THE UNIVERSITY OF CHICAGO

Pandemic-Induced Anti-Asian Sentiment in Chicago:

An Exploratory Analysis of Restaurant Yelp Reviews

By

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August 2022

A paper submitted in partial fulfillment of the requirements for the
Master of Arts degree in the
Master of Arts Program in the Social Sciences

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Table of Contents

ABSTRACT

The outbreak of the COVID-19 virus in 2020 marked the beginning of a tide of racist sentiment against Asian Americans in the United States. Spurred on by the Trump administration's use of xenophobic slurs to refer to the virus, anti-Asian sentiment dominated the national conversation about the epidemic and fueled a dramatic increase in hate crimes (*Covid "hate Crimes" against Asian Americans on Rise - BBC News*, 2021). Much research is still being conducted to uncover the extent of the psychological, physical, and financial harm incurred by Asian Americans at this time. The restaurant industry is one sector that faced uniquely severe circumstances; loss of business during lockdown was compounded by mounting social stigma. In this study, I offer a potential framework for investigating negative public sentiment using average sentiment scores from Yelp reviews for restaurants in the Chicago area. I employ an exploratory spatial data analysis approach to 1) identify potential patterns in the spatial distribution of negative sentiment and 2) determine which communities contain restaurants that experienced highly negative and subjective reviews, indicating the presence of anti-Asian sentiment. As explained by *Intergroup Threat Theory*, there are a multitude of social, situational, and structural factors that contribute to anti-Asian prejudice. Among such factors are certain demographic characteristics associated with a higher risk of engaging in prejudicial behavior or buying into fake news content targeting Asian-Americans (Lambe et al. 2021, Tan et al. 2021, Wright & Duong 2021). Through a spatially lagged-X regression model using data from the American Community Survey and the Chicago Data Portal, I examined associations between neighborhood demographic contexts and instances of negative sentiment within Yelp reviews. Results of each regression identified trends consistent with the predictors of Anti-Asian prejudice, most notably lower educational attainment.

INTRODUCTION

As we approach the third year of the COVID-19 pandemic, it is essential to take stock of how this world-shattering event began and what has since changed. The crisis has put a massive strain on our health infrastructure, economy, systems of governance, and sense of social cohesion. Immigrant communities and people of color have disproportionately borne the brunt of the adverse effects. When COVID-related death tolls began to rise in March of 2020, the Trump administration endeavored to deflect attention away from the government's inadequate response to the pandemic by rebranding the virus with racialized language. At a rally in Tulsa, Oklahoma, he referred to the virus as "kung-flu", a reference to its origin in Wuhan, China meant to redirect frustration towards the Chinese government (Frias, 2020). Trump then continued to use the term "China-virus" with great frequency when discussing the pandemic, despite warnings from experts that the language could inspire dangerous antagonism against Asian-Americans. Other political elites chimed in to solidify the association. Senator John Cornyn, a republican from Texas, said in a conference on March 18th, 2020, that the virus was the result of "cultural practices" in China: "people eat bats and snakes and dogs and things like that. These viruses are transmitted from the animal to the people, and that's why China has been the source of a lot of these viruses" (Samuels, 2020). The comment was one of many to deploy racist tropes and reinvigorate xenophobic sentiment among the public and online.

As narratives linking Asians to the virus continued to circulate, we saw a dramatic rise in acts of violence against ethnic Asians across the United States. According to FBI data, hate crimes against Asian-Americans increased by more than 73% in 2020, where more than 55% of offenders were white (Venkatraman, 2021). One attack on Asian-owned business in Atlanta, Georgia resulted in the deaths of six women of Asian descent, with a total of eight fatalities in March 2020 (Treisman, 2021). Far more common were verbal attacks involving racial slurs or racially motivated aggression. The advocacy group Stop AAPI hate released a breakdown of reported instances of hate for late March through December of 2020 in which 71% of the 2,800 reports involved verbal aggression and 21% involved avoidance or shunning of Asian-Americans (Turton, 2021). The atmosphere online soured at an alarming rate. A report from late March of 2020 showed that instances of hate speech toward China and Chinese people on Twitter increased by 900% ("Coronavirus: Huge Surge of Hate Speech"). Coupled with the insidious spread of misinformation about the virus on social media, public sentiment toward Asian Americans shifted in a way that took a massive toll on their businesses and families. Though restaurants across the U.S. experienced an extraordinary decline in revenue, Asian-owned restaurants were by far the worst-hit segment of the industry when shutdowns went into effect (Alcorn, 2020).

By investigating online discourse pertaining to Asian restaurants, this paper aims to propose one potential avenue for geospatially contextualizing anti-Asian sentiment. Yelp review content and ratings for local restaurants may be able to tell us about residents' attitudes towards businesses of different ethnic backgrounds. Though certain Yelp reviews may come from users outside of the communities that surround these restaurants, a significant portion of business is likely to come from customers that live in the area. In the field of spatial econometrics, access to and use of establishments is largely determined by proximity (Penchansky & Thomas, 1981; Talen & Anselin, 1998; Apparicio et al., 2007). Prior research has shown that consumers generally prefer to minimize travel time to a food destination and will factor distance into their decision; locals tend to purchase from sit-down restaurants in their own neighborhoods at a higher frequency than those at a further distance (Jeffery et al. 2006, Peng et al. 2020). The spatial clustering of consumers' food purchasing habits within or around their tract of residence allows us to pinpoint areas where negative sentiment is more prevalent, opening the door for more in-depth analyses of the structural forces at play within at-risk communities.

Yelp reviews of restaurants are useful indicators of general sentiment toward Asian-Americans because the experience of dining out is governed by a series of social and cultural expectations. Our ideas about what food should taste like, how it should be presented, and who should be preparing it are largely influenced by media exposure and our social surroundings (Rozin, 2015; Stano, 2016). Dietary customs are also a powerful tool in the articulation of national identity, likely because food practices are retained across generations "even when language or other cultural forms of expression tend to be forgotten or lost” (Lopez-Rodriguez, 2014, p. 13). Ethnic groups are often represented by the specific types of food they are known to consume; *potatoes* are associated with the Irish, for example, *pasta* with Italians, *rice* with East Asian groups (Lopez-Rodriguez, 2014). In her analysis of the semantics of food and identity, Lopez-Rodriguez goes on to enumerate the complex ways in which food metaphors have been used to convey the idea of assimilation as well as initialize out-groups within public discourse (p. 14). The deep semantic ties between ethnic food and the framing of immigration politics and ‘otherness’ in the United States make the language of Yelp reviews a fruitful site of investigation into anti-Asian sentiment.

Data-driven research on pandemic-induced anti-Asian sentiment is vital because it can provide support for policies that better protect communities from both online and in-person hate. Regulation of communication technologies that reproduce social inequality is at a woefully nascent stage, stalled by the legal protections afforded to corporate speech (Noble, 2018, p.151). Hate speech on social media platforms has real and lasting impacts; racist micro and macro aggressions have been shown to have significantly more negative mental and physical health outcomes for Latines and Asian Americans than other minority groups (Huynh, 2012; Paradies et al., 2015). The process of data extraction from Yelp and the analytical processes contained herein may be able to help inform future research on anti-Asian sentiment, its localizations, and the structures that reproduce it. Subsequent efforts to combat hate speech through *counter-speech* or displays of support for afflicted communities can be made more strategic and effective (Noble, 2018). The following sections of this paper devote time to reviewing the historical precedent for racism set by pandemics of the past and evaluating previous literature before performing exploratory spatial data analysis (ESDA) and spatial regression.

HISTORICAL CONTEXT

Racial othering has long been a salient response to disease. Western medicine has worked hand in hand with white-dominant political interests to reinforce the association between ethnic minorities and pathogens for centuries. At the height of anxiety surrounding an unprecedented influx of migrants, Congress passed the Chinese Exclusion Act which prohibited entrance of Chinese merchants, teachers, students, travelers, and diplomats for 10 years (*Chinese Exclusion Act (1882)*). The following decade, it passed the U.S. Immigration Act of 1891 which formally codified the association between immigrants and foreign viruses by initiating strict medical requirements for incoming passengers. The application of these requirements varied deliberately along class and racial lines. As new arrivals stepped off the boat at Ellis Island, American doctors frequently singled out minorities and lower-class passengers to perform more invasive examinations, taking blood and urine samples and disinfecting them with chemical agents (Markel & Stern, 2002). When the bubonic plague reached San Francisco in 1900, Chinese and Japanese migrants were inspected upon arrival and subjected to detention while white merchants were allowed to leave (Gover et al., 2020). The Public Health Service (USPH) grew in tandem with the push to filter incoming migrants. Although the USPH did not have the legal authority to prohibit entry outright, immigrants diagnosed with a “loathsome or dangerous contagious disease” were almost always deported (Markel & Stern, 2002, p. 762). These early policies set a dangerous precedent; exclusive practices on the basis of race, class, or deviation from the norm have continued to proliferate under the guise of public health.

Throughout the 80s and early 90s, prejudicial policies were inherent in the management of the U.S. AIDS epidemic. The Center for Disease Control executed an infamous campaign termed the ‘four Hs’ which identified the four groups deemed most at risk of transmission:

homosexuals, heroin addicts, hemophiliacs, and Haitians. Those living with HIV/AIDS were subject to a myriad of discriminatory practices, including loss of employment, housing, violence, and even murder (Gonsalves & Staley, 2014). In 1986, William Buckley, a commentator for the New York Daily News, wrote that positive persons should be marked with a mandatory "AIDS tattoo" to protect the public against potential contact with the disease. He also questioned the right of a positive person to marry and produce offspring. The article invokes logic borrowed from the eugenics movement, stokes mass hysteria, and promotes segregation with a clearly racial subtext. Nearly forty years later, members of the four H's are still burdened by the negative stereotypes that circulated at that time. The FDA only recently announced that it would scale back restrictions on blood donations from gay men (Stein, 2015). Haitians endured a resurgence of public denigration in 2017 when Trump asserted that they all had AIDS after he discovered an influx of Haitian refugees had been granted visas to enter the U.S. despite his ban (Danticat, 2017). The negative stigma surrounding disease can act an amplifier for pre-existing prejudices, especially when disseminated through media.

The most distinct precursor to the COVID-19 response was the SARS outbreak of 2003. Rumors of an outbreak triggered racialized panic in both Boston and New York. Word about the supposed contagion began as an April fool's joke on a MIT discussion board, saying that employees at a nearby restaurant in Boston's Chinatown had been infected by SARS. Similar claims about a Vietnamese owned restaurant in New York began circulating around the same time. Before long, news networks were airing warnings of airborne transmission alongside images of people of Asian descent wearing masks, creating a dangerous and false association between them and the disease. The coverage caused "financial difficulties for business owners in urban Asian neighborhoods" as well as a "surge of racial discrimination in the community at large" (Schram, 2003). Without a single confirmed case of the virus, residents responded immediately to negative messaging by avoiding Asian-owned restaurants and businesses. The same pattern defined the beginning of the COVID-19 pandemic, but with a few key differences: the threat of the virus was indeed real, and it was combined with direct, discriminatory messaging from political elites and aided by online platforms where hate content could spread at a rapid pace. The urgent need to understand the digital side of this phenomenon has influenced numerous new studies that utilize the power of natural language processing techniques and geospatial visualization to produce key insights. The next section will explore the results and methodologies of these studies as the source of inspiration for the approach used in this paper.

LITERATURE REVIEW

Sentiment Analysis

Efforts to investigate anti-Asian sentiment online have focused mainly on the analysis of data collected from the popular social media platform Twitter. Though not as broadly used as Facebook or Instagram, the content giant has over 229 million daily active users worldwide (Statista, 2022) and its API allows researchers to retrieve 10 million tweets per month with access to a full archive of tweets and advanced search techniques ("Twitter API Documentation," 2022). The relative ease of data collection makes it an attractive platform for public opinion research. Compared to traditional surveys, self-published tweets may also be better at capturing and monitoring prejudicial attitudes. In controlled experiments, participants are limited by a set of predetermined questions and their responses may be governed by what is considered socially desirable (Nguyen et al., 2020). With a certain degree of anonymity, users are less likely to self-censor, a phenomenon called *the online disinhibition effect* (Suler, 2004). Several groups of researchers were able to collect tweets from the beginning of the pandemic and record the evolution of disinhibited hate speech as it spread across the internet.

One of the earlier studies was performed on a collection of 16,000 tweets from April 11-16 of 2020 using key terms associated with the virus: *#ChineseVirus, #ChineseVirusCorona, and #WuhanVirus* (Dubey, 2020, p.2). Dubey used sentiment analysis to assign scores to the language of each tweet categorized by anger, anticipation, disgust, fear, joy, sadness, surprise, trust, as well as positive and negative overall sentiment. The majority of tweets labelled with COVID-19 specific hashtags contained overwhelmingly negative language, evoking feelings of fear, sadness, anger, and distrust. Many tweets contained phrases unrecognized by the sentiment analysis package in R but were directly targeted at the Chinese government and people: “ccpisterrorist,” “ccpliedpeopledied,” “ccpvirus,” “chinamustexplain,” “chinamustpay,” “chinesebioterrorism,” “kungflu,” and “makechinapay,” among others (p.5). Dubey gives a sample of tweets in each emotional category, showing how several sordid themes emerge from the corpus: violent political imagery, nationalism, and xenophobia (p. 4).

A 2021 study by Costello et al. produced similar findings with an analysis of tweets sampled over the course of the first year of the pandemic (January 2020 to February 2021). They found that language surrounding these terms became increasingly negative and hateful as the pandemic continued. Several large spikes in usage of anti-Asian hateful keywords corresponded with salient political events: in early January when the first COVID-19 case was confirmed in the U.S., in mid-March when Trump first used the term “Chinese Virus” on Twitter, when Trump was diagnosed with COVID-19 in October 2020, and when Biden signed the executive order on racial equality in February 2021 (pp. 111-112). The team also performed a qualitative analysis of the tweets, unpacking how the use of derogatory hashtags served to efficiently galvanize and normalize hate speech on the platform (p. 115).

A study by Nguyen et al. in 2020 helped verify the rise in anti-Asian hate speech against the backdrop of xenophobic content on the platform in general. Through a mixed-methods approach, researchers used sentiment analysis on aggregated tweets to identify topical themes within the corpus, focusing on tweets evoking racism, blame, anti-racism, misinformation, news, politics, call to action, and the impact of COVID-19 on daily life (p. 7). They found that negative sentiment on the platform existed at higher rates for other ethnic groups (e.g., African Americans and Latinx) prior to the start of the pandemic, and the increase in negative tweets targeting Asians occurred between February to April of 2020 (p. 9). Importantly, they also tracked tweets that countered anti-Asian sentiment with messages of solidarity and sympathy for the Asian community, showcasing the efficacy of community support in dampening the effect of xenophobic content (p. 9).

Aiello et al. published a study in 2021 that initiated the use of an advanced, deep learning tool for natural language processing to capture the phases of Twitter users' response to the COVID-19 pandemic according to Philip Strong's model of *epidemic psychology*. Researchers hand-coded Strong's model to identify keywords associated with the three psycho-social epidemic stages: refusal, anger, and acceptance (Strong, 1990, p. 253). Each phase was associated with various emotions evoked in the language of individual tweets: fear encompassed feelings of anxiety, panic, disorientation, suspicion, irrationality, and contagion; moralization covered language that connoted risk avoidance, polarization, segregation, stigmatization, blame, and abuse, among others; action was associated with words about restrictions, travel, and privacy (p. 4). According to the results, public reaction to the reality of the global health crisis did in fact follow three distinct phases, but in a cyclical way. Every new cycle of fear, anger, and acceptance began when the "diffusion rate of the virus reached a local maximum," suggesting that online expression shifted in tandem with spatially localized viral events (p. 10). The identification of this general pattern is important because the anger stage of epidemic psychology influences the use of language that targets the perceived vectors of the disease. It could be useful in anticipating the timing and origin of hate speech waves in future epidemics.

Spatial Analytics

As the above study suggests, the reactions to and consequences of the COVID-19 pandemic are spatially and contextually contingent. A 2022 publication focusing on COVID-19 related tweets in India was able to demonstrate the importance of the spatial dimension by combining sentiment analysis and GIS-based techniques (Kumar, 2022). Kumar collected geotagged tweets and ran them through a Convolutional Neural Network (CNN) model that was able to predict the sentiment of tweets to a high degree of accuracy during the four stages of lockdown and subsequent unlock phases in India (p. 4). Using district level spatial data, Kumar identified hotspots for negative and positive sentiment throughout each phase. Results showed that metropolitan cities like Delhi, Mumbai, and Bangalore were host to some of the most negative tweets, a pattern consistent with the high number of cases and severe resource crises in those areas during times of lockdown (p. 8). The synthesis of sentiment analysis and GIS techniques has successfully been used in other studies to identify similar trends. Hohl et al. produced a spatiotemporal distribution of geolocated tweets containing anti-Asian hate language during the early phase of the pandemic. The results revealed significant clusters of hate across the United States, the most drastic of which was in Ross County, Ohio where the proportion of hateful tweets was over 300 times higher than the rest of the country (Hohl et al., 2022, p. 646).

Spatial analysis has also been helpful in visualizing the distribution of other COVID-19 related behaviors outside of online discourse. In 2021, Schneider et al. published a study on Americans' use of protective behaviors (i.e. mask wearing, physical distancing, hand-washing, COVID testing, etc.). The study utilizes LISA (Local Indicators of Spatial Association) analysis to detect clusters of contiguous counties with statistically high 7-day averages for new COVID-19 cases. It then implements a multivariable logistic regression model for each outcome variable, testing against various demographic and ideological predictors. While they found little evidence to support the hypothesis that local hotspots or state public health policies influence respondents' protective behaviors, they did find that certain demographic characteristics, economic and social circumstances, and political values are all associated with different protective behaviors (p. 7). The key findings were that older residents reported higher usage of protective behaviors, female respondents were more likely to use face coverings and avoid large gatherings, and respondents with prior criminal justice involvement as well as republican affiliated respondents were more likely to have been COVID-19 tested (p. 8-9).

Research into the social determinants of COVID-19 health outcomes has also utilized spatial analysis to explore disparities. In 2022, Lin et al. published a study that investigated how COVID-19 morality rates vary along racial and ethnic lines within different rural, suburban, and urban contexts. They used county level characteristics of community health factors in 50 states and mortality rates reported by the CDC from late January 2020 to late February 2021 and applied an exploratory approach to discover unanticipated patterns (p. 5). Colocation analysis, a technique that helps pinpoint areas where specific conditions are met, was used to identify counties with consistently high mortality rates and high numbers of residents of a particular ethnic or racial group. A dot density map was generated to help visualize variation of racial and ethnic composition at the county level across the US and to show how many days these populations endured top quintile death rates (p. 10). They then ran spatial regime regression models that tested COVID-19 mortality rate against social determinants of health as predictors. Other social factors were associated with more severe COVID-19 mortality rates, such as high-income inequality, higher percentages of uninsured young people, greater proportions of residents to healthcare providers, higher rates of severe housing problems, among others (p. 9). The design of the analysis allowed Lin et al. to unpack the dimensions of disparities in health outcomes in different communities, resulting in a set of textured and spatially cognizant findings.

The analytical plan used in this study is based in the logic and methods of the existing literature on public sentiment analysis and spatial determinants of social phenomena. It replicates some of the same techniques and applies them to original and existing datasets to extract insights into how consumers' regional environments affected their interactions with local Asian restaurants.

RESEARCH PLAN

Theoretical Framework

Previous research has approached the analysis of anti-Asian sentiment from a number of different theoretical positionings. Hofstede's theory of cultural dimensions has been widely used to measure cultural values, comparing cultures on the basis of individualism, distribution of emotional roles between genders, the extent to which members avoid uncertainty, and the extent to which members accept power differentials (Hofstede, 2011; Ng, 2021). Others have organized their analyses around Kim's racial triangulation theory, which situates Asian Americans within a racial paradigm that falsely and systematically considers them foreign and inferior to Whites while being superior to African Americans (Kim 1999, 108). The model minority myth has also been used to explain racial tension generated by the stereotype that Asian Americans attain greater degrees of financial and educational success as compared to other minority groups (Hartlep et al., 2013).

This paper takes the approach laid out by *intergroup threat theory* (ITT), a paradigm for understanding racially motivated behavior that is particularly useful in the context of epidemiological psychology (Stephen et al., 2008). ITT posits that humans respond to the *perception* of threat rather than actual threat levels. The theory focuses on two different types of threats: realistic and symbolic. Stephen et al. identify four main sets of variables that influence the majority's perception of the realistic and symbolic threats that minority groups pose: intergroup relations, cultural dimensions, situational factors, and individual differences. Intergroup relations are the sociocultural understandings of different ethnic groups informed by history and power differentials between majority and minority groups. Cultural dimensions account for the way ethnic groups are portrayed in society and how their social structures are traditionally organized. Situational factors refer to the conditions of intergroup interaction, often sculpted by specific media narratives. Lastly, individual differences express the predictive power of demographic variability in people's willingness to engage in prejudicial behavior (Lambe et al., 2021, p. 148).

Earlier sections of this paper have 1) established the importance of historical precedent in determining how Asian-Americans are conceptualized by the public, and 2) demonstrated the role of media narratives in constructing the false link between Asians and the virus. The model that follows considers the remaining two of the four contributors to the perception of Asian Americans as a symbolic threat. It utilizes variables related to situational factors and individual differences to investigate the spatial distribution of negative Yelp review sentiment. Recent research shows that disinformation and negative messaging from elites about ethnic minorities is more likely to influence non-Hispanic whites, conservatives, and respondents with lower levels of educational attainment (Flores, 2018, p.1651). Flores finds that these effects are largely dependent on repetition of these ideas in a respondents' media ecosystem (p. 1650). Lambe et al. similarly identify political ideology, levels of education, and sex as potential indicators of communities at higher risk of adopting prejudicial behaviors (p. 151). According to the results of the study's survey, men were more likely to express higher levels of anti-Asian sentiment than women, educated individuals were less likely to accept and believe anti-Asian misinformation, and conservatism was associated with finding it more acceptable to use the phrase "Chinese virus" (p. 152).

Applications of the spatial perspective to psychological phenomena such as this are still in an early stage (Ebert et al., 2022), but previous studies in spatial econometrics have shown that knowledge can spill over from one region to another (Anselin et al, 2000; Moreno et al. 2005). Using a combination of demographic data from the American Community Survey and the City of Chicago's data portal, I will be testing the hypothesis that areas containing residents at greater risk of developing prejudicial attitudes as a result of disinformation will yield more negative sentiment scores and lower restaurant ratings (i.e., majority white, lower educational attainment, majority male, lower vaccination rate). See Figure 1 for a visualization of the theoretical model.

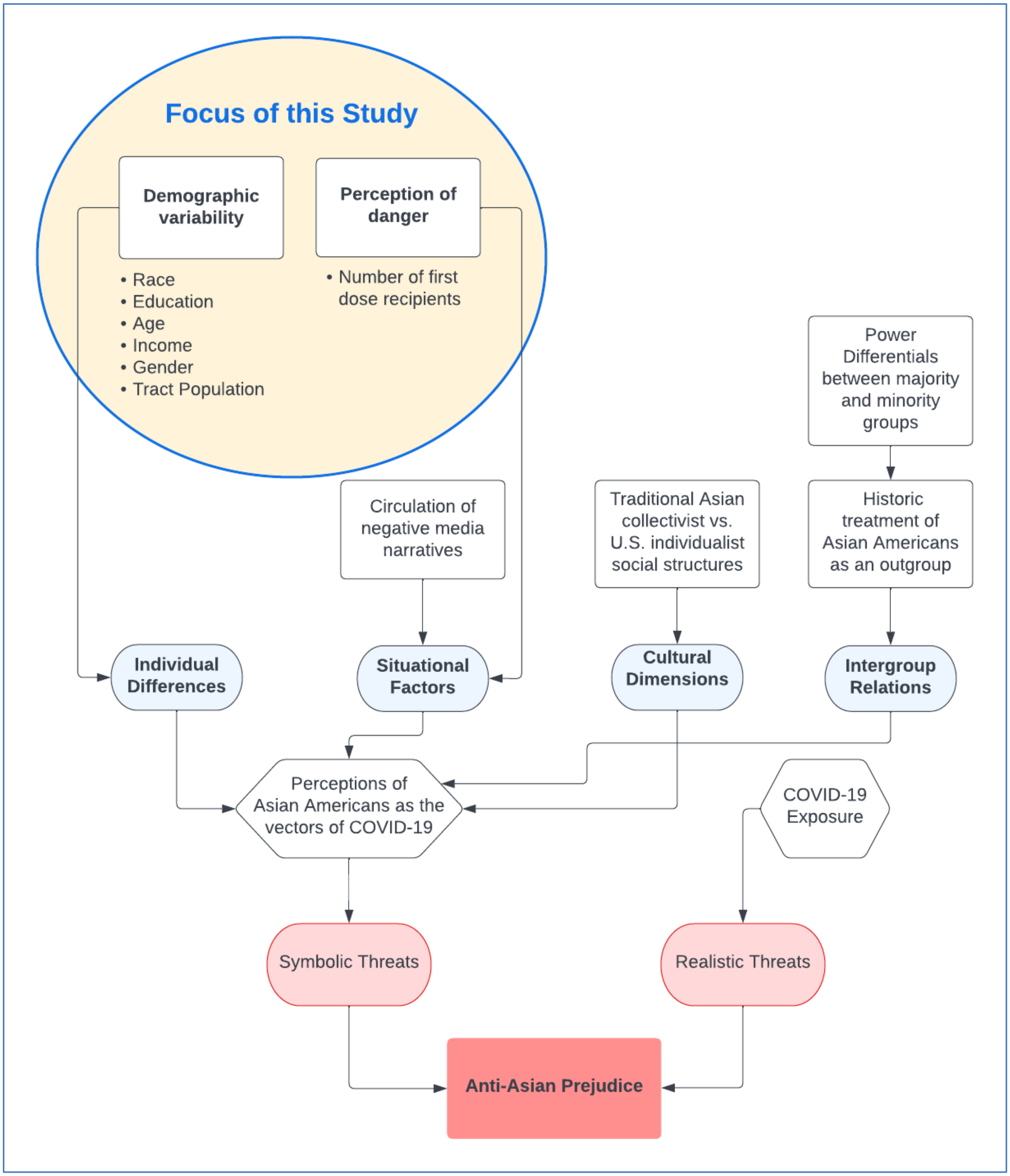

Figure 1. Theoretical Model

DATA AND METHODS

Data Collection

The primary dataset for this paper was sourced from *Yelp.com* using a combination of requests through their application programming interface *Yelp Fusion* and subsequent web scraping of individual reviews from each restaurant's page. The process resulted in a collection of the first page of user reviews from 783 Asian, Italian, and Latin American-affiliated restaurants situated within a 40000-meter radius of Chicago's city center. When browsing a restaurant's Yelp page, visitors are more likely to scan only the first page of reviews prior to making their dining decision (Moran & Goray, 2019). As such, the first page is often the most influential in attracting or repulsing potential customers. Collecting this smaller batch rather than the entirety of each restaurant's review catalogue should afford a sample that is representative of how reviews either deter or encourage consumers.

Restaurants are classified on Yelp through a series of tags that include nationality of origin as well as food types (i.e. 'ramen', 'Japanese', 'noodles', etc.). It is important to note that some restaurants do not fit neatly into classifications of national origin. Fusion restaurants, for example, may be included in the dataset but do not necessarily present an explicit ethnic identity and are not guaranteed to be owned or operated by ethnic minorities which may affect the degree to which they were subjected to prejudice. From the available classifications, I chose tags related to Asian-affiliated, Latin American, and Italian cuisines. Originally, Latin American restaurants were sampled in addition to Asian restaurants to act as a control group when assessing whether Asian restaurants had incurred a disproportionate share of negative public sentiment. This was based on data that confirmed that both cuisines are consumed by a wide demographic at a similar rate prior to the start of the pandemic and throughout (*COVID-19 Impact on Foodservice: One*

Year Later - US - 2021 - Market Research Report, n.d.). However, studies have shown that COVID-19-related prejudice has affected more than just Asian communities. A nationally representative survey experiment performed by Lu et al. found that amplified COVID-19 salience increases discriminatory intent against East Asians, South Asians, and Hispanics alike (Lu et al., 2021, p. 5). Considering this effect, I chose to incorporate Italian restaurants as a more stable control group. Despite being thoroughly embedded in the American food landscape and more closely associated with 'whiteness', Italian food is still considered an "ethnic" cuisine (Park, 2017, p. 368). Moreover, Italian food was also consumed by the American public in comparable frequency to Latin American and Asian foods during the pandemic (*COVID-19 Impact on Foodservice: One Year Later - US - 2021 - Market Research Report*, n.d.).

Once reviews for each sampled restaurant were retrieved, the raw text from each review was cleaned using the natural language toolkit package in Python (NLTK). Each review was given a set of two scores: one that measured the polarity of the language (representing the average negativity/positivity of review on a scale of -1 to 1) and another that measured subjectivity (the average use of emotional language rather than objective on a scale of 0 to 1). Combined with star-ratings from 1 to 5 available on Yelp, these three measurements provide a multi-dimensional understanding of how users interacted with establishments. Individual polarity and subjectivity scores were then aggregated to produce average scores for each restaurant, allowing for a comparison between the positivity or negativity of user engagement across establishments. Because all three dependent variables were measured on different scales, outcomes for each were converted to z-scores after the exploratory spatial data analysis stage. This standardization process allows for an easier comparison between the dependent variables throughout the analysis. The point data for each restaurant was then used to create aggregate scores per cuisine within each tract. In other words, scores for star rating, polarity, and subjectivity reflect the total average scores of Asian-affiliated, Latin American, and Italian restaurants within each tract. The code for the process of data collection, sentiment analysis, and data cleaning is publicly available on my GitHub account (LaBelle-Hahn, 2022a/2022b).

The demographic data describing community contexts was sourced primarily from the 2020 American Community Survey estimates using the *tidycensus* package in 'R'. To test the hypothesis that sex, education, race, and income are predictors of negative sentiment scores, the following variables were extracted:

- Estimate of population per block group
- Estimate of Racial composition per block group
- Estimate of Educational Attainment for the population 25 years and over per tract
- Estimate of median age by sex for workers 16 to 64 per tract
- Estimate of median income in the past 12 months by nativity per tract
- Estimate of sex by age per block group

Variables for race and educational attainment were transformed to obtain proportional estimates per tract population. The variable representing sex was summed across ages to procure an estimate of the percentage of males within each tract. Similarly, median age was divorced from its gender binary to create an average age per tract irrespective of sex. Next, the City of Chicago Data portal was used to extract information on COVID-19 vaccination coverage. I isolated the percentage of individuals within each tract who had received at least the first dose of the COVID-19 vaccine by May 18th, 2022. Though vaccination against the coronavirus is a decision mired by complex social factors, this variable may be able to serve as a proxy for an area's political affiliation, since previous research has shown that political affiliation shapes fear of contracting COVID-19 (Calvillo et al., 2020., Medina & Gebelof, 2020, Franz & Dhanani 2021). Each variable included in the model provides estimates at the tract level. A visualization of the data extraction and processing procedures as well as the various software used for each step is provided in Figure 2.

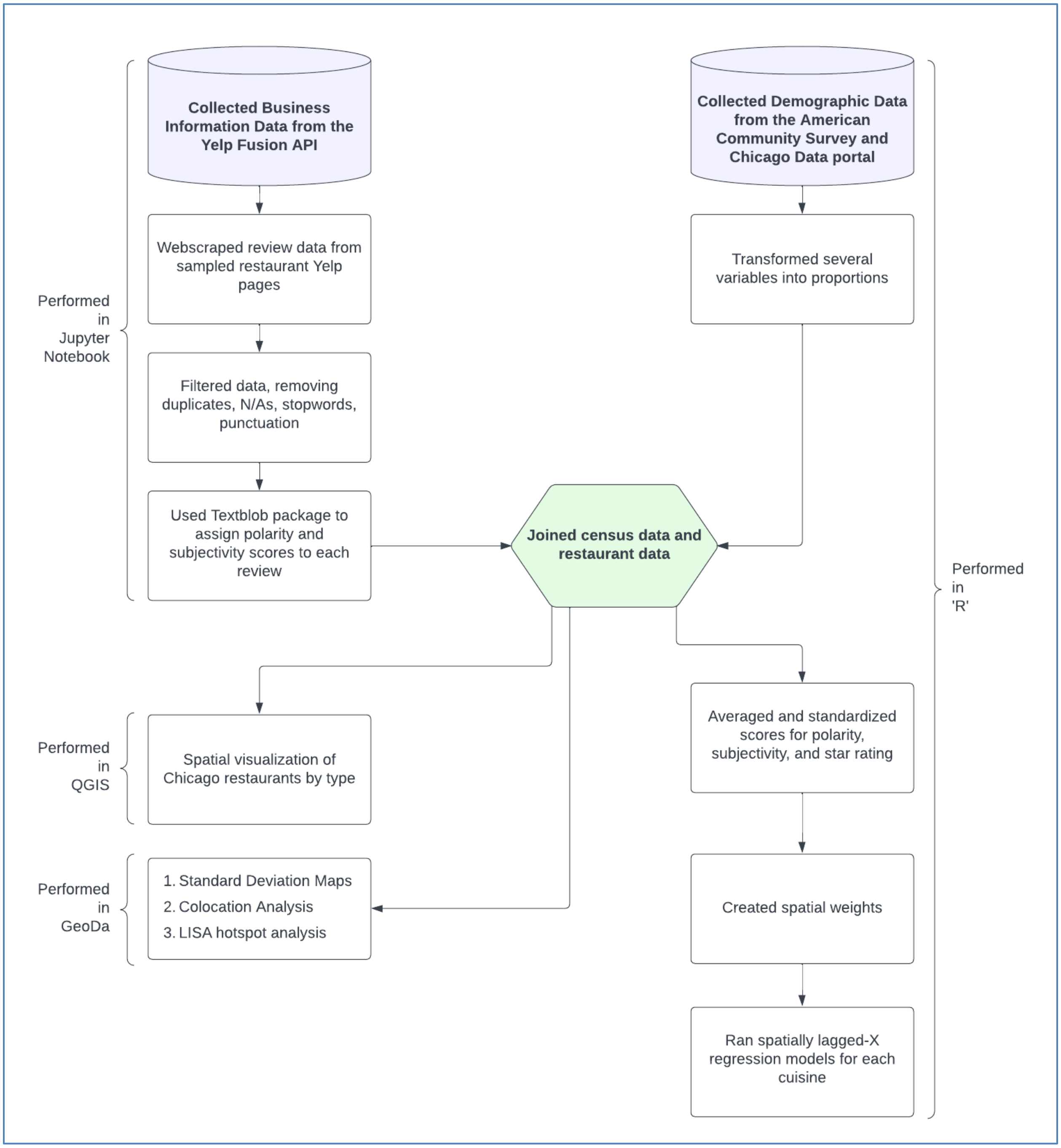

Figure 2. Data Processing Procedures

Data Limitations

In its current state, the above method for collecting Yelp review data is insufficient for capturing all instances of anti-Asian sentiment in the early days of the pandemic. Because the review collection process does not encode the date of each post, a time-series analysis of user sentiment is not possible. In addition, Yelp has a unique algorithm that does not list reviews in the order they were submitted, but rather based on user voting and review quality factors in addition to recency. This means that reviews from several weeks or months ago can be positioned further up the page, which can result in a potential bias in the presentation of reviews. Even when a majority of a restaurant's reviews are negative, Yelp can sometimes prioritize uniquely-positive reviews over 1-star reviews on the first page of results (Lum, 2016). The sampled data may not be representative of the extent of negative language used on the platform, and likewise, may not reflect the residual anxiety and hate speech that characterized the initial outbreak.

A more extensive review extraction process is required to obtain time-series capable data. In the same vein, advanced sentiment analysis techniques such as those employed in previously mentioned studies (Dubey, 2020; Nguyen et al., 2020; Costello et al., 2021; Aiello et al., 2021; Kumar, 2022) are required in order to pinpoint specific instances of hate speech on the platform. The textual analyzer included in the *textblob* package is not tailored to the context of this research and may not yield accurate results. It awards scores on the basis of a word's general connotation within the English language and does not account for the context within which the word is situated. For example, the analyzer may read the word "fried" in the body of a review and give it a negative score based on its broad implication rather than its specific application in this context. Comprehension of complex ideas is thus extremely limited with this technology and the resulting scores should be interpreted with caution.

Lastly, the majority of census tracts outside the 40000-meter radius of the city center (around 740 tracts) contain no restaurant data because the API retrieval method could not reach beyond the inquiry boundary. There may well be restaurants located on the periphery of the inquiry zone. Future research should broaden the scope of data extraction by using multiple search radiuses within the Yelp fusion API call. This paper will focus on the interpretation of the data that *is* available with the understanding that the complete picture is not being provided and that calculations may be affected by discontinuities.

EXPLORATORY SPATIAL DATA ANALYSIS

Choropleth Maps

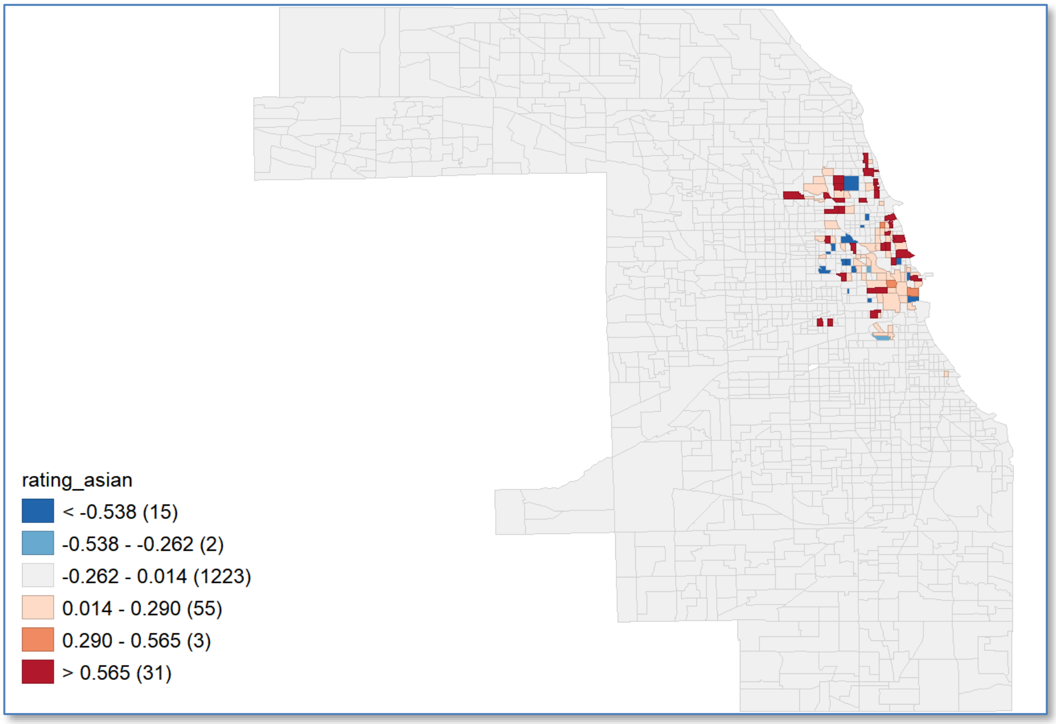

Figure 3. Choropleth Map of Ratings for Asian Restaurants

The first step in understanding the outcome variables was to visualize their distribution, search for outliers, and identify potential patterns using choropleth maps. This method provides spatial context for scores, reflecting how restaurants within each tract perform against restaurants of the same cuisine type within neighboring tracts. The maps were created using the free spatial data analysis software, GeoDa. Neighborhood labels and other geographic features were excluded from these maps for the sake of providing a clearer picture of the data. A full set of choropleth maps for each cuisine are organized by outcome variable in Appendix 1. For the response variable, *rating*, there appear to be more tracts for which scores are overwhelmingly negative for both Latin American restaurants and Asian restaurants as compared to Italian restaurants (see Fig.3).

Areas colored in blue indicate tracts within which ratings for Asian restaurants fall at least 0.538 standard deviations from the norm. Areas colored in red show tracts within which ratings are higher by at least 0.565 standard deviations. Lighter colors encompass other tracts in Chicago for which scores fall in between the two extremes. Gray areas signify tracts for which no restaurant data is available. For the response variable, *polarity*, the same pattern persists; tracts within which Latin American and Asian restaurants reside have consistently more polar reviews than Italian restaurants (see Fig 4).

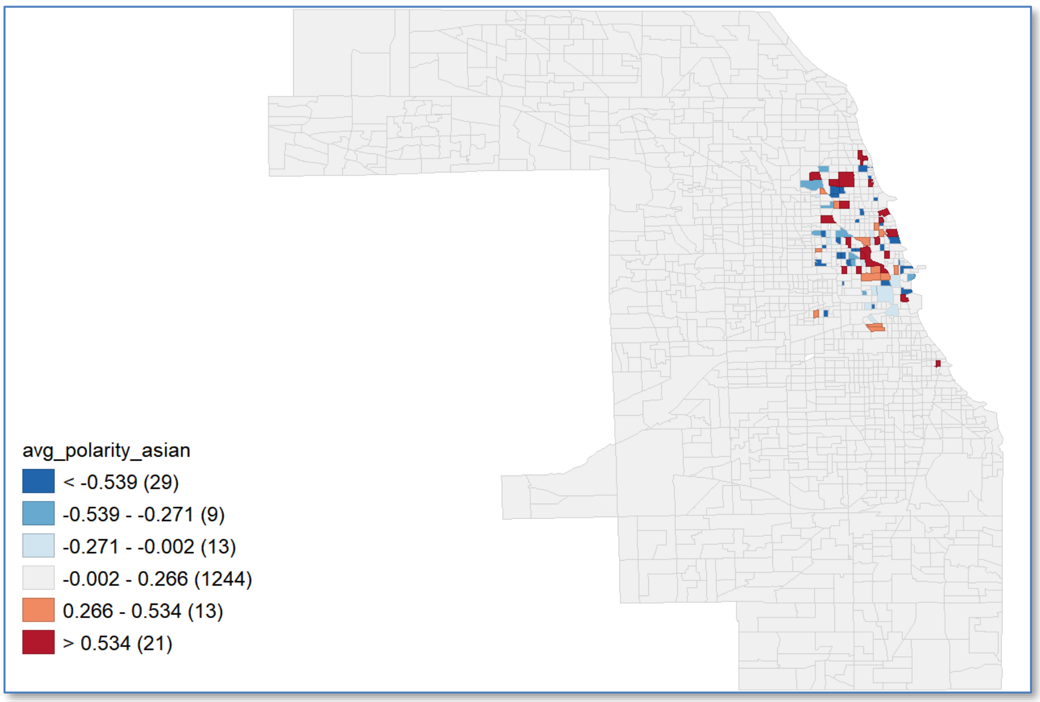

Figure 4. Choropleth Map of Polarity for Asian Restaurants

Latin American restaurants appear to experience more negative reviews on the lower west side. Italian restaurants experience a more moderate overall polarity score. In terms of review subjectivity, the same trend applies. Reviews for Italian restaurants appear to contain less subjective, or emotional language than Latin American or Asian restaurants. These exploratory maps provide a glimpse of some potentially interesting patterns in review data that can be tested for local hotspots using a technique developed by Luc Anselin, *local indicators of spatial association* (LISA).

Local Indicators of Spatial Autocorrelation (LISA)

The purpose of a LISA test is to determine whether there is significant spatial clustering of similar values around an individual observation. Local indicators of spatial autocorrelation allow for global indicators of spatial dependence to be decomposed into the contribution of each observation (Anselin, 1995, p. 95). In other words, we can assess the degree to which outcome variables for certain census tracts influence surrounding tracts, which helps identify local hotspots. To investigate whether outcomes for rating, polarity, and subjectivity exhibited spatial clustering, I performed LISA analyses for each cuisine. The resulting choropleth maps for spatial dependence and statistical significance are available in Appendix 1. The tracts in red indicate areas for which restaurant ratings, polarity, or subjectivity are not only considered high but surrounded by other tracts with high values for the respective dependent variable. Light red indicates that the tract contains high scores but is surrounded by lower scoring tracts. Blue tracts reflect areas where scores are low as well as surrounded by other tracts with low values. Light blue identifies tracts with low local scores that are surrounded by tracts with high scores. Light gray tracts are areas where the analysis was statistically insignificant or undefined due to lack of data.

Though the piecemeal nature of the restaurant data makes it difficult to identify hotspots in these choropleth maps, they do seems to reflect 1) lower ratings for Asian restaurants in the on the west side of Cook county, 2) more tracts with low subjectivity scores for Italian restaurants (that is, more infrequent use of emotional language in Italian restaurant reviews) in peripheral areas, and 3) a greater number of tracts in central downtown for which Latin American restaurant ratings are low and surrounded by other tracts with low ratings.

Colocation

One of the primary goals of this analysis is to identify areas where negative language coincides with highly emotional language; the presence of overwhelmingly negative and emotional reviews for Asian restaurants within tracts may be indicative of their susceptibility to anti-Asian messaging. Colocation is a technique that allows researchers to discover regions that meet two specific criteria (Li et al., 2016; Lin et al 2022). To apply colocation in this context, I generated dummy variables in the dataset that represented *high negative sentiment* by combining the lowest tertile of polarity and the highest tertile of subjectivity for each cuisine type. Using the co-location map function in GeoDa, I created maps that show where these tracts are situated within Cook County (See Appendix 1). This method was able to identify 20 unique tracts within which reviews for Asian restaurants contained particularly negative sentiment. For Latin American restaurants, 14 tracts with negative sentiment were identified. Among Italian restaurants, 18 tracts were located.

If we compare the demographic contexts of colocated tracts to other tracts within Cook County, we can see some significant differences, some of which align with the predictors of susceptibility to anti-Asian sentiment. Tracts that contained high negative sentiment for Asian restaurants are majority white (64%) with higher proportions of high school graduates, a lower average age (32.2), a higher median income for state natives ($52,479), and a higher percentage of first dose vaccine recipients (81%). To varying degrees, the same is true of colocated tracts for Italian and Latin American restaurants (see Table 1 below and Tables 1-3 in Appendix 1). However, it should be noted that restaurant data was not collected for tracts outside the 40,000-

meter radius of Chicago's city center and as such, the colocation technique could be missing relevant tracts at the periphery for which demographic contexts are significantly different. To further investigate associations between neighborhood demographic contexts and instances of negative sentiment, the next section will apply a spatially lagged-X regression model.

Table 1. Colocation Summary Table for Asian Restaurants

Variable	Overall, N = 1,329[1]	Non-Colocated Tracts, N = 1,309[1]	Colocated Tracts, N = 20[1]	p-value[2]
Percent White	39 (7, 68)	38 (7, 67)	64 (49, 70)	0.007
Percent H.S. Graduate	21 (12, 28)	21 (13, 28)	6 (3, 11)	<0.001
Population Estimate	3,791 (2,523, 5,076)	3,783 (2,523, 5,076)	4,702 (2,656, 5,022)	0.5
Average Age	39.5 (36.2, 42.7)	39.5 (36.3, 42.8)	32.2 (30.8, 33.1)	<0.001
Median Income of State Native	33,784 (25,066, 46,066)	33,611 (25,025, 45,734)	52,479 (30,216, 61,817)	0.020
Percent Male	0.49 (0.46, 0.51)	0.49 (0.46, 0.51)	0.51 (0.47, 0.53)	0.14
Average First Dose	0.63 (0.00, 0.78)	0.63 (0.00, 0.78)	0.81 (0.78, 0.84)	<0.001

[1]Median (IQR)

[2]Wilcoxon rank sum test

SPATIAL REGRESSION

Using a spatially lagged X model, we can consider how outcomes for restaurant star rating, review polarity, and review subjectivity are influenced by the demographic composition of neighboring tracts. The model can be represented with the following equation:

$$Y = x\beta + Wx\theta + \varepsilon$$

The spatial weights matrix used was of first order queen contiguity which takes into account all census tracts that share common borders and common vertices. When testing for correlation among dependent variables, all exhibited low to moderate amounts of positive correlation (see Figures 30-33 in Appendix 2), confirming the assumption that star rating, polarity, and subjectivity are related measures of sentiment, but they are different enough to be useful in generating a textured understanding of the phenomenon.

It should be noted that I cannot draw concrete conclusions about where residents eat or how far they travel to do so. The model is predicated on the assumption that people will more often source food from restaurants that are close to where they live rather than travel to retrieve food from distant places (Jeffery et al. 2006, Peng et al. 2020). With this assumption in place, I regressed each of the dependent variables on the established predictors of anti-Asian bias: percentage of White residents, percentage of high school graduates, average population age, logged median income of Illinois state natives, percentage male, population size, and the percentage of residents who had received the first dose of the vaccine. For each predictor, two variables were generated to be included in the model, one capturing the measure for its own tract, another capturing the average measure for neighboring tracts.

RESULTS

The outcome tables for each regression are available in Appendix 2. Among Asian restaurants, there were two significant results. Population estimate appears to have a very slight positive effect on restaurant rating (0.0001, SE = 0.0001, p = 0.04). In other words, tracts with larger populations yield slightly more positive ratings. Second, higher proportions of high school graduates within a tract are associated with a decrease in polarity, suggesting an increase in negatively tinged language (-0.006, SE = 0.01, p = 0.03). See Table 4 below and Tables 4-6 in Appendix 2.

Results for Latin American Restaurants indicate that tracts with higher overall age are associated an increase in restaurant rating (0.09, SE = 0.04, p = 0.02). Tracts that contain residents with higher median income among state natives are associated with a decrease in star rating (-2.02, SE = 0.59, p = 0.00) *and* a decrease in review polarity (-1.03, SE =0.53, p = 0.05). Neighboring tracts with higher proportions of high school graduates are correlated with a decrease in ratings (-0.11, SE = 0.04, p = 0.01). Higher percentages of male residents within each tract are associated with a decrease in review polarity (-4.73, SE = 2.32, p = 0.04), suggesting the use of much more negative language.

For Italian Restaurants, neighboring tracts with older residents are associated with an increase in star rating (0.11, SE = 0.04, p = 0.01) *and* increase in polarity, or positive language (0.11, SE = 0.5, p=0.01). Neighboring tracts with a greater proportion of high school graduates are associated with a decrease in subjective language as well (-0.10, SE = 0.03, p = 0.005). The significant demographic predictors for Italian restaurants are correlated with benefits to the language of reviews, an interesting contrast to the results for both Asian and Latin American restaurants.

Table 4. Spatially Lagged-X Model for Asian Restaurants

	Dependent variable:		
Predictor Variable:	**Rating**	**Polarity**	**Subjectivity**
Percent White	-0.001 (0.009)	-0.006 (0.009)	-0.002 (0.009)
Percent H.S. Grad	-0.013 (0.024)	-0.052^{**} (0.024)	-0.021 (0.023)
Average Age	0.042 (0.034)	0.033 (0.034)	-0.020 (0.033)
Log(Median Income of State Native)	-0.247 (0.325)	-0.148 (0.321)	-0.271 (0.312)
Percent Male	-1.474 (2.342)	3.295 (2.314)	1.226 (2.247)
Population Estimate	0.0001^{**} (0.0001)	0.0001 (0.0001)	0.00003 (0.0001)
Percentage of First Dose recipients	0.760 (1.210)	0.579 (1.195)	-1.193 (1.161)
Lag Percent White	-0.002 (0.013)	0.010 (0.013)	-0.017 (0.013)
Lag Percent H.S. Grad	-0.042 (0.030)	-0.0005 (0.030)	-0.022 (0.029)
Lag Average Age	0.051 (0.051)	0.058 (0.051)	-0.021 (0.049)
Lag Log(Median Income of State Native)	-0.247	-0.166 (0.289)	0.224 (0.281)
Lag Percent Male	3.242 (3.421)	4.572 (3.380)	2.504 (3.283)
Lag Population Estimate	-0.0001 (0.0001)	0.00004 (0.0001)	-0.00001 (0.0001)
Lag Average First Dose	-3.021 (1.890)	-3.231. (1.867)	-1.225 (1.814)
Constant	0.445 (3.694)	-1.742 (3.649)	3.756 (3.545)
Observations	102	102	102
R^2	0.213	0.205	0.129
Adjusted R^2	0.086	0.077	-0.011
Residual Std. Error (df = 87)	0.936	0.925	0.898
F Statistic (df = 14; 87)	1.679^{*}	1.600^{*}	0.919
Note:	Signif. codes: 0 = '***' 0.001= '**' 0.01= '*' 0.05='.' 0.1= '' 0.1		

DISCUSSION

This study contributes to existing literature on pandemic-induced anti-Asian sentiment in numerous ways: it encodes review data using three different indicators (star rating, polarity, and subjectivity) for a more comprehensive evaluation of sentiment; it borrows guiding practices from exploratory spatial data analysis to geographically situate the phenomenon and locate areas of high negative sentiment; and, it investigates the associations between community context and negativity in and around census tracts with a spatially lagged-X regression model.

The model was designed around the contributing factors to anti-Asian prejudice outlined by Intergroup Threat Theory. Individual differences and situational factors are two major contributors to the perception of Asian Americans as a symbolic threat. They were tested using the variability in demographics and vaccination rate within each tract. The results of the regressions show several significant predictors that are consistent with the original hypothesis. Features of neighboring tracts were prevalent predictors, contributing to the idea that social phenomena can exhibit a spatial spillover effect (Anselin et al. 2000; Moreno et al. 2005). Lower levels of educational attainment appear to be associated with a negative impact on review sentiment for Asian restaurants.

Latin American restaurants also displayed significantly negative correlations with the predictors. Tracts with higher median income of state natives, greater proportion of high school graduates, and higher proportion of male residents resulted in deductions in restaurant rating and review polarity. These results echo the findings presented by Lu et al. that suggest COVID-19 salience impacts discriminatory behavior against East Asians, South Asians, as well as Hispanics. Though racial composition of tracts was not associated with negative effects for Asian or Latin American restaurants, it did influence outcomes for Italian restaurants in significant ways. Overall, tracts with older residents and higher proportions of white residents were associated with positive effects for Italian restaurants across each dependent variable. Italian restaurants experienced higher star ratings and less use of negative and emotional language across the predictors identified as significant.

The use of colocation to recognize tracts that exhibit high negativity is a vital contribution because it paves the way for more strategic approaches to combating the disinformation that leads to anti-Asian sentiment. Hate speech is gaining a stronger foothold on our democracy, and it is circulating through the news and media ecosystems of everyday Americans. Commercial tech companies are not obligated to act as arbiters of public discourse and their information policies are situated under the "auspices of free speech and protected corporate speech" (Noble, 2018, p. 143). Attorneys Foxman and Wolf argue that formal regulations dictating how these companies moderate content may be difficult to implement as well as insufficient and ineffective (p. 71). Instead, they argue for the practice of mitigating techniques like *counter-speech*, which includes various ways to publicly display support for embattled groups. Local counter-speech movements could take the form of community "teach-ins" with films, speeches, and plays advocating inclusion; street fairs where local businesses and institutions open their doors to share traditions from different backgrounds; art and music festivals that draw attention away from politically divisive events hosted by hate groups (Foxman & Wolf, 2013, p. 146). To strategically implement measures of counter-speech, we need to be able to identify and better understand the communities that are most at risk of adopting prejudicial behaviors.

Future research can incorporate these techniques to investigate other regions that have experienced unprecedented spikes in anti-Asian sentiment during the pandemic, cities like Los

Angeles and D.C. (Chens & Contreras, 2022). In fact, data for these cities was collected using the same procedure but was not analyzed in this paper due to time considerations. These datasets are available on my GitHub page and can be used to replicate and build upon the analytical methods presented here. Subsequent research should incorporate more sophisticated natural language processing techniques, such as the use of dictionaries of key terms that help differentiate between explicitly biased terminology versus implicitly biased phrasing. References to restaurant workers, atmosphere, or culture could be encoded separately from language regarding the quality and taste of the food. Instances of explicit and implicit bias could also be tracked over the course of the pandemic. The lack of time-sensitive data within this study does not allow for an exploration of the period of high anti-Asian sentiment we experienced from January of 2020 to February of 2021. However, it can still be retrieved from Yelp with a more robust data extraction technique.

CONCLUSION

This study offers an innovative framework for investigating anti-Asian sentiment from a spatial perspective through the language of Yelp reviews. It makes use of freely available online commentary to extract authentic insights into how users have interacted with Asian restaurants in comparison to their Latin American and Italian counterparts. Exploratory spatial analysis of this data allows for an investigation of potential patterns and the identification of communities where disinformation about Asian Americans may be particularly influential. Results of a spatially lagged-X regression model show patterns consistent with the predictors of Anti-Asian prejudice. Further improvements to the data extraction, processing, and regression procedures could yield crucial insights into the localizations of negative sentiment and contribute to positive social change within those communities.

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APPENDIX 1: Exploratory Spatial Data Analysis Maps

Maps of Restaurant Distribution

Figure 6. Map of Restaurant Distribution by Type

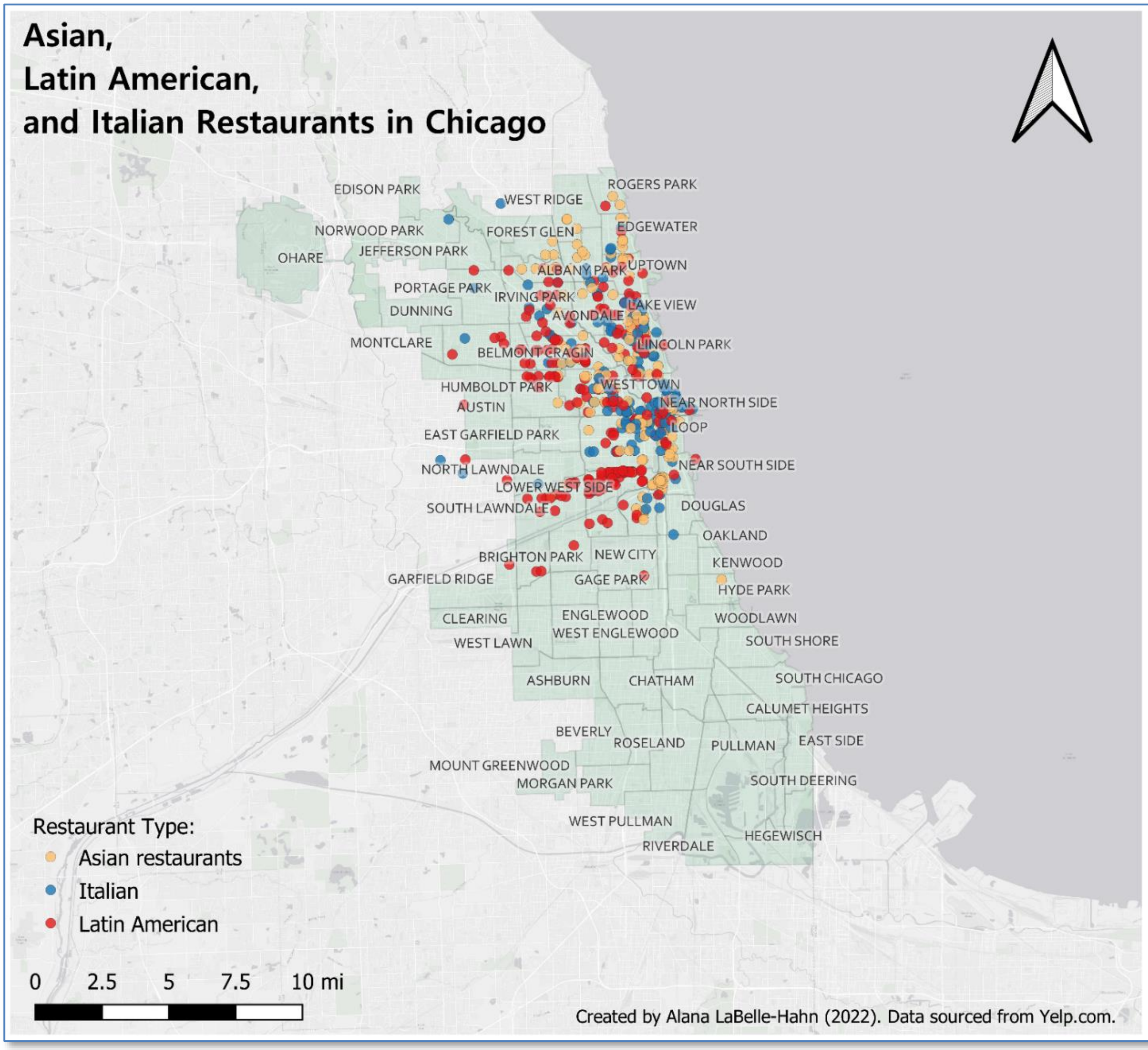
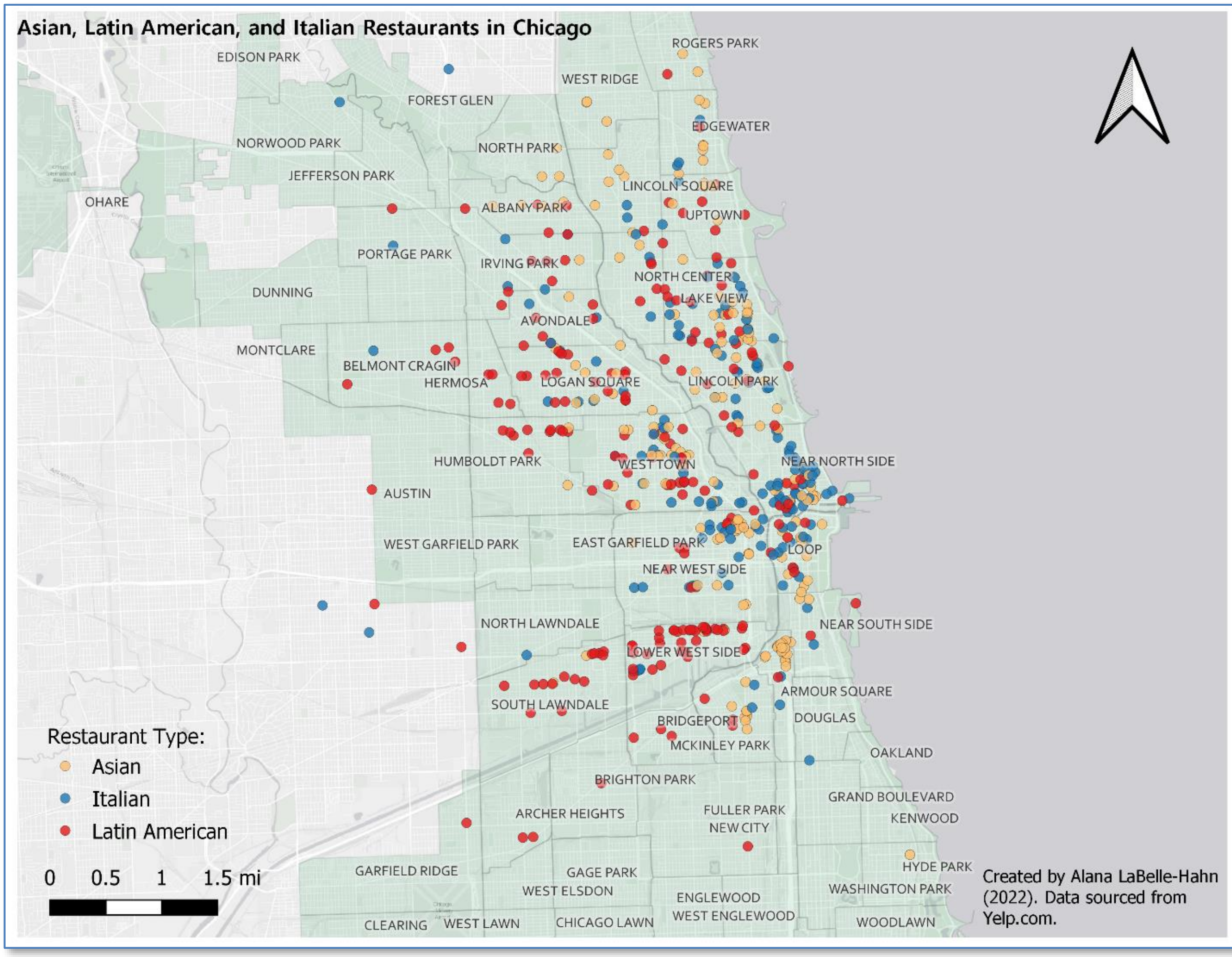


Figure 7. Zoomed in Map of Restaurant Distribution by Type



Distribution Choropleth Maps

Figure 8. Asian Restaurant Overall Star Ratings

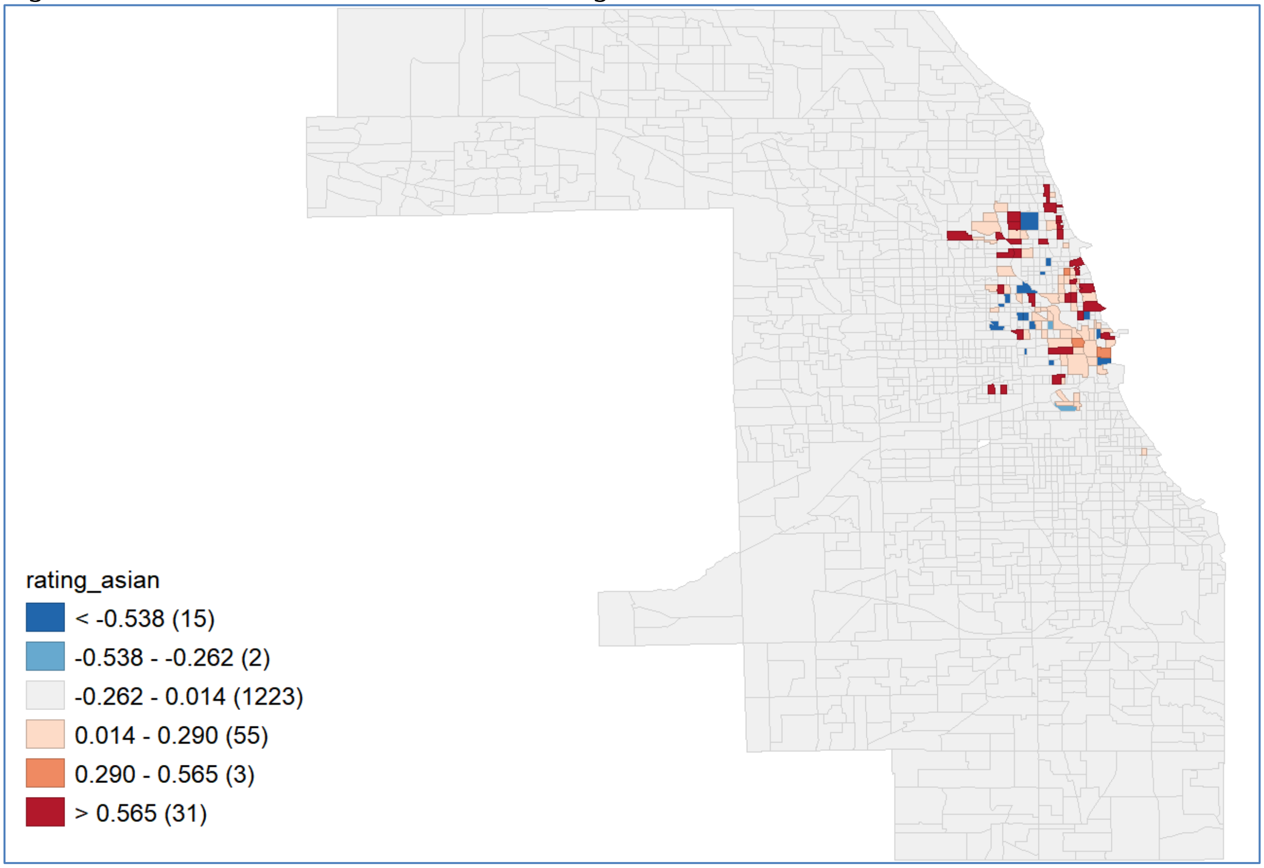


Figure 9. Latin American Restaurant Overall Star Ratings

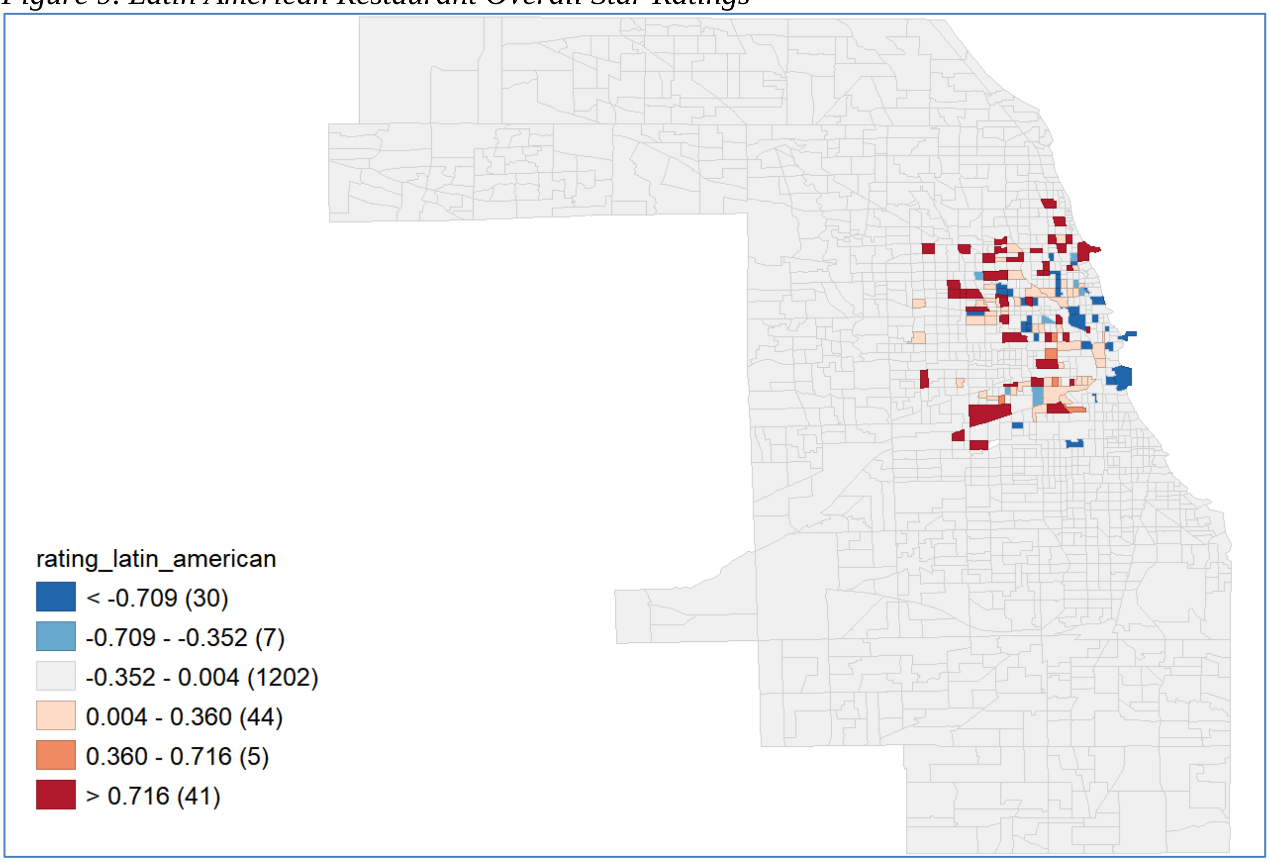


Figure 10. Italian Restaurant Overall Star Ratings

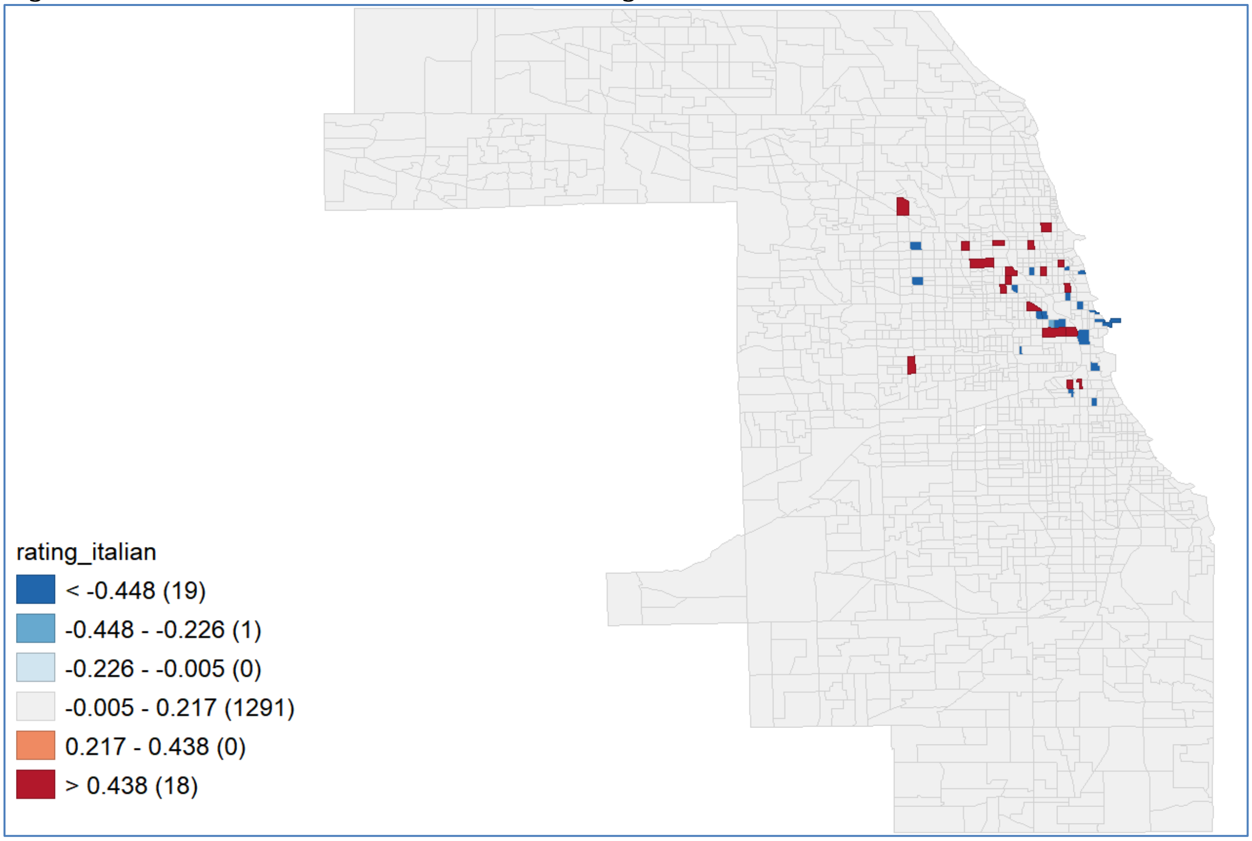


Figure 11. Asian Restaurant Review Polarity

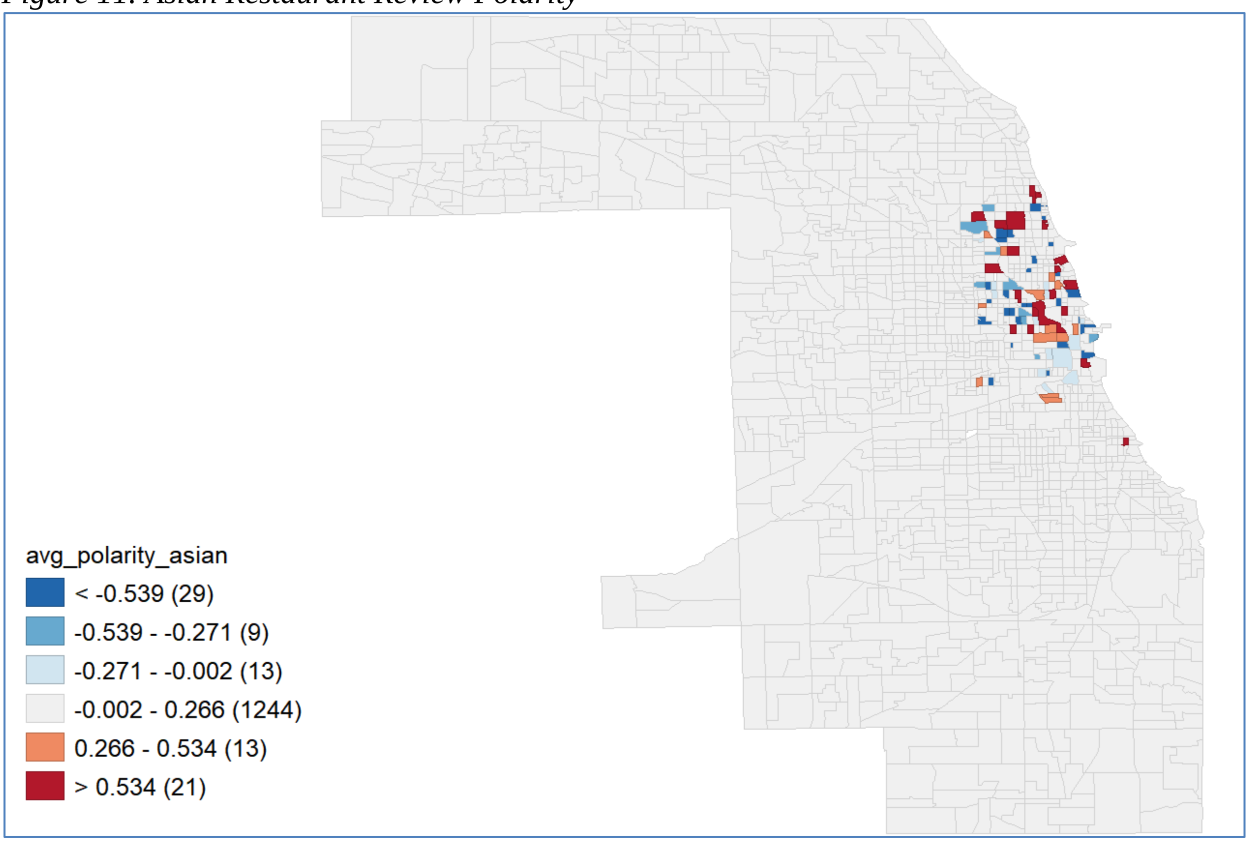


Figure 12. Latin American Restaurant Review Polarity

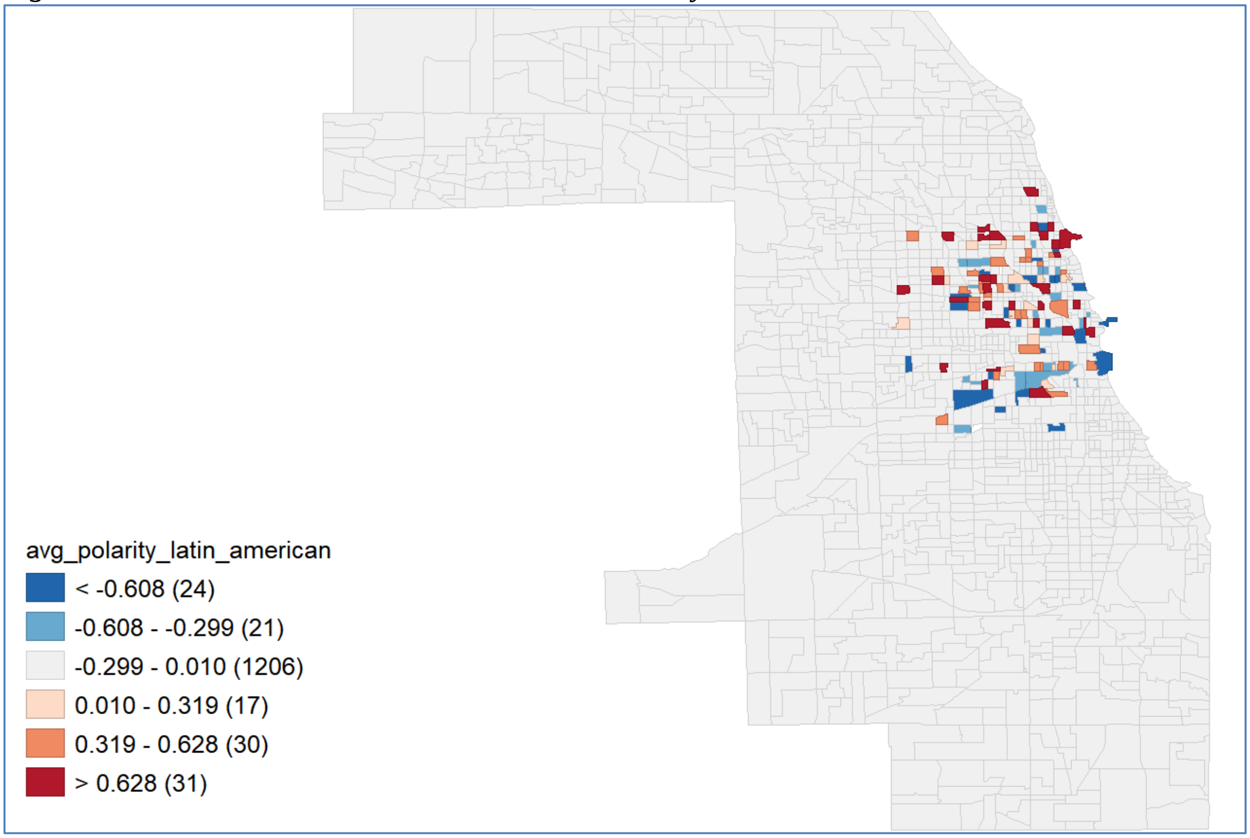


Figure 13. Italian Restaurant Review Polarity

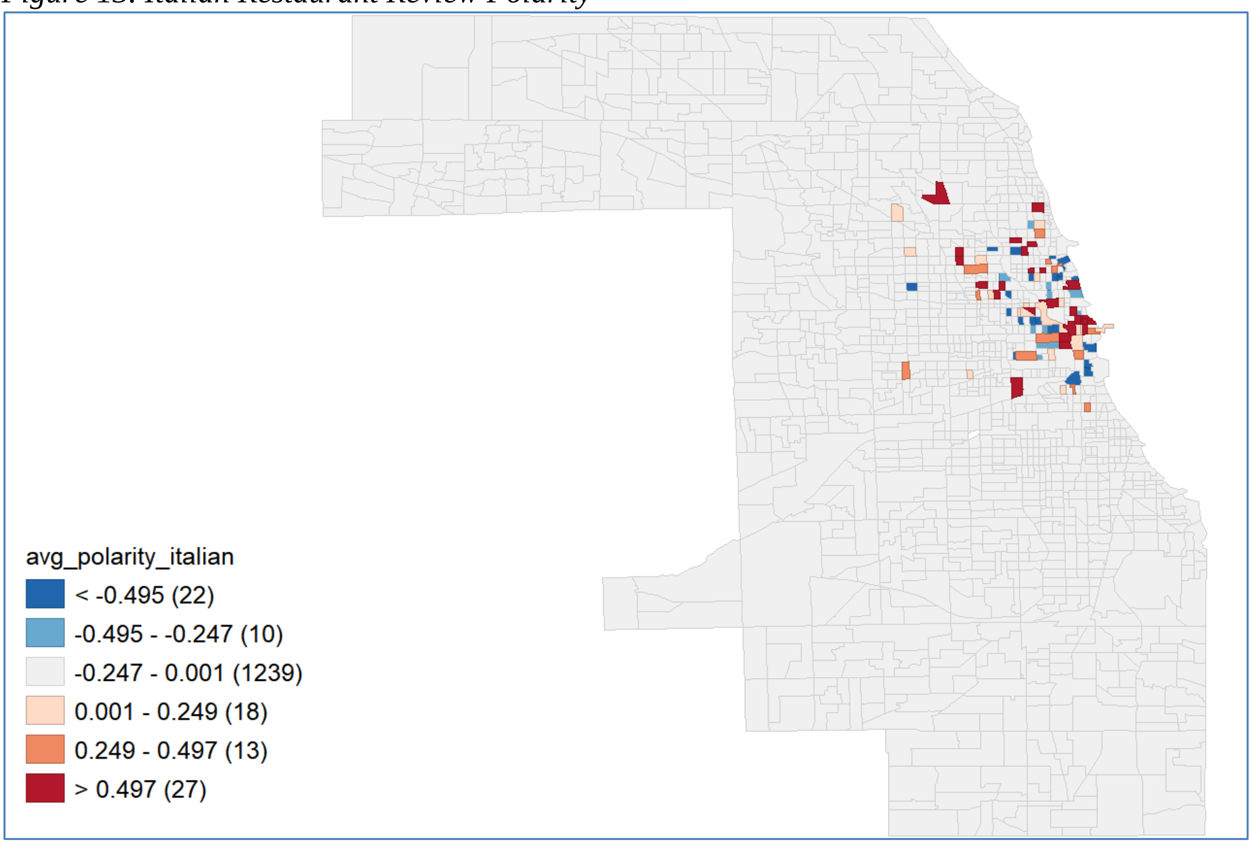


Figure 14. Asian Restaurant Review Subjectivity

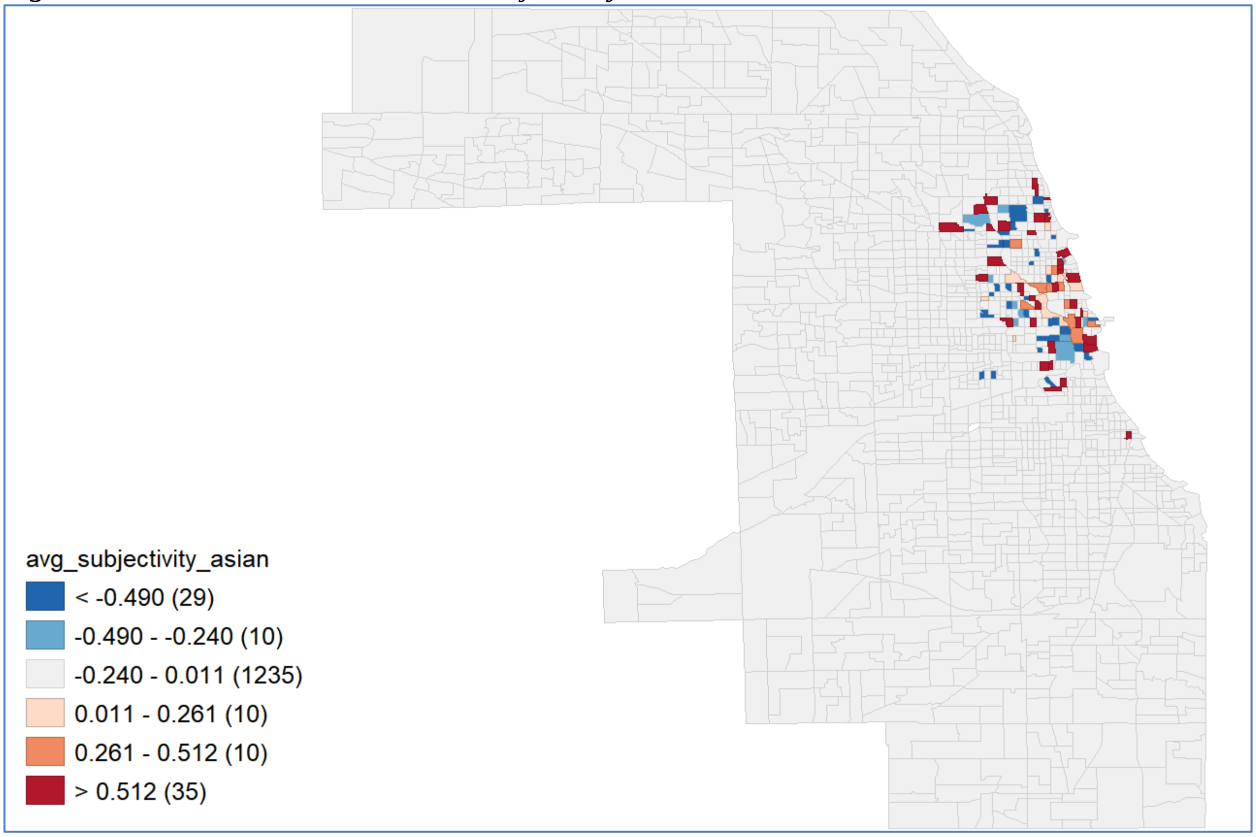


Figure 15. Latin American Restaurant Review Subjectivity

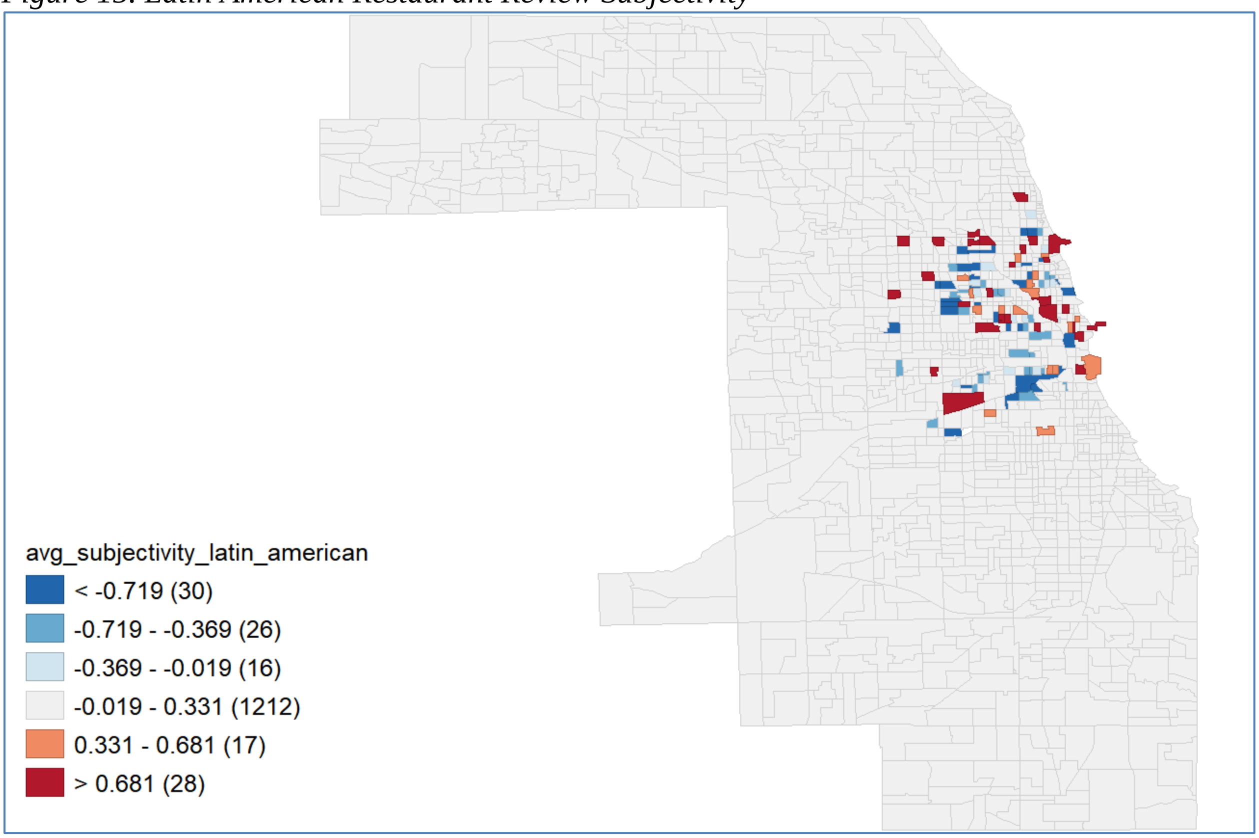
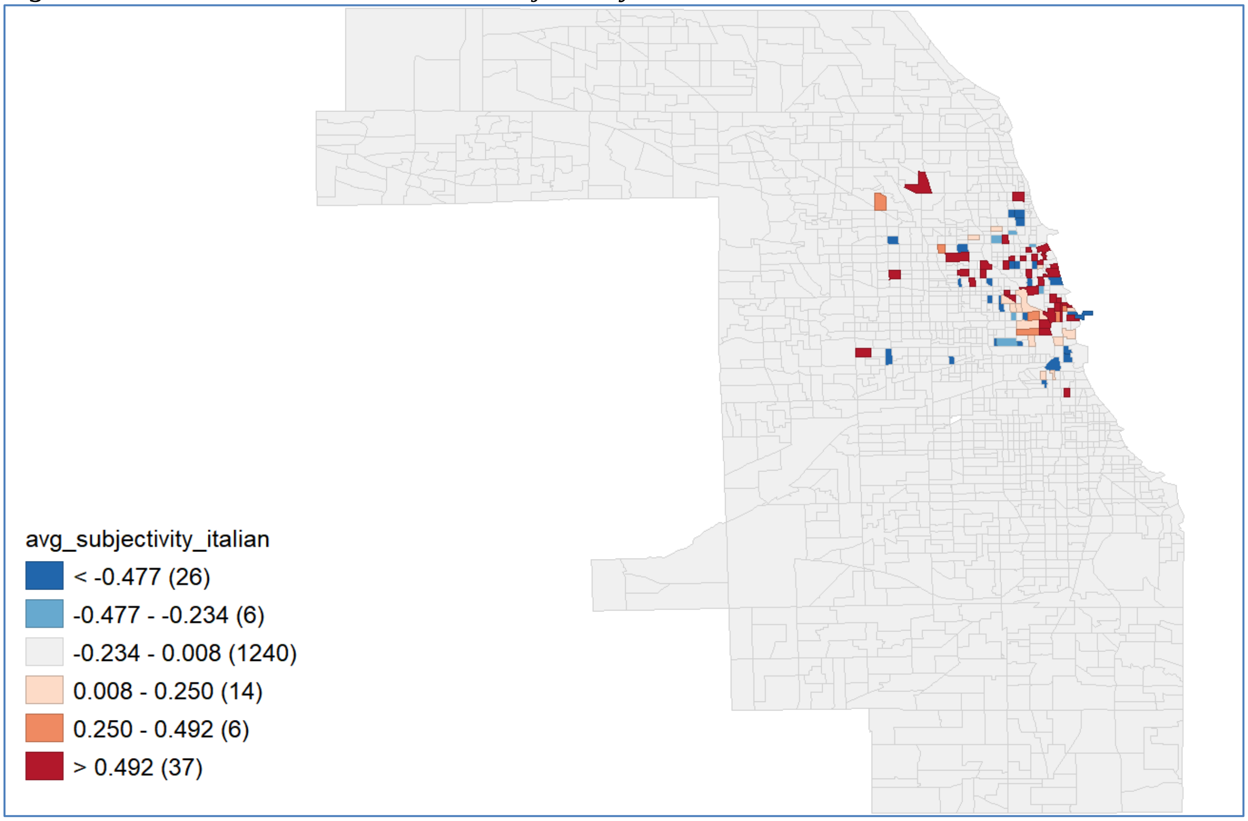


Figure 16. Italian Restaurant Review Subjectivity



Local Indicators of Spatial Association

Asian Restaurants

Figure 17. LISA Analysis of Star Ratings for Asian Restaurants

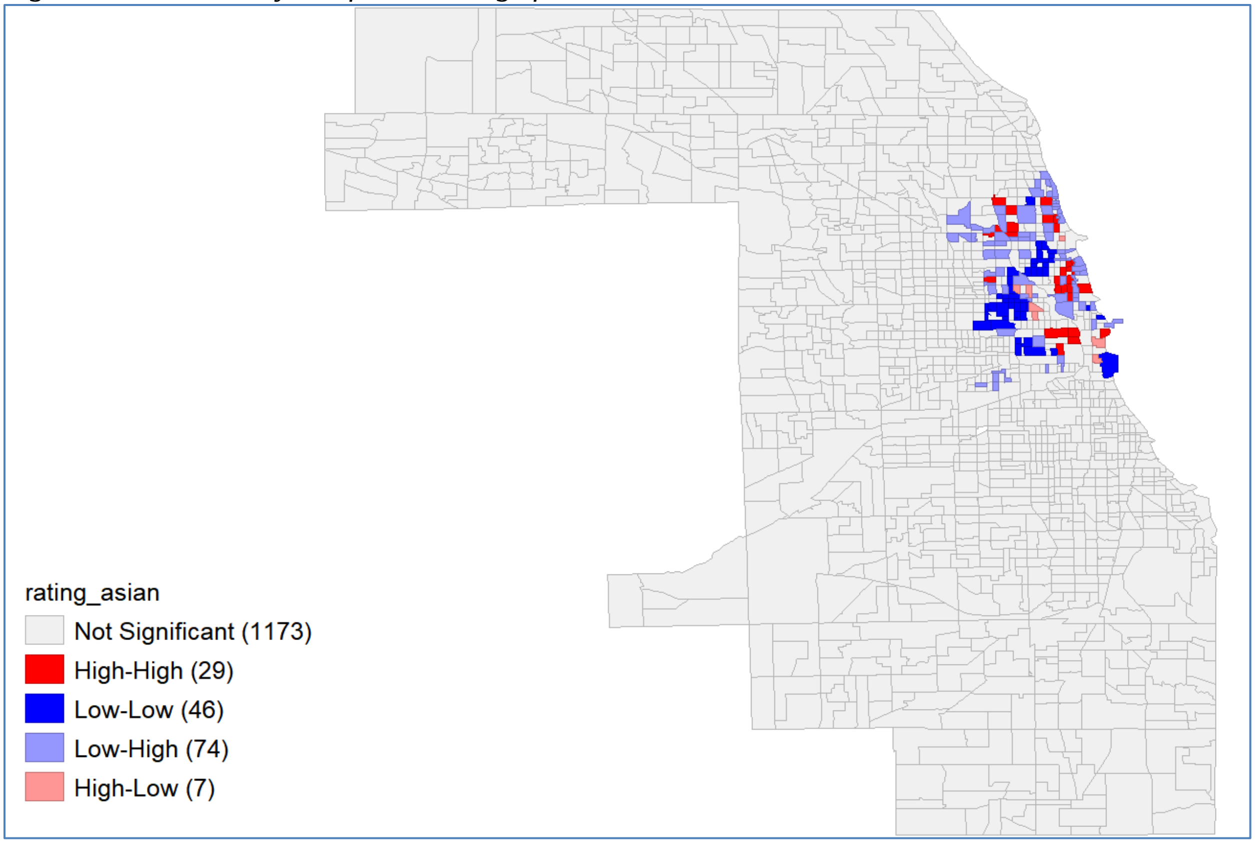


Figure 18. LISA Analysis of Polarity for Asian Restaurants

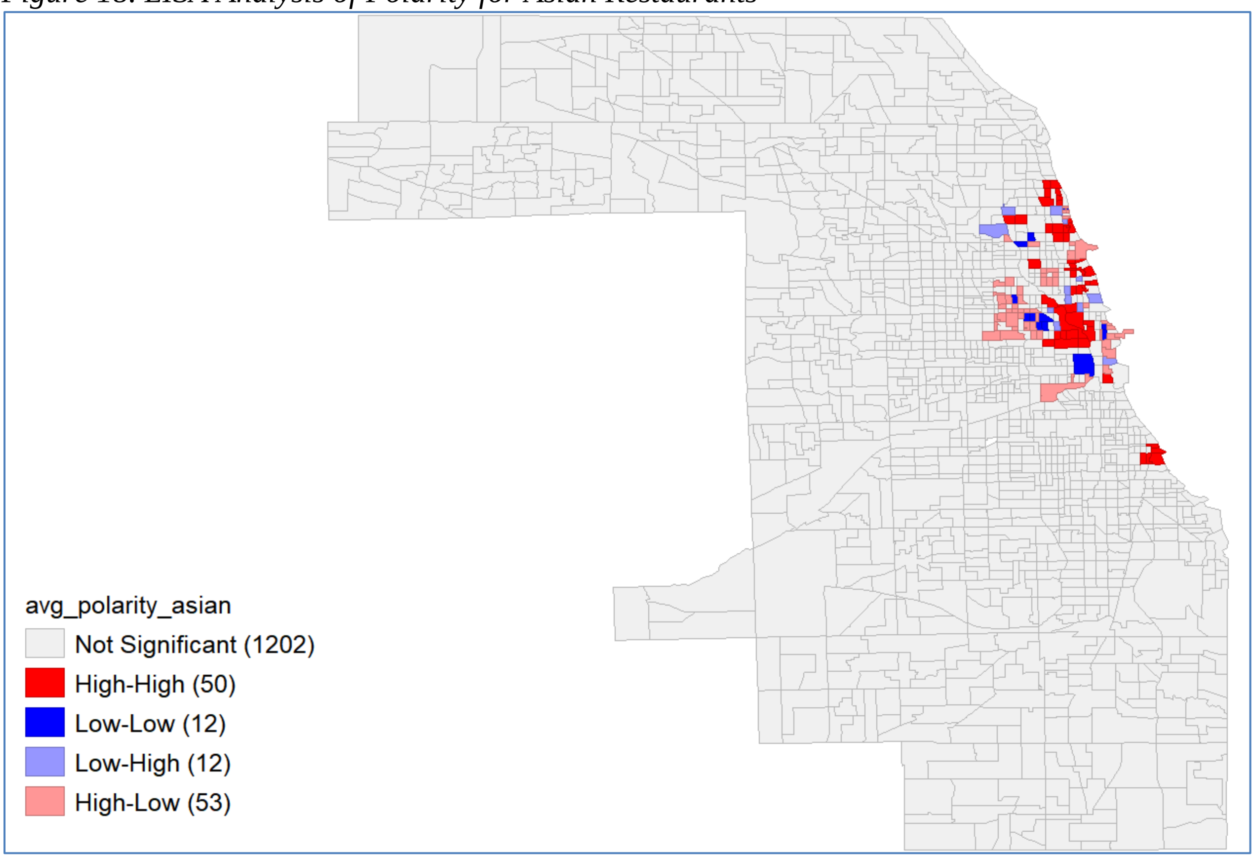
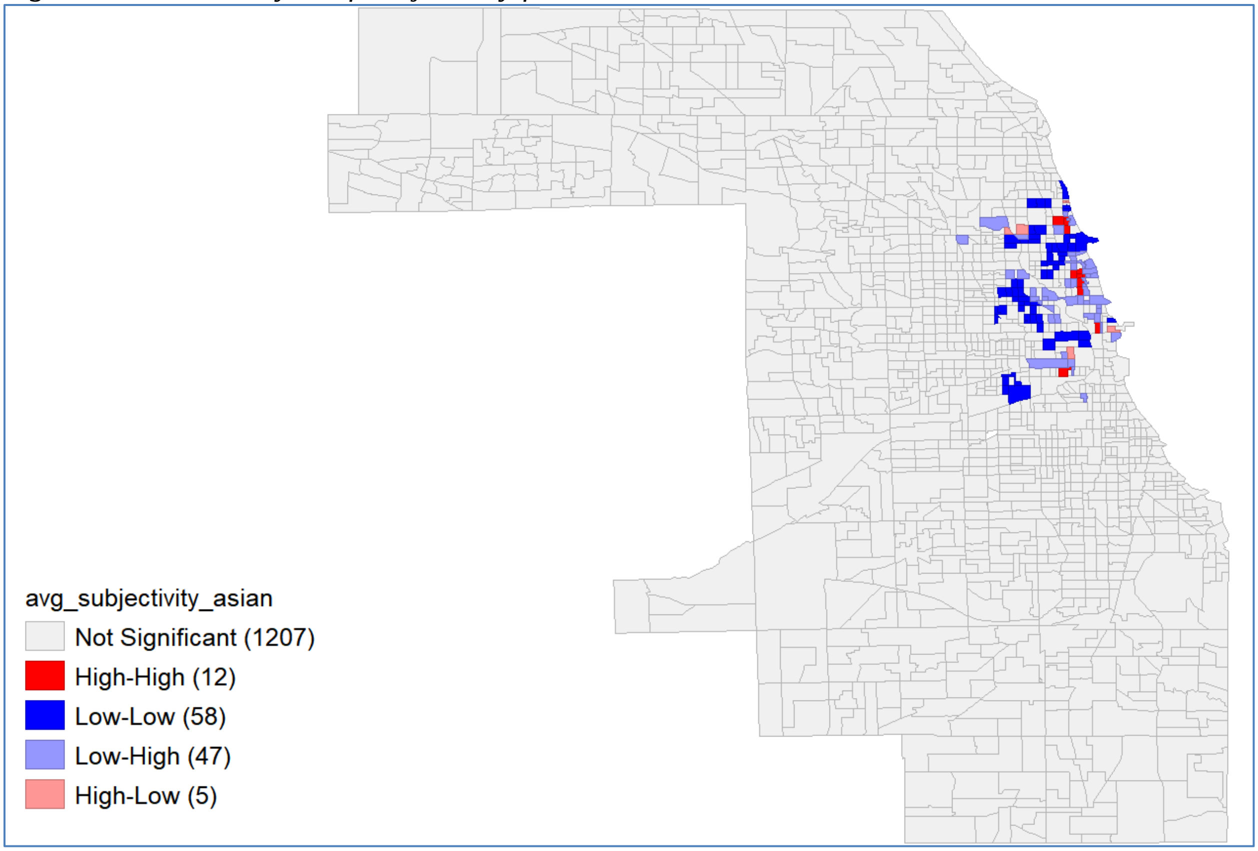


Figure 19. LISA Analysis of Subjectivity for Asian Restaurants



Latin American Restaurants

Figure 20. LISA Analysis of Star Rating for Latin American Restaurants

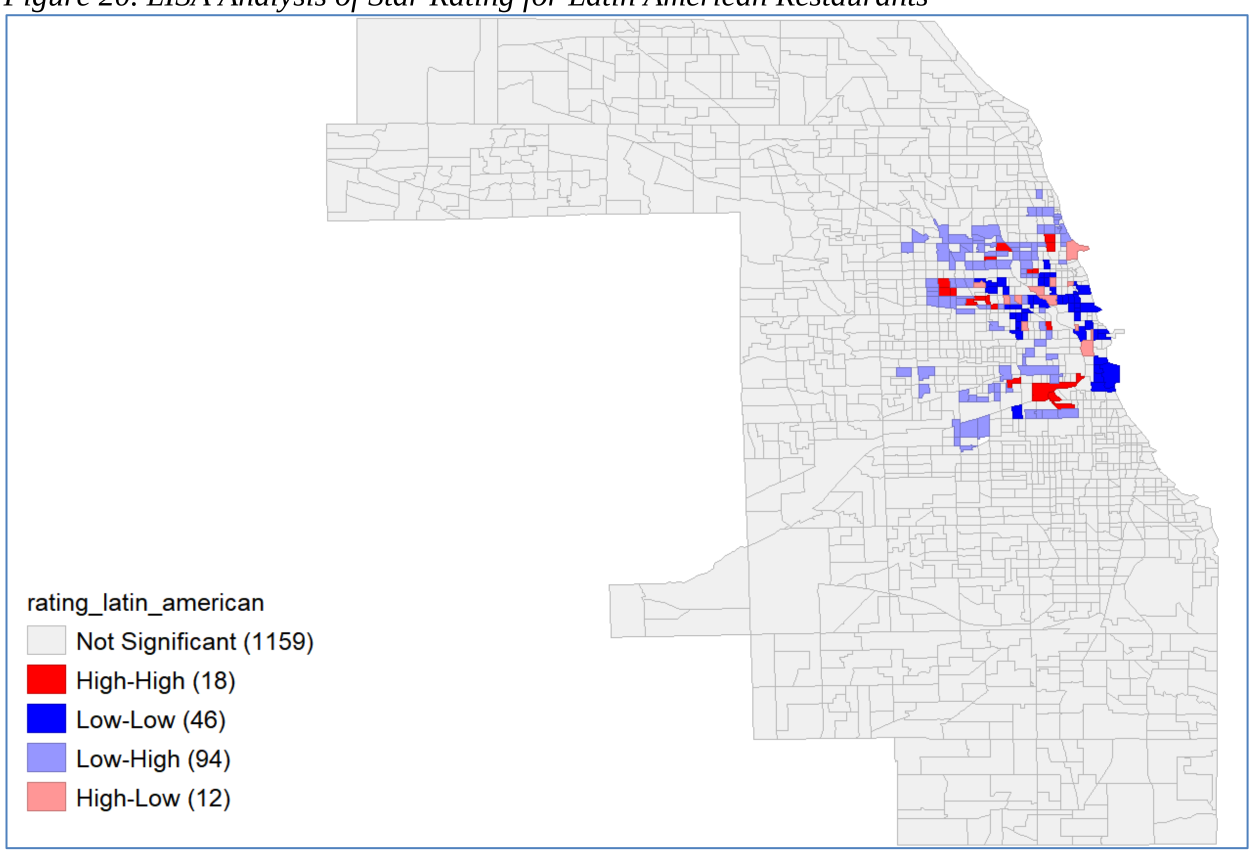


Figure 21. LISA Analysis of Polarity for Latin American Restaurants

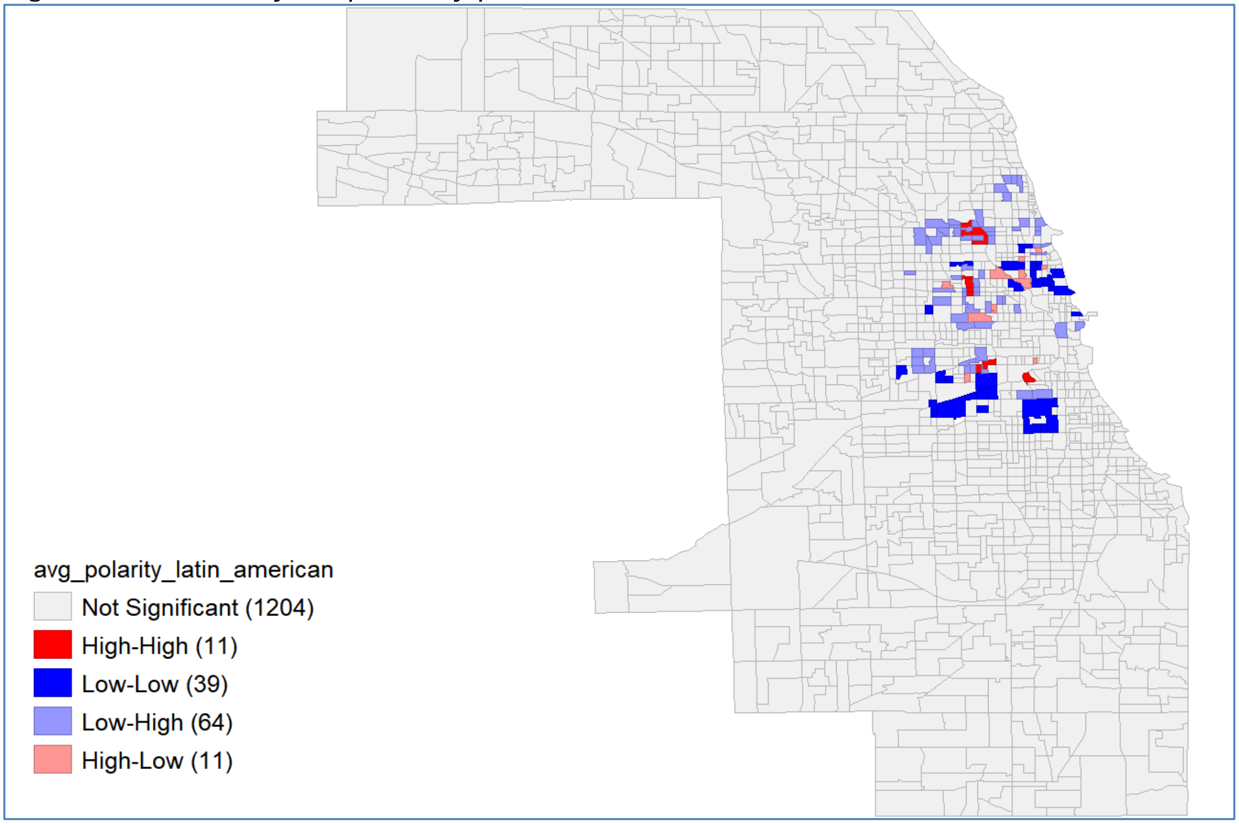
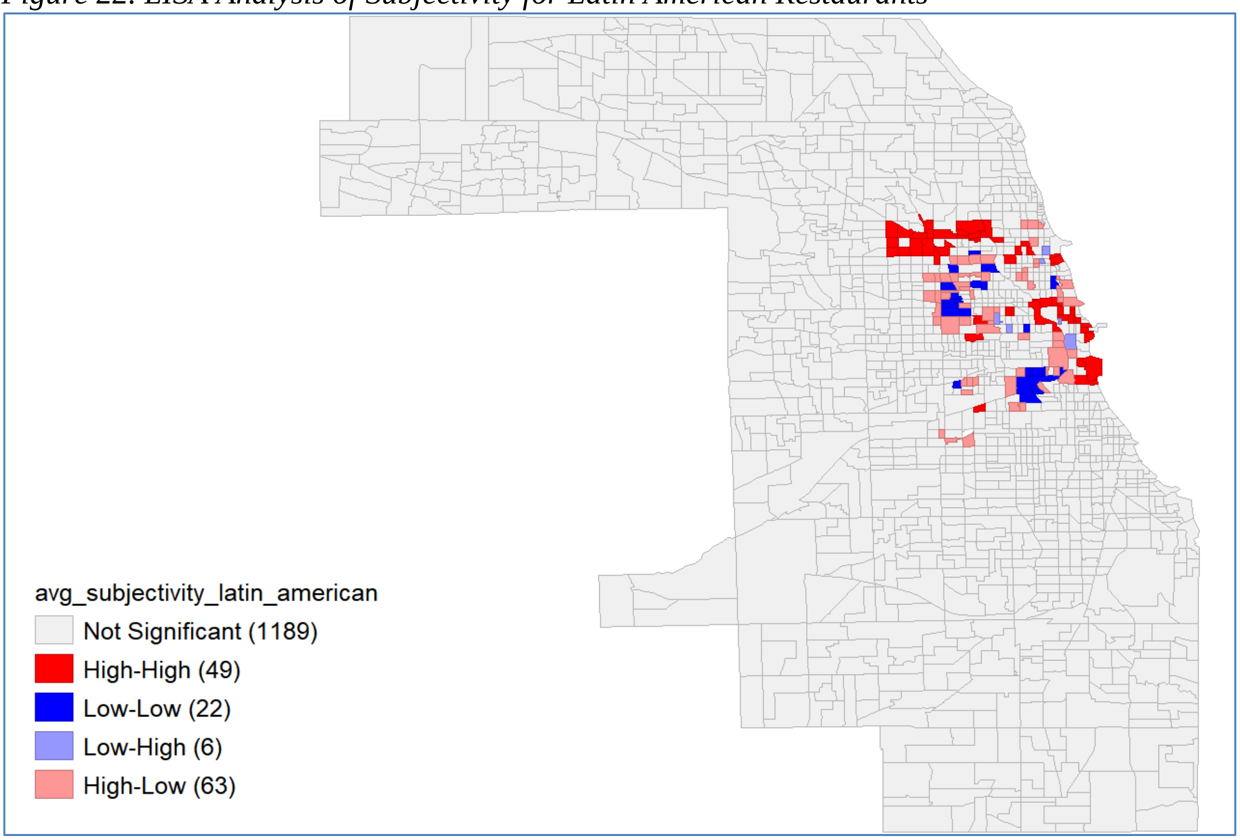
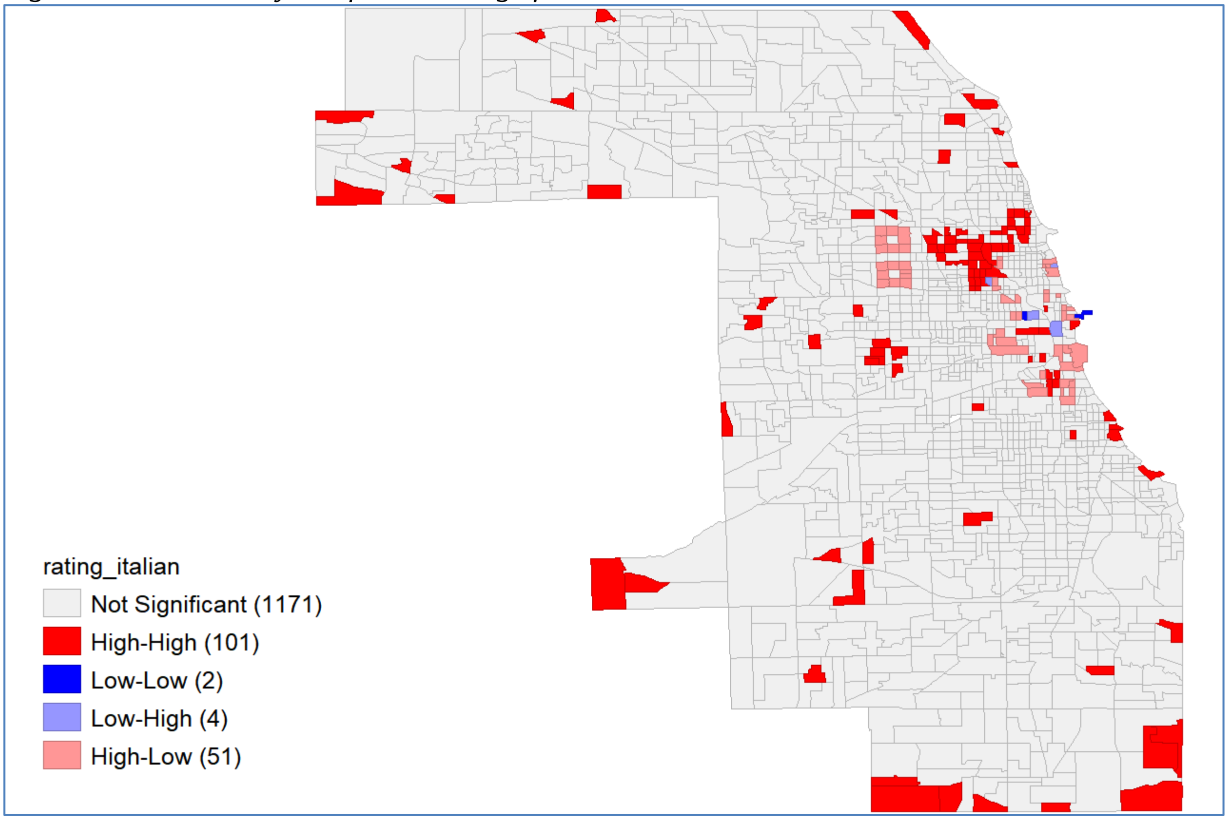


Figure 22. LISA Analysis of Subjectivity for Latin American Restaurants



Italian Restaurants

*Figure 23. LISA Analysis of Star Ratings for Italian Restaurants***



**Note: GeoDa erroneously registered high star rating scores for certain tracts at the periphery even though the existing data table reflects missing values for these tracts. To the author's knowledge, this is the only variable for which this error occurred.

Figure 24. LISA Analysis of Polarity for Italian Restaurants

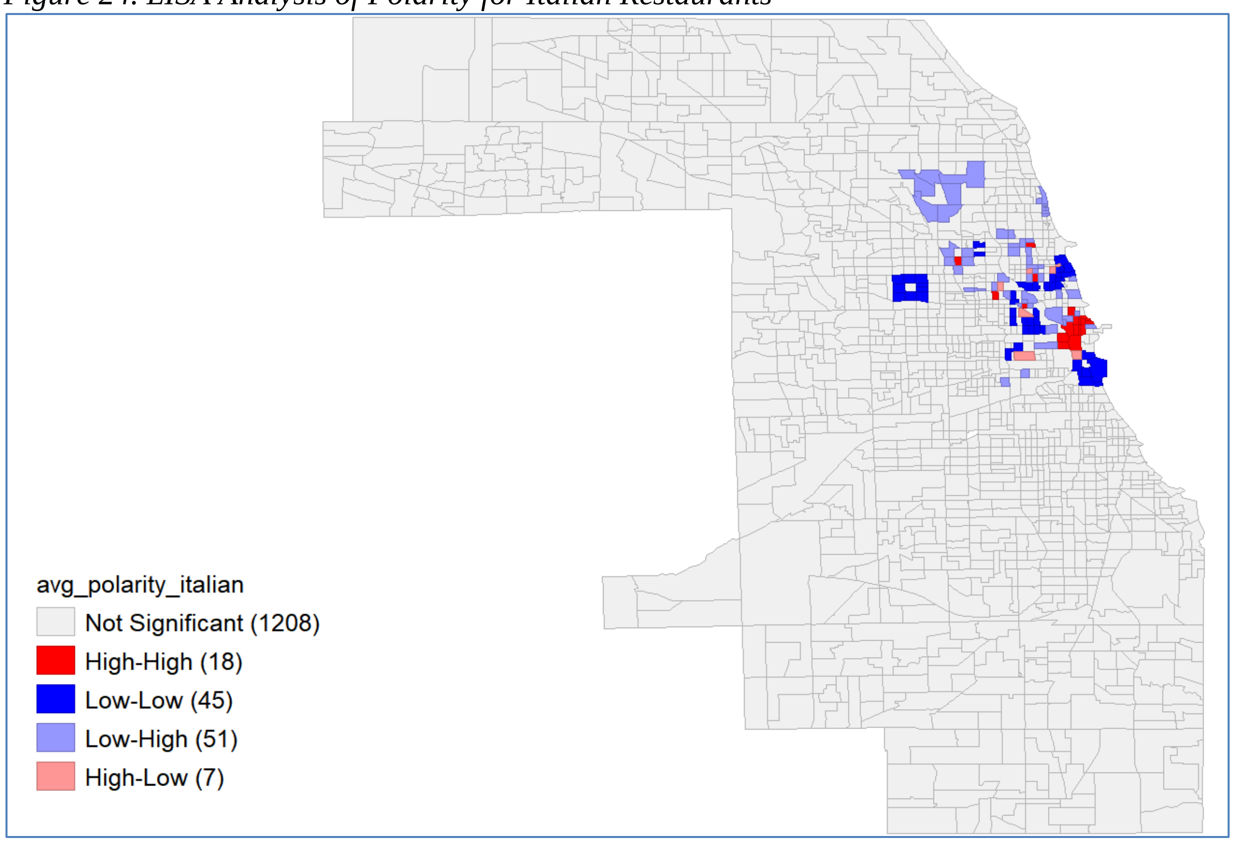
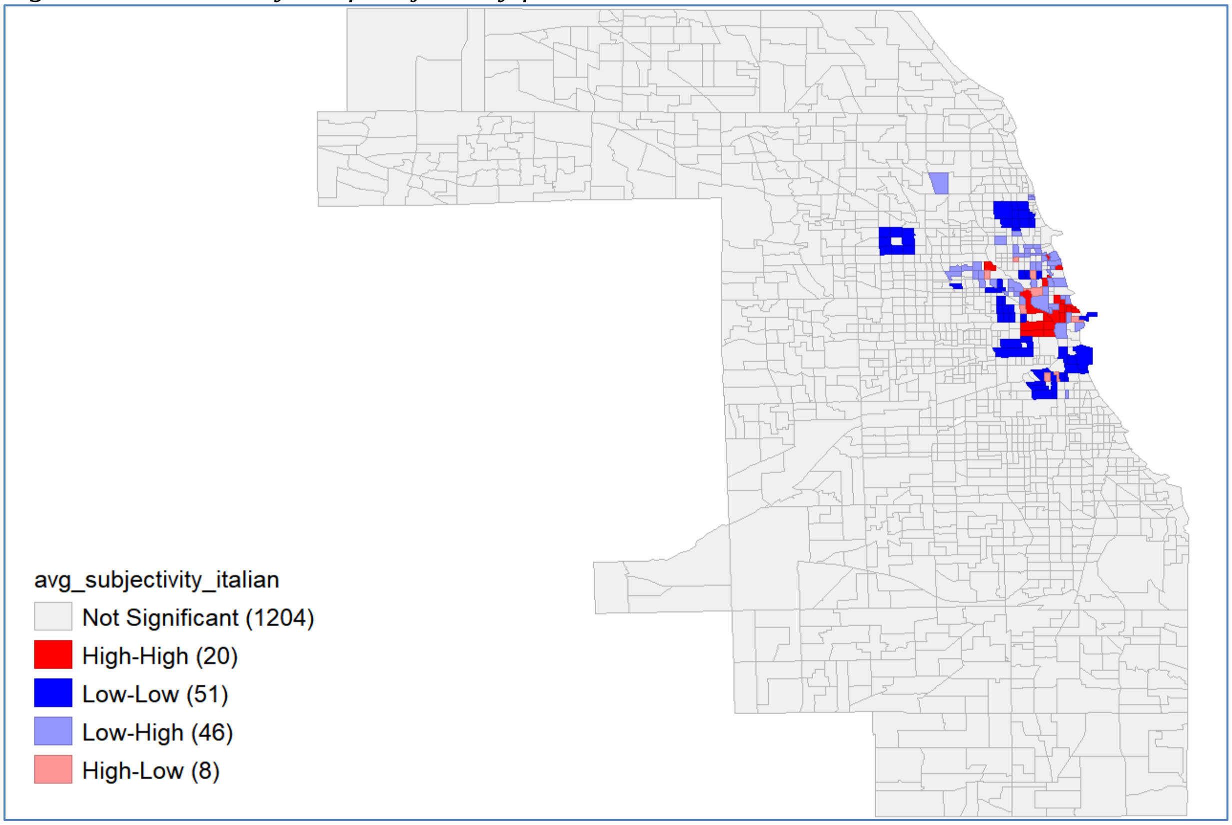


Figure 25. LISA Analysis of Subjectivity for Italian Restaurants



Colocation Choropleth Maps

Figure 26. Areas of Negative Sentiment for Asian Restaurants

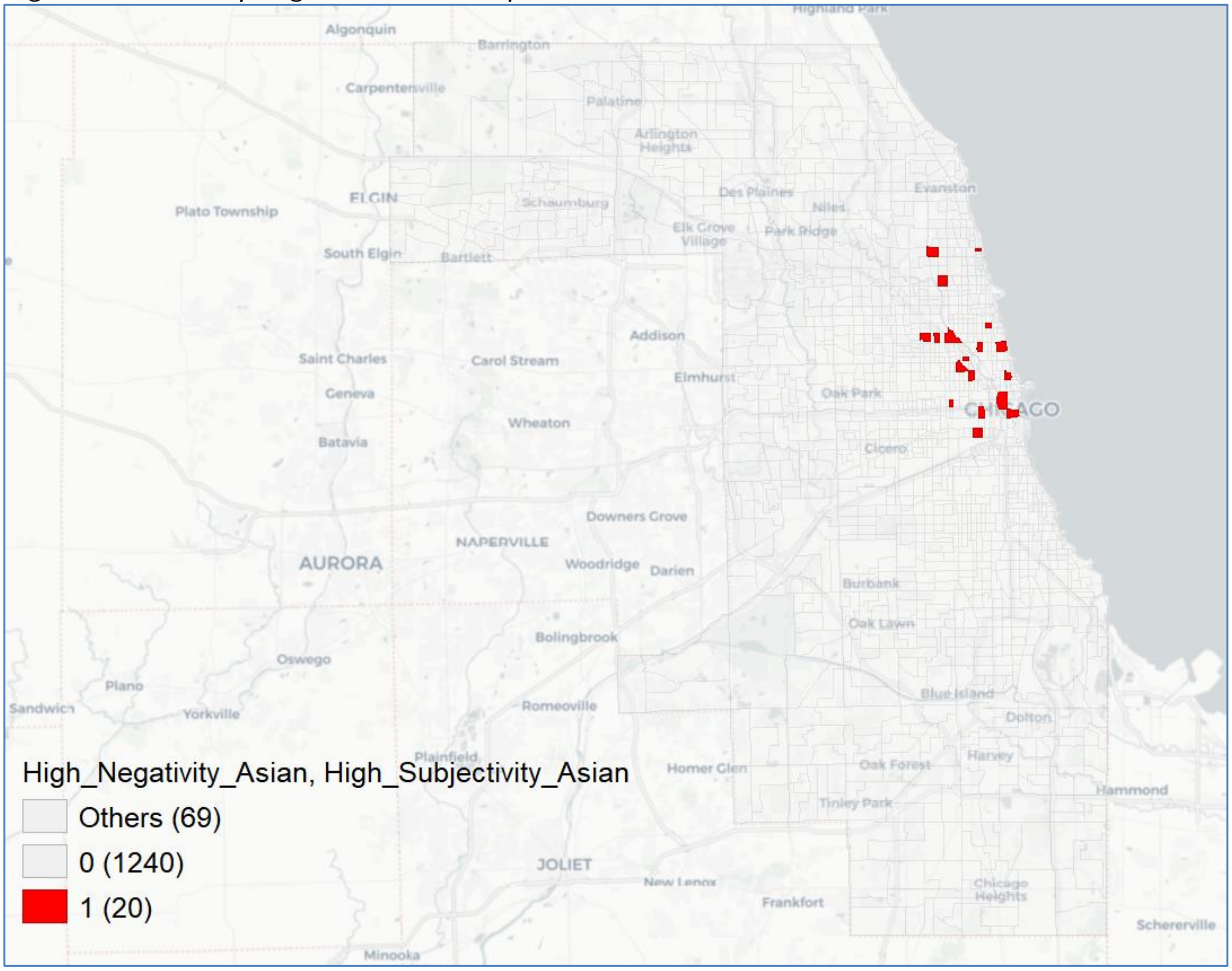


Figure 27. Areas of Negative Sentiment for Latin American Restaurants

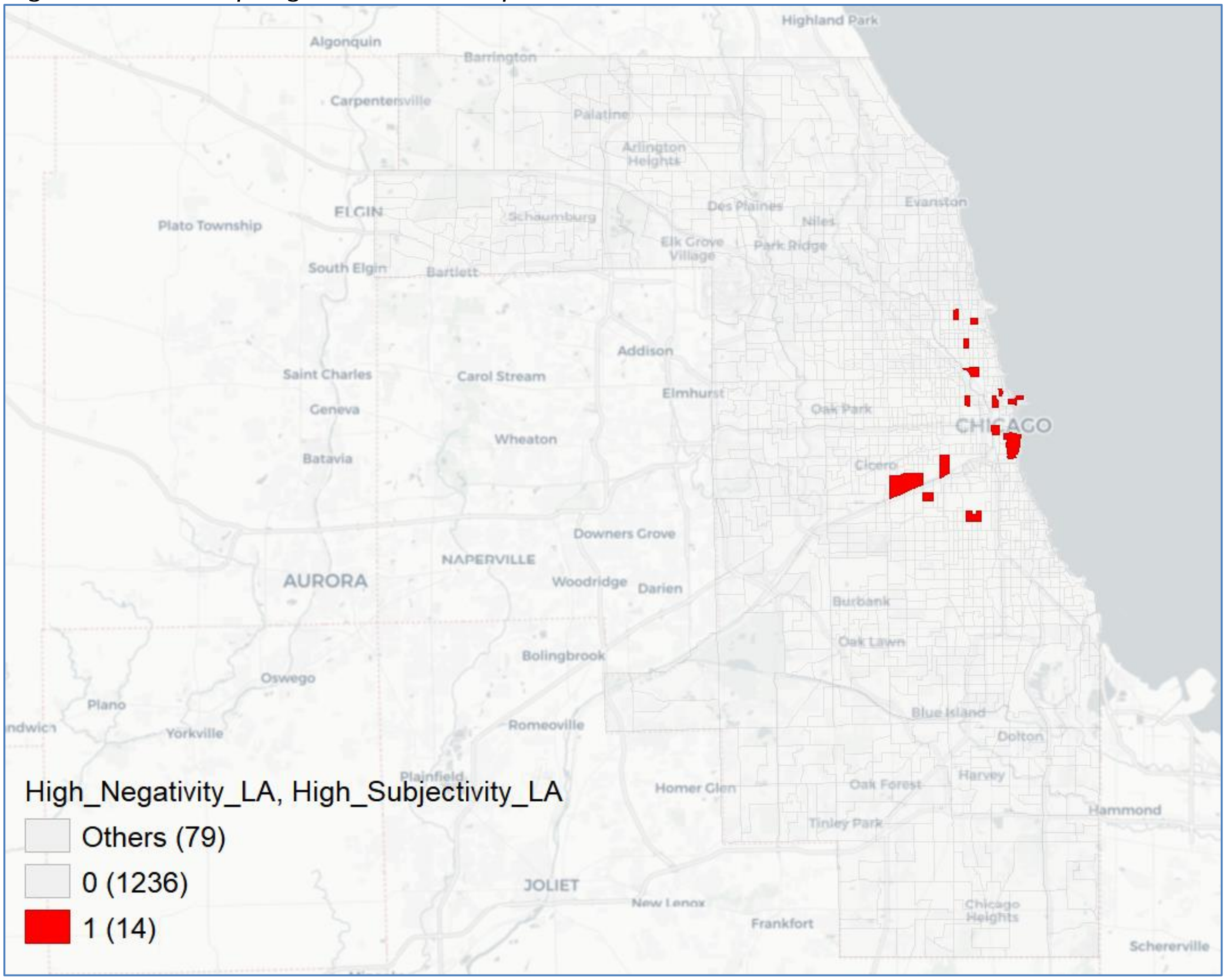
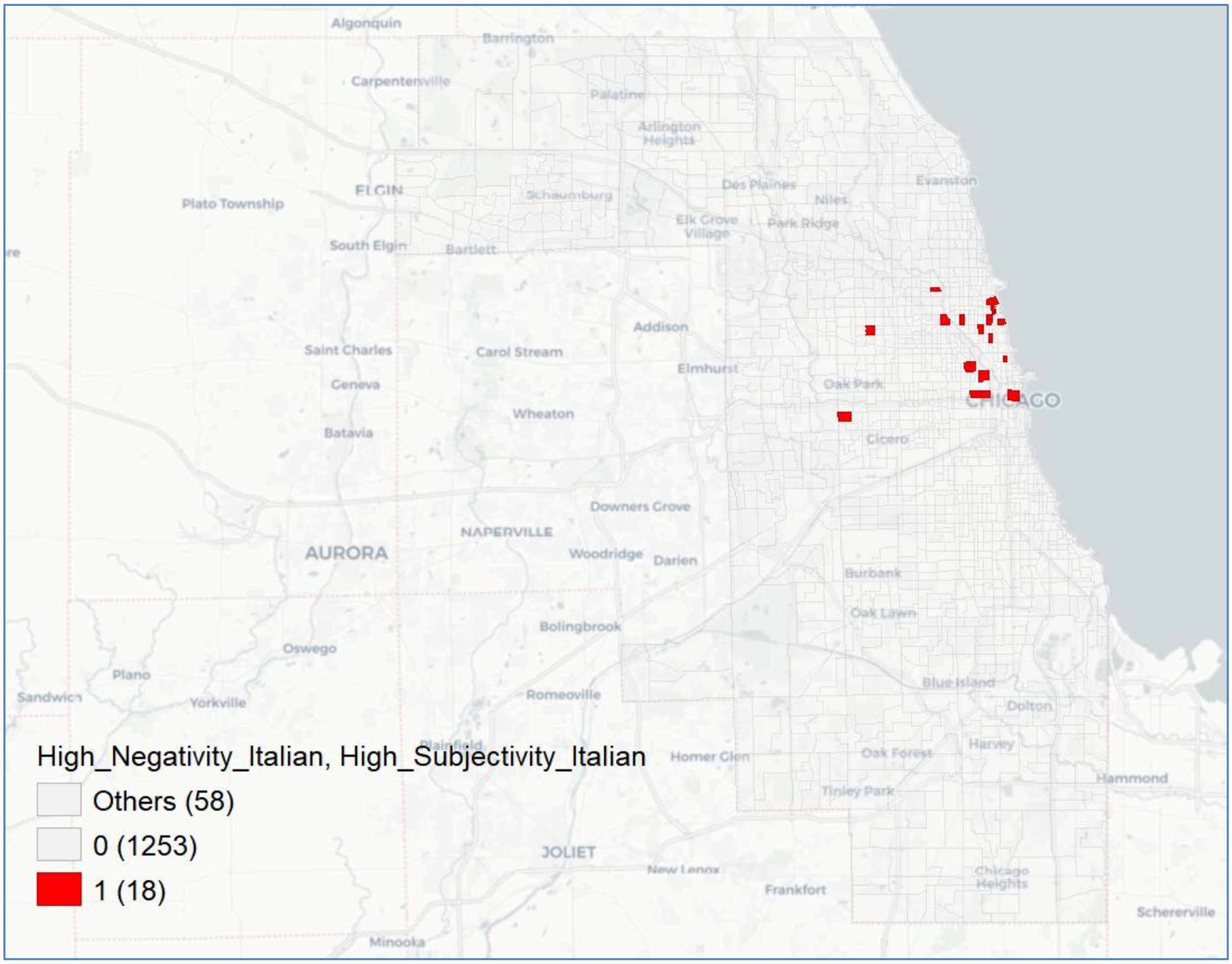


Figure 29. Areas of Negative Sentiment for Italian Restaurants



Colocation Summary Tables

Table 1. Colocation Summary Table for Asian Restaurants

Variable	Overall, N = 1,329[1]	Non-Colocated Tracts, N = 1,309[1]	Colocated Tracts, N = 20[1]	p-value[2]
Percent White	39 (7, 68)	38 (7, 67)	64 (49, 70)	0.007
Percent H.S. Graduate	21 (12, 28)	21 (13, 28)	6 (3, 11)	<0.001
Population Estimate	3,791 (2,523, 5,076)	3,783 (2,523, 5,076)	4,702 (2,656, 5,022)	0.5
Average Age	39.5 (36.2, 42.7)	39.5 (36.3, 42.8)	32.2 (30.8, 33.1)	<0.001
Median Income of State Native	33,784 (25,066, 46,066)	33,611 (25,025, 45,734)	52,479 (30,216, 61,817)	0.020
Percent Male	0.49 (0.46, 0.51)	0.49 (0.46, 0.51)	0.51 (0.47, 0.53)	0.14
Average First Dose	0.63 (0.00, 0.78)	0.63 (0.00, 0.78)	0.81 (0.78, 0.84)	<0.001

[1]Median (IQR)

[2]Wilcoxon rank sum test

Table 2. Colocation Summary Table for Latin American Restaurants

Variable	Overall, N = 1,329[1]	Non-Colocated Tracts, N = 1,315[1]	Colocated Tracts, N = 14[1]	p-value[2]
Percent White	39 (7, 68)	39 (7, 68)	57 (27, 77)	0.13
Percent H.S. Graduate	21 (12, 28)	21 (13, 28)	3 (2, 14)	0.001
Population Estimate	3,791 (2,523, 5,076)	3,783 (2,512, 5,076)	4,160 (3,612, 4,661)	0.3
Average Age	39.5 (36.2, 42.7)	39.5 (36.2, 42.8)	34.3 (31.7, 36.6)	<0.001
Median Income of State Native	33,784 (25,066, 46,066)	33,611 (25,040, 45,729)	59,984 (38,233, 67,977)	0.002
Percent Male	0.49 (0.46, 0.51)	0.49 (0.46, 0.51)	0.50 (0.48, 0.53)	0.074
Average First Dose	0.63 (0.00, 0.78)	0.63 (0.00, 0.78)	0.84 (0.79, 0.90)	<0.001

[1]Median (IQR)

[2]Wilcoxon rank sum test

Table 3. Colocation Summary Table for Italian Restaurants

Variable	Overall, N = 1,329[1]	Non-Colocated Tracts, N = 1,311[1]	Colocated Tracts, N = 18[1]	p-value[2]
Percent White	39 (7, 68)	38 (7, 67)	67 (57, 82)	<0.001
Percent H.S. Graduate	21 (12, 28)	21 (13, 28)	5 (3, 7)	<0.001
Population Estimate	3,791 (2,523, 5,076)	3,793 (2,514, 5,076)	3,299 (2,962, 4,574)	0.7
Average Age	39.5 (36.2, 42.7)	39.5 (36.2, 42.8)	33.8 (31.5, 35.3)	<0.001
Median Income of State Native	33,784 (25,066, 46,066)	33,446 (24,979, 45,602)	60,858 (52,182, 72,017)	<0.001
Percent Male	0.49 (0.46, 0.51)	0.49 (0.46, 0.51)	0.49 (0.44, 0.51)	0.9
Average First Dose	0.63 (0.00, 0.78)	0.63 (0.00, 0.78)	0.83 (0.81, 0.84)	<0.001

[1]Median (IQR)

[2]Wilcoxon rank sum test

APPENDIX 2: Spatial Regression

Correlation Matrix of Dependent Variables

Figure 30. Correlation Matrix for Overall Dependent Variables (Undifferentiated by Restaurants Type)

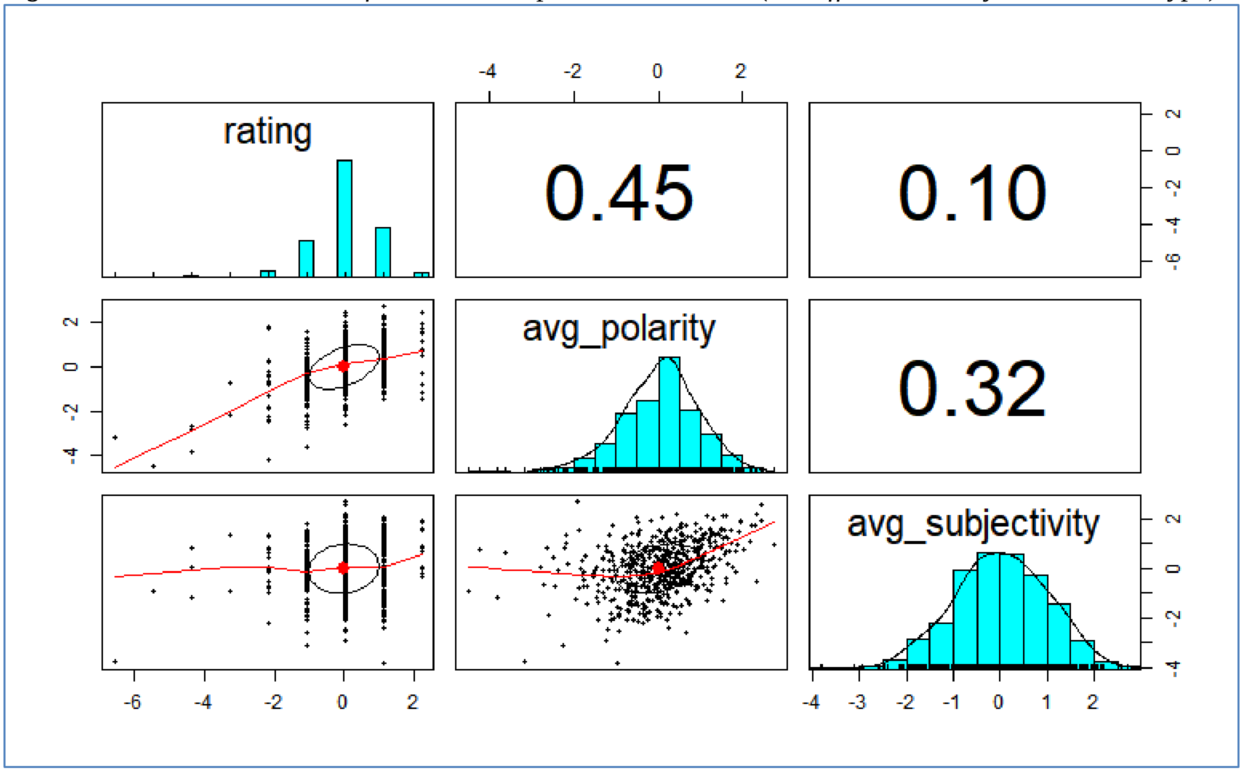
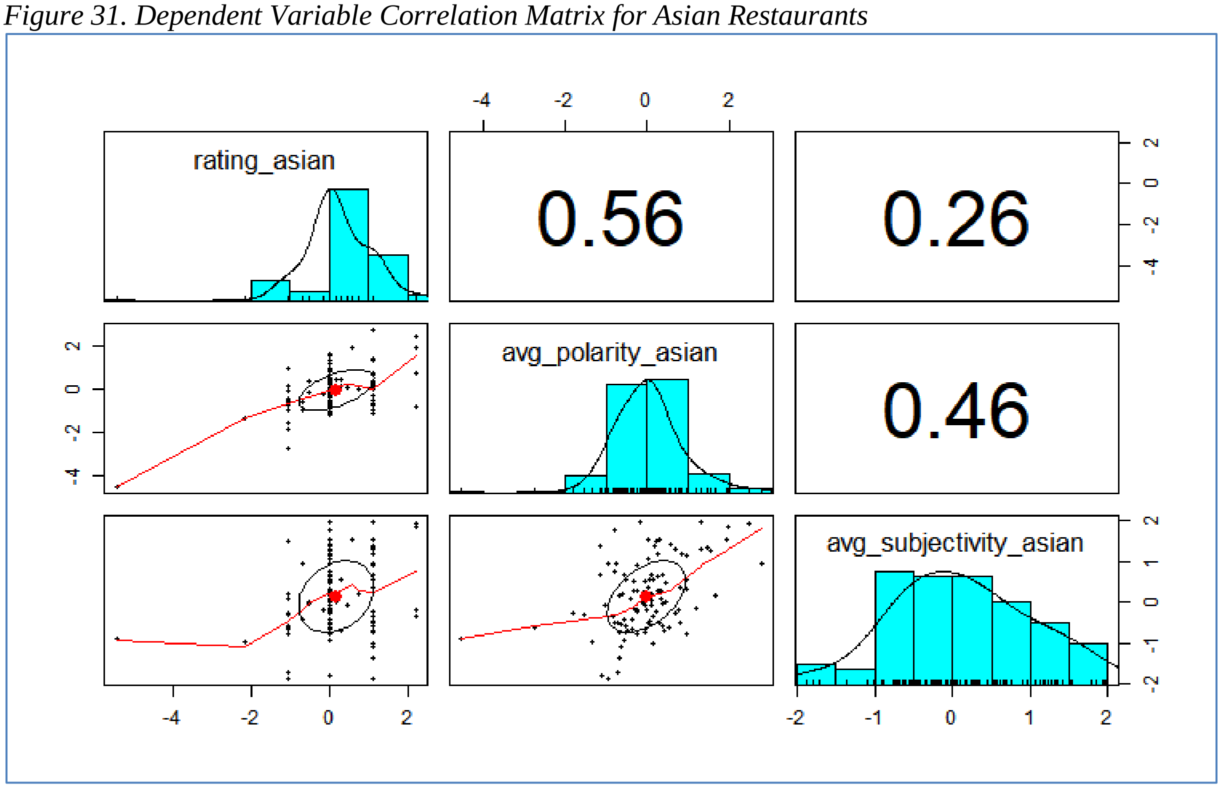


Figure 31. Dependent Variable Correlation Matrix for Asian Restaurants



Dependent Variable Correlation Matrix for Latin American Restaurants

Figure 32. Dependent Variable Correlation Matrix for Latin American Restaurants

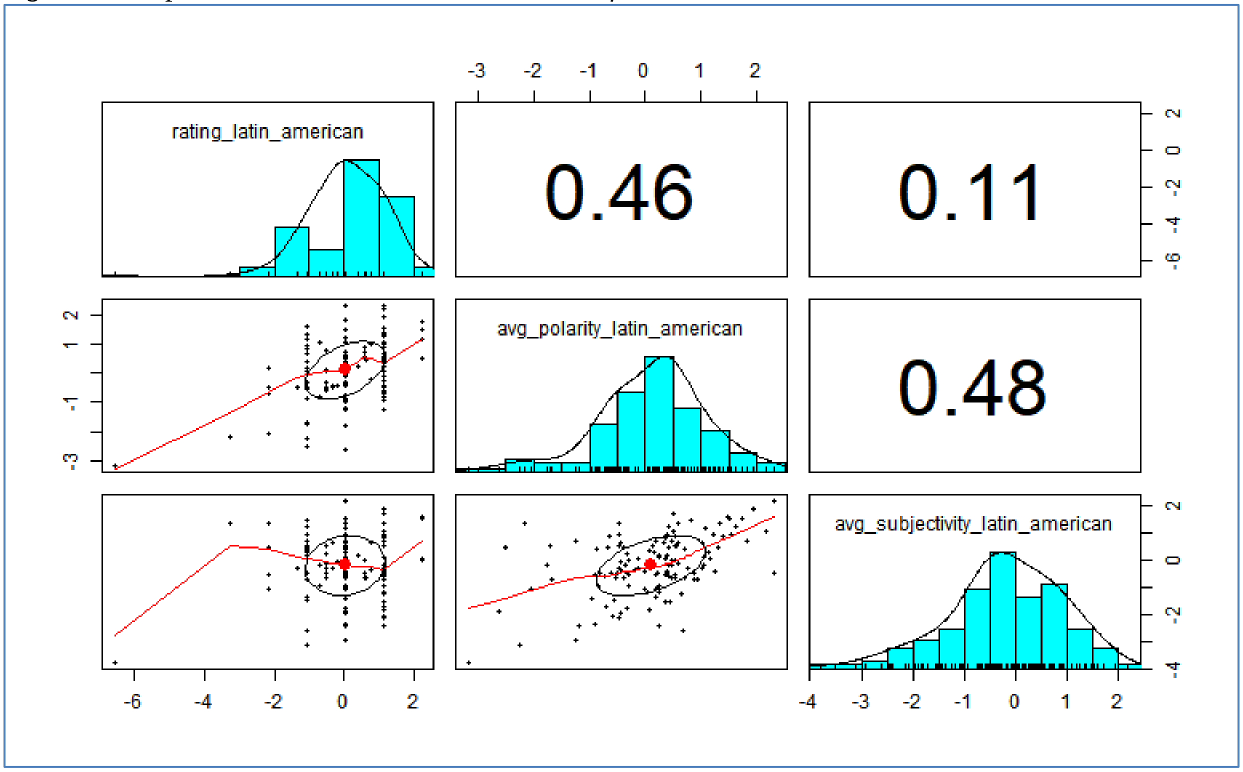
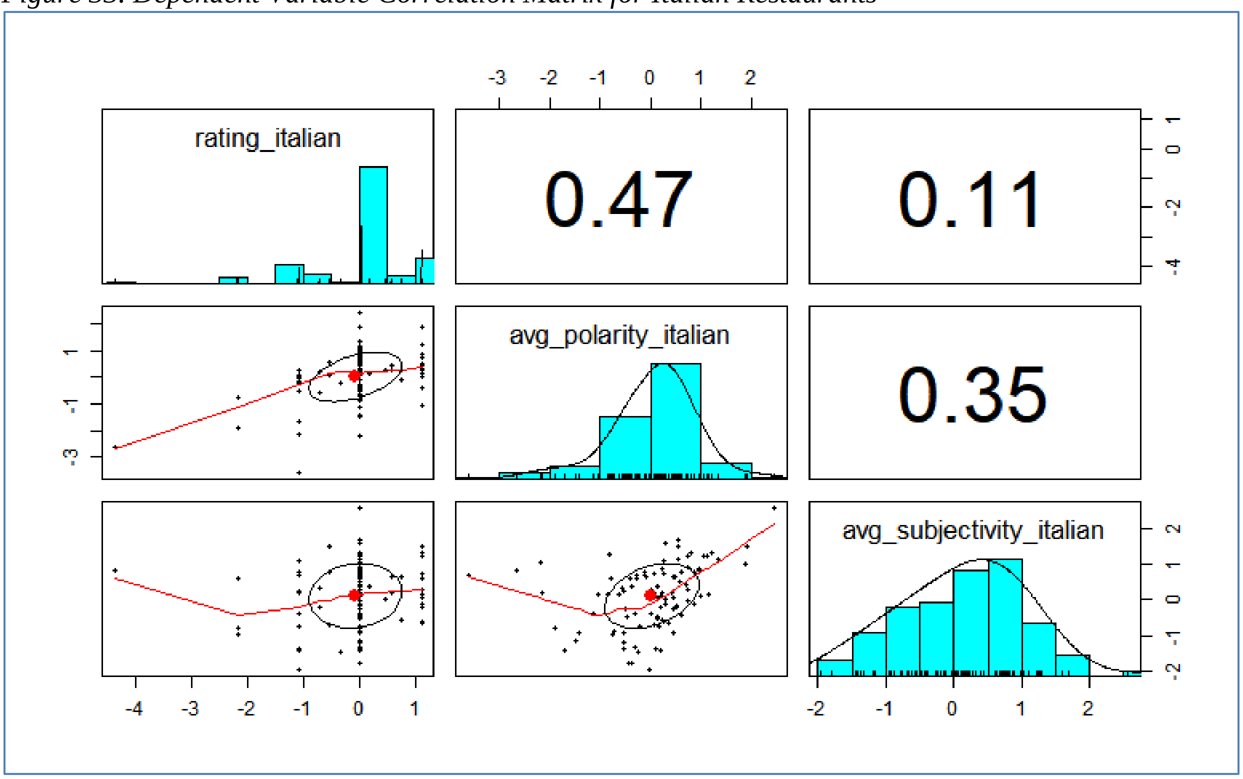


Figure 33. Dependent Variable Correlation Matrix for Italian Restaurants



Spatially Lagged- X Regression Tables for Each Cuisine

Table 4. Spatially Lagged-X Model for Asian Restaurants

	Dependent variable:		
Predictor Variable:	**Rating**	**Polarity**	**Subjectivity**
Percent White	-0.001 (0.009)	-0.006 (0.009)	-0.002 (0.009)
Percent H.S. Grad	-0.013 (0.024)	-0.052** (0.024)	-0.021 (0.023)
Average Age	0.042 (0.034)	0.033 (0.034)	-0.020 (0.033)
Log(Median Income of State Native)	-0.247 (0.325)	-0.148 (0.321)	-0.271 (0.312)
Percent Male	-1.474 (2.342)	3.295 (2.314)	1.226 (2.247)
Population Estimate	0.0001** (0.0001)	0.0001 (0.0001)	0.00003 (0.0001)
Percentage of First Dose recipients	0.760 (1.210)	0.579 (1.195)	-1.193 (1.161)
Lag Percent White	-0.002 (0.013)	0.010 (0.013)	-0.017 (0.013)
Lag Percent H.S. Grad	-0.042 (0.030)	-0.0005 (0.030)	-0.022 (0.029)
Lag Average Age	0.051 (0.051)	0.058 (0.051)	-0.021 (0.049)
Lag Log(Median Income of State Native)	-0.247	-0.166 (0.289)	0.224 (0.281)
Lag Percent Male	3.242 (3.421)	4.572 (3.380)	2.504 (3.283)
Lag Population Estimate	-0.0001 (0.0001)	0.00004 (0.0001)	-0.00001 (0.0001)
Lag Average First Dose	-3.021 (1.890)	-3.231* (1.867)	-1.225 (1.814)
Constant	0.445 (3.694)	-1.742 (3.649)	3.756 (3.545)
Observations	102	102	102
R^2	0.213	0.205	0.129
Adjusted R^2	0.086	0.077	-0.011
Residual Std. Error (df = 87)	0.936	0.925	0.898
F Statistic (df = 14; 87)	1.679*	1.600*	0.919
Note:	Signif. codes: 0 = '***' 0.001= '**' 0.01= '*' 0.05='.' 0.1= '' 0.1		

Table 5. Spatially Lagged-X Model for Latin American Restaurants

	Dependent variable:		
Predictor Variable:	**Rating**	**Polarity**	**Subjectivity**
Percent White	0.015 (0.010)	0.006 (0.009)	-0.004 (0.011)
Percent H.S. Grad	0.011 (0.021)	-0.007 (0.019)	-0.026 (0.023)
Average Age	0.090^{**} (0.039)	0.002 (0.035)	0.001 (0.042)
Log(Median Income of State Native)	-2.020^{***} (0.589)	-1.030^{*} (0.529)	-0.340 (0.643)
Percent Male	-1.435 (2.579)	-4.727^{**} (2.316)	-1.794 (2.815)
Population Estimate	-0.00003 (0.0001)	-0.0001 (0.0001)	-0.00000 (0.0001)
Percentage of First Dose recipients	-0.778 (1.716)	-1.693 (1.541)	-2.418 (1.873)
Lag Percent White	-0.021 (0.013)	0.001 (0.012)	0.009 (0.015)
Lag Percent H.S. Grad	-0.110^{***} (0.039)	-0.031 (0.035)	-0.021 (0.043)
Lag Average Age	0.080 (0.061)	0.057 (0.054)	0.027 (0.066)
Lag Log(Median Income of State Native)	0.071 (0.331)	-0.276 (0.298)	-0.183 (0.362)
Lag Percent Male	-2.762 (3.816)	-1.118 (3.428)	-2.765 (4.166)
Lag Population Estimate	0.00002 (0.0001)	0.0001 (0.0001)	0.00001 (0.0001)
Lag Average First Dose	1.357 (1.898)	2.121 (1.705)	2.281 (2.072)
Constant	18.380^{***} (6.462)	14.626^{**} (5.805)	7.128 (7.055)
Observations	118	118	118
R^2	0.257	0.127	0.087
Adjusted R^2	0.156	0.008	-0.037
Residual Std. Error (df = 103)	1.057	0.949	1.153
F Statistic (df = 14; 103)	2.544^{***}	1.070	0.703

Note: Signif. codes: 0 = '***' 0.001= '**' 0.01= '*' 0.05='.' 0.1= '' 0.1

Table 6. Spatially Lagged-X Model for Italian Restaurants

	Dependent variable:		
Predictor Variable:	**Rating**	**Polarity**	**Subjectivity**
Percent White	0.011 (0.008)	0.007 (0.009)	0.008 (0.008)
Percent H.S. Grad	-0.013 (0.026)	-0.004 (0.029)	0.009 (0.026)
Average Age	-0.029 (0.031)	-0.045 (0.034)	-0.051* (0.030)
Log(Median Income of State Native)	0.002 (0.358)	0.358 (0.403)	0.179 (0.353)
Percent Male	2.537 (1.912)	1.207 (2.153)	-1.759 (1.888)
Population Estimate	0.0001 (0.0001)	-0.00003 (0.0001)	0.0001 (0.0001)
Percentage of First Dose recipients	-0.607 (1.146)	-0.457 (1.290)	-0.621 (1.131)
Lag Percent White	-0.014 (0.014)	-0.005 (0.015)	-0.024* (0.013)
Lag Percent H.S. Grad	-0.015 (0.035)	-0.004 (0.040)	-0.101*** (0.035)
Lag Average Age	0.109*** (0.041)	0.115** (0.046)	0.034 (0.040)
Lag Log(Median Income of State Native)	-0.281 (0.251)	-0.347 (0.282)	0.185 (0.248)
Lag Percent Male	0.913 (2.699)	-3.611 (3.039)	0.161 (2.665)
Lag Population Estimate	0.00000 (0.0001)	0.00004 (0.0001)	0.00002 (0.0001)
Lag Average First Dose	-0.178 (1.498)	1.730 (1.687)	-1.462 (1.480)
Constant	-0.508 (3.757)	-2.445 (4.230)	0.516 (3.711)
Observations	88	88	88
R^2	0.179	0.157	0.253
Adjusted R^2	0.022	-0.005	0.110
Residual Std. Error (df = 73)	0.814	0.916	0.804
F Statistic (df = 14; 73)	1.139	0.971	1.766*

Note: Signif. codes: 0 = '***' 0.001= '**' 0.01= '*' 0.05='.' 0.1= '' 0.1