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Major "L": How the Chicago Transit Authority Gentrified its Elevated Trains

Analyzing the relationship between urban re-valorization and ridership change to inform equitable urban policy in Chicago

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Abstract

The City of Chicago has pursued a path of urban valorization based on advertising the city as a nexus of entertainment, leisure, and consumption made possible by its dense, walkable environment. This valorization was carried out in the context of an economically neoliberal approach that consisted of market-focused policy choices and general government non-interventionism except to support market-based approaches. These policies aggravated existing inequality in discriminated-against communities while advancing gentrification in others in the form of new, higher-income residents and the restructuring of neighborhoods around their preferences. Despite being one of the few areas where Chicago undertook direct government investment, the Chicago Transit Authority's "L" elevated train system's ridership changed in ways that mirror this gentrification-disinvestment pattern, with Chicago's more affluent/gentrifying North and and less-well off South Sides experiencing ridership increases and decreases disproportionate to their population changes. In the context of this data and the city government's own observation that Chicago's incentivizing of market-based development near "L" stations failed to produce development in disadvantaged neighborhoods, Chicago implicitly gentrified the "L" by leaving the development of the built environments surrounding stations up to the uneven distribution of the market. This market-first, hands-off approach on the part of the city government resulted in the "L"'s functioning as an amenity in certain neighborhoods and an

afterthought in others based on presence or absence of development in surrounding stations. My argument is supported by multiple linear regression analyses that identify significant, strong positive correlations between ridership and census-tract change in median income (as estimated by the US Census Bureau's American Community Survey Five Year Estimates) between 2010 (2006-2010) and 2019 (2015-2019) at the citywide level and on the North Side. I obtained these findings by comparing Chicago census tracts to their closest "L" station (excluding O'Hare Airport (Blue) and including Oak Park-Austin (Blue)). I also found significant, strong positive correlations between these variables when I analyzed only tracts ≤ 0.5 miles from their closest station. Although there is a positive relationship between population and ridership change at the citywide level and certain regional levels when broken down by line, I observe no relationship between them at the overall regional level. These results support my argument that the "L" essentially functioned like an amenity whose increased ridership paralleled increased income on the North Side even as ridership decreased on the South Side, where I observed a significant, weak negative correlation between median income and ridership for all tracts. Chicago is now fashioning a set of government-involved policies (in contrast to its prior neoliberal/purely market-focused approach to transit-oriented development) to address gentrification and inequality (including funding of development near neglected "L" stations). With this policy ongoing, it is relevant to understand the correlating characteristics of neighborhoods with "L" stations – particularly those outside of the Loop – that experienced the greatest increases and decreases in ridership. This data will ideally help drive long-term equitable development around the CTA that expands on current initiatives.

Introduction

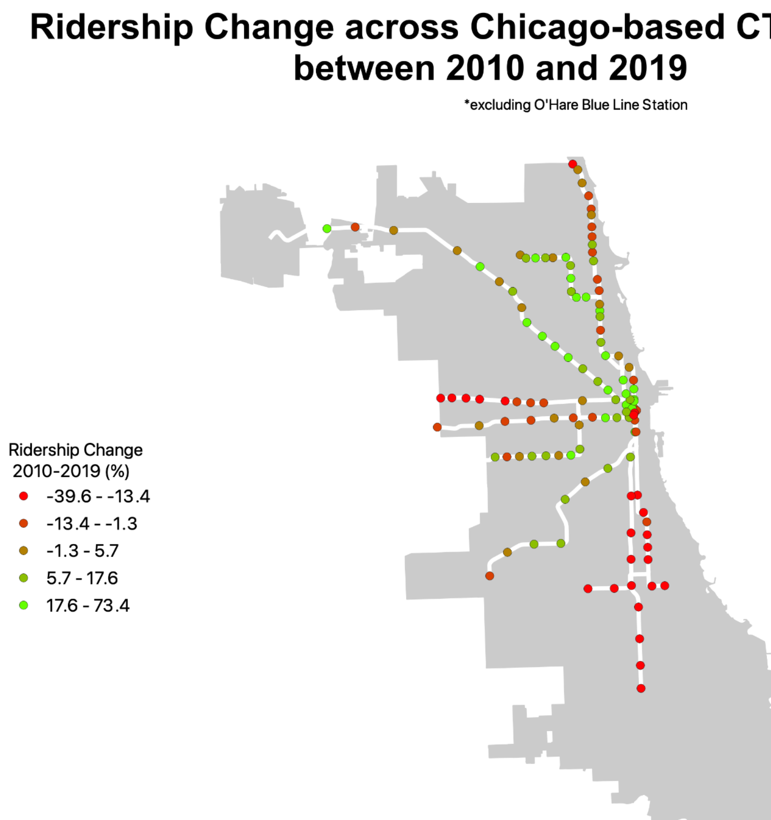


Figure 1: *Map of CTA ridership percentage change between 2010 and 2019 using Regional Transit Authority Mapping and Statistics and Chicago Data Portal data. Map by Micah Wilcox*

From 2010 to 2019, the Chicago Transit Authority saw dramatic increases and decreases in ridership on its North and South Side branches of the "L" elevated rail service. What made these changes noteworthy is that each were disproportionate to the population increases and decreases that took place in each region. According to the Chicago Data Portal, average weekday "L" ridership increased between 2010 and 2019, although ridership in 2019 was below that in 2014 and well below its peak in 2015. However, this decade-wide ridership change was distributed unequally, with stations on the South Side dramatically losing ridership as those on the North Side gained riders. While the North Side's population grew from 1,099,427 to 1,120,290, a change of 1.9%, its average weekday ridership grew from 4,148,526.5 to

4,452,077.75, a change of 7.32%. In contrast, the South Side's population declined from 771,538 to 722,173, a change of -6.34%. At the same time, its average weekday ridership dramatically declined from 1,347,932.58 to 1,077,232.92, a change of -20.08%. Excluding the Greater Loop, a combination of Chicago's downtown Loop, West and South Loop, and parts of its Streeterville and River North neighborhoods, the West Side's share of ridership remains static (18.99% in 2010 to 18.59% in 2019), reflecting its proportional population-ridership relationship of a population change of -1.65% and a ridership change of -1.98%). In contrast, the South Side's share of ridership shrinks from 19.75% to 15.77% as the North Side's grows from 60.8% to 65.16%. Note: all population numbers are from the American Community Survey's Five Year Estimates data. All geographic definitions can be found in the Mapping & Definitions section following the Introduction.

Each region's disproportionate ridership change relative to their population changes coincided with changes happening across the city at large. During this period, investment and high income residents came to the Greater Loop and North Side, while the South and West Sides experienced negligible investment or growth (McClellan 2019; McClellan 2021; Matthews and Ali, 2016; Husain et al., 2020; Koziarz 2020). Moreover, many communities across the North Side experienced physical and social gentrification resulting from rising rents and the catering of businesses and developers to the desires of higher-income newcomers (Anderson 2016, Institute for Housing Studies, n.d.). Despite being a public service that has received substantial public investment across the entire system for the past three decades, non-Greater Loop "L" ridership trends by 2019 reflected Chicago's broader socioeconomic inequality, with wealthy and gentrifying areas experiencing increasing ridership, and everywhere else, with few exceptions, showcasing decreases. The story told by ridership data alone is strengthened by a regression analysis of the American Community Survey (ACS) Five-Year Estimate data and CTA "L" ridership numbers by station between 2010 and 2019. Regression analysis identifies a significant positive correlation at the system-wide level and on the North Side between changes in ACS median income estimates at the census tract level and changes in ridership at each tract's closest station, relationships that hold even when excluding all tracts greater than 0.5 miles away from the station (the threshold for Chicago's Transit-Oriented Development zoning rules).

This data suggests that the presence of the "L" alone was not a determining factor in Chicago urban development in the early 21st century. More directly, it underscores the extent to which successful transportation systems rely on broader socioeconomic contexts to succeed. In principle, public transit systems like the "L" are useful in connecting points A and B. But such systems only provide utility to riders if what is at either (ideally both) is necessary, desirable, and accessible to the people connected to it. Moreover, the system is only truly usable if people can conveniently, comfortably, and safely access and use it. Although the CTA maintained and expanded a system that interconnected much of the city, the CTA and the City of Chicago left this utility and usability-determining context up to the same market forces upon which they relied to drive growth and address inequality. This simultaneous embrace of neoliberalism and urban commodification during the mayorships of Richard M. Daley (1989-2011) and Rahm Emmanuel (2011-2019, almost all of my study period), resulted in an unequal process of growth across Chicago, where some neighborhoods received considerable attention, new residents, and investment while others received nothing. Such growth also brought gentrification to those neighborhoods, resulting in a further bifurcation of economic benefits as market forces prioritized the needs and tastes of those with the most disposable income over other residents. Similarly, the contexts surrounding "L" stations were developed unequally – only in neighborhoods with outside interest (which have often had "L" stations) and, given the significant positive correlation between median income change and ridership growth, in ways that likely primarily served higher income newcomers.

This analysis refutes the notion that public transportation by rail is, in economic terms, solely an "inferior good" (Staley 2008) (a good that follows the negative relationship between income and ridership demonstrated on the South Side). The citywide positive correlation between median income and ridership, and particularly the North Side positive correlation between those variables, suggests that rail transit in Chicago can be interpreted as an amenity consumed by those with means. Moreover, the South Side's disproportionate ridership decline coupled with the North Side's disproportionate ridership increase (when compared to their population decrease and increase) demonstrates a second reality: that "L" ridership on the North and South Side was being structured by forces beyond population change. The only region with a significant positive relationship between median income change and ridership also saw the most stations experience ridership gain, while the only region with a significant negative relationship between median income change and ridership saw the most stations lose riders. These findings suggest that, like an amenity, the CTA "L" outside the Greater Loop was likely being "consumed" more by the city's wealthier residents. Such changes in the composition of the "L"'s users, when compared to the change in socioeconomic makeup happening in Chicago neighborhoods, could be called "gentrification" as defined by National Geographic (National Geographic, 2022).

Chicago "gentrified" the "L" by leaving the broader context of system utility and usability up to the market, which responded to the desires of those with capital. The result was that whole groups of stations located in historically neglected and disinvested areas of Chicago received little to no investment around them, while stations that did, such as those in Wicker Park and Logan Square, received investment that some argued was geared less towards existing residents and more towards the desires of new, higher income residents. The greatest exemplification of the unequal consequences of market-only policy was seen in the first six years of Chicago's market-incentivizing Transit-Oriented Development rules. Implemented in 2013 and expanded in 2015, these rules were found to have largely facilitated development only on the North Side between 2016 and 2019 (Mayor's Press Office 2022a). Their impact is potentially present in the significant positive correlation I identify between median income change and ridership change for tracts within 0.5 miles of their closest station on the North Side. As Chicago's geographically disparate and socioeconomically-linked changes in ridership demonstrate, merely having a station in a neighborhood or region did not result in ridership gain (much less one correlated with median income change) in the absence of broader, context-defining policy intended to correct for market oversights.

This conclusion is important because Chicago is in the midst of a multiyear turn away from the market-focused neoliberalism of the Daley-Emmanuel era to a new period of direct government involvement to combat inequality. This new reality is best manifested by two programs that Mayor Lori Lightfoot has supported: invest South/West and Equitable Transit-Oriented Development (ETOD), both of which invest substantial government funds into business and infrastructure development in neglected areas (City of Chicago 2022; City of Chicago, n.d.). Chicago's substantial investment in ETOD projects like the mixed-use Gateway 79 development near the 79th Street Red Line Station (Blumberg 2021) makes clear that policymakers see rapid transit as essential to equitable, environmentally sustainable urban growth. Chicago and the CTA will be best served by acting on the finding I advance that median income was correlated with ridership change for Chicago's North Side, a region that saw the most consistent increase in ridership across its stations on the Red, Blue, and Brown Lines. My takeaway from this finding is that investment in close-by infrastructure that serves residents (high income or otherwise) to increase their quality of life is the way that the CTA can increase ridership. This lesson is embodied in the spirit of current ETOD programs. All transit policies going forward should embody this finding to ensure that the CTA and other institutional transit stakeholders coordinate resources to better serve all residents, something that the "L" clearly failed to do by the end of 2019.

This paper will begin with a literature review discussing how ridership on the "L" is connected to movements of urban revitalization in the early 21st century that are primarily perpetuated by young professionals. It will also connect Chicago's market-focused approach to urban development before and during the study period with my argument about the selective reconfiguration of neighborhoods surrounding the non-Greater Loop "L," selective development to which I attribute the "L"'s gentrification. I will then review my data and methods that I use to create my multiple linear regression models (as well as my limitations) before moving into my data analysis and conclusion about my findings' importance. Note: although I include data analysis results for the Greater Loop, I do not focus on it in my essay. My focus is on the relationship between the "L" and the rest of the city of Chicago.

Maps & Definitions

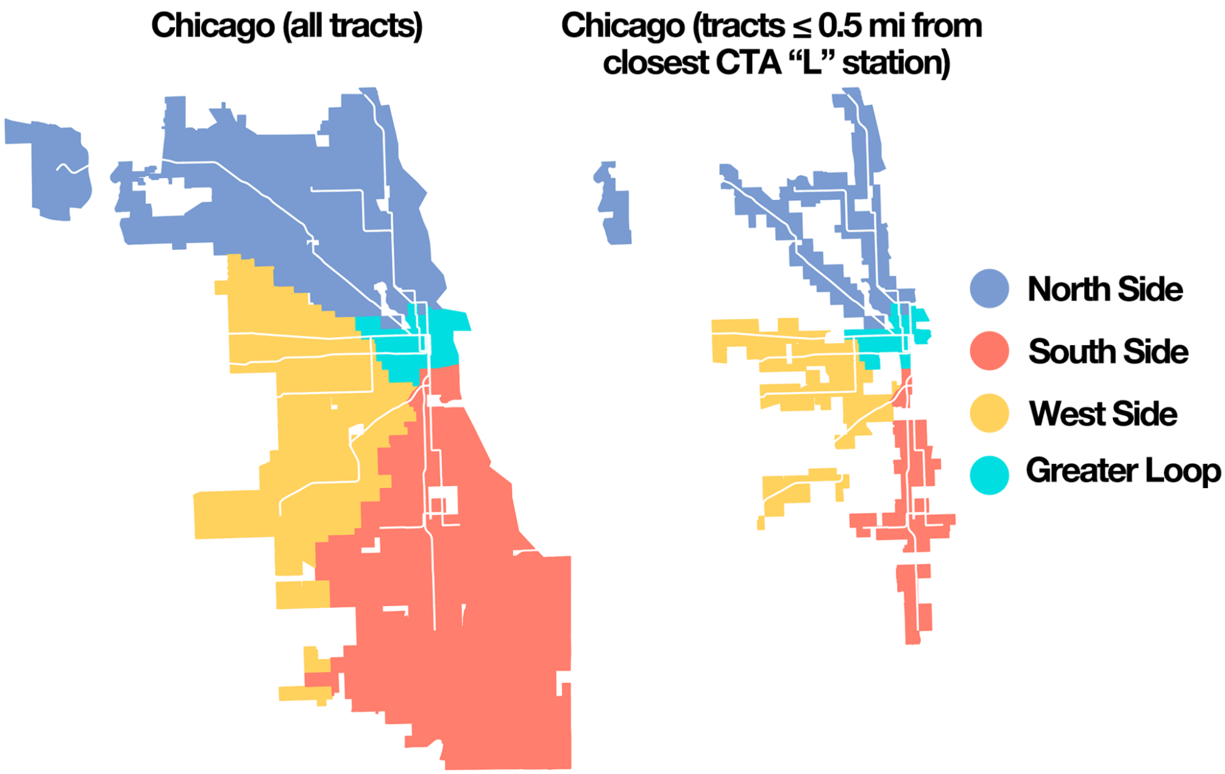


Figure 2: *Division of Chicago into regions used for analysis and reference. Shapefiles from the US Census Bureau and Chicago Data Portal. Map by Micah Wilcox*

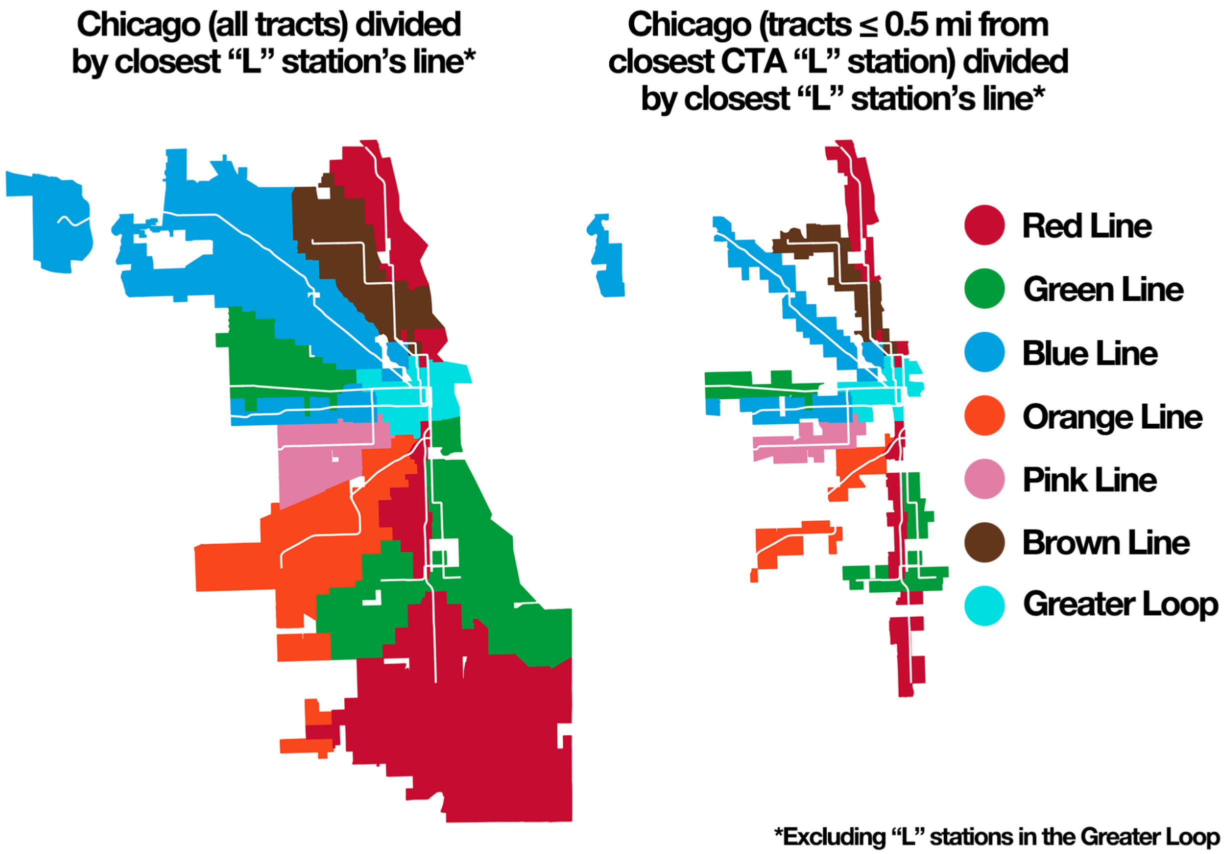


Figure 3: *Division of Chicago into subregions categorized by their closest "L" station's line used for analysis and reference. Shapefiles from the US Census Bureau and Chicago Data Portal. Map by Micah Wilcox*

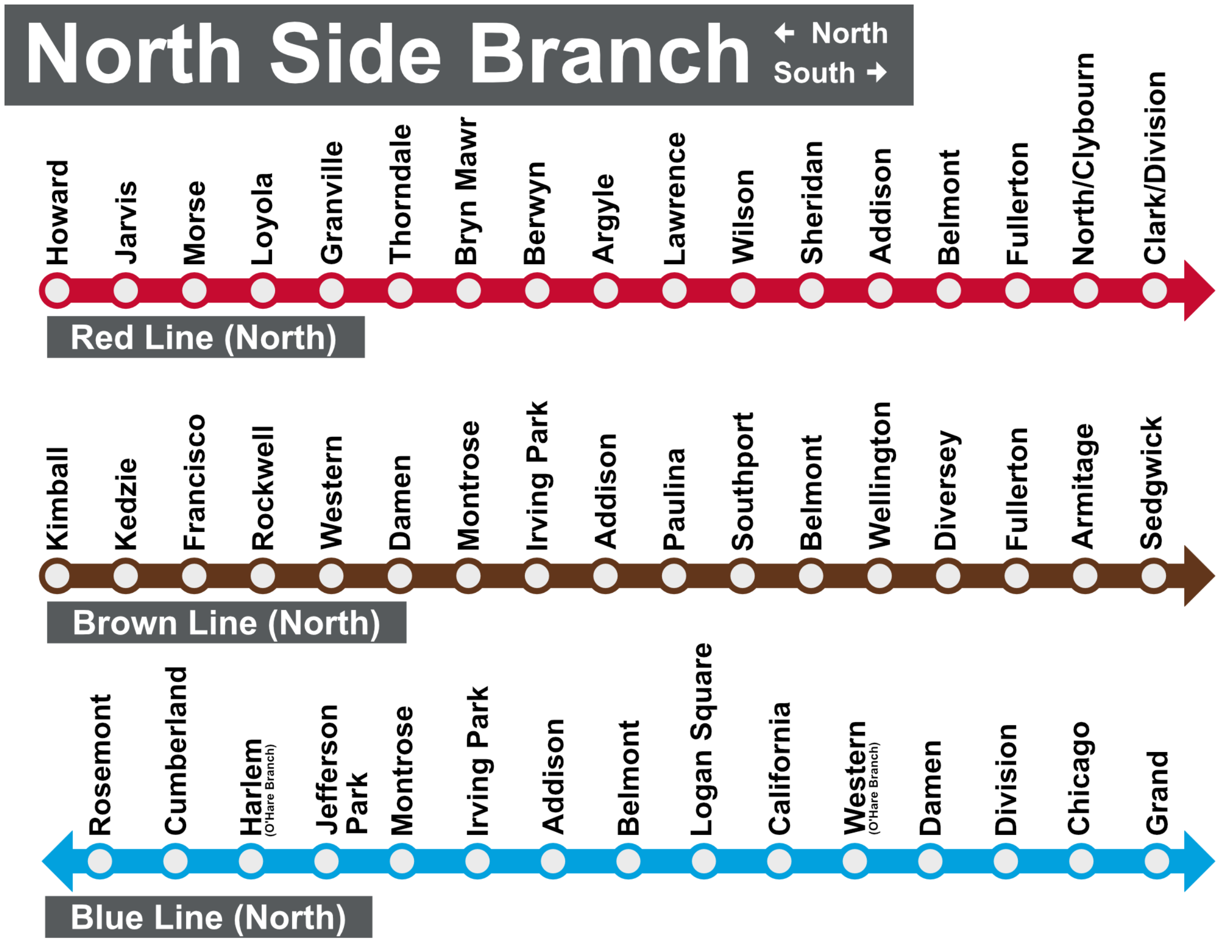


Figure 4: *CTA "L" Stations included in my North Side Branch. Design by Micah Wilcox*

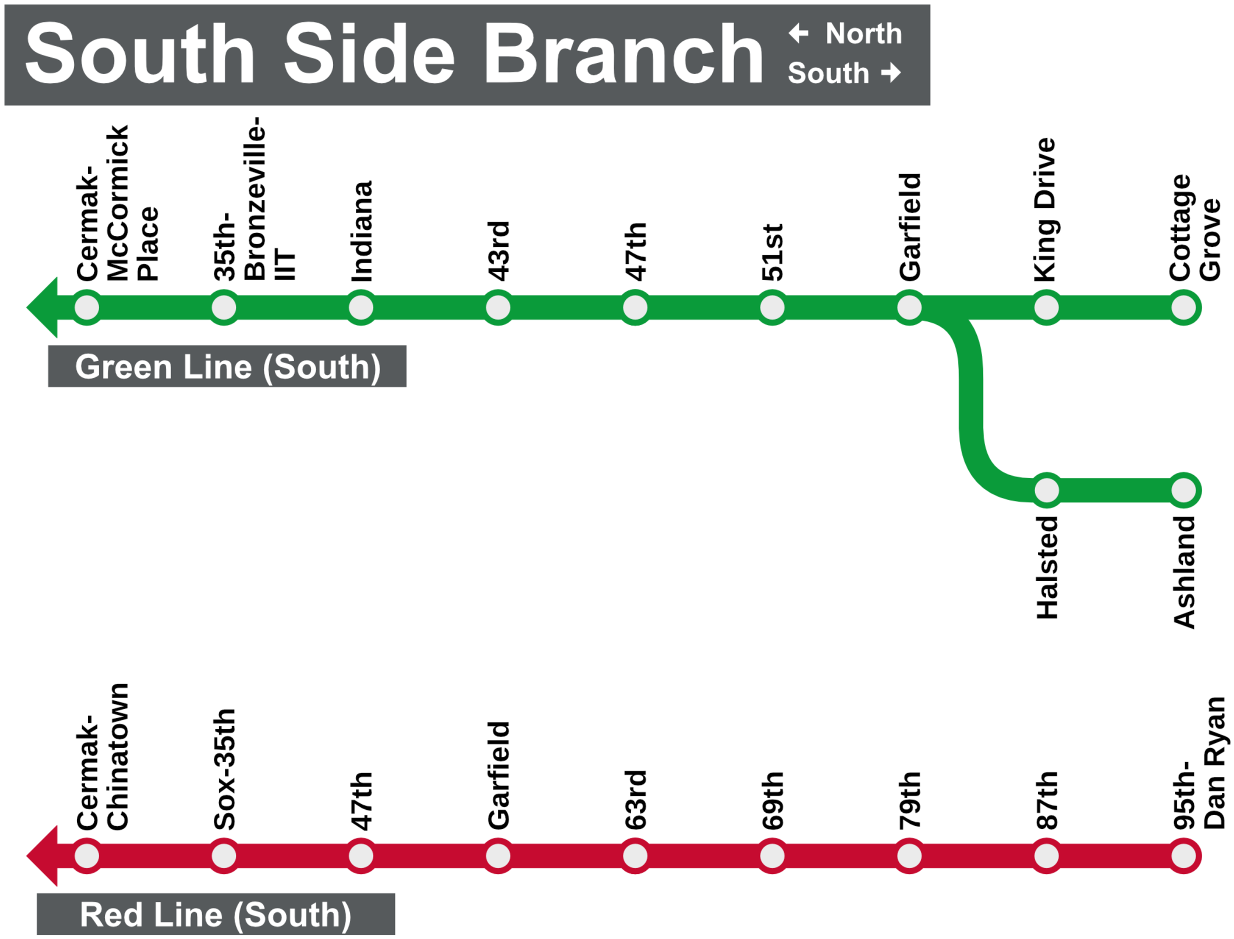


Figure 5: *CTA "L" Stations included in my South Side Branch. Design by Micah Wilcox*

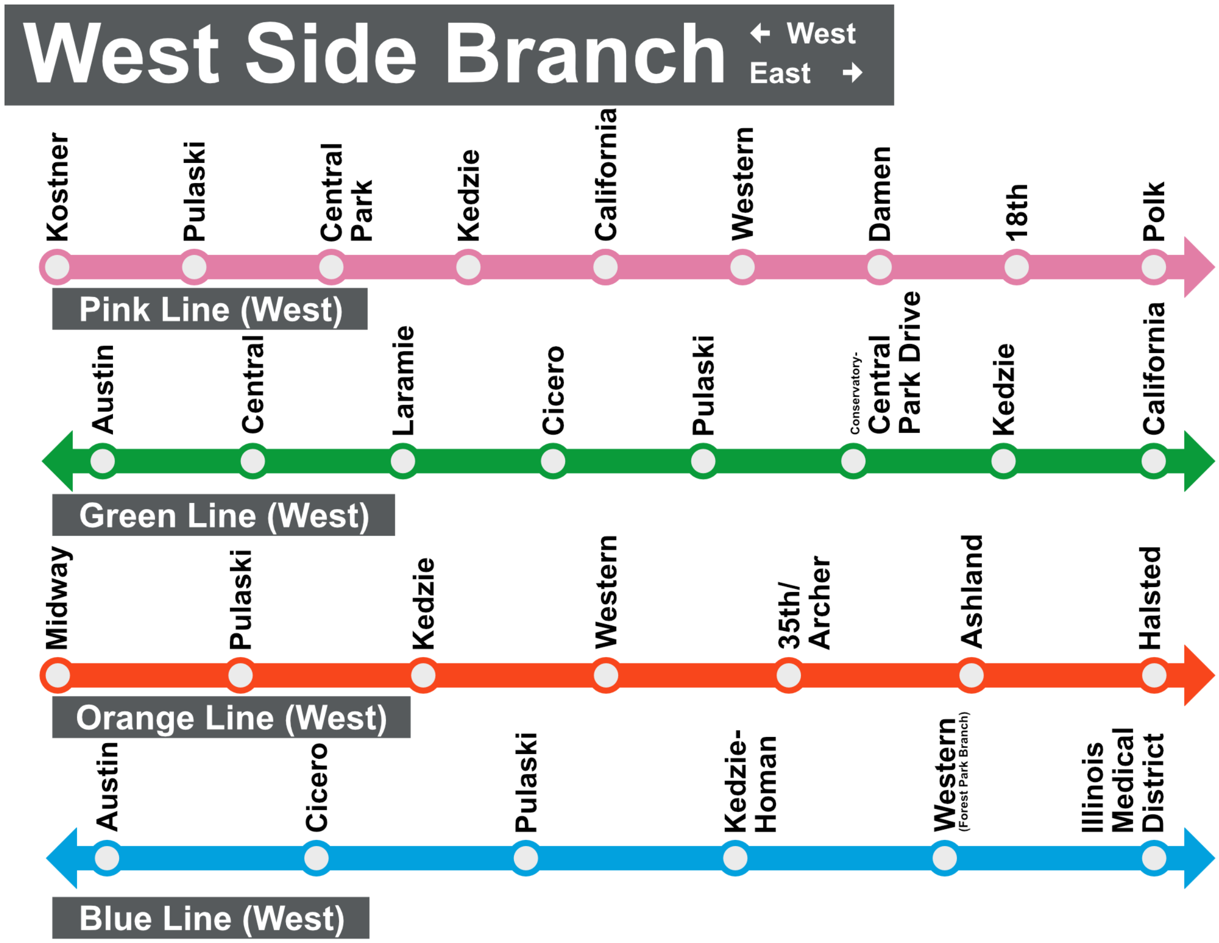


Figure 6: *CTA "L" Stations included in my West Side Branch. In addition to O'Hare Airport (Blue), any station excluded from these three figures are either outside the City of Chicago or within the "Greater Loop." Design by Micah Wilcox*

Literature Review

The broader story of Chicago's urban development and how it interacts with the "L" outside of the Greater Loop between 2010 and 2019 can best be explained by understanding the sociopolitical trends of neoliberalism and gentrification, the process of new urban growth, and the psychology behind support for rail transit systems across the American urban landscape. Each phenomenon has helped shape the current, different built and socioeconomic environments surrounding "L" stations, which in turn have influenced ridership. This literature review will discuss how neoliberalism and gentrification impacted urban governance and development and how all of the above relate to the late twentieth-century and early twenty-first century growth trends in certain urban areas based on desire for different, “urban” amenities. None of the literature I reviewed compares transit ridership and urban development trends over time in the way I do. However, all the literature reviewed here provides necessary context as to how “L” ridership trends relate to urban development trends across different parts of Chicago.

Neoliberalism and gentrification are distinct but intertwined movements in American cities. The former is the elevation of markets in place of direct government intervention to provide services, construct infrastructure, and achieve policy goals from increasing access to education to providing affordable housing (Hague, Lorr, and Sternberg 2017, 15-26). The latter is the valorization (even the commodification) of urban areas’ built form, proximity to diverse goods and services (read: density), and culture/identity in a way that leads to an increase in the number of new residents, particularly high-earning residents, as well as a reconfiguration of area infrastructure to more directly serve these new residents’ needs and desires (Smith 1996, 3-29, 50-74). As gentrification is partially a market-based phenomenon due to its direct ties to economic forces regarding land value, construction, business viability, etc., neoliberalism can be interpreted as setting the stage for gentrification. Although this argument is nuanced by the role government zoning restrictions play on housing supply, this issue will not be discussed in this thesis.

This relationship should be considered in the context of rent-gap theory. As explained by urban theorist Neil Smith (in his 1996 book *The New Urban Frontier*), “Capital flows where the rate of return is highest, and the movement of capital to the suburbs along with the continual devalorization of inner-city capital, eventually produces the rent gap” (Smith 1996, 70).

Gentrification occurs when rents in "devalorized" urban areas are low enough that redevelopment can produce favorable rates of returns for developers. Although Smith argues that the "back-to-the-city" movement was a capital-induced movement, urban policy theorist Terry Clark argues in *The City as an Entertainment Machine* (2011) that such urban growth is a product of individual preferences for the urban environment and amenities within that environment.

Clark argues that urban changes are a reflection of the rise of consumption as a key organizer of city economies and environments. In particular, he sees this rise of consumption as a result of the power awarded to [middle class and wealthy] individuals to act on their desires and tastes by the global economy's then-new ability to respond to an ever-expanding range of tastes. (Clark 2011, 212-218, 222). Most important among these tastes is the desire to live in urban environments. Key to this argument is Clark's analysis of globalization and the internet as forces freeing employers and employees to locate based on taste rather than more business-related concerns, which is what Clark sees as facilitating the rise of different cities with different amenities, from nature to built amenities (Clark 2011, 125).

Clark, along with Lloyd, Wong, and Jain, describes new urban residents as such: "a residential population of young professionals with more education and fewer children [that] creates a social profile geared toward recreation and consumption concerns. They value the city over other forms of settlement space because of its responsiveness to a wide array of aesthetic concerns, because it can become a cultural center offering diverse, sophisticated and cosmopolitan entertainment lacking elsewhere" (Clark, Lloyd, Wong, and Jain 2011, 218). Breaking this statement down, multiple tastes drive urban growth. Richard Florida and Gary Gates, in their essay in *The City as an Entertainment Machine,* discuss tolerance – particularly in the context of suburban homogeneity and exclusion (National Low Income Housing Coalition, 2021), cities can be seen as places of diversity and tolerance (Florida and Gates 2011, 157-158, 171-172). Equally salient are arguments associated with New Urbanism, the movement to increase urban walkability and density for reasons ranging from increasing social connection and public health to undoing the exclusion of the suburbs (Wieckowski 2010). Similarly related is Edward Glaeser, Jed Kolko, and Albert Saiz's argument (also in *The City as an Entertainment Machine)* that traditional, walkable cities have the ability to concentrate goods, services, events, and other amenities in distances easily accessible without cars due to walkability and public transit – in short, the ability to respond to different consumption tastes (alongside the general aesthetic preference for cities themselves) (Glaeser, Kolko, and Saiz 2011, 136).

This thesis does not attempt to answer qualitative questions relating to what motivated people to move to cities in the 21st century, nor does it attempt to answer Smith and Clark's "chicken and egg" problem regarding which came first, capital investment in underinvested cities or consumer demand. What is relevant to this thesis is that both forces occurred concurrently. Reviewing a paper by Lee, Lee, and Shubho for *Journal of Regional Science* in *Bloomberg Citylab,* the urban sociologist Richard Florida writes in 2019, "over the three decades, each passing cohort of young adults became progressively more urban" (Florida 2019). Businesses and corporations alike followed these young adults back to the cities. Wieckowski begins her article in the *Harvard Business Review* by discussing United Airlines's decision to move their headquarters from the Chicagoland suburbs to downtown Chicago (Wieckowski 2010). Target has prioritized opening smaller-footprint stores in dense urban neighborhoods like Logan Square and Hyde Park (PYMNTS 2015, 2021). Writing in 2017 for *REJournals*, Aaron Lanski, the then-managing director of the Chicago office of BMO Harris Bank, noted that "since

2011… the annual growth rate of cities has surpassed the suburbs, according to U.S. Census Bureau data" (Lanski 2017).

More importantly for this thesis, a third force sought to benefit from and catalyze both movements: urban governments. Their actions revolve around what Clark calls Amenity Theory, wherein amenities attract human capital (particularly those skilled, mobile "[citizen]/consumer[s]" (Clark 2011, 214)) that in turn catalyzes economic growth. Urban governments in the United States have followed this theory, investing in large and small amenities to make their cities appealing to workers and companies (Clark 105-106, 110-111), with the hope of spurring a virtuous cycle where growth would beget more amenities coming to take advantage of a thriving economy with high-income spenders seeking consumption experiences. As Clark writes, "Edward Glaeser (2000b), Harvard urban economist, even suggests that 'non-market transactions,' especially amenities, have grown even more important than market transactions in explaining urban growth and decline" (Clark 2011, 213). Glaeser, writing with Kolko and Saiz, writes that urban population growth (which they write has grown "fastest in high amenity-areas" (Glaeser, Kolko, and Saiz 138)) is tied to consumer tastes for different amenities.

Among these amenities being constructed by governments is light rail transit. Portland, Denver, Seattle, Phoenix, and Los Angeles constructed light rail systems in the period spanning the late 20th century to the present. Although part of the benefit of rail transit is in its transportation ability (Glaeser, Kolko, and Saiz 136-137), in the context of growth and, particularly, in the context of gentrification, it is crucial to understand rail's significance beyond connecting different neighborhoods. Assessing rail expansion in Los Angeles in *Transport of Delight* (2005), transportation expert Jonathan Richmond talks of technology's ability to represent “a particular style of life” (Richmond 2005, 309). In particular, he talks of people’s observations of trains as “[thrilling]” and “[elegant]:” “Their symbolic power, extending far beyond any functionality as providers of transportation, derives from a rich context of experiences, memories, and historical associations,” to which Richmond adds that trains fulfill desire for pleasure (Richmond 2005, 343). Surveying public officials across Portland, San Jose, and San Diego, Richmond finds they argue that rail is perceived in their communities as representing the “good life” and broader city aspirations for themselves; one official compares them to Washington D.C.’s monuments, while another described Portland’s MAX system as essentially a kind of ride, drawing visitors to Portland to experience it (Richmond 2005, 339, 344). In short, Richmond identifies transit as a true amenity, something to be consumed for pleasure even if the system lacks inherent transit value (Richmond 2005, 8).

Even as cities pursued such consumption-centric growth strategies, it was observed from the start that this growth was “structurally uneven” (Clark 2011, 213); the rise in what Clark calls the “[citizen]/consumer” (Clark 2011, 214) as well as their role in urban growth has been marked by a duality with poverty. This power to consume, as its name implies, is awarded only to those with wealth or the ability to earn wealth based on their education/skills. Inner-city residents in particular were shut out from the consumption world by virtue of being shut out from wealth acquisition; Smith and Clark both talk about the proximity of poverty to new wealth in urban growth (Clark 2011, 217; Smith 1996, 3-29). Gentrification is directly related to this point. The growth system Clark and Smith describe functions in part on urban development/redevelopment to meet the tastes of new residents. Although “amenity” as a concept includes concepts like safety and education that do relate to the needs of lower income residents (Clark 2011, 102), the market-directed growth most American cities experienced was oriented around profitable endeavors – endeavors that focused on the needs and consumption habits of new, high-income residents (NCRC 2019).

Cities dealing with gentrification experienced affordability crises and conflicts over displacement both physically by high rents and culturally by neighborhood reconfiguration to serve new, higher-income (many times White) residents in neighborhoods that had been historically populated largely by communities of color (Hyra 2008; Hyra 2014; USC 2018; NCRC 2019; Demsas 2021). Portland offers an example of this phenomenon in North/Northeast Portland, where conflicts over gentrification played out under the shadow of urban renewal that had displaced many members of the historically Black neighborhood decades before (Portland Housing Bureau, n.d.).

All these themes were present in Chicago from 2010 to 2019. Chicago was the center of what Clark calls the New Political Culture movement (Clark 2011, 219-236) that began focusing urban governance on urban re-valorization through amenity development and the commodification of the city to attract human capital under Richard M. Daley, mayor from 1989 to 2011. This trend continued through the 2010s during Rahm Emmanuel's mayorship, among other ways in the form of policies such as the TOD ordinances (LaTrace 2014; Greenfield 2016; Metropolitan Planning Council 2022) and the construction of the 606 elevated trail (Trotter 2015; Hague, Lorr, and Sternberg 2017, 15-26). As Clark notes, in 2000, the city's biggest economic industry was entertainment (Clark 2011, 221). Consumption in Chicago spans large public projects such as Millennium Park, done explicitly to better residential quality of life while also, in the words of Richard M. Daley, to "[attract]" new residents over the past two decades (Bennett 2010; 6-7, Chapter 3) to private amenities like thrift stores in Wicker Park. Moreover, Chicago is a city that has been shaped by its continued investment in public transportation. The "L" is among the oldest rail transit systems in the world (Civitatis 2021), and it has received consistent public investment. Prior to the study period, the CTA reorganized the L's naming system to the current colors system and created the Orange Line, Chicago's southwest-area elevated line that went to Midway Airport. Opened in 1993 alongside the color branding rollout, was the first CTA rail line to be placed in the Southwest Side. Station closings on the Green Line were paired with a 1996 modernization of existing stations; a branch of the Blue Line system was refashioned into the Pink Line in 2006, while new stations were opened in the newly residential Morgan neighborhood on the West Side and at McCormick place in 2015 ("The CTA Reinvents Itself," CTA 2016, CTA 2018, and CTA (n.d.). Neighborhoods served by the "L" have been among some of Chicago's most desirable as measured by market demand. These neighborhoods include Wicker Park (served by elevated "L" stations on the Blue Line) Lincoln Park/Old Town/Near North (Red and Brown Lines), and West Loop (Green/Pink, including Morgan) (Bungalow 2022). However, the "L" is also prominently located in neighborhoods that have not seen investment or growth in consumption amenities (such as those aforementioned neighborhoods) and have even seen population decline, such as Chatham (CMAP 2022c). These stations are primarily concentrated on the South Side branches of the Green and Red Lines.

Chicago's changes in the past few decades also exemplify the uneven nature of market-driven growth and its limits in terms of benefiting all residents. For more than 20 years, Chicago lost population (Malagón, Boyle, and Hinton 2021). In addition, Chicago's proportion of high earners making more than $150K jumped between the 2008-2012 ACS estimate and the 2015-2019 ACS estimate (CMAP 2022b), while those making <$25K declined. Notably, Chicago's Black population declined 9.7% between 2010 and 2020 (Malagón, Boyle, and Hinton 2021), with the Metropolitan Planning Council saying that "low-wage and low-skill workers

[are] among the most likely to leave Cook County, outnumbering new arrivals by a ratio of about 2 to 1" (Lee 2022).

As mentioned, having an "L" station offered no guarantee that the neighborhood would experience growth, much less equitable growth. "L"-served neighborhoods like Wicker Park, Lincoln Park, and other parts of the North Side have been centers of ongoing gentrification and controversy (Anderson 2016; Betancur 2011; McClelland 2019). By 2019, the TOD ordinances enacted in 2013 and 2015 were seen as having failed to bring equitable investment to all station areas (Day 2021) and were seen by some as accelerating gentrification in Logan Square (Greenfield 2016). Logan Square in particular exemplified concerns regarding gentrification in going from majority Hispanic to majority White while also going from a neighborhood where the largest income bracket in the ACS 2008-2012 estimate was $25-49,999 to a neighborhood where the largest income bracket in the ACS 2015-2019 estimate was >$150K (CMAP 2022a). When one compares the history of gentrification and neoliberal policies in Chicago in the 21st century to CTA ridership trends, it makes sense to argue that leaving the system's utility and usability context to the private market resulted in its effective gentrification into a system most accessible and useful for high-income newcomers. In this way, neoliberalism, new urban growth, support for transit, and gentrification all were manifested in Chicago through specific government policy and market choices as well as the resulting changes to Chicago's population, built environment, and "L" utilization by station.

Data and Methods

Overview of Methods

I argue that the City of Chicago effectively gentrified the CTA "L" by leaving development in the neighborhoods where stations are located almost entirely up to private developers, who responded to market demand for certain neighborhoods rather than a need for social equity. To assess this hypothesis, I compare the change in ridership at each CTA "L" station between 2010 and 2019 to changes between those years for three census tract-level variables: population; median income; and median age. I predicted that stations with increased ridership over time would experience significant positive correlations with median income and negative correlations with median age. Although I expected some stations to have significant correlations between population change and ridership change, I was not sure if this trend would hold because I expect there are tracts where population growth has been slow or negative, but use of the "L" among those residents has still increased. I expected to see these results hold less as distance from CTA "L" stations increases and transit-oriented development (by definition, development near transportation stations) opportunities recede. For that reason, I conducted regression analysis for all Chicago census tracts (where ridership change for each tract corresponded to that of the closest "L" station) and tracts that were ≤ 0.5 miles from their closest "L" station.

Data Selection and Acquisition

I acquired my map of CTA "L" stations from the City of Chicago Data Portal (City of Chicago 2011) and my ridership data from the Regional Transportation Authority Mapping and Statistics (RTAMS) website (RTAMS n.d.). I acquired my map of the 2010 census tract boundaries from the US Census's TIGER/Line® Shapefiles website (US Census Bureau 2023). For my other data, I utilize the U.S. Census Bureau's American Community Survey 5-Year Estimate Detailed Table data to create 10-year percentage change variables by subtracting 2019 variables from their 2010 counterparts, dividing the result by the 2010 variable, and then multiplying the result by 100. Because each variable is a five-year estimate, my dataset may be more appropriately classified as change variables between 2015-2019 and 2006-2010. I chose the ACS 5-Year Data because it is the ACS's most geographically granular dataset. While the ACS 1-Year dataset is limited to population areas ≤ 65,000 people, the 5-Year Data can be accessed at a census tract level, with the Detailed Table data being their most granular in terms of available data (US Census Bureau 2022a, Census Bureau 2022b). I follow Census Bureau guidance on joining five-year estimate data with boundaries and maps (like census tracts), which states to always use the final year of the range (Census Bureau 2022c). For this reason, I refer to my variables' temporal start and endpoints throughout this thesis as 2010 and 2019.

Variable Details

Change in Total Population (ACS Detailed Table Variable: B03002_001E): As I described earlier, I was unsure how this variable would relate to ridership change in different regions of Chicago, which motivated me to include it to see how population change related to ridership when ridership's relationship to median income and median age was also being assessed.

Change in Median Income (ACS Detailed Table Variable: B06011_001E): Median income is a metric that one can use to measure the economic vitality of a given area. The higher the median value is, the higher the incomes of the general population in a given area (in contrast to average income, which would be biased due to the presence of individuals with outlier incomes). I include it because I want to see if station ridership change is related to changes in the economic vitality of surrounding census tracts (which I hypothesize it is, given that I argue that CTA "L" stations benefited from urban gentrification. I expect stations with increased ridership to be surrounded by tracts with increased median income).

Changes in Median Age (ACS Detailed Table Variable: B06002_001E_2019): As described in my Literature Review, young people moving to cities has been perceived as a sign of urban vitality. I want to see how changes in median age in census tracts relate to changes in nearby CTA "L" station ridership. My hypothesis is that tracts with increased ridership over time will also have a younger population relative to stations with decreased ridership over time.

Data Acquisition (Continued) & Cleaning

To acquire my data, I used the ACS API, a URL where one can specify the year, variable, and geographic levels and range (one block group or all block groups, one tract or all tracts, one county or all counties, one state or all states) to produce a text file that can be saved as either a JSON file or a comma separated values (CSV) file (Census Bureau 2011). I saved my variables as CSV files, revising their headers and removing errant brackets and quotes in Excel. I downloaded my CTA map as a shapefile (a file type used by GIS software) and the ridership data as a CSV from the City of Chicago Data Portal and RTAMS websites, respectively. For the ACS data, I used PyCharm (a Python IDE) to calculate percentage changes for each value before isolating each variable's percentage change value and Census Tract FIPS code, which I then joined to my Chicago 2010 Census Tracts shapefile (downloaded from the US Census TIGER/Line® Shapefiles website). For the ridership data, I created change variables for each station between the yearly averages I calculated for 2010 and 2019 before joining the data to the ridership shapefile.

Process of Data Analysis

In QGIS, I removed all CTA “L” stations outside of City of Chicago limits save for the Oak Park, IL Austin Blue Line “L” station due to its close proximity to the city of Chicago and the distance between it and the nearest Chicago-based Blue Line “L” station. Similarly, I also removed O’Hare Airport’s Blue Line “L” station because it is accessible only through the airport itself (compared to Midway Airport’s Orange Line “L” station, which is located outside of the airport itself).

I extracted the centroid (central location) of each census tract. Using the Geometry Selection tool, I created a map consisting only of tracts whose centroids are within 0.5 miles of a CTA “L” station. Chicago’s TOD rules apply to the 0.5 mile radius around CTA “L” stations, which is why I controlled for tracts in that range. I chose to analyze all of Chicago as well to better understand how ridership relates to change as measured across the city.

I used QGIS to make citywide equal count quantile breaks (which creates a set of divisions in data values to ensure each range has an equal number of values) maps of each change variable surrounding the CTA “L” station (with five ranges/breaks for each variable). I used natural breaks (an algorithm that creates however many clusters that the user requests based on its own assessment of value similarity to one another) to map the change in ridership at each CTA “L” station included in my analysis.

Using RStudio, an IDE for the R statistical programming language, I conduct multiple linear regression analyses. To resolve heteroskedasticity in my variables’ residuals (homoscedasticity is required to conduct linear regression), I located and removed influential points, or values that are located more than three standard deviations from the mean. I then construct two sets of multiple linear regression models – one for all tracts, one for tracts ≤ 0.5

miles from CTA "L" stations – with change in population, median income, and median age serving as independent variables and ridership change serving as the dependent variable.

Limitations

This study focuses on data visualization and multiple linear regressions of three specific variables: population change, median income change, and median age change. Attempts to incorporate other variables from the ACS were prevented by incomplete data. Moreover, this paper acknowledges that other analytical techniques, from spatial regression analysis to spatial cluster analysis, would be useful for further investigating this data, and encourages further study of this topic using these and other analysis techniques and more data. It is important to state that this paper does not seek to establish causality between any one factor and ridership change. While I do hypothesize about the origins of the correlations I observe in my research, my visualization and regression analysis does not provide evidence for causality. In terms of specific takeaways for stations, detailed explanations of trends occurring at particular stations are beyond the scope of system-level regression analysis. My thesis's intention is to provide broad correlations between my three variables and ridership to validate the potential for the "L" to be a popular public service accessible by all Chicagoans if the CTA heeds the lessons I extrapolate from my data analysis.

Data Analysis Results

Overview of Results

Analyzing the relationship between CTA stations' ridership change between 2010 and 2019 and change in population, median income, and median age in the census tracts geographically closest to each yields statistically significant findings connecting ridership change to median income change, population change, and median income change at different levels of analysis. Most important to my thesis is the finding that median income is significantly positively correlated with "L" ridership change for all "L" stations (both for all tracts and those ≤ 0.5 miles from their closest "L" station) and the replication of this finding for North Side stations and tracts (all tracts and those ≤ 0.5 miles from their closest "L" station). Overall, my findings provide statistically significant support for my hypothesis that Chicago's ridership gain on the North Side is tied to population growth of high-income populations (and corresponding investment and development) in areas whose growth has coincided with public recognition of the Back to the City movement as assessed by literature written on the movement. Exact data can be found in my Appendix.

Results of all tracts' change compared to their closest station

All Stations:

Assessing all tracts and trains in Chicago (excluding the O'Hare Blue Line station and Oak Park's Austin Blue Line station) reveals significant, positive correlations between changes in median income and population and changes in ridership ($p<0.001$ significance level). In addition, this analysis reveals a weak negative correlation between median income and ridership change at the $p<0.1$ significance level.

Stations Broken Down by Region:

Assessing only tracts whose closest "L" station is on the Red, Blue, or Brown Lines north of the Loop reveals a positive correlation between median income and ridership change at the $p<0.001$ significance level. It also reveals a weak negative relationship between population change and ridership change at the $p<0.1$ significance level. Assessing only tracts whose closest "L" station is on the Red and Green Lines south of the Loop reveals a positive relationship between population and ridership change at the $p<0.001$ significance level, and a weak negative relationship between change in median income and population at the $p<0.1$ significance level. Assessing only tracts whose closest "L" station is on the Blue, Green, Pink, or Orange Lines west of the Loop yields no significant findings.

Stations by Line by Region:

Breaking down stations by geography and by line yields the following results. The Orange Line west of the Loop has a positive correlation between change in median age and change in ridership at the $p<0.01$ significance level. The Red Line south of the Loop has a positive correlation between population change and ridership change at the $p<0.05$ significance level and a weak positive correlation between change in the median age and ridership change at the $p<0.1$ significance level. The Green Line south of the Loop has a positive relationship between change in population and ridership change at the $p<0.001$ significance level and negative relationships between change in median income and median age at the $p<0.05$ significance level. The Green Line west of the Loop has a negative correlation between change in population and median income and ridership change at the $p<0.001$ and $p<0.1$ significance levels, respectively. The Blue Line west of the Loop has no significant values, while the Pink Line west of the Loop has a positive relationship between change in median income and ridership change at the $p<0.05$ significance level. Greater Loop Findings can be found in the Appendix. The Blue Line north of the Loop has a positive relationship between income and ridership change at the 0.01 significance level. While the Brown Line north of the Loop has no significant values, the Red Line north of the Loop has a negative correlation between median age and ridership at the $p<0.01$ significance value.

Assessing Ridership Change Compared to Tracts at or within 0.5 miles of Closest Stations

All Stations:

Moving to only tracts at or within 0.5 miles of their closest "L" station, an assessment of all stations reveals positive correlations between population change and median income changes and ridership changes at the $p<0.01$ and $p<0.001$ significance levels, respectively.

Stations Broken Down by Region:

Addressing geographic regions, stations on the Red, Brown, and Blue lines north of the Loop have a positive correlation between change in median income and ridership change at the $p<0.05$ significance level. Stations on the Red and Green Lines south of the Loop have a positive correlation between population change and ridership change at the $P<0.05$ significance level. Once again, an analysis of stations west of the Greater Loop yields no significant findings.

Stations by Line by Region:

At the geography-line breakdown level, the Red Line south of the Loop has no significant relationships, while the Green Line south of the Loop has a positive relationship between ridership change and population change at the $p<0.05$ significance level. There is a negative relationship between change in median income and ridership change on the Orange Line west of the loop at a $p<0.05$ significance level. On the Green Line west of the Loop, there is a negative relationship between population change and median income change and ridership change at the $p<0.05$ and $p<0.01$ significance levels, respectively. There are no significant relationships on the Blue and Pink Lines west of the Loop. Loop data can be found in the Appendix. The Blue Line north of the Loop yields no significant values, while the Brown Line north of the Loop has a weak negative relationship between population change and ridership change at the $p<0.1$ significance level. The Red Line north of the Loop has a negative relationship between change in median age and ridership at the $p<0.05$ significance levels.

Outside of the Loop, which has a mix of growing and declining stations, growth in Chicago was concentrated on the North Side (particularly the Milwaukee Corridor and the upper part of the Brown Line) and, to a lesser extent, the Southwest side. Save for Cermak-Chinatown on the Red Line, all stations south of Roosevelt on the Green and Red Lines lost ridership.

Analysis of Results

Assessing my regression analysis results reveals that median income change is positively correlated with ridership growth when all census tracts are appraised compared to the ridership change of their closest CTA station as well as when stations are assessed in terms of geographic regions. The North Side – with Blue, Red, and Brown Lines north of the Loop – sees a strong correlation between income change and ridership growth. This finding suggests a relationship between the past decade of gentrification and transit-oriented development that has occurred in places like Logan Square, whose Blue Line station of the same name experienced some of the greatest ridership increase between 2010 and 2019. It supports my hypothesis that CTA “L” ridership growth – and the “L”’s “gentrification” – resulted from the development of areas surrounding stations in ways that encouraged use of the “L” as a primary means of transit, development that was catalyzed by outside interest in these neighborhoods.

Compared to what I expected to see prior to conducting my data analysis, I expected to see the fairly consistent relationship between the North Side (and the city at large) and median income change as well as the uneven significant relationship between population change and ridership. Given that I expected to see median age correlate almost perfectly (with a consistently inverse relationship to ridership gain), the uneven findings for that variable surprised me and suggest the relationship between age and transit use in Chicago requires more study in and of itself.

Focusing on median income, my hypothesis is supported by the findings and non-findings observed on the South and West Sides. Interestingly, the West Side – consisting of Blue, Orange, Pink, and Green Lines – has no strong correlations, a non-finding I believe relates to the region's mixed ridership changes during the study period. While the Pink and Orange Lines in particular see increases in ridership between 0-14% between 2010 and 2019, the Blue and Green Lines generally see decreases between 0-16% or 16-40% during the same period, suggesting something other than changes in population, median age, and median income is associated with ridership changes in this region. With its widespread decline in ridership and population, that the South Side sees a positive correlation between population growth and ridership growth makes empirical sense (more people, more riders). That the South Side has a significant negative correlation between income and ridership strongly supports my hypothesis because it indicates the presence of an inferior good-style relationship occurring in one region of Chicago that contrasts with the amenity-esque relationship occurring in another region.

This dichotomy supports my thesis because I argue that transit on the North Side should be conceived of as an amenity due its ridership change's correlation with positive median income change. I see this relationship as structured by transit's valorization as a part of the Back to the City movement and its utilization through implicit and explicit transit-oriented development, a phenomenon that is acknowledged to have largely taken place on the North Side. The South and West Sides did not receive this kind of interest and investment, with the result being that the South Side – the region where the rate of ridership decrease was far greater than population decrease – demonstrates relationships that reaffirm the traditional conception of transit as an inferior good taken by people who may not have another option.

Regional line-level correlations nuance my analysis, as they indicate that there are unique sub-regional effects at play around certain lines. In particular, the Pink Line's positive relationship between median income change and ridership change supports my hypothesis and my speculation regarding line-specific relationships that warrant further study. Similarly, the positive correlations between median age and ridership on the Orange (all tracts) and Red (tracts ≤ 0.5 miles from their closest "L" stations) Lines west and north of the Loop provide context for specific study of those branches' transit bases and how they relate to those branches where ridership change is positively correlated with median age decrease.

Adjusting my models to only include tracts that are ≤ 0.5 miles from the closest station similarly supports my hypothesis at the citywide and regional level, with those tracts that are ≤ 0.5 miles of "L" stations on the North Side demonstrating a positive correlation between median income change and ridership change. Breaking regional numbers down by line offers a few interesting statistics that support my hypothesis – an inferior good (negative correlation between median income and ridership growth) relationship is revealed on the Orange Line southwest of the Loop, while the Red Line north of the Loop reveals the median age.

In both cases, my data analysis supports my hypothesis regarding the positive relationship between investment/development and high-income population growth on the North Side and ridership growth at those stations. As with the analysis of all tracts regardless of distance between them and their closest "L" stations, the citywide and North Side positive correlation between median income change and "L" ridership for tracts that are ≤ 0.5 miles from their closest "L" supports my hypothesis of the "L"'s gentrification.

Conclusion

"L" 2010-2019: Amenity for Some

Assessing Chicago Transit Authority ridership data for the City of Chicago's "L" stations (excluding O'Hare Airport (Blue) and including Oak Park-Austin (Blue)) alongside American Community Survey data on tract-level changes in population, median income, and median age between 2010 and 2019 reveals a city/system-wide positive correlation between median income change and ridership change that is complemented by the same correlation at the North Side level. Moreover, this relationship holds at both levels of analysis when tracts greater than 0.5 miles away from their closest "L" stations are included. These results are accompanied by findings on the South Side that detail a negative correlation between median income change and ridership change on certain lines and at certain levels of analysis. All of the above results provide statistically significant support to my argument that Chicago allowed the gentrification of the "L" to take place implicitly (and explicitly, in the case of pre-2021/2022 transit-oriented development policy (Mayor's Press Office 2022b)) by leaving neighborhood development surrounding stations entirely up to market forces. As those forces reacted to (and sought to catalyze) outside interest in certain areas, interest prompted by the back-to-the-city movement of young professionals in particular, it resulted in certain neighborhoods (mainly those on the North Side) experiencing a valorization of the "L" as part of the urban experience (which resulted in the correlation between median income change and ridership change). At the same time, other stations on the West and South Sides experienced locally-influenced ridership growth or decline or, in certain cases, the emergence of a negative relationship between median income and ridership change that suggested that the "L" was an inferior good in these areas frequented primarily by low-income residents (and potentially avoided by higher-income residents). Taken alongside the fact that the ridership growth between 2010 and 2019 was concentrated on the

North Side and that decline was concentrated on the South Side (with the West Side experiencing a combination of both), my findings verify my hypothesis. The “L” effectively gentrified as the North and South Side’s ridership increased and decreased disproportionate to their population changes against the backdrop of developers responding to residential interest in (North Side) “L”-served neighborhoods to create walkable, transit-friendly infrastructure.

Conclusive, causal results regarding the role specific events (such as Logan Square’s gentrification) cannot be interpreted from these results. However, the city-level and North and South Side findings do tie ridership change to median income change, a metric that reflects the socioeconomic changes stemming from both gentrification and disinvestment. As such, it serves as a strong critique of the city of Chicago for letting a public service be made less “public” through its lack of interest in using its own resources to ensure equitable development in the neighborhoods around all “L” stations. It reflects poorly on the city’s neoliberal orientation during the study period that the city effectively chose to limit ridership growth to a few stations by not intervening in development outcomes in all the neighborhoods surrounding the “L.” This conclusion holds even while accounting for study limitations, including the use of census estimates and the limiting of analysis to regression and visualization.

Even while acknowledging this critique, recognizing that Chicago also demonstrated that rail transit could become an amenity to be sought out as Richmond conceptualized it is a meaningful empirical finding in the context of U.S. transit policy. Higher-income people chose to move near and use rail transit in Chicago, and companies chose to build implicitly and explicitly (following the passage of Chicago’s TOD rules) transit-oriented development to make the “L” even more useful and usable to those residents. This finding corroborates the positive role public transit can play as a public service, utilized not just by lower-income residents (as assumed in the inferior good conceptualization of transit) but by higher-income residents as well. It validates the idea that equitable transit-oriented development (ETOD), funded and distributed across the entire "L" can surround all stations with infrastructure that makes the "L" convenient and useful for all riders regardless of income and other factors. In this way, my analysis has revealed a new challenge for the CTA: how to effectively grow ridership across all stations in the 2020s.

Implications of Research

Even though the North Side branch of the "L" can be considered an "amenity" from 2010 to 2019, that may be a moot point in 2023. COVID-19 and the abject collapse in ridership, coupled with real and perceived safety concerns, breakdowns in cleanliness and frequency has severely damaged the conception of the CTA "L" as a public service, much less a desirable amenity. However, the relationships identified in this thesis are crucial to understanding how the CTA can move forward with restoring ridership on all parts of the "L." Although every station deserves a holistic, granular analysis of their history and surroundings, from a community/institutional standpoint as well as a built environment standpoint, the guiding policy for stations is clear: ridership is correlated with median income growth. Transit policy should be focused on building and maintaining infrastructure around stations that enables public transit to be useful to people as a means of improving their quality of life.

The arrival of higher-income residents (and the departure/displacement of lower-income residents) in certain tracts may be the driving factor behind the positive relationships identified between median income change and ridership change, given the gentrification that has occurred on the North Side in particular. However, the reality is that their arrival, and the investment that followed to cater to them/attract more new, high-earning residents transformed/enhanced the built environment to make transit useful in their daily lives. In Chicago today, the Equitable

Transit Oriented Development program is actively funding initiatives on the South and West Side to create transit-oriented infrastructure in areas overlooked by the market's focus on the North Side (Blumberg 2021). Transit policy moving forward should aim to expand ETOD to include provision of public and essential services, from schools to medical care to fresh groceries to opportunities for work, in addition to the retail and affordable housing opportunities currently being supported. The goal should be to recreate the positive correlation between change in median income and ridership growth through the provision of infrastructure that can help raise current residents' incomes while also attracting more residents to take advantage of those services and their proximity to transit.

While the relationship between median age and ridership growth is not something that necessarily needs to be addressed through policy, transit policy should look to recreate the positive correlation identified on the South Side between population growth and ridership across the city. Even if the city fails to grow (it has lost population throughout the 21st century), the city benefits if internal migration patterns move residents closer to "L" stations through reduced vehicle emissions. From an equity standpoint, assuming the city follows through with my proposal to concentrate public and essential services around "L" stations alongside commercial and housing infrastructure, people will also benefit from closer proximity to all of the above.

It is likely that the Chicago Transit Authority will take its time with considering, much less implementing such projects, with their substantial investment requirements. Restoring ridership through addressing ghost buses, "L" station cleanliness, staffing shortages, and safety concerns are their top priorities for the time being. However, the CTA will eventually overcome its current crisis. When it does, the lessons of how part of Chicago valorized its rail transit system – and how it effectively gentrified it – during the 2010s will become relevant as a roadmap to revalorize transit and a warning for the social and economic consequences of not using government policy to prioritize equitable investment.

Bibliography

1. “Census Data API: /Data/2021/ACS/ACS5/Examples.” US Census Bureau. US Census Bureau, November 28, 2011. https://api.census.gov/data/2021/acs/acs5/examples.html.

2. “Chicago ‘L’.Org: History - The CTA (1990-Present),” Chicago ‘L’.Org, Accessed October 31, 2022. https://www.chicago-l.org/history/CTA4.html.

3. “CTA Ridership.” RTAMS. Regional Transportation Authority Mapping and Statistics (RTAMS), October 24, 2022. https://rtams.org/dataset/cta-ridership

4. “Displacement in North and Northeast Portland – An Historical Overview.” Your Neighborhood, Your Voice, Portland Housing Bureau North/Northeast Neighborhood Housing Strategy, n.d. www.portlandoregon.gov/phb/article/655460., pp. 3.

5. “Gentrification.” In National Geographic. National Geographic Society, May 19, 2022. https://education.nationalgeographic.org/resource/gentrification/.

6. “INVEST South/West.” Chicago. City of Chicago. Accessed December 9, 2022. https://www.chicago.gov/city/en/sites/invest_sw/home.html.

7. “Mayor Lightfoot Launches First Phase of $10 Million Equitable Transit-Oriented Development Program.” Chicago. City of Chicago, November 22, 2022. City of Chicago. https://www.chicago.gov/city/en/depts/mayor/press_room/press_releases/2022/november/FirstPhaseEquitableTransitOrientedDevelopmentProgram.html.

8. “Target Making Push Into Urban Areas,” PYMNTS, December 24, 2015. https://www.pymnts.com/news/2015/why-target-is-targeting-urban-customers/.

9. “The 10 Oldest Subways in the World,” April 5, 2021, Civitatis, https://www.civitatis.com/blog/en/10-oldest-subways-world/.

10. “The 9 Best Neighborhoods to Live in Chicago in 2022.” Bungalow. Bungalow Living, Inc., March 10, 2022. https://bungalow.com/articles/best-neighborhoods-in-chicago-illinois.

11. “The Myth of the White Suburb and ‘Suburban Invasion.’” Web log. National Low Income Housing Coalition (blog). National Low Income Housing Coalition, February 22, 2021. https://nlihc.org/resource/myth-white-suburb-and-suburban-invasion.

12. “Tiger/Line® Shapefiles.” United States Census Bureau. US Census Bureau. Accessed January 24, 2023. https://www.census.gov/cgi-bin/geo/shapefiles/index.php.

13. “Why Small Stores Are A Big Deal For Target,” PYMNTS, April 7, 2021. https://www.pymnts.com/news/retail/2021/why-small-stores-are-a-big-deal-for-targets-future/.

14. Anderson, Sean. “Gentrification and Chicago.” ESSAI 14, Article 9 (2016): 3–12. https://core.ac.uk/download/pdf/84305691.pdf.

15. Bennett, Larry, Roberta Garner, and Euan Hague. Neoliberal Chicago. Urbana: University of Illinois Press, 2017.

16. Bennett, Larry, Roberta Garner, and Euan Hague. Neoliberal Chicago. Urbana: University of Illinois Press, 2017.

17. Bennett, Larry. The Third City: Chicago and American Urbanism. Chicago: The University of Chicago Press, 2010.

18. Betancur, John. “Gentrification and Community Fabric in Chicago.” Urban Studies 48, no. 2 (February 2011): 383–406. https://www.jstor.org/stable/43081742?seq=1.

19. Blumberg, Nick. “Grant Program Aims to Boost Equitable Development Near Train, Bus Lines.” WTTW. October 21, 2021. https://news.wttw.com/2021/10/21/grant-program-aims-boost-equitable-development-near-train-bus-lines.

20. Chicago Metropolitan Agency of Planning (CMAP) (A). “Logan Square | Community Data Snapshot | Chicago Community Area Series | July 2022 Release,” CMAP, July 2022. https://www.cmap.illinois.gov/documents/10180/126764/Logan+Square.pdf.

21. Chicago Metropolitan Agency of Planning (CMAP) (B). “Chicago | Community Data Snapshot | Municipality Series | July 2022 Release,” CMAP, July 2022. https://www.cmap.illinois.gov/documents/10180/102881/Chicago.pdf.

22. Chicago Metropolitan Agency of Planning (CMAP) (C). “Chatham | Community Data Snapshot | Chicago Community Area Series | July 2022 Release,” CMAP, July 2022. https://www.cmap.illinois.gov/documents/10180/126764/Chatham.pdf.

24. Chicago Transit Authority (CTA). “Completed Station Projects,” CTA, https://www.transitchicago.com/newsprojects/system-improvement-projects/completed-station-projects/.

25. Chicago Transit Authority (CTA). “CTA Celebrates 25th Anniversary of Orange Line Service to SW Chicago & Midway Airport,” CTA, October 30, 2018, https://www.transitchicago.com/happy-10th-birthday-cta-pink-line/.

26. Chicago Transit Authority (CTA). “Happy 10th Birthday, CTA Pink Line!” CTA, June 28, 2016, https://www.transitchicago.com/happy-10th-birthday-cta-pink-line/.

27. Chicago Transit Authority. “CTA-L-Rail-Stations-Shapefile: City of Chicago: Data Portal.” Chicago Data Portal. City of Chicago, August 31, 2011. https://data.cityofchicago.org/dataset/CTA-L-Rail-Stations-Shapefile/vmyy-m9qj;

28. Clark, Terry Nichols. The City as an Entertainment Machine. Lanham, MD: Lexington Books, 2011.

29. Costa, Vincius. “Chicago Named Best Big City To Visit In The U.S.” Travel Off Path. October 10, 2022. https://www.traveloffpath.com/chicago-named-best-big-city-to-visit-in-the-u-s/.

30. Day, Richard. “Bringing TOD to South, West Sides Will Require More Resources, Less Red Tape,” Streetsblog Chicago, August 26, 2021. https://chi.streetsblog.org/2021/08/26/bringing-tod-to-south-west-sides-will-require-more-resources-less-red-tape/.

31. Demsas, Jerusalem. “What We Talk about When We Talk about Gentrification.” Vox. September 5, 2021. https://www.vox.com/22629826/gentrification-definition-housing-racism-segregation-cities.

32. Florida, Richard. “U.S. Millennials Really Do Prefer Cities,” Bloomberg Citylab, May 28, 2019. https://www.bloomberg.com/news/articles/2019-05-28/u-s-millennials-really-do-prefer-cities.

33. Greenfield, John. “Activists Worry CTA-Friendly Housing Will Accelerate Logan Square Gentrification.” Chicago Reader. April 18, 2016. https://chicagoreader.com/columns-opinion/activists-worry-cta-friendly-housing-will-accelerate-logan-square-gentrification/.

34. Hyra, Derek. “The Back-to-the-City Movement Is Leading to Political and Cultural Displacement, Transforming the Inner City into Condo City.” Web log. The London School of Economics and Political Science (blog). The London School of Economics and Political Science, August 14, 2014. https://blogs.lse.ac.uk/usappblog/2014/08/14/the-back-to-the-city-movement-is-leading-to-political-and-cultural-displacement-transforming-the-inner-city-into-condo-city/.

35. Hyra, Derek. “The Back-to-the-City Movement: Neighbourhood Redevelopment and Processes of Political and Cultural Displacement.” Urban Studies 52, no. 10 (2015): 1753–73.

36. Lanski, Aaron. “Back to the City: Re-Urbanization Movement Brings Opportunities,” REJournals. April 5, 2017, https://rejournals.com/back-to-the-city-re-urbanization-movement-brings-opportunities/.

37. LaTrace, AJ. “Mapping the Development Boom Along Milwaukee Avenue.” Curbed Chicago. October 28, 2014. https://chicago.curbed.com/maps/mapping-milwaukee-avenues-development-boom.

38. Lee, William. "As the Black Population Continues to Drop in Chicago and Illinois, Few Regret Their Move: 'I Have Peace.'" Chicago Tribune. November 22, 2021. https://www.chicagotribune.com/news/breaking/ct-chicago-black-residents-exodus-census-20211122-uphhe7bakngtjoh45uhnqjepwy-story.html.

39. Malagón, Elvia, Andy Boyle, and Rachel Hinton. "Chicago Population up 2% over the Past Decade as City Keeps Title of Third-Largest City in U.S." Chicago Sun-Times. August 12, 2021. https://chicago.suntimes.com/2021/8/12/22622062/chicago-census-2020-illinois-population-growth-decline-redistricting-racial-composition#:~:text=Overall%2C%20the%20city%27s%20population%20grew,nearly%207%25%20of%20its%20population.

40. Mayor's Press Office 2022a: "Mayor Lightfoot Introduces Connected Communities Ordinance." City of Chicago. City of Chicago, June 22, 2022. City of Chicago. https://www.chicago.gov/city/en/depts/mayor/press_room/press_releases/2022/june/ConnectedCommunitiesOrdinance.html#:~:text=The%20Connected%20Communities%20Ordinance%20is%20the%20result%20of%20over%20two,Plan%20Commission%20in%20June%202021.

41. Mayor's Press Office 2022b: "City Council Passes the Connected Communities Ordinance to Grow Economy, Make Streets Safer, and Promote Affordability." City of Chicago. City of Chicago, July 20, 2022. City of Chicago. https://www.chicago.gov/city/en/depts/mayor/press_room/press_releases/2022/july/PassesConnectedCommunitiesOrdinance.html.

42. McClelland, Edward. "The Rise and Fall of Chicago Neighborhoods." Chicago Magazine. Chicago Magazine, November 29, 2021. https://www.chicagomag.com/chicago-magazine/december-2021/the-rise-and-fall-of-chicago-neighborhoods/.

43. McClelland, Edward. "Where Is Gentrification Happening? Follow the Mayors." Chicago Magazine. Chicago Magazine, April 25, 2019. https://www.chicagomag.com/news/april-2019/where-is-gentrification-happening-follow-the-mayors/.

44. Metropolitan Planning Council. "Equitable Transit-Oriented Development." Metropolitan Planning Council. Metropolitan Planning Council. https://www.metroplanning.org/work/project/30/subpage/4.

45. Metropolitan Transportation Commission (MCS). "Profiles of 10 Bay Area TOD Projects." NCLS, September 9, 2017, https://mtc.ca.gov/sites/default/files/TOD_Book_part2.pdf.

46. National Conference of State Legislatures (NCLS). "Transit-Oriented Development in the States." NCLS, December 2012. https://www.ncsl.org/documents/transportation/TOD_final.pdf.

47. Qi, Yunlei. "Transit-Induced Gentrification in U.S. Metropolitan Areas," October 2020. http://conservancy.umn.edu/handle/11299/217777.

48. Richmond, Jonathan. Transport of Delight: The Mythical Conception of Rail Transit in Los Angeles. Akron, OH: University of Akron Press, 2005.

49. Smith, Neil. The New Urban Frontier: Gentrification and the Revanchist City. New York, NY: Routledge, 1996.

50. Staley, Samuel. “Why Transit Is an 'Inferior Good'.” Web log. Planetizen (blog). Planetizen, Inc., June 25, 2008. https://www.planetizen.com/node/33371.

51. Trotter, Greg. “The 606 Trail Debuts to Sunshine, Happy Crowds.” Chicago Tribune. June 6, 2015. https://www.chicagotribune.com/news/breaking/ct-606-bloomingdale-trail-opening-met-20150606-story.html.

52. University of Southern California. “Gentrification Draws More Whites to Minority Neighborhoods.” Web log. Phys.org (blog). Science X Network, May 1, 2018. https://phys.org/news/2018-05-gentrification-whites-minority-neighborhoods.html.

53. US Census Bureau 2022a: Bureau, US Census. “American Community Survey 1-Year Data (2005-2021).” Census.gov. US Census Bureau, September 8, 2022. https://www.census.gov/data/developers/data-sets/acs-1year.html.

54. US Census Bureau 2022b: Bureau, US Census. “American Community Survey 5-Year Data (2009-2021).” Census.gov. US Census Bureau, November 30, 2022. https://www.census.gov/data/developers/data-sets/acs-5year.html.

55. US Census Bureau 2022c: Bureau, US Census. “Geography Boundaries by Year.” Census.gov. US Census Bureau, September 1, 2022. https://www.census.gov/programs-surveys/acs/geography-acs/geography-boundaries-by-year.html .

56. Wieckowski, Ania G. “Back to the City.” Harvard Business Review, May 1, 2010. https://hbr.org /2010/05/back-to-the-city.

57. Wiltse-Ahmad, Alyssa. “Study: Gentrification and Cultural Displacement Most Intense in America’s Largest Cities, and Absent from Many Others,” NCRC, March 18, 2019. https://ncrc.org/study-gentrification-and-cultural-displacement-most-intense-in-americas-largest-cities-and-absent-from-many-others/.

58. Institute for Housing Studies - DePaul University. “Displacement Risk in Chicago.” Institute for Housing Studies at DePaul University. DePaul University Driehaus College of Business, n.d.. https://displacement-risk.housingstudies.org/.

59. Koziarz, Jay. “Mapping the West Loop’s Development Boom.” Curbed Chicago. April 28, 2020. https://chicago.curbed.com/maps/west-loop-construction-development.

60. Husain, Nausheen, Darcel Rockett, Christian A Johnson, and Jemal R Brinson. “Disinvestment in Black and Latino Chicago Neighborhoods Is Rooted in Policy. Here’s How

These Communities Continue to Be Held Back." *Chicago Tribune*. July 28, 2020. https://www.chicagotribune.com/living/health/ct-life-inequity-data-policy-roots-chicago-20200726-r3c7qykvvbfm5bdjm4fpb6g5k4-story.html.

61. Matthews, David, and Tanveer Ali. "Downtown Keeps Growing As Rest Of Chicago Shrinks." Web log. *Dnainfo* (blog). New York Public Radio, May 20, 2016. https://www.dnainfo.com/chicago/20160520/downtown/downtown-keeps-growing-as-rest-of-chicago-shrinks/.

Appendix

Systemwide Multiple Linear Regression Analysis, All Tracts

```
> summary(total_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_a)

Residuals:
    Min      1Q  Median      3Q     Max 
-57.541 -16.666   2.398  13.102  49.329 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -8.01942    0.94306  -8.504  < 2e-16 ***
C_POP        0.14563    0.02477   5.880 6.01e-09 ***
C_MI         0.15461    0.02036   7.596 8.49e-14 ***
C_MAGE      -0.07691    0.04010  -1.918   0.0554 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 18.45 on 806 degrees of freedom
  (6 observations deleted due to missingness)
Multiple R-squared:  0.1088,	Adjusted R-squared:  0.1055 
F-statistic: 32.81 on 3 and 806 DF,  p-value: < 2.2e-16
```

Systemwide Multiple Linear Regression Analysis, Tracts ≤ 0.5 miles from their closest "L" station

```
> summary(total_0.5_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = Total_STATIONS_0.5_2)

Residuals:
    Min      1Q  Median      3Q     Max 
-37.594  -9.836   1.423  10.836  39.106 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -3.35364    1.31042  -2.559  0.01097 *  
C_POP        0.10021    0.03529   2.839  0.00482 ** 
C_MI         0.15621    0.02650   5.894 9.85e-09 ***
C_MAGE      -0.07832    0.05004  -1.565  0.11857    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 16.03 on 309 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared:  0.1327,	Adjusted R-squared:  0.1243 
F-statistic: 15.76 on 3 and 309 DF,  p-value: 1.463e-09
```

Regions

North

```
> summary(north_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_q)

Residuals:
    Min      1Q  Median      3Q     Max 
-26.859  -8.814  -2.766   9.350  26.515 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  6.42759    1.18918   5.405 1.37e-07 ***
C_POP       -0.09468    0.05414  -1.749   0.0814 .  
C_MI         0.11181    0.02444   4.575 7.09e-06 ***
C_MAGE       0.08421    0.07958   1.058   0.2909    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 11.57 on 286 degrees of freedom
Multiple R-squared:   0.09,	Adjusted R-squared:  0.08046 
F-statistic: 9.429 on 3 and 286 DF,  p-value: 5.83e-06
```

South

```
> summary(south_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_p)

Residuals:
    Min      1Q  Median      3Q     Max 
-17.204  -4.613  -1.068   3.944  37.610 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -24.66810    0.59648 -41.356  < 2e-16 ***
C_POP         0.10572    0.01998   5.292 2.58e-07 ***
C_MI         -0.02562    0.01350  -1.899   0.0587 .  
C_MAGE       -0.01212    0.02627  -0.461   0.6450    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.427 on 259 degrees of freedom
  (4 observations deleted due to missingness)
Multiple R-squared:  0.1264,	Adjusted R-squared:  0.1163 
F-statistic:  12.5 on 3 and 259 DF,  p-value: 1.173e-07
```

West

```
> summary(west_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_o)

Residuals:
    Min      1Q  Median      3Q     Max 
-30.822  -5.944   2.642   9.485  21.774 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.105042   1.250040   0.084    0.933
C_POP        0.019141   0.044291   0.432    0.666
C_MI        -0.006089   0.028889  -0.211    0.833
C_MAGE       0.022492   0.055492   0.405    0.686

Residual standard error: 10.57 on 190 degrees of freedom
Multiple R-squared:  0.001815,	Adjusted R-squared:  -0.01395 
F-statistic: 0.1152 on 3 and 190 DF,  p-value: 0.9511
```

Loop

```
> summary(West_South_Loop_NNS_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_i)

Residuals:
    Min      1Q  Median      3Q     Max 
-18.309  -8.141  -3.129   8.870  20.877 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept)  2.55874    3.78205   0.677   0.5052  
C_POP        0.11726    0.05744   2.042   0.0523 .
C_MI         0.09377    0.05481   1.711   0.1000 .
C_MAGE       0.05461    0.23793   0.230   0.8204  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10.94 on 24 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared:  0.2447,	Adjusted R-squared:  0.1503 
F-statistic: 2.592 on 3 and 24 DF,  p-value: 0.07615
```

Regions – Broken Down by Line

North

Red Line

```
> summary(red_north_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_m)

Residuals:
     Min       1Q   Median       3Q      Max 
-17.4998  -3.0825   0.8243   4.3466  18.0659 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)   
(Intercept) -3.61350    1.45818  -2.478  0.01559 * 
C_POP       -0.06543    0.06335  -1.033  0.30524   
C_MI         0.05977    0.03662   1.632  0.10707   
C_MAGE      -0.24930    0.08911  -2.798  0.00662 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 7.258 on 71 degrees of freedom
Multiple R-squared:  0.1346,	Adjusted R-squared:  0.09805 
F-statistic: 3.681 on 3 and 71 DF,  p-value: 0.01591
```

Blue Line

```
> summary(blue_north_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_b)

Residuals:
    Min      1Q  Median      3Q     Max 
-23.560 -10.207  -1.527  10.330  27.505 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 10.29834    1.90238   5.413 2.66e-07 ***
C_POP       -0.02380    0.08875  -0.268  0.78895    
C_MI         0.10789    0.03447   3.130  0.00214 ** 
C_MAGE       0.08354    0.11503   0.726  0.46890    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.13 on 138 degrees of freedom
Multiple R-squared:  0.07193,	Adjusted R-squared:  0.05176 
F-statistic: 3.565 on 3 and 138 DF,  p-value: 0.01589
```

Brown Line

```
> summary(brown_out_of_loop_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_l)

Residuals:
     Min       1Q   Median       3Q      Max 
-16.6981  -6.0987  -0.1865   7.5848  21.1636 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 10.34160    1.68925   6.122 2.75e-08 ***
C_POP       -0.00356    0.08148  -0.044    0.965    
C_MI         0.03007    0.03652   0.823    0.413    
C_MAGE       0.17275    0.14465   1.194    0.236    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9.305 on 85 degrees of freedom
Multiple R-squared:  0.0266,	Adjusted R-squared:  -0.007758 
F-statistic: 0.7742 on 3 and 85 DF,  p-value: 0.5116
```

South:

Green Line

```
> summary(green_south_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_d)

Residuals:
    Min      1Q  Median      3Q     Max 
-14.385  -4.940   1.228   3.859  21.618 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -23.10903    0.77006 -30.009  < 2e-16 ***
C_POP         0.10478    0.02358   4.444 1.79e-05 ***
C_MI         -0.03877    0.01550  -2.501   0.0135 *  
C_MAGE       -0.07351    0.03366  -2.184   0.0306 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 7.365 on 139 degrees of freedom
  (4 observations deleted due to missingness)
Multiple R-squared:  0.2369,	Adjusted R-squared:  0.2204 
F-statistic: 14.38 on 3 and 139 DF,  p-value: 3.252e-08
```

Red Line

```
> summary(red_south_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_f)

Residuals:
    Min      1Q  Median      3Q     Max 
-3.5914 -2.0984 -1.1871  0.5211 11.5379 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -27.96171    0.46698 -59.877   <2e-16 ***
C_POP         0.05208    0.02350   2.216   0.0288 *  
C_MI         -0.01084    0.01439  -0.753   0.4529    
C_MAGE        0.03642    0.02053   1.773   0.0790 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.4 on 109 degrees of freedom
Multiple R-squared:  0.06135,	Adjusted R-squared:  0.03552 
F-statistic: 2.375 on 3 and 109 DF,  p-value: 0.07408
```

West/Southwest:

Green Line

```
> summary(green_west_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_e)

Residuals:
     Min       1Q   Median       3Q      Max 
-11.7647  -4.3851   0.2176   4.7031  10.8016 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -17.730832   1.462835 -12.121 2.67e-15 ***
C_POP        -0.304386   0.069637  -4.371 7.96e-05 ***
C_MI         -0.058398   0.033030  -1.768   0.0843 .  
C_MAGE        0.001464   0.064622   0.023   0.9820    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 6.637 on 42 degrees of freedom
Multiple R-squared:  0.3274,	Adjusted R-squared:  0.2794 
F-statistic: 6.816 on 3 and 42 DF,  p-value: 0.0007591
```

Blue Line

```
> summary(blue_west_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_g)

Residuals:
    Min      1Q  Median      3Q     Max 
-11.112  -2.546  -1.363   2.747   9.325 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept) -3.93979    1.50999  -2.609   0.0164 *
C_POP       -0.05298    0.06981  -0.759   0.4563  
C_MI         0.02794    0.04125   0.678   0.5055  
C_MAGE       0.07048    0.07086   0.995   0.3313  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5.42 on 21 degrees of freedom
Multiple R-squared:  0.1097,	Adjusted R-squared:  -0.01748 
F-statistic: 0.8626 on 3 and 21 DF,  p-value: 0.4759
```

Pink Line

```
> summary(pink_west_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_h)

Residuals:
    Min      1Q  Median      3Q     Max 
-11.898  -5.876   1.195   3.371  15.407 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept)  0.54682    2.73650   0.200   0.8428  
C_POP       -0.02866    0.06634  -0.432   0.6684  
C_MI         0.10897    0.04732   2.303   0.0275 *
C_MAGE       0.04674    0.09069   0.515   0.6096  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.74 on 34 degrees of freedom
Multiple R-squared:  0.1486,	Adjusted R-squared:  0.07351 
F-statistic: 1.979 on 3 and 34 DF,  p-value: 0.1357
```

Orange Line

```
> summary(orange_south_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = df_c)

Residuals:
    Min      1Q  Median      3Q     Max 
-12.305  -5.475   1.229   5.009   9.947 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)   
(Intercept)  2.88443    1.09125   2.643  0.00984 **
C_POP       -0.05025    0.05168  -0.972  0.33372   
C_MI         0.02029    0.03188   0.636  0.52631   
C_MAGE       0.19385    0.06271   3.091  0.00272 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.083 on 82 degrees of freedom
Multiple R-squared:  0.1553,	Adjusted R-squared:  0.1244 
F-statistic: 5.024 on 3 and 82 DF,  p-value: 0.003017
```

0.5 ----

Regions

North

```
> summary(north_0.5_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = north_0.5_2

Residuals:
    Min      1Q  Median      3Q     Max 
-19.494  -9.803  -1.544   9.392  26.602 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  7.08811    1.65422   4.285 3.47e-05 ***
C_POP       -0.08420    0.07177  -1.173   0.2428    
C_MI         0.09073    0.03269   2.776   0.0063 ** 
C_MAGE       0.09641    0.12111   0.796   0.4274    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 11.21 on 134 degrees of freedom
Multiple R-squared:  0.08214,	Adjusted R-squared:  0.06159 
F-statistic: 3.997 on 3 and 134 DF,  p-value: 0.009192
```

South

```
> summary(south_0.5_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = south_0.5_2

Residuals:
    Min      1Q  Median      3Q     Max
-15.910  -4.849  -1.051   3.071  33.116

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -21.599048   1.518243 -14.226   <2e-16 ***
C_POP         0.151743   0.062653   2.422   0.0188 *
C_MI         -0.006108   0.039931  -0.153   0.8790
C_MAGE        0.018001   0.070075   0.257   0.7982
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9.332 on 55 degrees of freedom
Multiple R-squared:  0.1279,	Adjusted R-squared:  0.08038
F-statistic:  2.69 on 3 and 55 DF,  p-value: 0.05512
```

West

```
> summary(west_0.5_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = west_0.5_2)

Residuals:
    Min      1Q  Median      3Q     Max 
-23.484  -6.731   2.449   6.580  19.256 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.828820   1.665818   1.098    0.276
C_POP        0.008893   0.055657   0.160    0.873
C_MI         0.025318   0.040483   0.625    0.534
C_MAGE      -0.024945   0.072303  -0.345    0.731

Residual standard error: 9.351 on 74 degrees of freedom
Multiple R-squared:  0.00927,	Adjusted R-squared:  -0.03089 
F-statistic: 0.2308 on 3 and 74 DF,  p-value: 0.8747
```

Loop

```
Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = West_South_Loop_NNS_0.5_2)

Residuals:
    Min      1Q  Median      3Q     Max 
-13.633  -6.221  -1.528   5.165  17.507 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept)  5.14431    4.42869   1.162   0.2636  
C_POP        0.11015    0.05876   1.875   0.0804 .
C_MI         0.07349    0.05570   1.319   0.2068  
C_MAGE       0.49624    0.28517   1.740   0.1023  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10.44 on 15 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared:  0.4326,	Adjusted R-squared:  0.3192 
F-statistic: 3.813 on 3 and 15 DF,  p-value: 0.0326
```

Regions – Broken Down by Line

North:

Red Line

```
Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = red_north_0.5_2)

Residuals:
     Min       1Q   Median       3Q      Max 
-19.0873  -3.2554   0.7416   3.8218  17.1593 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept) -1.86357    1.52233  -1.224   0.2270  
C_POP       -0.07531    0.06175  -1.220   0.2287  
C_MI         0.03696    0.03615   1.022   0.3118  
C_MAGE      -0.25776    0.09850  -2.617   0.0119 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.412 on 47 degrees of freedom
Multiple R-squared:  0.1624,	Adjusted R-squared:  0.109 
F-statistic: 3.039 on 3 and 47 DF,  p-value: 0.03811
```

Blue Line

```
Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = blue_north_0.5_2)

Residuals:
    Min      1Q  Median      3Q     Max 
-22.478 -10.416   2.063   9.150  22.777 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 15.53553    3.13348   4.958 1.06e-05 ***
C_POP        0.05824    0.12604   0.462    0.646    
C_MI         0.03880    0.04943   0.785    0.437    
C_MAGE       0.18574    0.22384   0.830    0.411    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 11.96 on 45 degrees of freedom
Multiple R-squared:  0.03452,	Adjusted R-squared:  -0.02984 
F-statistic: 0.5363 on 3 and 45 DF,  p-value: 0.6598
```

Brown Line

```
Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = brown_out_of_loop_0.5_2)

Residuals:
     Min       1Q   Median       3Q      Max 
-16.4337  -6.9749  -0.5502   6.1057  23.4249 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 11.48533    2.53714   4.527 4.22e-05 ***
C_POP       -0.24342    0.12420  -1.960   0.0561 .  
C_MI         0.03075    0.05671   0.542   0.5902    
C_MAGE       0.18629    0.20738   0.898   0.3737    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 9.716 on 46 degrees of freedom
Multiple R-squared:  0.1035,	Adjusted R-squared:  0.04501 
F-statistic:  1.77 on 3 and 46 DF,  p-value: 0.1661
```

South:

Green Line

```
> summary(green_south_0.5_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = green_south_0.5_2)

Residuals:
    Min      1Q  Median      3Q     Max 
-14.519  -3.436  -0.765   2.195  18.645 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -21.75165    1.46307 -14.867   <2e-16 ***
C_POP         0.13690    0.05859   2.337    0.025 *  
C_MI         -0.01756    0.03697  -0.475    0.638    
C_MAGE       -0.06120    0.06850  -0.893    0.377    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 7.411 on 37 degrees of freedom
Multiple R-squared:  0.2816,	Adjusted R-squared:  0.2234 
F-statistic: 4.835 on 3 and 37 DF,  p-value: 0.006138
```

Red Line

```
> summary(red_south_0.5_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = red_south_0.5_2)

Residuals:
    Min      1Q  Median      3Q     Max 
-7.3054 -2.3265 -0.7397  1.6321  8.0689 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept) -24.584003   1.552679 -15.833 2.08e-08 ***
C_POP         0.121752   0.092972   1.310    0.220    
C_MI         -0.001638   0.049462  -0.033    0.974    
C_MAGE        0.082661   0.111863   0.739    0.477    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5 on 10 degrees of freedom
Multiple R-squared:  0.1704,	Adjusted R-squared:  -0.07845 
F-statistic: 0.6848 on 3 and 10 DF,  p-value: 0.5815
```

West/Southwest:

Green Line

```
> summary(green_west_0.5_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = green_west_0.5_2)

Residuals:
    Min      1Q  Median      3Q     Max 
-8.4943 -2.5734  0.5525  2.7403  9.9162 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -15.86549    2.05724  -7.712 1.62e-05 ***
C_POP        -0.35268    0.11326  -3.114  0.01099 *  
C_MI         -0.17149    0.04977  -3.446  0.00627 ** 
C_MAGE       -0.07685    0.08964  -0.857  0.41133    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.377 on 10 degrees of freedom
Multiple R-squared:  0.6661,	Adjusted R-squared:  0.5659 
F-statistic:  6.65 on 3 and 10 DF,  p-value: 0.009541
```

Blue Line

```
> summary(blue_west_0.5_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = blue_west_0.5_2)

Residuals:
    Min      1Q  Median      3Q     Max 
-11.258  -2.519  -1.316   3.222   9.656 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)  
(Intercept) -4.23130    1.63851  -2.582   0.0194 *
C_POP       -0.05067    0.07353  -0.689   0.5001  
C_MI         0.01641    0.05077   0.323   0.7504  
C_MAGE       0.07777    0.07530   1.033   0.3162  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.618 on 17 degrees of freedom
Multiple R-squared:  0.1192,	Adjusted R-squared:  -0.03618 
F-statistic: 0.7672 on 3 and 17 DF,  p-value: 0.528
```

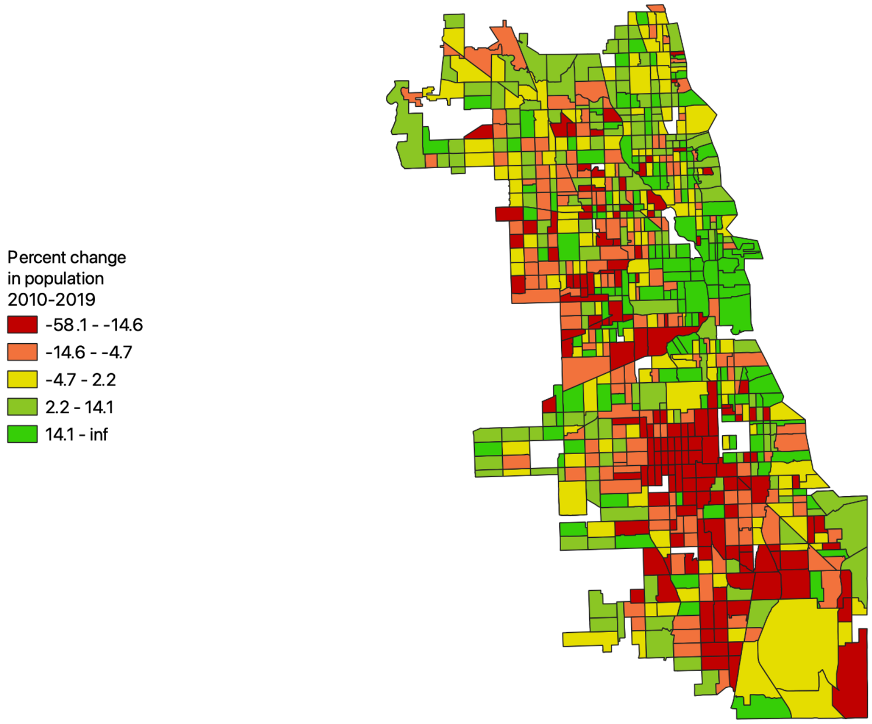
Pink Line

```
> summary(pink_west_0.5_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = pink_west_0.5_2)

Residuals:
    Min      1Q  Median      3Q     Max 
-13.453  -2.650   1.144   1.757  14.271 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.049676   3.424657   1.183    0.252
C_POP       -0.030506   0.075905  -0.402    0.692
C_MI         0.072926   0.067142   1.086    0.292
C_MAGE       0.002156   0.123006   0.018    0.986

Residual standard error: 6.474 on 18 degrees of freedom
Multiple R-squared:  0.06707,	Adjusted R-squared:  -0.08842 
F-statistic: 0.4313 on 3 and 18 DF,  p-value: 0.7331
```

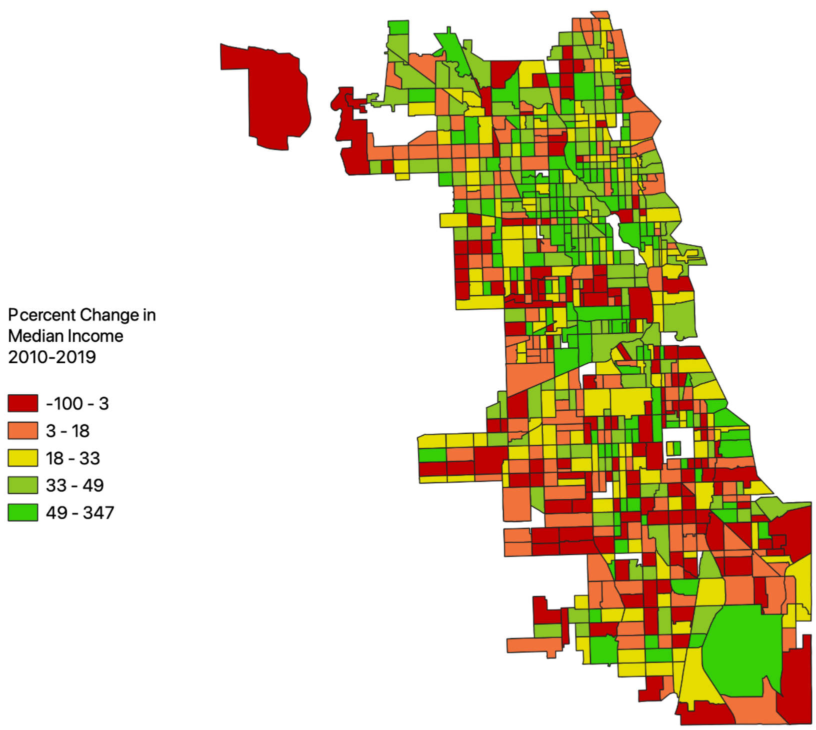
Orange Line

```
> summary(orange_south_0.5_MLR_2)

Call:
lm(formula = PC10_19 ~ C_POP + C_MI + C_MAGE, data = orange_south_0.5_2)

Residuals:
    Min      1Q  Median      3Q     Max 
-8.1101 -1.8041  0.0074  2.7695  5.7118 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept)  9.303875   1.669160   5.574 3.36e-05 ***
C_POP       -0.111640   0.078605  -1.420   0.1736    
C_MI        -0.110638   0.046344  -2.387   0.0289 *  
C_MAGE       0.005381   0.118499   0.045   0.9643    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.043 on 17 degrees of freedom
Multiple R-squared:  0.403,	Adjusted R-squared:  0.2977 
F-statistic: 3.825 on 3 and 17 DF,  p-value: 0.02916
```

Population Change, 2010-2019



Median Income Change, 2010-2019



Median Age Change, 2010-2019