Effect of Public Housing on House Prices

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Abstract

This paper measures the effect of public housing on house prices. Due to extensive research on the negative spillover effects of public housing, one might question why policymakers still push public housing policy. However, many low-income families cannot afford their housing costs and demand more affordable housing. Using data from the Department of Housing and Urban Development (HUD) and the US Census, I run a fixed-effects regression of distance away from public housing, controlling for characteristics in the area. For every one mile increase away from public housing, there is an associated 11.6 percent increase in average house prices, assuming constant slope. For this non-linear model, the effect of public housing on house prices is diminished for each additional mile. Overall, public housing is associated with a decline in house prices.

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1 Introduction

> "Helping our cities adapt and thrive in this new era of unprecedented urban growth is perhaps the central challenge of our time (Remarks by Secretary 2016)."
> – *Julián Castro, former HUD Secretary*

Roughly 12 million American households are paying more than half of their income on housing, and over 25 percent of American renters are paying over thirty percent of their incomes (Charette et. al 2015). Additionally, a person working full-time at a minimum wage position does not cover rent for a two bedroom apartment anywhere in the United States (Aurand et al. 2017). With high housing costs, many families are finding it increasingly difficult to afford all their necessities such as housing, medical expenses, food, and commuting costs. Low-income families increasingly demand more affordable housing in cities full of opportunity. Public housing provides a solution to this problem by allowing low-income renters to afford housing in cities closer to work and other amenities. This paper studies the magnitude of the effect of the proximity to public housing on median house values.

The Department of Housing and Urban Development (HUD) spends over $40 billion dollars a year to try to solve the problem of housing affordability. They plan, develop, manage, and incentivize public housing developments (Shester 2013) with hopes to benefit societal welfare. Low-income families and individuals may apply to receive an affordable rent based on income, citizenship status, and market rates in that area.

However, there are costs to consider. Previous literature suggests that public housing lowers property values (Diamond and McQuade 2016), and has other negative local economic effects. Despite the negative spillovers, studies found that public housing does have positive effects on society. Children growing up in public housing experience higher earnings and a higher standard of living (Chetty et al. 2016). Overall, it is unclear whether public housing has a net positive or net negative impact on societal wealth.

To measure the impact of living near public houses, I use house prices between 2013 and 2015 from the American Consumer Survey. House prices are a good indicator of wealth because, for the average American, wealth is stored primarily in their homes. I study the effect at the census block-group level: the smallest Census Bureau geographical unit for which data is available[1]. A block-group covers 600 to 3,000 people, an area smaller than a neighborhood. I regress the median house price in a census block-group on the distance to public housing, controlling for local characteristics, population characteristics, and amenities in that area. Since proximity to public housing has a diminishing effect on house prices, a squared term is added. In addition, for a more complete analysis, I estimate the effect of median earnings, and proportions of the population that are white or black as an outcome variable with the same measures.

I find that when a census block-group is 0 miles away from public housing, house prices are associated with a 11.6 percent increase for every additional mile away from public housing if the slope remained the same. Due to our non-linear model, each additional mile from public housing decreases the slope by 1.57 percent. Overall, living near public housing is associated with a decline in house prices, and nearby developments will have more of a negative impact. I also find that areas containing public housing have lower earned incomes and a higher percentage of minorities.

2 Literature Review

2.1 Public Housing Background

Public housing programs started up in the 1930s with the goal of slum clearance and revitalization of neighborhoods, focusing in urban areas. The first expansion of public housing between the 1930s and 1970s was deemed a failure due to increased levels of poverty, mismanagement of the programs, and other negative local economic effects (Radford 1996). Public housing authorities lacked sufficient authority to raise rents, manage, and maintain the properties. Since residents pay different rates at or below the market rate, there may not be sufficient funds for maintenance and other building necessities. During the early area

[1] A census block is not the same as a census block-group. A census block is smaller than a block-group, but has limited reports at this level

of public housing, these buildings deteriorated and were renowned for unsatisfactory quality and upkeep (Shester 2013). In 1973, President Nixon turned the program into voucher-only assistance, but HUD later subsidized and incentivized public housing development. Since then, more power was given to housing authorities to afford maintenance and management. Today, HUD distributes housing public assistance across multiple programs including the Low-Income Housing Tax Credit (LIHTC), certificates and vouchers, state assistance, and other HUD-assisted housing programs (Newman and Schnare 1997).

The LIHTC was created with the Tax Reform Act of 1986, allocating $8 billion in tax credits for construction, repair, or acquisition of public housing (Shester 2013). Properties allocate a proportion of their units to target low-income earners, but they can charge some residents market rates. Most residents will pay rent below the local market rate. The LIHTC accounts for over 90 percent of funding for public housing, so this paper will use developments funded by this credit.

To live in public housing, a resident must meet gross income requirements annually. The lower income limit is 80 percent of the median income, and the very low income limit is 50 percent of the median income. Note that income limits will differ by county. In addition, some public housing developments allow senior residents only, so applicants must also meet age requirements. HUD calculates rent depending on monthly income, charging a minimum of $25 a month (Charette et al.). Prospective residents may be interviewed in person, and they must report financial and familial information for the past 12 months, as well as what they expect to earn for the next year. Overall, the process may take months or over a year depending on availability.

2.2 Literature Background

Prior literature suggests that proximity to affordable housing effects house prices; however, the characteristics of these neighborhoods matter. Diamond and McQuade (2016) find public housing results in positive gains to total welfare if built in lower-income neighborhoods and negative gains to welfare if constructed in median-income neighborhoods. The authors estimate that affordable housing decreases property values by about 2.5 percent in a middle-income neighborhood over a ten-year period (Diamond and McQuade 2016). These authors employ house-level data but in areas that are highly urbanized, concentrated in the Northeast and West. To contribute to the findings of Diamond and McQuade, I include cities in every region of the US (Northeast, West, South, Midwest) for a unique perspective. For example, I study less urbanized cities such as Tucson, Arizona and rapidly growing cities such as Denver, Colorado[2].

Historically, public housing built in low-wealth areas often reinforces the concentration of minorities and elevated levels of poverty (Schill and Wachter 1995). However, it is important to note that households tend to self-segregate to communities of similar race and education level (Bayer et al. 2007). Over time, policymakers attempted to avoid concentrating negative by designing voucher programs such as Moving to Opportunity (MTO) to try to move lower-income people into higher-income neighborhoods.

In addition to concentrating the poor in an area, public housing may also affect the housing supply in a county. An increase in publicly funded construction, especially if government purchases are too high, may crowd out private investment and could potentially eliminate private sector spending. Sinai and Waldfogel (2002) study the extent to which affordable housing effects total housing supply, finding minimal evidence for crowding out of private investment in most neighborhoods. The authors estimate that, on average, three units financed by the government would displace two units privately provided (Sinai and Waldfogel 2002). I assume that construction incentivized by the LIHTC does not crowd out investment.

Placement of public housing is most likely nonrandom. Developers who receive incentives from HUD do not know when they will receive funding and where exactly in the county there will be space to build public housing (Diamond and McQuade 2016). Although other public houses may be spread randomly across town, clustered housing has more of an

[2]For a complete list of 12 locations used see Figure 1

effect on the local area than housing in a random spread. Haberman et al. find that public housing increases crime in an area if buildings are clustered together, and they suggest that policies should incentivize developers to build housing at least two blocks away from each other (2013). In this paper, I cannot interpret a causal relationship between proximity to public housing and house prices, but I can add controls, fixed-effects, and run robustness checks.

Depending on the local or state policies, affordable housing incentives and regulation differ by region. Baum-Snow and Marion find that developers choose to build subsidized housing in areas with more tax credit incentives and gentrifying neighborhoods (2009). Because of different incentives, the effects of public housing may be disproportionately concentrated in a county. I will include a measure of distance where public housing developments are in mutually exclusive distances away from a neighborhood to capture these clustered groups. Additionally, Newman and Schnare find that overall, public housing fares worse than other forms of housing assistance: it is more densely located in low-income neighborhoods, houses the highest percentages of men not working regularly, and has the highest poverty rates comparatively (1997).

The effects of public housing differ depending on the type of federal housing assistance. Lee et al. (1999) in a Philadelphia case study find that the relationship between local property values and house prices depends on the different type of public program. They find that section 8 vouchers, scattered public housing sites, and LIHTC sites have slightly negative effects on property values, but that Housing Administration units, homeownership program units, and Section 8 New Construction and Rehabilitation units have positive effects on property values (Lee et al. 1999). Due to the data limitations, this paper only focuses on LIHTC developments; however, it is possible a resident of public housing is receiving support supplements from Section 8.

Public housing has been shown to be beneficial for the children of the residents living in public housing. Although some studies link public housing developments with poor educational achievement (Shester 2013, Aaronson 1998), Chetty et al. find an association between public assistance and positive long-term benefits among children (2016). Individuals who lived in public housing as children were more likely to graduate high school, attend college, live in wealthier neighborhoods, and were less likely to raise a child as a single parent (Chetty et al. 2016). Andersson et al. find positive statistically significant benefits as well, including less incarceration and higher expected earnings later in life; these positive effects were highest among ethnic minorities and women (2016).

Since public housing has been around for almost a century, it is important to understand the past trends and compare to the present. However, literature on public housing before 1987 is limited since the data is not digitized. Therefore, the literature is limited before this time period. Shester (2013) finds that households in counties with more public housing had lower median family incomes, lower property values, and a higher density of low-income residents between 1940-1970. Overall, public housing had a negative spillover effect, probably due to poor management, lack of maintenance, lack of housing authority control, and lack of funds. Importantly, she finds that most public housing developments built during this period are still in use today, but many have undergone major restorations (Shester 2013). This paper will compare current local economic conditions of public housing to this period of massive public housing expansion to see how prevalent these negative effects of public housing are today.

2.3 Theoretical Background

Working city inhabitants will choose where to live in a city that maximizes their utility (Glaeser 2008). They maximize their income, size of land, and amenities they can access in a city; they minimize their commuting costs and distance to the city center (Glaeser 2008, 39). The amenity spillover depends on the wealth of the neighborhood, and since rich people will usually consume more land, they are more likely to live away from the central city (Glaeser 2008, 40). For example, there will be more amenity spillover effects in a wealthy neighborhood than in a low-income neighborhood. When we change local amenities, current residents may decide to leave the neighborhood and optimize their local benefits elsewhere (Tiebout 1956). Diamond argues that higher income consumers are willing to pay for more neighborhood amenities, and further studies suggest that these higher-income individuals, as well as more-educated individuals, endogenously improve local neighborhood amenities (Diamond 2017, Bayer et al. 2007).

I adapt the data I have available for a simple Glaeser model. For this paper, an observation is not an individual but a geographical area smaller than a neighborhood, but the theory is based off how a city dweller chooses to live in city. I assume that everyone receives the same flow of amenities (e.g. a park in a block-group benefits everyone equally in that block group), and that wages are exogenously determined. I employ a model where city dwellers choose to live close to the central business district (CBD) and far away from public housing, they minimize their commuting time to work, and they maximize their amenities in the area. Unfortunately, the list of amenities I include are extremely limited.

3 Data

To measure the impact of public housing on house prices, census, HUD, and geolocation data were used. Twelve counties were chosen nationwide that contained a city. Three cities were chosen in one of four census-defined regions: the Northeast, the Midwest, the South, and the West. The twelve counties are listed in Table 1. I use data that makes up a county because I can theoretically capture the movement of people in, out, and around the city. All data sets are merged and appended with a census identifier.[3]

3.1 Census Data

Each observation in the dataset is a 2010 census block-group, identified with a twelve-digit FIPS code and selected by population. Block-groups typically have 600 to 3,000 people and cover an area smaller than a neighborhood, but they optimally have 1,500 people. These block-groups are convenient for studies because they represent a small area with mostly

[3]the census identifier used lists a 12-digit FIPS code with numbers for state, county, tract, and block in that order

Table 1: Data Locations

Region	State	County	City
Midwest	MN	Hennepin	Minneapolis
Midwest	WI	Milwaukee	Milwaukee
Midwest	MI	Wayne	Detroit
Northeast	PA	Allegheny	Pittsburgh
Northeast	MD	Baltimore	Baltimore
Northeast	MA	Suffolk	Boston
South	TN	Davidson	Nashville
South	KY	Jefferson	Louisville
South	TX	Travis	Austin
West	CO	Denver	Denver
West	WA	King	Seattle
West	AZ	Pima	Tucson

homogeneous properties. They capture an area smaller than a neighborhood, are uniquely numbered, and do not cross state, county, or census tract boundaries. A block-group of 0 indicates an area containing only water, so I dropped all water-only blocks. I used 2010 census shape files for each county to match the house price data. Using QGIS, I found the centroid of each census block and then kept the latitude, longitude, and block-group identifier.

Also taken from the US Census, the American Consumer Survey (ACS) was used. This survey covers job status, education level, if people own a home, median house prices in an area, etc. I used median house prices in dollars, earned income in dollars, race demographics, and travel time to work in minutes from 2013 until 2015 for a given block-group. For the race control, I only used percent white and percent black since they accounted for most of the data. The census data reports the number of people who are a certain race, so I divided the number of people that were white or black over the total. Thus, I have a measure of the fraction of people in a block-group that represent a race. For travel time, the census table recorded the count of people that took less than 5 minutes to work, 5 to 9 minutes to work, 9 to 11 minutes to work, etc. I took a weighted average of each category to measure average travel time to work in minutes. I merged controls and public housing location data at the county-level first and then appended every county and year.

3.2 HUD Data

I found the locations and characteristics of public housing from the Department of Housing and Urban Development (HUD) open data. HUD publishes two datasets of public housing locations: one includes public housing buildings and the other includes public housing developments. The public housing locations file lists every single building in a development (e.g. an apartment complex with a building "A" and a building "B"). Similar to Shester and Diamond & McQuade, I study the effect of public housing developments (2013, 2016). However, since the public housing development file did not include many of the public housing characteristics, I condensed the public housing buildings file. Each development is identified with a building code, so each building in a development has the same code. I collapsed the data by this code to represent a development of public housing instead of each individual building. The intuition behind this is that people will decide whether to live near a public housing complex; they do not choose to live there because it has multiple buildings per complex.

3.3 Other Data

I used Google Earth to locate the central business district[4], and then calculated the centroid of this area. I merged the latitude and longitudes of these districts to each city, and then measured the distance between the centroid of each census block and the centroid of the business district in miles.

4 Research Method

The main dependent variable is log house prices for a census block-group, and the main coefficient of interest is distance from public housing. I use three different measures of distance from public housing as the independent variable. For a more complete picture, I will regress distance from public housing on log earned income, log proportion of the population

[4]for some cities the CBD was found using the key term "downtown"

that is white, and log proportion of the population that is black.

4.1 Model and Controls

To measure the effect of public housing, I regress the distance from public housing on average house prices in a census block-group. I use fixed effects to control for unobserved heterogeneity over county and year. Since housing markets in the twelve counties are vastly different, county fixed effects will control for these differences. Also, housing markets will change over time, so year fixed-effects controls for time-variant effects. By adding fixed effects, I control for the average difference across counties for observable or unobservable predictors. I am left with within-county variation with reduced omitted variable bias. However, I must make the strong assumption that unobservables that effect either the dependent or independent variable of the regression are time-invariant and county-invariant. Since housing markets are quite volatile over time and by county, I am satisfied with this assumption to begin.

In addition to fixed-effects, there are controls I must add. I include distance to the CBD in miles and distance to CBD squared since, in our utility-maximizing model, users will want to maximize their distance to the CBD. I assume that living close to the CBD will have more of a positive impact on house prices than if a household lives at the edge of the city. To capture the increasing effect each additional mile away from the CBD has on house prices, I include a squared term of distance to CBD. I add a control for travel time to work (in minutes) because households, to maximize their utility, will choose housing that minimizes the time it takes for them to get to work. Race demographics for all years are added because block-groups with a high percent of white or black is a possible determinant for where a policymaker will place public housing and/or for house prices. Additionally, city dwellers tend to self-segregate into geographical areas (Bayer et al. 2007). I also control for the geolocation of a census block-group since block-groups in a county are not located in the same place throughout the city.

4.2 Three Measures of Distance

The first measure is distance from the closest public housing development. Theoretically, the closest public housing development should have the greatest impact on local house prices. To calculate this measure, I subtract the distance between the centroid of a census block-group and the location of the closest public housing development. The variables are labeled *mindistance* and add *mindistance2* so that shorter distances are given greater weights. Due to the sensitivity of this model, I cut off the minimum distance from a public housing development at 13.95 miles. This distance captures 99 percent of the data and removes the outliers that go up to 80 miles away from a public housing development and would not logically represent the sample. The observations that were dropped were mostly from Pima County in Arizona since it has a few large sprawling rural block-groups outside of the city.

The second model employs a binary indicator that equals 1 if there is public housing in the census block and equals 0 otherwise. Table 2 tabulates average house prices if the public housing indicator equals 1 or 0 for 2014. For 11 out of 12 cities, house prices with public housing in their block are lower than house prices without public housing in their block. The percent difference between the two blocks are quite large, so I would expect the coefficient of interest to reflect this.

The third model breaks down the number of public housing developments in the county into mutually exclusive distances away from a census block-group. Note that I am now looking at how an increase in one public housing development impacts house prices for six increments of distance away from the observed block-group. I expect that the closer the distance groups are to a census block-group, the addition of another public housing development will have more of an impact on house prices.

Table 3 tabulates average house prices if there is public housing within 0-1, 1-2, 2-3, 3-4, 4-5, or 5-10 miles from a census block. Trends can more clearly be seen in Figure 1. The county that contains Pittsburgh, PA highlights a positive trend: as the distance away from a census block increases, housing prices go up. For Denver, note that the change in house prices becomes negative 4-5 miles away from public housing. This may be because of other competing factors such as distance to the central business district, but it could also mean that the distance increments are now targeting an area outside of the city where the effect of public housing is no longer applicable. We see a positive trend for Boston, MA in Suffolk County: adding public housing within all increments increases house prices. Boston is already a high-wealth area, so there may be other factors occurring here. Note, however, that the changes between distance increments are small. Therefore, the coefficients on these increments in the regression should be small as well. As seen in Figure 1, I expect that adding public housing developments in the closer increments to have more of an impact on house prices than farther increments.

4.3 Regression

Since housing markets and characteristics differ across county and year, I use county and year fixed effects. Additional controls include percentage of a census block-group that is white or black, the number of housing units in a census block, the amount of time in minutes to travel to work, the latitude and longitude of a census block, distance to the central business district (CBD) and distance to the CBD squared.

Measure (1): Closest Public Housing Developments

$$Y_{bct} = \beta_0 + \beta_1 mindistance_{bct} + \beta_2 mindistance_{bct}^2 + \beta_3 CBDdistance_{bct} + \beta_4 CBDdistance_{bct}^2 + controls_{bct} + \delta_t + \phi_c + \epsilon_{bct}$$

Where the median house price is measured by block b in one of the twelve counties c between 2013 and 2015 t.

Measure (2): Effect of Distance to Public Housing on Earned Income

$$Y_{bct} = \beta_0 + \beta_1 housingindicator_{bct} + \beta_2 CBDdistance_{bct} + \beta_3 CBDdistance_{bct}^2 + controls_{bct} + \delta_t + \phi_c + \epsilon_{bct}$$

Where the housing binary indicator equals 1 if public housing is located in the observed census block group and equals 0 otherwise. This measure is similar to measure (1).

Measure (3): Public Housing Nearby (In census block-group)

$$Y_{bct} = \beta_0 + \beta_1 publichousingdistance_{bct} + \beta_2 CBDdistance_{bct} + \beta_3 CBDdistance^2_{bct} + controls_{bct} + \delta_t + \phi_c + \epsilon_{bct}$$

where the distance is the amount of public housing developments divided into the following increments: 0-1 miles away, 1-2 miles away, 2-3 miles away, 3-4 miles away, 4-5 miles away, and 5-10 miles away from the observed area.

4.4 Additional Dependent Variables

Since there are many competing factors in this model, we look at different dependent variables that are significantly correlated with distance to public housing. Three dependent variables are log earned income, log proportion of the population that is white, and log proportion of the population that is black.

Earned income in an area determines house price, and conversely, house prices determine earned income. It is fully possible that low-income earners self-selected to areas near public housing due to lower house prices, and that investors and policymakers placed public housing in an area because of poverty. Earned income may be bi-directional in our model, but it is important to study how public housing effects it. Not everyone owns a home, so we can capture total wealth in an area by using earned income instead. Average earned income here captures renters, homeowners, and more individual-level people. For instance, instead of looking at house price sales for a household, we capture individual wealth. Therefore, I run measures (1) to (3) with log earned income as the dependent variable. I expect the coefficient of interest to be smaller in magnitude because we are looking at the average earnings of more individuals.

Since researchers find that public housing concentrates poverty in area (Bayer et al. 2007, Shester 2013), it is important to study the effect of public housing on ethnic minorities. House prices may be lower near public housing due to lower land values, and as a result people with lower incomes may afford these areas. Coincidentally, these lower-income earners are disproportionately minorities. However, investors and policymakers perhaps placed public housing in this area due to a high concentration of minorities. Therefore, we run into endogeneity concerns. Nevertheless, studying the effect of living near public housing on the percentage of minorities in an area does show us more of a complete story. I take the log of proportion of the population that is white and the log of the proportion of the population that is black so that my results will show a percent change on house prices as opposed to a percentage point change on house prices.

5 Results

5.1 Effect of Distance from Public Housing on House Prices

Three regressions were run to observe the effect of distance from public housing on house prices (Table 4). For each of these models, distance from public housing and distance from the central business district are competing since households will want to live away from public housing but near the CBD.

The first model looked at the closest public housing development to a census block-group (Column 1). When a census block-group is 0 miles away from public housing, housing prices would be associated with a 11.6 percent increase for every additional mile away from public housing if the slope remained the same. However, each additional mile from public housing decreases the slope by 1.57 percent. On the contrary, moving away by one mile from the CBD decreases house prices by 3 percent and increases the slope by 0.282 percent for each additional mile. Note that the effect of living away from public housing was greater in absolute magnitude than the effect of living near the CBD.

The second model looked at not only one public housing development, but measured the effect of public housing nearby in the same block-group (Column 2). If public housing was in a census block-group, there would be an 8.83 percent decrease to house prices.

In the third model, I look at the effect mutually exclusive distances away from public housing developments (Column 3). For the addition of one public housing development 0-1 miles away from the observed area, there would be a .561 percent decrease to house prices. For all the increments, the effect was small and negative, but adding developments in the

0-1 and 1-2 distances had more of an impact on house prices.

5.2 Effect of Distance from Public Housing on Earnings

The main regressions were run again with earnings as the dependent variable (Table 5). For the closest public housing development, there was a positive percent increase to earnings (Column 1). For public housing in the same census block-group, there was also a diminishing effect to earnings (Column 2). When I divide public housing into incremental distances away from the census block-group, there is a slight negative effect for the first four miles, but then a positive effect for public housing within between 4 and 10 miles away (Column 3). Similar to previous findings, public housing developments that were added nearby had more of an impact than if added across town.

5.3 Effect of Public Housing on Demographics

Next, I consider the effect of public housing on proportions of the population that are white or black (Tables 6-7). When comparing the two regression tables, many of the coefficient directions are opposite. For example, a one mile increase from the closest public housing is associated with a 23.9 percent increase to the proportion of the population that is white, assuming a constant change in distance (Column 1). In contrast, a one mile increase from the closest public housing is associated with a 39.0 percent decrease to the proportion of the population that is black, assuming constant slope. If public housing is in a census block, there is an associated 41.4 percent decrease in the proportion of people that are white but a 60 percent increase in the proportion of people that are black (Column 2).

6 Discussion

6.1 House Prices

Our results align with a Glaeser model: city dwellers choose to live in the city in a place that maximizes their utility (Glaeser 2008). For measure (1), if the closest public housing is 0 miles away, there is a 11.8 percent increase to house prices with a 0.816 percent decrease to house prices for every additional mile added. Additionally, if the CBD is 0 miles away, there is a 3.00 percent decrease to house prices with a .114 increase to house prices for every additional mile added. These results indicate that city dwellers want to live away from public housing and near the CBD. More importantly, the effect due to the closest public housing development is absolutely greater than the effect due to the CBD. Therefore, our results make sense: for the first few miles, the effect of the closest public housing dominates the effect of the CBD.

As compared with Diamond and McQuade, our estimate of the impact of public housing on house prices is much more negative; they estimate an overall 2.5 percent decrease to house prices over a ten year period (2016). We do find a relationship in the same direction but with different magnitudes. Since I am using a quadratic model, the closest public housing development will have the greatest impact on house prices, so I would expect a larger coefficient.

For Measure (1,) if I plug in our estimates into the derivative of the regression equation with respect to minimum distance and set this equal to zero, we can find the maximum of this non-linear portion: 7.23 miles. If we do this with respect of distance to CBD, we get 13.16 miles. Clearly, the distance from the CBD covers a wider area, but the distance from the closest public housing covers all our distance of interest. If the minimum distance between an observed block-group and a public housing development is greater than 14.46 miles, I assume the model is now targeting an area outside of the city. Therefore, our results, in regard to the coefficient of interest and the CBD, span a significant distance over the dataset.

Measure (2) shows a similar story to Measure (1): living near public housing is associated with a large and significant decrease to house prices. Here, the magnitude on the coefficient of interest, 8.83 percent, is less than the 11.6 percent associated decline for the closest public housing. Using an indicator variable, I am accounting for public housing nearby and not necessarily the closest public housing. I may capture more than one public housing development, but not necessarily the public housing development that has the strongest negative impact on house prices. Also, this model does not capture a diminishing effect of public housing on house prices as distance away from public housing increases, but I do capture a significant difference in average house prices if public housing is contained within a census block-group.

Measure (3) indicates a trend: an increase in public housing development 1 within closer increments is associated with a greater decrease to house prices than in further increments. Adding 1 development 0-1 miles away from a census block-group is associated with a .561 percent decrease to house prices. Each coefficient for up to 4 miles away from public housing is associated with a slightly smaller decrease in house prices. Therefore, this measure captures the diminishing effect of public housing on house prices as well.

Coefficients from measure (3) are significant but small and align with expectations found from Figure 1. These small changes may be because there are few public housing developments in a city. For instance, Denver County has 28 public housing developments. Therefore, the addition of one more development of public housing may have a small impact on house prices, but when considering the impact all 28 developments have on Denver County, this impact is probably large.

6.2 Earnings and Race Demographics

House prices are higher in areas of high income. If I want to further study the effect of house prices on wealth, I study the effect of proximity to public housing on earned income. Not all city-dwellers own a home, so I study the effect of house prices on earned income to hopefully capture more individuals in a census block-group. The unit of observation is not by individual, but the median earnings represents a different subset of the population. We find that areas of public housing are associated with lower incomes, but that this effect is smaller than the effect of house prices. These findings align with Newman and Schnare: public housing is located in areas of low-income (1997). Overall, the effect of proximity to public housing on earnings is negative. Clearly those who live in public housing themselves are low-income, so this relationship makes sense.

I look at the effect of race demographics on house prices, and find that there is a disproportionate difference between the effect of public housing developments on white versus black population proportions. Since these populations already have higher percentages of white people, the effect on black proportions would already be larger. However, not only are the magnitudes larger but the signs are opposite. Areas of public housing are associated with an increase in black proportions but a decrease in white proportions. This may indicate that public housing developments are still built in low-wealth and high-minority areas comparable to the time when public housing was first constructed in the 1930s. However, this could also be because areas of lower income are already associated with areas higher in minorities and will then have lower house values. Bi-directionality is discussed in the next section.

6.3 Limitations

This paper suffers from omitted variable bias. Even though a few controls for amenities in the area were added, not all factors could be included. For example, I am not controlling for the number of parks nearby, school quality in an area, or crime levels. Since I assume positive amenities in the area such as school quality and number of parks are positively correlated with the dependent variable distance from public housing, the omitted variable has a positive bias. Omitting crime would lead to negative bias.

Additionally, this paper has selection bias. From the regressions, I cannot interpret a causal relationship because the placement of public housing is non-random. Because of the competing effects of house prices, earnings, race, public housing locations, distance from the city center, I do run several regressions to make sure the findings of make sense. I include controls and fixed-effects, but overall, the methodology does not resemble an experiment.

This paper also suffers from endogeneity concerns. People will choose to live in area that maximizes their utility: minimal rents, minimal distance to the CBD, maximized amenities, etc. Since public housing is deemed as a negative amenity, people will choose to live far away from public housing given income, rent, ethnicity, travel time, and CBD distance constraints. As a result, people who live near public housing should receive less rents, lower property values, lower house prices, and less amenities overall. These areas are associated with lower incomes, higher percentage of minorities, and lower house prices. However, it is perfectly reasonable to argue that public housing was placed in these areas because of lower property values. Coincidentally, these areas are associated with more poverty, lower incomes, and more minorities. Or, public housing was placed in these areas because of a higher concentration of ethnicities who are coincidentally more likely to receive lower incomes. Public housing historically suffers from mismanagement and lower profit margins, so investors would want to maximize profits by placing these buildings in cheaper areas. The rents they receive may not be enough to sustain maintenance costs.

Furthermore, I am limited by house price data. Diamond and McQuade use a third party named DataQuick to collect and aggregate individual house sales for quite a few urban areas (2016). My dataset represents a wider variety of cities over three years at the block-group level, but my results do not reflect individual sales. Also, the calculation of distance assumes that the effect of public housing on house prices is the same for any point in the block. In this paper, block-groups are targeted by their center, but in reality, the edges would be closer or farther away from public housing than the center. I do assume that the centroid represents the entire block-group, but house-level data would be more ideal.

If I were to work on this project in the future, I would perhaps study the period before and after the institution of the LIHTC for a differences-in-differences study. I would like to study public housing in a setting that resembles more of an experiment. However, public housing and some relevant census data before 1987 is not digital and would have to be manually entered into a computer. I would also want to study the wealth, education, and employment factors of residents living in affordable housing, but data on residents is limited. Additionally, I would want to include more controls and amenities such as parks, school quality, and crime rates.

7 Conclusion

This paper studies the effect of public housing on house prices. The results show a competing effect between distance to CBD and distance to public housing: city dwellers want to live near the CBD but away from public housing. For the first few miles, the effect of public housing is greater than the effect of the CBD, but the CBD will eventually dominate due a positive marginal effect. Overall, the nearby public housing developments are associated with a decrease in house prices. The closer the development to the observed block-group, the larger the negative impact on house prices.

Areas of public housing developments tend to have lower incomes and a higher percentage of minorities, similar to the rapid period of public housing growth in the 1930-1950s. The results indicate that historical trends of concentrating poor minorities in areas of public housing attenuated to the present. Given the current demand for more affordable housing, policymakers and investors must consider the most beneficial placement of LIHTC public housing to address concerns of poverty and minority concentration.

Even though the results display negative effects of nearby public housing, it is important to note that there are long-term positive effects. Reiterating work by Chetty et al., researchers show that children growing up in public housing receive higher incomes, lower unemployment rates, and women have children at older ages (2016). As a result, the net impact of public housing may not be as negative as this paper suggests.

Overall, the point of this study was to help measure the effectiveness of public housing policy. To motivate potential gains from public housing, I look at mobility scores in our areas of public housing as reported by the Equality of Opportunity Project. Spending a year or more of childhood in the twelve counties increases or decreases household income by the following amounts: -47 percent for Denver, -8 percent for Hennepin, -50 percent for Milwaukee, -57 percent for Wayne, -21 percent for Allegheny, -5 percent for Baltimore, -31 percent for Suffolk, -44 percent for Davidson, -43 percent for Jefferson, -46 percent for Travis, 47 percent for King, and -45 percent for Pima (Chetty and Hendren 2017). These percentages are for households in the 25th income percentile. Only for the county containing Seattle, WA did household incomes increase. When considering the long-term positive benefits of public housing, lower-income children growing up in these counties could benefit from living in public housing.

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Table 2: Average House Prices if Public Housing located in Census Block-Group

Location			Public Housing NOT in Block	Public Housing in Block	Percent Difference
State	County	City	$	$	%
PA	Allegheny	Pittsburgh	137,677	96,456	-29.9
MD	Baltimore	Baltimore	180,160	136,262	-24.4
TN	Davidson	Nashville	214,694	155,368	-27.6
CO	Denver	Denver	330,017	230,981	-30.0
MN	Hennepin	Minneapolis	269,645	193,044	-28.4
KY	Jefferson	Louisville	167,361	108,797	-35.0
WA	King	Seattle	408,085	367,085	-10.0
WI	Milwaukee	Milwaukee	161,363	94,367	-41.5
AZ	Pima	Tucson	193,690	125,988	-35.0
MA	Suffolk	Boston	392,836	396,935	1.0
TX	Travis	Austin	272,301	216,035	-20.7
MI	Wayne	Detroit	87,515	55,734	-36.3

Table 3: Average House Prices in Incremental Distances Away from Public Housing in 2014

	0-1 miles away	1-2 miles away	2-3 miles away	3-4 miles away	4-5 miles away	5-10 miles away
Pittsburgh	104,928	112,921	119,443	121,317	122,583	129,565
Baltimore	152,685	157,591	159,764	158,041	158,748	157,261
Nashville	175,516	204,168	205,500	209,967	215,074	192,664
Denver	240,925	277,745	294,206	295,944	292,206	280,754
Boston	396,855	392,403	392,986	392,069	391,897	389,206
Minneapolis	182,276	209,420	225,224	242,616	233,076	242,181
Louisville	137,621	137,251	139,751	144,311	146,345	157,215
Seattle	360,708	385,204	399,389	400,297	403,672	398,436
Milwaukee	108,423	120,559	130,949	137,032	139,694	147,541
Tucson	132,565	126,617	137,133	139,754	142,390	168,477
Austin	249,383	270,746	276,106	269,899	273,954	268,788
Detroit	55,996	57,042	59,725	63,562	66,236	80,018

Figure 1: Average House Prices in Incremental Distances Away from Public Housing

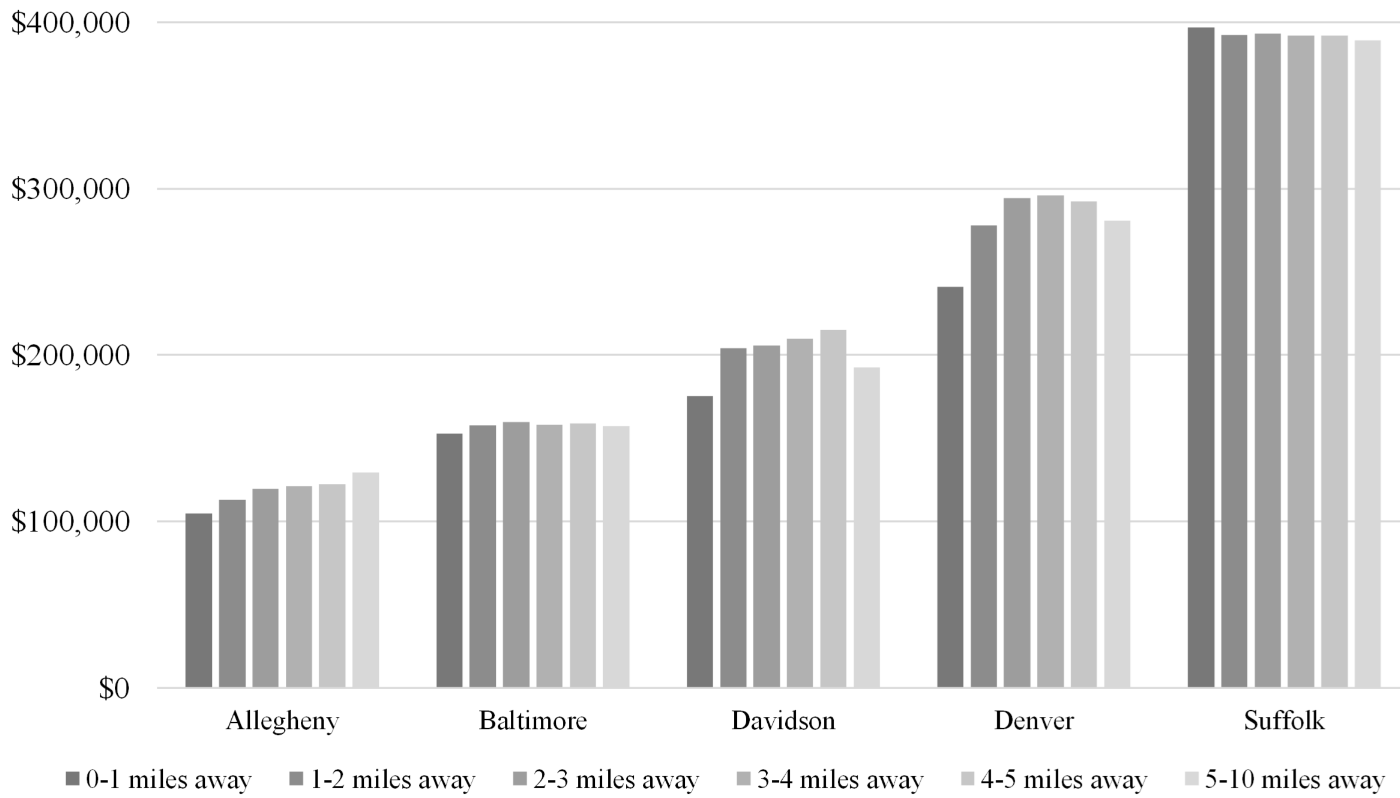

Figure shows 2014 data only for five out of the twelve counties listed. Table 3 lists exact amounts for these counties.

Table 4: Effect of the Distance to Public Housing Development on log House Prices

	(1) Closest PH	(2) PH in Block	(3) Incremental Distances
Min Distance to PH	0.116***		
	(0.00408)		
Min Distance to PH Squared	-0.00785***		
	(0.000370)		
Public Housing Indicator		-0.0883***	
		(0.00703)	
Public Housing within [0,1] miles			-0.00561**
			(0.00193)
Public Housing within (1,2] miles			-0.00108
			(0.00119)
Public Housing within (2,3] miles			-0.00543***
			(0.00108)
Public Housing within (3,4] miles			-0.00376***
			(0.000986)
Public Housing within (4,5] miles			-0.00485***
			(0.000843)
Public Housing within (5,10] miles			-0.00444***
			(0.000453)
Distance to CBD	-0.0351***	0.00500***	-0.00294
	(0.00232)	(0.00108)	(0.00157)
Distance to CBD Squared	0.00141***	-0.0000201	0.0000409
	(0.000106)	(0.0000240)	(0.0000240)
Constant	-70.75***	-64.46***	-67.56***
	(3.006)	(2.903)	(2.944)
Observations	28753	29212	29212
R^2	0.670	0.657	0.657

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Effect of the Distance to Public Housing on log Earned Income

	(1) Closest PH	(2) PH in Block	(3) Incremental Distances
Min Distance to PH	0.0784***		
	(0.00338)		
Min Distance to PH Squared	-0.00566***		
	(0.000300)		
Public Housing Indicator		-0.0478***	
		(0.00649)	
Public Housing within [0,1] miles			-0.0149***
			(0.00207)
Public Housing within (1,2] miles			-0.00600***
			(0.00116)
Public Housing within (2,3] miles			-0.00581***
			(0.00103)
Public Housing within (3,4] miles			-0.000780
			(0.000877)
Public Housing within (4,5] miles			0.00102
			(0.000797)
Public Housing within (5,10] miles			0.000175
			(0.000380)
Distance to CBD	0.0286***	0.0212***	0.0141***
	(0.00212)	(0.00129)	(0.00157)
Distance to CBD Squared	-0.00102***	-0.000278***	-0.000163***
	(0.0000882)	(0.0000448)	(0.0000350)
Constant	-22.16***	-26.40***	-27.04***
	(2.332)	(2.293)	(2.270)
Observations	29929	30386	30386
R^2	0.366	0.346	0.352

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Effect of Distance to Public Housing on log Proportion of White Population

	(1) Closest PH	(2) PH in Block	(3) Incremental Distances
Min Distance to PH	0.239***		
	(0.00708)		
Min Distance to PH Squared	-0.0180***		
	(0.000649)		
Public Housing Indicator		-0.414***	
		(0.0169)	
Public Housing within [0,1] miles			-0.0654***
			(0.00373)
Public Housing within (1,2] miles			-0.0468***
			(0.00233)
Public Housing within (2,3] miles			-0.0307***
			(0.00222)
Public Housing within (3,4] miles			-0.0303***
			(0.00211)
Public Housing within (4,5] miles			-0.0320***
			(0.00198)
Public Housing within (5,10] miles			-0.0158***
			(0.000799)
Distance to CBD	0.00363	0.0774***	0.00427
	(0.00389)	(0.00222)	(0.00279)
Distance to CBD Squared	0.00130***	-0.00163***	-0.000776***
	(0.000162)	(0.0000809)	(0.0000752)
Constant	-50.01***	-46.82***	-67.84***
	(4.834)	(4.682)	(4.802)
Observations	28810	29269	29269
R^2	0.343	0.335	0.356

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Effect of Distance to Public Housing on log Proportion of Black Population

	(1) Closest PH	(2) PH in Block	(3) Incremental Distances
Min Distance to PH	-0.390***		
	(0.0130)		
Min Distance to PH Squared	0.0261***		
	(0.00134)		
Public Housing Indicator		0.600***	
		(0.0203)	
Public Housing within [0,1] miles			0.129***
			(0.00406)
Public Housing within (1,2] miles			0.0730***
			(0.00293)
Public Housing within (2,3] miles			0.0460***
			(0.00277)
Public Housing within (3,4] miles			0.0523***
			(0.00259)
Public Housing within (4,5] miles			0.0632***
			(0.00250)
Public Housing within (5,10] miles			0.0318***
			(0.00135)
Distance to CBD	-0.0156***	-0.0520***	0.0535***
	(0.00287)	(0.00300)	(0.00584)
Distance to CBD Squared			-0.000299
			(0.000196)
Constant	129.6***	117.7***	165.3***
	(9.917)	(11.27)	(9.819)
Observations	24701	24953	24953
R^2	0.347	0.334	0.369

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Effect of the Distance to Public Housing Development on log House Prices Including Controls

	(1) Closest PH	(2) PH in Block	(3) Incremental Distances
Min Distance to PH	0.116***		
	(0.00408)		
Min Distance to PH Squared	-0.00785***		
	(0.000370)		
Public Housing Indicator		-0.0883***	
		(0.00703)	
Public Housing within [0,1] miles			-0.00561**
			(0.00193)
Public Housing within (1,2] miles			-0.00108
			(0.00119)
Public Housing within (2,3] miles			-0.00543***
			(0.00108)
Public Housing within (3,4] miles			-0.00376***
			(0.000986)
Public Housing within (4,5] miles			-0.00485***
			(0.000843)
Public Housing within (5,10] miles			-0.00444***
			(0.000453)
Distance to CBD	-0.0351***	0.00500***	-0.00294
	(0.00232)	(0.00108)	(0.00157)
Distance to CBD Squared	0.00141***	-0.0000201	0.0000409
	(0.000106)	(0.0000240)	(0.0000240)
Travel Time (min)	-0.0115***	-0.0107***	-0.0108***
	(0.000621)	(0.000604)	(0.000606)
Block Latitude	1.136***	1.030***	1.030***
	(0.0346)	(0.0338)	(0.0338)
Block longitude	-0.385***	-0.364***	-0.399***
	(0.0297)	(0.0288)	(0.0297)
Housing Units	0.000117***	0.000156***	0.000155***
	(0.00000967)	(0.00000937)	(0.00000937)
Proportion White	0.967***	1.029***	1.036***
	(0.0264)	(0.0260)	(0.0259)
Proportion Black	0.0644*	0.0685*	0.0724**
	(0.0275)	(0.0273)	(0.0274)
Constant	-70.75***	-64.46***	-67.56***
	(3.006)	(2.903)	(2.944)
Observations	28753	29212	29212
R^2	0.670	0.657	0.657

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Effect of the Distance to Public Housing on log Earned Income Including Controls

	(1) Closest PH	(2) PH in Block	(3) Incremental Distances
Min Distance to PH	0.0784***		
	(0.00338)		
Min Distance to PH Squared	-0.00566***		
	(0.000300)		
Public Housing Indicator		-0.0478***	
		(0.00649)	
Public Housing within [0,1] miles			-0.0149***
			(0.00207)
Public Housing within (1,2] miles			-0.00600***
			(0.00116)
Public Housing within (2,3] miles			-0.00581***
			(0.00103)
Public Housing within (3,4] miles			-0.000780
			(0.000877)
Public Housing within (4,5] miles			0.00102
			(0.000797)
Public Housing within (5,10] miles			0.000175
			(0.000380)
Distance to CBD	0.0286***	0.0212***	0.0141***
	(0.00212)	(0.00129)	(0.00157)
Distance to CBD Squared	-0.00102***	-0.000278***	-0.000163***
	(0.0000882)	(0.0000448)	(0.0000350)
Travel Time (min)	-0.000325	0.000535	-0.0000142
	(0.000667)	(0.000653)	(0.000641)
Block Latitude	0.592***	0.704***	0.659***
	(0.0259)	(0.0274)	(0.0267)
Block longitude	-0.0768***	-0.0746***	-0.103***
	(0.0231)	(0.0223)	(0.0225)
Proportion White	1.009***	0.984***	0.970***
	(0.0233)	(0.0229)	(0.0230)
Proportion Black	0.374***	0.309***	0.319***
	(0.0241)	(0.0241)	(0.0243)
Housing Units	0.000175***	0.000177***	0.000187***
	(0.00000948)	(0.00000899)	(0.00000897)
Constant	-22.16***	-26.40***	-27.04***
	(2.332)	(2.293)	(2.270)
Observations	29929	30386	30386
R^2	0.366	0.346	0.352

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Effect of Distance to Public Housing on log Proportion of White Population Including Controls

	(1) Closest PH	(2) PH in Block	(3) Incremental Distances
Min Distance to PH	0.239***		
	(0.00708)		
Min Distance to PH Squared	-0.0180***		
	(0.000649)		
Public Housing Indicator		-0.414***	
		(0.0169)	
Public Housing within [0,1] miles			-0.0654***
			(0.00373)
Public Housing within (1,2] miles			-0.0468***
			(0.00233)
Public Housing within (2,3] miles			-0.0307***
			(0.00222)
Public Housing within (3,4] miles			-0.0303***
			(0.00211)
Public Housing within (4,5] miles			-0.0320***
			(0.00198)
Public Housing within (5,10] miles			-0.0158***
			(0.000799)
Distance to CBD	0.00363	0.0774***	0.00427
	(0.00389)	(0.00222)	(0.00279)
Distance to CBD Squared	0.00130***	-0.00163***	-0.000776***
	(0.000162)	(0.0000809)	(0.0000752)
Travel Time (min)	-0.0456***	-0.0432***	-0.0434***
	(0.00131)	(0.00125)	(0.00122)
Block Latitude	-1.276***	-1.260***	-1.405***
	(0.0524)	(0.0489)	(0.0470)
Block longitude	-1.106***	-1.062***	-1.365***
	(0.0481)	(0.0482)	(0.0504)
Housing Units	0.0000963***	0.000126***	0.000144***
	(0.0000139)	(0.0000136)	(0.0000134)
Constant	-50.01***	-46.82***	-67.84***
	(4.834)	(4.682)	(4.802)
Observations	28810	29269	29269
R^2	0.343	0.335	0.356

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Effect of Distance to Public Housing on log Proportion of Black Population Including Controls

	(1) Closest PH	(2) PH in Block	(3) Incremental Distances
Min Distance to PH	-0.390***		
	(0.0130)		
Min Distance to PH Squared	0.0261***		
	(0.00134)		
Public Housing Indicator		0.600***	
		(0.0203)	
Public Housing within [0,1] miles			0.129***
			(0.00406)
Public Housing within (1,2] miles			0.0730***
			(0.00293)
Public Housing within (2,3] miles			0.0460***
			(0.00277)
Public Housing within (3,4] miles			0.0523***
			(0.00259)
Public Housing within (4,5] miles			0.0632***
			(0.00250)
Public Housing within (5,10] miles			0.0318***
			(0.00135)
Distance to CBD	-0.0156***	-0.0520***	0.0535***
	(0.00287)	(0.00300)	(0.00584)
Distance to CBD Squared			-0.000299
			(0.000196)
Travel Time (min)	0.0554***	0.0518***	0.0512***
	(0.00146)	(0.00146)	(0.00142)
Block Latitude	1.440***	1.066***	1.297***
	(0.122)	(0.120)	(0.117)
Block longitude	2.103***	1.805***	2.452***
	(0.0924)	(0.106)	(0.0939)
Housing Units	-0.000248***	-0.000333***	-0.000336***
	(0.0000289)	(0.0000299)	(0.0000273)
Constant	129.6***	117.7***	165.3***
	(9.917)	(11.27)	(9.819)
Observations	24701	24953	24953
R^2	0.347	0.334	0.369

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$