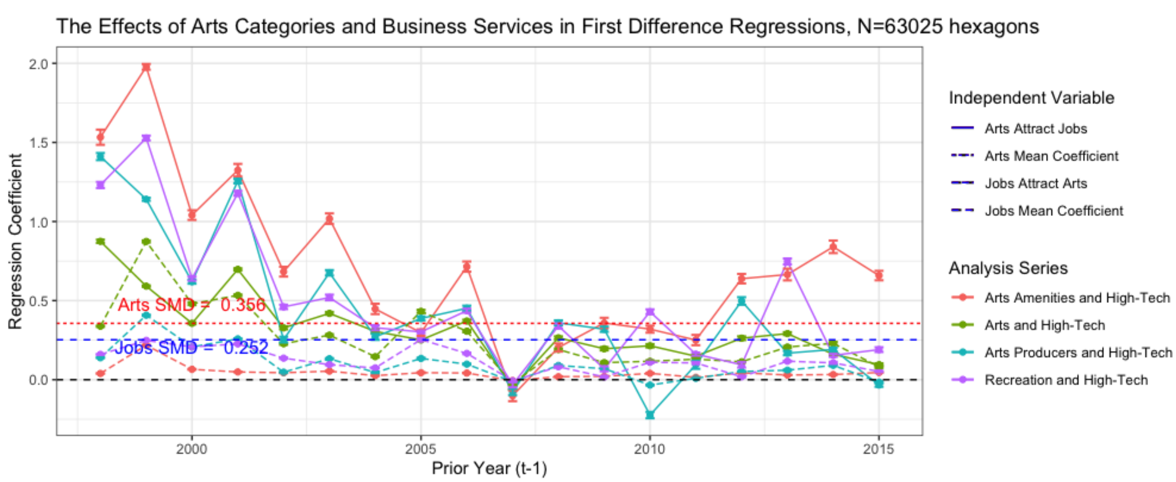

Figure 5.34: The reciprocal relationship between arts categories and high tech

For better visualization, figure 5.34 shows a close-up of the dashed lines at the bottom of figure 5.33. These lines represent the effects of high-tech jobs on the arts. In comparison to the arts effects on high-tech jobs, the high-tech jobs effects on the arts is generally smaller, resulting also in the smaller SMD.

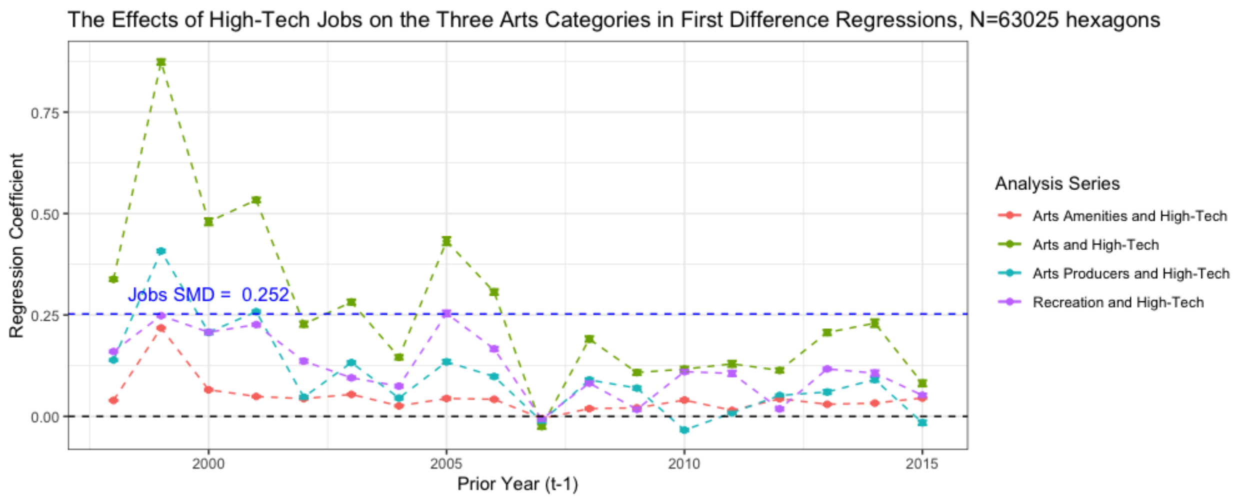

Figure 5.35: Close-up of the high tech to arts categories coefficients from figure 5.33

The arts amenities category is the one with the lowest effects received from high-tech jobs, with arts producers and recreation interspersed throughout the years with higher effects received from high-tech jobs. Similar to the analysis in the business services section, we see that the arts amenities are the ones that need larger audiences in order to grow.

Coefficient Means after Meta-Analysis for Arts Subcategories and High-Tech

	Arts Effect on Jobs	Jobs Effect on Arts
Arts Amenities	0.75	0.04
Arts Producers	0.47	0.10
Recreation	0.42	0.13
Arts (Combined)	0.36	0.25

Table 5.12 Fixed-effect meta-analysis coefficients for the relationship between arts and business services

As the growth of the internet sector makes internet companies look more alike with those in the business services sector, their needs also start to look similar. In other words, as high-tech and internet companies grew, their needs for artistic and recreational environments for their employees evolved to look similar to the well-established business services industries.

5.4 Conclusion

In this chapter, we explored the relationships between the arts and two industries: business services and high tech, as these are both industries that are commonly associated with urban living and the arts. We explored the relationship of the arts to both business services and high tech using different methods. In section 5.1, I show that the distribution of the arts, business services, and high-tech variables are extremely skewed and could be improved by log-transformation, which also standardizes the variables, making their coefficients comparable. Then, I show the growth trajectory of all industry categories from 1998 and 2016, with an emphasis on arts, business services, and high-tech subcategories. We learn that the trajectories of most industries are not ones of constant growth but contain periodical declines that recover over time.

The internet industry experienced sharp growth after 2008 as high-tech manufacturing declined, just as goods-producing industries were losing jobs in that period. We also observe how New York and Los Angeles have an outlying number of arts jobs even when compared to the other largest urban areas. I also discuss the correlations among industries by using the time average for each industry category. We see high correlations in both metrics among the arts categories (arts amenities, arts producers, and recreation), business services and high-tech variables, varying from .537 to .865 in the original metric and from .59 to .882 for the log-transformed variables (table 5.2).

Section 5.2 discusses the reciprocal relationship between the arts and business services industries, as we narrow down to a subsection of the non-arts jobs variables discussed in chapter 4 to the business services-related employment. Section 5.3 discusses the reciprocal relationship between the arts and high tech in the same manner.

In the first model (baseline models), we used the first and last years of data to establish the basis for comparison of incremental models. We found that for both business services and high tech, the arts have a stronger effect on jobs in the natural employment numbers. The same type of effect is true for business services with log-transformed variables, but not for high tech after log-transformation, which presented a stronger jobs to arts coefficient and a negative arts to jobs coefficient. The first difference baseline models for both industries resulted in an R^2 close to zero, as change variables from years so far apart have weaker relationships.

In the second model (time lags), we analyzed the cross-lagged regressions for each combination of years from 1998 and 2016 for one- and ten-year lags for the log-transformed variables and in first differences. For both business services and high tech, we observed that the two models using log-transformed variables showed that jobs attract arts; for both, the first differences models showed that the arts attract jobs. In other words, when we examine each industry as a whole, considering both well-established and new employment together, year after year, jobs attract the arts. But when we consider only the yearly changes in the size of industries, we see the arts have a higher impact on jobs, indicating that the arts effects are more dynamic.

These models represented a general analysis, with all sizes of urban areas included. But we also observed the results for each urban area separately, in the third model. Table 5.13 shows the first differences cross-lagged regression results for the fifteen largest urban areas for both business services and high tech, by number of associated hexagons. Values in bold indicate the highest coefficient in order to determine the stronger direction (whether arts attract jobs or jobs attract arts).

In Chicago, the arts seem to have a stronger impact on both business services and high tech, but the arts show a clear multiplier effect, almost doubling its additional number of artists in the business services industries. This effect is still lower for high tech, but we should keep in mind that the high-tech industry grew the most in the second half of the period studied. On the other hand, the arts demand a smaller audience from high tech compared to business services in order to grow, as the high-tech coefficient to the arts is smaller than the business services coefficient to the arts. Chicago is one example where for both industries and in the general analysis, we see that the arts have a multiplier effect, and that jobs have an audience effect on the arts. This interpretation can also be applied to Philadelphia, PA; Houston, TX; Phoenix, AZ; and Seattle, WA.

Other cities also show that the arts have a stronger effect on jobs for both industries, but for some, neither arts coefficient is larger than one, so the multiplier effect is much weaker. This does not mean that the arts are not significant for these cities or industries; as we analyzed in chapter 4, many of these cities have arts coefficients larger than one in the general analysis. These smaller coefficients stem from narrowing down the employment numbers from the general analysis to more specific industries. Examples of these urban areas are Atlanta, GA; Boston, MA; Washington, DC; Detroit, MI; and Tampa, FL.

Arts and Jobs Coefficients by Industry Type for the Top 15 Urban Areas. Results are from First Difference Cross-Lagged Regressions for One Year Lags from 1998 to 2016 and After Meta-Analysis for All Resulting Coefficients and Standard Errors Also by Urban Area

		Arts and Business Services Jobs		Arts and High-Tech Jobs	
Urban Area	**Hex N[1]**	**Effect of Arts Jobs on Business Services Jobs[2]**	**Effect of Business Service Jobs on Arts Jobs[3]**	**Effect of Arts Jobs on High-Tech Jobs[2]**	**Effect of High-Tech Jobs on Arts Jobs[3]**
New York, NY	2383	**1.722 (0.007)**	0.223 (0.001)	0.425 (0.003)	**0.459 (0.004)**
Atlanta, GA	1781	**0.201 (0.012)**	0.096 (0.002)	**0.157 (0.005)**	0.114 (0.003)
Chicago, IL	1570	**1.909 (0.025)**	0.074 (0.001)	**0.804 (0.010)**	0.175 (0.002)
Boston, MA	1501	**0.510 (0.014)**	0.055 (0.001)	**0.456 (0.009)**	0.144 (0.003)
Philadelphia, PA	1388	**1.260 (0.016)**	0.097 (0.001)	**0.402 (0.005)**	0.296 (0.004)
Dallas, TX	1189	**0.570 (0.022)**	0.063 (0.001)	**0.312 (0.010)**	0.113 (0.003)
Los Angeles, CA	1127	**0.469 (0.011)**	0.104 (0.002)	0.132 (0.004)	**0.337 (0.008)**
Houston, TX	1089	**1.502 (0.023)**	0.072 (0.001)	**0.382 (0.009)**	0.093 (0.003)
Washington, DC	914	**0.869 (0.014)**	0.114 (0.001)	**0.474 (0.007)**	0.179 (0.004)
Detroit, MI	909	**0.921 (0.023)**	0.061 (0.001)	**0.230 (0.008)**	0.114 (0.004)
Miami, FL	781	**0.474 (0.018)**	0.111 (0.003)	0.174 (0.006)	**0.256 (0.009)**
Phoenix, AZ	756	**1.034 (0.025)**	0.081 (0.002)	**0.191 (0.010)**	0.114 (0.006)
Tampa, FL	720	**0.844 (0.037)**	0.039 (0.001)	**0.399 (0.014)**	0.098 (0.004)
Pittsburgh, PA	708	-0.137 (0.013)	**0.025 (0.003)**	**0.232 (0.006)**	0.094 (0.006)
Seattle, WA	703	**1.060 (0.022)**	0.116 (0.002)	**0.507 (0.016)**	0.116 (0.003)

Results are from cross-lagged coefficients for one year lag. The standard errors are in parenthesis.

otherwise.

1 Number of hexagons of 5sqkm associated with each urban area

2 Arts coefficients where the difference of arts jobs in time t minus t-1 are compared to jobs in time t minus t-1: jobs_(t-(t-1)) = a + b*arts_(t-(t-1)) + error

3 Jobs coefficients where the difference of jobs in time t minus t-1 are compared to arts jobs in time t minus t-1: arts_(t-(t-1)) = a + b*jobs_(t-(t-1)) + error

Table 5.13: Coefficients for the relationships between arts and business services, and arts and high tech from first difference models for the fifteen largest urban areas

Similar to Chicago, New York shows a multiplier effect of the arts on jobs, and an audience effect of business services jobs on the arts, with a very small audience requirement. However, in the high-tech model, jobs have a stronger effect on the arts. Therefore, in New York, the business services sector is more traditional and better established as the arts offer business services a multiplier effect, while the arts and high tech have similar synergies as both coefficients are close. Los Angeles, CA, and Miami, FL, show similar cases as New York, where the arts show larger effects on business services, but high tech shows a larger effect on the arts.

These analyses were performed in each one of the 481 urban areas considered in this study, even though a few of them did not present statistically significant results or enough cases to be examined.

When we break down the results into three tiers of urban area sizes, we see that 90 percent of the fifty largest urban areas showed that the arts have stronger effects on business services, with 8 percent presenting stronger business services effects on the arts. Seventy-four percent of the largest urban areas showed arts effects on high tech and 20 percent showed stronger high-tech effects on the arts. In the middle tier, 59 percent of urban areas showed stronger arts effects on business services, and 26 percent showed stronger business services effects on the arts. Fifty-three percent showed stronger arts effects on high tech and 36 percent showed stronger high-tech effects on the arts. And in the bottom-tier cities, we observed that 47 percent of urban areas showed stronger arts effects on business services against 41 percent of stronger business services effects on the arts; 46 percent of urban areas had stronger arts effects on high tech, and 43 percent had stronger high-tech effects on the arts. Based on these results, we observe that larger cities show a stronger arts effect on business services and high tech as their arts markets are larger and better established than in smaller urban areas. However, we still see that about half of the middle- and bottom-tier urban areas also benefit from the arts. Therefore, the positive impact of the arts on jobs may not be restricted to larger urban areas.

In the fourth analysis, we separated the arts variable into each one of its three categories: arts amenities, arts producers, and recreation, in order to examine how each arts category interacted with the other industries. The analyses are done individually by arts category, using the first differences model. For both business services and high tech, arts amenities showed the largest impact on jobs out of the three arts categories, but it also demanded the largest audiences to grow.

Arts producers and recreation had more moderate and less dramatic coefficients. In both the general analysis and industry-specific analysis, we observed that the arts amenities coefficient dipped below zero during the 2007–2008 financial crisis. Therefore, due to the nature of the funding structure in which arts amenities establishments operate and their apparent benefits to the overall economy, these establishments need more assistance during times of crisis, such as during the COVID-19 pandemic.

Besides the research presented in this chapter, I also plan on using structural equation modeling to build better models using latent variables as the impact of the arts and industry categories may be larger than the sum of its parts. I also plan on applying the same models to other industries, such as the goods-producing, education, and health sectors. Additionally, more research is necessary to understand urban area specific results and why some urban areas present negative coefficients from arts to jobs. As we add more data points over time, we will also be able to obtain better insight into the industries, especially the high-tech industry.

CHAPTER 6

CONCLUSION

What drives economic growth in modern American urban areas, employment or the arts? Do people move to cities only seeking employment or do they also move for the amenities and lifestyles that a city offers? Up until the first half of the past century, most people moved from rural to urban areas searching for employment and better wages. But since the 1960s, more and more people were seeking to enjoy urban amenities, such as popular arts districts, famous nightlife, access to beautiful natural landscapes, a wide range of cultural activities, and more often than not, a combination of all of them. Thus, as people moved to cities for amenities, they joined the pool of talented workers in the local labor force, attracting more companies that want to hire those talented workers, which would then increase the job market, attracting more companies, attracting more workers, attracting more amenities, and so on.

The reciprocal relationship between the arts and employment have become more dynamic in modern urban areas as people seek to move to cities not only for employment but also for the amenities and recreation opportunities offered in areas of higher population density. However, this dynamic does not happen equally in all urban areas. New York City is the classic example of an urban area that is so exceedingly global, diverse, and populated that the city has something to offer to anyone and satisfy any tastes at any time. Thus, we can say that the cultural and artistic densities in New York are major attractors for people who seek an urban and culturally rich lifestyle. However, these urban amenities depend on heavy and long-term investments in order to operate, as well as the human capital to not only produce but also to consume arts. These amenities may then be the reason why culturally inclined people move to New York, but at the same time, these amenities may be the result of having many culturally inclined people *in* New York.

Other industries benefit from being around the arts. The “Arts in the Loop Economic Impact Study” (Stevens 2015) points to the $2.25 billion direct and indirect economic impact of the arts in the Loop in Chicago each year. This revenue is not only generated directly from the arts, but also from restaurants, hotels, real estate, retail, transportation, taxes, and other services that patrons use in order to enjoy the arts in the Loop. On top of this revenue, there is also the appeal of other types of businesses, such as corporations, business services, high tech, and other industries, to be around reputable artistic, cultural, and recreational amenities in the city. The proximity of the arts to the industries mentioned elevates the location where they operate, increasing the attraction of highly educated workers to the area, who would then enjoy the urban amenities as they are conveniently located to where they live and/or work. The above narrative is what motivated me to explore the questions proposed in this dissertation: Do people move mostly for their jobs or do they also move for urban amenities? Even though not many cities are like New York City or Chicago, many urban areas also benefit from supporting the arts and entertainment industries.

This research demonstrates that the arts and non-arts industries have close relationships, and each one provides a different pillar in joint processes in which one reinforces the other. The two pillars are the multiplier effect, most of the time generated from the arts industries, and the audience effect, mostly generated on the side of the non-arts industries. The arts multiplier effect is the number of non-arts jobs that one arts job attracts to a city as a result of people moving to cities seeking lifestyle and entertainment options. The audience effect is the number of additional audience members a city needs to attract more artists to the city, or the local population necessary to have a market large enough for a certain number of additional artists. Therefore, both effects are necessary to have continuous growth of both types of industries: as the arts attract more non-arts related jobs, these non-arts jobs aggregate an audience that then attracts more artists, in a looping cycle. These two processes were the results most commonly found; however, we see variations, some of which are dependent on the size of a city, the amount of art a city has or has not, and more specific circumstances not all explored in this dissertation.

In order to understand how these dynamics take place, I explore the reciprocal relationship between arts and employment by using a collection of quantitative methods and analyses that when combined, provide promising results to further our understanding. This study is a product of quantitative data analyses, with passages on a few case studies.

This dissertation is presented in five chapters. In chapter 1, I present the main arguments from the current literature that inform this research. In chapter 2, I restructure the dataset from the US Census Bureau that is originally provided at the ZIP code level into uniformly sized hexagons throughout all urban areas in the US. In chapter 3, I redefine categories of arts and non-arts industry categories to estimate the employment numbers based on the total number of establishments data. In chapter 4, I analyze the relationship between arts and non-arts employment as general variables, in different time lags, interactions, by urban area, and by arts categories. And in chapter 5, I focus on the business services and high-tech industries as the non-arts categories to be compared with the arts categories.

In this dissertation, I focus on the methodology as much as I do on the analyses. This strong emphasis on the methods revolves around issues of comparability among units of analysis, as each ZIP code and urban area have different dimensions that require standardization in order to make a nationwide analysis possible. The methodological section is divided into two chapters: chapter 2 discusses the standardization of datasets in urban areas, and chapter 3 discusses the computation of the data based on the pattern established in chapter 2. The empirical section is also divided into two chapters in which I apply the dataset calculated in the methodological chapters to explore the questions about the impact of arts on non-arts employment.

The methodological section connects two distinct elements to enable the empirical analysis: first, we deal with issues related to the geographical representation of data; and second, we recalculate the US Census County Business Patterns (CBP) dataset based on the geographical standards modified in the first part.

Data transparency have increased the availability of quality data for the social sciences. However, we must still take care when adopting datasets for studies, especially if the data is supposed to be aggregated as a time series, which is the case in this dissertation. In chapters 2 and 3, I show how time and geographical inconsistencies in the data affect the reporting of employment numbers if the data was kept at the ZIP code level. Even though ZIP codes somehow reflect population size and density, their area sizes vary, boundary updates are not scheduled or predicted, and the main purpose of ZIP codes is to deliver mail, not data analysis. In addition, as the variables are calculated as estimates based on two separate datasets (from the same series), we cannot afford to include even more differences by limiting the dataset to a unit that is not proper for analysis.

In chapter 2, I propose a method to standardize datasets based on location and area in order to improve estimates of employment numbers and the continuity throughout the different years. By equalizing the area using the proposed hexagonal method, we solve not only the yearly inconsistencies and areas size differences found in ZIP code data, but we accommodate a more realistic approach to how people move around in cities. For example, single buildings in Midtown Manhattan have their own ZIP codes due to high volumes of mail; however, the impact of the businesses within that single building cannot be measured only within that single ZIP code as the economic activities reach further to neighboring areas. The reach of these economic activities is a topic for another research project; however, people who work in single-building-ZIP codes patronize businesses and are patronized by customers from neighboring ZIP codes. While the ZIP code is a legitimate geographical codification, the human activities in cities travel beyond those boundaries. In the case of Midtown Manhattan, hexagons incorporate the establishments in very small ZIP codes into their surrounding areas, attempting to cover the distances people move through in a regular day.

At the same time, many ZIP codes that are classified as urban also contain large portions of rural land. In the case of hybrid urban-rural ZIP codes, hexagons are useful to narrow down the area of the original ZIP code, placing them on to built-in urban hexagons and reducing the distribution of employment to overlap the urban areas while excluding from the analysis the rural areas where urban employment does not exist. Thus, the process of transforming ZIP code data into hexagons benefits both dense urban areas such as New York City and spread-out urban areas found in most of the country.

The initial total number of urban ZIP codes is 11,200, which were then transformed into 63,166 hexagons of five square kilometers in area. The increase in the number of cases is due to the readjustment of large ZIP codes into smaller (and therefore multiple) hexagons. To be sure, the placement of hexagons could be arbitrary, as a slight difference in a few feet could change the entire configuration of the hexagonal grid and how it is used to recalculate the data. However, here I used the edges of the Census Bureau's continental US map as a parameter to define the placement of the hexagon grid, but as long as the position of the hexagons consistently correspond to the position of the data points throughout the study, this hexagon method should benefit the empirical analysis.

Chapter 2 shows the techniques that details the geographical transformations of the maps to create a correspondences table that intersects the shapes of ZIP codes and hexagons, creating "slivers" as the proportional areas used in the algorithm to recalculate the number of jobs per industry. Each sliver is at the same time part of a ZIP code and part of a hexagon. Slivers are used to calculate the proportion of the number of jobs based on the area of a ZIP code to be assigned onto a hexagon.

Chapter 3 describes the format of the US Census County Business Patterns (CBP) datasets, the processes to recalculate the estimated number of jobs by industry and sliver, and the methodologies used in the empirical chapters, where we combine cross-lagged regressions and meta-analysis.

An important argument from chapter 3 regards the continuity of the time series data. Industries are identified in the CBP by the North American Industry Classification System (NAICS), which changes every five years. As the economy evolves, the classification system adapts to reflect the growth of new industries. The CBP data considered in this study is annual and from the period between 1998 and 2016, during which the data had gone through four NAICS updates. After each update, some (not all) industries were classified differently, with different codes or industry groupings, generating possible time consistency issues. In chapter 3, I propose aggregating industry codes in meaningful ways for this study by creating category and subcategory variables that are later used for regressions. Subcategories should be linked to a single category, and the sum of the subcategories should equal the value of the parent category. Managing industry classifications into categories and subcategories is critical because the analysis compares one time period with a later time period; therefore, the different time periods must be compatible with each other. Appendix B.2 presents the full tables of the main industry codes that were included in each category and subcategory.

Chapter 3 outlines the methodology used in chapters 4 and 5 to analyze the impact of arts and non-arts employment. Even though I have tried many methods over the years, in this dissertation, I present a combination of cross-lagged regressions and meta-analysis as the main empirical methodology. Each cross-lagged regression analysis comprises a pair of regression equations that takes one arts-related variable and one non-arts-related variable in two different years.

As classical economic theories posit that people move to cities for employment, the null hypothesis is that jobs attract arts. In other words, people from rural areas would move to cities with the goal of escaping poverty and finding employment. As the number of people in the cities grew, arts establishments could be sustained, and therefore, the arts followed jobs. The alternative hypothesis is that the arts attract jobs. A more recent phenomenon has highly educated and talented workers choosing to move to urban areas that offer arts and recreation establishments, increasing the interest of companies in the local labor force and attracting companies to these urban areas. Thus, jobs follow the arts.

There are many possible methods to examine the impact of arts on jobs and vice versa, making it hard to choose which methods to use. After years of testing, the best methodology was a combination of cross-lagged OLS regressions with fixed-effect meta-analysis that would analyze all possible combinations of pairs of years from 1998 to 2016 in each model. Each analysis requires a pair of years as the independent variable should be a year prior to the year in the dependent variable; in other words, cause should precede the effect. Even though the theory and hypothesis in this study are outlined and justified by other research in the literature, I do not discuss the results in causality terms as there are still other methods to be tried before attempting that type of interpretation. For example, I have been exploring the use of structural equation modeling and growth curve modeling that could better inform a causal interpretation of the phenomenon discussed here.

One regression equation has the non-arts jobs variable as the dependent variable in the later year, and the arts jobs variable in the earlier year as the independent variable, from which we obtain a coefficient that indicates how jobs attracts arts (the null hypothesis). The other equation has the arts jobs variable as the dependent variable in the later year, and the non-arts jobs variable in the earlier year as the independent variable from which we obtain a coefficient that indicates how arts attract jobs (the alternative hypothesis). Thus, we have a pair of coefficients, one in the direction of arts to jobs and another in the direction of jobs to arts. For each pair of coefficients with the different directions, we compare both coefficients to find which one had the biggest impact on the other. After obtaining the coefficients for both equations, if the "arts attract jobs" coefficient is bigger than the "jobs attract arts" coefficient, we interpret that pair of regressions as the arts having a larger impact on jobs than the reverse. And if the "jobs attract arts" coefficient is bigger than the "arts attract jobs" coefficient, we interpret that pair of regressions as jobs having a bigger impact on arts than the reverse.

The biggest challenge with the cross-lagged regression method discussed here is the vast number of possibilities in the combination of pairs of years, pairs of categories and subcategories, and types of regressions. In this dissertation, I run three types of regressions: one-year lag, ten-year lag, and first differences. In the one-year lag, the difference of the years between the dependent and independent variables is one year; similarly, the difference in the ten-year lag regressions between dependent and independent variables is ten years. The first difference regressions compare only the changes between two consecutive years instead of the total number of jobs in each category. The regressions are also run for three pairs of categories: arts and non-arts jobs, arts and business services jobs, and arts and high-technology jobs.

Defining the cross-lagged regression types as mentioned helps narrow down the analyses; however, there are still a large number of results to be analyzed as the output of each pair of regressions generates a pair of coefficients. The fixed effects meta-analyses are useful here to reduce the number of coefficients into a single pair of coefficients, which we can then compare against each other. In most studies that apply meta-analysis methods, the random-effects meta-analysis is recommended as for most studies the regression results are derived from different subjects and data collection methods. However, in this dissertation, the fixed-effects meta-analyses is most appropriate as for each separate study, the subjects and methodologies are identical. From the meta-analysis, we obtain the standardized mean difference (SMD), which are effect size measures that prioritize coefficients with lower standard errors, summarizing findings from equivalent studies. After the two fixed-effects SMDs have been calculated, we perform the same comparison for each single pair of regressions, observing which variable, arts or jobs, had the bigger impact on the other.

The methodologies presented in chapters 2 and 3 are products of years of trial and error, looking for better ways to deal with such a large, skewed, and intricate dataset. There were many other data wrangling and analysis methods that could have been implemented, but the methods selected for this study were the simplest to perform and interpret out of all of them; and following the parsimony principle, the simplest methods were preferred.

The empirical analyses are presented in chapters 4 and 5. Chapter 4 explores the models in which there are only two employment categories—those related to the arts, and those that are not related to the arts, with hexagons as geographical units—for nineteen years of data, from 1998 to 2016. By separating the arts from non-arts employment, we are able to observe how the two categories interact with each other over time.

Similarly, chapter 5 investigates the relationships between the arts and two industry categories by replacing the non-arts jobs variable with either business services or high-technology categories. These two industries are frequently featured in studies due to their synergy with the arts. The business services category comprises industries such as accounting, advertising, consulting, finance, insurance, law, real estate, and business supporting industries. Even though high technology is very often considered synonymous to the internet industry, it also includes industries such as design, biotechnology, high-tech manufacturing, research, and telecom—i.e., industries where most of the workers are required to have specialized knowledge to perform their functions.

At this point, it is important to note that the arts and jobs variables (as well as the variables in their categories and subcategories) in their natural employment numbers are extremely skewed to the right as the vast majority of hexagons have low numbers of arts and jobs, and a small number of hexagons in the largest urban areas show outlying employment numbers in the variables. Approximately half of the hexagons are within the boundaries of the top fifty largest urban areas, but even so, the number of outlying hexagons is sparsely distributed. These differences in size and the inclusion of outliers in the same analysis bring the coefficient values down, not reflecting the differences in results in larger and smaller urban areas. The outliers are especially important in this study as they refer to the largest urban areas where most arts and a great deal of industry activities happen.

The variables in chapter 4 are aggregated by industry parent category as either arts or non-arts. The aggregated variables provide the baseline analyses of the data for a general understanding of the two types of industries. In the first model, we regressed the variables from 1998 as the independent variable and the variables from 2016 as the dependent variables, as both natural employment numbers, their log, and first differences. In all three regressions, the arts presented a coefficient much larger than jobs, indicating that the arts have a multiplier effect over jobs. The arts had a 1.25 multiplier for each non-arts job in the natural employment number analysis, a .25 percent for each 1 percent additional non-arts jobs in the log regressions, and 1.82 arts multiplier for each non-arts job when considering only the first differences in the first and last one-year period. On the other hand, the coefficients for the non-arts jobs on the arts were .0145, -.295, and .033, respectively. Thus, the arts coefficients were larger than jobs in the three analyses, and the very small (but statistically significant) coefficients from jobs to arts show that in order for non-arts jobs to attract one additional arts job, there should be an increase of multiple non-arts jobs. In conclusion, this simple model indicates that even when we consider all hexagons in all urban areas at the same time, the arts have a strong impact on jobs as a multiplier effect as non-arts jobs make up for the audiences necessary to attract more artists.

Therefore, these results are indicative of two interrelated theories: the arts offer multiplier effects on jobs, and jobs require a critical mass to attract the arts—what I call the audience effect. In other words, while the arts attract many jobs to a city, the audience needs to increase significantly in order to attract more artists. Take, for example, the first differences analysis mentioned above: one arts job could attract on average 1.82 non-arts jobs (as the multiplier effect), but non-arts jobs have a coefficient of .033, which indicates that on average, thirty non-arts jobs are necessary to attract one additional artist (as the audience effect). But in this case, the regressions consider how the changes in each variable from 1998 to 1999 affects the changes in the number of arts and jobs from 2015 and 2016, and that effect is not statistically satisfactory.

The analysis described above includes all hexagons in all urban areas while considering only the first and last year of data, over a nineteen-year period. However, results may vary year by year according to systemic and local circumstances, and by different lengths of time as results for one-year periods should be different than for ten-year periods. Therefore, for each one- and ten-year period possible within the nineteen years of data, we run a pair of cross-lagged regressions in order to observe how results would differ year by year, in the short and long terms, using log-transformed variables and first differences. Then, we use fixed effects meta-analysis in order to reduce the number of coefficients to be analyzed. To help us compare the results of the relationship between the arts and the three non-arts industries in this research, I present next a series of graphs summarizing the findings from each type of regression in chapters 4 and 5.

The business services and high-tech variables are part of the "jobs" variable, along with other industry categories; thus, the size of the coefficients for "arts attract jobs" tend to be bigger than the "arts attract business services" and the "arts attract high-tech" coefficients, while the size of the coefficients for "jobs attract arts" tend to be smaller than the "business services attract arts" and the "high tech attract arts" coefficients. With the exception of when the coefficient is near zero or the confidence interval includes zero, the coefficients are statistically significant, even if they are small or negative.

Figure 6.1 shows the results for the arts effects on jobs on the three models using log-transformed variables in 1-year lags—i.e., we are looking for the arts effects from one year prior on non-arts jobs, business services, and high-tech variables in the next year. As the data is released yearly, the 1-year lag represents the shortest term possible. We observe a higher range of coefficients and ranges for the "arts attract jobs" regression than for the other two industries, which also presented higher spikes and also declines over time. The business services and high tech were in a range much smaller than the non-arts variable and had milder periods of growth and decline.

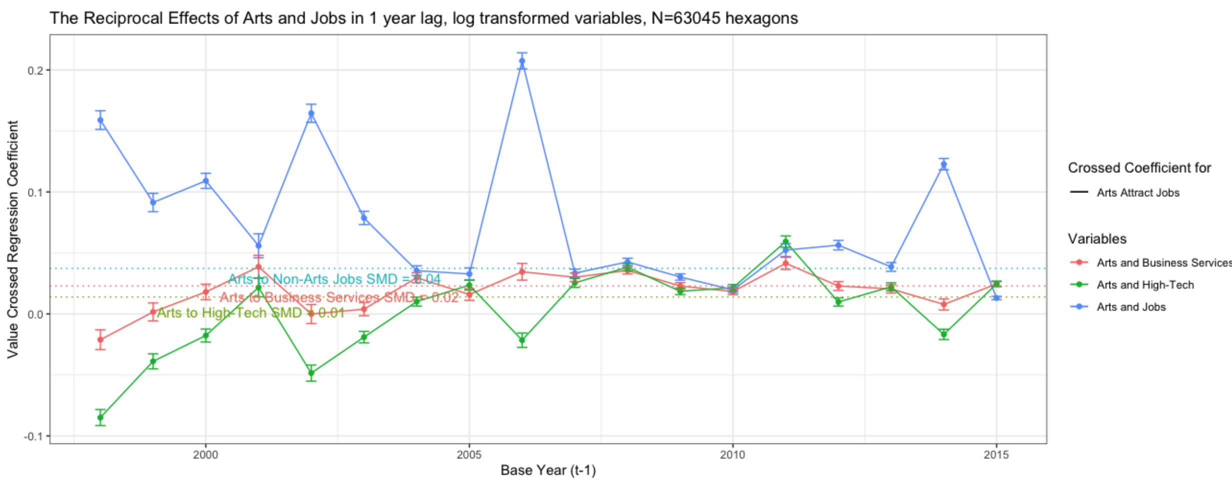

Figure 6.1: Coefficients for arts effects on jobs, business services, and high tech in one-year lag model

For most of this period, the coefficients for business services and high tech seem to run roughly in parallel, with periods of great differentiation from the non-arts jobs coefficients. This may indicate to us that business services and high tech may operate at similar levels and patterns when it comes to the arts. The SMD for business services is higher than high tech, indicating that in this period, the arts attracted more jobs in business services than in high tech.

On the other hand, figure 6.2 shows the results for the jobs effects on the arts on the three models using log-transformed variables in 1-year lags, or the effects of non-arts jobs, business services, and high tech on the arts from one year to the next. In this case, we see that the non-arts jobs coefficients are (with the exception of two years) mostly cumulative effects.

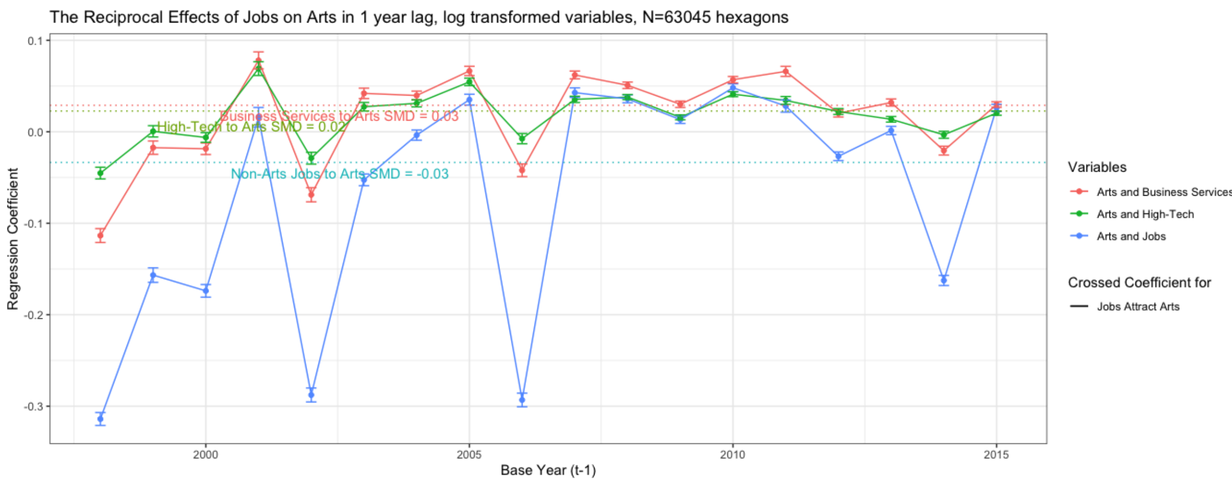

Figure 6.2: Coefficients for jobs, business services, and high-tech effects on arts in one-year lag model

The SMD for non-arts jobs to arts is negative, again relating to the differences in the arts industry size across all hexagons. For example, some hexagons may have similar amounts of non-arts jobs, but very different sizes of the arts industries, throwing off the relationship between the two variables and bringing the coefficient to a negative. The SMD for high tech is smaller than the SMD for business services, indicating that high-tech audiences need to be larger than business services audiences in order to help the growth of the arts. It is also the case in this analysis that the effects of business services and high tech individually span a much smaller range than the effects of the non-arts jobs industries as a whole.

Figure 6.3 shows the results for the arts effects on three categories of jobs using log-transformed variables in 10-year lags; in other words, the independent variable year is from ten years prior than the dependent variable. This type of analysis shows us longer term results, which can reduce the noise of the 1-year analysis to emphasize hidden differences. The coefficients for "arts attract non-arts jobs" are the largest of all three models, with business services in second and high tech in third. Again, we see that the arts attracted more business services jobs than high-tech jobs in that period. We also see that both industries run similar and parallel trajectories, which can be very different from the tendencies of the non-arts jobs coefficients. For example, in the analysis from 2002 to 2012, we see a growth spike in non-arts jobs, while business services and high-tech jobs showed a decline compared to the previous period.

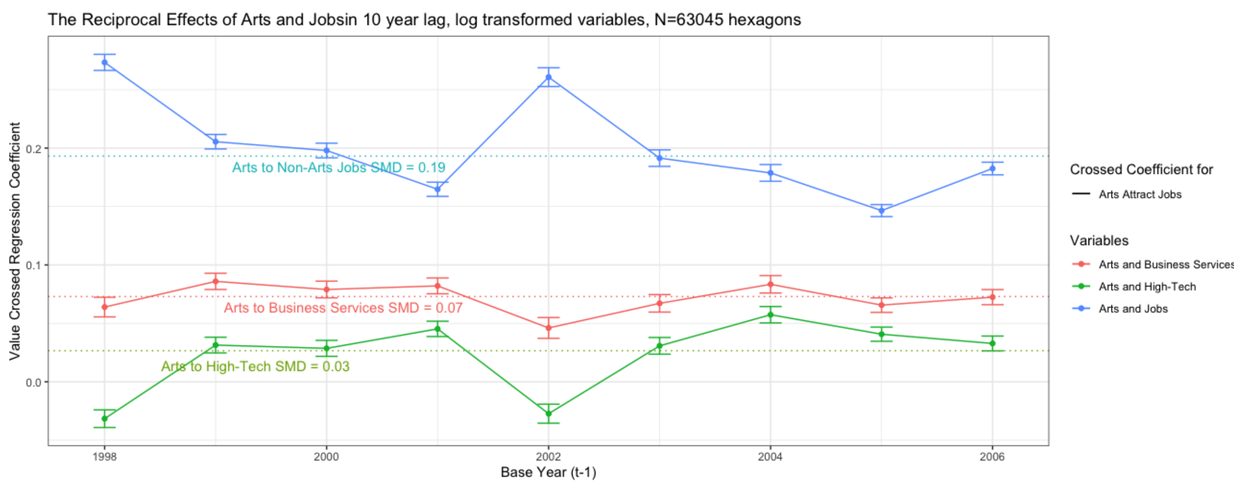

Figure 6.3: Coefficients for arts effects on jobs, business services, and high tech in ten-year lag model

In the long term, the ranges and variations of the coefficients seem smoother than in the short-term analyses. We also see that in the long term, the SMDs are more pronounced, with an arts to non-arts jobs SMD of .19 compared to the equivalent SMD in the short term analysis of .04. The business services SMD in the 10-year analysis is .07, and .02 in the 1-year analysis. The high-tech SMD is .03 in the 10-year analysis and .01 in the 1-year analysis. Again, the smaller difference in SMD from the short- to the long-term analyses may be attributed to the slower growth of the high-tech industry in the first half of the period with great acceleration in the second half.

Figure 6.4 shows the results for the jobs effects on the arts on the three models using log-transformed variables in 10-year lags. The non-arts jobs coefficients and SMD are much smaller than for the two industries. The SMD for business services and high tech are the same, 0.09, while the SMD for non-arts jobs is -0.16, again due to the larger differences in the size of the arts industries in relation to non-arts jobs in general than when compared to business services or high tech.

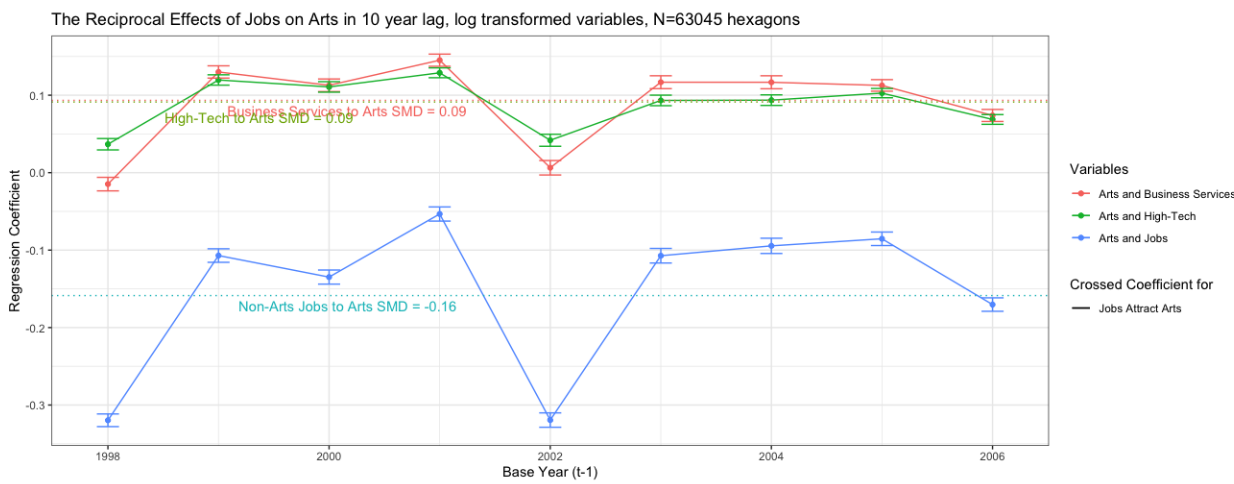

Figure 6.4: Coefficients for jobs, business services, and high-tech effects on arts in ten-year lag model

In the long-term analysis, we see business services and high tech attracting the arts at similar rates and ranges and in parallel, but the pattern seems more similar to the non-arts jobs coefficients than in previous analyses.

Therefore, in the log-log regression models above, the short-term coefficients for the arts show smaller changes than the long-term coefficients, illustrated by the SMDs from arts to jobs that increase from .04 in the one-year regression to .19 in the ten-year regression. On the other hand, the jobs to arts coefficients for both the short and long terms are negative, again, due to the uneven number of arts jobs when we consider all hexagons at once. However, we still observe an absolute increase of the jobs SMD -.0335 to -.16 in the long term. In other words, the long-term effects are much larger than the short-term effects, as changes accumulate over time. This finding reinforces the idea that the arts are long-term investments, as argued by Blau (1989), and they should be treated as such with long-term planning. At the same time, non-arts industries are not as impactful in attracting the arts, on average. This result may be a symptom of high investment in the arts in each urban area, where the arts make those places attractive to other industries, but the presence of other industries alone is not sufficient to have a strong arts presence.

The first difference analyses regress the changes from one year to another for one variable on the changes from the same two years for the other variable. Figure 6.5 shows the results for the cross-lagged regressions in first differences for the three models. The coefficients for the arts to non-arts jobs are larger than each of the other two industries, but we see again that the arts attracted more business services jobs than high-tech jobs. We also observe a larger variation in the business services coefficients, while the arts to high-tech coefficients have a smaller range and are closer to zero.

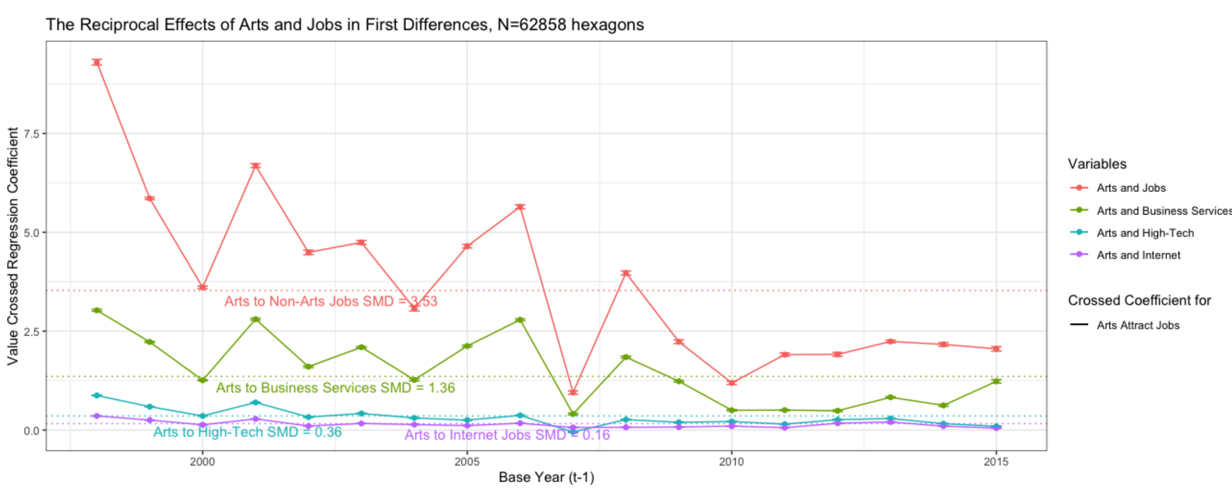

Figure 6.5: Coefficients for arts effects on jobs, business services, high tech and internet in first differences

The results from figure 6.5 are interpreted in employment numbers as the variables refer to the changes in number of jobs. Therefore, each arts job attracted 3.53 non-arts jobs, while each arts job attracted 1.36 business services jobs, .36 high-tech jobs, and 0.16 internet jobs. These numbers show that for non-arts jobs in general and business services, the arts have a multiplier effect, but that is not the case for the high-tech and internet industries.

Figure 6.6 shows the coefficients of the effects of non-arts jobs, business services, high tech, and internet on the arts. In this graph, the high-tech and internet coefficients have a wider range of values than the other two industries. Due to these disparities, I calculated the partial SMDs, cutting the period in two parts for the jobs effects on the arts. The first half of the period showed an SMD for the effects of high tech on the arts of .3775, and of .11 for the second half of the period. The effects of internet jobs on the arts are .5448 for the first half and .1299 for the second half. These differences are indicative of the evolution of the internet industry and its impact on the high-tech industry as a whole.

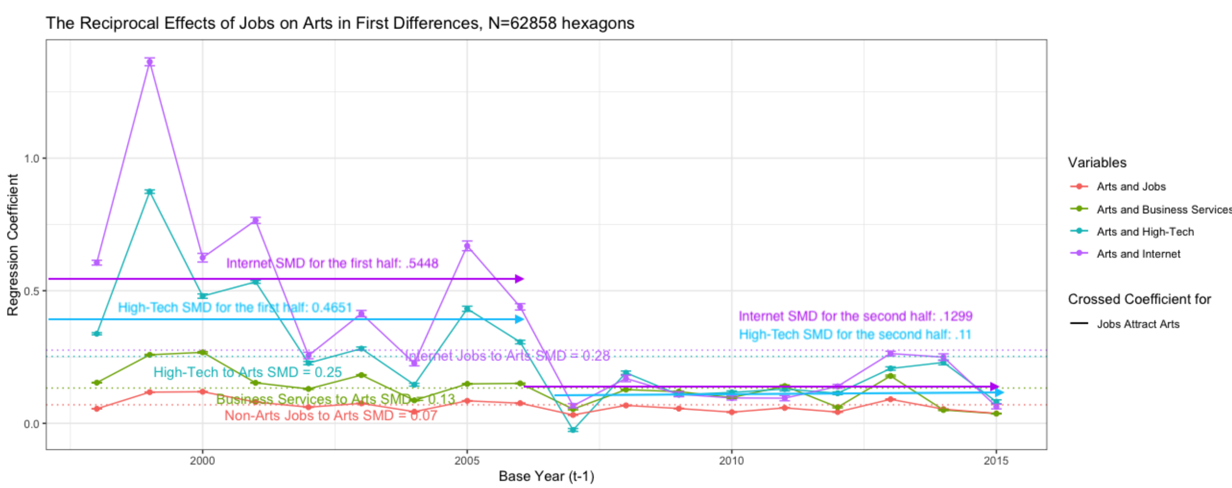

Figure 6.6: Coefficients for jobs, business services, high-tech and internet effects on arts in first differences

From 1998 to 2007, different types of high-tech companies had more influence, such as design and high-tech manufacturing. From 2008 on, the internet industry gradually grew, overtaking the influence of the other industries. Therefore, in the first half of the period, we observe that the arts did not have a multiplier effect on high-tech or internet jobs, but high-tech and internet jobs had very low audience effects on the arts: about two additional high-tech jobs were necessary in order to attract one more artist. However, in the second half of the period, the arts still did not present a multiplier effect on high tech, but the high-tech coefficients started to look more similar to the coefficients for business services, requiring larger audiences to attract more artists.

These small coefficients indicate that in order to receive one more artist, there should be multiple additional audience members. Therefore, non-arts jobs in general need to attract larger audiences than individual industries, with the exception of one year, when high tech has an even smaller coefficient, and thus, the requirement of a larger audience. Compared to the general non-arts job category, business services need a smaller audience in order to attract additional artists, but high tech seems to require an even smaller audience, indicating that high tech has a strong pull on the arts. High tech attracted artists with smaller audiences in the first half of the period. As the internet industry boomed in the second half, the size of the audiences started to look similar to the business services audiences.

Considering the differences in each urban area, the next analysis nests the cases for each urban area to run the first differences regression models individually, generating unique results for each city. Then, for each urban area, we compare the SMDs for the path from arts to jobs and from jobs to arts to find which direction showed the larger coefficient. If the arts SMD was larger than the jobs SMD, then the urban area is classified as having "arts attracting jobs" while a larger jobs SMD classified the urban area as having "jobs attracting arts."

In table 6.1, 61 percent of the urban areas showed that arts attract jobs, 27 percent of the urban areas showed that jobs attract arts, and 12 percent of urban areas either did not present statistically significant results or did not have enough cases for the model. However, when we break down the hexagons according to population size into three tiers, 94 percent of the fifty largest urban areas showed that arts attract jobs, compared to 70.3 percent for the middle-sized urban areas, and 56.5 percent of the smaller urban areas. This indicates that larger cities have more influential arts industries compared to smaller cities, as artists find larger cities more attractive to their craft as those are the places where audiences are. The full table of results can be found in appendix E.

	Non-Arts Jobs		Business Services		High-Tech	
	Arts Effect on Jobs	Jobs Effect on Arts	Arts Effect on Jobs	Jobs Effect on Arts	Arts Effect on Jobs	Jobs Effect on Arts
All Urban Areas	294 (61%)	131 (27%)	248 (52%)	159 (33%)	226 (47%)	179 (37%)
Top Tier	47 (94%)	2 (4%)	45 (90%)	4 (8%)	37 (74%)	10 (20%)
Middle Tier	78 (70.3%)	25 (22.5%)	66 (59%)	29 (26%)	59 (53%)	40 (36%)
Bottom Tier	169(56.5%)	104 (34.8%)	142 (47%)	123 (41%)	139 (46%)	130 (43%)

* The residual percentage points refer to urban areas with not significant results or not enough data to produce results

Table 6.1: Proportion of arts and jobs effects by industry and urban area size

But we still cannot discount the benefits from the arts industries in over half of the smaller urban areas. In a notable case, the population of the small town of Colquitt, GA, was declining as manufacturing industries moved overseas and the younger population moved to larger cities. Then, in an unusual artistic move, the talented people of the town came together to produce a new musical, called Swamp Gravy[1] (Geer 1996), telling some of the townspeople's stories. This new

[1]Kenny Malone and Noel King, Swamp Gravy (Update). Radio Broadcast. NPR. https://www.npr.org/2020/11/25/939016028/swamp-gravy-updated.

musical led to visitors coming from nearby towns, the development of the local businesses on Main Street and the areas surrounding Cotton Hall Theater, and the establishment of an arts council to support the artistic development of the town. The case of this single theater in a small town illustrates the clear economic benefits that one arts establishment brings to revive the local economy: the community got involved in the production of the musical, and the restaurants, hotels, and shops gained more business as a bigger sense of place and belonging transpired.

Colquitt, GA, is not classified as an urban area, so the city is not included in our analysis. However, similar to Colquitt, some of the smallest urban areas in the dataset show large arts multiplier coefficients. For example, the town of Sumter, SC, has a population of forty thousand people, but its arts coefficient indicates that each arts job attracts on average 25.7 non-arts jobs to the town. Sumter is a historical city, with seventeen historical buildings registered on the National Register of Historical Places, a public garden featuring all eight species of swans, and a regional baseball team stadium. The coefficient of 25.7 is very high when compared to Chicago's arts coefficient at 4.6, the largest of all top fifty urban areas. At the same time, Sumter and Chicago have similar jobs coefficients, .035 and .038 respectively, and thus, their audience effects are very similar. Therefore, larger urban areas have even larger scales in the impact of their arts industries to the local economy: as the size of the urban areas grow, the volume of the impact multiplies, but the coefficients and total size seem to go down.

On the jobs side of the general analysis, only 4 percent of the fifty largest urban areas showed that jobs attract arts, compared to 22.5 percent in the middle-sized urban areas, and 34.8 percent of the smaller urban areas. In other words, smaller urban areas are more likely to have jobs attracting arts. However, we should note that most of the smaller urban areas where jobs attract arts usually have a negative arts coefficient, as most of their hexagons might present a low number of employment in the arts, or numbers not large enough to have an effect on non-arts industries.

Table 6.1 also shows the different proportions of effects in urban areas based on the business services and high-tech industry analyses. Ninety percent of the top-tier urban areas show that arts attract business services jobs, but that proportion drops to 59 percent of the middle-tier urban areas and to 47 percent of the bottom-tier urban areas, indicating again that the arts attract more business services in larger urban areas than in smaller urban areas. On the other hand, 8 percent of the top-tier urban areas showed that business services attract arts, while 26 percent of the middle-tier and 41 percent of the bottom-tier urban areas showed the same results. In other words, as the size of the urban area decreases, there are more cases of stronger jobs effects than arts effects.

Similarly, we see that 74 percent of the top-tier urban areas show that arts attract high-tech jobs, but that proportion drops to 53 percent of the middle tier and 46 percent of the bottom-tier urban areas. Again, we see that larger urban areas will have the arts attracting high-tech jobs, but in fewer places than in the general and business services analyses. Twenty percent of the top tier urban areas showed that high tech attracts arts jobs, while 36 percent of the middle tier and 43 percent of the bottom tier showed the same result. In comparing the results from business services and high tech, we observe that there are still more urban areas where high tech attracts arts, while arts attract business services. The proportion of the two results in the bottom tier are very similar for both business services and high tech, but in larger urban areas, we see higher proportions of urban areas with higher effects of the arts on jobs.

Lastly, Table 6.2 shows the SMDs for the models from both chapters 4 and 5, where the arts variable was broken down into its three arts categories: arts amenities, arts producers, and recreation. This type of analysis allows us to observe how different types of arts interact with the non-arts industries.

	Non-Arts Jobs		Business Services		High-Tech	
	Arts Effect on Jobs	Jobs Effect on Arts	Arts Effect on Jobs	Jobs Effect on Arts	Arts Effect on Jobs	Jobs Effect on Arts
Arts Amenities	5.99	0.01	2.34	0.02	0.75	0.04
Arts Producers	4.54	0.03	1.93	0.06	0.47	0.10
Recreation	3.87	0.03	1.40	0.06	0.42	0.13
Arts (Combined)	3.53	0.07	1.36	0.13	0.36	0.25

Table 6.2: Meta-analyses coefficients between arts categories and jobs

Arts amenities show the highest SMDs, followed by arts producers, and then recreation. The arts amenities also showed more frequently the highest arts coefficients out of the three types of arts in all three models. However, we see that the lowest coefficient also belongs to arts amenities during the 2008 financial crisis. In other words, during economic prosperity, the arts amenities are the category that most contribute to attracting non-arts jobs to a city. But in periods of economic crisis, the arts amenities also take the hardest hit as most of their funding depends on how well their patrons (e.g., corporate earnings, government, and individuals) are doing in the same time period. Also, in bad times, we may lose even more performing arts establishments than other types of establishments, but as they are needed for economic rebound, more support should be available for arts establishments during periods of crisis, such as the COVID-19 pandemic.

The arts amenities are also the arts category with highest audience effect; in other words, a larger audience needs to be formed in order to attract more jobs in arts amenities than for arts producers and recreation. The arts amenities are more susceptible to fluctuations, but are also the most attractive of the three arts categories. The higher level of individual involvement in the production in the arts producers and recreation industries protects these industries from the vulnerabilities that the arts amenities are subjected to.

In all the analyses presented in this dissertation, we observe the multiplier effect of the arts and the audience effect of the non-arts industries. These two effects explain the chicken and egg reciprocal relationship between arts and jobs, as artists need audiences in order to move into cities, while the audience can also move to cities where the arts are.

Further research is required in this field—for example, the use of different statistical analysis methods, such as structural equation modeling, growth curve modeling, and the use of latent variables to better portray the different markets. This research can also be expanded by including more industry-specific analyses, such as manufacturing and retail, as well as including more socio-demographic variables, such as education and real estate values.

By continuously understanding the reciprocal relationship between the arts and jobs, we get closer to unveiling the importance of a charming, interesting, and exciting aspect of the city that attracts people and businesses, and what turns them into the center of modern urban living.

APPENDIX A: CHAPTER 2 SUPPLEMENTS

APPENDIX A.1: MAP OF ZIP CODES THAT INTERSECT URBAN AREAS

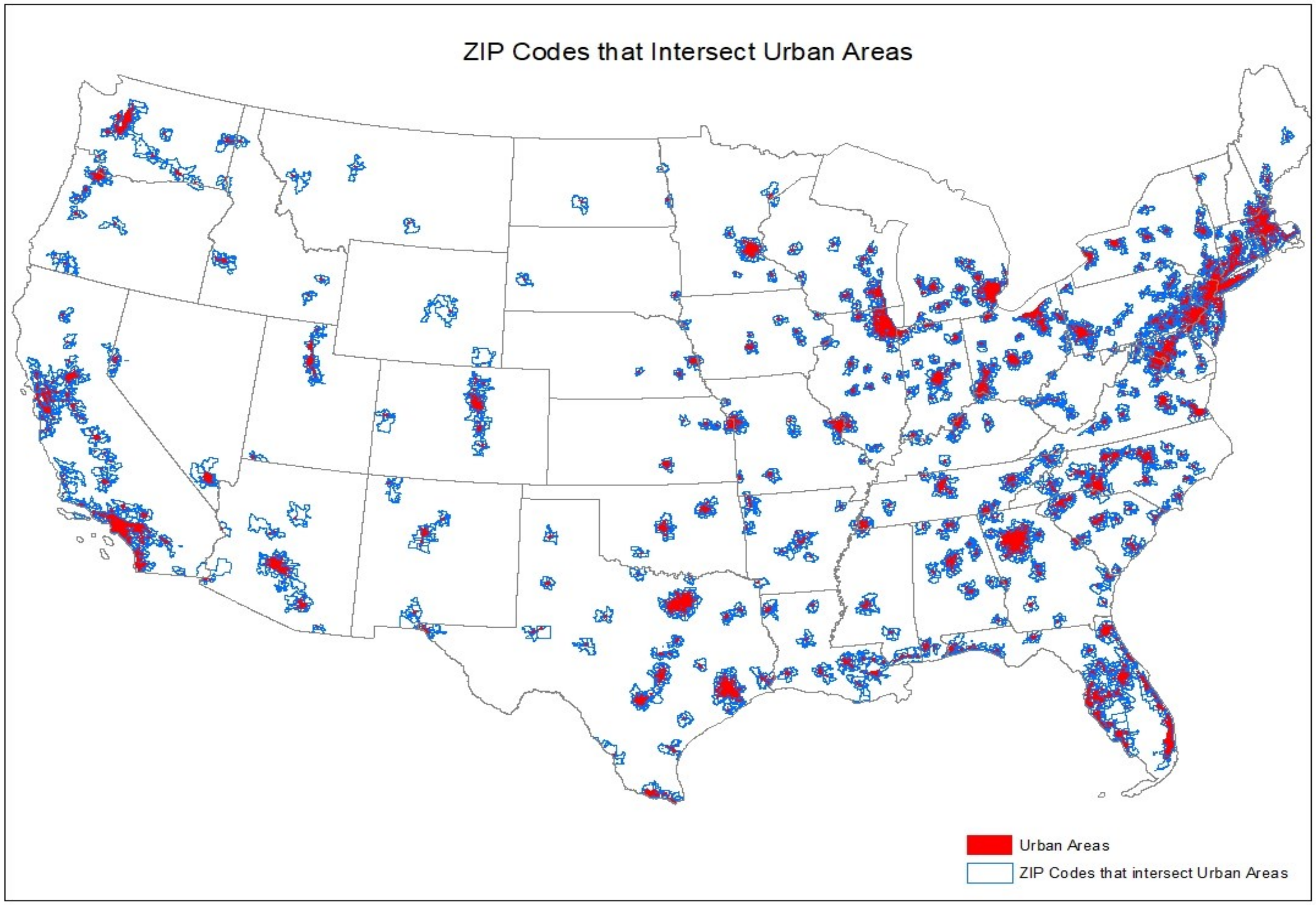

Figure A.1: Map of zip codes that intersect urban areas

APPENDIX A.2: ARCMAP TOOLS AND SETTINGS

Setting Projection System

Download the shapefiles from Tiger/Census website. Several layers: states, zip codes, county, and urban areas and clusters.

Using the Project tool on ArcMap: ArcToolbox > Data Management Tools > Projection and Transformations > Project Input dataset or feature class: map layer that needs to be projected Output coordinate system: US_NATIONAL_ATLAS_EQUAL_AREA

Tessellate Hexagons over Continental US States Map

This process generates a new polygon layer with hexagons that cover the geographical area as defined by the used. For this process, I used a continental States boundary map to define the extent to which the software should create the grid of hexagons. The details of this process follows:

On ArcMap: ArcToolbox > Data Management Tools > Sampling > Generate Tessellation Extent: "same as layer states" (assuming the States map is added to the map document) Top: 732381.943925 Right: 2521880.995939 Bottom: -2116998.903044 Left: -2037337.707595 (these fields are filled automatically by the software) Shape type: Hexagon Size: 5 square kilometers Spatial reference: "US_National_Atlas_Equal_Area"

The final product should be the same hexagon overlay used in this study. Because of the geographic dimensions, this task, performed in ESRI ArcMap, takes a long time to complete and render.

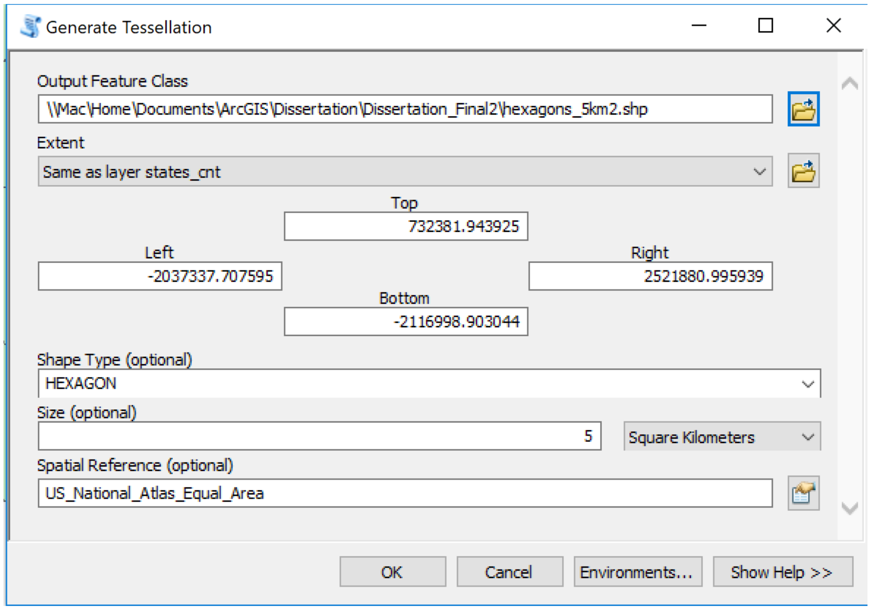

Figure A.2: Tessellation settings for placing the hexagonal grid on the maps

Crossing ZIP codes with hexagons, to make the pieces that make up the parts

Use the *identity* tool to draw slivers. The settings

Using the identity tool on ArcMap: ArcToolbox > Analysis Tools > Overlay > Identity Input features: layer of zip codes that intersect with urban areas “ZIP_overlap_UAC” Identity features: 5 square kilometer hexagons that intersect with urban areas “Hexagon_5km_UAC_ZIP” Join attributes: ALL Keep relationships: NO_RELATIONSHIPS Creates “ZIP_overlap_UAC_Identity”

Using the Spatial Join tool on ArcMap: ArcToolbox > Analysis Tools > Overlay > Spatial Join Target features: identity layer created in the step above. “ZIP_overlap_UAC_Identity” Join features: “Urban_Areas_and_Clusters” Join operation: JOIN_ONE_TO_ONE Keep all target features: KEEP_ALL Match option: INTERSECT Creates “ZIP_overlap_UAC_Identity_Spa”

APPENDIX B: CHAPTER 3 SUPPLEMENTS

APPENDIX B.1: COMPUTATION NOTES

All computation and even the writing of this dissertation were done using the University of Chicago's server, Cronusx. Although powerful, it was still worth considering ways of performing the computations quickly and efficiently.

- Always reduced the number of ZIP codes from the total of 40k ZIP codes to reduce the number of rows requiring calculations to about 11k;
- In the algorithm, I isolated the data from each year, and ran each year separately until the end, to keep it quick;
- After each year had finished computing and the variables recorded, I recycled temporary variables to free up memory;
- Whenever possible, reduced rows of data also to reduce number of rows requiring calculations, for example, after replacing the NAICS codes with subcategories;
- Separated each type of variable into their own object to make objects lighter, for example, by assigning one object to all jobs variables or establishment variables.

APPENDIX B.2: NAICS CODES PER CATEGORY AND SUBCATEGORY

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Arts Amenities	Museums	519120: Libraries and Archives; 712110: Museums; 712120: Historical Sites
Arts Amenities	Performing Arts	711110: Theater Companies and Dinner Theaters; 711120: Dance Companies; 711130: Musical Groups and Artists
Arts Amenities	Spectator Sports	711211: Sports Teams and Clubs; 711212: Racetracks; 711310: Promoters of Performing Arts, Sports, and Similar Events with Facilities; 711320: Promoters of Performing Arts, Sports, and Similar Events without Facilities; 711410: Agents and Managers for Artists, Athletes, Entertainers, and Other Public Figures
Arts Producers	Broadcasting	515111: Radio Networks; 515112: Radio Stations; 515120: Television Broadcasting; 515210: Cable and Other Subscription Programming
Arts Producers	Motion Pictures	512110: Motion Picture and Video Production; 512120: Motion Picture and Video Distribution; 512131: Motion Picture Theaters (except Drive-Ins); 512132: Drive-In Motion Picture Theaters; 512191: Teleproduction and Other Postproduction Services
Arts Producers	Publishers	511110: Newspaper Publishers; 511120: Periodical Publishers; 511130: Book Publishers; 511140: Directory and Mailing List Publishers; 511191: Greeting Card Publishers
Arts Producers	Sound	334613: Blank Magnetic and Optical Recording Media Manufacturing; 334614: Software and Other Prerecorded Compact Disc, Tape, and Record Reproducing; 512210: Record Production; 512220: Integrated Record Production/Distribution; 512230: Music Publishers; 512240: Sound Recording Studios
Arts Producers	Writers	519110: News Syndicates; 711510: Independent Artists, Writers, and Performers
Business Services	Accountants	541211: Offices of Certified Public Accountants; 541213: Tax Preparation Services; 541214: Payroll Services
Business Services	Advertising	541810: Advertising Agencies; 541820: Public Relations Agencies; 541830: Media Buying Agencies; 541840: Media Representatives; 541850: Outdoor Advertising; 541860: Direct Mail Advertising; 541870: Advertising Material Distribution Services; 541910: Marketing Research and Public Opinion Polling; 541921: Photography Studios, Portrait; 541922: Commercial Photography
Business Services	Business Support	541930: Translation and Interpretation Services; 551111: Offices of Bank Holding Companies; 551112: Offices of Other Holding Companies; 551114: Corporate, Subsidiary, and Regional Managing Offices; 561110: Office Administrative Services; 561210: Facilities Support Services; 561311: Employment Placement Agencies; 561312: Executive Search Services; 561320: Temporary Help Services; 561330: Professional Employer Organizations; 561410: Document Preparation Services; 561421: Telephone Answering Services; 561422: Telemarketing Bureaus and Other Contact Centers; 561431: Private Mail Centers; 561440: Collection Agencies; 561450: Credit Bureaus; 561491: Repossession Services; 561492: Court Reporting and Stenotype Services; 561910: Packaging and Labeling Services; 561920: Convention and Trade Show Organizers

Table B.1: NAICS codes associated to each category and subcategory

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Business Services	Consulting	541611: Administrative Management and General Management Consulting Services; 541612: Human Resources Consulting Services; 541613: Marketing Consulting Services; 541614: Process, Physical Distribution, and Logistics Consulting Services; 541620: Environmental Consulting Services
Business Services	Finance	521110: Monetary Authorities-Central Bank; 522110: Commercial Banking; 522120: Savings Institutions; 522130: Credit Unions; 522210: Credit Card Issuing; 522220: Sales Financing; 522291: Consumer Lending; 522292: Real Estate Credit; 522293: International Trade Financing; 522294: Secondary Market Financing; 522310: Mortgage and Nonmortgage Loan Brokers; 522320: Financial Transactions Processing, Reserve, and Clearinghouse Activities; 523110: Investment Banking and Securities Dealing; 523120: Securities Brokerage; 523130: Commodity Contracts Dealing; 523140: Commodity Contracts Brokerage; 523210: Securities and Commodity Exchanges; 523910: Miscellaneous Intermediation; 523920: Portfolio Management; 523930: Investment Advice; 523991: Trust, Fiduciary, and Custody Activities; 523999: Miscellaneous Financial Investment Activities; 525110: Pension Funds; 525120: Health and Welfare Funds; 525910: Open-End Investment Funds; 525920: Trusts, Estates, and Agency Accounts
Business Services	Insurance	524113: Direct Life Insurance Carriers; 524114: Direct Health and Medical Insurance Carriers; 524126: Direct Property and Casualty Insurance Carriers; 524127: Direct Title Insurance Carriers; 524130: Reinsurance Carriers; 524210: Insurance Agencies and Brokerages; 524291: Claims Adjusting; 524292: Third Party Administration of Insurance and Pension Funds
Business Services	Law	541110: Offices of Lawyers; 541120: Offices of Notaries; 541191: Title Abstract and Settlement Offices
Business Services	Real Estate	531110: Lessors of Residential Buildings and Dwellings; 531120: Lessors of Nonresidential Buildings (excpet Miniwarehouses); 531130: Lessors of Miniwarehouses and Self-Storage Units; 531190: Lessors of Other Real Estate Property; 531210: Offices of Real Estate Agents and Brokers; 531311: Residential Property Managers; 531312: Nonresidential Property Managers; 531320: Offices of Real Estate Appraisers
Education	Education	611110: Elementary and Secondary Schools; 611210: Junior Colleges; 611310: Colleges, Universities, and Professional Schools; 611410: Business and Secretarial Schools; 611420: Computer Training; 611430: Professional and Management Development Training; 611511: Cosmetology and Barber Schools; 611512: Flight Training; 611513: Apprenticeship Training; 611610: Fine Arts Schools; 611630: Language Schools; 611691: Exam Preparation and Tutoring; 611692: Automobile Driving Schools; 611710: Educational Support Services
Food	Food	721310: Rooming and Boarding Houses; 722310: Food Service Contractors; 722320: Caterers; 722330: Mobile Food Services; 722410: Drinking Places (Alcoholic Beverages); 722511: Full-Service Restaurants; 722513: Limited-Service Restaurants; 722514: Cafeterias, Grill Buffets, and Buffets; 722515: Snack and Nonalcoholic Beverage Bars

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Goods	Agriculture	111110: Soybean Farming; 111120: Oilseed (except Soybean) Farming; 111130: Dry Pea and Bean Farming; 111140: Wheat Farming; 111150: Corn Farming; 111160: Rice Farming; 111191: Oilseed and Grain Combination Farming; 111211: Potato Farming; 111310: Orange Groves; 111320: Citrus (except Orange) Groves; 111331: Apple Orchards; 111332: Grape Vineyards; 111333: Strawberry Farming; 111334: Berry (except Strawberry) Farming; 111335: Tree Nut Farming; 111336: Fruit and Tree Nut Combination Farming; 111411: Mushroom Production; 111421: Nursery and Tree Production; 111422: Floriculture Production; 111910: Tobacco Farming; 111920: Cotton Farming; 111930: Sugarcane Farming; 111940: Hay Farming; 111991: Sugar Beet Farming; 111992: Peanut Farming; 112111: Beef Cattle Ranching and Farming; 112112: Cattle Feedlots; 112120: Dairy Cattle and Milk Production; 112130: Dual-Purpose Cattle Ranching and Farming; 112210: Hog and Pig Farming; 112310: Chicken Egg Production; 112320: Broilers and Other Meat Type Chicken Production; 112330: Turkey Production; 112340: Poultry Hatcheries; 112410: Sheep Farming; 112420: Goat Farming; 112511: Finfish Farming and Fish Hatcheries; 112512: Shellfish Farming; 112910: Apiculture; 112920: Horses and Other Equine Production; 112930: Fur-Bearing Animal and Rabbit Production; 113110: Timber Tract Operations; 113210: Forest Nurseries and Gathering of Forest Products; 113310: Logging; 114111: Finfish Fishing; 114112: Shellfish Fishing; 114210: Hunting and Trapping; 115111: Cotton Ginning; 115112: Soil Preparation, Planting, and Cultivating; 115113: Crop Harvesting, Primarily by Machine; 115114: Postharvest Crop Activities (except Cotton Ginning); 115115: Farm Labor Contractors and Crew Leaders; 115116: Farm Management Services; 115210: Support Activities for Animal Production; 115310: Support Activities for Forestry
Goods	Construction	236115: New Single-Family Housing Construction (except For-Sale Builders); 236116: New Multifamily Housing Construction (except For-Sale Builders); 236117: New Housing For-Sale Builders; 236118: Residential Remodelers; 236210: Industrial Building Construction; 236220: Commercial and Institutional Building Construction; 237110: Water and Sewer Line and Related Structures Construction; 237120: Oil and Gas Pipeline and Related Structures Construction; 237130: Power and Communication Line and Related Structures Construction; 237210: Land Subdivision; 237310: Highway, Street, and Bridge Construction; 238110: Poured Concrete Foundation and Structure Contractors; 238120: Structural Steel and Precast Concrete Contractors; 238130: Framing Contractors; 238140: Masonry Contractors; 238150: Glass and Glazing Contractors; 238160: Roofing Contractors; 238170: Siding Contractors; 238210: Electrical Contractors and Other Wiring Installation Contractors; 238220: Plumbing, Heating, and Air-Conditioning Contractors; 238310: Drywall and Insulation Contractors; 238320: Painting and Wall Covering Contractors; 238330: Flooring Contractors; 238340: Tile and Terrazzo Contractors; 238350: Finish Carpentry Contractors; 238910: Site Preparation Contractors

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Goods	Manufacturing	311111: Dog and Cat Food Manufacturing; 311211: Flour Milling; 311212: Rice Milling; 311213: Malt Manufacturing; 311221: Wet Corn Milling; 311224: Soybean and Other Oilseed Processing; 311225: Fats and Oils Refining and Blending; 311230: Breakfast Cereal Manufacturing; 311313: Beet Sugar Manufacturing; 311314: Cane Sugar Manufacturing; 311340: Nonchocolate Confectionery Manufacturing; 311351: Chocolate and Confectionery Manufacturing from Cacao Beans; 311352: Confectionery Manufacturing from Purchased Chocolate; 311411: Frozen Fruit, Juice, and Vegetable Manufacturing; 311412: Frozen Specialty Food Manufacturing; 311421: Fruit and Vegetable Canning; 311422: Specialty Canning; 311423: Dried and Dehydrated Food Manufacturing; 311511: Fluid Milk Manufacturing; 311512: Creamery Butter Manufacturing; 311513: Cheese Manufacturing; 311514: Dry, Condensed, and Evaporated Dairy Product Manufacturing; 311520: Ice Cream and Frozen Dessert Manufacturing; 311611: Animal (except Poultry) Slaughtering; 311612: Meat Processed from Carcasses; 311613: Rendering and Meat Byproduct Processing; 311615: Poultry Processing; 311710: Seafood Product Preparation and Packaging; 311811: Retail Bakeries; 311812: Commercial Bakeries; 311813: Frozen Cakes, Pies, and Other Pastries Manufacturing; 311821: Cookie and Cracker Manufacturing; 311824: Dry Pasta, Dough, and Flour Mixes Manufacturing from Purchased Flour; 311830: Tortilla Manufacturing; 311911: Roasted Nuts and Peanut Butter Manufacturing; 311920: Coffee and Tea Manufacturing; 311930: Flavoring Syrup and Concentrate Manufacturing; 311941: Mayonnaise, Dressing, and Other Prepared Sauce Manufacturing; 311942: Spice and Extract Manufacturing; 311991: Perishable Prepared Food Manufacturing; 312111: Soft Drink Manufacturing; 312112: Bottled Water Manufacturing; 312113: Ice Manufacturing; 312120: Breweries; 312130: Wineries; 312140: Distilleries; 312230: Tobacco Manufacturing; 313110: Fiber, Yarn, and Thread Mills; 313210: Broadwoven Fabric Mills; 313220: Narrow Fabric Mills and Schiffli Machine Embroidery; 313230: Nonwoven Fabric Mills; 313240: Knit Fabric Mills; 313310: Textile and Fabric Finishing Mills; 313320: Fabric Coating Mills; 314110: Carpet and Rug Mills; 314120: Curtain and Linen Mills; 314910: Textile Bag and Canvas Mills; 314994: Rope, Cordage, Twine, Tire Cord, and Tire Fabric Mills; 315110: Hosiery and Sock Mills; 315210: Cut and Sew Apparel Contractors; 315220: Men's and Boys' Cut and Sew Apparel Manufacturing; 315240: Women's, Girls', and Infants' Cut and Sew Apparel Manufacturing; 315990: Apparel Accessories and Other Apparel Manufacturing; 316110: Leather and Hide Tanning and Finishing; 316210: Footwear Manufacturing; 316992: Women's Handbag and Purse Manufacturing; 321113: Sawmills; 321114: Wood Preservation; 321211: Hardwood Veneer and Plywood Manufacturing; 321212: Softwood Veneer and Plywood Manufacturing; 321213: Engineered

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Goods	Manufacturing	321219: Reconstituted Wood Product Manufacturing; 321911: Wood Window and Door Manufacturing; 321912: Cut Stock, Resawing Lumber, and Planing; 321920: Wood Container and Pallet Manufacturing; 321991: Manufactured Home (Mobile Home) Manufacturing; 321992: Prefabricated Wood Building Manufacturing; 322110: Pulp Mills; 322121: Paper (except Newsprint) Mills; 322122: Newsprint Mills; 322130: Paperboard Mills; 322211: Corrugated and Solid Fiber Box Manufacturing; 322212: Folding Paperboard Box Manufacturing; 322220: Paper Bag and Coated and Treated Paper Manufacturing; 322230: Stationery Product Manufacturing; 322291: Sanitary Paper Product Manufacturing; 323111: Commercial Printing (except Screen and Books); 323113: Commercial Screen Printing; 323117: Books Printing; 323120: Support Activites for Printing; 324110: Petroleum Refineries; 324121: Asphalt Paving Mixture and Block Manufacturing; 324122: Asphalt Shingle and Coating Materials Manufacturing; 324191: Petroleum Lubricating Oil and Grease Manufacturing; 325110: Petrochemical Manufacturing; 325120: Industrial Gas Manufacturing; 325130: Synthetic Dye and Pigment Manufacturing; 325193: Ethyl Alcohol Manufacturing; 325194: Cyclic Crude, Intermediate, and Gum and Wood Chemical Manufacturing; 325211: Plastics Material and Resin Manufacturing; 325212: Synthetic Rubber Manufacturing; 325220: Artificial and Synthetic Fibers and Filaments Manufacturing; 325311: Nitrogenous Fertilizer Manufacturing; 325312: Phosphatic Fertilizer Manufacturing; 325314: Fertilizer (Mixing Only) Manufacturing; 325320: Pesticide and Other Agricultural Chemical Manufacturing; 325510: Paint and Coating Manufacturing; 325520: Adhesive Manufacturing; 325611: Soap and Other Detergent Manufacturing; 325612: Polish and Other Sanitation Good Manufacturing; 325613: Surface Active Agent Manufacturing; 325620: Toilet Preparation Manufacturing; 325910: Printing Ink Manufacturing; 325920: Explosives Manufacturing; 325991: Custom Compounding of Purchased Resins; 325992: Photographic Film, Paper, Plate, and Chemical Manufacturing; 326111: Plastics Bag and Pouch Manufacturing; 326112: Plastics Packaging Film and Sheet (including Laminated) Manufacturing; 326113: Unlaminated Plastics Film and Sheet (except Packaging) Manufacturing; 326121: Unlaminated Plastics Profile Shape Manufacturing; 326122: Plastics Pipe and Pipe Fitting Manufacturing; 326130: Laminated Plastics Plate, Sheet (except Packaging), and Shape Manufacturing; 326140: Polystyrene Foam Product Manufacturing; 326150: Urethane and Other Foam Product (except Polystyrene) Manufacturing; 326160: Plastics Bottle Manufacturing; 326191: Plastics Plumbing Fixture Manufacturing; 326211: Tire Manufacturing (except Retreading); 326212: Tire Retreading; 326220: Rubber and Plastics Hoses and Belting Manufacturing; 326291: Rubber Product Manufacturing for Mechanical Use; 327110: Pottery, Ceramics, and

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Goods	Manufacturing	327213: Glass Container Manufacturing; 327215: Glass Product Manufacturing Made of Purchased Glass; 327310: Cement Manufacturing; 327320: Ready-Mix Concrete Manufacturing; 327331: Concrete Block and Brick Manufacturing; 327332: Concrete Pipe Manufacturing; 327410: Lime Manufacturing; 327420: Gypsum Product Manufacturing; 327910: Abrasive Product Manufacturing; 327991: Cut Stone and Stone Product Manufacturing; 327992: Ground or Treated Mineral and Earth Manufacturing; 327993: Mineral Wool Manufacturing; 331110: Iron and Steel Mills and Ferroalloy Manufacturing; 331210: Iron and Steel Pipe and Tube Manufacturing from Purchased Steel; 331221: Rolled Steel Shape Manufacturing; 331222: Steel Wire Drawing; 331313: Alumina Refining and Primary Aluminum Production; 331314: Secondary Smelting and Alloying of Aluminum; 331315: Aluminum Sheet, Plate, and Foil Manufacturing; 331410: Nonferrous Metal (except Aluminum) Smelting and Refining; 331420: Copper Rolling, Drawing, Extruding, and Alloying; 331491: Nonferrous Metal (except Copper and Aluminum) Rolling, Drawing, and Extruding; 331492: Secondary Smelting, Refining, and Alloying of Nonferrous Metal (except Copper and Aluminum); 331511: Iron Foundries; 331512: Steel Investment Foundries; 331513: Steel Foundries (except Investment); 331523: Nonferrous Metal Die-Casting Foundries; 331524: Aluminum Foundries (except Die-Casting); 332111: Iron and Steel Forging; 332112: Nonferrous Forging; 332114: Custom Roll Forming; 332117: Powder Metallurgy Part Manufacturing; 332119: Metal Crown, Closure, and Other Metal Stamping (except Automotive); 332215: Metal Kitchen Cookware, Utensil, Cutlery, and Flatware (except Precious) Manufacturing; 332216: Saw Blade and Handtool Manufacturing; 332311: Prefabricated Metal Building and Component Manufacturing; 332312: Fabricated Structural Metal Manufacturing; 332313: Plate Work Manufacturing; 332321: Metal Window and Door Manufacturing; 332322: Sheet Metal Work Manufacturing; 332323: Ornamental and Architectural Metal Work Manufacturing; 332410: Power Boiler and Heat Exchanger Manufacturing; 332420: Metal Tank (Heavy Gauge) Manufacturing; 332431: Metal Can Manufacturing; 332510: Hardware Manufacturing; 332613: Spring Manufacturing; 332710: Machine Shops; 332721: Precision Turned Product Manufacturing; 332722: Bolt, Nut, Screw, Rivet, and Washer Manufacturing; 332811: Metal Heat Treating; 332812: Metal Coating, Engraving (except Jewelry and Silverware), and Allied Services to Manufacturers; 332813: Electroplating, Plating, Polishing, Anodizing, and Coloring; 332911: Industrial Valve Manufacturing; 332912: Fluid Power Valve and Hose Fitting Manufacturing; 332913: Plumbing Fixture Fitting and Trim Manufacturing; 332991: Ball and Roller Bearing Manufacturing; 332992: Small Arms Ammunition Manufacturing; 332993: Ammunition (except Small Arms) Manufacturing; 332994: Small

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Goods	Manufacturing	333111: Farm Machinery and Equipment Manufacturing; 333112: Lawn and Garden Tractor and Home Lawn and Garden Equipment Manufacturing; 333120: Construction Machinery Manufacturing; 333131: Mining Machinery and Equipment Manufacturing; 333132: Oil and Gas Field Machinery and Equipment Manufacturing; 333241: Food Product Machinery Manufacturing; 333242: Semiconductor Machinery Manufacturing; 333243: Sawmill, Woodworking, and Paper Machinery Manufacturing; 333244: Printing Machinery and Equipment Manufacturing; 333314: Optical Instrument and Lens Manufacturing; 333316: Photographic and Photocopying Equipment Manufacturing; 333413: Industrial and Commercial Fan and Blower and Air Purification Equipment Manufacturing; 333414: Heating Equipment (except Warm Air Furnaces) Manufacturing; 333415: Air-Conditioning and Warm Air Heating Equipment and Commercial and Industrial Refrigeration Equipment Manufacturing; 333511: Industrial Mold Manufacturing; 333514: Special Die and Tool, Die Set, Jig, and Fixture Manufacturing; 333515: Cutting Tool and Machine Tool Accessory Manufacturing; 333517: Machine Tool Manufacturing; 333519: Rolling Mill and Other Metalworking Machinery Manufacturing; 333611: Turbine and Turbine Generator Set Units Manufacturing; 333612: Speed Changer, Industrial High-Speed Drive, and Gear Manufacturing; 333613: Mechanical Power Transmission Equipment Manufacturing; 333911: Pump and Pumping Equipment Manufacturing; 333912: Air and Gas Compressor Manufacturing; 333913: Measuring and Dispensing Pump Manufacturing; 333921: Elevator and Moving Stairway Manufacturing; 333922: Conveyor and Conveying Equipment Manufacturing; 333923: Overhead Traveling Crane, Hoist, and Monorail System Manufacturing; 333924: Industrial Truck, Tractor, Trailer, and Stacker Machinery Manufacturing; 333991: Power-Driven Handtool Manufacturing; 333992: Welding and Soldering Equipment Manufacturing; 333993: Packaging Machinery Manufacturing; 333994: Industrial Process Furnace and Oven Manufacturing; 333995: Fluid Power Cylinder and Actuator Manufacturing; 333996: Fluid Power Pump and Motor Manufacturing; 333997: Scale and Balance Manufacturing; 335110: Electric Lamp Bulb and Part Manufacturing; 335121: Residential Electric Lighting Fixture Manufacturing;

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Goods	Manufacturing	335122: Commercial, Industrial, and Institutional Electric Lighting Fixture Manufacturing; 335210: Small Electrical Appliance Manufacturing; 335221: Household Cooking Appliance Manufacturing; 335222: Household Refrigerator and Home Freezer Manufacturing; 335224: Household Laundry Equipment Manufacturing; 335311: Power, Distribution, and Specialty Transformer Manufacturing; 335312: Motor and Generator Manufacturing; 335313: Switchgear and Switchboard Apparatus Manufacturing; 335314: Relay and Industrial Control Manufacturing; 335911: Storage Battery Manufacturing; 335912: Primary Battery Manufacturing; 335921: Fiber Optic Cable Manufacturing; 335931: Current-Carrying Wiring Device Manufacturing; 335932: Noncurrent-Carrying Wiring Device Manufacturing; 335991: Carbon and Graphite Product Manufacturing; 336111: Automobile Manufacturing; 336112: Light Truck and Utility Vehicle Manufacturing; 336120: Heavy Duty Truck Manufacturing; 336211: Motor Vehicle Body Manufacturing; 336212: Truck Trailer Manufacturing; 336213: Motor Home Manufacturing; 336214: Travel Trailer and Camper Manufacturing; 336310: Motor Vehicle Gasoline Engine and Engine Parts Manufacturing; 336320: Motor Vehicle Electrical and Electronic Equipment Manufacturing; 336330: Motor Vehicle Steering and Suspension Components (except Spring) Manufacturing; 336340: Motor Vehicle Brake System Manufacturing; 336350: Motor Vehicle Transmission and Power Train Parts Manufacturing; 336360: Motor Vehicle Seating and Interior Trim Manufacturing; 336370: Motor Vehicle Metal Stamping; 336510: Railroad Rolling Stock Manufacturing; 336611: Ship Building and Repairing; 336612: Boat Building; 336991: Motorcycle, Bicycle, and Parts Manufacturing; 336992: Military Armored Vehicle, Tank, and Tank Component Manufacturing; 337110: Wood Kitchen Cabinet and Countertop Manufacturing; 337121: Upholstered Household Furniture Manufacturing; 337122: Nonupholstered Wood Household Furniture Manufacturing; 337124: Metal Household Furniture Manufacturing; 337125: Household Furniture (except Wood and Metal) Manufacturing; 337127: Institutional Furniture Manufacturing; 337211: Wood Office Furniture Manufacturing; 337212: Custom Architectural Woodwork and Millwork Manufacturing; 337214: Office Furniture (except Wood) Manufacturing; 337215: Showcase, Partition, Shelving, and Locker Manufacturing; 337910: Mattress Manufacturing; 337920: Blind and Shade Manufacturing; 339112: Surgical and Medical Instrument Manufacturing; 339113: Surgical Appliance and Supplies Manufacturing; 339114: Dental Equipment and Supplies Manufacturing; 339115: Ophthalmic Goods Manufacturing; 339116: Dental Laboratories; 339910: Jewelry and Silverware Manufacturing; 339920: Sporting and Athletic Goods Manufacturing; 339930: Doll, Toy, and Game Manufacturing; 339940: Office Supplies (except Paper) Manufacturing; 339950: Sign Manufacturing;

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Goods	Manufacturing	339991: Gasket, Packing, and Sealing Device Manufacturing; 339992: Musical Instrument Manufacturing; 339993: Fastener, Button, Needle, and Pin Manufacturing; 339994: Broom, Brush, and Mop Manufacturing; 339995: Burial Casket Manufacturing; 333921: Elevator and Moving Stairway Manufacturing; 333922: Conveyor and Conveying Equipment Manufacturing; 333923: Overhead Traveling Crane, Hoist, and Monorail System Manufacturing; 333924: Industrial Truck, Tractor, Trailer, and Stacker Machinery Manufacturing; 333991: Power-Driven Handtool Manufacturing; 333992: Welding and Soldering Equipment Manufacturing; 333993: Packaging Machinery Manufacturing; 333994: Industrial Process Furnace and Oven Manufacturing; 333995: Fluid Power Cylinder and Actuator Manufacturing; 333996: Fluid Power Pump and Motor Manufacturing; 333997: Scale and Balance Manufacturing; 335110: Electric Lamp Bulb and Part Manufacturing; 335121: Residential Electric Lighting Fixture Manufacturing; 335122: Commercial, Industrial, and Institutional Electric Lighting Fixture Manufacturing; 335210: Small Electrical Appliance Manufacturing; 335221: Household Cooking Appliance Manufacturing; 335222: Household Refrigerator and Home Freezer Manufacturing; 335224: Household Laundry Equipment Manufacturing; 335311: Power, Distribution, and Specialty Transformer Manufacturing; 335312: Motor and Generator Manufacturing; 335313: Switchgear and Switchboard Apparatus Manufacturing; 335314: Relay and Industrial Control Manufacturing; 335911: Storage Battery Manufacturing; 335912: Primary Battery Manufacturing; 335921: Fiber Optic Cable Manufacturing; 335931: Current-Carrying Wiring Device Manufacturing; 335932: Noncurrent-Carrying Wiring Device Manufacturing; 335991: Carbon and Graphite Product Manufacturing; 336111: Automobile Manufacturing; 336112: Light Truck and Utility Vehicle Manufacturing; 336120: Heavy Duty Truck Manufacturing; 336211: Motor Vehicle Body Manufacturing; 336212: Truck Trailer Manufacturing; 336213: Motor Home Manufacturing; 336214: Travel Trailer and Camper Manufacturing; 336310: Motor Vehicle Gasoline Engine and Engine Parts Manufacturing; 336320: Motor Vehicle Electrical and Electronic Equipment Manufacturing; 336330: Motor Vehicle Steering and Suspension Components (except Spring) Manufacturing; 336340: Motor Vehicle Brake System Manufacturing; 336350: Motor Vehicle Transmission and Power Train Parts Manufacturing; 336360: Motor Vehicle Seating and Interior Trim Manufacturing; 336370: Motor Vehicle Metal Stamping; 336510: Railroad Rolling Stock Manufacturing; 336611: Ship Building and Repairing; 336612: Boat Building; 336991: Motorcycle, Bicycle, and Parts Manufacturing; 336992: Military Armored Vehicle, Tank, and Tank Component Manufacturing; 337110: Wood Kitchen Cabinet and Countertop Manufacturing; 337121: Upholstered Household Furniture Manufacturing; 337122: Nonupholstered

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Goods	Mining	211111: Crude Petroleum and Natural Gas Extraction; 211112: Natural Gas Liquid Extraction; 212111: Bituminous Coal and Lignite Surface Mining; 212112: Bituminous Coal Underground Mining; 212113: Anthracite Mining; 212210: Iron Ore Mining; 212221: Gold Ore Mining; 212222: Silver Ore Mining; 212231: Lead Ore and Zinc Ore Mining; 212234: Copper Ore and Nickel Ore Mining; 212291: Uranium-Radium-Vanadium Ore Mining; 212311: Dimension Stone Mining and Quarrying; 212312: Crushed and Broken Limestone Mining and Quarrying; 212313: Crushed and Broken Granite Mining and Quarrying; 212321: Construction Sand and Gravel Mining; 212322: Industrial Sand Mining; 212324: Kaolin and Ball Clay Mining; 212325: Clay and Ceramic and Refractory Minerals Mining; 212391: Potash, Soda, and Borate Mineral Mining; 212392: Phosphate Rock Mining; 213111: Drilling Oil and Gas Wells; 213112: Support Activities for Oil and Gas Operations; 213113: Support Activities for Coal Mining; 213114: Support Activities for Metal Mining; 213115: Support Activities for Nonmetallic Minerals (except Fuels) Mining
Health	Health	621111: Offices of Physicians (except Mental Health Specialists); 621112: Offices of Physicians, Mental Health Specialists; 621210: Offices of Dentists; 621310: Offices of Chiropractors; 621320: Offices of Optometrists; 621330: Offices of Mental Health Practitioners (except Physicians); 621340: Offices of Physical, Occupational and Speech Therapists, and Audiologists; 621391: Offices of Podiatrists; 621399: Offices of All Other Miscellaneous Health Practitioners; 621410: Family Planning Centers; 621420: Outpatient Mental Health and Substance Abuse Centers; 621491: HMO Medical Centers; 621492: Kidney Dialysis Centers; 621493: Freestanding Ambulatory Surgical and Emergency Centers; 621511: Medical Laboratories; 621512: Diagnostic Imaging Centers; 621610: Home Health Care Services; 621910: Ambulance Services; 621991: Blood and Organ Banks; 622110: General Medical and Surgical Hospitals; 622210: Psychiatric and Substance Abuse Hospitals; 622310: Specialty (except Psychiatric and Substance Abuse) Hospitals; 623110: Nursing Care Facilities (Skilled Nursing Facilities); 623210: Residential Intellectual and Developmental Disability Facilities; 623220: Residential Mental Health and Substance Abuse Facilities; 623311: Continuing Care Retirement Communities; 623312: Assisted Living Facilities for the Elderly; 624110: Child and Youth Services; 624120: Services for the Elderly and Persons with Disabilities; 624210: Community Food Services; 624221: Temporary Shelters; 624230: Emergency and Other Relief Services; 624310: Vocational Rehabilitation Services; 624410: Child Day Care Services
High-Tech	Design	541310: Architectural Services; 541320: Landscape Architectural Services; 541330: Engineering Services; 541340: Drafting Services; 541350: Building Inspection Services; 541360: Geophysical Surveying and Mapping Services; 541370: Surveying and Mapping (except Geophysical) Services; 541380: Testing Laboratories; 541410: Interior Design Services; 541420: Industrial Design Services; 541430: Graphic Design Services
High-Tech	HT Bio	325411: Medicinal and Botanical Manufacturing; 325412: Pharmaceutical Preparation Manufacturing; 325413: In-Vitro Diagnostic Substance Manufacturing; 325414: Biological Product (except Diagnostic) Manufacturing

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
High-Tech	HT Manufacturing	334111: Electronic Computer Manufacturing; 334112: Computer Storage Device Manufacturing; 334118: Computer Terminal and Other Computer Peripheral Equipment Manufacturing; 334210: Telephone Apparatus Manufacturing; 334220: Radio and Television Broadcasting and Wireless Communications Equipment Manufacturing; 334310: Audio and Video Equipment Manufacturing; 334412: Bare Printed Circuit Board Manufacturing; 334413: Semiconductor and Related Device Manufacturing; 334416: Capacitor, Resistor, Coil, Transformer, and Other Inductor Manufacturing; 334417: Electronic Connector Manufacturing; 334418: Printed Circuit Assembly (Electronic Assembly) Manufacturing; 334510: Electromedical and Electrotherapeutic Apparatus Manufacturing; 334511: Search, Detection, Navigation, Guidance, Aeronautical, and Nautical System and Instrument Manufacturing; 334512: Automatic Environmental Control Manufacturing for Residential, Commercial, and Appliance Use; 334513: Instruments and Related Products Manufacturing for Measuring, Displaying, and Controlling Industrial Process Variables; 334514: Totalizing Fluid Meter and Counting Device Manufacturing; 334515: Instrument Manufacturing for Measuring and Testing Electricity and Electrical Signals; 334516: Analytical Laboratory Instrument Manufacturing; 334517: Irradiation Apparatus Manufacturing; 336411: Aircraft Manufacturing; 336412: Aircraft Engine and Engine Parts Manufacturing; 336414: Guided Missile and Space Vehicle Manufacturing; 336415: Guided Missile and Space Vehicle Propulsion Unit and Propulsion Unit Parts Manufacturing; 811211: Consumer Electronics Repair and Maintenance; 811212: Computer and Office Machine Repair and Maintenance; 811213: Communication Equipment Repair and Maintenance; 811310: Commercial and Industrial Machinery and Equipment (except Automotive and Electronic) Repair and Maintenance
High-Tech	Internet	511210: Software Publishers; 519130: Internet Publishing and Broadcasting and Web Search Portals; 541511: Custom Computer Programming Services; 541512: Computer Systems Design Services; 541513: Computer Facilities Management Services
High-Tech	Research	541711: Research and Development in Biotechnology; 541712: Research and Development in the Physical, Engineering, and Life Sciences (except Biotechnology); 541720: Research and Development in the Social Sciences and Humanities
High-Tech	Telecom	517110: Wired Telecommunications Carriers; 517210: Wireless Telecommunications Carriers (except Satellite); 517410: Satellite Telecommunications; 517911: Telecommunications Resellers; 518210: Data Processing, Hosting, and Related Services

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Infra-Structure	Transportation	481111: Scheduled Passenger Air Transportation; 481112: Scheduled Freight Air Transportation; 481211: Nonscheduled Chartered Passenger Air Transportation; 481212: Nonscheduled Chartered Freight Air Transportation; 482111: Line-Haul Railroads; 482112: Short Line Railroads; 483111: Deep Sea Freight Transportation; 483112: Deep Sea Passenger Transportation; 483113: Coastal and Great Lakes Freight Transportation; 483114: Coastal and Great Lakes Passenger Transportation; 483211: Inland Water Freight Transportation; 483212: Inland Water Passenger Transportation; 484110: General Freight Trucking, Local; 484121: General Freight Trucking, Long-Distance, Truckload; 484122: General Freight Trucking, Long-Distance, Less Than Truckload; 484210: Used Household and Office Goods Moving; 484220: Specialized Freight (except Used Goods) Trucking, Local; 484230: Specialized Freight (except Used Goods) Trucking, Long-Distance; 485111: Mixed Mode Transit Systems; 485112: Commuter Rail Systems; 485113: Bus and Other Motor Vehicle Transit Systems; 485210: Interurban and Rural Bus Transportation; 485310: Taxi Service; 485320: Limousine Service; 485410: School and Employee Bus Transportation; 485510: Charter Bus Industry; 485991: Special Needs Transportation; 486110: Pipeline Transportation of Crude Oil; 486210: Pipeline Transportation of Natural Gas; 486910: Pipeline Transportation of Refined Petroleum Products; 488111: Air Traffic Control; 488210: Support Activities for Rail Transportation; 488310: Port and Harbor Operations; 488320: Marine Cargo Handling; 488330: Navigational Services to Shipping; 488410: Motor Vehicle Towing; 488510: Freight Transportation Arrangement; 488991: Packing and Crating; 491110: Postal Service; 492110: Couriers and Express Delivery Services; 492210: Local Messengers and Local Delivery; 493110: General Warehousing and Storage; 493120: Refrigerated Warehousing and Storage; 493130: Farm Product Warehousing and Storage
Infra-Structure	Utilities	221111: Hydroelectric Power Generation; 221112: Fossil Fuel Electric Power Generation; 221113: Nuclear Electric Power Generation; 221114: Solar Electric Power Generation; 221115: Wind Electric Power Generation; 221116: Geothermal Electric Power Generation; 221117: Biomass Electric Power Generation; 221121: Electric Bulk Power Transmission and Control; 221122: Electric Power Distribution; 221210: Natural Gas Distribution; 221310: Water Supply and Irrigation Systems; 221320: Sewage Treatment Facilities; 221330: Steam and Air-Conditioning Supply

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Infra-Structure	Wholesale	423110: Automobile and Other Motor Vehicle Merchant Wholesalers; 423120: Motor Vehicle Supplies and New Parts Merchant Wholesalers; 423130: Tire and Tube Merchant Wholesalers; 423140: Motor Vehicle Parts (Used) Merchant Wholesalers; 423210: Furniture Merchant Wholesalers; 423220: Home Furnishing Merchant Wholesalers; 423310: Lumber, Plywood, Millwork, and Wood Panel Merchant Wholesalers; 423320: Brick, Stone, and Related Construction Material Merchant Wholesalers; 423330: Roofing, Siding, and Insulation Material Merchant Wholesalers; 423410: Photographic Equipment and Supplies Merchant Wholesalers; 423420: Office Equipment Merchant Wholesalers; 423430: Computer and Computer Peripheral Equipment and Software Merchant Wholesalers; 423450: Medical, Dental, and Hospital Equipment and Supplies Merchant Wholesalers; 423460: Ophthalmic Goods Merchant Wholesalers; 423510: Metal Service Centers and Other Metal Merchant Wholesalers; 423520: Coal and Other Mineral and Ore Merchant Wholesalers; 423610: Electrical Apparatus and Equipment, Wiring Supplies, and Related Equipment Merchant Wholesalers; 423620: Household Appliances, Electric Housewares, and Consumer Electronics Merchant Wholesalers; 423710: Hardware Merchant Wholesalers; 423720: Plumbing and Heating Equipment and Supplies (Hydronics) Merchant Wholesalers; 423730: Warm Air Heating and Air-Conditioning Equipment and Supplies Merchant Wholesalers; 423740: Refrigeration Equipment and Supplies Merchant Wholesalers; 423810: Construction and Mining (except Oil Well) Machinery and Equipment Merchant Wholesalers; 423820: Farm and Garden Machinery and Equipment Merchant Wholesalers; 423830: Industrial Machinery and Equipment Merchant Wholesalers; 423840: Industrial Supplies Merchant Wholesalers; 423850: Service Establishment Equipment and Supplies Merchant Wholesalers; 423860: Transportation Equipment and Supplies (except Motor Vehicle) Merchant Wholesalers;

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Infra-Structure	Wholesale	423910: Sporting and Recreational Goods and Supplies Merchant Wholesalers; 423920: Toy and Hobby Goods and Supplies Merchant Wholesalers; 423930: Recyclable Material Merchant Wholesalers; 423940: Jewelry, Watch, Precious Stone, and Precious Metal Merchant Wholesalers; 424110: Printing and Writing Paper Merchant Wholesalers; 424120: Stationery and Office Supplies Merchant Wholesalers; 424130: Industrial and Personal Service Paper Merchant Wholesalers; 424210: Drugs and Druggists' Sundries Merchant Wholesalers; 424310: Piece Goods, Notions, and Other Dry Goods Merchant Wholesalers; 424320: Men's and Boys' Clothing and Furnishings Merchant Wholesalers; 424330: Women's, Children's, and Infants' Clothing and Accessories Merchant Wholesalers; 424340: Footwear Merchant Wholesalers; 424410: General Line Grocery Merchant Wholesalers; 424420: Packaged Frozen Food Merchant Wholesalers; 424430: Dairy Product (except Dried or Canned) Merchant Wholesalers; 424440: Poultry and Poultry Product Merchant Wholesalers; 424450: Confectionery Merchant Wholesalers; 424460: Fish and Seafood Merchant Wholesalers; 424470: Meat and Meat Product Merchant Wholesalers; 424480: Fresh Fruit and Vegetable Merchant Wholesalers; 424510: Grain and Field Bean Merchant Wholesalers; 424520: Livestock Merchant Wholesalers; 424610: Plastics Materials and Basic Forms and Shapes Merchant Wholesalers; 424710: Petroleum Bulk Stations and Terminals; 424720: Petroleum and Petroleum Products Merchant Wholesalers (except Bulk Stations and Terminals); 424810: Beer and Ale Merchant Wholesalers; 424820: Wine and Distilled Alcoholic Beverage Merchant Wholesalers; 424910: Farm Supplies Merchant Wholesalers; 424920: Book, Periodical, and Newspaper Merchant Wholesalers; 424930: Flower, Nursery Stock, and Florists' Supplies Merchant Wholesalers; 424940: Tobacco and Tobacco Product Merchant Wholesalers; 424950: Paint, Varnish, and Supplies Merchant Wholesalers; 425110: Business to Business Electronic Markets; 425120: Wholesale Trade Agents and Brokers
Other	Cleaning Services	561710: Exterminating and Pest Control Services; 561720: Janitorial Services; 561730: Landscaping Services; 561740: Carpet and Upholstery Cleaning Services; 812310: Coin-Operated Laundries and Drycleaners; 812320: Drycleaning and Laundry Services (except Coin-Operated); 812331: Linen Supply; 812332: Industrial Launderers
Other	Funeral Services	812210: Funeral Homes and Funeral Services; 812220: Cemeteries and Crematories
Other	Organizations	813110: Religious Organizations; 813211: Grantmaking Foundations; 813212: Voluntary Health Organizations; 813311: Human Rights Organizations; 813312: Environment, Conservation and Wildlife Organizations; 813410: Civic and Social Organizations; 813910: Business Associations; 813920: Professional Organizations; 813930: Labor Unions and Similar Labor Organizations; 813940: Political Organizations; 814110: Private Households

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Other	Personal Services	812111: Barber Shops; 812112: Beauty Salons; 812113: Nail Salons; 812191: Diet and Weight Reducing Centers; 812921: Photofinishing Laboratories (except One-Hour); 812922: One-Hour Photofinishing; 812930: Parking Lots and Garages
Other	Rental Services	532111: Passenger Car Rental; 532112: Passenger Car Leasing; 532120: Truck, Utility Trailer, and RV (Recreational Vehicle) Rental and Leasing; 532210: Consumer Electronics and Appliances Rental; 532220: Formal Wear and Costume Rental; 532230: Video Tape and Disc Rental; 532291: Home Health Equipment Rental; 532292: Recreational Goods Rental; 532310: General Rental Centers; 532411: Commercial Air, Rail, and Water Transportation Equipment Rental and Leasing; 532412: Construction, Mining, and Forestry Machinery and Equipment Rental and Leasing; 532420: Office Machinery and Equipment Rental and Leasing; 533110: Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)
Other	Repair and Maintenance	811111: General Automotive Repair; 811112: Automotive Exhaust System Repair; 811113: Automotive Transmission Repair; 811121: Automotive Body, Paint, and Interior Repair and Maintenance; 811122: Automotive Glass Replacement Shops; 811191: Automotive Oil Change and Lubrication Shops; 811192: Car Washes; 811411: Home and Garden Equipment Repair and Maintenance; 811412: Appliance Repair and Maintenance; 811420: Reupholstery and Furniture Repair; 811430: Footwear and Leather Goods Repair
Other	Security Services	561611: Investigation Services; 561612: Security Guards and Patrol Services; 561613: Armored Car Services; 561621: Security Systems Services (except Locksmiths); 561622: Locksmiths
Other	Veterinary Services	541940: Veterinary Services; 812910: Pet Care (except Veterinary) Services
Other	Waste Collection Services	562111: Solid Waste Collection; 562112: Hazardous Waste Collection; 562211: Hazardous Waste Treatment and Disposal; 562212: Solid Waste Landfill; 562213: Solid Waste Combustors and Incinerators; 562910: Remediation Services; 562920: Materials Recovery Facilities; 562991: Septic Tank and Related Services
Recreation	Gambling	713210: Casinos (except Casino Hotels)
Recreation	Parks	712130: Zoos and Botanical Gardens; 712190: Nature Parks and Other Similar Institutions; 713110: Amusement and Theme Parks; 713120: Amusement Arcades
Recreation	Sports	611620: Sports and Recreation Instruction; 713910: Golf Courses and Country Clubs; 713920: Skiing Facilities; 713930: Marinas; 713940: Fitness and Recreational Sports Centers; 713950: Bowling Centers

Table B.1: NAICS codes associated to each category and subcategory (cont.)

Category	Subcategory	NAICS Codes and Categories Included (Excluding "Other" and "All Other" Categories)
Recreation	Tourism	487110: Scenic and Sightseeing Transportation, Land; 487210: Scenic and Sightseeing Transportation, Water; 487990: Scenic and Sightseeing Transportation, Other; 561510: Travel Agencies; 561520: Tour Operators; 561591: Convention and Visitors Bureaus; 721110: Hotels (except Casino Hotels) and Motels; 721120: Casino Hotels; 721191: Bed-and-Breakfast Inns; 721211: RV (Recreational Vehicle) Parks and Campgrounds; 721214: Recreational and Vacation Camps (except Campgrounds)
Retail	Retail	441110: New Car Dealers; 441120: Used Car Dealers; 441210: Recreational Vehicle Dealers; 441222: Boat Dealers; 441228: Motorcycle, ATV, and All Other Motor Vehicle Dealers; 441310: Automotive Parts and Accessories Stores; 441320: Tire Dealers; 442110: Furniture Stores; 442210: Floor Covering Stores; 442291: Window Treatment Stores; 443141: Household Appliance Stores; 443142: Electronics Stores; 444110: Home Centers; 444120: Paint and Wallpaper Stores; 444130: Hardware Stores; 444210: Outdoor Power Equipment Stores; 444220: Nursery, Garden Center, and Farm Supply Stores; 445110: Supermarkets and Other Grocery (except Convenience) Stores; 445120: Convenience Stores; 445210: Meat Markets; 445220: Fish and Seafood Markets; 445230: Fruit and Vegetable Markets; 445291: Baked Goods Stores; 445292: Confectionery and Nut Stores; 445310: Beer, Wine, and Liquor Stores; 446110: Pharmacies and Drug Stores; 446120: Cosmetics, Beauty Supplies, and Perfume Stores; 446130: Optical Goods Stores; 446191: Food (Health) Supplement Stores; 447110: Gasoline Stations with Convenience Stores; 448110: Men's Clothing Stores; 448120: Women's Clothing Stores; 448130: Children's and Infants' Clothing Stores; 448140: Family Clothing Stores; 448150: Clothing Accessories Stores; 448210: Shoe Stores; 448310: Jewelry Stores; 448320: Luggage and Leather Goods Stores; 451110: Sporting Goods Stores; 451120: Hobby, Toy, and Game Stores; 451130: Sewing, Needlework, and Piece Goods Stores; 451140: Musical Instrument and Supplies Stores; 451211: Book Stores; 451212: News Dealers and Newsstands; 452111: Department Stores (except Discount Department Stores); 452112: Discount Department Stores; 452910: Warehouse Clubs and Supercenters; 453110: Florists; 453210: Office Supplies and Stationery Stores; 453220: Gift, Novelty, and Souvenir Stores; 453310: Used Merchandise Stores; 453910: Pet and Pet Supplies Stores; 453920: Art Dealers; 453930: Manufactured (Mobile) Home Dealers; 453991: Tobacco Stores; 454111: Electronic Shopping; 454112: Electronic Auctions; 454113: Mail-Order Houses; 454210: Vending Machine Operators; 454310: Fuel Dealers

Table B.1: NAICS codes associated to each category and subcategory (cont.)

APPENDIX B.3: DESCRIPTIVE STATISTICS OF VARIABLES

Descriptive Statistics - Original Metric

Descriptive Statistics for Arts and Jobs Variables, 1998-2016, Original Metric

Type	Year	N	Mean	S.D.	S.E.	Median	Min.	Max.	Skew
	2016	63049	87.5	629.3	2.5	29.6	0.0	93487.6	80.4
	2015	63049	86.2	624.3	2.5	28.8	0.0	90187.4	77.2
	2014	63049	82.1	614.8	2.4	27.8	0.0	92895.7	83.5
	2013	63049	79.9	596.3	2.4	26.9	0.0	89625.7	83.0
	2012	63049	78.8	580.3	2.3	26.8	0.0	85192.6	79.9
	2011	63049	79.0	584.3	2.3	26.5	0.0	85956.0	79.3
	2010	63049	78.4	582.4	2.3	26.4	0.0	89082.8	83.9
	2009	63049	80.2	578.7	2.3	26.9	0.0	87846.8	83.2
	2008	63049	84.2	606.0	2.4	27.8	0.0	90717.2	81.3
Arts	2007	63049	81.7	597.1	2.4	27.5	0.0	88506.9	81.8
	2006	63049	81.1	584.4	2.3	26.3	0.0	88458.2	83.2
	2005	63049	80.2	581.4	2.3	25.4	0.0	86976.0	80.0
	2004	63049	79.9	576.2	2.3	25.2	0.0	86208.2	79.4
	2003	63049	78.4	584.3	2.3	24.4	0.0	92567.0	87.0
	2002	63049	75.8	561.2	2.2	23.3	0.0	87215.6	83.7
	2001	63049	79.0	595.1	2.4	23.8	0.0	98166.0	92.0
	2000	63049	77.6	554.7	2.2	23.1	0.0	84114.4	79.3
	1999	63049	74.5	464.3	1.8	22.5	0.0	57926.3	55.6
	1998	63049	70.4	455.1	1.8	20.5	0.0	57497.6	58.2
	2016	63072	1712.8	4942.0	19.7	898.3	0.0	556368.9	50.8
	2015	63072	1681.6	4864.6	19.4	878.1	0.0	553403.6	50.8
	2014	63072	1616.8	4777.7	19.0	847.8	0.0	552477.1	53.5
	2013	63072	1580.6	4639.5	18.5	826.8	0.0	538554.2	53.4
	2012	63072	1548.7	4513.7	18.0	809.8	0.0	517310.5	52.7
	2011	63072	1523.8	4367.2	17.4	801.1	0.0	493524.1	51.9
	2010	63072	1500.6	4262.6	17.0	790.4	0.0	476102.0	51.5
	2009	63072	1537.9	4320.8	17.2	803.7	0.0	474672.3	50.4
	2008	63072	1624.1	4532.1	18.0	847.3	0.0	507291.6	51.3
Jobs	2007	63072	1619.9	4466.6	17.8	844.9	0.0	498043.5	50.5
	2006	63072	1601.0	4230.7	16.8	827.1	0.0	488026.5	48.4
	2005	63072	1558.3	4279.6	17.0	790.4	0.0	476812.8	49.6
	2004	63072	1540.2	4262.4	17.0	772.3	0.0	469078.8	49.0
	2003	63072	1511.1	4283.2	17.1	742.9	0.0	459608.2	49.9
	2002	63072	1463.5	4219.4	16.8	701.0	0.0	458129.6	50.1
	2001	63072	1519.6	4347.9	17.3	717.9	0.0	488614.3	51.1
	2000	63072	1498.0	4220.1	16.8	700.6	0.0	474109.1	48.9
	1999	63072	1463.1	3896.0	15.5	681.5	0.0	334630.6	37.3
	1998	63072	1373.4	3862.6	15.4	629.8	0.0	406448.2	43.5

Table B.2: Descriptive statistics for the original metric variables by year and type of jobs

Descriptive Statistics - Log-Transformed

Descriptive Statistics for Arts and Jobs Variables, 1998-2016, Log

Type	Year	N	Mean	S.D.	S.E.	Median	Min.	Max.	Skew
	2016	63049	3.3	1.6	0.0	3.4	-6.9	11.4	-1.2
	2015	63049	3.3	1.6	0.0	3.4	-6.9	11.4	-1.1
	2014	63049	3.2	1.7	0.0	3.3	-6.9	11.4	-1.5
	2013	63049	3.2	1.7	0.0	3.3	-6.9	11.4	-1.5
	2012	63049	3.2	1.7	0.0	3.3	-6.9	11.4	-1.5
	2011	63049	3.1	1.7	0.0	3.3	-6.9	11.4	-1.3
	2010	63049	3.1	1.7	0.0	3.3	-6.9	11.4	-1.3
	2009	63049	3.2	1.7	0.0	3.3	-6.9	11.4	-1.3
	2008	63049	3.2	1.7	0.0	3.3	-6.9	11.4	-1.3
Arts	2007	63049	3.2	1.6	0.0	3.3	-6.9	11.4	-1.3
	2006	63049	3.1	1.7	0.0	3.3	-6.9	11.4	-1.6
	2005	63049	3.1	1.7	0.0	3.2	-6.9	11.4	-1.5
	2004	63049	3.1	1.7	0.0	3.2	-6.9	11.4	-1.4
	2003	63049	3.0	1.8	0.0	3.2	-6.9	11.4	-1.6
	2002	63049	2.9	2.0	0.0	3.1	-6.9	11.4	-1.9
	2001	63049	3.0	1.8	0.0	3.2	-6.9	11.5	-1.5
	2000	63049	3.0	1.9	0.0	3.1	-6.9	11.3	-1.7
	1999	63049	2.9	1.9	0.0	3.1	-6.9	11.0	-1.7
	1998	63049	2.7	2.2	0.0	3.0	-6.9	11.0	-2.0
	2016	63072	6.8	1.1	0.0	6.8	-6.9	13.2	-0.7
	2015	63072	6.8	1.2	0.0	6.8	-6.9	13.2	-0.9
	2014	63072	6.7	1.4	0.0	6.7	-6.9	13.2	-3.1
	2013	63072	6.7	1.4	0.0	6.7	-6.9	13.2	-3.0
	2012	63072	6.6	1.4	0.0	6.7	-6.9	13.2	-3.1
	2011	63072	6.7	1.3	0.0	6.7	-6.9	13.1	-2.3
	2010	63072	6.6	1.3	0.0	6.7	-6.9	13.1	-2.2
	2009	63072	6.7	1.3	0.0	6.7	-6.9	13.1	-2.5
	2008	63072	6.7	1.3	0.0	6.7	-6.9	13.1	-2.2
Jobs	2007	63072	6.7	1.3	0.0	6.7	-6.9	13.1	-2.2
	2006	63072	6.7	1.5	0.0	6.7	-6.9	13.1	-3.5
	2005	63072	6.6	1.4	0.0	6.7	-6.9	13.1	-3.0
	2004	63072	6.6	1.4	0.0	6.6	-6.9	13.1	-3.0
	2003	63072	6.5	1.5	0.0	6.6	-6.9	13.0	-3.3
	2002	63072	6.4	1.8	0.0	6.6	-6.9	13.0	-3.9
	2001	63072	6.5	1.5	0.0	6.6	-6.9	13.1	-3.0
	2000	63072	6.5	1.6	0.0	6.6	-6.9	13.1	-3.3
	1999	63072	6.4	1.7	0.0	6.5	-6.9	12.7	-3.4
	1998	63072	6.2	2.1	0.0	6.4	-6.9	12.9	-3.7

Table B.3: Descriptive statistics for the log-transformed variables by year and type of jobs

Descriptive Statistics - First Differences

Descriptive Statistics for Arts and Jobs First Differences Variables, 1998-2016

Type	Year	N	Mean	S.D.	S.E.	Median	Min.	Max.	Skew
Arts	1999-98	63049	4.0	55.6	0.2	0.3	-3444.9	4976.6	11.7
	2000-99	63049	3.2	151.0	0.6	0.3	-8105.5	26188.1	116.7
	2001-00	63049	1.3	84.3	0.3	0.1	-7711.4	14051.7	63.8
	2002-01	63049	-3.2	104.4	0.4	0.0	-10950.4	14376.1	26.2
	2003-02	63049	2.6	66.4	0.3	0.1	-3066.9	5351.4	16.6
	2004-03	63049	1.5	54.5	0.2	0.3	-6358.8	3279.9	-29.3
	2005-04	63049	0.4	47.0	0.2	0.0	-3292.4	3475.6	5.9
	2006-05	63049	0.9	65.8	0.3	0.4	-9279.3	3351.8	-49.2
	2007-06	63049	0.5	69.0	0.3	0.1	-2822.6	9663.0	45.2
	2008-07	63049	2.6	46.9	0.2	0.1	-1978.2	2788.0	11.8
	2009-08	63049	-4.1	44.2	0.2	-0.6	-3153.1	1800.1	-24.9
	2010-09	63049	-1.7	40.5	0.2	-0.3	-2732.9	2493.8	-5.5
	2011-10	63049	0.6	37.2	0.1	0.0	-3126.8	2449.0	3.3
	2012-11	63049	-0.2	66.8	0.3	0.3	-5439.4	2375.3	-25.0
	2013-12	63049	1.1	39.6	0.2	0.1	-2580.8	4433.0	20.0
	2014-13	63049	2.2	55.1	0.2	0.2	-1943.0	6153.2	50.4
	2015-14	63049	4.1	89.1	0.4	0.3	-2708.3	9352.6	54.1
	2016-15	63049	1.3	50.0	0.2	0.3	-5837.8	3300.2	-42.3
Jobs	1999-98	63072	89.7	723.8	2.9	16.4	-71817.6	55513.1	-2.0
	2000-99	63072	34.9	1065.2	4.2	17.2	-137104.8	139478.5	26.1
	2001-00	63072	21.6	463.9	1.8	6.1	-45195.3	41146.8	-4.6
	2002-01	63072	-56.1	952.2	3.8	0.0	-33617.7	176859.7	100.2
	2003-02	63072	47.6	570.1	2.3	11.9	-16683.9	39799.8	20.2
	2004-03	63072	29.1	432.6	1.7	15.2	-34220.9	30912.8	-21.0
	2005-04	63072	18.0	393.6	1.6	9.2	-36185.0	34098.3	-8.8
	2006-05	63072	42.7	486.7	1.9	23.4	-88306.3	13556.8	-102.8
	2007-06	63072	18.9	594.4	2.4	5.7	-19953.7	81597.9	56.5
	2008-07	63072	4.2	256.7	1.0	0.6	-23050.0	15788.6	3.6
	2009-08	63072	-86.2	338.9	1.3	-36.1	-32619.3	19853.2	-22.1
	2010-09	63072	-37.3	256.3	1.0	-13.2	-19654.3	8572.8	-21.6
	2011-10	63072	23.2	197.6	0.8	7.0	-7065.9	17422.1	21.1
	2012-11	63072	24.9	382.0	1.5	13.8	-31525.4	23786.4	-11.6
	2013-12	63072	31.9	265.1	1.1	11.5	-10291.9	26274.6	36.8
	2014-13	63072	36.2	273.6	1.1	14.0	-10664.0	25125.1	24.8
	2015-14	63072	64.8	566.2	2.3	17.4	-19500.0	59737.0	51.9
	2016-15	63072	31.2	371.3	1.5	17.0	-54370.5	12596.7	-96.9

Table B.4: Descriptive statistics for the first difference variables by year and type of job

APPENDIX C: CHAPTER 4 SUPPLEMENTS

APPENDIX C.1: CORRELATION MATRICES

Correlations Among Log-Transformed Arts Variables per Pair of Years (1998-2016)

	Arts 2016	**Arts 2015**	**Arts 2014**	**Arts 2013**	**Arts 2012**	**Arts 2011**	**Arts 2010**	**Arts 2009**	**Arts 2008**	**Arts 2007**	**Arts 2006**	**Arts 2005**	**Arts 2004**	**Arts 2003**	**Arts 2002**	**Arts 2001**	**Arts 2000**	**Arts 1999**
Arts 2016	1.00																	
Arts 2015	0.98	1.00																
Arts 2014	0.92	0.93	1.00															
Arts 2013	0.91	0.92	0.96	1.00														
Arts 2012	0.90	0.91	0.94	0.96	1.00													
Arts 2011	0.91	0.91	0.91	0.92	0.92	1.00												
Arts 2010	0.90	0.90	0.89	0.90	0.91	0.97	1.00											
Arts 2009	0.90	0.90	0.89	0.90	0.90	0.95	0.97	1.00										
Arts 2008	0.89	0.89	0.88	0.89	0.90	0.94	0.95	0.97	1.00									
Arts 2007	0.88	0.88	0.87	0.88	0.88	0.92	0.93	0.94	0.95	1.00								
Arts 2006	0.81	0.82	0.79	0.80	0.79	0.82	0.82	0.83	0.84	0.86	1.00							
Arts 2005	0.81	0.82	0.79	0.80	0.80	0.82	0.83	0.83	0.84	0.86	0.93	1.00						
Arts 2004	0.81	0.81	0.79	0.79	0.79	0.81	0.82	0.83	0.83	0.85	0.90	0.94	1.00					
Arts 2003	0.78	0.79	0.77	0.78	0.77	0.80	0.80	0.80	0.81	0.83	0.85	0.88	0.91	1.00				
Arts 2002	0.70	0.70	0.69	0.69	0.69	0.71	0.71	0.72	0.73	0.74	0.77	0.80	0.81	0.83	1.00			
Arts 2001	0.77	0.77	0.75	0.76	0.76	0.78	0.78	0.79	0.80	0.81	0.81	0.83	0.83	0.84	0.79	1.00		
Arts 2000	0.73	0.74	0.71	0.72	0.72	0.74	0.74	0.75	0.75	0.76	0.76	0.78	0.79	0.80	0.76	0.89	1.00	
Arts 1999	0.74	0.74	0.71	0.72	0.72	0.74	0.75	0.75	0.77	0.77	0.76	0.78	0.79	0.80	0.75	0.86	0.86	1.00
Arts 1998	0.65	0.65	0.63	0.63	0.64	0.65	0.66	0.66	0.67	0.68	0.66	0.68	0.69	0.70	0.66	0.76	0.75	0.84

Table C.1: Correlations among log- transformed arts variables for all years

Correlations Among Log-Transformed Jobs Variables per Pair of Years (1998-2016)

	Jobs 2016	**Jobs 2015**	**Jobs 2014**	**Jobs 2013**	**Jobs 2012**	**Jobs 2011**	**Jobs 2010**	**Jobs 2009**	**Jobs 2008**	**Jobs 2007**	**Jobs 2006**	**Jobs 2005**	**Jobs 2004**	**Jobs 2003**	**Jobs 2002**	**Jobs 2001**	**Jobs 2000**	**Jobs 1999**
Jobs 2016	1.00																	
Jobs 2015	0.99	1.00																
Jobs 2014	0.86	0.85	1.00															
Jobs 2013	0.86	0.85	0.94	1.00														
Jobs 2012	0.85	0.84	0.91	0.93	1.00													
Jobs 2011	0.91	0.90	0.87	0.88	0.87	1.00												
Jobs 2010	0.91	0.91	0.85	0.86	0.86	0.97	1.00											
Jobs 2009	0.90	0.90	0.84	0.85	0.85	0.95	0.96	1.00										
Jobs 2008	0.91	0.90	0.85	0.87	0.87	0.95	0.96	0.96	1.00									
Jobs 2007	0.90	0.89	0.85	0.86	0.85	0.94	0.93	0.93	0.95	1.00								
Jobs 2006	0.78	0.77	0.69	0.70	0.69	0.73	0.73	0.73	0.74	0.73	1.00							
Jobs 2005	0.81	0.81	0.72	0.73	0.72	0.77	0.77	0.76	0.77	0.76	0.90	1.00						
Jobs 2004	0.80	0.80	0.72	0.73	0.72	0.76	0.76	0.76	0.76	0.76	0.84	0.93	1.00					
Jobs 2003	0.77	0.77	0.69	0.70	0.69	0.73	0.74	0.73	0.74	0.73	0.78	0.83	0.86	1.00				
Jobs 2002	0.64	0.63	0.57	0.57	0.56	0.60	0.61	0.60	0.61	0.60	0.65	0.69	0.70	0.73	1.00			
Jobs 2001	0.78	0.78	0.69	0.69	0.69	0.74	0.75	0.74	0.75	0.74	0.74	0.78	0.77	0.79	0.68	1.00		
Jobs 2000	0.72	0.71	0.63	0.63	0.63	0.68	0.69	0.68	0.69	0.68	0.66	0.70	0.70	0.75	0.65	0.81	1.00	
Jobs 1999	0.73	0.73	0.64	0.65	0.64	0.70	0.71	0.70	0.71	0.71	0.65	0.70	0.70	0.74	0.63	0.78	0.75	1.00
Jobs 1998	0.56	0.56	0.49	0.50	0.49	0.54	0.54	0.54	0.55	0.54	0.49	0.54	0.54	0.57	0.49	0.61	0.59	0.73

Table C.2: Correlations among log-transformed jobs variables for all years

Correlation Among Arts and Jobs Variables per Year (1998-2016)

	Arts 2016	**Arts 2015**	**Arts 2014**	**Arts 2013**	**Arts 2012**	**Arts 2011**	**Arts 2010**	**Arts 2009**	**Arts 2008**	**Arts 2007**	**Arts 2006**	**Arts 2005**	**Arts 2004**	**Arts 2003**	**Arts 2002**	**Arts 2001**	**Arts 2000**	**Arts 1999**	**Arts 1998**
Jobs 2016	0.79	0.79	0.76	0.76	0.75	0.77	0.77	0.78	0.78	0.77	0.73	0.73	0.74	0.72	0.65	0.72	0.69	0.70	0.61
Jobs 2015	0.78	0.80	0.75	0.75	0.74	0.76	0.77	0.77	0.77	0.76	0.72	0.73	0.73	0.71	0.65	0.72	0.68	0.70	0.60
Jobs 2014	0.70	0.71	0.81	0.78	0.77	0.73	0.72	0.72	0.72	0.72	0.66	0.67	0.67	0.65	0.59	0.64	0.62	0.63	0.54
Jobs 2013	0.70	0.71	0.78	0.81	0.77	0.73	0.72	0.72	0.73	0.73	0.66	0.67	0.67	0.65	0.59	0.65	0.62	0.64	0.55
Jobs 2012	0.69	0.69	0.76	0.76	0.81	0.72	0.71	0.71	0.72	0.71	0.65	0.66	0.66	0.65	0.58	0.64	0.62	0.63	0.54
Jobs 2011	0.74	0.74	0.74	0.75	0.74	0.80	0.79	0.79	0.78	0.78	0.69	0.70	0.69	0.68	0.62	0.68	0.66	0.68	0.59
Jobs 2010	0.74	0.73	0.73	0.74	0.74	0.78	0.80	0.79	0.79	0.78	0.69	0.70	0.70	0.69	0.62	0.69	0.66	0.68	0.59
Jobs 2009	0.73	0.73	0.73	0.74	0.74	0.78	0.78	0.80	0.79	0.78	0.69	0.70	0.69	0.68	0.62	0.69	0.66	0.68	0.59
Jobs 2008	0.73	0.73	0.74	0.74	0.75	0.78	0.78	0.79	0.80	0.78	0.70	0.70	0.70	0.69	0.63	0.69	0.66	0.68	0.60
Jobs 2007	0.72	0.72	0.73	0.74	0.74	0.77	0.77	0.78	0.78	0.81	0.69	0.70	0.70	0.68	0.62	0.69	0.66	0.68	0.59
Jobs 2006	0.61	0.62	0.60	0.60	0.60	0.61	0.61	0.62	0.62	0.62	0.82	0.74	0.71	0.68	0.63	0.65	0.61	0.61	0.52
Jobs 2005	0.64	0.64	0.62	0.63	0.62	0.63	0.64	0.64	0.65	0.64	0.77	0.81	0.78	0.72	0.66	0.68	0.64	0.65	0.56
Jobs 2004	0.63	0.63	0.62	0.62	0.62	0.63	0.63	0.64	0.64	0.64	0.73	0.77	0.82	0.73	0.66	0.67	0.64	0.65	0.56
Jobs 2003	0.61	0.61	0.59	0.60	0.59	0.61	0.61	0.61	0.62	0.62	0.68	0.71	0.73	0.82	0.68	0.67	0.66	0.66	0.57
Jobs 2002	0.49	0.49	0.48	0.48	0.48	0.49	0.50	0.50	0.50	0.50	0.56	0.59	0.59	0.61	0.84	0.57	0.56	0.56	0.48
Jobs 2001	0.61	0.62	0.59	0.60	0.60	0.62	0.62	0.62	0.63	0.63	0.66	0.68	0.68	0.69	0.65	0.81	0.71	0.69	0.61
Jobs 2000	0.56	0.56	0.54	0.54	0.54	0.56	0.56	0.57	0.57	0.57	0.59	0.61	0.61	0.64	0.61	0.67	0.82	0.65	0.57
Jobs 1999	0.57	0.57	0.55	0.55	0.55	0.57	0.58	0.58	0.59	0.59	0.59	0.62	0.62	0.65	0.60	0.66	0.66	0.82	0.68
Jobs 1998	0.44	0.45	*0.43*	*0.43*	*0.43*	0.45	0.45	0.46	0.46	0.46	0.45	0.48	0.48	0.50	0.47	0.53	0.52	0.62	0.85

Table C.3: Correlation among log-transformed arts and jobs variables

Correlation Among First Differences Arts Variables per Pairs of Years (1998-2016)

	Arts 1999 98	Arts 2000 99	Arts 2001 00	Arts 2002 01	Arts 2003 02	Arts 2004 03	Arts 2005 04	Arts 2006 05	Arts 2007 06	Arts 2008 07	Arts 2009 08	Arts 2010 09	Arts 2011 10	Arts 2012 11	Arts 2013 12	Arts 2014 13	Arts 2015 14
Arts_2000_99	-0.226	1.000															
Arts_2001_00	-0.015	0.553	1.000														
Arts_2002_01	0.000	-0.492	-0.470	1.000													
Arts_2003_02	0.066	0.268	0.199	-0.249	1.000												
Arts_2004_03	-0.010	-0.207	-0.319	0.228	-0.367	1.000											
Arts_2005_04	0.008	0.121	0.126	-0.082	0.093	-0.245	1.000										
Arts_2006_05	-0.126	0.221	0.041	-0.027	0.038	-0.105	-0.006	1.000									
Arts_2007_06	0.044	0.089	0.069	-0.043	0.051	-0.038	-0.112	-0.493	1.000								
Arts_2008_07	0.155	-0.024	0.129	-0.113	0.095	-0.145	0.033	-0.153	0.027	1.000							
Arts_2009_08	-0.096	-0.251	-0.212	0.016	-0.163	0.154	-0.088	-0.007	-0.242	-0.306	1.000						
Arts_2010_09	-0.077	0.144	-0.050	-0.086	0.018	-0.082	-0.124	0.202	-0.115	-0.194	-0.092	1.000					
Arts_2011_10	0.096	-0.250	-0.307	0.293	0.017	0.140	0.008	0.053	-0.060	-0.092	-0.175	0.088	1.000				
Arts_2012_11	0.034	0.027	0.112	-0.167	-0.047	0.038	-0.010	-0.167	0.157	-0.052	0.043	-0.185	-0.160	1.000			
Arts_2013_12	-0.081	0.428	0.403	-0.231	0.266	-0.257	0.069	0.066	0.112	0.119	-0.125	0.016	-0.064	-0.118	1.000		
Arts_2014_13	0.100	0.325	0.264	-0.306	-0.044	-0.030	0.027	0.021	0.197	-0.008	-0.149	-0.008	-0.122	0.115	0.049	1.000	
Arts_2015_14	0.052	-0.135	-0.054	0.161	0.032	0.125	0.015	-0.007	-0.200	0.076	-0.107	-0.019	0.158	-0.496	-0.117	-0.088	1.000
Arts_2016_15	0.005	0.145	0.099	-0.066	0.254	-0.136	0.102	-0.102	0.057	0.222	-0.050	-0.024	-0.150	-0.080	0.176	-0.461	-0.032

Table C.4: Correlation among first difference arts variables for all years

Correlation Among First Differences Jobs Variables per Pairs of Years (1998-2016)

	Jobs 1999 98	**Jobs 2000 99**	**Jobs 2001 00**	**Jobs 2002 01**	**Jobs 2003 02**	**Jobs 2004 03**	**Jobs 2005 04**	**Jobs 2006 05**	**Jobs 2007 06**	**Jobs 2008 07**	**Jobs 2009 08**	**Jobs 2010 09**	**Jobs 2011 10**	**Jobs 2012 11**	**Jobs 2013 12**	**Jobs 2014 13**	**Jobs 2015 14**
Jobs_2000_99	*-0.383*	1.000															
Jobs_2001_00	0.063	0.099	1.000														
Jobs_2002_01	0.019	-0.547	-0.220	1.000													
Jobs_2003_02	0.050	0.013	-0.009	-0.274	1.000												
Jobs_2004_03	-0.026	-0.086	-0.058	0.047	-0.289	1.000											
Jobs_2005_04	-0.031	-0.021	-0.047	0.036	-0.017	-0.275	1.000										
Jobs_2006_05	-0.021	-0.078	-0.051	0.050	0.014	0.061	-0.032	1.000									
Jobs_2007_06	0.013	-0.048	0.076	0.228	0.003	-0.123	-0.005	-0.488	1.000								
Jobs_2008_07	0.009	-0.029	0.052	0.054	0.057	-0.059	0.085	-0.108	0.073	1.000							
Jobs_2009_08	0.090	-0.199	-0.189	-0.028	-0.023	-0.042	-0.180	0.112	-0.380	-0.228	1.000						
Jobs_2010_09	-0.112	-0.122	-0.084	0.180	-0.039	-0.018	0.145	0.180	-0.050	-0.042	-0.110	1.000					
Jobs_2011_10	0.008	0.151	0.164	0.005	0.089	0.055	0.028	0.097	0.191	0.011	-0.314	-0.185	1.000				
Jobs_2012_11	0.019	0.184	0.112	-0.107	0.000	0.013	0.032	-0.093	0.219	0.107	-0.267	-0.172	0.179	1.000			
Jobs_2013_12	-0.024	0.169	0.162	-0.029	0.014	-0.047	0.049	0.086	0.161	0.194	-0.250	-0.070	0.238	0.033	1.000		
Jobs_2014_13	-0.024	0.120	0.077	0.041	0.043	-0.036	0.078	-0.220	0.349	0.180	-0.367	-0.130	0.245	0.168	0.083	1.000	
Jobs_2015_14	0.069	0.115	0.031	-0.157	0.072	0.021	-0.200	-0.076	-0.210	0.016	0.176	-0.340	0.033	-0.245	0.026	-0.041	1.000
Jobs_2016_15	0.023	-0.003	0.035	0.061	-0.019	-0.030	0.286	0.023	0.289	0.074	-0.429	0.339	0.137	0.059	0.109	0.147	-0.505

Table C.5: Correlation among first difference jobs variables for all years

Correlation Among First Differences Arts and Jobs Variables per Pairs of Years (1998-2016)

	Jobs 1999 98	Jobs 2000 99	Jobs 2001 00	Jobs 2002 01	Jobs 2003 02	Jobs 2004 03	Jobs 2005 04	Jobs 2006 05	Jobs 2007 06	Jobs 2008 07	Jobs 2009 08	Jobs 2010 09	Jobs 2011 10	Jobs 2012 11	Jobs 2013 12	Jobs 2014 13	Jobs 2015 14	Jobs 2016 15
Arts_1999_98	0.714	-0.329	0.013	0.101	0.084	0.010	0.026	-0.030	0.087	0.034	0.024	-0.107	0.115	0.056	0.027	0.062	0.082	0.028
Arts_2000_99	-0.244	0.830	0.319	-0.339	0.072	-0.163	-0.019	-0.144	0.127	0.028	-0.337	-0.125	0.232	0.213	0.242	0.244	0.059	0.056
Arts_2001_00	0.005	0.304	0.656	-0.131	0.090	-0.179	-0.064	-0.158	0.144	0.052	-0.237	-0.125	0.192	0.141	0.141	0.124	0.038	0.039
Arts_2002_01	-0.058	-0.513	-0.346	0.733	-0.188	0.187	0.011	0.251	0.024	-0.001	0.104	0.220	-0.076	-0.164	-0.070	-0.079	-0.100	-0.034
Arts_2003_02	-0.005	0.183	0.047	-0.107	0.523	-0.175	0.057	-0.011	0.131	0.067	-0.187	-0.053	0.241	0.126	0.122	0.094	0.032	0.073
Arts_2004_03	-0.029	-0.102	-0.135	-0.002	-0.149	0.598	-0.235	0.049	-0.106	0.019	0.055	-0.056	-0.027	-0.017	-0.055	0.026	0.084	-0.113
Arts_2005_04	-0.046	0.131	0.107	-0.060	0.091	-0.140	0.367	0.017	-0.094	0.033	-0.017	-0.061	0.143	0.062	0.114	0.018	0.122	-0.118
Arts_2006_05	-0.111	0.277	0.049	-0.135	0.022	-0.011	0.027	0.628	-0.383	-0.095	-0.008	0.163	0.084	-0.070	0.076	-0.159	-0.064	0.121
Arts_2007_06	-0.048	0.018	0.022	0.095	-0.048	-0.078	0.057	-0.460	0.655	0.108	-0.328	0.003	0.109	0.208	0.120	0.351	-0.200	0.243
Arts_2008_07	0.101	-0.079	0.068	0.047	0.076	-0.076	0.032	-0.160	0.187	0.173	-0.085	-0.090	0.089	0.013	0.045	0.142	0.046	0.111
Arts_2009_08	0.037	-0.104	-0.171	-0.103	-0.058	0.096	-0.166	0.043	-0.312	-0.160	0.518	-0.050	-0.285	-0.163	-0.202	-0.343	0.079	-0.317
Arts_2010_09	0.004	0.114	0.027	-0.095	0.003	-0.073	0.082	0.079	-0.064	0.007	-0.035	0.353	-0.078	-0.075	-0.025	-0.111	-0.140	0.174
Arts_2011_10	0.078	-0.252	-0.125	0.190	0.036	0.126	0.005	0.258	-0.053	0.122	0.006	0.058	0.224	-0.020	0.063	0.017	0.014	-0.006
Arts_2012_11	0.028	0.090	0.091	-0.196	-0.011	0.019	-0.016	-0.036	-0.004	-0.010	0.002	-0.085	0.006	0.333	0.007	0.004	-0.118	0.000
Arts_2013_12	-0.042	0.289	0.202	-0.039	0.127	-0.166	-0.003	-0.024	0.105	0.141	-0.188	-0.052	0.197	0.068	0.285	0.106	0.001	0.075
Arts_2014_13	0.011	0.246	0.108	-0.171	0.012	-0.067	0.054	-0.186	0.141	0.033	-0.189	-0.110	0.106	0.140	0.076	0.451	-0.012	0.016
Arts_2015_14	-0.004	-0.138	-0.023	0.166	0.012	0.068	-0.029	0.077	-0.027	0.068	-0.042	-0.025	0.101	-0.147	0.042	0.049	0.341	-0.092
Arts_2016_15	0.016	0.111	0.093	-0.014	0.049	-0.084	0.002	-0.093	0.160	0.061	-0.089	0.062	0.076	0.021	0.073	-0.073	-0.079	0.277

Table C.6: Correlation among first difference arts and jobs variables for all years

APPENDIX C.2: CROSS-LAGGED REGRESSION RESULTS FOR THE RECIPROCAL RELATIONSHIP BETWEEN ARTS AND NON-ARTS JOBS

Regression Results for One Year Lags, All Urban Areas and Hexagons as Unit of Analysis

N = 63049		**"Arts Attract Jobs" Hypothesis** Dependent Variable: Jobs				**"Jobs Attract Arts" Hypothesis** Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	0.159	0.004	0.000	0.548	-0.314	0.004	0.000	0.731	Arts are stronger
2000	1999	0.091	0.004	0.000	0.571	-0.157	0.004	0.000	0.741	Arts are stronger
2001	2000	0.109	0.003	0.000	0.660	-0.174	0.004	0.000	0.792	Arts are stronger
2002	2001	0.056	0.005	0.000	0.466	0.016	0.005	0.004	0.628	Arts are stronger
2003	2002	0.165	0.004	0.000	0.547	-0.288	0.004	0.000	0.707	Arts are stronger
2004	2003	0.079	0.003	0.000	0.734	-0.053	0.003	0.000	0.828	Arts are stronger
2005	2004	0.036	0.002	0.000	0.869	**-0.004**	0.003	0.204	0.886	Arts are stronger
2006	2005	0.033	0.003	0.000	0.807	0.035	0.003	0.000	0.873	Jobs are stronger
2007	2006	0.208	0.003	0.000	0.559	-0.293	0.004	0.000	0.761	Arts are stronger
2008	2007	0.033	0.002	0.000	0.896	0.043	0.003	0.000	0.908	Jobs are stronger
2009	2008	0.043	0.002	0.000	0.916	0.036	0.002	0.000	0.936	Arts are stronger
2010	2009	0.030	0.001	0.000	0.933	0.013	0.002	0.000	0.939	Arts are stronger
2011	2010	0.020	0.001	0.000	0.949	0.048	0.002	0.000	0.937	Jobs are stronger
2012	2011	0.052	0.003	0.000	0.758	0.028	0.003	0.000	0.851	Arts are stronger
2013	2012	0.056	0.002	0.000	0.865	-0.027	0.002	0.000	0.915	Arts are stronger
2014	2013	0.039	0.002	0.000	0.888	**0.001**	0.002	0.542	0.924	Arts are stronger
2015	2014	0.123	0.002	0.000	0.740	-0.163	0.003	0.000	0.876	Arts are stronger
2016	2015	0.013	0.001	0.000	0.979	0.026	0.002	0.000	0.952	Jobs are stronger

*Values in bold are not significant

Table C.7: Regression results and statistics presented in figure 4.12

Regression Results for One Year Lags, Top 10 Urban Areas, Hexagons as Unit of Analysis

N = 13990		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	0.289	0.010	0.000	0.375	-0.531	0.008	0.000	0.661	Arts are stronger
2000	1999	0.114	0.007	0.000	0.659	-0.146	0.008	0.000	0.801	Arts are stronger
2001	2000	0.101	0.007	0.000	0.725	-0.109	0.007	0.000	0.849	Arts are stronger
2002	2001	0.092	0.009	0.000	0.580	-0.043	0.010	0.000	0.727	Arts are stronger
2003	2002	0.154	0.006	0.000	0.732	-0.193	0.007	0.000	0.808	Arts are stronger
2004	2003	0.041	0.003	0.000	0.921	0.042	0.005	0.000	0.931	Jobs are stronger
2005	2004	0.037	0.004	0.000	0.914	-0.032	0.006	0.000	0.923	Arts are stronger
2006	2005	**0.004**	0.005	0.398	0.836	0.077	0.007	0.000	0.889	Jobs are stronger
2007	2006	0.123	0.005	0.000	0.808	-0.106	0.007	0.000	0.859	Arts are stronger
2008	2007	0.008	0.002	0.001	0.962	0.102	0.005	0.000	0.933	Jobs are stronger
2009	2008	0.028	0.002	0.000	0.973	0.085	0.004	0.000	0.954	Jobs are stronger
2010	2009	0.022	0.003	0.000	0.954	**0.007**	0.004	0.136	0.949	Arts are stronger
2011	2010	0.006	0.001	0.000	0.997	0.044	0.004	0.000	0.954	Jobs are stronger
2012	2011	0.030	0.005	0.000	0.835	0.072	0.007	0.000	0.882	Jobs are stronger
2013	2012	0.015	0.003	0.000	0.956	0.052	0.004	0.000	0.954	Jobs are stronger
2014	2013	0.048	0.004	0.000	0.884	-0.027	0.005	0.000	0.921	Arts are stronger
2015	2014	0.113	0.005	0.000	0.788	-0.119	0.006	0.000	0.882	Arts are stronger
2016	2015	0.005	0.001	0.000	0.997	0.046	0.004	0.000	0.959	Jobs are stronger

* Values in bold are not significant

Table C.8: Regression results and statistics presented in figure 4.13

Regression Results for Ten Year Lags, All Urban Areas, Hexagons as Unit of Analysis

N = 63049		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
2008	1998	0.273	0.004	0.000	0.360	-0.320	0.004	0.000	0.501	Arts are stronger
2009	1999	0.205	0.003	0.000	0.524	-0.107	0.004	0.000	0.573	Arts are stronger
2010	2000	0.198	0.003	0.000	0.502	-0.135	0.005	0.000	0.557	Arts are stronger
2011	2001	0.165	0.003	0.000	0.571	-0.053	0.005	0.000	0.609	Arts are stronger
2012	2002	0.261	0.004	0.000	0.356	-0.319	0.005	0.000	0.509	Arts are stronger
2013	2003	0.191	0.004	0.000	0.508	-0.107	0.005	0.000	0.604	Arts are stronger
2014	2004	0.179	0.004	0.000	0.541	-0.094	0.005	0.000	0.624	Arts are stronger
2015	2005	0.146	0.003	0.000	0.665	-0.085	0.004	0.000	0.669	Arts are stronger
2016	2006	0.183	0.003	0.000	0.631	-0.170	0.004	0.000	0.664	Arts are stronger

Table C.9: Regression results and statistics presented in figure 4.14

Regression Results for Ten Year Lags, Top 10 Urban Areas, Hexagons as Unit of Analysis

N = 13990		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
2008	1998	0.296	0.008	0.000	0.359	-0.356	0.009	0.000	0.526	Arts are stronger
2009	1999	0.150	0.006	0.000	0.698	0.022	0.009	0.011	0.702	Arts are stronger
2010	2000	0.124	0.006	0.000	0.686	0.047	0.009	0.000	0.676	Arts are stronger
2011	2001	0.116	0.006	0.000	0.703	0.056	0.010	0.000	0.681	Arts are stronger
2012	2002	0.198	0.008	0.000	0.507	-0.128	0.010	0.000	0.598	Arts are stronger
2013	2003	0.080	0.007	0.000	0.668	0.122	0.010	0.000	0.700	Jobs are stronger
2014	2004	0.047	0.007	0.000	0.700	0.177	0.011	0.000	0.701	Jobs are stronger
2015	2005	0.032	0.003	0.000	0.912	0.249	0.009	0.000	0.793	Jobs are stronger
2016	2006	0.112	0.005	0.000	0.807	0.054	0.009	0.000	0.748	Arts are stronger

Table C.10: Regression results and statistics presented in figure 4.15

Regression Results for the Relationship Between Arts and Non-Arts Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 63049		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	9.302	0.036	0.000	0.510	0.055	0.000	0.000	0.510	Arts are stronger
2000	1999	5.857	0.016	0.000	0.689	0.118	0.000	0.000	0.689	Arts are stronger
2001	2000	3.607	0.017	0.000	0.430	0.119	0.001	0.000	0.430	Arts are stronger
2002	2001	6.686	0.025	0.000	0.537	0.080	0.000	0.000	0.537	Arts are stronger
2003	2002	4.492	0.029	0.000	0.274	0.061	0.000	0.000	0.274	Arts are stronger
2004	2003	4.745	0.025	0.000	0.358	0.075	0.000	0.000	0.358	Arts are stronger
2005	2004	3.073	0.031	0.000	0.135	0.044	0.000	0.000	0.135	Arts are stronger
2006	2005	4.649	0.023	0.000	0.395	0.085	0.000	0.000	0.395	Arts are stronger
2007	2006	5.646	0.026	0.000	0.429	0.076	0.000	0.000	0.429	Arts are stronger
2008	2007	0.949	0.021	0.000	0.030	0.032	0.001	0.000	0.030	Arts are stronger
2009	2008	3.972	0.026	0.000	0.268	0.068	0.000	0.000	0.268	Arts are stronger
2010	2009	2.232	0.024	0.000	0.125	0.056	0.001	0.000	0.125	Arts are stronger
2011	2010	1.192	0.021	0.000	0.050	0.042	0.001	0.000	0.050	Arts are stronger
2012	2011	1.907	0.021	0.000	0.111	0.058	0.001	0.000	0.111	Arts are stronger
2013	2012	1.912	0.026	0.000	0.082	0.043	0.001	0.000	0.082	Arts are stronger
2014	2013	2.239	0.018	0.000	0.203	0.091	0.001	0.000	0.203	Arts are stronger
2015	2014	2.166	0.024	0.000	0.116	0.054	0.001	0.000	0.116	Arts are stronger
2016	2015	2.053	0.028	0.000	0.076	0.037	0.001	0.000	0.076	Arts are stronger

Table C.11: Regression results and statistics presented in figure 4.16

Regression Results for the Relationship Between Arts and Non-Arts Jobs in One Year First Differences, Ten Largest Urban Areas, Hexagons as Unit of Analysis

N = 13990		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	10.967	0.081	0.000	0.567	0.052	0.000	0.000	0.567	Arts are stronger
2000	1999	6.009	0.030	0.000	0.745	0.124	0.001	0.000	0.745	Arts are stronger
2001	2000	3.673	0.026	0.000	0.593	0.161	0.001	0.000	0.593	Arts are stronger
2002	2001	6.846	0.047	0.000	0.601	0.088	0.001	0.000	0.601	Arts are stronger
2003	2002	4.596	0.052	0.000	0.357	0.078	0.001	0.000	0.357	Arts are stronger
2004	2003	4.945	0.044	0.000	0.469	0.095	0.001	0.000	0.469	Arts are stronger
2005	2004	2.260	0.067	0.000	0.075	0.033	0.001	0.000	0.075	Arts are stronger
2006	2005	5.669	0.051	0.000	0.468	0.083	0.001	0.000	0.468	Arts are stronger
2007	2006	6.583	0.053	0.000	0.529	0.080	0.001	0.000	0.529	Arts are stronger
2008	2007	1.283	0.037	0.000	0.079	0.062	0.002	0.000	0.079	Arts are stronger
2009	2008	4.953	0.056	0.000	0.357	0.072	0.001	0.000	0.357	Arts are stronger
2010	2009	3.316	0.048	0.000	0.252	0.076	0.001	0.000	0.252	Arts are stronger
2011	2010	1.512	0.040	0.000	0.093	0.061	0.002	0.000	0.093	Arts are stronger
2012	2011	2.196	0.055	0.000	0.101	0.046	0.001	0.000	0.101	Arts are stronger
2013	2012	2.526	0.053	0.000	0.140	0.055	0.001	0.000	0.140	Arts are stronger
2014	2013	1.990	0.033	0.000	0.205	0.103	0.002	0.000	0.205	Arts are stronger
2015	2014	2.025	0.052	0.000	0.096	0.048	0.001	0.000	0.096	Arts are stronger
2016	2015	2.557	0.067	0.000	0.093	0.036	0.001	0.000	0.093	Arts are stronger

Table C.12: Regression results and statistics presented in figure 4.17

APPENDIX C.3: CROSS-LAGGED REGRESSION RESULTS FOR THE RECIPROCAL RELATIONSHIP BETWEEN ARTS CATEGORIES AND NON-ARTS JOBS

Regression Results for the Relationship Between Arts Amenities and Non-Arts Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 61127		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	17.025	0.193	0.000	0.113	0.007	0.000	0.000	0.113	Arts are stronger
2000	1999	20.091	0.066	0.000	0.605	0.030	0.000	0.000	0.605	Arts are stronger
2001	2000	12.276	0.090	0.000	0.233	0.019	0.000	0.000	0.233	Arts are stronger
2002	2001	12.387	0.160	0.000	0.089	0.007	0.000	0.000	0.089	Arts are stronger
2003	2002	10.943	0.105	0.000	0.150	0.014	0.000	0.000	0.150	Arts are stronger
2004	2003	12.094	0.103	0.000	0.184	0.015	0.000	0.000	0.184	Arts are stronger
2005	2004	2.034	0.097	0.000	0.007	0.004	0.000	0.000	0.007	Arts are stronger
2006	2005	7.923	0.097	0.000	0.099	0.012	0.000	0.000	0.099	Arts are stronger
2007	2006	10.900	0.123	0.000	0.114	0.010	0.000	0.000	0.114	Arts are stronger
2008	2007	-1.778	0.067	0.000	0.012	-0.006	0.000	0.000	0.012	Jobs are stronger
2009	2008	4.897	0.084	0.000	0.053	0.011	0.000	0.000	0.053	Arts are stronger
2010	2009	2.331	0.078	0.000	0.014	0.006	0.000	0.000	0.014	Arts are stronger
2011	2010	1.542	0.044	0.000	0.019	0.013	0.000	0.000	0.019	Arts are stronger
2012	2011	3.889	0.087	0.000	0.031	0.008	0.000	0.000	0.031	Arts are stronger
2013	2012	3.417	0.067	0.000	0.041	0.012	0.000	0.000	0.041	Arts are stronger
2014	2013	5.670	0.077	0.000	0.082	0.014	0.000	0.000	0.082	Arts are stronger
2015	2014	10.052	0.151	0.000	0.068	0.007	0.000	0.000	0.068	Arts are stronger
2016	2015	3.832	0.105	0.000	0.021	0.006	0.000	0.000	0.021	Arts are stronger

Table C.13: Regression results and statistics presented in figure 4.23 and 4.24

Regression Results for the Relationship Between Arts Producers and Non-Arts Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 63045		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	14.601	0.085	0.000	0.320	0.022	0.000	0.000	0.320	Arts are stronger
2000	1999	11.328	0.035	0.000	0.624	0.055	0.000	0.000	0.624	Arts are stronger
2001	2000	6.058	0.037	0.000	0.301	0.050	0.000	0.000	0.301	Arts are stronger
2002	2001	12.384	0.050	0.000	0.495	0.040	0.000	0.000	0.495	Arts are stronger
2003	2002	5.511	0.063	0.000	0.111	0.020	0.000	0.000	0.111	Arts are stronger
2004	2003	7.215	0.051	0.000	0.241	0.033	0.000	0.000	0.241	Arts are stronger
2005	2004	3.904	0.055	0.000	0.076	0.020	0.000	0.000	0.076	Arts are stronger
2006	2005	7.062	0.060	0.000	0.184	0.026	0.000	0.000	0.184	Arts are stronger
2007	2006	5.498	0.064	0.000	0.107	0.019	0.000	0.000	0.107	Arts are stronger
2008	2007	1.093	0.038	0.000	0.013	0.012	0.000	0.000	0.013	Arts are stronger
2009	2008	6.143	0.046	0.000	0.223	0.036	0.000	0.000	0.223	Arts are stronger
2010	2009	3.840	0.037	0.000	0.146	0.038	0.000	0.000	0.146	Arts are stronger
2011	2010	-0.567	0.040	0.000	0.003	-0.006	0.000	0.000	0.003	Jobs are stronger
2012	2011	1.833	0.070	0.000	0.011	0.006	0.000	0.000	0.011	Arts are stronger
2013	2012	3.058	0.053	0.000	0.050	0.016	0.000	0.000	0.050	Arts are stronger
2014	2013	1.665	0.027	0.000	0.057	0.034	0.001	0.000	0.057	Arts are stronger
2015	2014	2.194	0.043	0.000	0.040	0.018	0.000	0.000	0.040	Arts are stronger
2016	2015	2.104	0.039	0.000	0.044	0.021	0.000	0.000	0.044	Arts are stronger

Table C.13: Regression results and statistics presented in figure 4.23 and 4.24 (cont.)

Regression Results for the Relationship Between Recreation and Non-Arts Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 63045		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	13.256	0.072	0.000	0.348	0.026	0.000	0.000	0.348	Arts are stronger
2000	1999	14.710	0.061	0.000	0.478	0.033	0.000	0.000	0.478	Arts are stronger
2001	2000	6.349	0.037	0.000	0.321	0.051	0.000	0.000	0.321	Arts are stronger
2002	2001	10.985	0.058	0.000	0.364	0.033	0.000	0.000	0.364	Arts are stronger
2003	2002	4.683	0.049	0.000	0.127	0.027	0.000	0.000	0.127	Arts are stronger
2004	2003	6.172	0.055	0.000	0.165	0.027	0.000	0.000	0.165	Arts are stronger
2005	2004	3.065	0.047	0.000	0.064	0.021	0.000	0.000	0.064	Arts are stronger
2006	2005	5.200	0.037	0.000	0.241	0.046	0.000	0.000	0.241	Arts are stronger
2007	2006	7.417	0.041	0.000	0.342	0.046	0.000	0.000	0.342	Arts are stronger
2008	2007	1.702	0.031	0.000	0.045	0.026	0.000	0.000	0.045	Arts are stronger
2009	2008	3.604	0.051	0.000	0.074	0.021	0.000	0.000	0.074	Arts are stronger
2010	2009	1.022	0.037	0.000	0.012	0.012	0.000	0.000	0.012	Arts are stronger
2011	2010	2.105	0.030	0.000	0.074	0.035	0.000	0.000	0.074	Arts are stronger
2012	2011	1.926	0.025	0.000	0.085	0.044	0.001	0.000	0.085	Arts are stronger
2013	2012	1.424	0.039	0.000	0.020	0.014	0.000	0.000	0.020	Arts are stronger
2014	2013	4.725	0.038	0.000	0.200	0.042	0.000	0.000	0.200	Arts are stronger
2015	2014	2.407	0.035	0.000	0.069	0.029	0.000	0.000	0.069	Arts are stronger
2016	2015	1.857	0.052	0.000	0.020	0.011	0.000	0.000	0.020	Arts are stronger

Table C.13: Regression results and statistics presented in figure 4.23 and 4.24 (cont.)

APPENDIX D: CHAPTER 5 SUPPLEMENTS

APPENDIX D.1: DISTRIBUTION OF FIRST DIFFERENCE VARIABLES

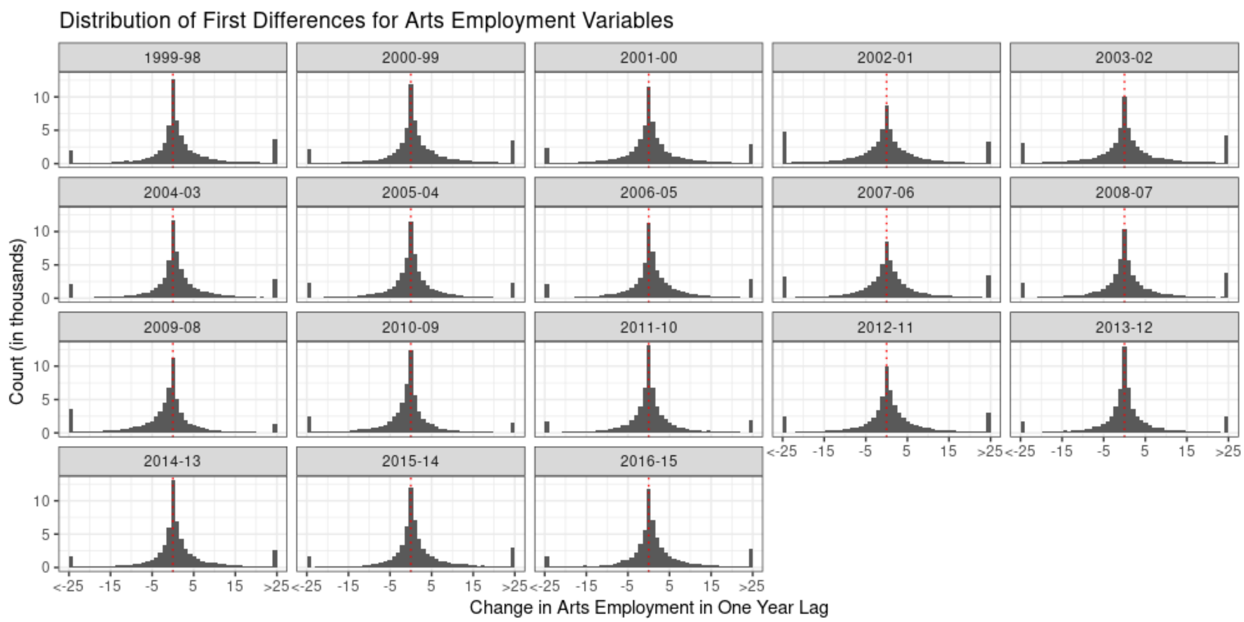

Figure D.1: Distribution of first differences arts variables

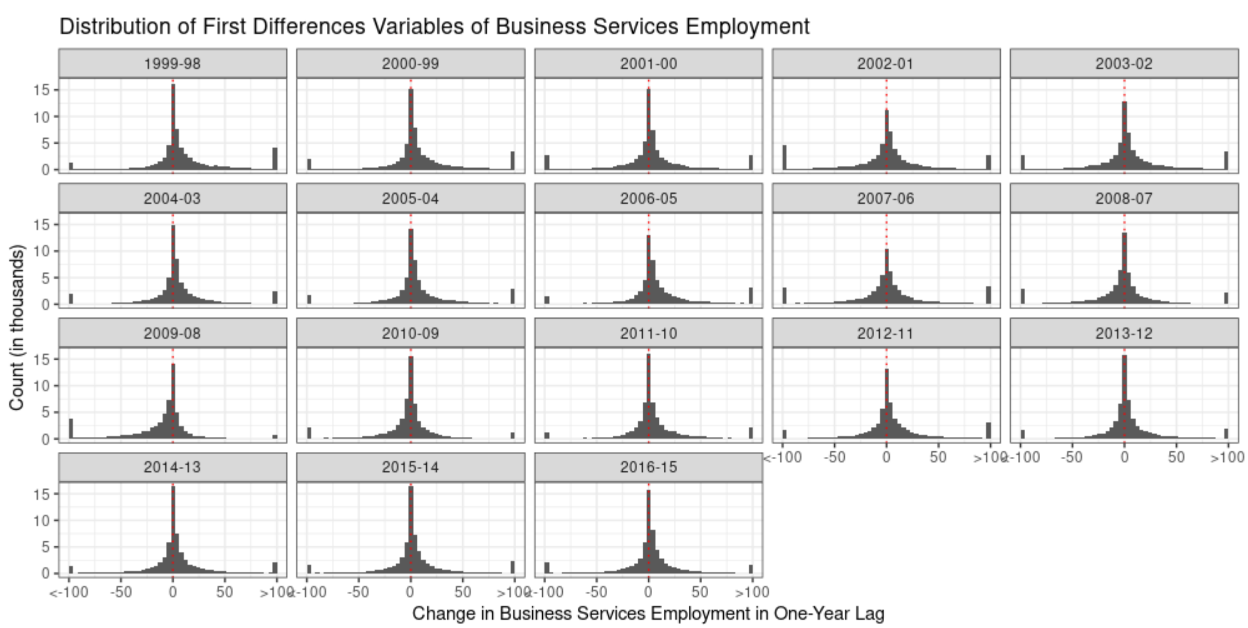

Figure D.2: Distribution of first differences business services variables

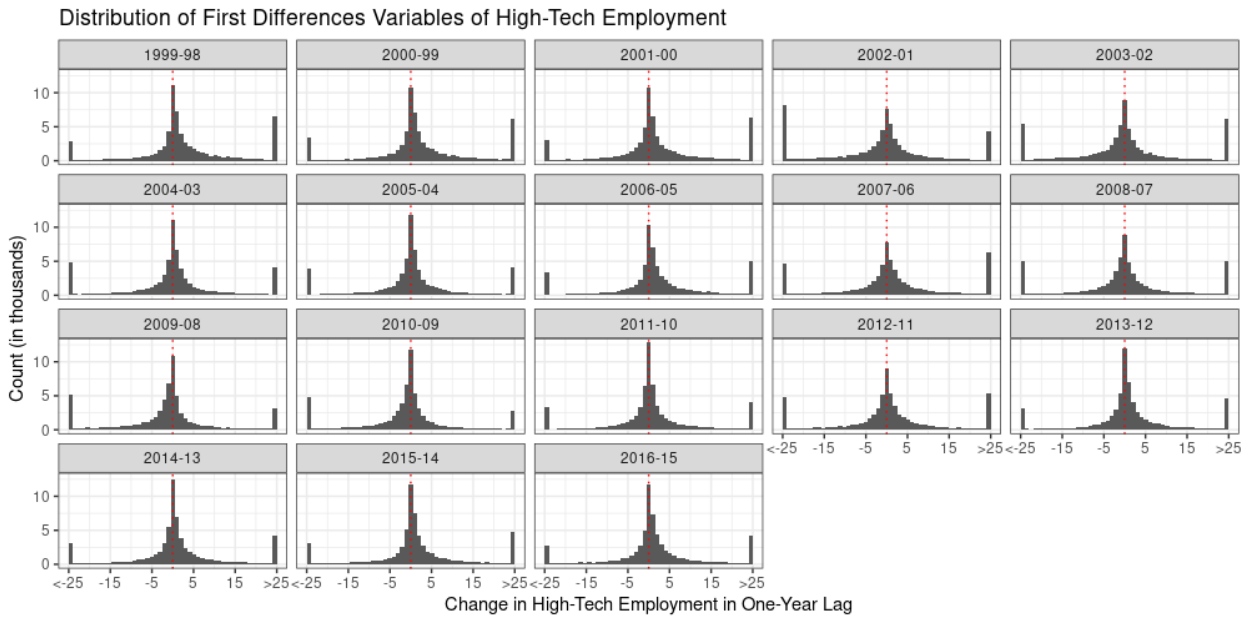

Figure D.3: Distribution of first differences high-tech variables

APPENDIX D.2: CORRELATIONS AMONG INDUSTRIES

Correlations Among Industries

Category 1	Category 2	cor	Category 1	Category 2	cor
Food	Retail	0.868	Construction	Health	0.533
Arts Amenities	Arts Producers	0.865	Other	Transportation	0.533
Food	Other	0.847	Arts Producers	Education	0.519
Other	Wholesale	0.844	Health	Wholesale	0.513
Other	Retail	0.834	Transportation	Wholesale	0.509
Other	Producer Services	0.812	Arts Producers	Health	0.505
Food	Recreation	0.812	Manufacturing	Retail	0.490
High-Tech	Producer Services	0.805	Health	Recreation	0.486
Food	Producer Services	0.789	Arts Producers	Construction	0.485
High-Tech	Other	0.788	Manufacturing	Transportation	0.484
Education	Health	0.785	Education	Recreation	0.482
Arts Amenities	Food	0.783	Construction	Transportation	0.479
Construction	Other	0.775	High-Tech	Manufacturing	0.445
Arts Producers	Producer Services	0.773	Recreation	Wholesale	0.444
Arts Producers	Other	0.763	Arts Amenities	Construction	0.440
Arts Producers	Food	0.752	Construction	Recreation	0.434
Food	Health	0.741	Education	Wholesale	0.434
Health	Retail	0.739	Food	Transportation	0.413
Education	Food	0.728	Food	Manufacturing	0.412
Construction	Wholesale	0.727	Organizations	Wholesale	0.410
Health	Other	0.727	Construction	Education	0.409
Food	High-Tech	0.726	Producer Services	Utilities	0.395
Arts Amenities	Other	0.723	Health	Manufacturing	0.393
Arts Amenities	Producer Services	0.722	Retail	Transportation	0.388
Organizations	Producer Services	0.710	High-Tech	Transportation	0.386
Manufacturing	Wholesale	0.706	Producer Services	Transportation	0.366
Food	Organizations	0.703	Manufacturing	Producer Services	0.364
High-Tech	Wholesale	0.702	Construction	Organizations	0.363
Arts Producers	Wholesale	0.686	Arts Producers	Manufacturing	0.349
Retail	Wholesale	0.662	Food	Utilities	0.332
Construction	Retail	0.662	High-Tech	Utilities	0.330
Producer Services	Retail	0.661	Arts Amenities	Manufacturing	0.322
Education	Other	0.661	Other	Utilities	0.316
Producer Services	Wholesale	0.657	Recreation	Transportation	0.311
Producer Services	Recreation	0.654	Arts Producers	Transportation	0.308
Organizations	Other	0.654	Arts Amenities	Transportation	0.307
Recreation	Retail	0.651	Health	Transportation	0.301
High-Tech	Retail	0.649	Education	Manufacturing	0.297
Arts Producers	Retail	0.648	Arts Amenities	Utilities	0.295
Other	Recreation	0.642	Health	Utilities	0.288
Education	Organizations	0.640	Transportation	Utilities	0.277
Education	Retail	0.640	Construction	Utilities	0.263
Arts Amenities	Recreation	0.638	Education	Transportation	0.262
Construction	Manufacturing	0.634	Education	Utilities	0.250
Arts Amenities	Retail	0.623	Manufacturing	Recreation	0.245

Table D.1: Correlations for each pair of industries in descending order

Correlations Among Industries

Category 1	Category 2	cor	Category 1	Category 2	cor
Arts Amenities	Education	0.620	Retail	Utilities	0.243
Construction	High-Tech	0.620	Recreation	Utilities	0.237
Food	Wholesale	0.616	Organizations	Transportation	0.236
Arts Producers	High-Tech	0.610	Manufacturing	Organizations	0.233
Arts Amenities	Wholesale	0.606	Mining	Transportation	0.227
Arts Producers	Recreation	0.605	Utilities	Wholesale	0.221
Health	Organizations	0.595	Organizations	Utilities	0.219
Arts Producers	Organizations	0.594	Mining	Producer Services	0.211
High-Tech	Organizations	0.592	Arts Producers	Utilities	0.203
Construction	Food	0.589	Construction	Mining	0.200
Education	Producer Services	0.587	Manufacturing	Utilities	0.193
Manufacturing	Other	0.583	High-Tech	Mining	0.180
Health	Producer Services	0.580	Food	Mining	0.159
Arts Amenities	Health	0.580	Mining	Other	0.142
Health	High-Tech	0.573	Mining	Wholesale	0.126
Arts Amenities	High-Tech	0.572	Mining	Recreation	0.121
Education	High-Tech	0.567	Arts Amenities	Mining	0.120
Organizations	Recreation	0.564	Mining	Retail	0.111
Arts Amenities	Organizations	0.562	Health	Mining	0.098
Construction	Producer Services	0.550	Manufacturing	Mining	0.094
Organizations	Retail	0.541	Arts Producers	Mining	0.068
Mining	Utilities	0.540	Mining	Organizations	0.068
High-Tech	Recreation	0.537	Education	Mining	0.055

Table D.1: Correlations for each pair of industries in descending order (cont.)

APPENDIX D.3: CROSS-LAGGED REGRESSION RESULTS FOR ARTS AND BUSINESS SERVICES

Regression Results for the Relationship Between Arts and Business Services in Log One Year Lags, All Urban Areas and Hexagons as Unit of Analysis

N = 63049		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	-0.021	0.004	0.000	0.669	-0.113	0.004	0.000	0.702	Arts Attract Jobs
2000	1999	0.002	0.004	*0.653*	0.721	-0.017	0.004	0.000	0.735	Not Significant
2001	2000	0.018	0.003	0.000	0.773	-0.019	0.003	0.000	0.784	Arts Attract Jobs
2002	2001	0.039	0.005	0.000	0.619	0.078	0.005	0.000	0.630	Jobs Attract Arts
2003	2002	0.000	0.004	0.989	0.674	-0.069	0.004	0.000	0.684	Not Significant
2004	2003	0.004	0.003	*0.150*	0.835	0.042	0.003	0.000	0.827	Jobs Attract Arts
2005	2004	0.030	0.002	0.000	0.910	**0.040**	0.002	0.000	0.886	Jobs Attract Arts
2006	2005	0.016	0.002	0.000	0.879	0.067	0.003	0.000	0.874	Jobs Attract Arts
2007	2006	0.035	0.003	0.000	0.719	-0.042	0.004	0.000	0.739	Arts Attract Jobs
2008	2007	0.030	0.002	0.000	0.929	0.062	0.002	0.000	0.909	Jobs Attract Arts
2009	2008	0.036	0.001	0.000	0.950	0.051	0.002	0.000	0.936	Jobs Attract Arts
2010	2009	0.023	0.001	0.000	0.953	0.030	0.002	0.000	0.940	Jobs Attract Arts
2011	2010	0.018	0.001	0.000	0.961	0.057	0.002	0.000	0.937	Jobs Attract Arts
2012	2011	0.042	0.003	0.000	0.854	0.066	0.003	0.000	0.852	Jobs Attract Arts
2013	2012	0.023	0.002	0.000	0.922	0.020	0.002	0.000	0.914	Arts Attract Jobs
2014	2013	0.021	0.002	0.000	0.934	**0.032**	0.002	0.000	0.924	Jobs Attract Arts
2015	2014	0.008	0.002	0.001	0.857	-0.021	0.002	0.000	0.869	Arts Attract Jobs
2016	2015	0.025	0.001	0.000	0.974	0.030	0.002	0.000	0.952	Jobs Attract Arts

Table D.2: Regression results and statistics presented in figure 5.11

Regression Results for the Relationship Between Arts and Business Services in Log One Year Lags, Ten Largest Urban Areas and Hexagons as Unit of Analysis

N = 13990		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	-0.062	0.011	0.000	0.515	-0.194	0.010	0.000	0.576	Arts Attract Jobs
2000	1999	0.035	0.008	0.000	0.779	0.005	0.007	0.521	0.797	Arts Attract Jobs
2001	2000	0.049	0.007	0.000	0.820	-0.012	0.006	0.063	0.847	Arts Attract Jobs
2002	2001	0.045	0.009	0.000	0.715	0.053	0.009	0.000	0.727	Jobs Attract Arts
2003	2002	0.023	0.007	0.001	0.817	0.005	0.007	0.466	0.799	Arts Attract Jobs
2004	2003	0.022	0.004	0.000	0.947	0.069	0.004	0.000	0.932	Jobs Attract Arts
2005	2004	0.007	0.004	0.071	0.937	**0.024**	0.004	0.000	0.923	Jobs Attract Arts
2006	2005	0.022	0.005	0.000	0.893	0.067	0.005	0.000	0.889	Jobs Attract Arts
2007	2006	0.040	0.006	0.000	0.877	0.038	0.006	0.000	0.858	Arts Attract Jobs
2008	2007	0.032	0.003	0.000	0.961	0.088	0.004	0.000	0.933	Jobs Attract Arts
2009	2008	0.044	0.003	0.000	0.974	0.081	0.003	0.000	0.954	Jobs Attract Arts
2010	2009	0.023	0.003	0.000	0.966	0.032	0.004	0.000	0.950	Jobs Attract Arts
2011	2010	0.024	0.002	0.000	0.986	0.032	0.004	0.000	0.954	Jobs Attract Arts
2012	2011	0.090	0.006	0.000	0.881	0.058	0.006	0.000	0.882	Arts Attract Jobs
2013	2012	0.013	0.003	0.000	0.969	0.063	0.003	0.000	0.955	Jobs Attract Arts
2014	2013	0.023	0.004	0.000	0.932	**0.011**	0.005	0.021	0.921	Arts Attract Jobs
2015	2014	-0.009	0.006	*0.133*	0.862	0.008	0.005	0.150	0.879	Not Significant
2016	2015	0.033	0.002	0.000	0.985	0.038	0.003	0.000	0.959	Jobs Attract Arts

Table D.3: Regression results and statistics presented in figure 5.12

Regression Results for the Relationship Between Arts and Business Services in Log Ten Year Lags, All Urban Areas and Hexagons as Unit of Analysis

N = 63049		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
2008	1998	0.064	0.004	0.000	0.466	-0.015	0.004	0.001	0.454	Arts Attract Jobs
2009	1999	0.086	0.004	0.000	0.639	0.130	0.004	0.000	0.576	Jobs Attract Arts
2010	2000	0.079	0.004	0.000	0.610	0.113	0.004	0.000	0.556	Jobs Attract Arts
2011	2001	0.082	0.003	0.000	0.677	0.145	0.004	0.00000000(	0.616	Jobs Attract Arts
2012	2002	0.046	0.005	0.000	0.495	0.006	0.005	0.184	0.473	Arts Attract Jobs
2013	2003	0.067	0.004	0.000	0.646	0.117	0.004	0.000	0.606	Jobs Attract Arts
2014	2004	0.083	0.004	0.000	0.672	0.117	0.004	0.000	0.626	Jobs Attract Arts
2015	2005	0.066	0.003	0.000	0.733	0.113	0.004	0.000	0.672	Jobs Attract Arts
2016	2006	0.072	0.003	0.000	0.713	0.074	0.004	0.000	0.658	Jobs Attract Arts

Table D.4: Regression results and statistics presented in figure 5.13

Regression Results for the Relationship Between Arts and Business Services in Log Ten Year Lags, Ten Largest Urban Areas and Hexagons as Unit of Analysis

N = 13990		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
2008	1998	0.029	0.010	0.005	0.445	-0.021	0.010	0.026	0.469	Arts Attract Jobs
2009	1999	0.088	0.007	0.000	0.765	0.167	0.007	0.000	0.712	Jobs Attract Arts
2010	2000	0.074	0.007	0.000	0.734	0.174	0.008	0.000	0.686	Jobs Attract Arts
2011	2001	0.061	0.007	0.000	0.761	0.204	0.008	0.000	0.694	Jobs Attract Arts
2012	2002	0.067	0.009	0.000	0.630	0.131	0.009	0.000	0.599	Jobs Attract Arts
2013	2003	0.077	0.008	0.000	0.749	0.213	0.008	0.000	0.711	Jobs Attract Arts
2014	2004	0.087	0.008	0.000	0.763	0.228	0.009	0.000	0.710	Jobs Attract Arts
2015	2005	0.107	0.005	0.000	0.875	0.233	0.007	0.00000000(	0.798	Jobs Attract Arts
2016	2006	0.097	0.006	0.000	0.831	0.175	0.008	0.000	0.757	Jobs Attract Arts

Table D.5: Regression results and statistics presented in figure 5.14

Regression Results for the Relationship Between Arts and Business Services Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 63049		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	3.028	0.013	0.000	0.464	0.153	0.001	0.000	0.464	Arts are stronger
2000	1999	2.228	0.008	0.000	0.576	0.258	0.001	0.000	0.576	Arts are stronger
2001	2000	1.258	0.007	0.000	0.337	0.268	0.001	0.000	0.337	Arts are stronger
2002	2001	2.803	0.013	0.000	0.428	0.153	0.001	0.000	0.428	Arts are stronger
2003	2002	1.601	0.012	0.000	0.208	0.130	0.001	0.000	0.208	Arts are stronger
2004	2003	2.095	0.011	0.000	0.381	0.182	0.001	0.000	0.381	Arts are stronger
2005	2004	1.269	0.014	0.000	0.110	0.087	0.001	0.000	0.110	Arts are stronger
2006	2005	2.125	0.012	0.000	0.316	0.149	0.001	0.000	0.316	Arts are stronger
2007	2006	2.787	0.013	0.000	0.420	0.151	0.001	0.000	0.420	Arts are stronger
2008	2007	0.406	0.011	0.000	0.022	0.054	0.001	7810160117	0.022	Arts are stronger
2009	2008	1.844	0.013	0.000	0.235	0.127	0.001	0.000	0.235	Arts are stronger
2010	2009	1.233	0.012	0.000	0.147	0.120	0.001	0.000	0.147	Arts are stronger
2011	2010	0.500	0.009	0.000	0.049	0.097	0.002	0.000	0.049	Arts are stronger
2012	2011	0.504	0.007	0.000	0.071	0.140	0.002	0.000	0.071	Arts are stronger
2013	2012	0.488	0.011	0.000	0.030	0.061	0.001	0.000	0.030	Arts are stronger
2014	2013	0.829	0.008	0.000	0.148	0.179	0.002	0.000	0.148	Arts are stronger
2015	2014	0.623	0.014	0.000	0.031	0.050	0.001	0.000	0.031	Arts are stronger
2016	2015	1.232	0.023	0.000	0.045	0.037	0.001	0.000	0.045	Arts are stronger

Table D.6: Regression results and statistics presented in figure 5.15

Regression Results for the Relationship Between Arts and Business Services Jobs in One Year First Differences, Ten Largest Urban Areas, Hexagons as Unit of Analysis

N = 13990		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	3.386	0.029	0.000	0.501	0.148	0.001	0.000	0.501	Arts are stronger
2000	1999	2.301	0.015	0.000	0.617	0.268	0.002	0.000	0.617	Arts are stronger
2001	2000	1.276	0.012	0.000	0.455	0.357	0.003	0.000	0.455	Arts are stronger
2002	2001	2.965	0.027	0.000	0.461	0.155	0.001	0.000	0.461	Arts are stronger
2003	2002	1.674	0.025	0.000	0.246	0.147	0.002	0.000	0.246	Arts are stronger
2004	2003	2.304	0.019	0.000	0.506	0.220	0.002	0.000	0.506	Arts are stronger
2005	2004	1.022	0.033	0.000	0.063	0.062	0.002	0.000	0.063	Arts are stronger
2006	2005	2.785	0.028	0.000	0.406	0.146	0.001	0.000	0.406	Arts are stronger
2007	2006	3.510	0.028	0.000	0.533	0.152	0.001	0.000	0.533	Arts are stronger
2008	2007	0.561	0.023	0.000	0.042	0.076	0.003	0.000	0.042	Arts are stronger
2009	2008	2.306	0.031	0.000	0.288	0.125	0.002	0.000	0.288	Arts are stronger
2010	2009	2.076	0.027	0.000	0.290	0.140	0.002	0.000	0.290	Arts are stronger
2011	2010	0.662	0.016	0.000	0.104	0.156	0.004	0.000	0.104	Arts are stronger
2012	2011	0.574	0.018	0.000	0.069	0.120	0.004	0.000	0.069	Arts are stronger
2013	2012	0.682	0.024	0.000	0.055	0.080	0.003	0.000	0.055	Arts are stronger
2014	2013	0.900	0.016	0.000	0.177	0.197	0.004	0.000	0.177	Arts are stronger
2015	2014	0.668	0.033	0.000	0.029	0.043	0.002	0.000	0.029	Arts are stronger
2016	2015	1.619	0.056	0.000	0.057	0.035	0.001	0.000	0.057	Arts are stronger

Table D.7: Regression results and statistics presented in figure 5.16.

APPENDIX D.4: CROSS-LAGGED REGRESSION RESULTS FOR ARTS CATEGORIES AND BUSINESS SERVICES

Regression Results for the Relationship Between Arts Amenities and Business Services Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 61127		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	5.928	0.066	0.000	0.118	0.020	0.000	0.000	0.118	Arts are stronger
2000	1999	7.642	0.031	0.000	0.506	0.066	0.000	0.000	0.506	Arts are stronger
2001	2000	3.754	0.038	0.000	0.140	0.037	0.000	0.000	0.140	Arts are stronger
2002	2001	4.640	0.076	0.000	0.057	0.012	0.000	0.000	0.057	Arts are stronger
2003	2002	4.350	0.043	0.000	0.142	0.033	0.000	0.000	0.142	Arts are stronger
2004	2003	5.659	0.043	0.000	0.220	0.039	0.000	0.000	0.220	Arts are stronger
2005	2004	0.708	0.044	0.000	0.004	0.006	0.000	0.000	0.004	Arts are stronger
2006	2005	3.800	0.050	0.000	0.087	0.023	0.000	0.000	0.087	Arts are stronger
2007	2006	5.011	0.062	0.000	0.097	0.019	0.000	0.000	0.097	Arts are stronger
2008	2007	-0.426	0.034	0.000	0.003	-0.006	0.000	0.000	0.003	Jobs are stronger
2009	2008	2.040	0.042	0.000	0.037	0.018	0.000	0.000	0.037	Arts are stronger
2010	2009	0.512	0.040	0.000	0.003	0.005	0.000	0.000	0.003	Arts are stronger
2011	2010	1.291	0.018	0.000	0.075	0.058	0.001	0.000	0.075	Arts are stronger
2012	2011	0.032	0.029	0.275	0.000	0.001	0.001	0.275	0.000	Not Significant
2013	2012	0.890	0.029	0.000	0.016	0.017	0.001	0.000	0.016	Arts are stronger
2014	2013	2.416	0.033	0.000	0.079	0.033	0.000	0.000	0.079	Arts are stronger
2015	2014	3.204	0.085	0.000	0.022	0.007	0.000	0.000	0.022	Arts are stronger
2016	2015	1.515	0.083	0.000	0.005	0.004	0.000	0.000	0.005	Arts are stronger

Table D.8: Regression results and statistics presented in figure 5.18 and 5.19

Regression Results for the Relationship Between Arts Producers and Business Services Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 62202		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	4.629	0.030	0.000	0.276	0.060	0.000	0.000	0.276	Arts are stronger
2000	1999	4.281	0.017	0.000	0.514	0.120	0.000	0.000	0.514	Arts are stronger
2001	2000	2.150	0.015	0.000	0.244	0.114	0.001	0.000	0.244	Arts are stronger
2002	2001	5.356	0.025	0.000	0.420	0.078	0.000	0.000	0.420	Arts are stronger
2003	2002	1.616	0.026	0.000	0.057	0.035	0.001	0.000	0.057	Arts are stronger
2004	2003	3.329	0.021	0.000	0.281	0.084	0.001	0.000	0.281	Arts are stronger
2005	2004	1.845	0.025	0.000	0.081	0.044	0.001	0.000	0.081	Arts are stronger
2006	2005	3.225	0.031	0.000	0.147	0.046	0.000	0.000	0.147	Arts are stronger
2007	2006	2.783	0.032	0.000	0.110	0.040	0.000	0.000	0.110	Arts are stronger
2008	2007	0.533	0.019	0.000	0.012	0.023	0.001	0.000	0.012	Arts are stronger
2009	2008	3.190	0.023	0.000	0.243	0.076	0.001	0.000	0.243	Arts are stronger
2010	2009	2.194	0.019	0.000	0.184	0.084	0.001	0.000	0.184	Arts are stronger
2011	2010	0.179	0.017	0.000	0.002	0.010	0.001	0.000	0.002	Arts are stronger
2012	2011	0.891	0.023	0.000	0.024	0.027	0.001	0.000	0.024	Arts are stronger
2013	2012	0.856	0.023	0.000	0.022	0.026	0.001	0.000	0.022	Arts are stronger
2014	2013	0.520	0.012	0.000	0.029	0.057	0.001	0.000	0.029	Arts are stronger
2015	2014	0.930	0.024	0.000	0.023	0.025	0.001	0.000	0.023	Arts are stronger
2016	2015	1.583	0.031	0.000	0.041	0.026	0.001	0.000	0.041	Arts are stronger

Table D.8: Regression results and statistics presented in figure 5.18 and 5.19 (cont.)

Regression Results for the Relationship Between Recreation and Business Services Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 63029		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	4.333	0.025	0.000	0.320	0.074	0.000	0.000	0.320	Arts are stronger
2000	1999	5.656	0.027	0.000	0.408	0.072	0.000	0.000	0.408	Arts are stronger
2001	2000	2.280	0.015	0.000	0.266	0.117	0.001	0.000	0.266	Arts are stronger
2002	2001	4.538	0.029	0.000	0.282	0.062	0.000	0.000	0.282	Arts are stronger
2003	2002	1.792	0.020	0.000	0.111	0.062	0.001	0.000	0.111	Arts are stronger
2004	2003	2.479	0.024	0.000	0.145	0.059	0.001	0.000	0.145	Arts are stronger
2005	2004	1.128	0.022	0.000	0.041	0.037	0.001	0.000	0.041	Arts are stronger
2006	2005	2.347	0.019	0.000	0.188	0.080	0.001	0.000	0.188	Arts are stronger
2007	2006	3.679	0.021	0.000	0.338	0.092	0.001	0.000	0.338	Arts are stronger
2008	2007	0.604	0.016	0.000	0.022	0.037	0.001	0.000	0.022	Arts are stronger
2009	2008	1.416	0.026	0.000	0.046	0.033	0.001	0.000	0.046	Arts are stronger
2010	2009	0.683	0.019	0.000	0.021	0.030	0.001	0.000	0.021	Arts are stronger
2011	2010	0.321	0.013	0.000	0.009	0.030	0.001	0.000	0.009	Arts are stronger
2012	2011	0.541	0.008	0.000	0.061	0.113	0.002	0.000	0.061	Arts are stronger
2013	2012	0.317	0.017	0.000	0.006	0.018	0.001	0.000	0.006	Arts are stronger
2014	2013	1.877	0.017	0.000	0.168	0.089	0.001	0.000	0.168	Arts are stronger
2015	2014	0.471	0.020	0.000	0.009	0.018	0.001	0.000	0.009	Arts are stronger
2016	2015	0.760	0.041	0.000	0.005	0.007	0.000	0.000	0.005	Arts are stronger

Table D.8: Regression results and statistics presented in figure 5.18 and 5.19 (cont.)

APPENDIX D.5: CROSS-LAGGED REGRESSION RESULTS FOR ARTS AND HIGH-TECH

Regression Results for the Relationship Between Arts and High-Tech in Log One Year Lags, All Urban Areas and Hexagons as Unit of Analysis

N = 63045

		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				**"Jobs Attract Arts" Hypothesis** Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	-0.085	0.003	0.000	0.708	-0.045	0.003	0.000	0.699	HT are stronger
2000	1999	-0.039	0.003	0.000	0.757	0.001	0.003	0.866	0.735	Not Significant
2001	2000	-0.018	0.003	0.000	0.805	-0.006	0.003	0.021	0.784	HT are stronger
2002	2001	0.022	0.004	0.000	0.661	0.069	0.004	0.000	0.630	HT are stronger
2003	2002	-0.048	0.003	0.000	0.711	-0.029	0.003	0.000	0.682	HT are stronger
2004	2003	-0.019	0.002	0.000	0.847	0.027	0.002	0.000	0.827	HT are stronger
2005	2004	0.010	0.002	0.000	0.912	**0.031**	0.002	0.000	0.886	HT are stronger
2006	2005	0.024	0.002	0.000	0.890	0.055	0.002	0.000	0.874	HT are stronger
2007	2006	-0.022	0.003	0.000	0.749	-0.007	0.003	0.009	0.738	HT are stronger
2008	2007	0.025	0.002	0.000	0.909	0.035	0.002	0.000	0.908	HT are stronger
2009	2008	0.038	0.002	0.000	0.937	0.038	0.001	0.000	0.936	Arts are stronger
2010	2009	0.019	0.001	0.000	0.948	0.016	0.001	0.000	0.940	Arts are stronger
2011	2010	0.022	0.001	0.000	0.952	0.041	0.001	0.000	0.937	HT are stronger
2012	2011	0.059	0.002	0.000	0.854	0.034	0.002	0.000	0.851	Arts are stronger
2013	2012	0.010	0.002	0.000	0.924	0.022	0.002	0.000	0.915	HT are stronger
2014	2013	0.022	0.002	0.000	0.929	**0.014**	0.002	0.000	0.924	Arts are stronger
2015	2014	-0.017	0.002	0.000	0.866	-0.003	0.002	0.091	0.870	Not Significant
2016	2015	0.025	0.001	0.000	0.963	0.020	0.001	0.000	0.952	Arts are stronger

*Values in bold are not significant

Table D.9: Regression results and statistics presented in figure 5.21

Regression Results for the Relationship Between Arts and High-Tech in Log One Year Lags, Ten Largest Urban Areas and Hexagons as Unit of Analysis

N = 13989		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	-0.134	0.009	0.000	0.553	-0.164	0.009	0.000	0.574	Arts are stronger
2000	1999	-0.002	0.006	*0.723*	0.798	-0.001	0.006	0.906	0.797	Not Significant
2001	2000	-0.016	0.006	0.006	0.841	0.005	0.005	0.405	0.847	Not Significant
2002	2001	0.046	0.008	0.000	0.729	0.037	0.007	0.000	0.727	Arts are stronger
2003	2002	-0.011	0.006	0.082	0.813	-0.006	0.006	0.325	0.799	Not Significant
2004	2003	-0.008	0.004	*0.026*	0.937	0.048	0.003	0.000	0.931	HT are stronger
2005	2004	-0.006	0.004	0.090	0.939	**0.019**	0.004	0.000	0.923	HT are stronger
2006	2005	0.026	0.004	0.000	0.907	0.050	0.004	0.000	0.889	HT are stronger
2007	2006	-0.017	0.005	0.001	0.874	0.026	0.005	0.000	0.857	HT are stronger
2008	2007	0.021	0.003	0.000	0.953	0.053	0.003	0.000	0.932	HT are stronger
2009	2008	0.051	0.003	0.000	0.957	0.052	0.003	0.000	0.954	HT are stronger
2010	2009	0.008	0.002	0.002	0.971	0.014	0.003	0.000	0.952	HT are stronger
2011	2010	0.015	0.002	0.000	0.976	0.027	0.003	0.000	0.954	HT are stronger
2012	2011	0.075	0.005	0.000	0.876	0.019	0.004	0.000	0.880	Arts are stronger
2013	2012	0.025	0.003	0.000	0.963	0.040	0.003	0.000	0.954	HT are stronger
2014	2013	0.018	0.004	0.000	0.924	**-0.002**	0.004	0.556	0.921	Arts are stronger
2015	2014	-0.018	0.005	0.000	0.876	0.009	0.004	0.026	0.880	HT are stronger
2016	2015	0.011	0.002	0.000	0.986	0.030	0.003	0.000	0.959	HT are stronger

*Values in bold are not significant

Table D.10: Regression results and statistics presented in figure 5.22

Regression Results for the Relationship Between Arts and High-Tech in Log Ten Year Lags, All Urban Areas and Hexagons as Unit of Analysis

N = 63045		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
2008	1998	-0.032	0.004	0.000	0.483	0.037	0.004	0.000	0.455	HT are stronger
2009	1999	0.031	0.003	0.000	0.629	0.120	0.003	0.00000000(	0.578	HT are stronger
2010	2000	0.029	0.003	0.000	0.606	0.111	0.003	0.000	0.558	HT are stronger
2011	2001	0.045	0.003	0.000	0.654	0.129	0.003	0.000	0.618	HT are stronger
2012	2002	-0.027	0.004	0.000	0.512	0.042	0.004	0.000	0.475	HT are stronger
2013	2003	0.031	0.004	0.000	0.635	0.093	0.003	0.000	0.606	HT are stronger
2014	2004	0.057	0.004	0.000	0.667	0.094	0.003	0.000	0.626	HT are stronger
2015	2005	0.041	0.003	0.000	0.715	0.103	0.003	0.00000000(	0.673	HT are stronger
2016	2006	0.033	0.003	0.000	0.695	0.069	0.003	0.000	0.659	HT are stronger

Table D.11: Regression results and statistics presented in figure 5.25

Regression Results for the Relationship Between Arts and High-Tech in Log Ten Year Lags, Ten Largest Urban Areas and Hexagons as Unit of Analysis

N = 13989		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
Year of Dependent Variable	**Year of Independent Variable**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
2008	1998	-0.094	0.009	0.000	0.471	-0.015	0.009	0.087	0.469	Not Significant
2009	1999	0.023	0.007	0.001	0.725	0.134	0.007	0.000	0.710	HT are stronger
2010	2000	0.010	0.007	*0.160*	0.710	0.130	0.007	0.000	0.686	HT are stronger
2011	2001	0.008	0.007	*0.260*	0.732	0.142	0.007	0.000	0.692	HT are stronger
2012	2002	-0.014	0.009	*0.100*	0.616	0.083	0.008	0.000	0.598	HT are stronger
2013	2003	0.026	0.007	0.000	0.729	0.127	0.007	0.000	0.706	HT are stronger
2014	2004	0.054	0.007	0.000	0.745	0.120	0.007	0.000	0.704	HT are stronger
2015	2005	0.074	0.005	0.000	0.837	0.144	0.006	0.000	0.790	HT are stronger
2016	2006	0.050	0.006	0.000	0.802	0.115	0.006	0.000	0.753	HT are stronger

Table D.12: Regression results and statistics presented in figure 5.26

Regression Results for the Relationship Between Arts and High-Tech Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 63045		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	0.875	0.005	0.000	0.295	0.338	0.002	0.000	0.295	Arts are stronger
2000	1999	0.591	0.002	0.000	0.517	0.874	0.003	0.000	0.517	Jobs are stronger
2001	2000	0.356	0.003	0.000	0.171	0.480	0.004	0.000	0.171	Jobs are stronger
2002	2001	0.697	0.004	0.000	0.372	0.533	0.003	0.000	0.372	Arts are stronger
2003	2002	0.328	0.005	0.000	0.074	0.227	0.003	0.000	0.074	Arts are stronger
2004	2003	0.419	0.005	0.000	0.118	0.282	0.003	0.000	0.118	Arts are stronger
2005	2004	0.305	0.006	0.000	0.044	0.146	0.003	0.000	0.044	Arts are stronger
2006	2005	0.251	0.003	0.000	0.109	0.432	0.005	0.000	0.109	Jobs are stronger
2007	2006	0.371	0.004	0.000	0.114	0.307	0.003	0.000	0.114	Arts are stronger
2008	2007	-0.051	0.006	0.000	0.001	-0.025	0.003	0.000	0.001	Jobs are stronger
2009	2008	0.265	0.005	0.000	0.051	0.191	0.003	0.000	0.051	Arts are stronger
2010	2009	0.196	0.005	0.000	0.021	0.108	0.003	0.000	0.021	Arts are stronger
2011	2010	0.215	0.005	0.000	0.025	0.117	0.003	0.000	0.025	Arts are stronger
2012	2011	0.148	0.004	0.000	0.019	0.129	0.004	0.000	0.019	Arts are stronger
2013	2012	0.262	0.006	0.000	0.030	0.113	0.003	0.000	0.030	Arts are stronger
2014	2013	0.291	0.005	0.000	0.060	0.207	0.003	0.000	0.060	Arts are stronger
2015	2014	0.161	0.003	0.000	0.037	0.230	0.005	0.000	0.037	Jobs are stronger
2016	2015	0.095	0.004	0.000	0.008	0.081	0.004	0.000	0.008	Arts are stronger

Table D.13: Regression results and statistics presented in figure 5.29

Regression Results for the Relationship Between Arts and Business Services Jobs in One Year First Differences, Ten Largest Urban Areas, Hexagons as Unit of Analysis

N = 13989		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	1.037	0.012	0.000	0.350	0.337	0.004	0.000	0.350	Arts are stronger
2000	1999	0.597	0.004	0.000	0.659	1.103	0.007	0.000	0.659	Jobs are stronger
2001	2000	0.383	0.005	0.000	0.317	0.828	0.010	0.000	0.317	Jobs are stronger
2002	2001	0.706	0.006	0.000	0.512	0.725	0.006	0.000	0.512	Jobs are stronger
2003	2002	0.332	0.008	0.000	0.099	0.298	0.008	0.000	0.099	Arts are stronger
2004	2003	0.363	0.008	0.000	0.126	0.347	0.008	0.000	0.126	Arts are stronger
2005	2004	0.157	0.013	0.000	0.011	0.069	0.006	0.000	0.011	Arts are stronger
2006	2005	0.341	0.005	0.000	0.240	0.703	0.011	0.000	0.240	Jobs are stronger
2007	2006	0.308	0.007	0.000	0.129	0.418	0.009	0.000	0.129	Jobs are stronger
2008	2007	-0.156	0.009	0.000	0.019	-0.122	0.007	0.000	0.019	Jobs are stronger
2009	2008	0.368	0.009	0.000	0.104	0.283	0.007	0.000	0.104	Arts are stronger
2010	2009	0.241	0.009	0.000	0.046	0.190	0.007	0.000	0.046	Arts are stronger
2011	2010	0.262	0.011	0.000	0.043	0.162	0.007	0.000	0.043	Arts are stronger
2012	2011	0.178	0.009	0.000	0.028	0.158	0.008	0.000	0.028	Arts are stronger
2013	2012	0.371	0.012	0.000	0.069	0.186	0.006	0.000	0.069	Arts are stronger
2014	2013	0.183	0.008	0.000	0.036	0.199	0.009	0.000	0.036	Jobs are stronger
2015	2014	0.137	0.006	0.000	0.038	0.281	0.012	0.000	0.038	Jobs are stronger
2016	2015	0.152	0.008	0.000	0.026	0.168	0.009	0.000	0.026	Jobs are stronger

Table D.14: Regression results and statistics presented in figure 5.30

APPENDIX D.6: CROSS-LAGGED REGRESSION RESULTS FOR ARTS CATEGORIES AND HIGH-TECH

Regression Results for the Relationship Between Arts Amenities and High-Tech Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 61127		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	5.928	0.066	0.000	0.118	0.020	0.000	0.000	0.118	Arts are stronger
2000	1999	7.642	0.031	0.000	0.506	0.066	0.000	0.000	0.506	Arts are stronger
2001	2000	3.754	0.038	0.000	0.140	0.037	0.000	0.000	0.140	Arts are stronger
2002	2001	4.640	0.076	0.000	0.057	0.012	0.000	0.000	0.057	Arts are stronger
2003	2002	4.350	0.043	0.000	0.142	0.033	0.000	0.000	0.142	Arts are stronger
2004	2003	5.659	0.043	0.000	0.220	0.039	0.000	0.000	0.220	Arts are stronger
2005	2004	0.708	0.044	0.000	0.004	0.006	0.000	0.000	0.004	Arts are stronger
2006	2005	3.800	0.050	0.000	0.087	0.023	0.000	0.000	0.087	Arts are stronger
2007	2006	5.011	0.062	0.000	0.097	0.019	0.000	0.000	0.097	Arts are stronger
2008	2007	-0.426	0.034	0.000	0.003	-0.006	0.000	0.000	0.003	Jobs are stronger
2009	2008	2.040	0.042	0.000	0.037	0.018	0.000	0.000	0.037	Arts are stronger
2010	2009	0.512	0.040	0.000	0.003	0.005	0.000	0.000	0.003	Arts are stronger
2011	2010	1.291	0.018	0.000	0.075	0.058	0.001	0.000	0.075	Arts are stronger
2012	2011	0.032	0.029	0.275	0.000	0.001	0.001	0.275	0.000	Not Significant
2013	2012	0.890	0.029	0.000	0.016	0.017	0.001	0.000	0.016	Arts are stronger
2014	2013	2.416	0.033	0.000	0.079	0.033	0.000	0.000	0.079	Arts are stronger
2015	2014	3.204	0.085	0.000	0.022	0.007	0.000	0.000	0.022	Arts are stronger
2016	2015	1.515	0.083	0.000	0.005	0.004	0.000	0.000	0.005	Arts are stronger

Table D.15: Regression results and statistics presented in figure 5.34 and 5.35

Regression Results for the Relationship Between Arts Producers and High-Tech Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 62022		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	4.629	0.030	0.000	0.276	0.060	0.000	0.000	0.276	Arts are stronger
2000	1999	4.281	0.017	0.000	0.514	0.120	0.000	0.000	0.514	Arts are stronger
2001	2000	2.150	0.015	0.000	0.244	0.114	0.001	0.000	0.244	Arts are stronger
2002	2001	5.356	0.025	0.000	0.420	0.078	0.000	0.000	0.420	Arts are stronger
2003	2002	1.616	0.026	0.000	0.057	0.035	0.001	0.000	0.057	Arts are stronger
2004	2003	3.329	0.021	0.000	0.281	0.084	0.001	0.000	0.281	Arts are stronger
2005	2004	1.845	0.025	0.000	0.081	0.044	0.001	0.000	0.081	Arts are stronger
2006	2005	3.225	0.031	0.000	0.147	0.046	0.000	0.000	0.147	Arts are stronger
2007	2006	2.783	0.032	0.000	0.110	0.040	0.000	0.000	0.110	Arts are stronger
2008	2007	0.533	0.019	0.000	0.012	0.023	0.001	0.000	0.012	Arts are stronger
2009	2008	3.190	0.023	0.000	0.243	0.076	0.001	0.000	0.243	Arts are stronger
2010	2009	2.194	0.019	0.000	0.184	0.084	0.001	0.000	0.184	Arts are stronger
2011	2010	0.179	0.017	0.000	0.002	0.010	0.001	0.000	0.002	Arts are stronger
2012	2011	0.891	0.023	0.000	0.024	0.027	0.001	0.000	0.024	Arts are stronger
2013	2012	0.856	0.023	0.000	0.022	0.026	0.001	0.000	0.022	Arts are stronger
2014	2013	0.520	0.012	0.000	0.029	0.057	0.001	0.000	0.029	Arts are stronger
2015	2014	0.930	0.024	0.000	0.023	0.025	0.001	0.000	0.023	Arts are stronger
2016	2015	1.583	0.031	0.000	0.041	0.026	0.001	0.000	0.041	Arts are stronger

Table D.15: Regression results and statistics presented in figure 5.34 and 5.35 (cont.)

Regression Results for the Relationship Between Recreation and High-Tech Jobs in One Year First Differences, All Urban Areas, Hexagons as Unit of Analysis

N = 63029		"Arts Attract Jobs" Hypothesis Dependent Variable: Jobs				"Jobs Attract Arts" Hypothesis Dependent Variable: Arts				
t	**t-1**	**Arts to Jobs Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Jobs to Arts Estimate**	**S.E.**	**Coefficient P-value**	**R-Squared**	**Conclusion**
1999	1998	4.333	0.025	0.000	0.320	0.074	0.000	0.000	0.320	Arts are stronger
2000	1999	5.656	0.027	0.000	0.408	0.072	0.000	0.000	0.408	Arts are stronger
2001	2000	2.280	0.015	0.000	0.266	0.117	0.001	0.000	0.266	Arts are stronger
2002	2001	4.538	0.029	0.000	0.282	0.062	0.000	0.000	0.282	Arts are stronger
2003	2002	1.792	0.020	0.000	0.111	0.062	0.001	0.000	0.111	Arts are stronger
2004	2003	2.479	0.024	0.000	0.145	0.059	0.001	0.000	0.145	Arts are stronger
2005	2004	1.128	0.022	0.000	0.041	0.037	0.001	0.000	0.041	Arts are stronger
2006	2005	2.347	0.019	0.000	0.188	0.080	0.001	0.000	0.188	Arts are stronger
2007	2006	3.679	0.021	0.000	0.338	0.092	0.001	0.000	0.338	Arts are stronger
2008	2007	0.604	0.016	0.000	0.022	0.037	0.001	0.000	0.022	Arts are stronger
2009	2008	1.416	0.026	0.000	0.046	0.033	0.001	0.000	0.046	Arts are stronger
2010	2009	0.683	0.019	0.000	0.021	0.030	0.001	0.000	0.021	Arts are stronger
2011	2010	0.321	0.013	0.000	0.009	0.030	0.001	0.000	0.009	Arts are stronger
2012	2011	0.541	0.008	0.000	0.061	0.113	0.002	0.000	0.061	Arts are stronger
2013	2012	0.317	0.017	0.000	0.006	0.018	0.001	0.000	0.006	Arts are stronger
2014	2013	1.877	0.017	0.000	0.168	0.089	0.001	0.000	0.168	Arts are stronger
2015	2014	0.471	0.020	0.000	0.009	0.018	0.001	0.000	0.009	Arts are stronger
2016	2015	0.760	0.041	0.000	0.005	0.007	0.000	0.000	0.005	Arts are stronger

Table D.15: Regression results and statistics presented in figure 5.34 and 5.35 (cont.)

APPENDIX E: CROSS-LAGGED REGRESSION RESULTS BY URBAN AREA FROM CHAPTERS 4 AND 5

		Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
Urban Area	**N**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**
New York, NY	2383	4.168 (0.018)	0.084 (0.000)	Arts Attract Jobs	1.730 (0.007)	0.224 (0.001)	Arts Attract Jobs	0.425 (0.003)	0.459 (0.004)	Jobs Attract Arts
Atlanta, GA	1781	0.905 (0.023)	0.048 (0.000)	Arts Attract Jobs	0.201 (0.011)	0.096 (0.002)	Arts Attract Jobs	0.157 (0.005)	0.114 (0.003)	Arts Attract Jobs
Chicago, IL	1570	4.601 (0.051)	0.038 (0.000)	Arts Attract Jobs	1.909 (0.025)	0.074 (0.001)	Arts Attract Jobs	0.804 (0.010)	0.175 (0.002)	Arts Attract Jobs
Boston, MA	1501	2.129 (0.032)	0.043 (0.001)	Arts Attract Jobs	0.514 (0.014)	0.055 (0.001)	Arts Attract Jobs	0.456 (0.009)	0.144 (0.003)	Arts Attract Jobs
Philadelphia, PA	1388	3.870 (0.034)	0.046 (0.000)	Arts Attract Jobs	1.261 (0.015)	0.097 (0.001)	Arts Attract Jobs	0.402 (0.005)	0.296 (0.004)	Arts Attract Jobs
Dallas, TX	1189	1.667 (0.047)	0.035 (0.001)	Arts Attract Jobs	0.580 (0.022)	0.064 (0.001)	Arts Attract Jobs	0.312 (0.010)	0.113 (0.003)	Arts Attract Jobs
Los Angeles, CA	1127	1.757 (0.024)	0.071 (0.001)	Arts Attract Jobs	0.470 (0.011)	0.104 (0.002)	Arts Attract Jobs	0.132 (0.004)	0.337 (0.008)	Jobs Attract Arts
Houston, TX	1089	2.216 (0.046)	0.036 (0.001)	Arts Attract Jobs	1.503 (0.023)	0.072 (0.001)	Arts Attract Jobs	0.382 (0.009)	0.093 (0.003)	Arts Attract Jobs
Washington, DC	914	2.803 (0.030)	0.065 (0.000)	Arts Attract Jobs	0.880 (0.014)	0.114 (0.001)	Arts Attract Jobs	0.474 (0.007)	0.179 (0.004)	Arts Attract Jobs
Detroit, MI	909	1.543 (0.040)	0.037 (0.001)	Arts Attract Jobs	0.923 (0.022)	0.061 (0.001)	Arts Attract Jobs	0.230 (0.008)	0.114 (0.004)	Arts Attract Jobs
Miami, FL	781	1.407 (0.044)	0.046 (0.001)	Arts Attract Jobs	0.474 (0.018)	0.112 (0.003)	Arts Attract Jobs	0.174 (0.006)	0.256 (0.009)	Jobs Attract Arts
Phoenix, AZ	756	2.206 (0.055)	0.037 (0.001)	Arts Attract Jobs	1.035 (0.025)	0.081 (0.002)	Arts Attract Jobs	0.191 (0.010)	0.114 (0.006)	Arts Attract Jobs
Tampa, FL	720	3.210 (0.075)	0.033 (0.001)	Arts Attract Jobs	0.848 (0.037)	0.039 (0.001)	Arts Attract Jobs	0.399 (0.014)	0.098 (0.004)	Arts Attract Jobs
Pittsburgh, PA	708	0.360 (0.034)	-0.005 (0.001)	Arts Attract Jobs	-0.132 (0.013)	0.025 (0.003)	Jobs Attract Arts	0.232 (0.006)	0.094 (0.006)	Arts Attract Jobs
Seattle, WA	703	3.934 (0.072)	0.028 (0.000)	Arts Attract Jobs	1.059 (0.022)	0.115 (0.002)	Arts Attract Jobs	0.507 (0.016)	0.116 (0.003)	Arts Attract Jobs
Minneapolis, MN	698	1.337 (0.050)	0.040 (0.001)	Arts Attract Jobs	0.924 (0.025)	0.100 (0.002)	Arts Attract Jobs	-0.017* (0.009)	0.046 (0.005)	Jobs Attract Arts
Charlotte, NC	609	4.387 (0.052)	0.053 (0.001)	Arts Attract Jobs	2.173 (0.031)	0.075 (0.001)	Arts Attract Jobs	0.371 (0.009)	0.256 (0.004)	Arts Attract Jobs
St. Louis, MO	609	0.447 (0.033)	0.040 (0.001)	Arts Attract Jobs	0.142 (0.016)	0.115 (0.003)	Arts Attract Jobs	0.169 (0.008)	0.179 (0.006)	Jobs Attract Arts
Cleveland, OH	602	4.110 (0.031)	0.081 (0.001)	Arts Attract Jobs	0.623 (0.012)	0.042 (0.002)	Arts Attract Jobs	0.234 (0.005)	0.076 (0.006)	Arts Attract Jobs
Cincinnati, OH	532	4.890 (0.039)	0.066 (0.000)	Arts Attract Jobs	2.595 (0.019)	0.145 (0.001)	Arts Attract Jobs	0.905 (0.007)	0.410 (0.003)	Arts Attract Jobs
San Diego, CA	499	0.720 (0.045)	0.037 (0.001)	Arts Attract Jobs	-0.040 (0.018)	0.071 (0.002)	Jobs Attract Arts	0.181 (0.012)	0.078 (0.006)	Arts Attract Jobs
Indianapolis, IN	491	2.208 (0.042)	0.063 (0.001)	Arts Attract Jobs	0.663 (0.017)	0.069 (0.003)	Arts Attract Jobs	0.363 (0.007)	0.437 (0.008)	Jobs Attract Arts
Orlando, FL	491	1.227 (0.013)	0.260 (0.003)	Arts Attract Jobs	0.298 (0.006)	0.234 (0.007)	Arts Attract Jobs	0.039 (0.003)	0.109 (0.019)	Jobs Attract Arts
Hartford, CT	469	-0.132 (0.055)	0.016 (0.001)	Jobs Attract Arts	-0.303 (0.027)	0.016 (0.002)	Jobs Attract Arts	0.202 (0.016)	0.048 (0.004)	Arts Attract Jobs
Denver, CO	456	1.442 (0.061)	0.030 (0.001)	Arts Attract Jobs	0.352 (0.022)	0.074 (0.004)	Arts Attract Jobs	0.124 (0.016)	0.042 (0.005)	Arts Attract Jobs
Kansas City, MO	456	1.317 (0.067)	0.024 (0.001)	Arts Attract Jobs	0.413 (0.032)	0.011 (0.003)	Arts Attract Jobs	0.198 (0.020)	0.028 (0.004)	Arts Attract Jobs
Baltimore, MD	447	2.658 (0.055)	0.050 (0.001)	Arts Attract Jobs	1.213 (0.027)	0.119 (0.002)	Arts Attract Jobs	0.701 (0.016)	0.166 (0.003)	Arts Attract Jobs
San Francisco, CA	423	3.843 (0.084)	0.036 (0.001)	Arts Attract Jobs	0.838 (0.024)	0.096 (0.002)	Arts Attract Jobs	0.658 (0.026)	0.090 (0.003)	Arts Attract Jobs
Nashville-Davidson, TN	417	0.928 (0.023)	0.060 (0.001)	Arts Attract Jobs	0.731 (0.009)	0.103 (0.003)	Arts Attract Jobs	0.051 (0.005)	-0.135 (0.002)	Arts Attract Jobs
Milwaukee, WI	398	2.512 (0.050)	0.062 (0.001)	Arts Attract Jobs	1.039 (0.029)	0.103 (0.001)	Arts Attract Jobs	0.494 (0.009)	0.370 (0.006)	Arts Attract Jobs
Raleigh, NC	390	1.301 (0.089)	0.029 (0.001)	Arts Attract Jobs	0.143 (0.045)	0.011 (0.002)	Arts Attract Jobs	0.884 (0.033)	0.078 (0.002)	Arts Attract Jobs
Jacksonville, FL	389	0.940 (0.081)	0.024 (0.001)	Arts Attract Jobs	0.248 (0.040)	0.038 (0.001)	Arts Attract Jobs	0.207 (0.016)	0.057 (0.003)	Arts Attract Jobs
Austin, TX	382	3.462 (0.052)	0.049 (0.001)	Arts Attract Jobs	1.016 (0.019)	0.137 (0.003)	Arts Attract Jobs	0.435 (0.016)	0.128 (0.003)	Arts Attract Jobs
San Antonio, TX	373	3.084 (0.030)	0.061 (0.001)	Arts Attract Jobs	1.586 (0.014)	0.225 (0.002)	Arts Attract Jobs	0.489 (0.007)	0.401 (0.007)	Arts Attract Jobs
Providence, RI	367	7.903 (0.044)	0.070 (0.000)	Arts Attract Jobs	3.041 (0.018)	0.158 (0.001)	Arts Attract Jobs	0.826 (0.005)	0.616 (0.005)	Arts Attract Jobs

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area

		Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
Urban Area	N	Effect of Arts on Jobs	Effect of Jobs on Arts	Conclusion	Effect of Arts on Jobs	Effect of Jobs on Arts	Conclusion	Effect of Arts on Jobs	Effect of Jobs on Arts	Conclusion
Bridgeport, CT	364	1.390 (0.058)	0.038 (0.001)	Arts Attract Jobs	0.527 (0.027)	0.106 (0.002)	Arts Attract Jobs	0.138 (0.011)	0.201 (0.005)	Jobs Attract Arts
Portland, OR	359	4.511 (0.051)	0.073 (0.001)	Arts Attract Jobs	2.281 (0.027)	0.141 (0.001)	Arts Attract Jobs	0.502 (0.010)	0.084 (0.004)	Arts Attract Jobs
Virginia Beach, VA	352	2.798 (0.029)	0.099 (0.001)	Arts Attract Jobs	1.072 (0.012)	0.250 (0.003)	Arts Attract Jobs	0.212 (0.007)	0.070 (0.007)	Arts Attract Jobs
Birmingham, AL	350	0.642 (0.073)	0.008 (0.000)	Arts Attract Jobs	0.299 (0.044)	0.025 (0.001)	Arts Attract Jobs	0.293 (0.017)	0.008 (0.004)	Arts Attract Jobs
Columbus, OH	347	2.468 (0.052)	0.062 (0.001)	Arts Attract Jobs	3.357 (0.020)	0.158 (0.001)	Arts Attract Jobs	0.594 (0.009)	0.384 (0.006)	Arts Attract Jobs
Greenville, SC	335	4.989 (0.118)	0.024 (0.000)	Arts Attract Jobs	1.482 (0.051)	0.057 (0.001)	Arts Attract Jobs	0.815 (0.027)	0.115 (0.002)	Arts Attract Jobs
Richmond, VA	333	1.087 (0.097)	0.027 (0.001)	Arts Attract Jobs	0.459 (0.056)	0.026 (0.001)	Arts Attract Jobs	0.173 (0.015)	0.063 (0.005)	Arts Attract Jobs
Knoxville, TN	330	1.251 (0.068)	0.035 (0.001)	Arts Attract Jobs	0.351 (0.026)	0.060 (0.002)	Arts Attract Jobs	0.178 (0.010)	0.184 (0.007)	Jobs Attract Arts
Riverside, CA	320	1.393 (0.086)	0.023 (0.001)	Arts Attract Jobs	0.039* (0.029)	0.006* (0.004)	Not Significant	0.022 (0.007)	-0.035 (0.014)	Arts Attract Jobs
Sacramento, CA	318	1.594 (0.080)	0.032 (0.001)	Arts Attract Jobs	0.415 (0.038)	0.044 (0.003)	Arts Attract Jobs	0.143 (0.019)	0.022 (0.006)	Arts Attract Jobs
Louisville, KY	313	0.033* (0.048)	0.013 (0.001)	Jobs Attract Arts	0.001* (0.024)	0.044 (0.002)	Jobs Attract Arts	0.003* (0.007)	0.004* (0.009)	Not Significant
Oklahoma City, OK	310	0.118* (0.076)	0.007 (0.001)	Not Significant	0.235 (0.038)	0.029 (0.003)	Arts Attract Jobs	-0.086 (0.018)	0.008* (0.007)	Not Significant
Memphis, TN	295	0.509 (0.084)	0.018 (0.001)	Arts Attract Jobs	0.203 (0.039)	0.039 (0.003)	Arts Attract Jobs	0.052 (0.010)	0.101 (0.013)	Jobs Attract Arts
Dayton, OH	284	0.609 (0.066)	0.018 (0.001)	Arts Attract Jobs	0.074 (0.029)	-0.008 (0.003)	Arts Attract Jobs	0.138 (0.019)	0.045 (0.005)	Arts Attract Jobs
Cape Coral, FL	272	0.659 (0.054)	0.038 (0.002)	Arts Attract Jobs	0.160 (0.014)	-0.046 (0.005)	Arts Attract Jobs	0.033 (0.005)	0.260 (0.022)	Jobs Attract Arts
Allentown, PA	271	0.033* (0.065)	0.026 (0.001)	Jobs Attract Arts	-0.374 (0.039)	0.016 (0.002)	Jobs Attract Arts	0.107 (0.010)	0.119 (0.008)	Jobs Attract Arts
Buffalo, NY	265	0.456 (0.082)	0.002* (0.001)	Arts Attract Jobs	0.203 (0.039)	-0.013 (0.003)	Arts Attract Jobs	-0.030 (0.012)	0.007* (0.006)	Not Significant
Winston-Salem, NC	263	0.080* (0.067)	0.024 (0.001)	Jobs Attract Arts	-0.132 (0.033)	0.013 (0.002)	Jobs Attract Arts	-0.211 (0.006)	0.104 (0.006)	Jobs Attract Arts
Columbia, SC	255	-0.426 (0.044)	0.004 (0.001)	Jobs Attract Arts	-0.815 (0.020)	-0.061 (0.001)	Jobs Attract Arts	0.215 (0.004)	-0.052 (0.003)	Arts Attract Jobs
McAllen, TX	255	7.234 (0.087)	0.039 (0.000)	Arts Attract Jobs	1.455 (0.033)	0.117 (0.002)	Arts Attract Jobs	0.233 (0.007)	0.137 (0.007)	Arts Attract Jobs
Poughkeepsie, NY	252	0.301 (0.032)	0.020 (0.001)	Arts Attract Jobs	0.233 (0.019)	0.005* (0.005)	Arts Attract Jobs	0.110 (0.007)	0.042 (0.003)	Arts Attract Jobs
Las Vegas, NV	244	0.735 (0.014)	0.134 (0.003)	Arts Attract Jobs	0.217 (0.006)	0.088 (0.009)	Arts Attract Jobs	0.067 (0.002)	1.147 (0.038)	Jobs Attract Arts
Tulsa, OK	244	0.322 (0.067)	0.019 (0.002)	Arts Attract Jobs	0.315 (0.030)	0.028 (0.004)	Arts Attract Jobs	0.245 (0.016)	0.000* (0.005)	Arts Attract Jobs
Albany, NY	242	0.173 (0.054)	0.005* (0.003)	Arts Attract Jobs	0.213 (0.024)	0.032 (0.005)	Arts Attract Jobs	0.069 (0.015)	0.029 (0.008)	Arts Attract Jobs
Tucson, AZ	240	0.019* (0.066)	0.005 (0.002)	Jobs Attract Arts	0.051* (0.027)	-0.031 (0.004)	Not Significant	0.138 (0.013)	0.067 (0.009)	Arts Attract Jobs
Baton Rouge, LA	239	1.279 (0.061)	0.034 (0.001)	Arts Attract Jobs	0.426 (0.019)	0.036 (0.003)	Arts Attract Jobs	0.165 (0.011)	0.147 (0.006)	Arts Attract Jobs
Harrisburg, PA	235	2.901 (0.024)	0.118 (0.001)	Arts Attract Jobs	0.522 (0.010)	0.117 (0.004)	Arts Attract Jobs	0.054 (0.005)	0.135 (0.008)	Jobs Attract Arts
Rochester, NY	232	0.746 (0.100)	0.012 (0.001)	Arts Attract Jobs	0.514 (0.039)	0.010 (0.003)	Arts Attract Jobs	-0.064 (0.025)	-0.054 (0.005)	Jobs Attract Arts
Charleston, SC	226	-0.132 (0.050)	0.028 (0.001)	Jobs Attract Arts	0.027* (0.020)	0.030 (0.004)	Jobs Attract Arts	0.200 (0.010)	0.039 (0.005)	Arts Attract Jobs
Asheville, NC	224	0.086 (0.027)	0.030 (0.002)	Arts Attract Jobs	0.009* (0.009)	0.020 (0.004)	Jobs Attract Arts	0.072 (0.003)	0.102 (0.011)	Jobs Attract Arts
Lancaster, PA	222	1.562 (0.107)	0.027 (0.001)	Arts Attract Jobs	0.954 (0.044)	0.076 (0.002)	Arts Attract Jobs	0.222 (0.018)	0.127 (0.006)	Arts Attract Jobs
Salt Lake City, UT	213	2.206 (0.093)	0.029 (0.001)	Arts Attract Jobs	1.008 (0.045)	0.057 (0.004)	Arts Attract Jobs	0.173 (0.023)	0.092 (0.006)	Arts Attract Jobs
Springfield, MA	213	2.414 (0.078)	0.050 (0.001)	Arts Attract Jobs	0.609 (0.028)	0.059 (0.004)	Arts Attract Jobs	0.391 (0.014)	0.206 (0.006)	Arts Attract Jobs
Akron, OH	208	4.328 (0.065)	0.038 (0.001)	Arts Attract Jobs	1.583 (0.030)	0.079 (0.002)	Arts Attract Jobs	0.348 (0.007)	0.128 (0.007)	Arts Attract Jobs
Chattanooga, TN	207	1.441 (0.110)	0.018 (0.001)	Arts Attract Jobs	0.553 (0.045)	0.019 (0.002)	Arts Attract Jobs	0.093 (0.014)	0.166 (0.004)	Jobs Attract Arts

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

Urban Area	N	Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
		Effect of Arts on Jobs	Effect of Jobs on Arts	Conclusion	Effect of Arts on Jobs	Effect of Jobs on Arts	Conclusion	Effect of Arts on Jobs	Effect of Jobs on Arts	Conclusion
Hickory, NC	207	1.160 (0.174)	0.017 (0.000)	Arts Attract Jobs	0.604 (0.038)	-0.002* (0.002)	Arts Attract Jobs	0.280 (0.011)	0.155 (0.007)	Arts Attract Jobs
Barnstable Town, MA	205	0.123 (0.045)	0.015 (0.003)	Arts Attract Jobs	-0.022* (0.016)	-0.037 (0.010)	Not Significant	0.056 (0.008)	0.005* (0.013)	Arts Attract Jobs
Sarasota, FL	203	2.955 (0.077)	0.031 (0.001)	Arts Attract Jobs	1.604 (0.025)	0.066 (0.002)	Arts Attract Jobs	0.141 (0.008)	0.263 (0.013)	Jobs Attract Arts
Little Rock, AR	195	9.117 (0.050)	0.073 (0.000)	Arts Attract Jobs	4.695 (0.031)	0.126 (0.001)	Arts Attract Jobs	1.362 (0.010)	0.419 (0.002)	Arts Attract Jobs
Grand Rapids, MI	193	0.172* (0.104)	0.004 (0.002)	Jobs Attract Arts	-0.220 (0.051)	0.006* (0.003)	Not Significant	-0.049 (0.014)	-0.074 (0.011)	Arts Attract Jobs
Palm Bay, FL	188	0.296 (0.069)	0.006 (0.002)	Arts Attract Jobs	0.075 (0.029)	-0.016 (0.003)	Arts Attract Jobs	0.264 (0.028)	0.035 (0.004)	Arts Attract Jobs
Omaha, NE	184	6.157 (0.044)	0.109 (0.001)	Arts Attract Jobs	2.789 (0.019)	0.232 (0.002)	Arts Attract Jobs	0.798 (0.006)	0.696 (0.006)	Arts Attract Jobs
Jackson, MS	183	1.301 (0.146)	0.020 (0.001)	Arts Attract Jobs	0.988 (0.058)	0.025 (0.002)	Arts Attract Jobs	0.006* (0.034)	0.014 (0.002)	Jobs Attract Arts
Pensacola, FL	182	-1.091 (0.082)	0.006 (0.001)	Jobs Attract Arts	-0.465 (0.033)	0.008 (0.002)	Jobs Attract Arts	0.085 (0.011)	0.000* (0.011)	Arts Attract Jobs
Augusta, GA	181	1.531 (0.049)	0.050 (0.001)	Arts Attract Jobs	0.233 (0.018)	0.151 (0.003)	Arts Attract Jobs	0.205 (0.006)	-0.145 (0.010)	Arts Attract Jobs
Palm Coast, FL	177	0.328 (0.046)	0.011 (0.004)	Arts Attract Jobs	0.167 (0.018)	-0.024 (0.008)	Arts Attract Jobs	0.055 (0.006)	0.102 (0.019)	Jobs Attract Arts
Albuquerque, NM	174	1.327 (0.114)	0.029 (0.002)	Arts Attract Jobs	0.117 (0.044)	0.040 (0.005)	Arts Attract Jobs	0.019* (0.040)	0.019 (0.007)	Not Significant
South Bend, IN	170	-0.210 (0.068)	0.005 (0.002)	Jobs Attract Arts	-0.088 (0.025)	0.015 (0.005)	Jobs Attract Arts	-0.064 (0.010)	-0.124 (0.010)	Arts Attract Jobs
Youngstown, OH	167	NA	NA	NA	0.179 (0.035)	0.004* (0.003)	Arts Attract Jobs	0.008* (0.011)	0.048 (0.008)	Jobs Attract Arts
San Jose, CA	166	1.038 (0.129)	0.018 (0.001)	Arts Attract Jobs	0.272 (0.055)	0.026 (0.004)	Arts Attract Jobs	0.291 (0.070)	0.012 (0.002)	Arts Attract Jobs
Worcester, MA	163	NA (NA)	0.018 (0.001)	NA	0.206 (0.012)	0.068 (0.003)	Arts Attract Jobs	0.071 (0.008)	0.032 (0.009)	Arts Attract Jobs
El Paso, TX	159	4.231 (0.124)	0.037 (0.001)	Arts Attract Jobs	1.582 (0.050)	0.060 (0.002)	Arts Attract Jobs	0.449 (0.021)	0.070 (0.006)	Arts Attract Jobs
Flint, MI	159	0.578 (0.098)	0.017 (0.001)	Arts Attract Jobs	0.333 (0.044)	0.022 (0.003)	Arts Attract Jobs	-0.635 (0.022)	-0.150 (0.006)	Jobs Attract Arts
Hagerstown, MD	154	-0.255 (0.086)	-0.003 (0.001)	Jobs Attract Arts	-0.469 (0.035)	-0.040 (0.003)	Jobs Attract Arts	-0.184 (0.012)	-0.129 (0.011)	Jobs Attract Arts
New Orleans, LA	154	0.649 (0.032)	0.035 (0.003)	Arts Attract Jobs	0.268 (0.012)	0.005* (0.006)	Arts Attract Jobs	-0.093 (0.005)	-0.513 (0.014)	Arts Attract Jobs
Toledo, OH	152	0.106* (0.079)	0.016 (0.001)	Not Significant	0.335 (0.031)	0.039 (0.004)	Arts Attract Jobs	0.003* (0.008)	0.145 (0.014)	Jobs Attract Arts
New Haven, CT	151	-1.081 (0.057)	0.024 (0.001)	Jobs Attract Arts	-0.950 (0.029)	-0.151 (0.002)	Jobs Attract Arts	0.139 (0.022)	0.034 (0.002)	Arts Attract Jobs
Syracuse, NY	150	-0.377 (0.121)	0.010 (0.002)	Jobs Attract Arts	-0.673 (0.044)	-0.061 (0.003)	Jobs Attract Arts	0.019* (0.030)	0.041 (0.004)	Jobs Attract Arts
Shreveport, LA	147	-0.186 (0.069)	0.004 (0.002)	Jobs Attract Arts	-0.328 (0.015)	0.064 (0.004)	Jobs Attract Arts	0.043 (0.018)	0.041 (0.008)	Arts Attract Jobs
Fayetteville, AR	146	2.734 (0.126)	0.033 (0.000)	Arts Attract Jobs	0.664 (0.044)	0.091 (0.002)	Arts Attract Jobs	0.349 (0.009)	0.053 (0.007)	Arts Attract Jobs
Huntsville, AL	145	-0.439 (0.130)	-0.007 (0.001)	Jobs Attract Arts	-0.593 (0.060)	-0.006 (0.003)	Jobs Attract Arts	0.373 (0.067)	0.015 (0.003)	Arts Attract Jobs
Des Moines, IA	144	8.151 (0.019)	0.112 (0.000)	Arts Attract Jobs	3.211 (0.011)	0.213 (0.001)	Arts Attract Jobs	1.039 (0.003)	0.738 (0.002)	Arts Attract Jobs
Colorado Springs, CO	143	0.174* (0.118)	0.017 (0.001)	Not Significant	0.130 (0.040)	0.032 (0.006)	Arts Attract Jobs	-0.127 (0.047)	0.036 (0.004)	Jobs Attract Arts
Wichita, KS	143	-0.416 (0.084)	0.018 (0.002)	Jobs Attract Arts	-0.555 (0.031)	-0.042 (0.005)	Jobs Attract Arts	0.254 (0.023)	0.082 (0.005)	Arts Attract Jobs
Norwich, CT	142	0.566 (0.023)	0.033 (0.002)	Arts Attract Jobs	0.013* (0.010)	0.003* (0.011)	Not Significant	0.040 (0.007)	0.066 (0.006)	Jobs Attract Arts
Myrtle Beach, SC	141	3.049 (0.011)	0.270 (0.001)	Arts Attract Jobs	0.579 (0.006)	0.737 (0.010)	Jobs Attract Arts	0.119 (0.001)	3.063 (0.027)	Jobs Attract Arts
Ogden, UT	141	0.385 (0.136)	0.015 (0.001)	Arts Attract Jobs	0.799 (0.068)	0.042 (0.003)	Arts Attract Jobs	0.300 (0.031)	0.032 (0.006)	Arts Attract Jobs
Spokane, WA	141	3.191 (0.046)	0.117 (0.002)	Arts Attract Jobs	1.657 (0.018)	0.284 (0.003)	Arts Attract Jobs	0.257 (0.010)	0.036 (0.010)	Arts Attract Jobs
Port St. Lucie, FL	140	1.130 (0.103)	0.018 (0.002)	Arts Attract Jobs	0.233 (0.037)	0.024 (0.004)	Arts Attract Jobs	-0.031 (0.012)	0.022 (0.008)	Jobs Attract Arts
Greensboro, NC	139	2.160 (0.115)	0.041 (0.001)	Arts Attract Jobs	1.300 (0.045)	0.088 (0.003)	Arts Attract Jobs	0.039 (0.015)	0.139 (0.006)	Jobs Attract Arts

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

		Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
Urban Area	**N**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**
Lafayette, LA	138	-0.462 (0.130)	-0.007 (0.002)	Jobs Attract Arts	-0.333 (0.032)	0.002* (0.004)	Not Significant	0.042* (0.027)	0.009* (0.008)	Not Significant
Concord, CA	137	2.259 (0.166)	0.027 (0.002)	Arts Attract Jobs	0.437 (0.082)	0.039 (0.003)	Arts Attract Jobs	0.146 (0.063)	0.003* (0.005)	Arts Attract Jobs
Scranton, PA	137	0.427 (0.086)	0.005 (0.002)	Arts Attract Jobs	0.781 (0.031)	0.110 (0.005)	Arts Attract Jobs	0.031* (0.019)	0.011* (0.008)	Not Significant
Lakeland, FL	135	0.316 (0.117)	0.024 (0.001)	Arts Attract Jobs	0.125 (0.059)	0.043 (0.003)	Arts Attract Jobs	0.198 (0.011)	0.389 (0.015)	Jobs Attract Arts
Fresno, CA	133	1.228 (0.120)	0.014 (0.002)	Arts Attract Jobs	0.112 (0.044)	0.005* (0.003)	Arts Attract Jobs	0.140 (0.010)	0.070 (0.016)	Arts Attract Jobs
Gulfport, MS	133	0.432 (0.006)	0.216 (0.003)	Arts Attract Jobs	0.177 (0.003)	0.288 (0.010)	Jobs Attract Arts	0.051 (0.001)	0.048 (0.010)	Arts Attract Jobs
Atlantic City, NJ	132	0.169 (0.007)	0.090 (0.005)	Arts Attract Jobs	0.011 (0.002)	0.182 (0.011)	Jobs Attract Arts	0.014 (0.002)	0.061* (0.042)	Not Significant
Savannah, GA	131	1.022 (0.058)	0.025 (0.002)	Arts Attract Jobs	-0.260 (0.019)	-0.049 (0.006)	Jobs Attract Arts	0.055 (0.009)	0.157 (0.007)	Jobs Attract Arts
Rockford, IL	129	0.900 (0.160)	0.019 (0.001)	Arts Attract Jobs	0.019* (0.077)	0.007 (0.003)	Jobs Attract Arts	-0.040 (0.018)	-0.046 (0.008)	Arts Attract Jobs
Fayetteville, NC	128	8.182 (0.186)	0.027 (0.000)	Arts Attract Jobs	1.269 (0.052)	0.015 (0.002)	Arts Attract Jobs	0.117 (0.026)	0.016 (0.003)	Arts Attract Jobs
Kingsport, TN	128	-0.469 (0.187)	0.013 (0.001)	Jobs Attract Arts	0.109* (0.108)	-0.014 (0.001)	Jobs Attract Arts	0.318 (0.015)	0.089 (0.005)	Arts Attract Jobs
Mobile, AL	128	0.262 (0.114)	0.003 (0.001)	Arts Attract Jobs	0.019* (0.056)	0.026 (0.003)	Jobs Attract Arts	-0.080 (0.019)	-0.025 (0.009)	Jobs Attract Arts
Portland, ME	124	-0.228 (0.065)	0.002* (0.002)	Not Significant	0.528 (0.027)	-0.012 (0.005)	Arts Attract Jobs	-0.254 (0.011)	0.008* (0.007)	Not Significant
Reno, NV	122	0.320 (0.028)	0.007 (0.004)	Arts Attract Jobs	0.007* (0.013)	0.034 (0.009)	Jobs Attract Arts	-0.023 (0.005)	-0.336 (0.029)	Arts Attract Jobs
Peoria, IL	119	0.385 (0.139)	0.010 (0.001)	Arts Attract Jobs	0.079* (0.052)	0.031 (0.003)	Not Significant	0.085 (0.014)	0.052 (0.005)	Arts Attract Jobs
Victorville, CA	119	0.385 (0.074)	0.007 (0.000)	Arts Attract Jobs	0.027* (0.022)	-0.041 (0.001)	Not Significant	0.149 (0.006)	-0.126 (0.002)	Arts Attract Jobs
Fort Collins, CO	116	1.345 (0.165)	0.011 (0.001)	Arts Attract Jobs	0.057* (0.050)	0.008 (0.004)	Jobs Attract Arts	-0.300 (0.047)	-0.019 (0.005)	Jobs Attract Arts
Huntington, WV	116	-0.502 (0.189)	0.007 (0.001)	Jobs Attract Arts	0.200 (0.040)	0.003* (0.003)	Arts Attract Jobs	-0.238 (0.022)	-0.110 (0.006)	Jobs Attract Arts
Madison, WI	113	1.129 (0.095)	0.034 (0.003)	Arts Attract Jobs	0.546 (0.050)	0.039 (0.005)	Arts Attract Jobs	0.210 (0.028)	0.063 (0.009)	Arts Attract Jobs
Lansing, MI	111	3.754 (0.070)	0.071 (0.001)	Arts Attract Jobs	1.515 (0.027)	0.160 (0.003)	Arts Attract Jobs	0.255 (0.010)	0.137 (0.005)	Arts Attract Jobs
Port Arthur, TX	111	2.068 (0.141)	0.009 (0.001)	Arts Attract Jobs	0.467 (0.029)	0.014 (0.002)	Arts Attract Jobs	0.650 (0.019)	0.047 (0.002)	Arts Attract Jobs
Fort Wayne, IN	110	-1.809 (0.129)	-0.010 (0.001)	Jobs Attract Arts	-0.205 (0.060)	0.002* (0.003)	Not Significant	0.038* (0.030)	0.014* (0.007)	Not Significant
Bonita Springs, FL	108	1.428 (0.051)	0.091 (0.002)	Arts Attract Jobs	0.316 (0.019)	0.219 (0.012)	Arts Attract Jobs	0.105 (0.004)	0.752 (0.036)	Jobs Attract Arts
Leesburg, FL	107	0.161 (0.075)	0.015 (0.001)	Arts Attract Jobs	-0.068 (0.027)	0.012 (0.003)	Jobs Attract Arts	0.277 (0.019)	0.004* (0.005)	Arts Attract Jobs
Springfield, MO	107	2.179 (0.080)	0.051 (0.001)	Arts Attract Jobs	-0.089 (0.020)	0.006* (0.006)	Not Significant	0.221 (0.017)	0.134 (0.009)	Arts Attract Jobs
Ocala, FL	106	0.633 (0.145)	0.017 (0.001)	Arts Attract Jobs	0.050* (0.067)	0.044 (0.003)	Not Significant	0.016* (0.019)	-0.023 (0.008)	Not Significant
Wilmington, NC	105	0.299 (0.077)	0.019 (0.002)	Arts Attract Jobs	0.010* (0.017)	0.032 (0.005)	Jobs Attract Arts	0.019* (0.013)	0.020 (0.008)	Jobs Attract Arts
Davenport, IA	104	1.477 (0.053)	0.053 (0.001)	Arts Attract Jobs	1.303 (0.029)	0.173 (0.003)	Arts Attract Jobs	0.266 (0.008)	0.263 (0.015)	Arts Attract Jobs
Murrieta, CA	103	0.094* (0.151)	0.012 (0.001)	Not Significant	0.263 (0.034)	0.040 (0.004)	Arts Attract Jobs	0.151 (0.013)	-0.054 (0.006)	Arts Attract Jobs
Indio, CA	102	-0.396 (0.034)	-0.018 (0.006)	Jobs Attract Arts	-0.120 (0.012)	-0.151 (0.020)	Arts Attract Jobs	0.027 (0.003)	1.055 (0.079)	Jobs Attract Arts
Kalamazoo, MI	102	0.217 (0.099)	0.015 (0.001)	Arts Attract Jobs	0.033* (0.035)	0.016 (0.002)	Not Significant	0.278 (0.014)	0.003* (0.006)	Arts Attract Jobs
Fort Walton Beach, FL	101	1.437 (0.055)	0.095 (0.002)	Arts Attract Jobs	0.002* (0.017)	0.072 (0.006)	Jobs Attract Arts	0.230 (0.016)	0.102 (0.008)	Arts Attract Jobs
Montgomery, AL	101	0.771 (0.104)	0.011 (0.002)	Arts Attract Jobs	0.274 (0.035)	0.021 (0.004)	Arts Attract Jobs	0.102 (0.013)	0.073 (0.010)	Arts Attract Jobs
Nashua, NH	100	0.340 (0.120)	0.017 (0.002)	Arts Attract Jobs	0.170 (0.056)	0.040 (0.004)	Arts Attract Jobs	0.056* (0.036)	0.020 (0.006)	Not Significant
Brownsville, TX	99	4.062 (0.117)	0.042 (0.001)	Arts Attract Jobs	0.983 (0.037)	0.092 (0.003)	Arts Attract Jobs	0.159 (0.006)	-0.020 (0.008)	Arts Attract Jobs

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

		Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
Urban Area	**N**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**
Bakersfield, CA	98	0.348 (0.072)	0.009 (0.003)	Arts Attract Jobs	-0.030* (0.025)	-0.096 (0.002)	Not Significant	0.268 (0.010)	0.072 (0.007)	Arts Attract Jobs
Tallahassee, FL	98	0.458 (0.069)	0.003 (0.001)	Arts Attract Jobs	0.069 (0.029)	-0.026 (0.003)	Arts Attract Jobs	-0.331 (0.019)	-0.047 (0.004)	Jobs Attract Arts
York, PA	96	NA	NA	NA	1.558 (0.016)	0.226 (0.002)	Arts Attract Jobs	0.005* (0.008)	-0.110 (0.010)	Not Significant
Boise City, ID	94	0.590 (0.151)	0.021 (0.002)	Arts Attract Jobs	0.283 (0.075)	0.031 (0.004)	Arts Attract Jobs	-0.129 (0.022)	0.046 (0.008)	Jobs Attract Arts
Durham, NC	94	0.694 (0.082)	-0.001* (0.002)	Arts Attract Jobs	0.040* (0.044)	-0.042 (0.006)	Not Significant	0.040* (0.025)	0.059 (0.009)	Jobs Attract Arts
Bremerton, WA	93	0.214 (0.031)	-0.003* (0.003)	Arts Attract Jobs	-0.039 (0.011)	-0.004* (0.005)	Not Significant	0.005* (0.007)	-0.029 (0.006)	Not Significant
Provo, UT	93	0.404 (0.159)	0.018 (0.001)	Arts Attract Jobs	-0.208 (0.075)	0.012 (0.003)	Jobs Attract Arts	-0.148 (0.045)	0.005* (0.007)	Not Significant
Saginaw, MI	91	0.559 (0.103)	0.026 (0.001)	Arts Attract Jobs	-0.246 (0.034)	0.031 (0.004)	Jobs Attract Arts	0.171 (0.014)	-0.033 (0.010)	Arts Attract Jobs
Modesto, CA	90	0.742 (0.143)	0.020 (0.001)	Arts Attract Jobs	0.315 (0.069)	0.033 (0.004)	Arts Attract Jobs	0.057 (0.019)	-0.006* (0.006)	Arts Attract Jobs
Stockton, CA	90	-0.276 (0.137)	0.012 (0.001)	Jobs Attract Arts	0.276 (0.060)	-0.007* (0.006)	Arts Attract Jobs	-0.011* (0.012)	0.040 (0.014)	Jobs Attract Arts
Evansville, IN	89	-0.277 (0.051)	0.035 (0.001)	Jobs Attract Arts	1.510 (0.033)	0.144 (0.002)	Arts Attract Jobs	0.032 (0.007)	0.097 (0.015)	Jobs Attract Arts
Santa Rosa, CA	89	1.083 (0.070)	0.034 (0.003)	Arts Attract Jobs	0.213 (0.020)	0.042 (0.008)	Arts Attract Jobs	0.060 (0.006)	0.073 (0.011)	Jobs Attract Arts
Muskegon, MI	88	-0.609 (0.073)	0.021 (0.002)	Jobs Attract Arts	-0.684 (0.034)	-0.055 (0.003)	Jobs Attract Arts	-0.044 (0.007)	-0.234 (0.008)	Arts Attract Jobs
Reading, PA	86	-0.666 (0.133)	-0.006 (0.003)	Jobs Attract Arts	-0.113* (0.064)	-0.012 (0.004)	Jobs Attract Arts	0.011* (0.019)	-0.016* (0.018)	Not Significant
Salinas, CA	85	1.923 (0.123)	0.028 (0.003)	Arts Attract Jobs	-0.092 (0.033)	0.040 (0.005)	Jobs Attract Arts	-0.111 (0.012)	-0.188 (0.015)	Arts Attract Jobs
Corpus Christi, TX	83	-0.426 (0.102)	0.014 (0.001)	Jobs Attract Arts	-0.104 (0.038)	0.006* (0.003)	Not Significant	0.054 (0.018)	-0.037 (0.012)	Arts Attract Jobs
Lancaster, CA	83	0.236* (0.154)	0.025 (0.001)	Not Significant	0.238 (0.036)	0.070 (0.003)	Arts Attract Jobs	0.025* (0.022)	0.064 (0.003)	Jobs Attract Arts
Killeen, TX	82	3.398 (0.133)	0.043 (0.001)	Arts Attract Jobs	1.045 (0.035)	0.021 (0.004)	Arts Attract Jobs	0.077 (0.020)	-0.070 (0.008)	Arts Attract Jobs
Clarksville, TN	81	12.211 (0.191)	0.033 (0.001)	Arts Attract Jobs	0.326 (0.026)	0.012 (0.002)	Arts Attract Jobs	0.154 (0.028)	0.002* (0.001)	Arts Attract Jobs
Olympia, WA	81	1.461 (0.130)	0.015 (0.001)	Arts Attract Jobs	0.355 (0.038)	-0.022 (0.001)	Arts Attract Jobs	0.240 (0.022)	0.082 (0.004)	Arts Attract Jobs
Portsmouth, NH	81	0.369 (0.093)	0.011 (0.003)	Arts Attract Jobs	0.127 (0.050)	0.010* (0.005)	Arts Attract Jobs	-0.080 (0.006)	0.025 (0.009)	Jobs Attract Arts
Roanoke, VA	80	0.350 (0.116)	0.017 (0.001)	Arts Attract Jobs	0.613 (0.039)	0.048 (0.002)	Arts Attract Jobs	0.024 (0.012)	-0.020 (0.005)	Arts Attract Jobs
Winter Haven, FL	80	0.142 (0.053)	0.011 (0.005)	Arts Attract Jobs	0.013* (0.022)	0.052 (0.010)	Jobs Attract Arts	0.034 (0.004)	0.182 (0.044)	Jobs Attract Arts
Houma, LA	79	17.454 (0.218)	0.033 (0.000)	Arts Attract Jobs	2.758 (0.042)	0.172 (0.003)	Arts Attract Jobs	0.819 (0.013)	0.264 (0.007)	Arts Attract Jobs
North Port, FL	79	0.586 (0.060)	0.023 (0.001)	Arts Attract Jobs	0.190 (0.015)	0.063 (0.002)	Arts Attract Jobs	0.011 (0.004)	-0.020* (0.016)	Arts Attract Jobs
Spartanburg, SC	79	1.288 (0.158)	0.016 (0.001)	Arts Attract Jobs	-1.109 (0.067)	0.004* (0.002)	Not Significant	0.226 (0.020)	0.101 (0.009)	Arts Attract Jobs
Ann Arbor, MI	78	-0.152 (0.061)	0.038 (0.001)	Jobs Attract Arts	0.547 (0.033)	0.170 (0.004)	Arts Attract Jobs	0.298 (0.023)	0.067 (0.004)	Arts Attract Jobs
Appleton, WI	78	-0.946 (0.114)	-0.016 (0.003)	Jobs Attract Arts	0.239 (0.053)	0.021 (0.007)	Arts Attract Jobs	0.108 (0.020)	-0.036 (0.012)	Arts Attract Jobs
Oxnard, CA	78	0.129* (0.133)	0.012 (0.003)	Not Significant	0.330 (0.053)	0.038 (0.005)	Arts Attract Jobs	-0.093 (0.013)	-0.107 (0.013)	Arts Attract Jobs
Gastonia, NC	77	-0.020* (0.199)	0.009 (0.001)	Jobs Attract Arts	0.087* (0.098)	0.003* (0.003)	Not Significant	0.020* (0.012)	-0.008* (0.004)	Not Significant
Binghamton, NY	76	0.123* (0.105)	-0.011 (0.002)	Not Significant	-0.019* (0.045)	-0.031 (0.005)	Not Significant	0.182 (0.040)	-0.014* (0.008)	Arts Attract Jobs
Concord, NC	76	1.177 (0.110)	0.004 (0.000)	Arts Attract Jobs	-0.128 (0.029)	0.006 (0.001)	Jobs Attract Arts	-0.071 (0.003)	0.021 (0.009)	Jobs Attract Arts
Green Bay, WI	76	0.210 (0.048)	0.033 (0.002)	Arts Attract Jobs	-0.198 (0.037)	-0.042 (0.003)	Jobs Attract Arts	0.104 (0.010)	0.165 (0.006)	Jobs Attract Arts
Lubbock, TX	76	4.106 (0.136)	0.057 (0.001)	Arts Attract Jobs	1.121 (0.049)	0.109 (0.004)	Arts Attract Jobs	0.461 (0.017)	0.213 (0.012)	Arts Attract Jobs
Warner Robins, GA	76	4.200 (0.227)	0.013 (0.001)	Arts Attract Jobs	0.027* (0.076)	0.015 (0.003)	Not Significant	0.194 (0.046)	0.020 (0.005)	Arts Attract Jobs

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

		Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
Urban Area	**N**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**
Athens-Clarke County, GA	74	2.996 (0.151)	0.028 (0.001)	Arts Attract Jobs	0.247 (0.072)	-0.010 (0.003)	Arts Attract Jobs	0.188 (0.015)	0.194 (0.014)	Jobs Attract Arts
Lynchburg, VA	74	2.806 (0.094)	0.031 (0.000)	Arts Attract Jobs	0.614 (0.017)	0.130 (0.002)	Arts Attract Jobs	0.122 (0.011)	0.190 (0.003)	Jobs Attract Arts
Panama City, FL	74	0.738 (0.045)	0.025 (0.003)	Arts Attract Jobs	0.169 (0.016)	0.051 (0.006)	Arts Attract Jobs	0.037 (0.011)	0.046 (0.009)	Jobs Attract Arts
Columbus, GA	73	0.099* (0.082)	0.010 (0.002)	Not Significant	-0.799 (0.045)	-0.065 (0.003)	Jobs Attract Arts	0.472 (0.010)	0.086 (0.008)	Arts Attract Jobs
Kennewick, WA	73	5.467 (0.061)	0.047 (0.000)	Arts Attract Jobs	1.303 (0.019)	0.127 (0.002)	Arts Attract Jobs	0.193 (0.005)	-0.063 (0.001)	Arts Attract Jobs
Springfield, IL	73	0.116 (0.047)	0.025 (0.002)	Arts Attract Jobs	-0.003* (0.033)	0.057 (0.004)	Jobs Attract Arts	-0.005* (0.016)	0.134 (0.010)	Jobs Attract Arts
Deltona, FL	72	-0.520 (0.102)	-0.004* (0.002)	Not Significant	-0.238 (0.022)	-0.010* (0.006)	Not Significant	0.078 (0.015)	-0.023 (0.004)	Arts Attract Jobs
Fairfield, CA	72	1.125 (0.138)	0.022 (0.001)	Arts Attract Jobs	0.082* (0.044)	0.053 (0.005)	Not Significant	-0.022* (0.017)	0.022* (0.013)	Not Significant
Round Lake Beach, IL	72	-0.053* (0.029)	0.009 (0.004)	Jobs Attract Arts	-0.072 (0.011)	0.003* (0.014)	Not Significant	0.006* (0.006)	0.162 (0.038)	Jobs Attract Arts
Visalia, CA	72	-0.661 (0.139)	0.001* (0.003)	Not Significant	-0.328 (0.053)	0.012 (0.004)	Jobs Attract Arts	0.061 (0.012)	0.263 (0.024)	Jobs Attract Arts
Homosassa Springs, FL	71	2.603 (0.089)	0.054 (0.001)	Arts Attract Jobs	0.506 (0.020)	0.129 (0.001)	Arts Attract Jobs	0.118 (0.006)	0.588 (0.043)	Jobs Attract Arts
Tuscaloosa, AL	71	1.191 (0.129)	0.012 (0.001)	Arts Attract Jobs	0.832 (0.035)	0.016 (0.003)	Arts Attract Jobs	0.098 (0.012)	0.008* (0.005)	Arts Attract Jobs
Lake Charles, LA	70	0.758 (0.076)	0.024 (0.002)	Arts Attract Jobs	0.255 (0.007)	0.109 (0.005)	Arts Attract Jobs	0.388 (0.018)	0.152 (0.007)	Arts Attract Jobs
Eugene, OR	69	1.406 (0.076)	0.027 (0.002)	Arts Attract Jobs	0.387 (0.026)	0.066 (0.005)	Arts Attract Jobs	0.156 (0.014)	0.051 (0.015)	Arts Attract Jobs
Sebastian, FL	69	1.025 (0.080)	0.023 (0.003)	Arts Attract Jobs	0.413 (0.024)	-0.006* (0.008)	Arts Attract Jobs	0.370 (0.010)	0.387 (0.011)	Jobs Attract Arts
Waco, TX	68	-1.200 (0.052)	0.021 (0.001)	Jobs Attract Arts	-0.103 (0.040)	0.033 (0.003)	Jobs Attract Arts	0.124 (0.015)	0.017 (0.008)	Arts Attract Jobs
Mandeville, LA	67	0.504 (0.096)	0.012 (0.001)	Arts Attract Jobs	0.197 (0.033)	0.029 (0.005)	Arts Attract Jobs	0.094 (0.012)	0.102 (0.014)	Jobs Attract Arts
Thousand Oaks, CA	67	1.585 (0.107)	0.051 (0.001)	Arts Attract Jobs	1.304 (0.050)	0.130 (0.005)	Arts Attract Jobs	1.232 (0.051)	0.135 (0.004)	Arts Attract Jobs
Charleston, WV	66	0.678 (0.090)	0.013 (0.002)	Arts Attract Jobs	0.411 (0.039)	0.054 (0.004)	Arts Attract Jobs	0.176 (0.012)	0.178 (0.010)	Jobs Attract Arts
Gainesville, FL	66	0.996 (0.127)	0.020 (0.002)	Arts Attract Jobs	0.077 (0.031)	0.061 (0.006)	Arts Attract Jobs	0.236 (0.025)	0.038 (0.012)	Arts Attract Jobs
Burlington, NC	65	11.286 (0.070)	0.044 (0.000)	Arts Attract Jobs	2.607 (0.007)	0.119 (0.001)	Arts Attract Jobs	0.041 (0.005)	-0.014 (0.004)	Arts Attract Jobs
Grand Junction, CO	65	-0.819 (0.058)	-0.030 (0.003)	Jobs Attract Arts	0.015* (0.030)	-0.011* (0.006)	Not Significant	0.132 (0.014)	-0.068 (0.009)	Arts Attract Jobs
Medford, OR	65	-0.347 (0.121)	0.017 (0.003)	Jobs Attract Arts	-0.218 (0.029)	-0.026 (0.007)	Jobs Attract Arts	0.086 (0.016)	0.119 (0.031)	Jobs Attract Arts
Pueblo, CO	64	-1.285 (0.105)	-0.003 (0.001)	Jobs Attract Arts	0.546 (0.041)	-0.008 (0.002)	Arts Attract Jobs	0.109 (0.010)	-0.030 (0.003)	Arts Attract Jobs
Florence, SC	63	6.458 (0.084)	0.055 (0.000)	Arts Attract Jobs	2.233 (0.029)	0.119 (0.002)	Arts Attract Jobs	0.593 (0.004)	1.181 (0.008)	Jobs Attract Arts
Johnson City, TN	63	-0.554 (0.141)	0.002* (0.001)	Not Significant	-0.432 (0.051)	-0.013 (0.001)	Jobs Attract Arts	0.095 (0.017)	0.152 (0.007)	Jobs Attract Arts
Monroe, LA	63	3.483 (0.157)	0.036 (0.001)	Arts Attract Jobs	-0.850 (0.020)	0.094 (0.002)	Jobs Attract Arts	-0.372 (0.038)	0.013 (0.004)	Jobs Attract Arts
Salisbury, MD	63	5.304 (0.086)	0.030 (0.000)	Arts Attract Jobs	3.885 (0.020)	0.196 (0.001)	Arts Attract Jobs	1.542 (0.012)	0.294 (0.002)	Arts Attract Jobs
Aberdeen, MD	62	0.405 (0.129)	0.008 (0.002)	Arts Attract Jobs	-0.108 (0.032)	0.033 (0.006)	Jobs Attract Arts	0.087 (0.034)	0.024 (0.008)	Arts Attract Jobs
Rock Hill, SC	62	21.414 (0.027)	0.036 (0.000)	Arts Attract Jobs	1.547 (0.015)	0.127 (0.001)	Arts Attract Jobs	1.655 (0.001)	0.295 (0.000)	Arts Attract Jobs
Tyler, TX	62	0.900 (0.127)	0.021 (0.001)	Arts Attract Jobs	-0.182 (0.045)	0.059 (0.003)	Jobs Attract Arts	0.182 (0.015)	0.113 (0.007)	Arts Attract Jobs
Gadsden, AL	61	1.823 (0.227)	0.007 (0.001)	Arts Attract Jobs	0.086* (0.091)	0.010 (0.001)	Not Significant	-0.040 (0.011)	-0.007* (0.008)	Not Significant
Lexington-Fayette, KY	61	0.611 (0.165)	0.008 (0.003)	Arts Attract Jobs	0.044* (0.078)	0.036 (0.005)	Not Significant	0.205 (0.024)	-0.012* (0.010)	Arts Attract Jobs
Los Lunas, NM	61	-1.022 (0.115)	-0.008 (0.001)	Jobs Attract Arts	-0.269 (0.012)	-0.197 (0.008)	Jobs Attract Arts	0.049 (0.004)	0.103 (0.029)	Jobs Attract Arts
Dover, DE	60	1.168 (0.113)	-0.002 (0.001)	Arts Attract Jobs	-1.826 (0.014)	-0.094 (0.001)	Jobs Attract Arts	0.026 (0.006)	0.049 (0.008)	Jobs Attract Arts

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

		Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
Urban Area	**N**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**
Duluth, MN	60	-2.798 (0.073)	-0.055 (0.002)	Jobs Attract Arts	-0.305 (0.035)	-0.061 (0.005)	Jobs Attract Arts	0.097 (0.013)	0.187 (0.011)	Jobs Attract Arts
Eau Claire, WI	60	0.370 (0.060)	0.014 (0.003)	Arts Attract Jobs	-0.561 (0.029)	0.015 (0.003)	Jobs Attract Arts	0.147 (0.021)	0.097 (0.012)	Arts Attract Jobs
Redding, CA	60	-0.524 (0.146)	0.003* (0.002)	Not Significant	0.968 (0.065)	0.047 (0.003)	Arts Attract Jobs	0.084 (0.029)	-0.032 (0.005)	Arts Attract Jobs
Cedar Rapids, IA	59	-0.243 (0.073)	0.007 (0.003)	Jobs Attract Arts	0.676 (0.043)	0.146 (0.004)	Arts Attract Jobs	-0.673 (0.024)	-0.083 (0.005)	Jobs Attract Arts
Erie, PA	59	0.545 (0.153)	0.011 (0.003)	Arts Attract Jobs	-0.112* (0.064)	-0.008* (0.007)	Not Significant	-0.018* (0.017)	-0.028 (0.014)	Not Significant
Fort Smith, AR	59	4.157 (0.169)	0.030 (0.001)	Arts Attract Jobs	-0.179* (0.099)	-0.006* (0.004)	Not Significant	0.200 (0.021)	0.081 (0.015)	Arts Attract Jobs
Amarillo, TX	58	1.540 (0.146)	0.031 (0.002)	Arts Attract Jobs	1.164 (0.045)	0.090 (0.005)	Arts Attract Jobs	0.177 (0.011)	0.050 (0.011)	Arts Attract Jobs
Macon, GA	58	-0.898 (0.045)	0.018 (0.001)	Jobs Attract Arts	-1.043 (0.015)	-0.044 (0.002)	Jobs Attract Arts	-0.068 (0.003)	0.052 (0.003)	Jobs Attract Arts
Mission Viejo, CA	58	1.872 (0.177)	0.034 (0.003)	Arts Attract Jobs	-0.120 (0.036)	0.031 (0.007)	Jobs Attract Arts	0.197 (0.047)	0.077 (0.011)	Arts Attract Jobs
Nampa, ID	58	0.829 (0.095)	0.001* (0.001)	Arts Attract Jobs	-0.112 (0.020)	0.005* (0.003)	Not Significant	-1.125 (0.021)	-0.005 (0.002)	Jobs Attract Arts
Burlington, VT	57	0.159 (0.064)	-0.039 (0.003)	Arts Attract Jobs	0.555 (0.014)	-0.018 (0.006)	Arts Attract Jobs	-0.049 (0.022)	0.089 (0.006)	Jobs Attract Arts
College Station, TX	55	-0.838 (0.105)	0.024 (0.001)	Jobs Attract Arts	-0.190 (0.034)	0.015 (0.003)	Jobs Attract Arts	0.252 (0.015)	-0.043 (0.005)	Arts Attract Jobs
Salem, OR	55	22.382 (0.122)	0.035 (0.000)	Arts Attract Jobs	4.009 (0.024)	0.190 (0.001)	Arts Attract Jobs	1.162 (0.012)	0.377 (0.006)	Arts Attract Jobs
Santa Clarita, CA	55	-1.061 (0.042)	0.028 (0.002)	Jobs Attract Arts	-0.331 (0.018)	0.068 (0.007)	Jobs Attract Arts	-0.057 (0.005)	0.006* (0.005)	Not Significant
Danbury, CT	54	0.346 (0.071)	0.046 (0.002)	Arts Attract Jobs	0.119 (0.035)	0.150 (0.009)	Jobs Attract Arts	-0.259 (0.017)	0.022 (0.007)	Jobs Attract Arts
Port Huron, MI	54	-0.494 (0.136)	0.007 (0.001)	Jobs Attract Arts	-0.216 (0.043)	0.016 (0.005)	Jobs Attract Arts	-0.061 (0.008)	0.116 (0.011)	Jobs Attract Arts
Anniston, AL	53	0.242* (0.316)	0.012 (0.001)	Not Significant	0.899 (0.053)	0.033 (0.003)	Arts Attract Jobs	0.106 (0.037)	0.043 (0.004)	Arts Attract Jobs
Frederick, MD	53	0.866 (0.170)	-0.012 (0.001)	Arts Attract Jobs	1.052 (0.092)	-0.012 (0.002)	Arts Attract Jobs	-0.530 (0.041)	-0.067 (0.005)	Jobs Attract Arts
Lincoln, NE	53	-0.245* (0.132)	0.016 (0.002)	Jobs Attract Arts	-0.367 (0.058)	0.026 (0.006)	Jobs Attract Arts	0.295 (0.027)	-0.028 (0.010)	Arts Attract Jobs
Waterloo, IA	53	-0.644 (0.070)	0.019 (0.002)	Jobs Attract Arts	0.020* (0.033)	-0.083 (0.006)	Not Significant	-0.019* (0.011)	-0.187 (0.019)	Not Significant
Bristol, TN	52	0.522 (0.137)	0.005 (0.001)	Arts Attract Jobs	-0.288 (0.060)	-0.017 (0.002)	Jobs Attract Arts	-0.051 (0.018)	0.018 (0.006)	Jobs Attract Arts
Fredericksburg, VA	52	-0.666 (0.086)	-0.021 (0.001)	Jobs Attract Arts	-0.404 (0.025)	-0.082 (0.003)	Jobs Attract Arts	-0.029 (0.011)	0.032 (0.007)	Jobs Attract Arts
Greenville, NC	52	2.857 (0.123)	0.026 (0.000)	Arts Attract Jobs	-0.670 (0.026)	0.032 (0.002)	Jobs Attract Arts	0.414 (0.019)	-0.011 (0.003)	Arts Attract Jobs
Lafayette, IN	52	0.323 (0.121)	0.015 (0.001)	Arts Attract Jobs	0.063* (0.072)	0.006 (0.003)	Not Significant	-0.126 (0.022)	-0.062 (0.013)	Jobs Attract Arts
Spring Hill, FL	52	-1.263 (0.142)	-0.021 (0.003)	Jobs Attract Arts	-0.624 (0.034)	-0.014* (0.009)	Not Significant	0.016* (0.021)	0.055 (0.019)	Jobs Attract Arts
Beckley, WV	51	-0.152* (0.150)	-0.007 (0.002)	Jobs Attract Arts	0.020* (0.044)	-0.009 (0.002)	Not Significant	-0.003* (0.013)	-0.006* (0.014)	Not Significant
Topeka, KS	51	-0.098* (0.128)	-0.004* (0.003)	Not Significant	0.039* (0.064)	-0.009* (0.006)	Not Significant	0.049 (0.014)	-0.047* (0.025)	Arts Attract Jobs
Carbondale, IL	50	-1.985 (0.185)	-0.001* (0.002)	Not Significant	-0.514 (0.052)	0.057 (0.004)	Jobs Attract Arts	0.051 (0.023)	0.013* (0.019)	Arts Attract Jobs
Dalton, GA	50	1.253 (0.180)	0.004 (0.000)	Arts Attract Jobs	-0.901 (0.057)	-0.036 (0.001)	Jobs Attract Arts	0.023 (0.008)	0.026 (0.002)	Jobs Attract Arts
Fargo, ND	50	2.364 (0.068)	0.025 (0.000)	Arts Attract Jobs	0.569 (0.018)	0.016 (0.002)	Arts Attract Jobs	0.241 (0.008)	0.189 (0.005)	Arts Attract Jobs
Hattiesburg, MS	50	1.224 (0.060)	0.012 (0.001)	Arts Attract Jobs	1.107 (0.023)	0.029 (0.002)	Arts Attract Jobs	-0.008 (0.001)	-0.030 (0.003)	Arts Attract Jobs
High Point, NC	50	1.517 (0.207)	0.019 (0.001)	Arts Attract Jobs	0.271 (0.059)	0.028 (0.002)	Arts Attract Jobs	0.018* (0.011)	0.265 (0.016)	Jobs Attract Arts
Hilton Head Island, SC	50	1.286 (0.015)	0.060 (0.001)	Arts Attract Jobs	0.318 (0.012)	0.110 (0.004)	Arts Attract Jobs	0.074 (0.002)	1.780 (0.024)	Jobs Attract Arts
Jackson, MI	50	1.137 (0.065)	-0.012 (0.001)	Arts Attract Jobs	0.406 (0.040)	-0.003* (0.002)	Arts Attract Jobs	0.349 (0.019)	0.057 (0.005)	Arts Attract Jobs
Valdosta, GA	50	-2.298 (0.063)	-0.068 (0.002)	Jobs Attract Arts	-1.154 (0.026)	-0.177 (0.003)	Jobs Attract Arts	-0.143 (0.004)	-0.469 (0.015)	Arts Attract Jobs

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

Urban Area	N	Arts and Non-Arts Jobs: Effect of Arts on Jobs	Arts and Non-Arts Jobs: Effect of Jobs on Arts	Arts and Non-Arts Jobs: Conclusion	Arts and Business Services: Effect of Arts on Jobs	Arts and Business Services: Effect of Jobs on Arts	Arts and Business Services: Conclusion	Arts and High-Tech: Effect of Arts on Jobs	Arts and High-Tech: Effect of Jobs on Arts	Arts and High-Tech: Conclusion
Yakima, WA	50	NA	NA	NA	0.219 (0.047)	0.101 (0.005)	Arts Attract Jobs	-0.008* (0.008)	-0.118 (0.022)	Not Significant
Daphne, AL	49	1.566 (0.142)	0.015 (0.002)	Arts Attract Jobs	0.002* (0.035)	-0.031 (0.004)	Not Significant	0.102 (0.023)	0.023 (0.009)	Arts Attract Jobs
Decatur, IL	49	-0.233 (0.107)	0.021 (0.001)	Jobs Attract Arts	0.524 (0.031)	0.107 (0.004)	Arts Attract Jobs	-0.014 (0.005)	0.337 (0.016)	Jobs Attract Arts
Elizabethtown, KY	49	-2.078 (0.161)	0.018 (0.001)	Jobs Attract Arts	2.237 (0.089)	0.045 (0.002)	Arts Attract Jobs	-0.191 (0.009)	0.046 (0.010)	Jobs Attract Arts
Joplin, MO	49	1.828 (0.026)	0.041 (0.000)	Arts Attract Jobs	0.904 (0.014)	0.004 (0.001)	Arts Attract Jobs	0.566 (0.002)	1.206 (0.004)	Jobs Attract Arts
Kissimmee, FL	49	-0.114* (0.102)	0.000* (0.001)	Not Significant	-0.038 (0.019)	0.102 (0.003)	Jobs Attract Arts	0.034 (0.006)	0.022* (0.018)	Arts Attract Jobs
Morristown, TN	49	-0.714 (0.200)	0.010 (0.000)	Jobs Attract Arts	3.608 (0.093)	0.075 (0.001)	Arts Attract Jobs	0.021 (0.007)	0.114 (0.002)	Jobs Attract Arts
Odessa, TX	49	-0.634 (0.124)	0.008 (0.003)	Jobs Attract Arts	0.702 (0.035)	0.125 (0.010)	Arts Attract Jobs	0.073 (0.018)	0.071 (0.013)	Arts Attract Jobs
Sumter, SC	49	25.763 (0.055)	0.035 (0.000)	Arts Attract Jobs	2.866 (0.007)	0.142 (0.000)	Arts Attract Jobs	0.378 (0.002)	0.179 (0.004)	Arts Attract Jobs
Vineland, NJ	49	1.785 (0.111)	-0.016 (0.001)	Arts Attract Jobs	-0.980 (0.039)	-0.143 (0.004)	Jobs Attract Arts	0.068 (0.008)	0.137 (0.015)	Jobs Attract Arts
Bellingham, WA	48	-0.398 (0.061)	-0.055 (0.001)	Jobs Attract Arts	-0.073 (0.016)	-0.114 (0.002)	Arts Attract Jobs	0.144 (0.016)	0.033 (0.004)	Arts Attract Jobs
Canton, OH	48	0.345 (0.144)	0.002* (0.001)	Arts Attract Jobs	0.331 (0.045)	0.032 (0.005)	Arts Attract Jobs	0.050 (0.007)	0.317 (0.031)	Jobs Attract Arts
Columbia, MO	48	-1.050 (0.045)	0.002 (0.001)	Jobs Attract Arts	-0.708 (0.002)	-0.057 (0.001)	Jobs Attract Arts	-0.122 (0.006)	0.001* (0.002)	Not Significant
Dover, NH	48	2.451 (0.102)	0.016 (0.001)	Arts Attract Jobs	0.409 (0.079)	0.007 (0.001)	Arts Attract Jobs	0.051* (0.046)	-0.056 (0.003)	Not Significant
Goldsboro, NC	48	-1.289 (0.106)	-0.001 (0.000)	Jobs Attract Arts	-1.288 (0.016)	-0.029 (0.001)	Jobs Attract Arts	-0.136 (0.004)	0.055 (0.002)	Jobs Attract Arts
Jacksonville, NC	48	0.138* (0.112)	0.001* (0.002)	Not Significant	0.833 (0.029)	0.088 (0.003)	Arts Attract Jobs	0.008 (0.004)	-0.113 (0.015)	Arts Attract Jobs
Slidell, LA	48	1.463 (0.137)	-0.016 (0.001)	Arts Attract Jobs	0.550 (0.027)	0.057 (0.002)	Arts Attract Jobs	0.083 (0.019)	-0.037 (0.002)	Arts Attract Jobs
Texarkana, TX	48	15.528 (0.043)	0.042 (0.000)	Arts Attract Jobs	2.012 (0.016)	0.190 (0.001)	Arts Attract Jobs	0.184 (0.002)	0.259 (0.008)	Jobs Attract Arts
Trenton, NJ	48	-0.975 (0.052)	0.023 (0.004)	Jobs Attract Arts	-1.002 (0.025)	-0.115 (0.006)	Jobs Attract Arts	0.141 (0.016)	0.143 (0.015)	Jobs Attract Arts
Alexandria, LA	47	-2.809 (0.097)	-0.015 (0.001)	Jobs Attract Arts	0.658 (0.030)	0.015 (0.002)	Arts Attract Jobs	-0.280 (0.006)	-0.252 (0.004)	Jobs Attract Arts
Anderson, IN	47	1.171 (0.132)	0.021 (0.001)	Arts Attract Jobs	0.198 (0.070)	0.011 (0.002)	Arts Attract Jobs	0.109 (0.012)	0.058 (0.018)	Arts Attract Jobs
Decatur, AL	47	0.306 (0.155)	-0.012 (0.000)	Arts Attract Jobs	-1.182 (0.023)	-0.027 (0.002)	Jobs Attract Arts	0.312 (0.005)	-0.025 (0.002)	Arts Attract Jobs
Denton, TX	47	2.985 (0.190)	0.019 (0.000)	Arts Attract Jobs	0.702 (0.066)	0.078 (0.004)	Arts Attract Jobs	0.299 (0.021)	0.233 (0.007)	Arts Attract Jobs
Midland, TX	47	2.661 (0.143)	0.026 (0.001)	Arts Attract Jobs	0.697 (0.057)	0.100 (0.003)	Arts Attract Jobs	0.678 (0.018)	0.191 (0.007)	Arts Attract Jobs
Santa Cruz, CA	47	-0.742 (0.119)	-0.003* (0.004)	Not Significant	0.062* (0.034)	0.032 (0.009)	Not Significant	0.095 (0.024)	0.092 (0.010)	Arts Attract Jobs
Sebring, FL	47	-1.261 (0.042)	0.014 (0.000)	Jobs Attract Arts	-0.917 (0.016)	0.022 (0.001)	Jobs Attract Arts	0.158 (0.006)	0.679 (0.012)	Jobs Attract Arts
Abilene, TX	46	1.930 (0.149)	0.048 (0.002)	Arts Attract Jobs	0.372 (0.045)	0.085 (0.011)	Arts Attract Jobs	0.006* (0.006)	0.699 (0.020)	Jobs Attract Arts
Blacksburg, VA	46	4.508 (0.105)	0.019 (0.000)	Arts Attract Jobs	-0.405 (0.008)	0.049 (0.003)	Jobs Attract Arts	-0.027 (0.011)	-0.008* (0.008)	Not Significant
La Crosse, WI	46	0.160 (0.044)	0.027 (0.003)	Arts Attract Jobs	0.078 (0.009)	0.027 (0.005)	Arts Attract Jobs	0.083 (0.009)	0.332 (0.009)	Jobs Attract Arts
Utica, NY	46	0.329* (0.186)	0.036 (0.002)	Not Significant	0.152* (0.104)	0.017 (0.006)	Not Significant	0.359 (0.027)	0.040 (0.007)	Arts Attract Jobs
Wausau, WI	46	-0.711 (0.082)	-0.005* (0.003)	Not Significant	-0.179 (0.044)	-0.044 (0.006)	Jobs Attract Arts	-0.086 (0.007)	-0.035* (0.020)	Not Significant
Beaumont, TX	45	8.065 (0.182)	0.042 (0.001)	Arts Attract Jobs	1.088 (0.067)	0.054 (0.003)	Arts Attract Jobs	0.111 (0.015)	-0.013* (0.014)	Arts Attract Jobs
Jackson, TN	45	0.820 (0.117)	-0.013 (0.001)	Arts Attract Jobs	-0.484 (0.034)	-0.047 (0.002)	Jobs Attract Arts	-0.257 (0.008)	-0.627 (0.023)	Arts Attract Jobs
Albany, GA	44	0.915 (0.120)	-0.001* (0.001)	Arts Attract Jobs	-0.645 (0.026)	0.010 (0.001)	Jobs Attract Arts	-0.027* (0.021)	-0.003* (0.003)	Not Significant
Florence, AL	44	3.547 (0.167)	0.036 (0.001)	Arts Attract Jobs	-0.253 (0.030)	0.028 (0.003)	Jobs Attract Arts	0.143 (0.007)	0.111 (0.004)	Arts Attract Jobs

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

		Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
Urban Area	N	Effect of Arts on Jobs	Effect of Jobs on Arts	Conclusion	Effect of Arts on Jobs	Effect of Jobs on Arts	Conclusion	Effect of Arts on Jobs	Effect of Jobs on Arts	Conclusion
Longview, TX	44	1.097 (0.152)	0.010 (0.001)	Arts Attract Jobs	0.204 (0.067)	0.004* (0.004)	Arts Attract Jobs	0.161 (0.031)	0.086 (0.007)	Arts Attract Jobs
Rochester, MN	44	0.368 (0.025)	0.034 (0.000)	Arts Attract Jobs	1.192 (0.005)	0.218 (0.001)	Arts Attract Jobs	0.423 (0.011)	-0.083 (0.001)	Arts Attract Jobs
Sioux Falls, SD	44	10.230 (0.109)	0.040 (0.000)	Arts Attract Jobs	3.533 (0.064)	0.083 (0.002)	Arts Attract Jobs	0.711 (0.018)	0.189 (0.006)	Arts Attract Jobs
Wheeling, WV	44	8.747 (0.083)	0.071 (0.001)	Arts Attract Jobs	0.433 (0.020)	0.147 (0.007)	Arts Attract Jobs	0.361 (0.003)	1.377 (0.012)	Jobs Attract Arts
Yuma, AZ	44	NA	NA	NA	0.593 (0.018)	-0.026 (0.002)	Arts Attract Jobs	-0.168 (0.010)	-0.331 (0.007)	Arts Attract Jobs
Auburn, AL	43	-4.066 (0.058)	-0.081 (0.001)	Jobs Attract Arts	2.779 (0.009)	0.270 (0.001)	Arts Attract Jobs	-0.131 (0.001)	-0.221 (0.010)	Arts Attract Jobs
Gainesville, GA	43	0.711* (0.455)	0.000* (0.001)	Not Significant	0.004* (0.035)	0.002* (0.002)	Not Significant	0.177 (0.012)	0.040 (0.013)	Arts Attract Jobs
Missoula, MT	43	-1.421 (0.079)	0.025 (0.002)	Jobs Attract Arts	-0.271 (0.024)	-0.056 (0.003)	Jobs Attract Arts	0.142 (0.007)	0.049 (0.012)	Arts Attract Jobs
Santa Barbara, CA	43	-0.588 (0.078)	0.022 (0.004)	Jobs Attract Arts	0.048* (0.032)	0.087 (0.011)	Jobs Attract Arts	-0.102 (0.032)	-0.039 (0.011)	Jobs Attract Arts
Sioux City, IA	43	0.154 (0.071)	0.033 (0.002)	Arts Attract Jobs	0.918 (0.045)	0.088 (0.004)	Arts Attract Jobs	0.045 (0.008)	0.130 (0.007)	Jobs Attract Arts
St. Cloud, MN	43	-0.318 (0.109)	-0.030 (0.003)	Jobs Attract Arts	0.259 (0.034)	0.024 (0.008)	Arts Attract Jobs	0.079 (0.011)	0.190 (0.011)	Jobs Attract Arts
Texas City, TX	43	0.094* (0.054)	0.029 (0.003)	Jobs Attract Arts	0.029 (0.005)	0.132 (0.016)	Jobs Attract Arts	0.016* (0.014)	0.024* (0.016)	Not Significant
Anderson, SC	42	2.175 (0.093)	0.023 (0.001)	Arts Attract Jobs	-1.045 (0.045)	-0.029 (0.002)	Jobs Attract Arts	0.282 (0.011)	0.035 (0.004)	Arts Attract Jobs
Battle Creek, MI	42	0.724 (0.018)	0.013 (0.000)	Arts Attract Jobs	-0.321 (0.010)	-0.052 (0.001)	Jobs Attract Arts	-0.042 (0.002)	-0.325 (0.003)	Arts Attract Jobs
Billings, MT	42	-0.151 (0.052)	0.039 (0.002)	Jobs Attract Arts	-0.189 (0.003)	-0.079 (0.004)	Jobs Attract Arts	-0.076 (0.004)	-0.160 (0.003)	Arts Attract Jobs
Janesville, WI	42	1.575 (0.105)	0.020 (0.002)	Arts Attract Jobs	0.184 (0.055)	0.001* (0.002)	Arts Attract Jobs	0.093 (0.002)	-0.066 (0.004)	Arts Attract Jobs
Lima, OH	42	-1.146 (0.098)	-0.003 (0.001)	Jobs Attract Arts	0.823 (0.049)	0.028 (0.002)	Arts Attract Jobs	0.006* (0.011)	-0.066 (0.018)	Not Significant
Racine, WI	42	2.043 (0.278)	0.028 (0.001)	Arts Attract Jobs	-0.526 (0.116)	0.003* (0.004)	Not Significant	-0.189 (0.008)	-0.785 (0.026)	Arts Attract Jobs
Terre Haute, IN	42	-1.053 (0.064)	-0.025 (0.002)	Jobs Attract Arts	-0.348 (0.037)	-0.038 (0.004)	Jobs Attract Arts	-0.050 (0.002)	-0.935 (0.008)	Arts Attract Jobs
Wichita Falls, TX	42	-0.372 (0.146)	0.015 (0.003)	Jobs Attract Arts	-0.144 (0.048)	0.003* (0.007)	Not Significant	0.021* (0.017)	0.004* (0.016)	Not Significant
Benton Harbor, MI	41	-2.342 (0.208)	-0.020 (0.002)	Jobs Attract Arts	-1.970 (0.110)	-0.048 (0.003)	Jobs Attract Arts	-0.095 (0.017)	-0.082 (0.009)	Jobs Attract Arts
Holland, MI	41	4.116 (0.204)	0.002 (0.001)	Arts Attract Jobs	1.525 (0.102)	-0.011 (0.001)	Arts Attract Jobs	0.499 (0.076)	-0.014 (0.003)	Arts Attract Jobs
Hot Springs, AR	41	-1.556 (0.006)	-0.163 (0.000)	Jobs Attract Arts	-0.072 (0.001)	-0.261 (0.001)	Arts Attract Jobs	-0.006 (0.000)	-0.105 (0.004)	Arts Attract Jobs
Kingston, NY	41	0.980 (0.112)	0.001* (0.002)	Arts Attract Jobs	-0.063 (0.031)	0.002* (0.004)	Not Significant	0.189 (0.011)	0.179 (0.011)	Arts Attract Jobs
Merced, CA	41	1.202 (0.211)	-0.003 (0.001)	Arts Attract Jobs	0.550 (0.034)	0.006* (0.003)	Arts Attract Jobs	0.192 (0.022)	-0.021 (0.006)	Arts Attract Jobs
New Bern, NC	41	-0.529 (0.078)	0.010 (0.001)	Jobs Attract Arts	0.770 (0.020)	-0.012 (0.002)	Arts Attract Jobs	0.145 (0.007)	0.214 (0.004)	Jobs Attract Arts
Santa Fe, NM	41	1.769 (0.040)	0.091 (0.002)	Arts Attract Jobs	0.233 (0.002)	1.019 (0.015)	Jobs Attract Arts	-0.047 (0.005)	0.193 (0.017)	Jobs Attract Arts
Arroyo Grande, CA	40	-1.116 (0.057)	-0.055 (0.003)	Jobs Attract Arts	-0.113 (0.012)	0.113 (0.009)	Jobs Attract Arts	-0.136 (0.007)	-0.267 (0.011)	Arts Attract Jobs
Harlingen, TX	40	14.200 (0.104)	0.038 (0.000)	Arts Attract Jobs	-1.509 (0.017)	-0.042 (0.001)	Jobs Attract Arts	-1.114 (0.010)	-0.221 (0.002)	Jobs Attract Arts
Jefferson City, MO	40	0.122 (0.015)	-0.017 (0.002)	Arts Attract Jobs	-0.502 (0.013)	-0.133 (0.005)	Jobs Attract Arts	-0.506 (0.004)	-0.169 (0.004)	Jobs Attract Arts
Logan, UT	40	-1.011 (0.051)	0.019 (0.002)	Jobs Attract Arts	-0.502 (0.030)	-0.108 (0.003)	Jobs Attract Arts	0.237 (0.008)	0.059 (0.003)	Arts Attract Jobs
Mansfield, OH	40	-0.155 (0.069)	0.021 (0.002)	Jobs Attract Arts	0.018* (0.032)	0.004* (0.003)	Not Significant	0.007* (0.009)	-0.081 (0.009)	Not Significant
Marysville, WA	40	-0.931 (0.111)	0.009 (0.004)	Jobs Attract Arts	-0.040 (0.011)	-0.289 (0.017)	Arts Attract Jobs	-0.109 (0.025)	-0.148 (0.009)	Arts Attract Jobs
Westminster, MD	40	4.965 (0.104)	0.033 (0.000)	Arts Attract Jobs	0.234 (0.031)	0.125 (0.007)	Arts Attract Jobs	0.610 (0.019)	0.503 (0.016)	Arts Attract Jobs
Antioch, CA	39	2.137 (0.101)	0.026 (0.001)	Arts Attract Jobs	0.259 (0.020)	-0.057 (0.004)	Arts Attract Jobs	-0.266 (0.012)	0.018* (0.013)	Not Significant

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

		Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
Urban Area	**N**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**
Dothan, AL	39	-0.065 (0.028)	0.015 (0.001)	Jobs Attract Arts	-0.210 (0.007)	-0.049 (0.000)	Jobs Attract Arts	0.006 (0.002)	0.266 (0.016)	Jobs Attract Arts
Laredo, TX	39	-0.979 (0.156)	0.021 (0.001)	Jobs Attract Arts	0.749 (0.025)	0.072 (0.003)	Arts Attract Jobs	0.232 (0.006)	0.920 (0.018)	Jobs Attract Arts
Michigan City, IN	39	-1.727 (0.112)	-0.012 (0.001)	Jobs Attract Arts	-0.502 (0.019)	-0.090 (0.002)	Jobs Attract Arts	-0.049 (0.005)	-0.033 (0.005)	Jobs Attract Arts
St. George, UT	39	1.027 (0.149)	0.039 (0.003)	Arts Attract Jobs	0.299 (0.042)	0.039 (0.005)	Arts Attract Jobs	-0.148 (0.017)	0.116 (0.015)	Jobs Attract Arts
Bangor, ME	38	0.352* (0.200)	-0.016 (0.001)	Jobs Attract Arts	0.215 (0.055)	0.003* (0.004)	Arts Attract Jobs	0.321 (0.026)	-0.014 (0.002)	Arts Attract Jobs
Bloomington, IL	38	-1.894 (0.042)	-0.028 (0.001)	Jobs Attract Arts	-3.334 (0.004)	-0.286 (0.000)	Jobs Attract Arts	-0.370 (0.005)	-0.230 (0.009)	Jobs Attract Arts
Glens Falls, NY	38	-0.279 (0.026)	0.021 (0.000)	Jobs Attract Arts	-0.215 (0.009)	-0.052 (0.002)	Jobs Attract Arts	-0.028 (0.002)	0.064 (0.001)	Jobs Attract Arts
Prescott Valley, AZ	38	1.083 (0.052)	0.032 (0.003)	Arts Attract Jobs	-0.117 (0.011)	-0.114 (0.013)	Jobs Attract Arts	0.110 (0.005)	0.876 (0.034)	Jobs Attract Arts
Rome, GA	38	-3.417 (0.195)	0.001 (0.001)	Jobs Attract Arts	0.575 (0.008)	0.077 (0.001)	Arts Attract Jobs	-0.264 (0.011)	0.028 (0.003)	Jobs Attract Arts
Staunton, VA	38	0.696 (0.194)	0.020 (0.001)	Arts Attract Jobs	0.546 (0.047)	-0.036 (0.004)	Arts Attract Jobs	0.208 (0.018)	0.008* (0.006)	Arts Attract Jobs
Bloomington, IN	37	3.094 (0.125)	0.027 (0.001)	Arts Attract Jobs	-0.097 (0.018)	0.034 (0.005)	Jobs Attract Arts	-0.196 (0.027)	-0.052 (0.002)	Jobs Attract Arts
Bowling Green, KY	37	1.345 (0.010)	-0.043 (0.000)	Arts Attract Jobs	-1.564 (0.008)	-0.107 (0.001)	Jobs Attract Arts	-0.084 (0.002)	-0.802 (0.010)	Arts Attract Jobs
Jonesboro, AR	37	3.608 (0.034)	0.026 (0.000)	Arts Attract Jobs	0.188 (0.004)	-0.016 (0.000)	Arts Attract Jobs	-0.142 (0.001)	-0.676 (0.006)	Arts Attract Jobs
Kankakee, IL	37	3.290 (0.111)	0.030 (0.001)	Arts Attract Jobs	-0.790 (0.017)	-0.014 (0.003)	Jobs Attract Arts	-0.102 (0.012)	0.003* (0.007)	Not Significant
Lafayette, CO	37	2.274 (0.182)	0.010 (0.002)	Arts Attract Jobs	-0.254 (0.063)	-0.055 (0.004)	Jobs Attract Arts	0.800 (0.081)	0.030 (0.003)	Arts Attract Jobs
Conroe, TX	36	10.629 (0.225)	0.022 (0.000)	Arts Attract Jobs	-0.705 (0.075)	0.002* (0.003)	Not Significant	0.139 (0.015)	0.004* (0.005)	Arts Attract Jobs
Lawton, OK	36	0.158* (0.084)	0.030 (0.001)	Not Significant	0.570 (0.031)	0.064 (0.004)	Arts Attract Jobs	0.460 (0.007)	0.546 (0.009)	Jobs Attract Arts
Leominster, MA	36	-0.369 (0.029)	-0.034 (0.003)	Jobs Attract Arts	-0.221 (0.026)	0.036 (0.007)	Jobs Attract Arts	0.005* (0.017)	-0.096 (0.020)	Not Significant
Rapid City, SD	36	1.497 (0.067)	0.055 (0.001)	Arts Attract Jobs	0.929 (0.025)	0.149 (0.003)	Arts Attract Jobs	-0.332 (0.006)	-0.083 (0.008)	Jobs Attract Arts
San Angelo, TX	36	0.889 (0.042)	0.013 (0.001)	Arts Attract Jobs	-0.124 (0.044)	0.035 (0.002)	Jobs Attract Arts	-0.052 (0.008)	0.014 (0.003)	Jobs Attract Arts
Sherman, TX	36	0.755 (0.092)	0.001* (0.002)	Arts Attract Jobs	1.123 (0.032)	0.071 (0.005)	Arts Attract Jobs	0.038 (0.010)	0.011* (0.009)	Arts Attract Jobs
Vallejo, CA	36	0.272 (0.052)	0.103 (0.003)	Arts Attract Jobs	0.218 (0.016)	0.107 (0.016)	Arts Attract Jobs	0.012 (0.003)	0.323 (0.038)	Jobs Attract Arts
Bismarck, ND	35	1.510 (0.059)	0.001* (0.002)	Arts Attract Jobs	0.027* (0.033)	-0.077 (0.003)	Not Significant	0.886 (0.007)	0.289 (0.004)	Arts Attract Jobs
Bloomsburg, PA	35	1.053 (0.163)	0.007 (0.001)	Arts Attract Jobs	0.021* (0.049)	0.023 (0.003)	Jobs Attract Arts	0.092 (0.021)	0.002* (0.004)	Arts Attract Jobs
Elmira, NY	35	-1.110 (0.083)	0.022 (0.001)	Jobs Attract Arts	-0.240 (0.032)	-0.084 (0.006)	Jobs Attract Arts	-0.019 (0.005)	0.218 (0.012)	Jobs Attract Arts
Johnstown, PA	35	0.924 (0.094)	-0.008 (0.001)	Arts Attract Jobs	0.310 (0.042)	0.002* (0.003)	Arts Attract Jobs	-0.142 (0.058)	-0.043 (0.007)	Jobs Attract Arts
Mount Vernon, WA	35	4.240 (0.210)	0.030 (0.001)	Arts Attract Jobs	-0.055 (0.027)	-0.195 (0.004)	Arts Attract Jobs	0.155 (0.013)	-0.092 (0.013)	Arts Attract Jobs
Zephyrhills, FL	35	NA	NA	NA	0.005* (0.017)	0.147 (0.005)	Jobs Attract Arts	-0.026 (0.005)	0.063 (0.006)	Jobs Attract Arts
Yuba City, CA	35	NA	NA	NA	0.402 (0.020)	0.111 (0.004)	Arts Attract Jobs	0.316 (0.009)	0.075 (0.008)	Arts Attract Jobs
Conway, AR	34	24.596 (0.081)	0.029 (0.000)	Arts Attract Jobs	1.458 (0.016)	0.000* (0.001)	Arts Attract Jobs	1.202 (0.004)	0.061 (0.001)	Arts Attract Jobs
Idaho Falls, ID	34	-2.070 (0.119)	0.005 (0.001)	Jobs Attract Arts	0.470 (0.094)	0.003* (0.002)	Arts Attract Jobs	0.007* (0.023)	-0.028 (0.004)	Not Significant
Lebanon, PA	34	0.772 (0.005)	-0.011 (0.001)	Arts Attract Jobs	2.897 (0.008)	0.143 (0.000)	Arts Attract Jobs	0.053 (0.004)	-0.046 (0.008)	Arts Attract Jobs
Muncie, IN	34	0.989 (0.212)	0.017 (0.001)	Arts Attract Jobs	-0.452 (0.061)	-0.018 (0.004)	Jobs Attract Arts	0.099 (0.009)	0.163 (0.006)	Jobs Attract Arts
Murfreesboro, TN	34	2.948 (0.186)	0.009 (0.000)	Arts Attract Jobs	-0.208 (0.018)	-0.029 (0.001)	Jobs Attract Arts	0.061 (0.017)	0.131 (0.004)	Jobs Attract Arts
Altoona, PA	33	1.807 (0.114)	0.021 (0.001)	Arts Attract Jobs	0.476 (0.050)	0.052 (0.003)	Arts Attract Jobs	0.000* (0.034)	0.034 (0.009)	Jobs Attract Arts

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

Urban Area	N	Arts and Non-Arts Jobs: Effect of Arts on Jobs	Arts and Non-Arts Jobs: Effect of Jobs on Arts	Arts and Non-Arts Jobs: Conclusion	Arts and Business Services: Effect of Arts on Jobs	Arts and Business Services: Effect of Jobs on Arts	Arts and Business Services: Conclusion	Arts and High-Tech: Effect of Arts on Jobs	Arts and High-Tech: Effect of Jobs on Arts	Arts and High-Tech: Conclusion
Danville, IL	33	1.830 (0.154)	0.009 (0.001)	Arts Attract Jobs	-0.371 (0.039)	0.017 (0.003)	Jobs Attract Arts	-0.216 (0.022)	-0.179 (0.011)	Jobs Attract Arts
Parkersburg, WV	33	0.127* (0.192)	0.002* (0.002)	Not Significant	0.058* (0.030)	-0.049 (0.007)	Jobs Attract Arts	-0.255 (0.018)	0.010* (0.007)	Not Significant
Bend, OR	32	24.897 (0.000)	0.037 (0.000)	Arts Attract Jobs	-1.119 (0.000)	0.036 (0.000)	Jobs Attract Arts	-0.403 (0.000)	-0.170 (0.000)	Jobs Attract Arts
Champaign, IL	32	2.249 (0.084)	0.038 (0.001)	Arts Attract Jobs	0.815 (0.031)	0.166 (0.005)	Arts Attract Jobs	0.200 (0.013)	0.310 (0.014)	Jobs Attract Arts
Pittsfield, MA	32	-1.035 (0.041)	-0.083 (0.003)	Jobs Attract Arts	-0.105 (0.006)	-0.071 (0.007)	Jobs Attract Arts	0.208 (0.005)	0.281 (0.007)	Jobs Attract Arts
Rocky Mount, NC	32	1.354 (0.098)	0.015 (0.001)	Arts Attract Jobs	1.064 (0.043)	0.084 (0.002)	Arts Attract Jobs	0.193 (0.015)	0.007 (0.004)	Arts Attract Jobs
Weirton, WV	32	0.977 (0.256)	0.012 (0.001)	Arts Attract Jobs	-0.153 (0.027)	0.042 (0.006)	Jobs Attract Arts	-0.044 (0.017)	-0.270 (0.022)	Arts Attract Jobs
Cape Girardeau, MO	31	0.030* (0.170)	0.004 (0.001)	Jobs Attract Arts	-0.249 (0.027)	0.017 (0.000)	Jobs Attract Arts	0.033 (0.008)	0.004* (0.003)	Arts Attract Jobs
El Centro, CA	31	-0.746 (0.256)	0.000* (0.001)	Not Significant	-0.488 (0.037)	-0.015 (0.004)	Jobs Attract Arts	-0.108 (0.023)	-0.087 (0.005)	Jobs Attract Arts
Iowa City, IA	31	-0.808 (0.117)	-0.009 (0.002)	Jobs Attract Arts	0.344 (0.072)	0.023 (0.010)	Arts Attract Jobs	0.058 (0.011)	-0.040 (0.004)	Arts Attract Jobs
Midland, MI	31	-1.329 (0.042)	-0.012 (0.001)	Jobs Attract Arts	-0.259 (0.006)	0.011 (0.001)	Jobs Attract Arts	0.062 (0.003)	-0.055 (0.005)	Arts Attract Jobs
Morgantown, WV	31	3.931 (0.071)	0.029 (0.001)	Arts Attract Jobs	-0.444 (0.032)	0.016 (0.001)	Jobs Attract Arts	-0.242 (0.009)	-0.077 (0.008)	Jobs Attract Arts
Newark, OH	31	-0.684 (0.281)	0.009 (0.002)	Jobs Attract Arts	1.010 (0.039)	-0.053 (0.003)	Arts Attract Jobs	0.527 (0.042)	0.015 (0.006)	Arts Attract Jobs
St. Joseph, MO	31	-0.562 (0.191)	0.004* (0.003)	Not Significant	0.149 (0.067)	0.002* (0.008)	Arts Attract Jobs	0.010* (0.013)	-0.054 (0.017)	Not Significant
State College, PA	31	0.176* (0.092)	-0.010 (0.001)	Not Significant	-0.397 (0.030)	0.007 (0.002)	Jobs Attract Arts	-0.085 (0.038)	0.043 (0.006)	Jobs Attract Arts
Casper, WY	30	2.951 (0.100)	0.003 (0.001)	Arts Attract Jobs	0.856 (0.018)	0.205 (0.006)	Arts Attract Jobs	-0.075 (0.002)	0.165 (0.009)	Jobs Attract Arts
Charlottesville, VA	30	0.877 (0.057)	0.027 (0.004)	Arts Attract Jobs	0.079 (0.008)	0.072 (0.018)	Arts Attract Jobs	0.078 (0.008)	0.096 (0.015)	Jobs Attract Arts
East Stroudsburg, PA	30	1.167 (0.008)	0.210 (0.001)	Arts Attract Jobs	0.219 (0.003)	0.300 (0.007)	Jobs Attract Arts	0.036 (0.000)	0.607 (0.051)	Jobs Attract Arts
Farmington, NM	30	19.556 (0.242)	0.033 (0.000)	Arts Attract Jobs	0.250 (0.027)	0.024 (0.003)	Arts Attract Jobs	0.888 (0.010)	0.458 (0.007)	Arts Attract Jobs
Hammond, LA	30	-1.151 (0.350)	-0.005 (0.002)	Jobs Attract Arts	-1.231 (0.045)	-0.075 (0.003)	Jobs Attract Arts	0.001* (0.017)	0.074 (0.008)	Jobs Attract Arts
Hazleton, PA	30	2.431 (0.073)	0.000* (0.001)	Arts Attract Jobs	1.631 (0.023)	0.106 (0.003)	Arts Attract Jobs	0.010 (0.004)	0.841 (0.020)	Jobs Attract Arts
Kokomo, IN	30	5.816 (0.065)	0.030 (0.000)	Arts Attract Jobs	0.094 (0.043)	0.067 (0.003)	Arts Attract Jobs	0.658 (0.012)	0.160 (0.001)	Arts Attract Jobs
Lexington Park, MD	30	-0.570 (0.189)	0.001* (0.002)	Not Significant	-0.153 (0.040)	0.002* (0.005)	Not Significant	-0.148 (0.071)	0.001* (0.003)	Not Significant
Sheboygan, WI	30	2.958 (0.077)	0.045 (0.002)	Arts Attract Jobs	0.604 (0.017)	-0.061 (0.003)	Arts Attract Jobs	-0.015 (0.004)	0.011* (0.007)	Not Significant
Winchester, VA	30	2.352 (0.126)	0.034 (0.001)	Arts Attract Jobs	-0.961 (0.022)	0.031 (0.002)	Jobs Attract Arts	0.103 (0.010)	0.188 (0.028)	Jobs Attract Arts
Cheyenne, WY	29	5.796 (0.027)	0.058 (0.000)	Arts Attract Jobs	-1.107 (0.002)	0.019 (0.000)	Jobs Attract Arts	0.342 (0.001)	0.559 (0.002)	Jobs Attract Arts
Chico, CA	29	2.591 (0.056)	0.095 (0.002)	Arts Attract Jobs	-0.584 (0.016)	0.043 (0.002)	Jobs Attract Arts	0.120 (0.006)	0.356 (0.011)	Jobs Attract Arts
Cleveland, TN	29	8.870 (0.226)	0.006 (0.000)	Arts Attract Jobs	3.264 (0.051)	0.030 (0.001)	Arts Attract Jobs	0.039 (0.011)	-0.027 (0.005)	Arts Attract Jobs
Cumberland, MD	29	-5.408 (0.159)	-0.022 (0.000)	Jobs Attract Arts	-0.100 (0.034)	-0.020 (0.000)	Jobs Attract Arts	0.506 (0.005)	0.021 (0.001)	Arts Attract Jobs
Harrisonburg, VA	29	1.000 (0.184)	0.021 (0.001)	Arts Attract Jobs	0.601 (0.012)	-0.107 (0.003)	Arts Attract Jobs	0.252 (0.005)	-0.091 (0.004)	Arts Attract Jobs
Lewiston, ME	29	-3.553 (0.117)	-0.002 (0.001)	Jobs Attract Arts	-1.520 (0.053)	-0.013 (0.000)	Jobs Attract Arts	-0.167 (0.011)	0.050 (0.005)	Jobs Attract Arts
Owensboro, KY	29	-0.165 (0.069)	-0.024 (0.001)	Jobs Attract Arts	-1.331 (0.014)	-0.166 (0.001)	Jobs Attract Arts	0.108 (0.001)	0.129 (0.001)	Jobs Attract Arts
Paso Robles, CA	28	-1.421 (0.071)	-0.073 (0.001)	Jobs Attract Arts	-1.799 (0.014)	-0.269 (0.002)	Jobs Attract Arts	0.204 (0.018)	0.087 (0.005)	Arts Attract Jobs
Great Falls, MT	28	3.092 (0.052)	0.125 (0.002)	Arts Attract Jobs	-0.780 (0.020)	-0.150 (0.003)	Jobs Attract Arts	0.115 (0.006)	0.623 (0.011)	Jobs Attract Arts
Lake Jackson, TX	28	0.177* (0.347)	0.011 (0.001)	Jobs Attract Arts	-0.447 (0.039)	-0.113 (0.007)	Jobs Attract Arts	0.221 (0.018)	0.024 (0.006)	Arts Attract Jobs

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

Urban Area	N	Arts and Non-Arts Jobs: Effect of Arts on Jobs	Arts and Non-Arts Jobs: Effect of Jobs on Arts	Arts and Non-Arts Jobs: Conclusion	Arts and Business Services: Effect of Arts on Jobs	Arts and Business Services: Effect of Jobs on Arts	Arts and Business Services: Conclusion	Arts and High-Tech: Effect of Arts on Jobs	Arts and High-Tech: Effect of Jobs on Arts	Arts and High-Tech: Conclusion
Middletown, NY	28	1.613 (0.084)	0.032 (0.002)	Arts Attract Jobs	-0.093 (0.029)	-0.082 (0.004)	Jobs Attract Arts	0.286 (0.005)	0.107 (0.010)	Arts Attract Jobs
Wenatchee, WA	28	-0.388 (0.085)	0.020 (0.001)	Jobs Attract Arts	-0.210 (0.001)	0.237 (0.004)	Jobs Attract Arts	0.189 (0.002)	-0.336 (0.007)	Arts Attract Jobs
Brunswick, GA	27	-0.792 (0.045)	-0.012 (0.001)	Jobs Attract Arts	-0.161 (0.049)	0.013 (0.002)	Jobs Attract Arts	-0.107 (0.003)	-0.130 (0.017)	Arts Attract Jobs
Grants Pass, OR	27	1.175 (0.077)	0.025 (0.001)	Arts Attract Jobs	0.557 (0.014)	0.130 (0.004)	Arts Attract Jobs	0.769 (0.008)	0.168 (0.002)	Arts Attract Jobs
Las Cruces, NM	27	1.934 (0.043)	0.076 (0.001)	Arts Attract Jobs	-1.651 (0.018)	-0.166 (0.001)	Jobs Attract Arts	0.123 (0.008)	0.088 (0.001)	Arts Attract Jobs
Lewiston, ID	27	6.565 (0.073)	0.053 (0.000)	Arts Attract Jobs	1.595 (0.004)	0.398 (0.001)	Arts Attract Jobs	0.233 (0.003)	0.271 (0.007)	Jobs Attract Arts
Santa Maria, CA	27	1.495 (0.154)	0.027 (0.003)	Arts Attract Jobs	1.338 (0.039)	0.028 (0.004)	Arts Attract Jobs	-0.256 (0.030)	-0.155 (0.011)	Jobs Attract Arts
Williamsport, PA	27	-1.512 (0.171)	-0.018 (0.002)	Jobs Attract Arts	0.353 (0.045)	0.053 (0.007)	Arts Attract Jobs	0.534 (0.016)	0.248 (0.009)	Arts Attract Jobs
Dubuque, IA	26	-0.812 (0.084)	0.007* (0.004)	Not Significant	-0.122 (0.019)	0.012* (0.008)	Not Significant	0.068 (0.008)	0.232 (0.018)	Jobs Attract Arts
Saratoga Springs, NY	26	1.201 (0.029)	0.085 (0.001)	Arts Attract Jobs	0.479 (0.001)	0.197 (0.001)	Arts Attract Jobs	-0.021 (0.003)	0.351 (0.019)	Jobs Attract Arts
Uniontown, PA	26	2.183 (0.215)	0.002* (0.001)	Arts Attract Jobs	0.214 (0.022)	-0.012 (0.001)	Arts Attract Jobs	0.033* (0.027)	-0.014 (0.002)	Jobs Attract Arts
Waldorf, MD	26	-0.505 (0.159)	-0.009 (0.004)	Jobs Attract Arts	0.381 (0.026)	0.054 (0.009)	Arts Attract Jobs	-0.098 (0.031)	-0.096 (0.008)	Jobs Attract Arts
West Bend, WI	26	-0.257 (0.042)	-0.032 (0.003)	Jobs Attract Arts	0.007* (0.020)	-0.187 (0.020)	Not Significant	0.040 (0.003)	0.564 (0.090)	Jobs Attract Arts
Corvallis, OR	25	0.655 (0.098)	0.027 (0.001)	Arts Attract Jobs	-0.840 (0.025)	-0.095 (0.003)	Jobs Attract Arts	1.446 (0.026)	0.053 (0.001)	Arts Attract Jobs
Elkhart, IN	25	-0.570 (0.191)	-0.004 (0.000)	Jobs Attract Arts	0.894 (0.035)	-0.029 (0.002)	Arts Attract Jobs	0.594 (0.006)	0.784 (0.006)	Jobs Attract Arts
Grand Island, NE	25	24.488 (0.047)	0.024 (0.000)	Arts Attract Jobs	-2.085 (0.024)	-0.068 (0.001)	Jobs Attract Arts	-1.388 (0.005)	-0.278 (0.001)	Jobs Attract Arts
Mauldin, SC	25	12.802 (0.236)	-0.003 (0.000)	Jobs Attract Arts	1.160 (0.068)	-0.023 (0.000)	Arts Attract Jobs	0.019* (0.045)	0.021 (0.004)	Jobs Attract Arts
Pocatello, ID	25	0.549 (0.020)	0.010 (0.000)	Arts Attract Jobs	0.482 (0.005)	0.282 (0.001)	Arts Attract Jobs	0.018 (0.002)	0.049 (0.001)	Jobs Attract Arts
Seaside, CA	25	-0.834 (0.030)	-0.149 (0.011)	Jobs Attract Arts	-0.045 (0.004)	-0.221 (0.007)	Arts Attract Jobs	-0.014 (0.003)	-0.319 (0.091)	Arts Attract Jobs
Walla Walla, WA	25	19.032 (0.001)	0.052 (0.000)	Arts Attract Jobs	1.480 (0.009)	0.102 (0.001)	Arts Attract Jobs	0.205 (0.013)	-0.038 (0.002)	Arts Attract Jobs
Watertown, NY	25	-2.242 (0.060)	-0.002 (0.001)	Jobs Attract Arts	-1.251 (0.012)	-0.033 (0.001)	Jobs Attract Arts	0.385 (0.012)	-0.080 (0.001)	Arts Attract Jobs
Columbus, IN	24	2.028 (0.109)	0.025 (0.000)	Arts Attract Jobs	0.865 (0.060)	0.020 (0.001)	Arts Attract Jobs	0.137 (0.017)	-0.033 (0.002)	Arts Attract Jobs
Longview, WA	24	1.818 (0.076)	0.040 (0.000)	Arts Attract Jobs	0.805 (0.006)	0.193 (0.004)	Arts Attract Jobs	0.399 (0.008)	0.530 (0.010)	Jobs Attract Arts
Lorain, OH	24	-0.713 (0.258)	0.001* (0.001)	Not Significant	0.696 (0.148)	0.017 (0.003)	Arts Attract Jobs	0.097 (0.025)	0.130 (0.003)	Jobs Attract Arts
Manhattan, KS	24	1.821 (0.043)	0.044 (0.002)	Arts Attract Jobs	0.345 (0.001)	0.261 (0.003)	Arts Attract Jobs	0.170 (0.002)	0.056 (0.003)	Arts Attract Jobs
Temple, TX	24	-2.219 (0.076)	-0.009 (0.000)	Jobs Attract Arts	1.756 (0.004)	0.009 (0.000)	Arts Attract Jobs	-0.026 (0.005)	0.035 (0.001)	Jobs Attract Arts
Victoria, TX	24	6.412 (0.100)	0.028 (0.000)	Arts Attract Jobs	3.288 (0.011)	0.213 (0.001)	Arts Attract Jobs	0.334 (0.012)	0.031 (0.004)	Arts Attract Jobs
Ithaca, NY	23	0.073* (0.041)	0.036 (0.002)	Not Significant	0.769 (0.014)	0.275 (0.003)	Arts Attract Jobs	-1.211 (0.010)	-0.144 (0.001)	Jobs Attract Arts
Lawrence, KS	23	-2.169 (0.074)	0.002* (0.002)	Not Significant	-1.005 (0.019)	-0.185 (0.005)	Jobs Attract Arts	0.045 (0.004)	-0.047 (0.007)	Arts Attract Jobs
Monroe, MI	23	-3.662 (0.027)	-0.082 (0.000)	Jobs Attract Arts	-0.419 (0.013)	0.024 (0.003)	Jobs Attract Arts	-0.037 (0.002)	-0.043 (0.002)	Arts Attract Jobs
Oshkosh, WI	23	-1.305 (0.135)	0.010 (0.001)	Jobs Attract Arts	-0.456 (0.036)	0.004* (0.003)	Not Significant	-0.030 (0.005)	0.133 (0.008)	Jobs Attract Arts
Pottstown, PA	23	-1.319 (0.048)	-0.035 (0.003)	Jobs Attract Arts	0.005* (0.016)	0.046 (0.004)	Jobs Attract Arts	-0.407 (0.012)	-0.113 (0.006)	Jobs Attract Arts
Villas, NJ	23	-0.750 (0.051)	-0.089 (0.006)	Jobs Attract Arts	0.113 (0.009)	0.324 (0.042)	Jobs Attract Arts	0.004* (0.003)	-0.375 (0.086)	Not Significant
Albany, OR	22	0.386 (0.075)	0.003 (0.001)	Arts Attract Jobs	4.569 (0.009)	0.163 (0.000)	Arts Attract Jobs	1.130 (0.012)	0.501 (0.005)	Arts Attract Jobs
DeKalb, IL	22	-0.901 (0.002)	-0.042 (0.000)	Jobs Attract Arts	1.242 (0.001)	-0.023 (0.000)	Arts Attract Jobs	0.119 (0.000)	-0.057 (0.000)	Arts Attract Jobs

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

		Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
Urban Area	**N**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**
Lake Havasu City, AZ	22	-1.808 (0.013)	0.023 (0.000)	Jobs Attract Arts	-0.053 (0.001)	0.304 (0.004)	Jobs Attract Arts	-0.041 (0.001)	-0.601 (0.003)	Arts Attract Jobs
Lee's Summit, MO	22	-1.235 (0.362)	-0.011 (0.001)	Jobs Attract Arts	1.650 (0.061)	0.013 (0.002)	Arts Attract Jobs	-1.313 (0.036)	-0.018 (0.002)	Jobs Attract Arts
Mankato, MN	22	-1.709 (0.013)	-0.017 (0.001)	Jobs Attract Arts	0.090 (0.004)	-0.032 (0.001)	Arts Attract Jobs	0.168 (0.001)	0.679 (0.002)	Jobs Attract Arts
Sierra Vista, AZ	22	2.624 (0.097)	0.035 (0.001)	Arts Attract Jobs	0.179 (0.008)	0.010 (0.002)	Arts Attract Jobs	1.435 (0.021)	0.017 (0.002)	Arts Attract Jobs
Alton, IL	21	3.045 (0.090)	0.094 (0.002)	Arts Attract Jobs	0.380 (0.022)	0.209 (0.003)	Arts Attract Jobs	0.261 (0.006)	0.806 (0.022)	Jobs Attract Arts
Carson City, NV	21	0.187 (0.075)	0.008* (0.008)	Arts Attract Jobs	-0.303 (0.022)	-0.195 (0.020)	Jobs Attract Arts	0.012* (0.021)	0.198 (0.065)	Jobs Attract Arts
Coeur d'Alene, ID	21	0.639 (0.140)	0.003* (0.004)	Arts Attract Jobs	0.019* (0.042)	0.058 (0.003)	Jobs Attract Arts	-0.078 (0.017)	-0.095 (0.014)	Arts Attract Jobs
Hemet, CA	21	0.006* (0.068)	-0.047 (0.003)	Not Significant	0.466 (0.009)	0.287 (0.002)	Arts Attract Jobs	-0.026 (0.006)	0.096 (0.001)	Jobs Attract Arts
Hinesville, GA	21	-3.799 (0.333)	-0.004 (0.001)	Jobs Attract Arts	0.122* (0.076)	-0.042 (0.001)	Not Significant	0.029* (0.036)	-0.005 (0.001)	Jobs Attract Arts
Manchester, NH	21	0.709 (0.184)	0.015 (0.004)	Arts Attract Jobs	-0.122 (0.040)	0.039 (0.013)	Jobs Attract Arts	-0.131 (0.019)	-0.117 (0.026)	Jobs Attract Arts
Porterville, CA	21	5.409 (0.092)	0.010 (0.000)	Arts Attract Jobs	-0.454 (0.061)	0.007 (0.000)	Jobs Attract Arts	-0.124 (0.003)	0.085 (0.005)	Jobs Attract Arts
Grand Forks, ND	20	-0.204 (0.071)	0.043 (0.001)	Jobs Attract Arts	0.209 (0.018)	0.186 (0.015)	Arts Attract Jobs	0.264 (0.000)	3.777 (0.001)	Jobs Attract Arts
New Bedford, MA	20	0.821 (0.283)	-0.008 (0.002)	Arts Attract Jobs	0.101* (0.067)	0.004* (0.003)	Not Significant	0.001* (0.040)	-0.055 (0.017)	Not Significant
Fond du Lac, WI	19	3.355 (0.021)	0.096 (0.001)	Arts Attract Jobs	-0.351 (0.002)	-0.026 (0.002)	Jobs Attract Arts	-0.260 (0.002)	-0.132 (0.001)	Jobs Attract Arts
South Lyon, MI	19	-1.029 (0.026)	-0.018 (0.000)	Jobs Attract Arts	-0.104 (0.005)	0.036 (0.001)	Jobs Attract Arts	0.046 (0.002)	-0.042 (0.003)	Arts Attract Jobs
Tracy, CA	19	10.163 (0.014)	-0.088 (0.000)	Jobs Attract Arts	-0.285 (0.009)	-0.035 (0.001)	Jobs Attract Arts	0.686 (0.007)	0.829 (0.007)	Jobs Attract Arts
Ames, IA	18	0.832 (0.005)	0.179 (0.001)	Arts Attract Jobs	-0.601 (0.001)	-1.172 (0.002)	Arts Attract Jobs	0.050 (0.002)	0.429 (0.005)	Jobs Attract Arts
Flagstaff, AZ	18	-0.128 (0.000)	-0.019 (0.000)	Jobs Attract Arts	0.001 (0.000)	0.161 (0.000)	Jobs Attract Arts	-0.051 (0.000)	0.091 (0.000)	Jobs Attract Arts
St. Augustine, FL	18	-2.284 (0.007)	-0.091 (0.000)	Jobs Attract Arts	1.512 (0.000)	0.636 (0.000)	Arts Attract Jobs	0.106 (0.000)	0.154 (0.002)	Jobs Attract Arts
Boulder, CO	17	-0.539 (0.115)	0.023 (0.002)	Jobs Attract Arts	-0.294 (0.018)	-0.182 (0.009)	Jobs Attract Arts	0.869 (0.035)	0.047 (0.007)	Arts Attract Jobs
Petaluma, CA	16	-4.569 (0.000)	-0.124 (0.000)	Jobs Attract Arts	-2.774 (0.000)	-0.359 (0.000)	Jobs Attract Arts	-1.091 (0.000)	-0.324 (0.000)	Jobs Attract Arts
Williamsburg, VA	16	-8.587 (0.001)	-0.116 (0.000)	Jobs Attract Arts	-0.086 (0.001)	0.079 (0.000)	Jobs Attract Arts	-0.006 (0.001)	0.185 (0.001)	Jobs Attract Arts
Hanover, PA	15	-2.831 (0.036)	-0.214 (0.003)	Jobs Attract Arts	2.855 (0.009)	0.270 (0.001)	Arts Attract Jobs	-0.083 (0.002)	-0.943 (0.017)	Arts Attract Jobs
Lady Lake, FL	14	-1.436 (0.091)	0.005 (0.001)	Jobs Attract Arts	-0.031 (0.004)	0.046 (0.001)	Jobs Attract Arts	-0.005 (0.001)	-0.081 (0.005)	Arts Attract Jobs
Pine Bluff, AR	14	14.835 (0.107)	-0.026 (0.000)	Jobs Attract Arts	6.653 (0.025)	0.091 (0.000)	Arts Attract Jobs	-0.011 (0.001)	-0.007 (0.003)	Jobs Attract Arts
Monessen, PA	13	-1.440 (0.660)	0.001* (0.001)	Not Significant	0.037* (0.150)	0.000* (0.001)	Not Significant	0.106* (0.061)	0.002* (0.006)	Not Significant
Delano, CA	12	18.186 (0.075)	-0.023 (0.000)	Jobs Attract Arts	-0.968 (0.028)	-0.023 (0.002)	Jobs Attract Arts	1.912 (0.007)	0.175 (0.000)	Arts Attract Jobs
McKinney, TX	12	0.048* (0.194)	0.004 (0.001)	Jobs Attract Arts	-0.103 (0.024)	-0.031 (0.003)	Jobs Attract Arts	-0.115 (0.010)	0.010* (0.005)	Not Significant
Titusville, FL	12	4.563 (0.003)	0.202 (0.000)	Arts Attract Jobs	4.790 (0.008)	0.120 (0.000)	Arts Attract Jobs	1.121 (0.002)	0.534 (0.001)	Arts Attract Jobs
Greeley, CO	11	-8.248 (0.077)	-0.029 (0.001)	Jobs Attract Arts	0.357 (0.124)	0.007 (0.002)	Arts Attract Jobs	0.256 (0.050)	0.049 (0.003)	Arts Attract Jobs
Bay City, MI	10	-0.388 (0.045)	-0.031 (0.001)	Jobs Attract Arts	0.134 (0.000)	0.105 (0.000)	Arts Attract Jobs	0.033 (0.000)	-0.511 (0.003)	Arts Attract Jobs
Springfield, OH	10	-3.375 (0.154)	0.012 (0.001)	Jobs Attract Arts	-0.429 (0.074)	-0.055 (0.005)	Jobs Attract Arts	0.053 (0.006)	-0.065 (0.014)	Arts Attract Jobs
Waterbury, CT	10	0.190* (0.126)	0.018 (0.003)	Not Significant	0.293 (0.023)	0.032 (0.003)	Arts Attract Jobs	-0.306 (0.023)	0.004* (0.007)	Not Significant
Davis, CA	8	0.657 (0.000)	-0.037 (0.000)	Arts Attract Jobs	-2.340 (0.000)	-0.179 (0.000)	Jobs Attract Arts	-0.137 (0.000)	0.022 (0.000)	Jobs Attract Arts
Middletown, OH	6	1.155 (0.002)	0.068 (0.000)	Arts Attract Jobs	-0.064 (0.000)	0.092 (0.000)	Jobs Attract Arts	-0.096 (0.000)	0.242 (0.000)	Jobs Attract Arts

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

		Arts and Non-Arts Jobs			Arts and Business Services			Arts and High-Tech		
Urban Area	**N**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**	**Effect of Arts on Jobs**	**Effect of Jobs on Arts**	**Conclusion**
Pascagoula, MS	6	4.157 (0.067)	0.011 (0.000)	Arts Attract Jobs	2.486 (0.023)	0.068 (0.000)	Arts Attract Jobs	-0.215 (0.005)	0.093 (0.004)	Jobs Attract Arts
Lodi, CA	3	-0.681 (0.000)	-0.003 (0.000)	Jobs Attract Arts	-0.109 (0.000)	0.048 (0.000)	Jobs Attract Arts	0.181 (0.000)	0.204 (0.000)	Jobs Attract Arts
Norman, OK	2	NA	NA	NA	NA	NA	NA	NA	NA	NA
Avondale, AZ		6.647 (0.000)	0.040 (0.000)	Arts Attract Jobs	NA	NA	NA	NA	NA	NA
Casa Grande, AZ		NA	NA	NA	NA	NA	NA	NA	NA	NA
Chambersburg, PA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Gilroy, CA		-6.231 (0.000)	-0.157 (0.000)	Jobs Attract Arts	NA	NA	NA	NA	NA	NA
Hanford, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Kenosha, WI		NA	NA	NA	NA	NA	NA	NA	NA	NA
Lompoc, CA		-1.617 (0.000)	-0.015 (0.000)	Jobs Attract Arts	NA	NA	NA	NA	NA	NA
Longmont, CO		NA	NA	NA	NA	NA	NA	NA	NA	NA
Manteca, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Turlock, CA		36.527 (0.314)	0.012 (0.000)	Arts Attract Jobs	NA	NA	NA	NA	NA	NA
Woodland, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Twin Rivers, NJ		NA	NA	NA	NA	NA	NA	NA	NA	NA
Simi Valley, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Vacaville, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Livermore, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Beloit, WI		NA	NA	NA	NA	NA	NA	NA	NA	NA
Watsonville, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Napa, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Madera, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Camarillo, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA
Cartersville, GA		NA	NA	NA	NA	NA	NA	NA	NA	NA
San Marcos, TX		NA	NA	NA	NA	NA	NA	NA	NA	NA
San Luis Obispo, CA		NA	NA	NA	NA	NA	NA	NA	NA	NA

Table E.1: Regression results for the relationship between arts to non-arts jobs, business services and high-tech by urban area (cont.)

REFERENCES

Baumol, W. J., and W. G. Bowen. 1965. "On the Performing Arts: The Anatomy of Their Economic Problems." *The American Economic Review* 55 (1/2): 495–502.

Becker, Howard S. 2008. *Art Worlds*. Berkeley; Los Angeles: University of California Press.

Bellégo, Christophe, and Louis-Daniel Pape. 2019. "Dealing with the Log of Zero in Regression Models." *Série Des Documents de Travail*, nos. 2019-13. Available at SSRN: https://ssrn.com/abstract=3444996 or http://dx.doi.org/10.2139/ssrn.3444996.

Berrington, Ann, Peter W. F. Smith, and Patrick Sturgis. 2006. "An Overview of Methods for the Analysis of Panel Data." *NCRM Methods Review Papers (NCRM/007)*. Available at: http://eprints.ncrm.ac.uk/415/1/MethodsReviewPaperNCRM-007.pdf.

Birch, Colin P. D., Sander P. Oom, and Jonathan A. Beecham. 2007. "Rectangular and Hexagonal Grids Used for Observation, Experiment, and Simulation in Ecology." *Ecological Modelling* 206: 347–59.

Blau, Judith R. 1989. *The Shape of Culture: A Study of Contemporary Cultural Patterns in the United States*. Cambridge: Cambridge University Press.

Blau, Judith R., Peter M. Blau, and Reid M. Golden. 1985. "Social Inequality and the Arts." *American Journal of Sociology* 91 (2): 309–31.

Bordieu, Pierre. 1984. *Distinction: A Social Critique of the Judgement of Taste*. London: Routledge & Kegan Paul.

Borenstein, Michael, Larry V. Hedges, Julian P. T. Higgins, and Hannah R. Rothstein. 2009. *Introduction to Meta-Analysis*. Chichester, U.K.: John Wiley & Sons.

Brooks, Arthur C., and Roland J. Kushner. 2001. "Cultural Districts and Urban Development." *International Journal of Arts Management* 3 (2): 4–15.

Carr, Daniel B., Anthony R. Olsen, and Denis White. 1992. "Hexagon Mosaic Maps for Display of Univariate and Bivariate Geographical Data." *Cartography and Geographic Information Systems* 19 (4): 228–36.

Caves, Richard E. 2003. "Contracts Between Art and Commerce." *The Journal of Economic Perspectives* 17 (2): 73–84.

Census. 2009. "2009 Tiger/Line® Shapefiles [Machine-Readable Data Files]/ Prepared by the US Census Bureau." https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2009.html.

———. 2012. “2010 Tiger/Line Shapefiles [Machine-Readable Data Files]/ Prepared by the US Census Bureau.”

———. 2017. “2010 Urban Areas FAQ.” https://www.census.gov/programs-surveys/geography/about/faq/2010-urban-area-faq.html.

———. 2018a. “2018 Tiger/Line® Shapefiles [Machine-Readable Data Files]/ Prepared by the US Census Bureau.” https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.2018.html.

———. 2018b. “County Business Patterns (CBP) - About This Program.” https://www.census.gov/programs-surveys/cbp/about.html.

———. 2019. “County Business Patterns (CBP) - Methodology.” https://www.census.gov/programs-surveys/cbp/technical-documentation/methodology.html.

Census, U. S. 2017. “North American Industry Classification System.” https://www.census.gov/eos/www/naics/.

Chen, Yong, and Stuart S. Rosenthal. 2008. “Local Amenities and Life-Cycle Migration: Do People Move for Jobs or Fun?” *Journal of Urban Economics* 64: 519–37.

Clark, Terry N. 2011. *The City as an Entertainment Machine*. Lanham, Md: Lexington Books.

Clark, Terry Nichols, and Lorna Crowley Ferguson. 1983. *City Money: Political Pressures, Fiscal Strain, and Retrenchment*. New York, NY: Columbia University Press.

Currid, Elizabeth. 2009. “Bohemia as Subculture; "Bohemia" as Industry.” *Journal of Planning Literature* 23 (4): 368–82.

Currid, Elizabeth, and Sarah Williams. 2010. “The Geography of Buzz: Art, Culture and the Social Milieu in Los Angeles and New York.” *Journal of Economic Geography* 10: 423–51.

Deller, Steven C., Tsung-Hsiu Tsai, David W. Marcouiller, and Donald B. K. English. 2001. “The Role of Amenities and Quality of Life in Rural Economic Growth.” *American Journal of Agricultural Economics* 83 (2): 352–65.

Desmet, Klaus, and Marcel Fafchamps. 2005. “Changes in the Spatial Concentration of Employment Across US Counties: A Sectoral Analysis 1972-2000.” *Journal of Economic Geography* 5 (3): 261–84.

Ellis, Mark, Richard Wright, and Virginia Parks. 2004. “Work Together, Live Apart? Geographies of Racial and Ethnic Segregation at Home and at Work.” *Annals of the Association of American Geographers* 94 (3): 602–37.

Ellison, Glenn, Edward L. Glaeser, and William R. Kerr. 2010. "What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns." *American Economic Review* 100 (3): 1195–1213.

Epstein, Edwin M. 1989. "Business Ethics, Corporate Good Citizenship and the Corporate Social Policy Process: A View from the United States." *Journal of Business Ethics* 8 (8): 583–95.

Feldman, Maryann P., and David B. Audretsch. 1999. "Innovation in Cities: Science-Based Diversity, Specialization, and Localized Competition." *European Economic Review* 43 (2): 409–29.

Ferguson, Mark, Kamar Ali, M. Rose Olfert, and Mark Partridge. 2007. "Voting with Their Feet: Jobs Versus Amenities." *Growth and Change* 38 (1): 77–110.

Flippen, Chenoa. 2014. "US Internal Migration and Occupational Attainment: Assessing Absolute and Relative Outcomes by Region and Race." *Population Research and Policy Review* 33 (1): 31–61.

Florida, Richard L. 2002. *The Rise of the Creative Class (And How It's Transforming Work, Leisure, Community, and Everyday Life)*. Cambridge, MA: Basic Books.

Frost-Krumpf, H. A. 1998. *Cultural Districts: The Arts as a Strategy for Revitalizing Our Cities*. Washington, D.C.: Americans for the Arts. https://www.americansforthearts.org/by-program/reports-and-data/legislation-policy/naappd/cultural-districts-the-arts-as-a-strategy-for-revitalizing-our-cities.

Fullerton, Andrew S., and Wayne J. Villemez. 2011. "Why Does the Spatial Agglomeration of Firms Benefit Workers? Examining the Role of Organizational Diversity in the US Industries and Labor Markets." *Social Forces* 89 (4): 1145–64.

Gabe, Todd, and Jaison R. Abel. 2011. "Agglomeration of Knowledge." *Urban Studies* 48 (7): 1353–71.

Gabriel, Stuart A., and Stuart S. Rosenthal. 2004. "Quality of the Business Environment Versus Quality of Life: Do Firms and Households Like the Same Cities?" *The Review of Economics and Statistics* 86 (1): 438–44.

Galligan, Ann M. 2008. "The Evolution of Arts and Cultural Districts." In *Understanding the Arts and Creative Sector in the United States*, edited by Joni Maya Cherbo, Ruth Ann Stewart, and Margaret Jane Wyszomirski, 129–42. New Brunswick, NJ: Rutgers University Press.

Gapinski, James H. 1981. "Economics, Demographics, and Attendance at the Symphony." *Journal of Cultural Economics* 5 (2): 79–83.

Geer, Richard Owen. 1996. "Out of Control in Colquitt: Swamp Gravy Makes Stone Soup." *TDR (1988 -)* 40 (2): 103–30.

Glaeser, Edward. 2009. "Growth: The Death and Life of Cities." In *Making Cities Work: Prospects and Policies for Urban America*, edited by Robert P. Inman, 22–62. Princeton, NJ: Princeton University Press.

Glaeser, Edward L., Hedi D. Kallal, José A. Scheinkman, and Andrei Shleifer. 1992. "Growth in Cities." *Journal of Political Economy* 100 (6): 1126–52.

Glaeser, Edward L., and Matthew G. Resseger. 2010. "The Complementarity Between Cities and Skills." *Journal of Regional Science* 50 (1): 221–44.

Goody, Kenneth. 1984. "Arts Funding: Growth and Change Between 1963 and 1983." *The Annals of the American Academy of Political and Social Science* 471 (1): 114–57.

Grodach, Carl, Elizabeth Currid-Halkett, Nicole Foster, and James Murdoch III. 2014. "The Location Patterns of Artistic Cluster: A Metro- and Neighborhood-Level Analysis." *Urban Studies* 51 (13): 2822–43.

Hart, David M., and Zoltan J. Acs. 2011. "High-Tech Immigrant Entrepreneurship in the United States." *Economic Development Quarterly* 25 (2): 116–29.

Havekes, Esther, Michael Bader, and Maria Krysan. 2016. "Realizing Racial and Ethnic Neighborhood Preferences? Exploring the Mismatches Between What People Want, Where They Search, and Where They Live." *Population Research and Policy Review* 35: 101–26.

Haworth, J., and P. Vincent. 1976. "Maximizing the Nearest-Neighbour Statistic." *Area* 8 (4): 299–302.

Hecker, Daniel E. 2005. "High-Technology Employment: A NAICS-Based Update." *Monthly Labor Review* 128 (7): 57–72.

Hiles, David R. H. 2001. "A First Look at Employment and Wages Using NAICS." *Monthly Labor Review* 124 (12): 22–31.

Johnson, Glen D., and Ganapati P. Patil. 1995. "Estimating Statewide Species Richness of Breeding Birds in Pennsylvania." *Coenoses, Special Statistical Ecology Issue* 10 (2/3): 81–87.

Kay, Alan. 2000. "Art and Community Development: The Role the Arts Have in Regenerating Communities." *Community Development Journal* 35 (4): 414–24.

Kirchberg, Volker. 1995. "Arts Sponsorship and the State of the City: The Impact of Local Socio-Economic Conditions on Corporate Arts Support." *Journal of Cultural Economics* 19 (4): 305–20.

Kundu, Amitabh, and Niranjan Sarangi. 2007. "Migration, Employment Status and Poverty: An Analysis Across Urban Centers." *Economic and Political Weekly* 42 (4): 299–306.

Leclair, Mark S., and Kelly Gordon. 2000. "Corporate Support for Artistic and Cultural Activities: What Determines the Distribution of Corporate Giving?" *Journal of Cultural Economics* 24 (3): 225–41.

Logan, John, and Harvey Molotch. 1987. *Urban Fortunes: The Political Economy of Place*. Berkeley: University of California Press.

Markusen, Ann, and Anne Gadwa. 2010. "Arts and Culture in Urban or Regional Planning: A Review and Research Agenda." *Journal of Planning Education and Research* 29 (3): 379–91.

Markusen, Ann R. 1983. "High-Tech Jobs, Markets and Economic Development Prospects: Evidence from California." *Built Environment* 9 (1): 18–28.

Markusen, Ann, and Greg Schrock. 2006. "The Artistic Dividend: Urban Artistic Specialisation and Economic Development Implications." *Urban Studies* 43 (10): 1661–86.

Marshall, Alfred. 1890. *Principles of Economics*. London: MacMillan.

Mathews, Vanessa. 2010. "Aestheticizing Space: Art, Gentrification and the City." *Geography Compass* 4 (6): 660–75.

McNicholas, Bernadette. 2004. "Arts, Culture and Business: A Relationship Transformation, a Nascent Field." *International Journal of Arts Management* 7 (1): 57–69.

Moretti, Enrico. 2010. "Local Multipliers." *The American Economic Review* 100 (2): 373–77.

———. 2012. *The New Geography of Jobs*. Boston: Houghton Mifflin Harcourt.

Murphy, John B., and Simon Burgess. 1998. "Introducing the North American Industry Classification System." *Monthly Labor Review* 121 (7): 43–47.

Muth, Richard F. 1971. "Migration: Chicken or Egg?" *Southern Economic Journal* 37 (3): 295–306.

Parker, Robert P. 2003. "More US Economic Data Series Incorporate the North American Industry Classification System." *Business Economics* 38 (2): 57–60.

Perloff, Harvey S. 1981. "The Arts in the Economic Life of the City." *Ekistics* 48 (288): 238–43.

Peterson, Richard A., and Roger M. Kern. 1996. "Changing Highbrow Taste: From Snob to Omnivore." *American Sociological Review* 61: 900–907.

Phillips, Rhonda. 2004. "Artful Business: Using the Arts for Community Economic Development." *Community Development Journal* 39 (2): 112–22.

Polèse, Mario. 2012. “The Arts and Local Economic Development: Can a Strong Arts Presence Uplift Local Economies? A Study of 135 Canadian Cities.” *Urban Studies* 49 (8): 1811–35.

Poorthuis, Ate, and Matthew Zook. 2015. “Small Stories in Big Data: Gaining Insights from Large Spatial Point Pattern Datasets.” *Cityscape: A Journal of Policy Development and Research* 17 (1).

Potter, Antony, and H. Doug Watts. 2011. “Evolutionary Agglomeration Theory: Increasing Returns, Diminishing Returns, and the Industry Life Cycle.” *Journal of Economic Geography* 11 (3): 417–55.

Pratt, Andy C. 2000. “New Media, the New Economy and New Spaces.” *Geoforum* 31: 425–36.

Rappaport, Jordan. 2007. “Moving to Nice Weather.” *Regional Science and Urban Economics* 37 (3): 375–98.

———. 2009. “The Increasing Importance of Quality of Life.” *Journal of Economic Geography* 9 (6): 779–804.

Rauhut, Daniel. 2010. “Viewpoint: Adam Smith on Migration.” *Migration Letters* 7 (1): 105–13.

Roback, Jennifer. 1982. “Wages, Rents, and the Quality of Life.” *Journal of Political Economy* 90 (6): 1257–78.

Robinson, Arthur H., James B. Lindberg, and Leonard W. Brinkman. 1961. “A Correlation and Regression Analysis Applied to Rural Farm Population Densities in the Great Plains.” *Annals of the Association of American Geographers* 51 (2): 211–21.

Rosen, S. 1979. “Wage-Based Indexes of Urban Quality of Life.” In *Current Issues in Urban Economics*, edited by P. Mieszkowski and M. Straszheim, 74–104. Baltimore: Johns Hopkins University Press.

Russel, Matthew, Paul Tack, and Lisa Usher. 2004. “Industry Productivity Trends Under the North American Industry Classification System.” *Monthly Labor Review* 127 (11).

Sassen, Saskia. 2001. *The Global City: New York, London, Tokyo*. 2nd ed. Princeton; Oxford: Princeton University Press.

Schwarzer, Guido. 2007. “Meta: An R Package for Meta-Analysis.” *R News* 7 (3): 40–45.

Scott, Allen J. 2004. “Cultural-Products Industries and Urban Economic Development: Prospects for Growth and Market Contestation in Global Context.” *Urban Affairs Review* 39 (4): 461–90.

Seifert, Susan C., and Mark J. Stern. 2005. "'Natural' Cultural Districts: Arts Agglomerations in Metropolitan Philadelphia and Implications for Cultural District Planning." *Social Impact of the Arts Project*.

Senici, Dominic, Han Y. H. Chen, Yves Bergeron, and Dominic Cyr. 2010. "Spatiotemporal Variations of Fire Frequency in Central Boreal Forest." *Ecosystems* 13 (8): 1227–38.

Shkuda, Aaron. 2015. "The Artist as Developer and Advocate: Real Estate and Public Policy in Soho, New York." *Journal of Urban History* 41 (6): 999–1016.

Silver, Daniel A., and Terry N. Clark. 2016. *Scenescapes: How Quality of Place Shape Social Life*. Chicago: University of Chicago Press.

Simon, Curtis J., and Clark Nardinelli. 2002. "Human Capital and the Rise of American Cities, 1900–1990." *Regional Science and Urban Economics* 32: 59–96.

Smith, Adam. 1786. *An Inquiry into the Nature and Causes of the Wealth of Nations*. 4th Edition. London: Printed for A. Strahan,; T. Cadell.

Stead, Bette Ann. 1985. "Corporate Giving: A Look at the Arts." *Journal of Business Ethics* 4 (3): 215–22.

Stern, Mark J., and Susan C. Seifert. 2010. "Cultural Clusters: The Implications of Cultural Assets Agglomeration for Neighborhood Revitalization." *Journal of Planning Education and Research* 29 (3): 262–79.

Stevens, Louise K. 2015. *Arts in the Loop Economic Impact Study*. Chicago Loop Alliance.

Storper, Michael. 2013. *Keys to the City: How Economics, Institutions, Social Interaction and Politics Shape Development*. Princeton, NJ: Princeton University Press.

Storper, Michael, and Allen J. Scott. 2009. "Rethinking Human Capital, Creativity and Urban Growth." *Journal of Economic Geography* 9: 147–67.

Throsby, David. 1994. "The Production and Consumption of the Arts: A View of Cultural Economics." *Journal of Economic Literature* 32 (1): 1–29.

Treyz, George I., Dan S. Rickman, Gary L. Hunt, and Michael J. Greenwood. 1993. "The Dynamics of US Internal Migration." *The Review of Economics and Statistics* 75 (2): 209–14.

U. S. Department of Commerce, Economic, and Statistics Administration. 1994. *Geographic Areas Reference Manual*.

White, Denis, A. Jon Kimerling, and W. Scott Overton. 1992. "Cartographic and Geometric Components of a Global Sampling Design for Environmental Monitoring." *Cartography and Geographic Information Systems* 19 (1): 5–22.

Whitt, J. Allen. 1987. “Mozart in the Metropolis: The Arts Coalition and the Urban Growth Machine.” *Urban Affairs Quarterly* 23 (1): 15–36.

Withers, Glenn A. 1980. “Unbalanced Growth and the Demand for Performing Arts: An Econometric Analysis.” *Southern Economic Journal* 46 (3): 735–42.

Zukin, Sharon. 1987. “Gentrification: Culture and Capital in the Urban Core.” *Annual Review of Sociology* 13.