Impacts of Housing Interventions on Neighborhoods in Durham County

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Abstract

Housing intervention models intended to revitalize neighborhoods and empower homeowners are frequently observed in cities across the United States. To determine the efficacy of these programs, this study analyzes the effects of a housing intervention on the price of the home and the changes in neighborhood characteristics that may lead to neighborhood stability or instability in the long run, including the home prices, the racial makeup, the median income, and crime rates of the neighborhood. To study these characteristics and how they interact with interventions, I implement a propensity score matching model to reduce variation in unobservable characteristics and to isolate the effect of interventions on the block group characteristics of interest. In addition, I implement a non-parametric kernel regression to allow for the possibility of a non-linear relationship between home prices and home interventions. The results show significant evidence that interventions increase neighborhood home values at the bottom 10th percentile and at the median of each block group, suggesting that housing interventions do serve to increase the quality of the neighborhood. However, there is evidence that these effects taper off after a certain percent of the households in the neighborhood have been intervened upon, reducing the marginal benefit of completing a new housing intervention.

JEL classification: J10, R20, R23

Keywords: Neighborhood Characteristics, Housing Interventions, Affordable Housing, Neighborhood Quality

I. Introduction

Affordable housing interventions are becoming an increasingly popular method of neighborhood revitalization and quality of life improvement for low-income families, which has historically been funded on a small scale by non-profits such as Habitat For Humanity International (HFHI), revitalizing Credit Unions, and community organizations such as community land trusts. More recently, funding of land trusts and housing rehabilitation programs by the U.S. government has increased the number of these housing interventions by over 50,000 homes since its inception in 1993 (HUD). The goals set forth by the government for these interventions are to benefit homeowners, communities, and low income families (Fuller 1990). The goal of this paper is to quantitatively determine the socioeconomic outcomes of homes and neighborhoods that fall under the housing intervention umbrella relative to the homes and neighborhoods that do not.

Some of the complexity in this topic comes into play when looking at the different models that different organizations use for land acquisition and the home building process. HFHI acquires most properties through the government's Self-Help Homeownership Opportunity Program (SHOP) which requires "sweat equity" from the future owners of the house; in other words, the people who are going to own the home must help build it in order to qualify for SHOP grants (Smith 2013). In contrast, every Land Trust program, which are frequently local organizations, follows their own model of home acquisition and building, making it difficult to aggregate them into a single "model". The same can be said for selection of future homeowners; different HFHI affiliates, Land Trusts, and Credit Unions have different qualifications for their future homeowners. However, many of these revitalization organizations follow similar financing models when completing their initial sale: no interest mortgages and very low costs are par for the course for home intervention models (Smith 2013, Lattimore and Lauria 2017).

Just as there is disparity in intervention models, there is debate about the benefits that neighborhoods and individuals see from these housing interventions. Almost every study is focused on HFHI, and various studies come to different conclusions. Lattimore and Lauria (2017) study the effect of Habitat homes on neighborhood collective efficacy, concluding that HHI had a positive outcome on neighborhoods. On the other hand Delmelle et al. (2017) find that HFHI homes had no substantive impact on neighborhood house values in comparison to non-Habitat neighborhoods. There is also very little literature on the effects of housing interventions on the homeowners. In 2019 Bowers found, via a survey-based study, that HFHI homeowners in South Carolina felt better about their experiences as homeowners in comparison to non-Habitat families, but the study fails to provide quantitative wealth and health outcomes for these families.

One of the gaps in the research I fill with this study is the effects of housing interventions on the characteristics of the neighborhood as a whole, by investigating variables such as income, racial makeup, and percentage of homeowners within the block group. In addition, I track home appreciation rates in order to ascertain the effects of interventions on home value itself, and I apply a similar appreciation model to neighborhoods as a whole to see how the community and home prices at the median and at the lower tenth percentile are affected. I expand on current literature by not limiting the scope of this study to just HFHI and their affiliates. Instead I additionally consider local reinvestment partners such as Land Trusts and Credit Unions that also play a large role in neighborhood housing rehabilitation. This increase in scope will hopefully expand the conversation surrounding low-income affordable housing to include all models of intervention.

II. Literature Review

Much existing literature surrounding low-income housing initiatives is based on theory and policy analysis as opposed to a data-driven approach to the issue. Early on, initiatives such as HFHI came to conclusions on how to best respond to the issue of low-income housing, and achieve its goals of increasing homeownership and neighborhood stability, initially making assumptions with little guidance from quantitative studies. Fuller (1990) put forward the theory that spillover effects of increased homeownership in a neighborhood leads to "better neighborhoods." This has been strongly debated in literature, as there is much anecdotal evidence that clustered HFHI neighborhoods can turn into "suburban ghettos," possibly through high taxes, and possibly through the concentration of new homeowners (Smith, 2013). However, Rohe and Stewart (1996) use census data and come to the conclusion that increased homeownership in a neighborhood led to higher educational attainment and better job prospects. With this in mind, HFHI and similar initiatives chose to cluster homes in one neighborhood as opposed to one home per neighborhood, though this can also be attributed to mass land grants under HOPE VI and SHOP (Smith, 2013).

These debates have led to some quantitative studies of whole-neighborhood outcomes as they relate to housing interventions, primarily those of HFHI. Some research shows negative outcomes in neighborhoods after the introduction of Habitat interventions relative to the state of the neighborhoods prior to intervention, with increased exposure to crime and low quality of schooling (Cummings et al., 2002). Others show positive effects in terms of community efficacy (Lattimore and Lauria, 2017), marginally beneficial income effects (Smith and Hevener, 2011), an increase to house prices within 1500 feet of Habitat homes (Rephann, 2014), and home stabilization effects through increased home prices (Herguth et al., 2012). Of course, other

studies have concluded that there is little evidence of an effect of HFHI homes on neighborhood stability or housing prices in either direction (Delmelle et al., 2017).

The lack of agreement in the empirical literature brings into question the efficacy of the housing revitalization model as a whole. Many residents in Habitat neighborhoods, especially those in neighborhoods of color find themselves dissatisfied with Habitat's tendency to overlook racial inequity and nuance in neighborhoods, preferring to do their own interventions rather than collaborate with local grassroots organizations (Bonds et al., 2015). This phenomenon is not limited to HFHI; in places where other housing intervention actors are recognized, there is similar dissatisfaction within the community surrounding the housing intervention projects, as noted by Durham-based organization Communities in Partnership. There are suggestions that the existence and scope of HFHI often excludes local organizations such as Community Land Trusts from getting a foothold with investors and partners to test out their models and improve their communities from the inside out (Baggett, 2000). However, HFHI remains well-regarded politically despite complaints from local organizations (Hackworth, 2009).

Even with the mission of HFHI stating that "Habitat homeowners help build their own homes alongside volunteers and pay an affordable mortgage. With your support, Habitat homeowners achieve the strength, stability and independence they need to build a better life for themselves and for their families" (HFHI 2020), there are few studies on the individual homeowners and their outcomes, with most studies focused on the neighborhood outcomes of housing interventions, despite HFHI's mission statement not being focused on neighborhood outcomes. A study by Manturuk (2012) shows that low-income homeowners in general feel a greater sense of control than renters, but does not differentiate between HFHI, Land Trust, and non-intervention homes. In contrast, Bowers (2019) shows evidence that the model implemented by HFHI in particular helps to increase self-efficacy in homeowners, increasing their confidence

in their personal finances and feelings of belonging, suggesting that homeowner programs funded by the federal government, while questionably beneficial to communities, do impact the owners positively. I expand on this research by estimating effects of interventions on the whole block group, and not just individual owners.

III. Empirical Specification

1. Identifying Intervention Effects on Individual House Prices

To determine the effects of an intervention on house prices on the intervened upon home, I use a simple hedonic model to isolate the effect of an intervention on house price. The data used for this regression is taken from Zillow's housing transaction data; important characteristics taken from the dataset are lot size (in square feet), house size (in square feet), number of full bathrooms, number of half bathrooms and number of bedrooms. House price values are taken from the transaction data from Zillow as well. To determine which houses have undergone intervention or revitalization, I implement RegEX matching on Zillow buyer name data. In addition, I geocode each house into its census block group using shapefiles from the U.S. Census Bureau website.

Following this cleaning, I implement the hedonic model using the following specifications:

(1) $$HousePrice_{i,t} = \alpha_1 Intervention_{i,t} + \alpha_n HousingCharacterisitcs_{n,i} + \eta_i + \epsilon_{i,t}$$

for house *i* at time *t,* where Intervention is a time-variant dummy variable indicating whether or not an intervention has taken place, and the housing characteristics are the time-invariant characteristics of lot size, house size, and room numbers. To control for location effects, I use a census block group fixed effect, captured in η. The model is then estimated using the Ordinary Least Squares method in STATA.

2. Identifying Neighborhood Spillover Effects from Intervention Homes

To determine the effects of housing interventions on a neighborhood, I examine how the presence of intervention homes in a neighborhood changes home sales price, percent renters, and percent white households in the neighborhood. Home value is considered the most holistic measure of neighborhood changes, as it is assumed that any improvements in a neighborhood are reflected in home values (Woo et al., 2016). I however, also choose to examine the changes in race mix and renter status as a measure of neighborhood stability, under the assumption that drastic changes in these measures are a hallmark of a shift in neighborhood characteristics that may not necessarily be measured in home values. This still represents a limited scope of neighborhood characteristics; while values such as the quality of the school catchment zone are often absorbed in home values, it would be ideal to separate the effects of characteristics such as school qualities or presence of a nearby highway on the home value, though this is outside the scope of this project.

To avoid bias in the definition of "neighborhoods" I chose not to use definitions of neighborhood boundaries provided by the city of Durham, which can exclude prominent neighborhoods of color (CIP, 2020), and instead use census block group definitions to create boundaries for the regression. I combine data from the U.S. Census Bureau with house price data from Zillow's ZTRAX data and with InfoUSA race, rental, income, and wealth data using geocoding techniques. To determine presence of intervention homes in the data, I use text expression matching on Zillow buyer data to identify homes that were purchased by home intervention organizations, which I use as a marker of intervention and revitalization. One limitation of this technique is that often, sales to intervention organizations are for extremely low prices. Frequently, transactions at low prices (known colloquially as "penny transactions") are

cleaned from house sale data to prevent the presence of any "bad" transactions that would add unnecessary noise to the model. These transactions can be the result of poor data management, but can also be the result of homeownership transfer within families, which can also be a reason to exclude them from the model. Because intervention homes are frequently sold to organizations at low values, and occasionally gifted for free, one cannot exclude this data from the model. After identifying the intervention homes, I define by census block the percentage of homes that had undergone an intervention, and create a dummy variable indicating that at least one home intervention has been implemented in the neighborhood at this time period.

Following this cleaning, I implement propensity score matching to create groups of block groups that were similar in 2007 but which had different intervention outcomes in 2017. To do this I ran the regression:

(2) $Prob(InterventionBy2017_i) = \alpha_0 + \alpha_n BlockGroupCharachteristics2007_{n,i} + \epsilon_i$

Where intervention by 2017 is a dummy variable indicating whether there are any interventions in the neighborhood by 2017, and the block group characteristics are a vector of block group characteristics in 2007 including percent white, percent black, percent renter, median home price, lower 10th percentile home price, median income, lower 10th percentile income, RSEI score, PM2.5 concentration, and school quality. Every block group is associated with a likelihood score to predict the presence of an intervention in 2017, and each block group with an intervention is matched to four block groups without interventions that had the nearest likelihood score.

After this, I found the marginal effect on the percent change in variables of interest for each additional percentage of interventions a block group had with block group fixed effects. The model was of the form:

(3) $ChangeInNeighborhoodCharacteristics_{i,g} = \alpha_0 + \alpha_1 PercentIntervention_{i,g} + \epsilon_{i,g}$

With the changes in neighborhood characteristics being the characteristics of percent homeownership, percent white, percent black, median home price, 10th percentile home price, median income, and 10th percentile income.

3. Non-Parametric Derivative Modeling

After recovering the relationship of housing interventions and home prices at the first decile and at the median using propensity score matching, I next ask what the effect of each additional intervention is. To do this I implement a non-parametric model that estimates the slope of the relationship between the percent of housing interventions and home prices within the block group. This creates at each block group in the dataset an estimation of the derivative of the function that models the relationship of the variable of interest, which can then be interpreted to find the effect of each intervention on median or tenth percentile home prices in a block group. The limitations of this type of model are that the traditional model frequently holds omitted variable bias in the form of fixed characteristics that are not necessarily measured. In a traditional OLS model, a fixed effects model can be used to minimize this omitted variable bias. To fix unobserved characteristics in the non-parametric model, I follow Lee and Mukherjee (2014) and Bishop and Timmins (2018) by using a two time-period difference model.

The goal of this model is to recover the marginal effect of interventions on home price in a block group without imposing a linear relationship between the two. Ideally, at each level of intervention, one could estimate the effect of an additional intervention separately. The initial specification of this relationship in a flexible model is shown by:

(4) $$P_{j,t} = f\left(Z_{j,t}\right) + X_j'\theta + v_{j,t},$$

Here, $f\left(Z_{j,t}\right)$ is an unspecified, flexible function of percent intervention, which varies over time *t* and block group *j*. X_j is representative of every observed and unobserved time-

invariant characteristic of block group *j*. To implement spatial fixed effects at the block group level, it is then necessary to take a first-order Taylor expansion of $f\left(Z_{j,t}\right)$ around a fixed vector represented by *z* that has the same dimensions as $Z_{j,t}$. This is shown below in equation (5).

(5) $$P_{j,t} = f(z) + \left(Z_{j,t} - z\right)' f'(z) + X_j'\theta + v_{j,t}$$

Then, this equation is rewritten using time $t-1$, which is, in this case, the first available period in the dataset 2007, leaving time *t* to be the last available period in the dataset, in this case 2017.

(6) $$P_{j,t-1} = f(z) + \left(Z_{j,t-1} - z\right)' f'(z) + X_j'\theta + v_{j,t-1}$$

It is then possible to subtract equation (6) from equation (5), which differences out the time-invariant characteristics X_j and the time-invariant $f(z)$. This gives equation (7).

(7) $$P_{j,t} - P_{j,t-1} = \left(Z_{j,t} - Z_{j,t-1}\right)' f'(z) + \left(v_{j,t} - v_{j,t-1}\right)$$

The time period differences are then denoted with a '$\sim$' and f' is rewritten with β to obtain:

(9) $$\widetilde{P_j} = \tilde{Z}_{j,t}'\beta(z) + \tilde{v}_{j,t}$$

The value of the slope at point *z,* written as β(z), is recovered using the following minimization problem:

(10) $$\beta(z) \;=\; arg \min_{\beta(z)} \sum_{j=1}^{J} \sum_{t=1}^{T_j} (\tilde{P}_{j,t} \;-\; \tilde{Z}_{j,t}'\,\beta(z))^{\,2} K_h(Z_{j,t} \;- z) K_h(Z_{j,t-1} - z)$$

where $\tilde{P}$ is the difference in price from 2007 to 2017, and $Z_{j,t}$ is the percent intervention in block group *j* in time period *t*, with $\tilde{Z}$ representing the difference in percent interventions in the block group between 2007 and 2017. These differences can be estimated either at the log or the level, and I will later implement both for ease of interpretation. Here, $K_h(.)$ is given by the Gaussian kernel:

(11) $$K_h(Z_{j,t} - z) = \prod_k \frac{1}{h\hat{\sigma}_{Z_k}} \frac{1}{\sqrt{2\pi}} exp\left\{-\frac{1}{2}\left(\frac{Z_{k,j,t} - z_k}{h\hat{\sigma}_{Z_k}}\right)^2\right\}$$

which has h as the kernel bandwidth, and $\hat{\sigma}$ as the standard deviation of the kth element of $Z_{j,t}$. The result is a vector of $\beta(z)$'s that represent the marginal effect of an intervention at each z. This is in contrast to a parametric estimation, which would require β to be fixed across all z.

Because the minimization procedure is linear, the same $\beta(z)$'s can also be recovered using the following linear algebra specification:

(12) $$\beta(z) = \left(\tilde{Z}' W_z \tilde{Z}\right)^{-1} \tilde{Z}' W_z \tilde{P}$$

where n is the total number of observations, $\tilde{Z}$ is an $(n \times 2)$ matrix of the difference in percent intervention from 2007 to 2017, $\tilde{P}$ is an $(n \times 1)$ matrix of the difference in price from 2007 to 2017, and W_Z is the matrix of weights, which is created by $W_Z = diag\left(K_h(Z_{j,t} - z)\right)$

4. Data and Data Cleaning

4.1. Zillow/ZTRAX

For this study, I use ZTRAX data acquired from Zillow to identify housing characteristics. This data is collected by Zillow from tax records associated with home sales to create a comprehensive view of transaction data in the housing market across the United States from 1995-2020. However, because the data comes from tax assessor records, there are discrepancies across counties as to which characteristics are reported. For example, Durham County, North Carolina lacks data on square footage for each home, while data from Harris County, Texas contains this information. Because of this discrepancy, some adjustments may need to be made in any further literature to ensure consistency in regressions.

This data set was provided to Duke University in the form of .txt files that needed to be processed on an SQL server for ease of use. This process was carried out over the course of

summer 2020, and was completed upon the beginning of this project. From there, the data could be downloaded in the form of .csv files by State, County, or Zip Code. I then formatted the data by county of interest and merged it with Census block group information using ArcGIS to allow for a block group fixed effect while identifying the effect on house prices of intervening on a home. This further allowed for data cleaning, where the characteristics of homes in the county could be identified by block group, which is an essential step for the identification of neighborhood spillover effects. After this step, intervention homes were identified by matching home buyer names with organizations identified as being a part of the home intervention process. This allowed me to isolate the effect of interventions on prices and neighborhoods. The relevant housing variables are summarized below in Table 1.

In Durham County, there are 124,394 recorded sales from the years of 1995-2020. After dropping the top 1% and bottom 1% of home prices, as is standard for hedonic home price estimations, the number of recorded sales drops to 121,890. Of these recorded sales, there are 59,612 individual homes that are sold in the time period. 256 of these houses can be matched to intervention homes that can be analyzed at the individual home level with price information, and there are 2,641 recorded sales of these houses both before and after the intervention. This number drops to 1,179 recorded sales for homes that have already been intervened upon, with 250 of the sales being the first sale after the intervention has taken place. However, 789 interventions that can be matched to a block group for neighborhood analysis, which can then be connected to InfoUSA and other data sources for salient neighborhood characteristics.

Table 1. Housing Characteristics Summary Statistics in Durham County, NC 1995-2020

VARIABLES	Median	Mean	SD
Sales Price	165000	191092.1	119826.1
Lot Size Square Feet	9713.88	14251.73	25338.15
Total Bedrooms	3	3.136124	0.7781306
Full Bathrooms	2	1.997662	0.6434046
Half Bathrooms	1	0.5324555	0.5137567

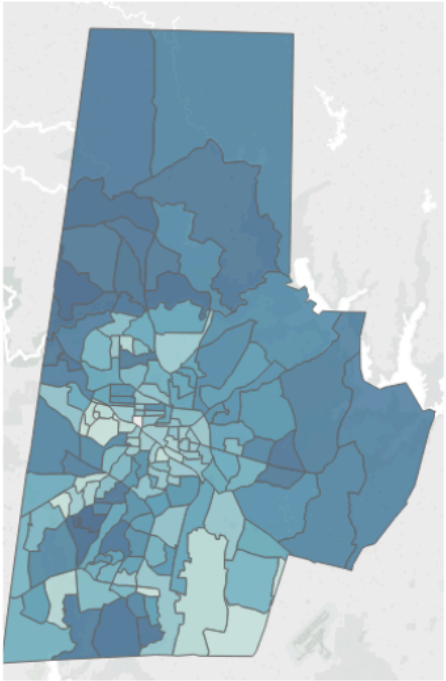
n = 121890

4.2. InfoUSA

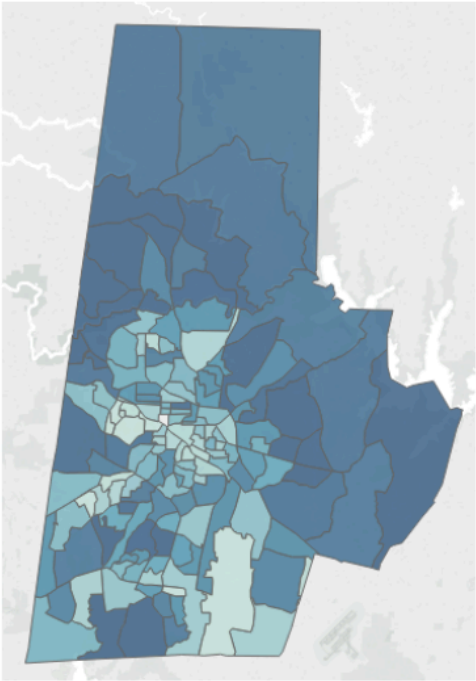
The way InfoUSA collects data is less clear than Zillow's ZTRAX data, but they store data on over 140 million households in the United States from 2006 to 2018. This can be downloaded as .csv files by zip code, which corresponds well with county borders. From there, the data was merged with Census block group shapefiles, in order to assure that it could be merged properly with the Zillow data for later analysis. After this step is completed, the characteristics of interest from the data are calculated at the block group level. These characteristics include average age, percent presence of children, median income, percent white households, and percent homeowners.

Below (Fig. 1) are two heat maps depicting the percent homeowner by block group in 2006 versus in 2018. Darker colors are higher percentages, with maximum percent homeowner equal to 100% and minimum percent homeowner equal to .24%. In addition, in Figure 2, there are two heat maps depicting the percent of white households by block group in 2006 versus in 2018. Darker colors are again indicative of higher percentages, with maximum percent of white households equal to 96.1% and minimum percent of white households equal to .09%.

Figure 1. Percent Homeowners by Block Group

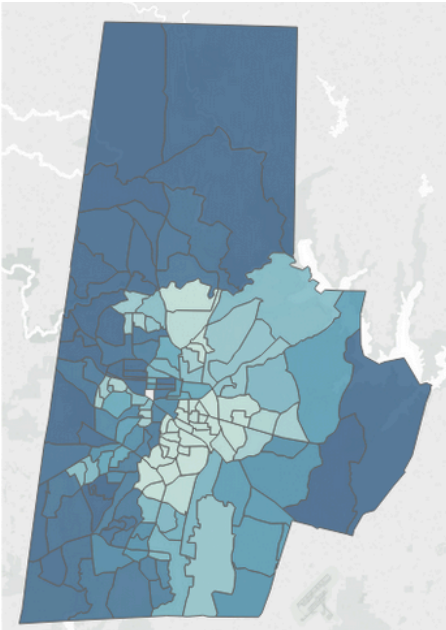


2006

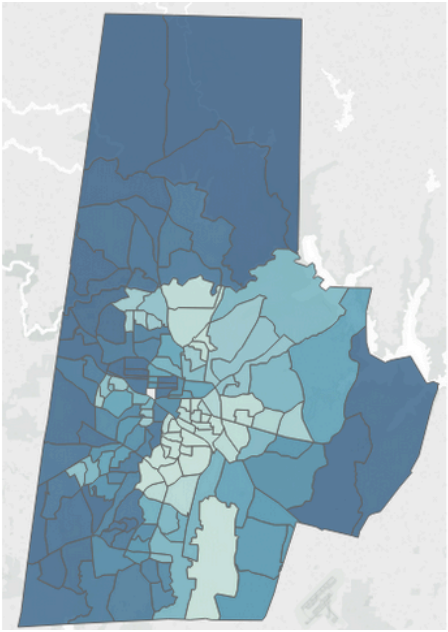


2018

Figure 2. Percent White Households by Block Group



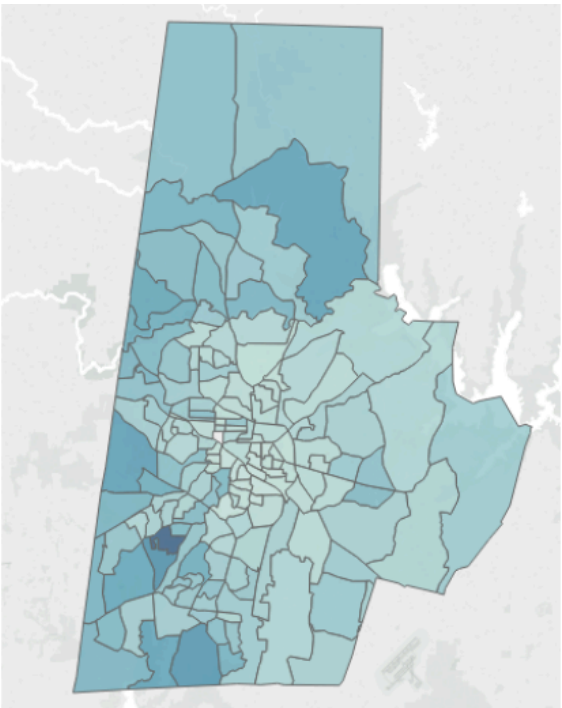
2006



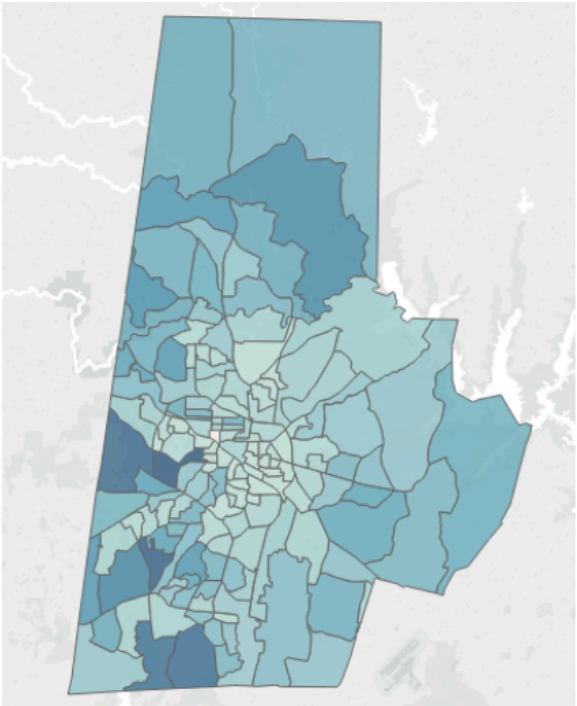
2018

Below (Fig. 3) are two heat maps depicting the median income of households by block group in 2006 versus in 2018. Darker colors are higher median incomes, with maximum median income equal to 222,000$ and minimum median income equal to 5,000$.

Figure 3. Median Income by Block Group



2006



2018

4.3. Additional Data Sources

In addition to the main data sources of InfoUSA and ZTRAX, I merged several data sources that were aggregated to the block group level in order to estimate important characteristics and match similar block groups. These data include Durham Police Department (DPD) crime reports, which are aggregated to yearly number of crime incidents reported within a block group. In addition, Durham County School District data on test scores is merged at a block group level with the previously mentioned data, to provide a salient variable for propensity score

matching, in order to reduce variation in future regressions. Lastly, two measures of air quality at the block group level were introduced to the data; the first is the concentration of particulate matter smaller than 2.5 micrometers, colloquially known as PM2.5, and the second is the Raster Value produced by the RSEI Toxic Release Inventory, produced by the Environmental Protection Agency.

IV. Results

In this section, I discuss the results of the models shown in the empirical specifications section of the paper. First, I discuss the effects of interventions on individual home prices determined by a difference-in-difference regression approach, then I interpret the fixed effects model that uses propensity score matching to estimate the effect of interventions on all salient neighborhood characteristics. Lastly, I interpret the results of the non-parametric model that shows the marginal effect of neighborhood characteristics.

1. Identifying Intervention Effects on Individual House Prices

Here I analyze the effects of an intervention on the price of an individual home. The regression for this effect is described by equation (1) in the empirical specifications section of this study. The results presented in Table 2 show that holding constant home characteristics, and with a block group fixed effect, a home selected to be an intervention home costs on average 16% less than other homes in the block group, and after an intervention sells for 16% more than before the intervention, bringing it up to par with the rest of the block group. The variable "first sale" indicates that the recorded sale is the first one after the intervention has occurred, and all sales after this sale are dropped. However, the sales prior to the first sale are recorded in order to estimate the change in home value based on an intervention. Sales to HFHI or other intervention

organizations were not removed, so there may be downward bias in the "intervention" coefficient, as intervention organizations often receive a discount on homes.

I also include other housing characteristics such as year built, which increases home value by .2% every additional year, total bedrooms, which shows an 11% home price increase for every additional bedroom, and bathrooms, which add 17% or 13% home value for full and half bathrooms respectively.

Table 2. Intervention Effects on Individual Home Prices

VARIABLES	Log Sale Price
First Sale	0.163***
	(0.0312)
Intervention	-0.161***
	(0.0127)
Lot Size (sq ft)	6.51e-07***
	(5.98e-08)
Year Built	0.00211***
	(8.89e-05)
Total Bedrooms	0.118***
	(0.00235)
Full Bathrooms	0.176***
	(0.00308)
Half Bathrooms	0.137***
	(0.00307)
Year Sold Dummy	In Appendix A.
	In Appendix A.
Constant	5.652***
	(0.489)
Observations	115,868
R-squared	0.236
Number of geoid	168

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2. Identifying Neighborhood Spillover Effects from Intervention Homes

In this section I interpret the results of the models specified in section 3.2 of this paper, following equations (2) and (3), as they pertain to neighborhood spillover effects from intervention homes. The results of the propensity score matching, specified using equation (2), in which I measure the probability of a neighborhood having an intervention based off of its observed characteristics, are found below in Table 3. All independent variables listed are 2007 values for each block group, while the dependent variable of intervention presence indicates a presence by the year 2017. After estimating the likelihood that each block group has an intervention by 2017, I then match each block group that did have an intervention at the end of the time period to the most similar four block groups that were not intervened upon, with replacement. The mean distance between matched block groups was .066, with a standard deviation of .077, and a median of .026. No caliper was used for this model, so all block groups have exactly four matches. All the following results are then created using a fixed effects model within these groups created by propensity score matching. Due to the propensity score matching on block groups, we can interpret all coefficients as the marginal effect of an additional percent of homes that are intervened upon on the variable of interest or dependent variable.

In Table 4, the regression run is the neighborhood characteristic as the dependent variable, and the independent variable is the percent of interventions. We see that at the .05 level, median home price and decile home price can be predicted at a significant level by percentage of home interventions in a block group. This indicates that at the median home price level, an additional percentage of intervention homes in the block group is associated with a 27% growth in home price from 2007 to 2017, while at the decile an additional percentage of intervention homes in the block group is associated with a 60% growth in home price from 2007 to 2017. Percent of intervention homes is also a significant predictor of number of crime incidents in this

first model, and each additional percentage of interventions in homes is associated with a 27% decrease in the rate of crime incidents in a block group from 2007 to 2017, which is expected from a housing or neighborhood revitalization project. These predictors are relative to the control block groups in the dataset, which have an intervention value of zero. It is beyond the scope of this project to drop control block groups that share a border with intervention block groups, but the results would be valuable to determine the extent of the spillover effects of an intervention.

Table 3. Results of Propensity Score Matching Probit

VARIABLES	Intervention by 2017
Median Income	0.0517*
	(0.0284)
10th Percentile Income	-0.0841**
	(0.0378)
Median Home Price	-9.48e-07
	(3.21e-06)
10th Percentile Home Price	-6.70e-06
	(4.26e-06)
Crime Incidents	0.00211*
	(0.00122)
Percent White	0.336
	(2.151)
Percent Black	0.345
	(2.132)
Percent Homeowners	-1.452
	(1.238)
School Average Scores	-0.0309*
	(0.0185)
PM2.5 Concentration	-0.000278
	(0.000362)
RSEI Raster Value	-0.392
	(0.388)
Block Group Population	0.000326
	(0.000205)
Constant	6.922
	(6.138)
Observations	136

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Percent Intervention Effects on Neighborhood Characteristics

VARIABLES	(1) Percent Homeowners	(2) Percent White	(3) Percent Black	(4) Crime Incidents	(5) Median Home Price	(6) Decile Home Price	(7) Median Income	(8) Decile Income
Percent Interventions	-2.169	96.70	-2.386	-27.64	27.93***	60.92***	-4.468	0.199
	(3.200)	(84.67)	(2.749)	(20.37)	(4.885)	(10.77)	(4.519)	(6.391)
Constant	0.0786***	0.380	-0.0137	0.358***	0.299***	0.315***	-0.128***	-0.121***
	(0.0120)	(0.317)	(0.0104)	(0.0767)	(0.0184)	(0.0406)	(0.0170)	(0.0241)
Observations	325	323	325	325	325	325	325	325
R-squared	0.002	0.005	0.003	0.007	0.113	0.111	0.004	0.000
Number of Groups	67	67	67	67	67	67	67	67

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Percent Intervention Effects on Neighborhood Characteristics with a Quadratic Term

VARIABLES	(1) Percent Homeowners	(2) Percent White	(3) Percent Black	(4) Crime Incidents	(5) Median Home Price	(6) Decile Home Price	(7) Median Income	(8) Decile Income
Percent Intervention	-7.435	384.5**	2.375	-91.47**	62.30***	118.7***	11.90	5.601
	(7.180)	(191.8)	(6.167)	(45.55)	(10.71)	(23.86)	(10.09)	(14.35)
Percent Intervention Squared	207.2	-11,224*	-187.3	2,512	-1,353***	-2,273***	-644.2*	-212.6
	(252.9)	(6,715)	(217.2)	(1,604)	(377.2)	(840.3)	(355.3)	(505.5)
Constant	0.0808***	0.260	-0.0157	0.385***	0.284***	0.290***	-0.135***	-0.123***
	(0.0124)	(0.324)	(0.0106)	(0.0785)	(0.0185)	(0.0411)	(0.0174)	(0.0247)
Observations	325	323	325	325	325	325	325	325
R-squared	0.004	0.016	0.006	0.017	0.155	0.135	0.016	0.001
Number of Groups	67	67	67	67	67	67	67	67

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To check for a non-linear relationship between the variables of interest, I then run the same regression with an added squared term, which will indicate the concavity of the relationship between percent interventions and the dependent variable. These results are shown in Table 5. Here we see that all variables found significant in the previous model continue to hold significance, with the added significant relationship of percent white and percent intervention, which is caused by the presence of an outlier. Because of the inconsistency demonstrated, the results of this will be discussed further in the appendices. To interpret the addition of the squared terms, we see that home price has a significant squared term at both the decile and the median, and that this term is negative for both variables. This indicates that as percent intervention increases, it's marginal effect on the change in home price decreases. However, the coefficient of the squared term for crime incidents is not found to be significant, which suggests that crime incidents and percent intervention may have a linear relationship.

It is important to note with these results that very rarely does a block group exceed one percent interventions: the median percent interventions is .329 %, with a mean of .583% and a standard deviation of .739%. Because of these small values, it can be easier to interpret the marginal effect of one additional intervention home, the results of which are shown below in Table 6.

These results show that at the decile home value for a block group, every additional intervention in the block group is associated with an 11% increase in home price from 2007 to 2017, while at the median every additional intervention is associated with a 5% increase. We see also that each additional intervention is associated with a 5% decrease in crime incidents. These results are consistent with the results of the model that utilizes percent intervention as opposed to numerical values, with the exception of percent white, which is significant and positive here, but insignificant in the percent intervention model.

Table 6. Number of Interventions Effects on Neighborhood Characteristics

VARIABLES	(1) Percent Homeowners	(2) Percent White	(3) Percent Black	(4) Crime Incidents	(5) Median Home Price	(6) Decile Home Price	(7) Median Income	(8) Decile Income
Number of Interventions	-0.00564	0.316**	-0.00234	-0.0635*	0.0555***	0.110***	-0.00494	-0.000359
	(0.00604)	(0.160)	(0.00520)	(0.0384)	(0.00916)	(0.0204)	(0.00854)	(0.0121)
Constant	0.0799***	0.280	-0.0147	0.370***	0.293***	0.308***	-0.129***	-0.120***
	(0.0122)	(0.320)	(0.0105)	(0.0776)	(0.0185)	(0.0413)	(0.0173)	(0.0244)
Observations	325	323	325	325	325	325	325	325
R-squared	0.003	0.015	0.001	0.011	0.125	0.102	0.001	0.000
Number of Groups	67	67	67	67	67	67	67	67

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

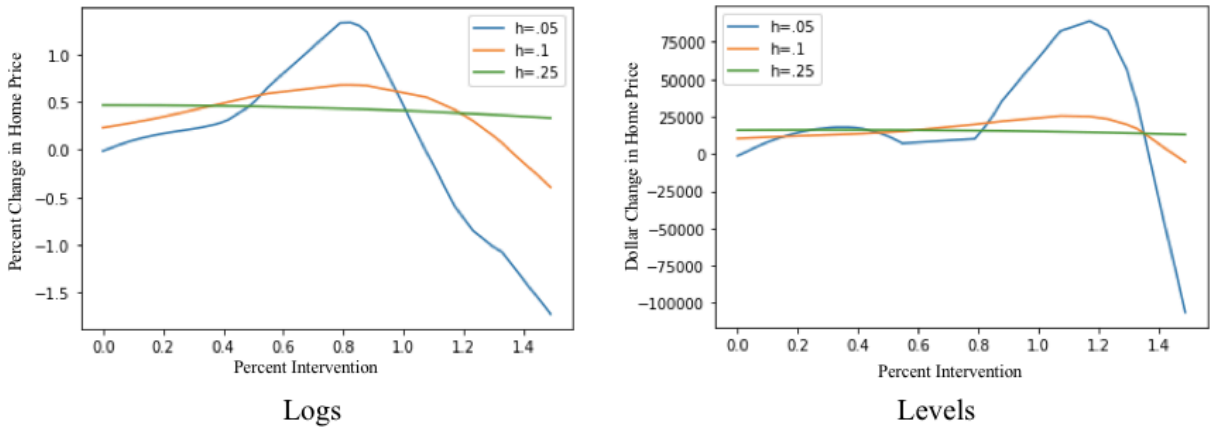
The results discussed here suggest that the effect of housing interventions can be seen primarily in the median and first decile home prices and crime rate of the neighborhoods. The effect of home price in the neighborhood is to be expected, as the revitalization of a home is frequently associated with an increase in quality, and therefore an increase in value; this can then affect the value of the neighboring homes. The reduction in crime is also often associated with an increase in neighborhood quality, and while this is also commonly assumed to be related to an influx of white residents, the reduction in crime and increase in white residents are not necessarily related. Interestingly, there is no significant effect of interventions on income or percent homeowners in the neighborhood, which will be discussed further later.

3. Non-Parametric Derivative Modeling

Here I look at the results of the non-parametric modeling technique specified in section 3.3 using equations (10), (11), and (12). The goal of these models is to estimate not only whether interventions have a positive or negative effect on price, but to expand upon this question to ask at what percentage of intervention homes in the block group are prices affected, and how does this change as the number of interventions changes. Due to the lack of a single constant for each estimation, a graph is the best way to display the data. The results of these estimations are displayed below.

Figure 4 shows the derivative of the price difference at the tenth percentile from 2007-2017 as it relates to the percent of the homes in the block group that were intervened upon between 2007-2017. Different bandwidths of *h* are included in the figures, but I focus on a bandwidth of .1 for all results in the non-parametric model based on a visual test.

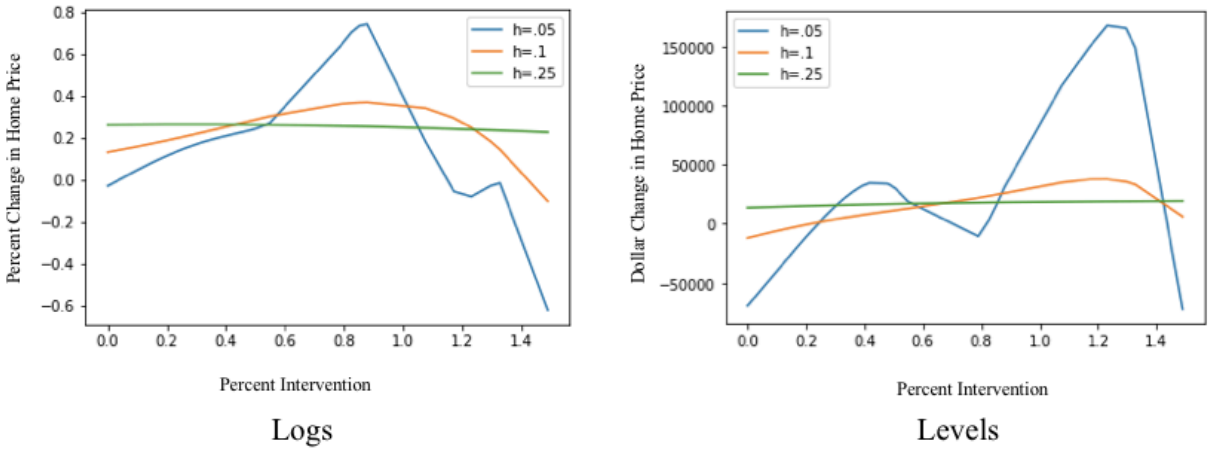
Figure 4. Derivative of 10th Percentile Home Price Against Percent Intervention



We can interpret these results by saying that at the first decile, home prices steadily grow until a block group reaches about 1.4% of homes intervened upon, at which point the effect of an additional intervention has a negative effect on the home prices at the first decile in the neighborhood.

We see similar results at the median home price, which is depicted below in Figure 5, though the effect of interventions is not as large at the peak of the median as at the first decile.

Figure 5. Derivative of Median Home Price Against Percent Intervention



What is more difficult to view in Figure 5 is that in the levels, the marginal effect of an additional intervention is negative until .2% of the homes in the block group have been intervened upon. However, after this threshold, the slope at the median is increasing until about 1.4% of homes have been intervened upon, at which point additional interventions begin having a negative effect on home prices at the median.

V. Conclusions

1. Main Findings

Based on regression results we can conclude that home interventions have a significant effect on home prices at the median and the first decile, both on the intervened upon home and the neighboring homes. This effect is found to be positive, and consistent at the house level and the median and first decile at the block group level. This is consistent with the goals of housing interventions, which are to increase the quality of the home, and therefore increase the value. However, this is not necessarily beneficial for the residents of the nearby homes. Increasing neighborhood quality can lead to higher home value which is an increase in wealth for homeowners but at the same time can lead to higher property taxes or higher rents, possibly forcing residents out of the area.

The statistically significant reduction in crime rate has a less clear relationship to the process of home interventions, but is consistent with the goals of most intervention organizations, which is to increase the living quality of the resident of the home. A decrease in crime is certainly a positive outcome for residents of a neighborhood, which contributes to the efficacy of these interventions and the achievement of their goals.

The significance of percent white residents, which is further discussed in Appendix B, fluctuates between models, but is consistently positive, indicating that interventions are associated with an increase in white residents. However, the coefficient percent black residents is not significant, and fluctuates between positive and negative, which indicates that the increase in percent white residents may come as a result of the reduction in a racial group, likely Hispanic, that is not black, which is the most represented minority in Durham County.

Lastly, we can see from the non-parametric estimation that interventions increase the home value of a neighborhood up to a certain percentage of homes intervened upon, before they begin to negatively affect the neighborhood home value. This could be an expected result of affordable housing interventions; the first several homes of low value being renovated increases the value of the neighborhood, but as more homes become affordable or seen as low-income housing, nearby residents begin to view the area as a low-income neighborhood, which could discourage people from living nearby, and therefore lowering the home value.

2. Limitations

Many of the limitations of this study revolve around the lack of knowledge surrounding the rate of displacement within each block group. One can see from the increase in percent white that there is clearly some amount of displacement, or replacement of residents of the block group, but this change does not tell the whole story of displacement occurring in the neighborhood. A more complete study on the efficacy of housing interventions would consider the change in residents as interventions are put into the block group, and could ask questions such as, who does a housing intervention help? The residents of the area before the intervention? Or the residents of the area who move in after the intervention? Is the increase in percent white a result of new residents moving into the block group without displacing others, or are white

residents replacing residents of other racial groups? It is also important to consider where displaced residents go after a housing intervention; do they find themselves, on average, worse or better off than they were before they move?

Another limitation of this study is the lack of rent data available for analysis. Often, changes in neighborhood quality can be seen at the rental level, which is also often where low-income communities can be found. Increasing home prices can be correlated with higher rents, which can force low income renters out of the neighborhood. Because the percent of homeowners does not change at a significant level based on percent of interventions, it is implied that percent of renters also does not change at a significant level based on variation in numbers of interventions. For intervention agencies that intend to increase homeownership in a neighborhood, this result does not indicate the success of their goal.

A natural continuation of this study is to separate the different housing intervention organizations and re-estimate the results of these models for each agency or each intervention model. Members of the Durham community have put forward anecdotal evidence that some housing interventions benefit the residents of a neighborhood and the community, while others have a negative effect on the people living there. By separating out the effect of each agency, this hypothesis could be tested. In addition, doing this analysis could shed light on the efficacy of specific programs and models for home interventions, and could help improve the neighborhood revitalization programs in place around the United States, not just the Durham community.

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Appendix A.

Here I present the full regression specified to estimate the effect of interventions upon individual homes. The log sale price is estimated as a function of the following variables, with the years acting as dummies for year of sale, and block group being used as a fixed effect to control for unobserved characteristics.

Table 7. Full Regression Results from Equation (1)

VARIABLES	Log Sale Price
First Sale	0.163***
	(0.0312)
Intervention	-0.161***
	(0.0127)
Lot Size (sqft)	6.51e-07***
	(5.98e-08)
Year Built	0.00211***
	(8.89e-05)
Total Bedrooms	0.118***
	(0.00235)
Full Bathrooms	0.176***
	(0.00308)
Half Bathrooms	0.137***
	(0.00307)
1995	-0.804
	(0.646)
1996	0.850*
	(0.511)
1997	0.979**
	(0.457)
1998	1.011**
	(0.457)
1999	1.084**
	(0.457)
2000	1.099**
	(0.457)
2001	1.161**
	(0.457)
2002	1.201***
	(0.457)

2003	1.213***
	(0.457)
2004	1.246***
	(0.457)
2005	1.288***
	(0.457)
2006	1.308***
	(0.457)
2007	1.333***
	(0.457)
2008	1.303***
	(0.457)
2009	1.298***
	(0.457)
2010	1.253***
	(0.457)
2011	1.206***
	(0.457)
2012	1.201***
	(0.457)
2013	1.243***
	(0.457)
2014	1.298***
	(0.457)
2015	1.383***
	(0.457)
2016	1.495***
	(0.457)
2017	1.582***
	(0.457)
2018	1.678***
	(0.457)
2019	1.729***
	(0.457)
2020	1.725***
	(0.458)
Constant	5.652***
	(0.489)
Observations	115,868
Number of geoid	168
R-squared	0.236

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix B.

The effect of interventions on percent white residents is shown to be unclear in the main model of the regression. However the sign of the coefficient is consistently positive, which indicates that the presence of interventions could be a positive predictor of an increase in percent white in the block group. Because of the uncertainty, this variable was further explored. I present below the three models run on percent white again in Table 8.

Table 8. Percent White as a Result of Interventions With Outlier

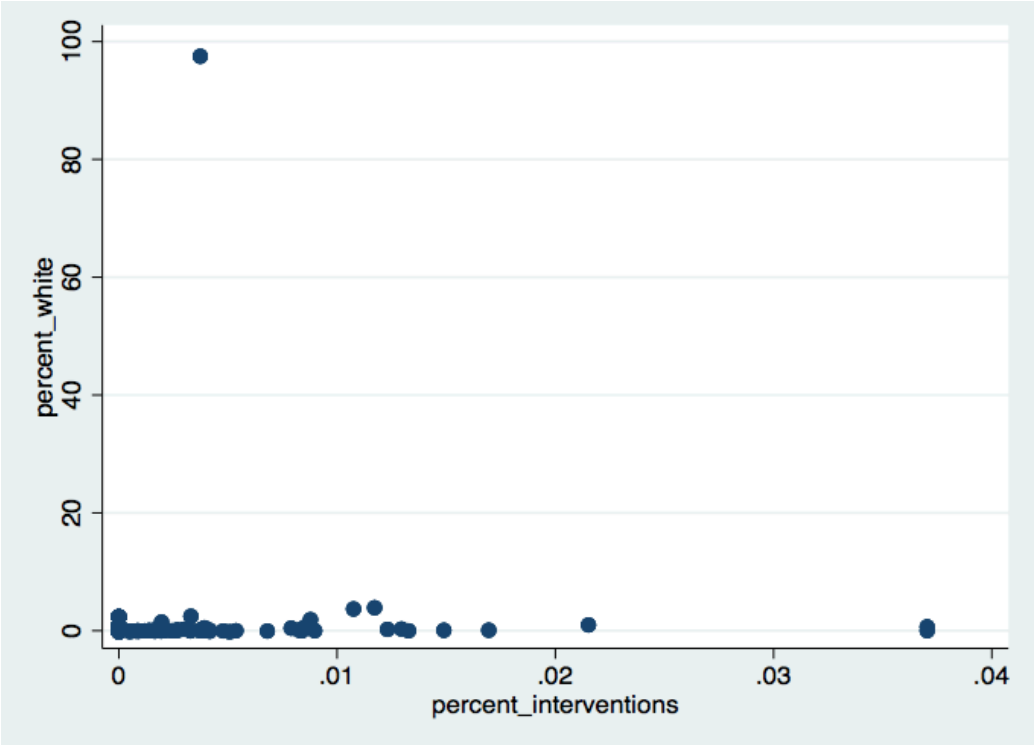
VARIABLES	(1) Percent White	(2) Percent White	(3) Percent White
Percent Interventions	96.70	384.5**	
	(84.67)	(191.8)	
Percent Interventions Squared		-11,224*	
		(6,715)	
Number of Interventions			0.316**
			(0.160)
Constant	0.380	0.260	0.280
	(0.317)	(0.324)	(0.320)
Observations	323	323	323
R-squared	0.005	0.016	0.015
Number of Groups	67	67	67

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Graphing a scatter plot of percent interventions against change in percent white from 2007-2017 shows the following, presented in Figure 6. It is clear from the graph that there is a strong outlier in percent white, which could be skewing the data and affecting the regression results. After consulting the original data, I found that the 2007 value of percent white was at under 1%, and it grew almost 100% by 2017. After finding which block group this was, and speaking to residents of the neighborhood, I found that colloquially, this block group was

traditionally a black neighborhood, and has experienced a huge influx of white residents in recent years.

Figure 6. Change in Percent White against Percent Interventions



After removing the outlier from the dataset, I gain the following results for change in percent white from 2007-2017, presented in Table 9. We see that following the removal of this outlier, there is a strong positive correlation that is statistically significant for all variations of the regression. It is unclear whether this outlier is a result of data errors or whether it is a true representation of the change in percent of white residents in this block group, so this result has been excluded from the body of the paper.

Table 9. Percent White as a Result of Interventions Without Outlier

VARIABLES	(1) Percent White	(2) Percent White	(3) Percent White
Percent Interventions	27.20***	68.05***	
	(8.872)	(20.08)	
Percent Interventions Squared		-1,589**	
		(702.3)	
Number of Interventions			0.0479***
			(0.0169)
Constant	0.152***	0.135***	0.150***
	(0.0332)	(0.0338)	(0.0337)
Observations	322	322	322
R-squared	0.036	0.055	0.031
Number of Groups	67	67	67

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1