Who Gets to Live Near Rail Transit?

Effects of Rail Transit Access and Walkability on the Housing Market in Large Southern Cities

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Research Question

Is there a relationship between access to rail transit, walkability, and wealth in large Southern cities (Atlanta, Dallas, DC, Houston, Miami)?

Abstract

In this study, we investigate areas with easy access to rail transit in major cities in the American South to understand what demographics are served by rail transit. In particular, we study the relationship between easily accessible rail transit and the median owner-occupied housing unit value. We first run regressions at the census block group level on average walking distance to the nearest rail transit station median home value while controlling for Walk Score®. To account for spatial clustering, we run a Moran's I and then a spatially lagged model to account for autocorrelation between our variables. We find that the results provide insight into the usage patterns and demographics of the areas surrounding rail transit stations in Southern cities. Further research could prove valuable in identifying regions that need more housing, improved rail transit service, or local infrastructure upgrades like sidewalks, crosswalks, and bike lanes.

Introduction, Background, and Significance

Private automobiles have been around since the late 18th century. However, beginning in the 1940s and 1950s, they grew rapidly in popularity. Aided by urban decay, white flight, robust highway infrastructure, plentiful parking, and zoning policies, they have since been the dominant form of travel in American cities. This creates a society where the vast majority of trips taken within a city are via private automobile. However, the sustainability of this urban form has been called into question. As cities continue to grow, more land is converted into residential areas, more highways are built, and traffic only continues to climb. As the study of urban planning has evolved, some scholars have begun to suggest alternatives to this so-called car dependency. Increasingly, contemporary urban projects are straying from this precedent and developing more walkable infrastructure (Gilderbloom et al. 2015). Similarly, many cities have begun to expand their public transportation infrastructure.

Before continuing, we note how and why people benefit from living near public transportation. For residents who don't have access to a car, public transportation is critical to access employment, schools, parks, healthcare, and recreation. Without it, people would need to rely on walking, micromobility (bikes, scooters, etc), and rideshare systems like Uber and Lyft. Walking and cycling simply require too much time and effort for cross-city journeys, and rideshare is prohibitively expensive for most as a primary means of transportation. Even for residents with cars, public transportation gives them flexibility by giving them more transportation options other than driving, which is useful when a car is temporarily unavailable or traffic is too bad, among other reasons. They also get the benefit of less congested roadways due to others taking public transportation.

However, public transportation is not always as useful as residents would like. Local buses, for example, are typically significantly slower than driving due to stopping frequently, taking non-direct routes, and getting caught in traffic (unless there is dedicated infrastructure like bus-only lanes) (Grablick 2023). Rail transit (defined as metro, light rail, and commuter rail, excluding streetcar) typically offers faster service, better frequency, and more comfort than buses, but is more expensive to build (Kille 2009). Thus not every location in a city, even in a major city, is close to rail transit.

This is especially true in the American South. Cities in this region tend to be less compact, lower-density, and more sprawled out than cities in other parts of the country at similar population levels (with the notable exception of Miami and Washington, DC) (Sultana and Weber 2007, Tombolini et al. 2015). Related to this, fewer locations within Southern cities have easy access to rail transit. This begs the question: who lives near rail transit in these cities?

Most of the previous literature in this field looks at the pricing of housing around either a single transportation line or in systems with well-connected infrastructure (Ryan 1999). Studies in the first category generally fail to capture non-city-specific attributes that contribute to land valuation. This makes it difficult to extrapolate results to different cities. On the other hand, studies in the second category are affected by the effects of well-adjusted urban development. In other words, cities that have strong public transit systems are likely to have laws and plans that assist in the economic utilization of the land surrounding the transit station (Binkovitz 2018). In effect, these property lots are in a nurturing environment that enables value appreciation.

Walkability, which is loosely defined as the accessibility of amenities by walking, is an increasingly talked-about metric of urban form. It is generally understood that if amenities are more accessible via walking, people will walk more (and therefore drive less). It tends to complement transit access well as it solves the so-called last mile problem (Tilahun et al. 2016). Measuring walkability is not straightforward, and can be done in many different ways. Walk Score is a company whose Walk Score® provides a quantitative measure of walkability. According to their methodology:

> Walk Score measures the walkability of any address using a patented system. For each address, Walk Score analyzes hundreds of walking routes to nearby amenities. Points are awarded based on the distance to amenities in each category. Amenities within a 5 minute walk (.25 miles) are given maximum points. A decay function is used to give points to more distant amenities, with no points given after a 30 minute walk.

> Walk Score also measures pedestrian friendliness by analyzing population density and road metrics such as block length and intersection density. Data sources include Google, Factual, Great Schools, Open Street Map, the U.S. Census, Localeze, and places added by the Walk Score user community. (Walk Score, 2024)

Walk Score also gives justification for why we should care about walkability:

> Walkability Raises Home Values
>
> The walkability of cities translates directly into increases in home values. Homes located in more walkable neighborhoods—those with a mix of common daily shopping and social destinations within a short distance—command a price premium over otherwise similar homes in less walkable areas. Houses with the above-average levels of walkability command a premium of about $4,000 to $34,000 over houses with just average levels of walkability in the typical metropolitan areas studied. Source: CEOs for Cities
>
> Walkable Urban Places Perform Better Economically
>
> This study of economic performance across the Washington, D.C. metropolitan area found that the average vacancy-adjusted annual office rent in walkable areas is $37 per square foot, compared to $21 for drivable sub-urban office rents, a 75% rental premium. And among for-sale housing, per-square-foot values in walkable places are 71% higher than the average of all other places. By itself, Walk Score is found to explain 67% of the increase in economic performance of walkable areas. Source: The George Washington University School of Business
>
> In a related study of places within metropolitan Washington, higher walkability was shown to be related to higher economic performance, controlling for a place's household income. On average, each step up the walkability ladder adds $9 per square foot to annual office rents, $7 per square foot to retail rents, more than $300 per month to apartment rents and nearly $82 per square foot to home values. Source: Metropolitan Policy Program at Brookings (Walk Score, 2024)

We hope to contribute to the literature on public transportation and housing by analyzing their relationship within several major cities in the American South. The focus of this study is the central cities of the five largest metropolitan areas in the US Census-defined region of the South. These are (in alphabetical order) Atlanta, Dallas, DC, Houston, and Miami. The South is generally underrepresented in rail transit infrastructure, and thus research on the impact of adding new forms in a contemporary environment may help to understand its most practical uses. More importantly, we also hope to understand how to keep transit accessible for communities who value it the most. While increasing prices may be seen as a positive consequence in terms of desirability, it also hints at the need for community or government intervention to provide affordable housing to focus on keeping transportation accessible.

Literature Review

Consistently, low-income neighborhoods are more likely to rely on public transportation services than high-income areas (Nelson 1998; Bowes and Ihlanfeldt 2001). The reduction of transportation costs provides valuable savings while permitting the community to participate in economic activity. Yet, this convenience puts surrounding housing at high risk of rent price increases (Bodaken and Nedwick 2012). Paradoxically, this study suggests that those who are most likely to benefit from the use of public transit could be the least likely to be able to live near it.

Current literature theorizes that this contradictory relationship occurs because of how individuals value property. Alonso (1964) formulated the bid-rent analysis, where “bidders” are willing to pay a certain amount of “rent” for a property depending on its location. In the traditional urban space, the deciding characteristic for a property’s location is its distance from the Central Business District (CBD). As housing approaches the CBD, locational utility ameliorates and renting prices soar. This cost increase is offset by reduced transportation costs.

Interestingly, transit infrastructure modifies this relationship, providing similar access to the CBD for a fraction of the transportation costs (Fejarang 1994). Further, commute time is also a valuable resource, and transit stations that fail to offer time savings present limited changes in housing demand (Ryan 1999, Boyce et al. 1972).

We theorize that two key characteristics determine the effects of rent-bid analysis. First, is the connectedness that public transit provides to the CBD. Given that insufficient linkage fails to trigger rent-bid analysis, rail systems that fall under this phenomenon will not produce a significant rise in housing prices surrounding the transit station. In other words, renters will not perceive the area as providing a time saving necessary to induce demand. We think this is particularly prevalent in southern cities, where rail transit systems are generally less developed.

The second mechanism is the degree of dispersion of economic affairs across the city. Some cities have CBDs that exist as primarily financial districts while in unison having multiple economic hubs littered through the municipal area each with significant activity. We define these as auxiliary business districts (ABD). Not only does the presence of ABDs make it more difficult for transit networks to sufficiently connect, but they should also disperse the pricing of housing across the city. Buyers will seek cost-time savings to the ABD most useful to them, meaning a large amount of ABD should create a stochastic pattern of housing prices across the city.

This may be why previous literature is mixed on the direct impact that transit services have on housing prices. An abundance of scholars have found that fully developed light rails are likely to increase property values (Davis 1970; Lee, Clemons, and Minister 1973; Baldassare et al. 1979; Benjamin and Sirmins 1996; Lewis-Workman and Brod 1997; Weinstein and Clower 2002; Cervero and Duncan 2002; Yan et al. 2012). Yet, in contrast, semi-developed light rails indicate no relationship (Gatzlaff and Smith 1993). This follows the logic that physical access to the rail systems is ineffective if there is a weak link to the CBD (Sanchez, Shen, and Peng 2004). Literature is much less coherent for heavy rail systems. In a literature review, seven studies presented correlations between property values and locations, while six failed to find a relationship (Ryan 1999).

A contested issue in studies measuring the relationship between housing prices and transit is determining the optimal buffer zones around stations around which to measure changes in pricing. According to government standards, public transit is generally considered usable to residents 400 meters away (UMTA 1978). This supposition follows the logic that residents use slower modes of transportation such as walking and biking to reach transit (Debriezon and Rietveld 2007). However, this may not represent the actuality of quotidian use by the surrounding residents. Previous studies have noted that housing prices begin to rise starting from a range of one to four kilometers away from the station transit (Gatzlaff and Smith 1993; Huang 1996; Ryan 1999). Even more, in sprawled areas, the distance is less concrete as inhabitants are more willing to travel greater distances to stations (O'Sullivan and Morrall 1996). Yet, using the traditional method of parcel distance from the transit station may not be sufficient. According to Von Eggermond and Erath, accessibility differs when estimates are based on more practical representations of travel (2016). Thus, more significant results are found when studies observe the distinction in travel time differences (Ryan 1999). There is no consensus on the appropriate travel time to observe pricing decay.

On another note, there is significant discussion on communities opposing the construction of rail transit, both in their community (known as NIMBY- Not In My Back Yard) and the wider city or metropolitan area. According to Mobility Lab, a program by Arlington County, VA, multiple groups oppose transit projects:

> Corporate opponents: These opponents are concerned that better transit could reduce their businesses' profits. They are concentrated in the auto and oil industries that transit systems compete against for customers.
> Fiscal opponents: These opponents feel that large-scale government expenditures, such as major transit improvements, needlessly disrupt the free market, comprising a form of unnatural "social engineering."
> Self-interested opponents: These opponents, better known as NIMBYs, worry that any substantial changes to their surroundings, such as a new transit route, will ruin the quality of their day-to-day lives. (Mobility Lab 2019)

In one particular case, residents of the Georgetown neighborhood of Washington D.C. advocated against the addition of an expanding metro station. Their sentiments were particularly motivated by social perceptions of what public transit would bring into their upper-class community (Weingroff 2019). However, these ideas are not historical artifacts. They have survived through generations, proliferating in contemporary times (Levey 1977, Aranti 2015, Schwenk 2018). Resilience against transit in the long term has created an artificial barrier between wealthy neighborhoods and transit stations.

Data and Methods

For this study, we used several data sources. These are IPUMS NHGIS, the respective transit agencies, Walk Score API, Google's Geocoding API, and Google's Routes API. Our unit of analysis is the census block group. Our scope is the city limits of five major cities in the American South: Houston, Dallas, Atlanta, Miami, and Washington DC.

Our primary unit of analysis is the census block group. We could have used several alternatives (census block, census tract, etc), but we think that census block groups are the most appropriate because they are the smallest scale that has the relevant data. Census blocks would have been better as they could capture variations on smaller scales and would have provided more data overall, but the data is not available. Census tracts have the relevant data but are simply too large to capture some meaningful variations and would give us far fewer data points.

From IPUMS NHGIS, we sourced census block group shapefile data and two measures of wealth at the block group level. These are Median Annual Household Income (hereafter referred to simply as income) and Median Value of Owner-Occupied Housing Units (hereafter referred to simply as value). The census block group shapefile data was from the 2020 census and was our foundation. It allowed us to determine which block groups should be part of our analysis. We chose to include block groups with any intersection with each of the five cities because we wanted to get full coverage of each city. Both of the measures of wealth are from the 2022 American Community Survey: 5-Year Data [2018-2022, Block Groups & Larger Areas]. We chose to use both income and value data so that we could run more analyses. It is important to note that some of our datasets had missing data; we will expand on this in our limitations section.

For the location of rail transit stations, we sourced data from the developer portals of the respective transit authorities' websites. We use data that adheres to the GTFS (General Transit Feed Specification) standard. This standard defines a common format for public transportation data, including geographic information and service schedules. We believe that using a standardized format benefits our study because it is easier to work with on its own and more straightforward to analyze with data from other sources. The relevant attributes are each station's name, latitude, and longitude.

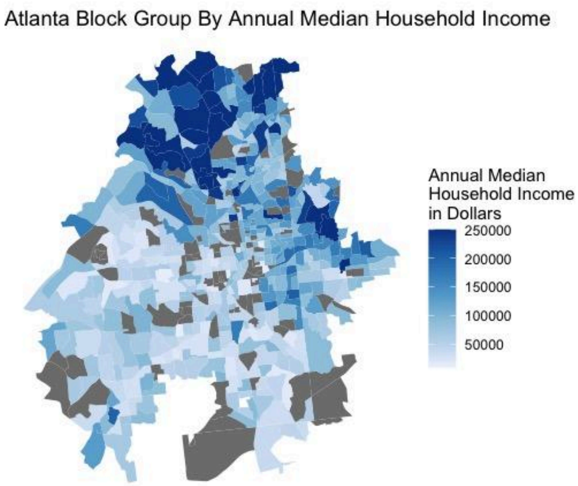
The Walk Score API is used to calculate the Walk Score® of any location in the United States or Canada, a measure of walkability (as explained in the Introduction, Background, and Significance section).

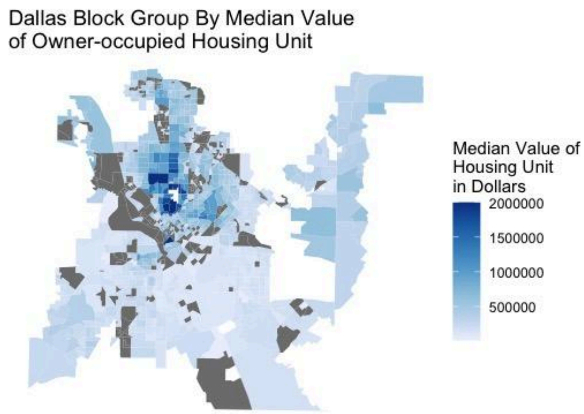
Finally, we have two APIs from Google. Google's Geocoding API is used to convert between coordinate and address representations of places. Most useful for us is reverse geocoding, or turning an address into coordinates. Google's Routes API is used to calculate a route between two locations and has options for different modes (driving, walking, cycling, public transportation), waypoints, different times of the day, and more. A route includes data on time, distance traveled, route components (for example, what roads or what transit lines to take), and more. Most useful to us is calculating the distance traveled for a walking route.

Our overall scope is the cities of Atlanta, Dallas, DC, Houston, and Miami. Specifically, we are concerned with the central cities themselves and not suburbs or unincorporated places within the metropolitan areas. It is worth noting that city limits can sometimes be misleading in terms of the overall size and importance of a city and that the metropolitan area is more intuitive to use than the city proper for many purposes. For example, according to the 2022 census estimates, the city of Houston has about 2.3 million people and covers 640 square miles, whereas the city of Miami has about 450,000 people and covers 36 square miles (U.S. Census Bureau). Regardless, we will use the central cities because they are fixed jurisdictions with enough usable data associated with them.

Our main variables of interest are walking distance to the nearest rail transit station and income. As stated above, we plan to use Google's Routes API for walking distance to the nearest rail transit station. In particular, we will calculate the walking distance from the centroid of each census block group to the nearest rail transit station. There is also functionality to visualize all locations within a certain distance or time away using a particular mode, which may also come in handy. For income, we will simply use the data that is in the census at the census block level. As stated above, we will measure income as either per capita income per year or household income per year.

We will now lay out the methodology, including our data preparation and then our analysis. We took multiple steps to prepare our data. We first downloaded block group shapefile data from NHGIS for Texas, Georgia, Florida, and DC. Then we created a separate shapefile dataset for each city from these state/district shapefiles by filtering for block groups that intersected with each city. Then, we downloaded income and value data from NHGIS for each relevant state/district. For each city, we performed a left join on that city's block group shapefile data and its state’s block group income data, and then again for value data. At this point, we can plot these two variables at the block group level, as shown below.





Then for each block group, we needed to decide what coordinates to use for calculating the Walk Score® and walking distance. We used what the census calls the “interior point.” Essentially, if the centroid of a geographic feature is within the feature, then that is the interior point. If the centroid is not within the feature (this can happen if there is a hole, the feature is not contiguous, or it is concave), then the interior point is the point in the feature closest to the centroid. This gives a single point that approximates any point in the block group.

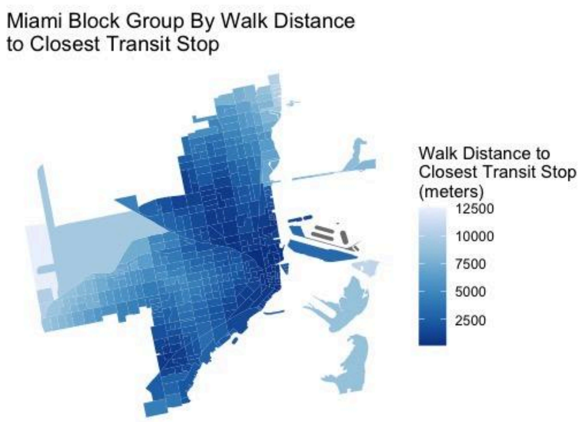
We used the Geocoding API to reverse geocode the coordinates of the interior point, giving us its street address. Then, we used the Walk Score API to calculate the Walk Score® for this address and set of coordinates. We then stored this as an attribute of that block group in the shapefile data. At this point, we can plot Walk Score® by block group, as shown below.

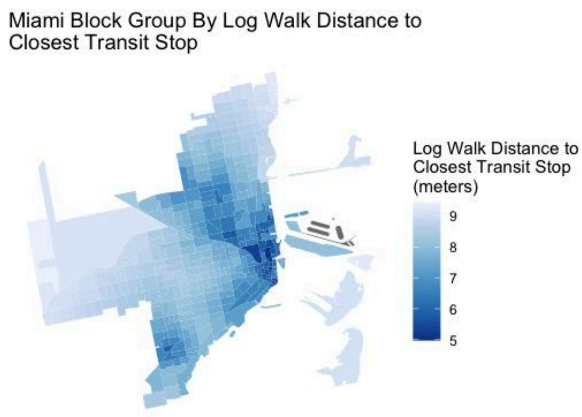
Houston Block Group By Walk Score ®

Next, we downloaded GTFS data from the transit agencies and created a dataset for each city with its rail transit stations. Then for each block group, we calculated the straight-line distance to each station in its city and noted the name, latitude, and longitude of the closest station. At this point, we can plot the closest station, as shown below.

DC Block Group By Closest Stop (from centroid)

Lastly, we needed to calculate the walking distance to the nearest rail transit station. We used the Routes API to calculate the walking distance from each block group to its closest station and stored it and the station name as attributes of that block group. We can plot the walking distance, as shown below. We also can plot the log of the walk distance for more visual clarity.





There are various potential limitations to our study. First, we declined to add a temporal aspect to the measurement of the lot values. Without observed data over some time, we will only be able to measure the isolated value of the land. This may not accurately represent the actualized value of public transportation, as over time, more desirable features are likely to follow the initial transit station addition. Thus, this adds another confounding variable which is the age of the transit station. Second, due to limited access to land value data, we will have to estimate values. Our estimation model may take public transit stations nearby into consideration when calculating the values. To maintain the integrity of the results, we must find an estimation practice based on consumer demand rather than perceived amenities. Our third limitation is the use of block data as spatial measurement. While this is the most precise method we could utilize, this does not necessarily account for barriers to accessing the public transit station. Using walking times from the centroid assumes equal accessibility for all households in the area. Additionally, the intra-block group location of housing units may not be accurately represented by the position of the block group centroid.

Second, as noted above, there is a significant amount of missing data, especially in income and value. This could be for several reasons, including a low (or no) population of those block groups due to parks or water features, restricted data due to government presence (especially in Washington DC), and low survey turnout. This confounded our results, given that many block groups with missing data are close to stations. Walk Score® data was available everywhere, however walking distance data was not. This is due to some locations being physically separated from all stations, whether because of heavy industrial or government areas with no public access, or bodies of water (especially relevant in Miami). We represented missing data on our plots with dark gray and excluded those block groups from our statistical analyses.

Results

To determine the relationship between housing prices and transit stations, we begin by building three simple regression models with our controls. Each model features a different distance threshold. Table 1 includes block groups that are less than 2 kilometers away from a transit stop, Table 2 increases to 4 kilometers, and Table 3 drops the distance threshold. The first two models align with the predetermined optimal thresholds, while the third model seeks to explore the underdeveloped measure of street networks. We expect the selected cities to have a variance in housing prices, where less developed rail systems resemble stochastic effects and D.C.'s developed rail system has a negative relationship between distance and prices. Our initial models reject this assumption. At multiple distance thresholds, all significant regression results exhibit a positive coefficient between the distance from a transit station and the median house value in the census block group, except for Miami at the no threshold level.

These results may be affected by spatial autocorrelation. The clustering effects of housing prices may be related to other attributes and not necessarily explained by the presence of transit stations. To test for endogenous effects, we run a spatially lagged Moran's I test on the spatial correlation between median home value and transit walking distance.

First, we must determine if our variables display spatial clustering in our selected cities. To do this, we run a simple Moran's I test on our variables of interest. We weight our variables through a binary scale using queen contiguity. Our Moran's I value is significant for all variables, informing us that the spatial distribution of the variables has considerable effects on the regression results. These results are visualized by the scatterplots in Figure 1. The trend of high-high values and low-low values signifies that the variables experience significant clustering. From a real-world perspective, intuitively, home value is spatially dependent and heavily influenced by the value of one's neighbors. Further testing is required to isolate the effects of spatial autocorrelation.

Thus we employ a spatially lagged model to account for neighboring effects the dependent variable has on itself. To verify statistical validity we run tests to confirm normal distribution and homoscedasticity. Next, we input our variables into a maximum likelihood estimation for a spatial simultaneous autoregressive lag model to estimate the dependency of median home value. Table 6 includes our spatially lagged regression model, where our rho value has a range of 0.78 to 0.55. In effect, on average, the median home value of a block group's neighbor is expected to be around two-thirds that of the block groups, relative to the baseline value. However, our table displays that walking distance has no significant outcome on median home value in any city. This signifies that our OLS estimates may overestimate the coefficient of walking distance.

Empirical Findings and Discussion

In our literature review, we provide a platform for which to understand the changing housing demands as a result of transit infrastructure. As long as the rail transit offers time-cost savings and provides a stable link to the CBD, there should be an increase in housing prices of the homes immediately surrounding the transit. Rather than seek to test the validity of these claims, we use this theory as a framework to recognize the role transit plays in Southern cities. Our initial OLS regression model displayed a decrease in housing prices as we approached transit stops in all cities except Miami. However, this does not necessarily contrast with findings in previous literature.

The link between communities and transit is the theoretical backing of housing prices. Consequently, many of the previous studies with significant findings also ascertained travel-time savings between public transit and other modes of transportation (Ryan 1999). Our study measures for absolute distance from a transit station and assumes a baseline state of time savings. Thus, when walking distance is held at a constant value, variation in median home value may be attributable to the unknown amount of travel-time savings. Though, we expect time savings to be relatively constant throughout a transit line, and more dependent on time spent walking than riding the transit. Through this concept, we can deduce that the time savings presented by the transit lines in these cities are minimal. The divergent relation we observe can be attributed to social fears attached to transit by wealthy neighborhoods.

Discerning what prevents travel-time savings presents a multitude of issues. We propose to start by referencing the coefficient values of our Walk Score® variable in our initial OLS regressions. Interestingly, higher Walk Score® for all cities were significantly correlated with block groups of higher median home value. These results affirm that, within city limits, neighborhoods are at least partially valued by their walkability.

Why then is there an absence of high-value housing near transit stations? This is likely not due to price stabilization or protection policies for low-income communities, but the social and political functions of transit in a city-specific context. Modern developments in transit face two primary mechanisms that align with our results, political opposition from wealthy neighborhoods and financial incentives to construct through low-income areas. As discussed in our literature review, wealthy neighborhoods generally reject the construction of rail stations due to social perceptions surrounding public transit. Recognizing that higher-value homes manufacture a distance between themselves from rail, our coefficient values begin to make sense. As a result, transit authorities often choose to build through lower-income areas. The second mechanism is primarily invoked to follow budgetary concerns. As opposed to designing transit around population densities, many transit authorities focus on implementing routes while incurring minimal costs (Binkovitz 2018, Danbeck 2022). In turn, travel-time savings are not optimized, and rail benefits are not realized. Through these two mechanisms, transit authorities build through lower-income neighborhoods and these neighborhoods never see an increase in the value of the housing because the routes are inefficient.

Conclusion

In this study, we collect data from five cities' transit and census information to analyze the relationship between home value and public transit infrastructure. Our five cities of selection are Atlanta, Dallas, Houston, Miami, and Washington D.C. where we focus on their rail transit stop locations. All of these cities represent major metropolitan areas in the American South, notably understood to have sprawled urban planning and less-developed public transit systems. In our initial test, we found a positive correlation in four of our five cities between median home values and the walking distance a block group is from its closest transit stop. However, after correction for spatial dependence, we found insignificant relationships in all of our cities. In our results, we find evidence that rail transit may be built in lower-income neighborhoods. Yet, in our latter results, we find that transit infrastructure may not impact the surrounding real-estate value in southern cities. Our results conflict with many studies of the past that claim rail transit increases the value of property. However, our tests may also affirm theoretical backgrounds that stress the importance of rail transit connecting individuals to zones of economic opportunity.

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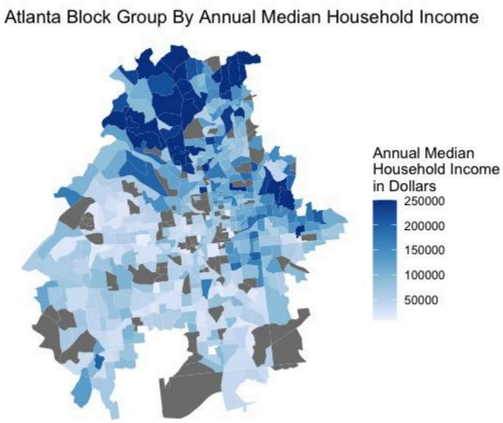
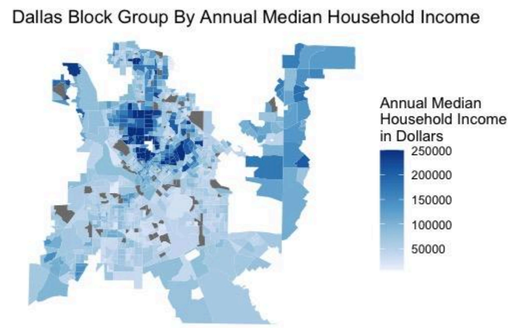
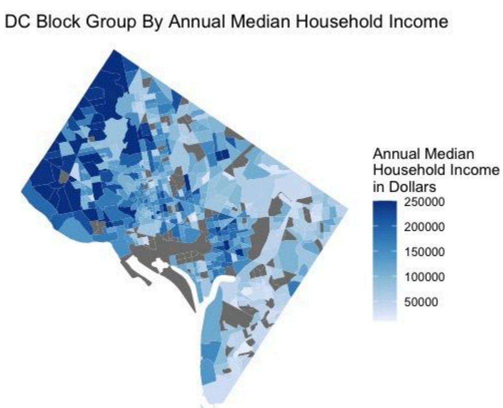
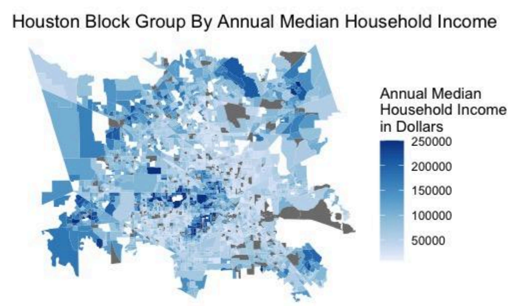
Addendum

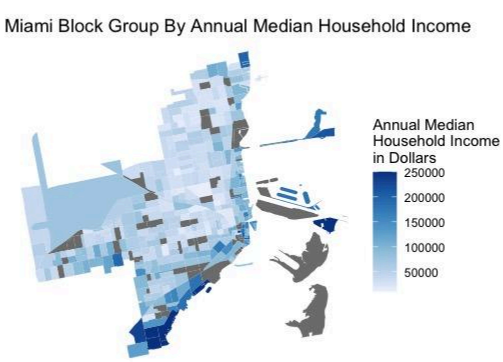
Annual Median Household Income



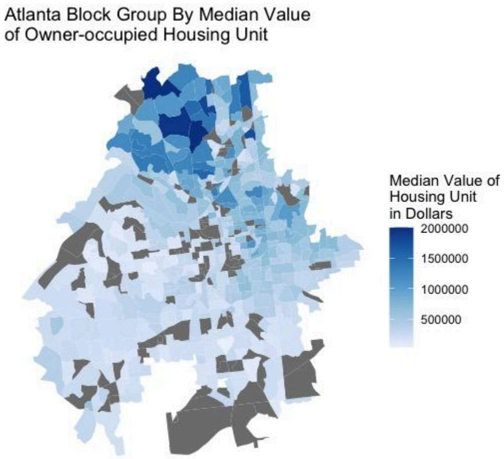


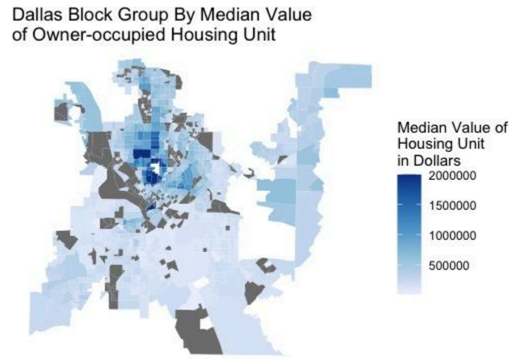


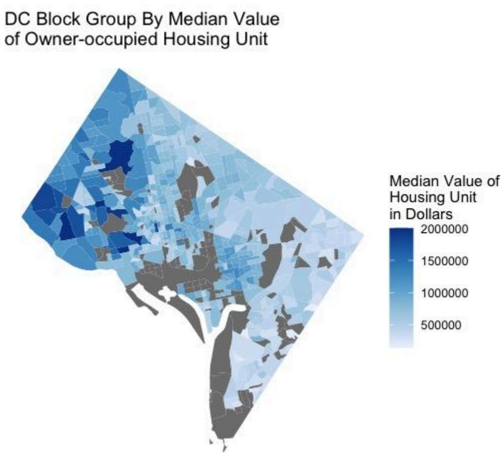


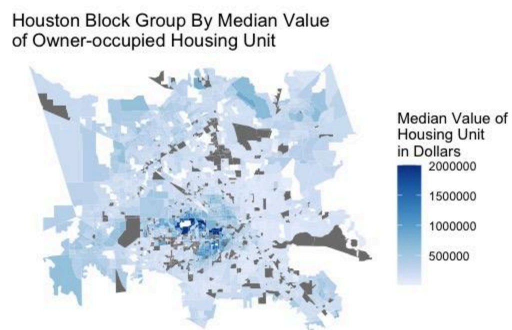


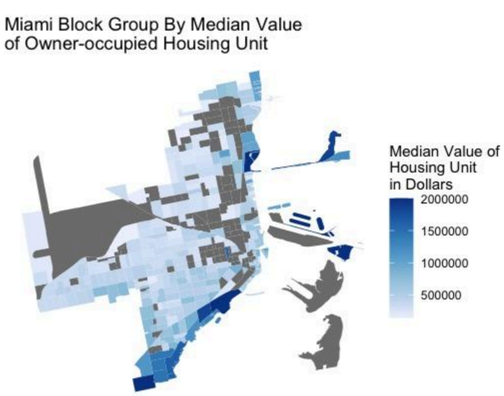
Median Value of Owner-Occupied Housing Unit



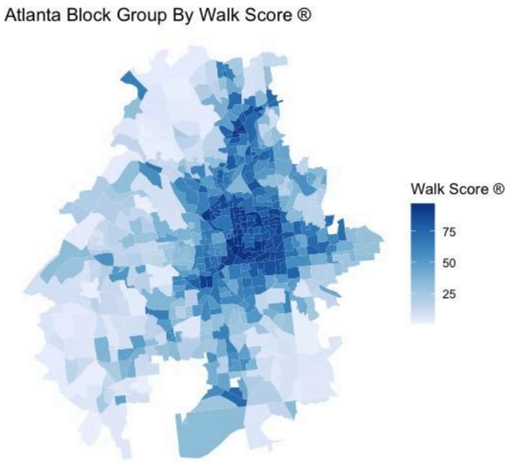


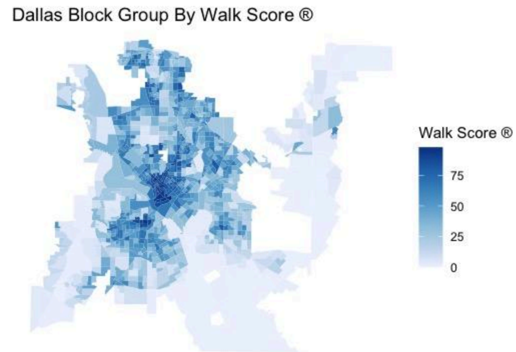


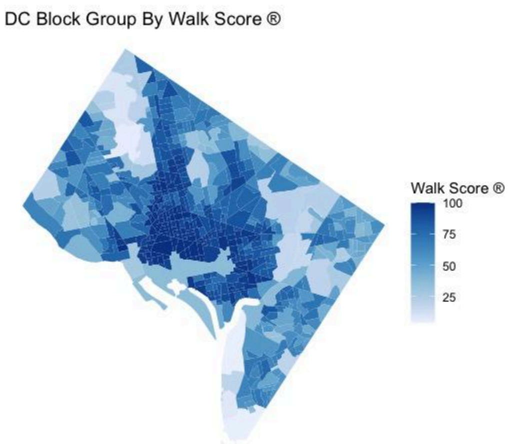


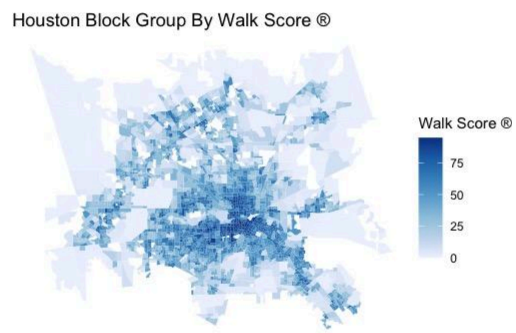


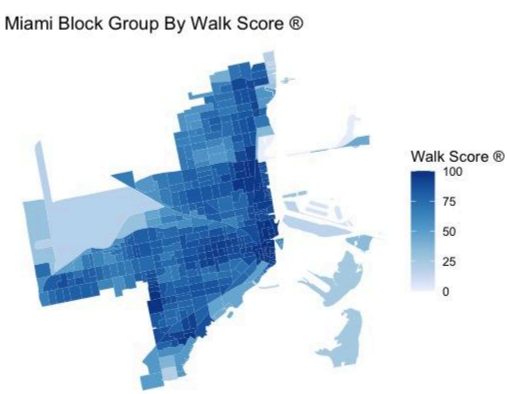
Walk Score


Atlanta Block Group By Walk Score ®
Walk Score ®
75
50
25

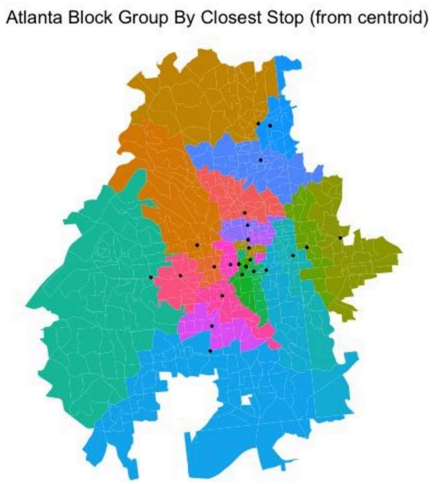

Dallas Block Group By Walk Score ®
Walk Score ®
75
50
25
0

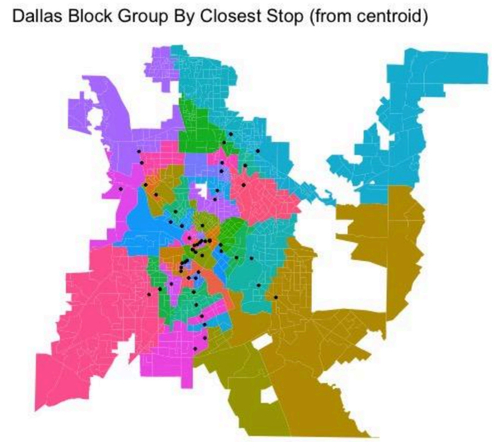

DC Block Group By Walk Score ®
Walk Score ®
100
75
50
25

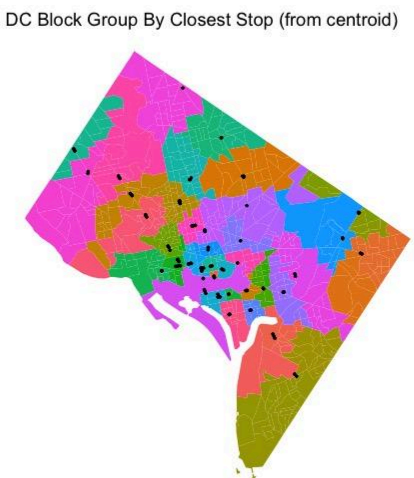

Houston Block Group By Walk Score ®
Walk Score ®
75
50
25
0

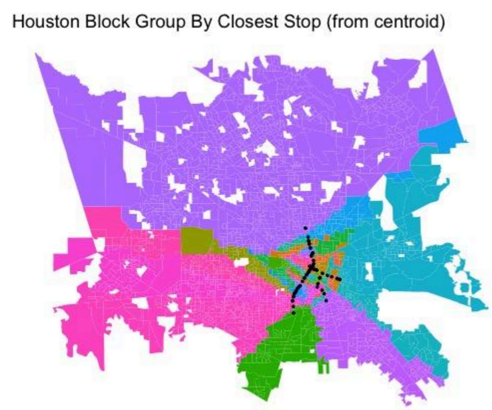

Miami Block Group By Walk Score ®
Walk Score ®
100
75
50
25
0

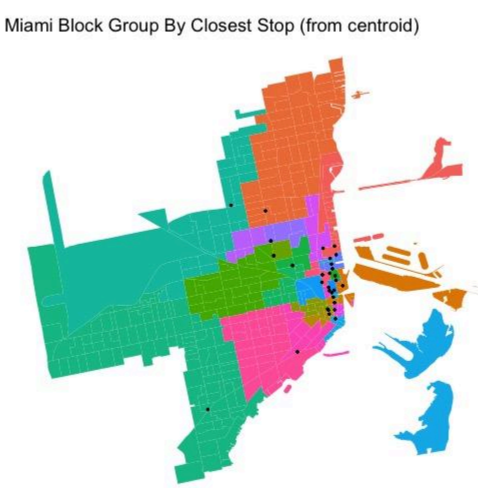
Closest Stop (from centroid)



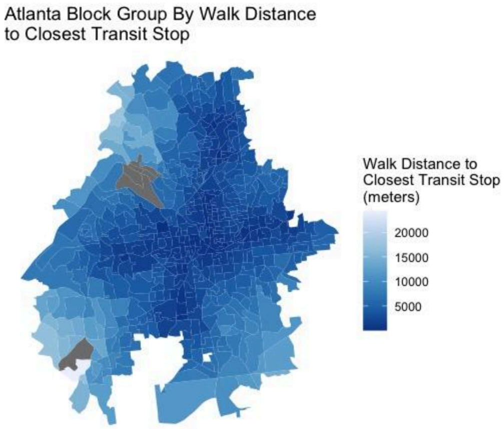


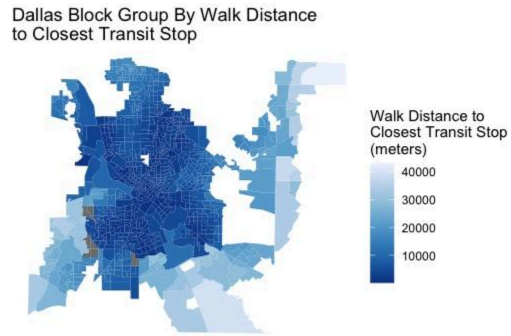


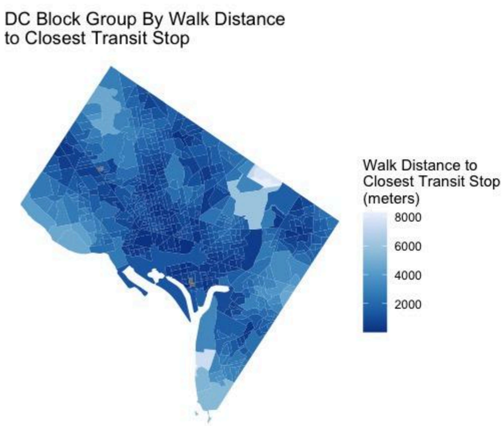


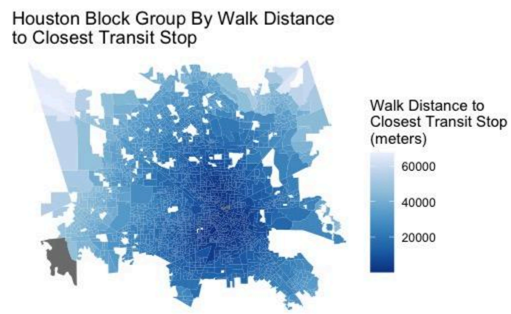


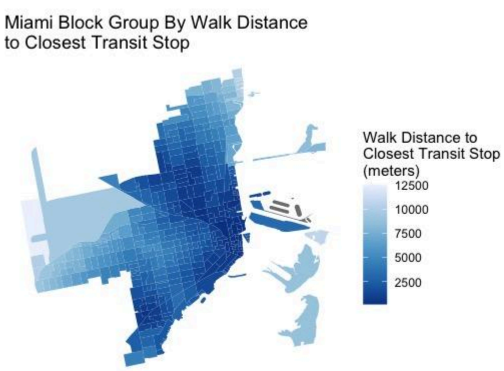
Walk Distance to Closest Transit Stop



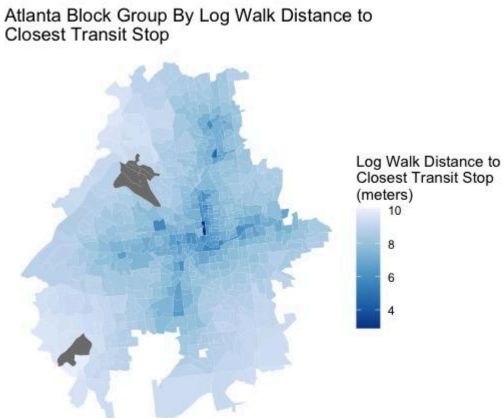


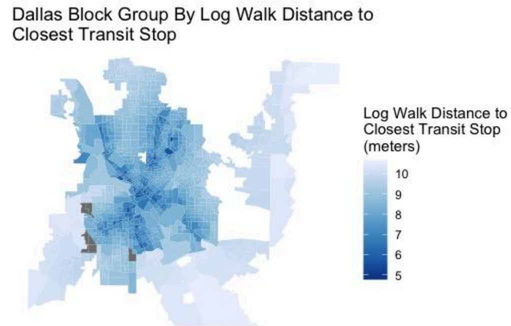


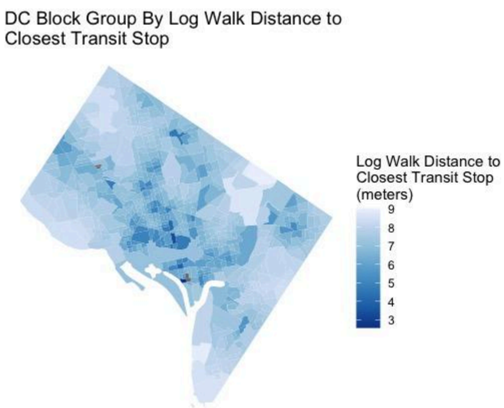


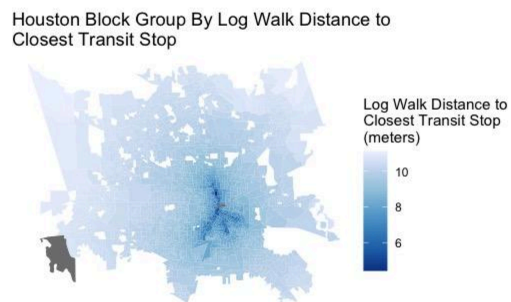


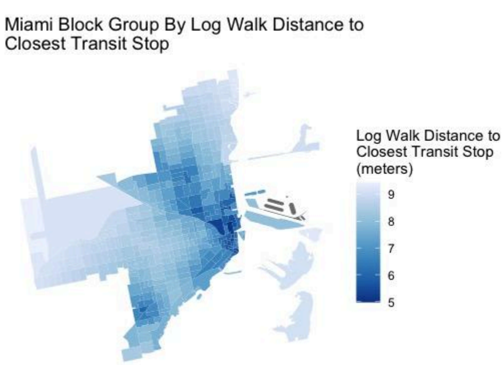
Log Walk Distance to Closest Transit Stop



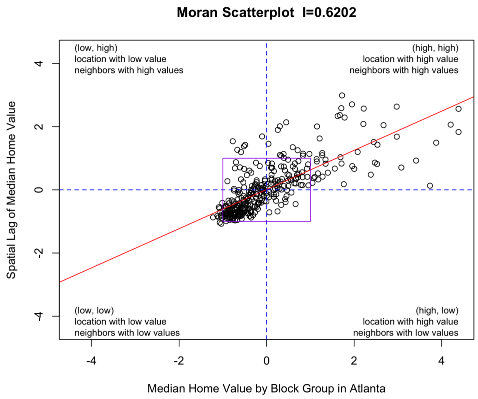


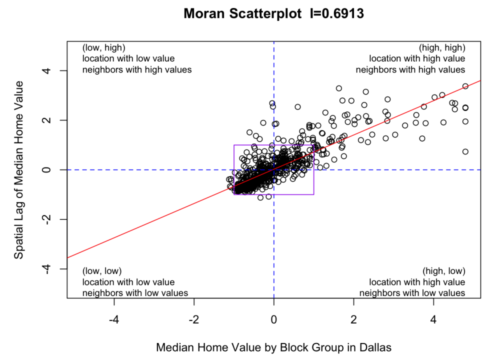


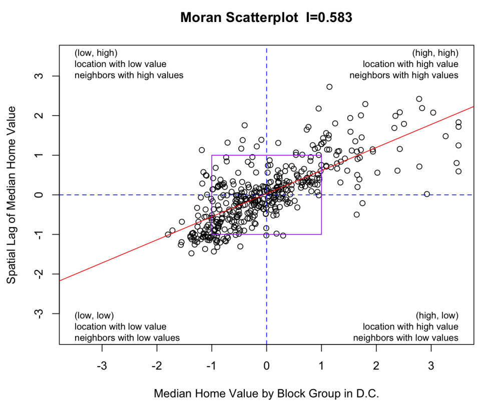


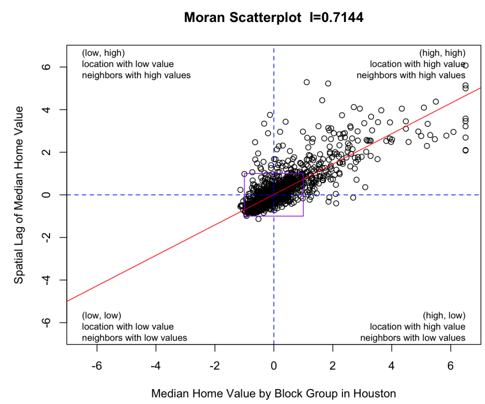


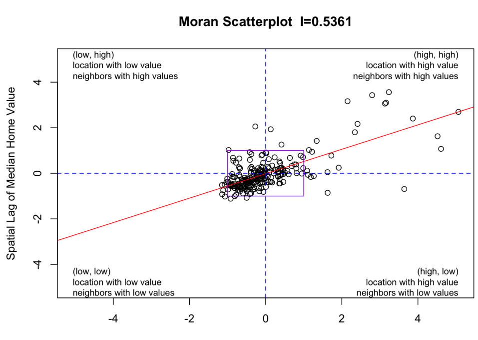
Moran scatterplot for Median Home Value











Models

Table 1. Less than 2km

	Dependent variable:				
	Atlanta	D.C.	Houston	Miami	Dallas
	(1)	(2)	(3)	(4)	(5)
Walking Distance (m)	0.301***	0.079**	-0.005	-0.048	0.049
	(0.090)	(0.034)	(0.087)	(0.077)	(0.114)
WalkScore	0.009***	0.008***	0.011***	0.004	0.013***
	(0.003)	(0.001)	(0.003)	(0.004)	(0.003)
Constant	10.141***	12.317***	11.907***	12.952***	11.390***
	(0.706)	(0.291)	(0.645)	(0.752)	(0.854)
Observations	104	337	110	85	154
R^2	0.159	0.095	0.085	0.034	0.147
Adjusted R^2	0.143	0.090	0.068	0.011	0.135
Note:					*p <0.1, **p<0.05, ***p<0.01

Table 2. Less than 4km

	Dependent variable:				
	Atlanta	D.C.	Houston	Miami	Dallas
	(1)	(2)	(3)	(4)	(5)
Walking Distance (m)	0.220***	0.053	0.105*	-0.093*	0.185**
	(0.064)	(0.033)	(0.063)	(0.054)	(0.076)
WalkScore	0.008***	0.004***	0.021***	-0.005*	0.007***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
Constant	10.784***	12.769***	10.503***	14.059***	10.860***
	(0.529)	(0.291)	(0.517)	(0.520)	(0.613)
Observations	211	410	232	160	324
R^2	0.102	0.031	0.262	0.028	0.038
Adjusted R^2	0.094	0.026	0.255	0.015	0.032
Note:					*p <0.1, **p<0.05, ***p<0.01

Table 3. All Observations

	Dependent variable:				
	Atlanta	D.C.	Houston	Miami	Dallas
	(1)	(2)	(3)	(4)	(5)
Walking Distance (m)	0.090	0.052	0.070***	-0.085**	0.031
	(0.055)	(0.032)	(0.017)	(0.038)	(0.032)
WalkScore	0.006***	0.004***	0.007***	-0.006***	0.005***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Constant	11.877***	12.791***	11.483***	14.081***	12.122***
	(0.495)	(0.288)	(0.182)	(0.386)	(0.307)
Observations	351	421	1,904	238	732
R^2	0.034	0.028	0.045	0.040	0.020
Adjusted R^2	0.028	0.024	0.044	0.032	0.018
Note:				*p <0.1, **p<0.05, ***p<0.01	

Table 4.

	City:				
	Atlanta	D.C.	Houston	Miami	Dallas
Moran I: Value	0.6202	0.5829	0.7143	0.5360	0.6913
Moran I: Walk Distance	0.8856	0.7533	0.9864	0.9417	0.8875
Expectation	-0.0029	-0.0023	-0.0005	-0.0042	-0.0013
Variance	0.0014	0.0011	0.0002	0.0025	0.0006
P-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

Table 5.

	City Model:				
	Atlanta	D.C.	Houston	Miami	Dallas
Moran I statistic	0.6378	0.5651	0.6546	0.4670	0.6696
Expectation	-0.0066	-0.0052	-0.0013	-0.0104	-0.0032
Variance	0.0014	0.0011	0.0002	0.0026	0.0006
P-value	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16	< 2.2e-16

Table 6

	Spatially Lagged Model				
	Atlanta (1)	D.C. (2)	Houston (3)	Miami (4)	Dallas (5)
Walking Distance (m)	0.006	0.002	-0.003	-0.016	0.001
	(0.025)	(0.018)	(0.008)	(0.026)	(0.016)
Constant	3.215^{***}	3.893^{***}	2.814^{***}	5.962^{***}	3.053^{***}
	(0.499)	(0.517)	(0.210)	(0.765)	(0.341)
Rho	0.745^{***}	0.709^{***}	0.775^{***}	0.550^{***}	0.755^{***}
	(0.036)	(0.037)	(0.015)	(0.055)	(0.025)
Observations	350	419	1897	235	726
Note:					$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$