The Effect of The Demolition of Derelict Housing on Home Property Values: Evidence from Detroit.

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This paper studies the effectiveness of the Detroit Demolition Program in increasing home property values in Detroit. The analysis focuses on both the short-term and long-term effects of the Program on Detroit's real estate market and controls for other initiatives aimed at revitalizing Detroit. The data show that, as of March 2017, the Detroit Demolition Program had increased the estimated median home value in Detroit by an estimated $1,171, which corresponds to a 3.41% increase since the program began in January 2014. The data also show that the program had a positive impact on home values in the bottom quintile of all Detroit home sale prices but a negative impact on home values in all other quintiles, indicating that future demolitions should only be performed near very low-valued homes.

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I. Introduction

It is rare to find a city that measures its mayor's success by the number of homes that are demolished under his watch, but such is the case for Detroit and Mayor Mike Duggan. Since Duggan took office in January 2014, the Detroit Land Bank Authority (DLBA) has demolished 16,541 blighted homes throughout the city through the Detroit Demolition Program. The stated goal of these demolitions is to boost Detroit's struggling economy by stabilizing neighborhoods, increasing property values, and decreasing foreclosure rates. This paper assesses the program's success toward this goal by answering the question: Has the Detroit Demolition Program increased properties values in Detroit? The results of this case study can then be used to answer the more general question: Does the Detroit Demolition Program provide evidence that the demolition of derelict housing increases property values of surrounding homes?

Under the Detroit Demolition Program, the DLBA primarily uses federally allocated funds from the US Treasury's Hardest Hit Fund (HHF) Program to identify and demolish blighted residential and commercial buildings in designated areas of the city that were "hardest hit" by the 2008 housing market crash ("HHF zones"). To be eligible for demolition, residential buildings must be publicly owned by the DLBA and in such poor condition that they negatively impact their surrounding neighborhoods. Privately owned commercial and residential buildings may also be eligible for demolition under the Nuisance Abatement Program if Detroit Building officials deem that they pose an immediate threat to public safety. Blighted building owners are notified that they have 6 months to fix up their building or hand over its ownership to the DLBA, who then puts the building on track for demolition or up for auction, depending on the severity of the building's condition.

In July 2015, Dynamo Metrics, LLC stated in their Detroit Demolition Impact Report that the Detroit Demolition Program had increased property values in the HHF zones by up to 13.8%. The city of Detroit also reports that "a recent study shows that Detroit's approach of strategically clustering demolitions in target areas has resulted in an increase in property values in those areas." This paper tests these claims by regressing median estimated home value in seventeen Detroit zip codes on corresponding demolition count data to determine the role that demolitions have actually played in the rise of Detroit home property values at an aggregate level. It also tests these claims at a parcel level by regressing the changes in sale price of 11,530 home properties on nearby demolition count data to determine the role that the demolitions have played in increasing the value of homes within 500 feet of at least one demolition.

II. Literature Review

The main inspiration for my research was the report produced by Dynamo Metrics, LLC entitled *Estimating Home Equity Impacts from Rapid, Targeted Residential Demolition in Detroit, MI: Application of a Spatially-Dynamic Data System for Decision Support*. The study, published in July 2015, utilizes spatially-dynamic econometric methods to estimate the effect of the Detroit Demolition program on single-family home values in Detroit from April 1st, 2014 to March 31st, 2015. The results suggest that each demolition within the HHF zones increased the value of nearby homes by a net 4.2%. The authors, therefore, conclude that the demolition program is having a "market-stabilizing effect" on home values within the neighborhoods it targets. However, since their analysis estimates the effect of the program after only one year of demolitions, not much can be concluded from the report about the long-term effects of the demolitions. This paper, therefore, aims to expand upon their analysis with data spanning a significantly longer timeframe to determine the longer-term effects that the Detroit Demolition program has had on Detroit home values.

Since the concept of large-scale demolition is relatively new, the collection of economic literature on its effects is scarce. However, the related concept of a "neighborhood effect" on the values of nearby homes is much more well-studied. In his paper *Good Home Improvers Make Good Neighbors*, Kevin Park defines the "neighborhood effect" as a situation wherein "the home improvement activities of an individual homeowner may impose costs and benefits on nearby property owners and thereby influence the general level of maintenance of the neighborhood." Park's analysis found that, for a given level of individual home improvement spending, house prices appreciated 15% more in neighborhoods that had high median home improvement spending than neighborhoods with low median home improvement spending. If we consider the demolition of a blighted home to be a home improvement funded by the HHF Program, Park's research would predict that neighborhoods with a high number of demolitions would experience greater appreciation in median home prices than neighborhoods with fewer demolitions.

III. Data

A. Demolitions

Data on each of the 16,541 recorded demolitions that have taken place in Detroit since January 2, 2014 are publicly available via the Detroit Open Data Portal. This dataset contains the street address, parcel ID, contractor name, price, demolition date, building type (commercial/non-commercial), council district, neighborhood, and coordinate location of each demolition. This study uses a condensed version of this dataset consisting of the 15,357 non-commercial building demolitions that occurred between January 1, 2014 and November 1, 2018.

Since the original dataset did not contain any zip code data, I utilized Geographic Information System Mapping Technology (ArcGIS Pro) to map each demolition to its corresponding zip code for my first round of analysis. First, I mapped Detroit's zip code boundaries with the "USA Zip Codes (2015)" data from the ArcGIS Living Atlas of the World. I then divided the demolition dataset into 39 subsets by month (e.g., January 2015) and plotted each subset onto the zip code map using the geographic coordinate of each demolition. Figure 1 shows the geographic distribution of demolitions across all subsets on the zip code boundary map, with the boundaries of the 17 zip codes selected for my first round of analysis shaded in a dark gray. To compile a dataset of demolition counts at the zip-code level, I used ArcGIS Pro's spatial join function on each subset to count the number of demolitions that took place in each of the 17 selected zip codes during each month within the January 2014 – March 2017 timeframe.

As the final step of cleaning the demolition data at the zip-code level, I used yearly housing data from the US Census Bureau to convert each demolition count to number of demolitions per 1,000 homes. This standardization is essential in controlling for variation in number of homes per zip code because, for example, we may expect 100 demolitions to have a much greater impact in zip code 48211, which had only 3,308 housing units in 2016, than in zip code 48227, which had over 22,000 housing units.

B. Estimated Total Housing Units

To convert the zip-code-level demolition count data to number of demolitions per 1,000 homes, I collected data on the estimated total housing units per zip code and year from the US Census Bureau's 2013-2017 American Community Survey. All estimates are given with a ~5%

or less margin of error, making them good indicators of the total numbers of homes in each of the 17 selected zips in 2014, 2015, 2016, and 2017.

C. Estimated Median Home Values

For my first round of analysis, I use Zillow's Home Value Index as a measure of Detroit home property values. This monthly index is a seasonally-adjusted measure of the estimated median home value across all housing types in a given zip code (single family residence, condo, co-op). For Detroit, data was only available for 17 of its zip codes: 48201, 48204, 48205, 48208, 48209, 48210, 48211, 48212, 48213, 48215, 48217, 48221, 48224, 48226, 48227, 48234, 48238; my zip code-level analysis is restricted to the effect of the Detroit Demolition Program on home values in these 17 zip codes. At the time of this study, Zillow has only published median home value estimates for Detroit through March 2017, so my zip-code-level analysis is therefore restricted to the timeframe from January 2012 through March 2017.

I chose January 2012 as the starting point for my analysis for two reasons. First, after the U.S. housing bubble popped in 2008, home prices across America plummeted. As Figures 2-18 show, Detroit was no exception; Detroit home values fell sharply from 2008 through the beginning of 2011 across all zip codes but leveled out and were relatively flat by 2012. Thus, my decision to choose a date as late as January 2012 as the start date for my analysis is in part to eliminate any omitted variable bias that could arise from the housing crisis of 2008. On the other hand, I choose a starting point as *early* as January 2012 (2 years before the Demolition Program began) in order to have ample control data for the regression software to pick up on the overall trend in Detroit housing prices that was already occurring prior to any homes being demolished.

Of the 17 selected zip codes, 2 zip codes (48201 and 48226) had no demolitions from January 2014 to March 2017. These two zip codes encompass Detroit's downtown and midtown neighborhoods, which largely consist of commercial buildings. As both Figure 2 and Figure 3 demonstrate, home values in 48201 and 48226 were decreasing fairly steadily from 2008 until mid-2013, when they began to increase back towards their pre-financial crisis values. As displayed in Figures 4 – 18, the housing value trends of the remaining zip codes all roughly follow a common trend of decreasing sharply from 2008 until around May 2011, when they level off and remain relatively steady through March 2017.

D. Residential Property Sales

For my second round of analysis, I use parcel-level property sale data as a measure of the value of a home in Detroit. Parcel-level data on each of Detroit's 976,969 property sales in recorded history are publicly available online via the Detroit Open Data Portal. This study uses a subset of this dataset, consisting of the addresses, parcel IDs, dates, terms of sale, and prices of select residential property sales that occurred between January 2012 and November 2018.

Multiple steps were taken in the process of cleaning this large dataset to prepare it for analysis. First, I removed any property sales that had "county LBS", "not arm's length", or "bank sale not used" listed as their terms of sale to ensure that my dataset consists solely of valid residential property sales involving two parties acting in their own self-interest. Next, I removed any duplicate sales present in the dataset, with a duplicate sale being defined as any property sale that has the same address, parcel ID, date, and price of any other property sale in the dataset.

I then restricted my dataset to include only the properties that sold for at least $1,000 and at most $345,000. I chose $1,000 as the lower bound on price for my analysis under the assumption that any sale price under $1,000 was only a reflection of the costs and fees associated with foreclosure or property transfer and not of the value of the home itself. I chose $345,000 as the upper bound on sale price as careful research of the remaining properties that sold for prices greater than $345,000 revealed that all of these properties are actually commercial properties, not residential homes.

From this cleaned dataset, I assigned each property sale to a quintile based on the sale price. Quintile 1 represents the residential property sales with prices in the lowest 20% of all residential property sale prices in the year in which it sold, whereas quintile 5 represents the sales with prices in the highest 20%. The price boundaries and median values of each quintile are recorded in Table 1.

Next, I removed from the dataset any property that did not have at least two sales between January 2012 and November 2018. This step was essential in ensuring that the *change* in individual home values could be measured over time. As a result of these measures, my final dataset consists of 13,987 pairs of residential property sales that occurred between January 2014 and November 2018.

As one of the final steps to prepare my residential property sale dataset for analysis, I used ArcGIS Pro's spatial join function along with the original demolition dataset from the Detroit

Open Data Portal to join each property sale with every demolition that occurred within 500 feet of the property. I then wrote a program in Python, included as Appendix A, that pairs up property sales by address, keeps only the demolitions that occurred between the two sale dates, and reformats the data corresponding to each sale/demolition so that it can be easily used for analysis. From this resulting dataset, many statistics could easily be calculated, such as the number of demolitions that occurred between the two sale dates, the number of demolitions that occurred during the month of the final sale, and the number of demolitions that occurred within 6-12 months of the final sale.

E. Project Green Light Locations

In addition to the Detroit Demolition Program, Mayor Mike Duggan aims to stabilize Detroit's neighborhoods by reducing violent crime rates through two main initiatives: Operation Ceasefire and Project Green Light. Operation Ceasefire is a program in which violent street gang members attend meetings with police, social workers, community leaders, and families of victims of violent crime as part of their parole requirements. The initiative started in 2013 and has been operating consistently since, so I chose to omit it from my analysis because of its lack of variation within my specified time frame.

On the other hand, Project Green Light started in January 2016 and has been expanding quickly ever since. Through this initiative, the Detroit Police Department has partnered with various gas stations, fast food restaurants, convenience stores, bars, etc. to install real-time video cameras that are monitored by the police. As a result, Duggan reports that there has been a 40% reduction in Detroit carjacking rates. The Detroit Open Data Portal provides a publicly available dataset of all of the current Project Green Light locations with their corresponding addresses, business names, and date on which they went live. Since the intended effect of this initiative is to decrease Detroit crime rates, and one would expect reduced crime to entice people to want to live in Detroit, I hypothesize that each Green Light location built would increase the values of nearby homes. Thus, I chose to include this data in my analysis to reduce the positive omitted variable bias that could arise from only considering demolitions as the cause of home value fluctuations in Detroit. I used ArcGIS Pro to map each newly built Green Light location to its corresponding zip code, and then used the spatial join function to count the number of new locations built in each zip code each month.

III. Regression Model

A. Approach I

To determine the role that demolitions have played in increasing Detroit home property values at the zip-code level, I use a fixed-effects model with least squares dummy variables for each zip code to regress the log of estimated median home value on the number of demolitions per 1,000 homes in the corresponding zip code. Using a fixed-effects model removes the effect of the time-invariant characteristics that are unique to each zip so that I may assess the net effect of demolitions on home property values. It also allows for the pooling together of all of the zip code data so that we have a single estimate for each slope parameter but different estimates for each zip code's intercept. I am choosing to use the log transformation on the dependent variable so that the results can be interpreted as the approximate percent change in estimated median home value due to demolitions; this controls for variation in initial median home values across Detroit's zip codes.

The first model I estimate is a simple linear regression of log estimated median home value on number of contemporaneous demolitions per 1,000 homes. This model takes the form:

$$lvalue_{zt} = \beta_0 + \gamma_z + \beta_1 demo_{zt} + u_{zt} \qquad (1)$$

where $lvalue_{zt}$ is the log estimated median home value for zip code z during month t, β_0 is the intercept common to all zip codes, γ_z is the additional intercept specific to zip code z, β_1 is the slope on number of demolitions per 1,000 homes, $demo_{zt}$ is the number of demolitions per 1,000 homes that took place in zip code z during month t, and u_{zt} is the error term. Note that $t = 0$ for January 2012 and $t > 0$ reflects the number of months passed since January 2012 (e.g., $t = 14$ is March 2013).

A problem with the simple regression of model (1) is that it fails to take into the account the cumulative effect of demolitions on home values. One would expect the demolition of a blighted home to not only impact home values that month, but also for all subsequent months as the blight is permanently removed. Thus, I estimate a second model of the following form:

$$lvalue_{zt} = \beta_0 + \gamma_z + \beta_1 cum\_demo_{zt} + u_{zt} \quad (2)$$

where $lvalue_{zt}$ is the log home value for zip code z at month t, β_0 is the intercept common to all zip codes, γ_z iis the additional intercept for zip code z, β_1 is the slope on cumulative number of demolitions per 1,000 homes, cum_demo_{zt} is the number of demolitions per 1,000 homes that have taken place in zip code z before but not including month t, and u_{zt} is the error term.

Perhaps the number of demolitions that occur in a month and the cumulative number of demolitions that occurred previously both play a role in determining log home value. For example, there could be a short-term effect of the number of blighted homes currently being demolished but a long-term effect of the number of blighted homes that are now gone. For a third model, both variables are taken into consideration in the following equation:

$$lvalue_{zt} = \beta_0 + \gamma_z + \beta_1 demo_{zt} + \beta_2 cum\_demos_{zt} + u_{zt} \qquad (3)$$

where the variables are as stated above.

Lastly, to control for potential omitted variable bias that could arise from only regressing on demolition data, my last model includes cumulative number of Project Green Light locations per zip as a third independent variable. This final model is of the form:

$$lvalue_{zt} = \beta_0 + \gamma_z + \beta_1 demo_{zt} + \beta_2 cum\_demos_{zt} + \beta_3 green\_light_{zt} + u_{zt} \qquad (4)$$

where β_3 is now the slope on number of Green Light locations and $green\_light_{zt}$ is the cumulative number of green light locations in zip code z at month t.

B. Approach II

While the change in estimated median home value can be a good metric for measuring the overall change in home prices in a zip code, it may overlook some more granular variation in home prices. Take, for a very simple example, a zip code that consists of three neighborhoods – A, B, and C – all of which initially contain 50 homes. Neighborhood A is a very run-down neighborhood, with 20 blighted homes valued at $5,000 each and 30 occupied homes valued at $20,000 each. Neighborhood B is a bit nicer, with 50 mid-sized, occupied homes valued at $50,000 each. Neighborhood C is a very well-off neighborhood, consisting of 50 large, occupied homes with well-manicured lawns, each valued at $80,000. The initial median home value for this zip code, therefore, is $50,000. Now imagine that the following year, the 20 blighted homes in Neighborhood A are demolished, and as a result the remaining occupied homes in Neighborhood A double in value to $40,000 while the home values in Neighborhoods B and C do not change. The median home value in this zip code would still be $50,000, regardless of the fact that 20% of its homes doubled in value. The models from my first approach, therefore, would correctly conclude that the 20 demolitions had no effect on the median home value in this zip code, but would not say anything about their effect in doubling the values of the homes closest to the demolitions.

My second approach aims to remedy this oversight by examining the effect of demolitions on the sale prices of individual homes within 500 feet of a demolition. To do so, I will first regress a detrended version of the log change in sale price for each property sale pair of the *Residential Property Sales* dataset on the number of demolitions that occurred between the two sale dates. I will divide the dataset by the quintile of the initial sale price and perform a separate regression for each quintile, as I hypothesize that the effect of demolitions will be stronger for properties that started off in the lowest quintile than for those that started off in higher quintiles. This model follows the form:

$$lprice\_change_{iq} = \beta_{0q} + \beta_{1q} num\_demos_i + u_{iq} \qquad (5)$$

where $lprice\_change_{iq}$ is the detrended log change in sale price for property sale pair i which had an initial sale price in quintile q, β_{0q} is the intercept for quintile q, β_{1q} is the demolition effect on homes in quintile q, num_demos_i is the number of demolitions that occurred within 500 feet of the property and between the two sale dates for property sale pair i, and u_{iq} is the error term. As before, I chose to use a log transformation on the response variable so that β_{1q} can be interpreted as the approximate percent change in sale price resulting from one additional demolition within 500 ft of the property.

I am using the term "detrend" in this context to refer to the removal of the overall trend in home prices over time for each of Detroit's zip codes that would have occurred independently of any demolitions taking place. To estimate how much of the sale price change of each property was caused by the time trend of its respective zip code, I will first perform the following regression for each zip code of the *Residential Property Sales* dataset:

$$lprice_{jz} = \beta_{0z} + \beta_{1z} sale\_month_j + r_{jz} \qquad (6)$$

where $lprice_{jz}$ is the log of the sale price for the individual property sale *j* in zip code *z*, β_{0z} is the intercept for zip code z, $sale\_month_j$ is the number of months passed from the start of 2012 to *j*'s sale date (e.g. a property sold in February 2012 would have a sale_month of 2 and a property sold in March 2013 would have a sale_month of 15), β_z is the monthly time trend of home prices in zip code z, and r_{jz} is the error term. Table 2 provides the monthly time trends for each of the zip codes in my dataset, which can be interpreted as the average monthly percent increase in residential property sale prices that occurred as a result of general improvements in the desirability to live in the zip code over time and/or inflation. In this context, the error term, r_{jz}, represents the contribution to the log sale price of property sale j by factors other than the common monthly time trend in zip code

z; the effect of the Demolition Program is included in these factors. Thus, the detrended log change in sale price for property sale pair i, consisting of initial property sale j and final property sale $j+1$, is simply the difference in the two error terms; that is, $lprice\_change_i = r_{(j+1)z} - r_{jz}$, where $i = \{j, j+1\}$.

Model (5) estimates the effect of demolitions on home values under the assumption that all demolitions within 500 feet of homes in a given quintile have the same effect, regardless of their timing. The next model that I will estimate allows for there to be different demolition effects based on the number of months between the demolition date and the final sale date. The equation to represent this model is:

$$lprice\_change_{iq} = \beta_{0q} + \beta_{1q} demos\_curr_i + \beta_{2q} demos\_1\_6_i + \beta_{3q} demos\_7\_12_i + \beta_{4q} demos\_over\_12_i + u_{iq} \qquad (7)$$

where $lprice\_change_{iq}$ is the detrended log change in sale price for property sale pair i which had an initial sale price in quintile q and β_{0q} is the intercept for quintile q. $demos\_curr_i$ is the number of demolitions that occurred within 500 feet and during the month of the final sale date for property sale pair i, $demos\_1\_6_i$ is the number that occurred between 1 and 6 months prior to the final sale date, $demos\_7\_12_i$ is the number that occurred between 7 and 12 months prior to the final sale date, and $demos\_over\_12_i$ is the number that occurred over 12 months before the final sale date. β_{1q}, β_{2q}, β_{3q}, and β_{4q} are the respective effects of these demolitions on the detrended log price change of homes that initially sold in quintile q. As before, u_{iq} represents the error term in this regression.

I chose to omit the Project Green Light location count variable from the regressions of my second approach for two reasons. First, due to the fact that there are only 473 Project Green Light locations to date and there are 11,530 properties in my dataset, there is simply not enough data to be able to estimate their effect at a level of granularity beyond the zip code level. Second, given that any general improvements to the desirability to live within a given zip code have already been identified and removed through the detrending of the price change variable, any omitted variable bias resulting from the exclusion of this variable at the zip code level has already been eliminated.

IV. Results

A. Approach I

1. Regression of Log Median Estimated Home Value on Demolition Count

Estimating model (1) through the regression of log home values on demolition counts per 1,000 homes yields unremarkable results. As Table 3 shows, model (1) predicts that each additional demolition per 1,000 homes in zip code i during month t will increase the estimated median home value of zip code i during month t by approximately 0.11% with a standard error of 0.19%. Since 0.11% is close to zero and the standard error of this predicted value is substantially larger than the predicted value itself, model (1) provides evidence that the number of demolitions that took place in a given month did not significantly affect median home values at the zip-code level during that month. The R^2 value of 0.9374 is fairly high, but this is likely just the result of the dummy variable estimates for each zip code.

2. Regression of Log Median Estimated Home Value on Cumulative Demolition Count

As noted in the model section, regressing log home value on monthly contemporaneous demolition count alone is not a good predictor of changes in home property values because the effects of demolishing blighted homes are expected to be long-term. The estimation of model (2) through the regression of log home values on cumulative number of demolitions per 1,000 homes yields results that more closely align with the reported effects of the Demolition Program. The model, as shown in Table 3, predicts that each additional demolition per 1,000 homes in zip code i will increase the estimated median home value of zip code i in subsequent months by approximately 0.13% with a standard error of 0.02%. This estimate is not only statistically significant but also economically significant because a single home demolition out of 1,000 homes is expected to increase the median estimated home value of its entire zip code by more than 1% is less than a year.

3. Regression of Log Median Estimated Home Value on Demolition Count and Cumulative Demolition Count

To estimate model (3), I regress log home value on both monthly demolition count and cumulative demolition count. As Table 3 demonstrates, the model predicts that each additional demolition per 1,000 homes decreases the estimated median home value of the current month by approximately 0.35% but increases the estimated median home value of all subsequent months by about 0.14%. The direction of these estimates make sense intuitively, as demolitions are taking place during harsh economic times and the local disturbance of the demolition process may decrease property values while the demolition is taking place. In the subsequent months following a demolition, one would expect property values to start to increase as the zip code becomes a more attractive place to live in the long-run. The standard errors of both slope estimates are relatively small compared to the estimates themselves and are therefore statistically significant. These estimates are quite economically significant as well; for example, the estimated median home value of zip code 48204 in January 2014 was $38,500, so these estimates predict that a single demolition in the zip code during that month would decrease the current estimated median home value by $134.75 but increase the estimated median home value of all subsequent months by $53.90.

As a result, I conclude that both contemporaneous and cumulative demolitions play a definitive role in driving changes in estimated median home values. However, cumulative demolition count plays a more definitive role in determining a given zip code's median home value in the long-run because its effect persists beyond a one-month timespan. The R^2 and mean squared error values of this regression are roughly the same as those of model (2), which omits monthly demolition count, so I conclude that including monthly demolition count is relatively inconsequential to the overall fit of the model.

4. Regression of Log Median Estimated Home Value on Demolition Count, Cumulative Demolition Count, and Number of Project Green Light Locations

Lastly, for model (4) I estimate the regression of log home values on monthly demolition count, cumulative demolition count, and Green Light location count. Table 3 shows that the estimated effect of the contemporaneous monthly demolition count per 1,000 homes on log home value is slightly less significant in this model than it was in model (3). The model predicts that each additional demolition per 1,000 homes decreases the estimated median home value of the current month by only 0.31% with a standard error of 0.19%. This corresponds to a $119.35 decrease in zip code 48204 in January 2014, which is still quite substantial.

The estimated percent increase in estimated median home values due to cumulative demolition count is 0.12% with a margin of error of 0.02%. This estimate decreased from that of model (3) because model (3) omitted the Green Light location variable. There was likely positive omitted variable bias included in the estimate in model (3) for two reasons. First, there is a positive correlation between number of cumulative demolitions and number of Green Light locations because both are cumulative measures that have increased over time. Second, the effect of the number of Green Light locations is expected to be positive because Green Light locations create safer neighborhoods that are more attractive to prospective buyers. Table 3 shows that the estimated increase in a zip code's estimated median home value from each additional Green Light location built in that zip code is approximately 0.15% with a standard error of 0.07%. This effect is economically significant as it has one of the largest coefficient of any of the non-dummy variables in the model and therefore plays the largest role in increasing home property values. The R^2 of this regression is 0.9420- the highest R^2 of the four models- and the root mean squared error is 0.0636- the lowest of the four models. Based on these statistics, I conclude that model (4) is the best model for predicting changes in estimated median home value from demolitions.

The estimated coefficients on the zip code dummy variables are all statistically significant across all four regressions. Given that the R^2 values of each regression are very similar, it is reasonable to conclude that most of the overall variation in home values can be explained by zip code. The remaining variation is explained by the regressions within each zip code and by the error terms.

5. Estimating the Cumulative Effects of the Demolition Program on Median Home Property Values

Table 4 displays the estimated cumulative percent increases in median home property values due to demolitions by zip code from January 2014 to March 2017. Using model (4) as the preferred model, I estimate that as of March 2017, the Detroit Demolition program had increased home property values in Detroit by 3.41%, on average. 3.41% may sound insignificant, but when converted to dollars, Table 5 shows that this estimate corresponds to a $1,171 increase in the estimated median home property value in Detroit. Therefore, although the per demolition effects may seem negligible, the aggregate effects of the Detroit Demolition program on home values have been substantial.

Along with the estimated benefits of the program, it is important to consider the costs associated with demolishing homes. Table 6 provides the median costs per demolition for each of the 15 selected zip codes, all of which are much larger than their respective estimated increases in median home value due to demolitions. So, if the success of the Detroit Demolition program were to be measured by its return on investment alone, I would conclude that the program has been an inefficient approach to increasing Detroit's home values.

B. Approach II

1. Regression of Log Change in Home Property Value on Demolition Count

The estimation of model (5) yields very different results for each quintile. As shown in Table 7, the model estimates that each demolition within 500 feet of a home that had an initial sale in Quintile 1 will increase the value of the home by about 0.49% with a standard error of 0.93%. Given this large standard error of this estimate is almost twice the size of the estimate itself, there is insufficient evidence from this model to conclude that these demolitions had an effect on the values of nearby homes.

The estimates of the model for the remaining four quintiles, however, tell a very different story. The estimated coefficients on number of demolitions from Table 7 are actually negative for Quintiles 2-5, meaning that the model predicts each demolition within 500 feet of homes in Quintiles 2-5 to decrease the values of these homes. The magnitude of this estimated effect increases as the quintile number increases, with the model predicting that each demolition within 500 feet of a home in Quintile 5 will decrease the value of the home by 22.88% with a standard error of only 1.86%. All of these estimates are quite large in magnitude compared to those of my first approach; this makes sense intuitively because, in general, one would expect a neighborhood improvement (or disturbance) to affect nearby homes much more strongly than other homes in the zip code that are too far away to fully enjoy its benefits (or disadvantages).

The R^2 values for these models increase as the quintile number increase, but in general are quite small; this is unsurprising due to the fact that I am predicting the percent change in the sale price of various homes, which is subject to a wide variety of factors outside of just the number of demolitions that took place nearby. The *Residential Property Sales* dataset is also very noisy in terms of sale prices, likely reflecting the fact that many sales were the result of the auctioning off of foreclosed properties.

At first glance, the direction of these slope estimates may appear to contradict the results of my first approach. However, as Table 8 shows, there is a strong skew in the counts of demolitions within 500 feet of homes in each quintile, with Quintile 1 having significantly more and Quintile 5 having significantly less than the other quintiles. Although the demolition dataset used in my second approach differs slightly from that of my first approach, I assume that they follow a similar distribution because they are subsets of the same larger dataset. Thus, since my first approach treats all demolitions within a zip code equally, I suspect that the resulting estimates are skewed towards the effect of demolitions that took place near Quintile 1 homes, hence their positive direction in most of the models.

2. Regression of Log Change in Home Property Value on Demolition Counts over Different Timeframes

Breaking up the num_demos regressor into multiple demolition count variables based on the timing of the demolitions provides a more granular view of the parcel-level effect of demolitions on home values. As shown in Table 9, model (6) estimates that each demolition within 500 feet of a home that had an initial sale in Quintile 1 during the same month of the demolition will increase the value of the home by about 25.57% with a standard error of 8.59%. The positive direction of this estimate suggests that, for homes in Quintile 1, a demolition is a positive driver of the value of the home because it improves the aesthetic appeal of the neighborhood and eliminates a threat to public safety. The magnitude of this estimate is surprisingly very high, especially compared to the modest estimates of my first approach. If a home valued at $5,000 had a demolition occur within 500 ft, this model estimates that the value of the home would increase by $1,250 within a month.

A closer look at the general timing of the demolitions relative to the timing of home property sales in Detroit provides one potential explanation for such an estimate. As Figure 19 shows, the spikes in the monthly demolition count are frequently accompanied concurrently (or shortly after) by spikes in the monthly Detroit home property sale count. So, this high estimate for the effect of demolitions that occurred during the month of the final sale could be a reflection of the fact that a lot of the demolitions occurred during a hotter time in the Detroit real estate market when demand for homes was high.

The estimates for the slopes on the rest of the regressors for Quintile 1 are close to 0 with relatively large standard errors, so there is insufficient statistical evidence to conclude that demolitions that occurred at least a month before the final sale of a home had a significant effect in determining the final sale price. However, it is interesting to note that these estimates start positive and decrease as the time between the demolitions and the final sale date increase. This trend suggests that for homes that start in Quintile 1 the effect of the Demolition Program is mostly contemporaneous and decreases with time.

The estimates of model (6) for Quintiles 2-5 tell almost the opposite story. The slope estimates on the number of demolitions that occurred during the month of the final sale shown in Table 9 are all quite large in magnitude but are all accompanied by very large standard errors; for example, the model estimates that each demolition occurring within 500 ft of a home in Quintile 2 will decrease the value of that home by 1.54% that month with a standard error of 8.01%. Similarly, the estimate for Quintile 4 is a 2.15% increase with a standard error of 8.77%, yielding a very conservative confidence interval of [-15.04%, 19.34%]. These large standard errors therefore indicate that the number of demolitions that happen during the month of the final sale doesn't play a very definitive role in driving changes in the value of homes in Quintiles 2-5.

On the other hand, the slope estimates on the number of demolitions that occurred 1-6 months, 7-12 months, and over 12 months before the final sale are all statistically significant at the 1% level. For Quintile 2 the predicted changes in home values as a result of these demolitions are relatively modest. The model predicts that each demolition will decrease the values of Quintile 2 homes within 500 feet by approximately 5.04% 1 to 6 months after the demolition takes place, 8.65% after 7 to 12 months, and 2.67% after a year. The higher magnitude of the 7 to 12-month lag estimate relative to the other two time-lag estimates may be a reflection of how far in advance homes in Quintile 2 are typically put up for sale. Perhaps if most Quintile 2 homes are listed for sale a year before they are actually sold, then the 7 to 12-month timeframe might be a time when there are a lot of viewings of the home and potential buyers would see the nearby demolitions first-hand.

These slope estimates for Quintiles 3 and 4 are negative as well but much larger in magnitude. The model predicts that each demolition within 500 feet of a Quintile 3 home will decrease the value of the home by 13.76% 1 to 6 months after the demolition, 11.87% 7 to 12 months after, and 5.47% over 12 months after. The variation in the sizes of these estimates could mean that the demolitions create more of a disturbance for nearby homes closer to their sale dates, or it could again be a reflection of the real estate timeline. The model for Quintile 4 provides similar estimates, predicting each demolition to decrease the value of Quintile 4 homes within 500 feet by 12.98% after 1 to 6 months, 9.68% after 7 to 12 months, and 18.73% after over a year.

Lastly, the estimated model for Quintile 5 provides the most extreme results, estimating each demolition within 500 feet to decrease the values of Quintile 5 homes by 40.94% after 1 to 6 months, 50.66% after 7 to 12 months, and 18.90% after a year. This implies that if a demolition occurred next-door to a $100,000 home in January 2015, the model predicts that, all other variables held constant, it would sell for $59,060 in February 2015 – July 2015, $49,340 in August 2015 – January 2016, or $81,100 in February 2016 onward. The pattern of these estimates suggests that the strong negative effect of demolitions on Quintile 5 home values is somewhat temporary in that it sharply decreases home values for about a year before they start to return towards their pre-demolition values.

There are many possible explanations for the negative direction of the slope estimates for Quintiles 2-5. First is the local disturbance that the demolition process creates. Perhaps, to potential home buyers, a bulldozer ripping down the house next-door makes for a worse neighbor than a blighted home decaying quietly into the weeds. This disturbance would decrease a consumer's willingness to pay for the home and therefore decrease the sale price. There could also be concerns about what, if anything, will replace the demolished homes in the neighborhood. The construction of new homes in their place would create as much commotion as the demolitions themselves but leaving the land untouched could leave some neighborhoods almost empty; this uncertainty about the neighborhood they are buying into might worry risk-averse buyers and therefore decrease their willingness to pay. It is likely that these two side-effects of demolitions would play less of a role in determining the sale price of Quintile 1 homes because, as shown in Table 1, the values of these homes are already so low that there is not much room for buyers to negotiate down the price to account for them.

There is also the possibility that demolitions are viewed by consumers, either consciously or unconsciously, as a signal of a low-value neighborhood. As Table 8 shows, the largest percentage of demolitions across all five quintiles occurred within 500 feet of a home that had a sale in Quintile 1. If people associate demolitions with the Quintile 1 price range as a result, then homes that previously sold for prices in Quintiles 2-5 may see a decrease in value if there is a demolition nearby.

Similar to model (5), model (6) has relatively small R^2 values across all quintiles. But again, this is likely the result of a high level of noise within the *Residential Property Sales* dataset as well as the exclusion of many other variables that could affect home values. These variables are all accounted for in the error term of the regression, hence the relatively high mean squared error values across quintiles.

V. Conclusion

Based on my analysis on the role that demolitions have played in the rise of Detroit's home property values, I determine that the cumulative number of demolitions that have taken place in each zip code increased overall home values in Detroit by about 3.41% from January 2014 to March 2017. In dollar terms, the program has increased overall home values by an estimated $1,171.

These overall effects, however, are not experienced by all homes. My parcel-level analysis shows that a demolition within 500 feet of a home valued at less than $6,000 increases the value of that home by an estimated 25.57% in less than a month, but that same demolition would decrease the value of a $60,000 home by an estimated 40.94% in only a few months.

My study therefore confirms the city of Detroit's statement that "Detroit's approach of strategically clustering demolitions in target areas has resulted in an increase in property values in those areas." Based on this result, I conclude that the demolition of derelict housing does indeed increase the property values of surrounding homes if the surrounding homes are valued at $6,000 or less. Therefore, going forward, I recommend that the Detroit Land Bank Authority cluster their demolitions in neighborhoods with very low-valued homes in order to maximize these gains and minimize any potential loss-in-value of more expensive homes.

However, given that the median cost of a single demolition is $12,336 alone, the estimated $1,171 cumulative increase in the median home value pales in comparison. My analysis shows that the Detroit Demolition Program yields a negative return on investment for its use of funds from the Hardest Hit Fund Program, suggesting that the program might not be the most efficient use these funds. But, as is the case with many public policies, a positive return on investment may not be the intended goal. Rather, if the goal of the Hardest Hit Fund Program is to redistribute wealth from wealthier American taxpayers to people that were hardest hit by the 2008 financial crisis, then one could argue that the Detroit Demolition Program has been a success to some degree. Further research into the benefits of alternative uses of funds from the Hardest Hit Fund Program is needed in order to determine if the Detroit Demolition Program is in fact the most efficient way to increase the wealth of the people of Detroit.

Furthermore, my study is limited in that it only assesses the effects of the Detroit Demolition Program on home values for up to four years. Perhaps in the next ten years the cumulative effects of current demolitions will yield much larger increases in home values that will eventually outweigh the median demolition cost of $12,336. As this is an ongoing program with over 1,600 demolitions currently in the pipeline, ongoing research into both the effectiveness and efficiency of the program is recommended.

VI. References

City of Detroit (2017). "About Project Green Light Detroit." Project Green Light Detroit. http://www.greenlightdetroit.org/about/.

City of Detroit (2018). "Detroit Demolition Program." http://www.detroitmi.gov/demolition.

Detroit Land Bank Authority (April 6, 2018). Detroit Demolitions. Distributed by the City of Detroit. https://data.detroitmi.gov/Property-Parcels/Detroit-Demolitions/rv44-e9di.

Detroit Office of the Assessor (March 6, 2019). Property Sales History. Distributed by the City of Detroit. https://data.detroitmi.gov/Property-Parcels/Property-Sales-History/xbvp-4is5.

Detroit Police Department (March 6, 2018). Project Green Light Locations. Distributed by the City of Detroit. https://data.detroitmi.gov/Public-Safety/Project-Green-Light-Locations/vrh6-6pvj.

Dynamo Metrics, LLC (July 2015). Estimating Home Equity Impacts from Rapid, Targeted Residential Demolition in Detroit, MI: Application of Spatially-Dynamic Data System for Decision Support. https://static1.squarespace.com/static/55e8c061e4b018cc4b5864bc/t/55f78eeee4b07bf949e5de03/1442287342508/Detroit_DemoStudy_FinalEditedVersion.pdf

Park, Kevin (April 2008). "Good Home Improvers Make Good Neighbors." Joint Center for Housing Studies of Harvard University, Working Paper W08-2.

Esri, TomTom, U.S. Census (April 18, 2017). USA Zip Codes (2015). Distributed by Esri. https://www.arcgis.com/home/item.html?id=5203d33eed8b4611859a2d9dca8b604e .

Strafford, Katrease (March 07, 2018). “Mayor Mike Duggan to Detroit Children: ‘We Want You to Stay’.” Detroit Free Press. https://www.freep.com/story/news/local/michigan/detroit/2018/03/06/mayor-mike-duggan-detroit-children-state-city/400824002/.

Zillow Research (2018). “ZHVI All Homes (SFR, Condo/Co-op).” Home Values. Distributed by Zillow. https://www.zillow.com/research/data/.

VII. Appendix

Figure 1. Detroit Demolition Geographic Distribution

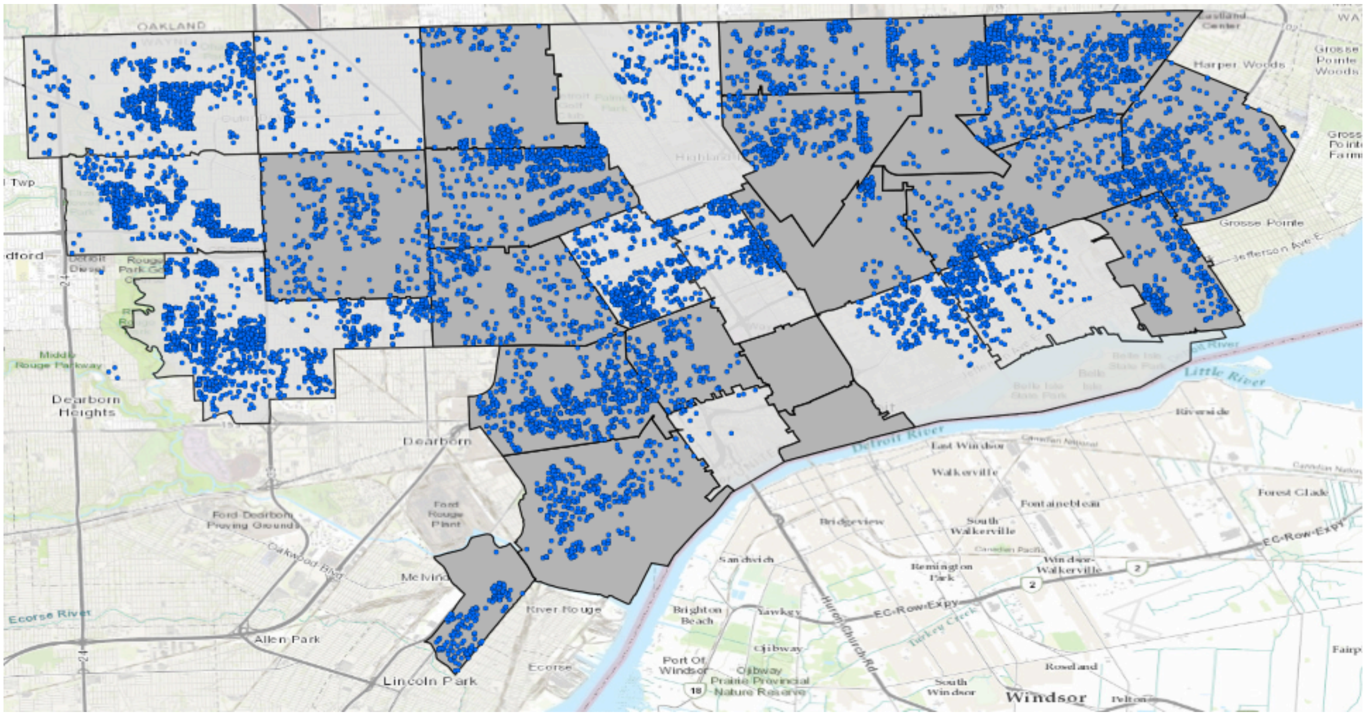

Figure 2. Estimated Median Home Values in Zip Code 48201, Jan. 2008 – March 2017

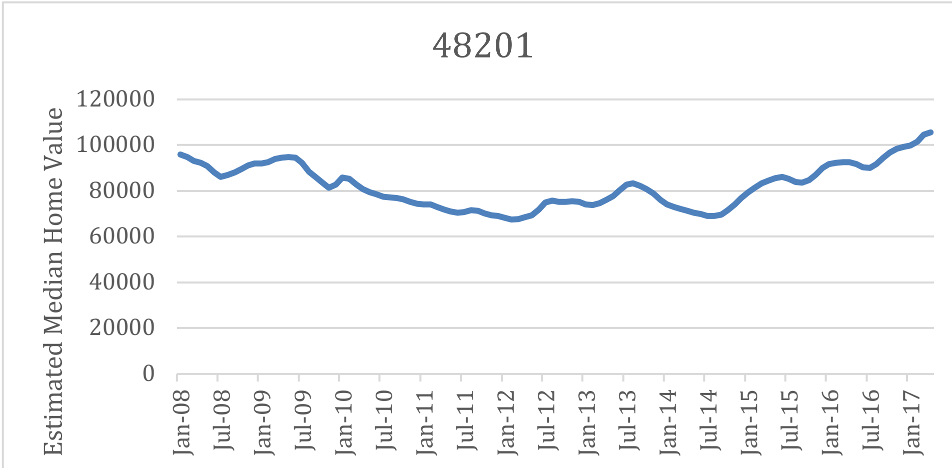

Figure 3. Estimated Median Home Values in Zip Code 48226, Jan. 2008 – March 2017

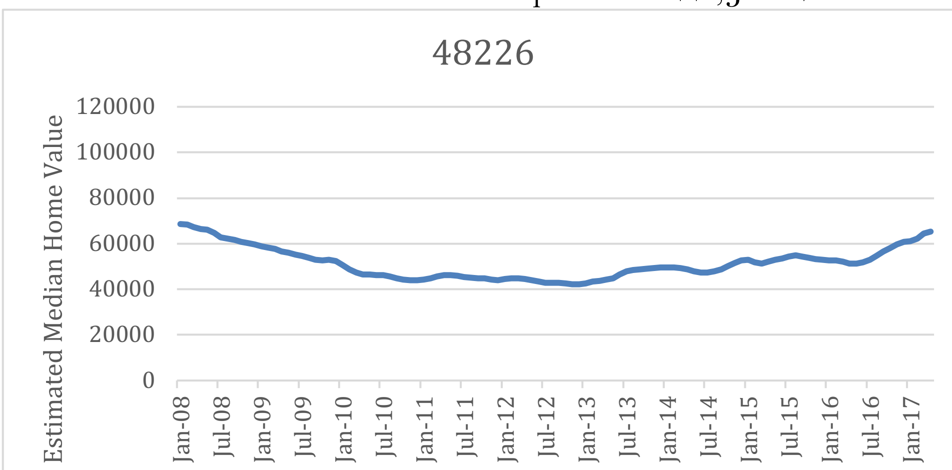

Figure 4. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48204, Jan. 2008 – March 2017

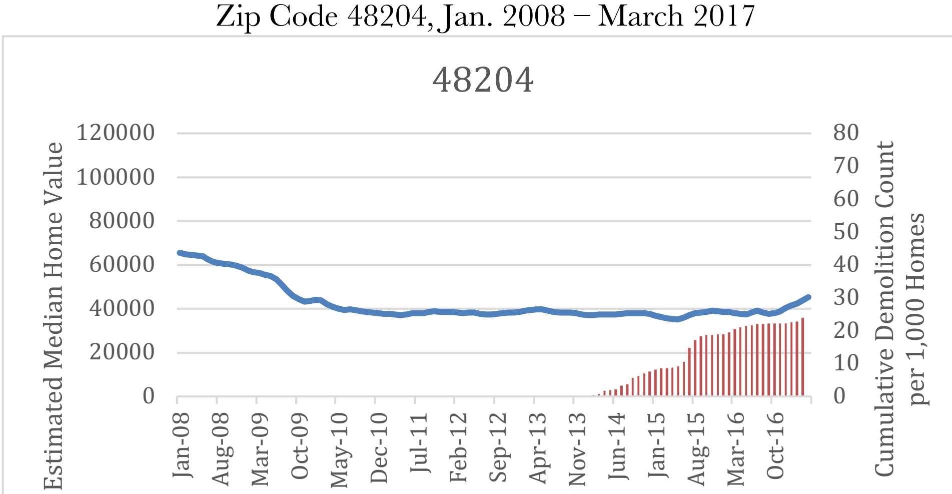

Figure 5. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48205, Jan. 2008 – March 2017

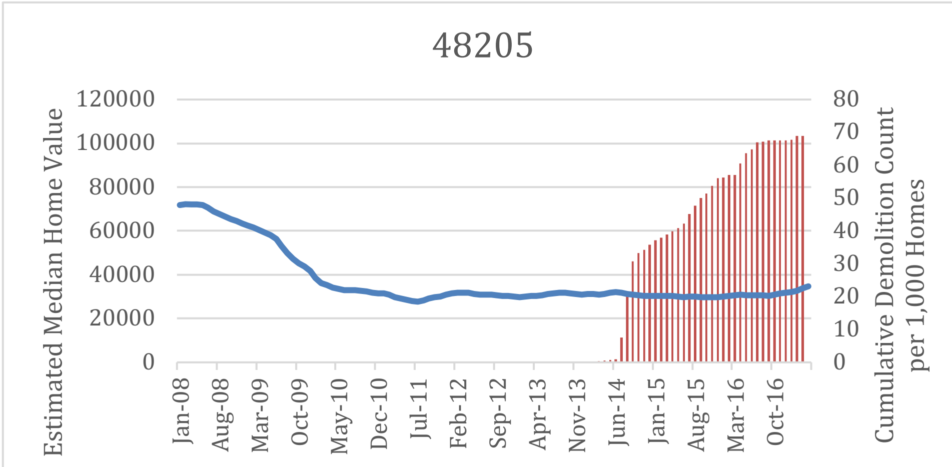

Figure 6. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48208, Jan. 2008 – March 2017

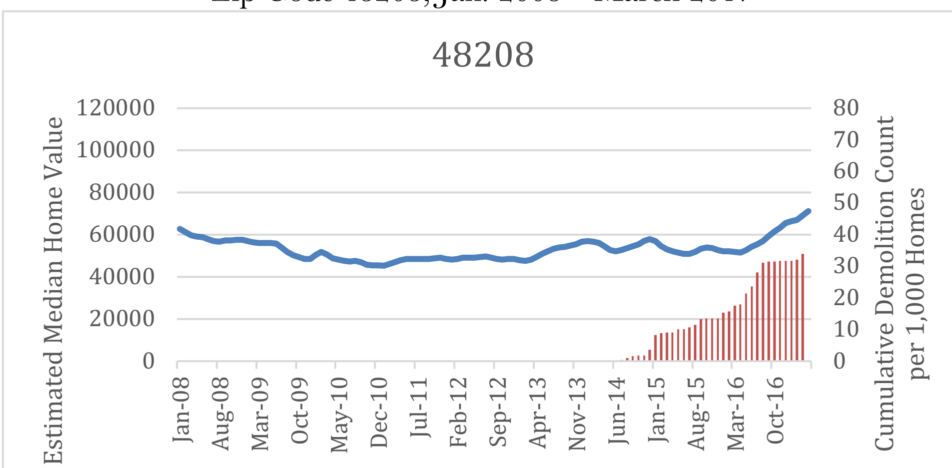

Figure 7. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48209, Jan. 2008 – March 2017

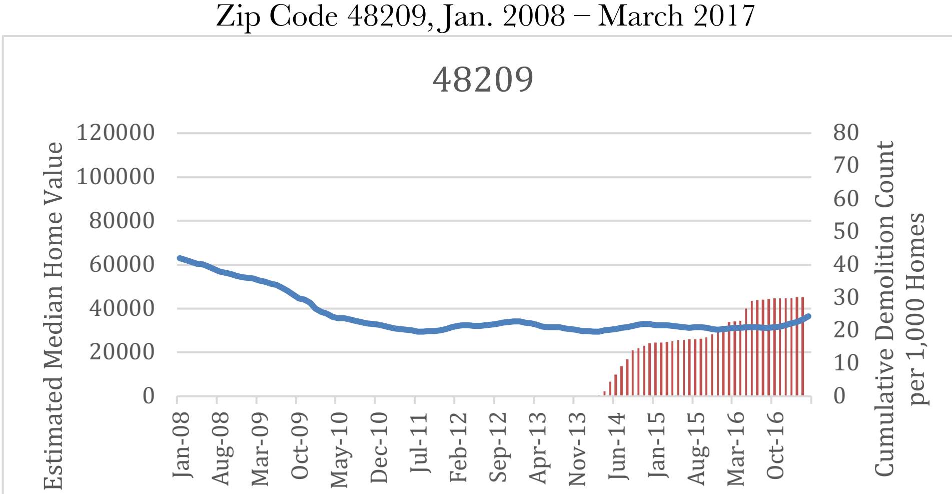

Figure 8. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48210, Jan. 2008 – March 2017

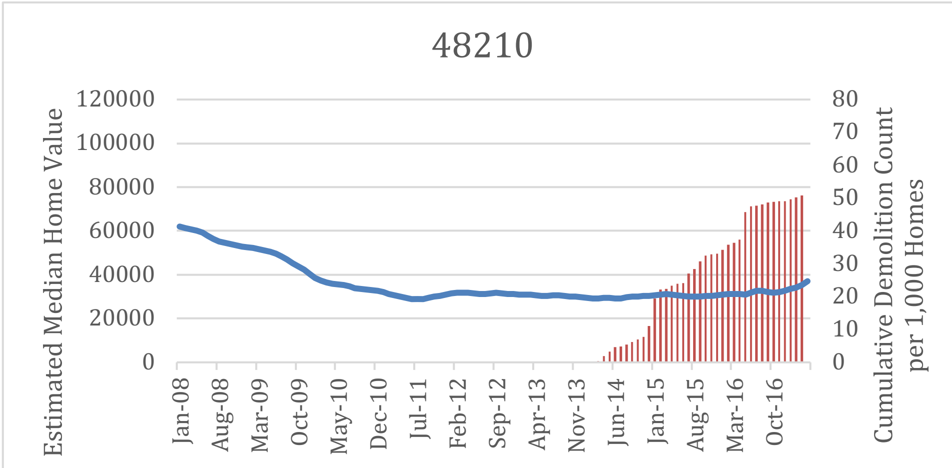

Figure 9. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48211, Jan. 2008 – March 2017

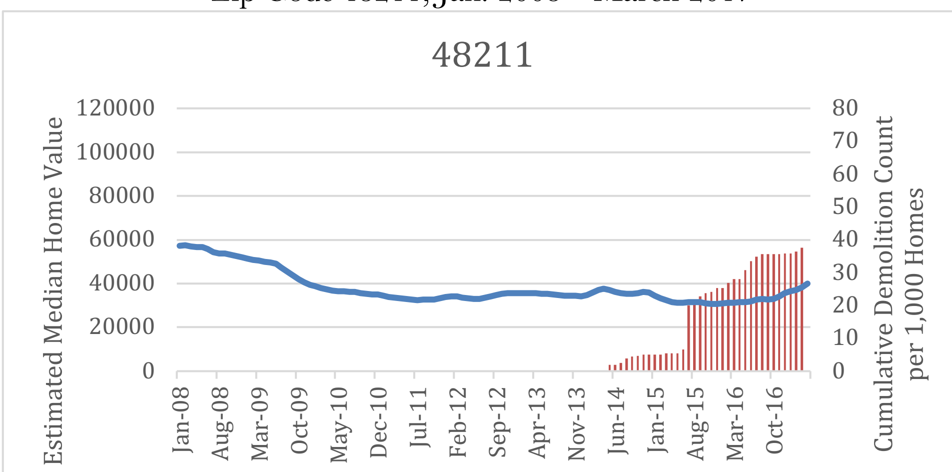

Figure 10. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48212, Jan. 2008 – March 2017

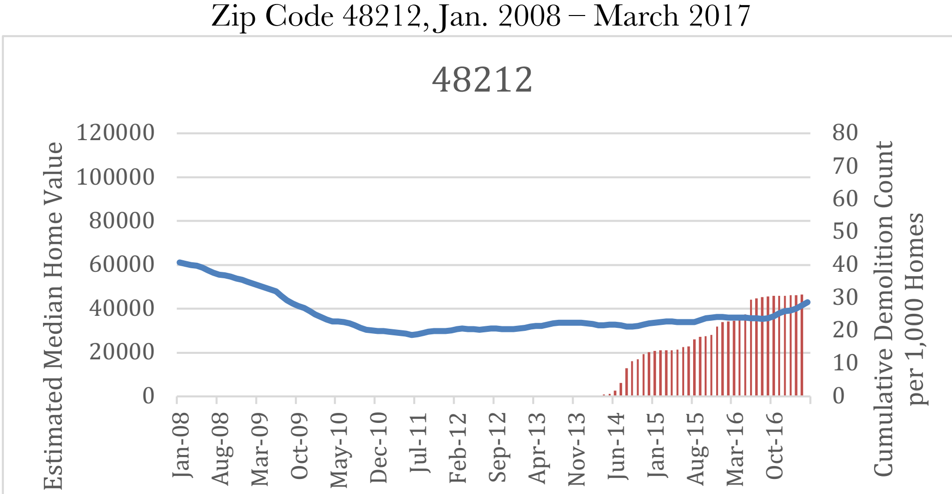

Figure 11. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48213, Jan. 2008 – March 2017

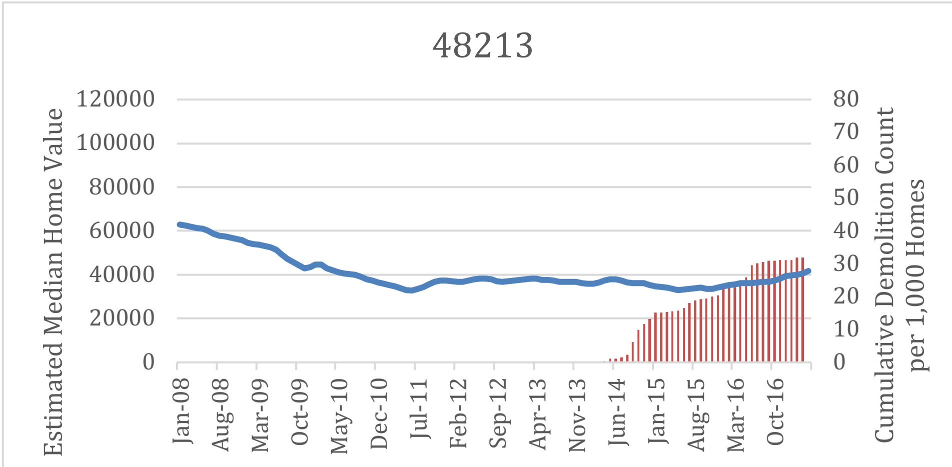

Figure 12. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48215, Jan. 2008 – March 2017

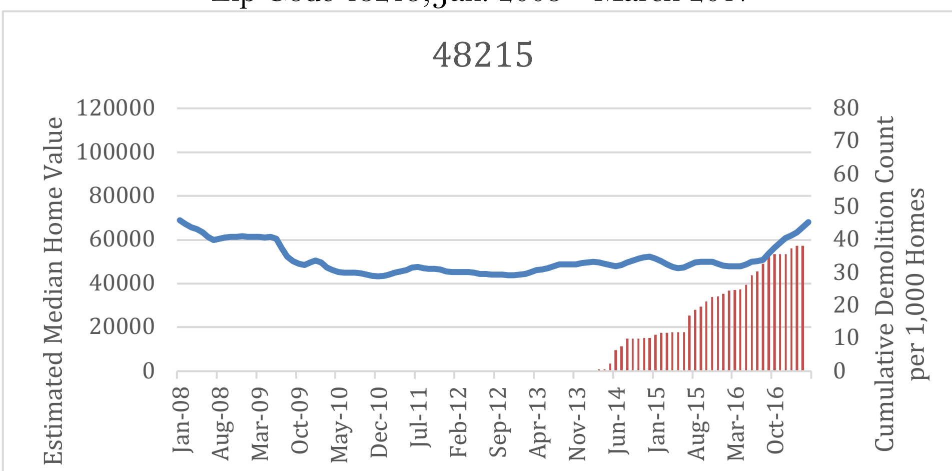

Figure 13. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48217, Jan. 2008 – March 2017

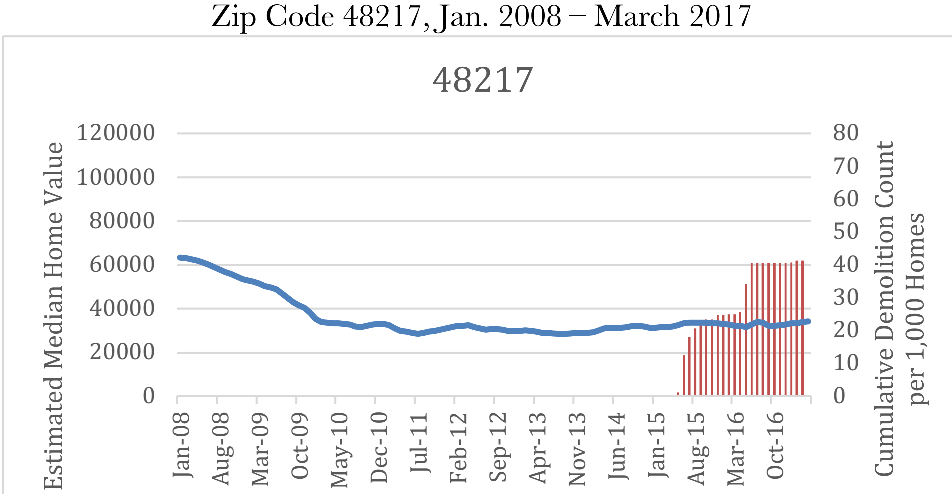

Figure 14. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48221, Jan. 2008 – March 2017

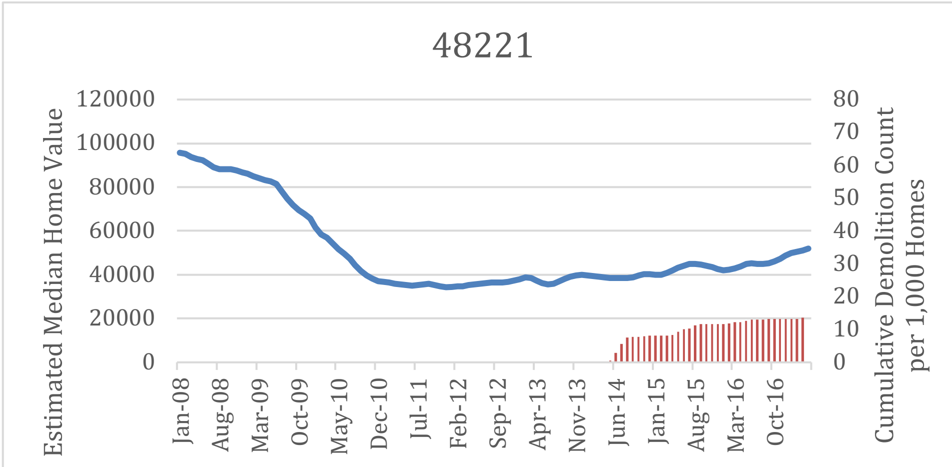

Figure 15. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48224, Jan. 2008 – March 2017

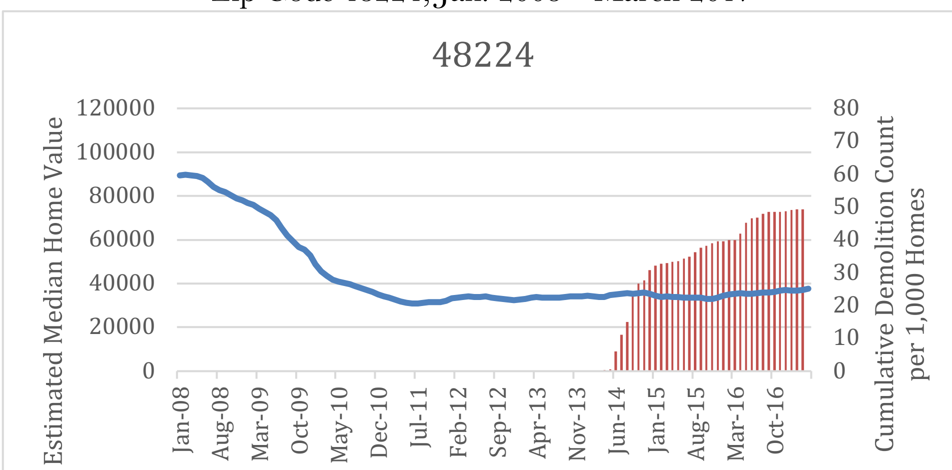

Figure 16. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48227, Jan. 2008 – March 2017

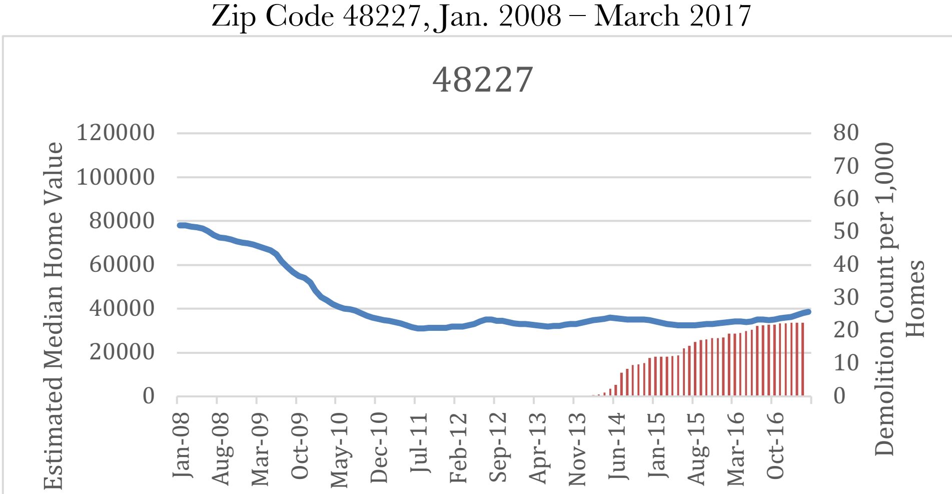

Figure 17. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48234, Jan. 2008 – March 2017

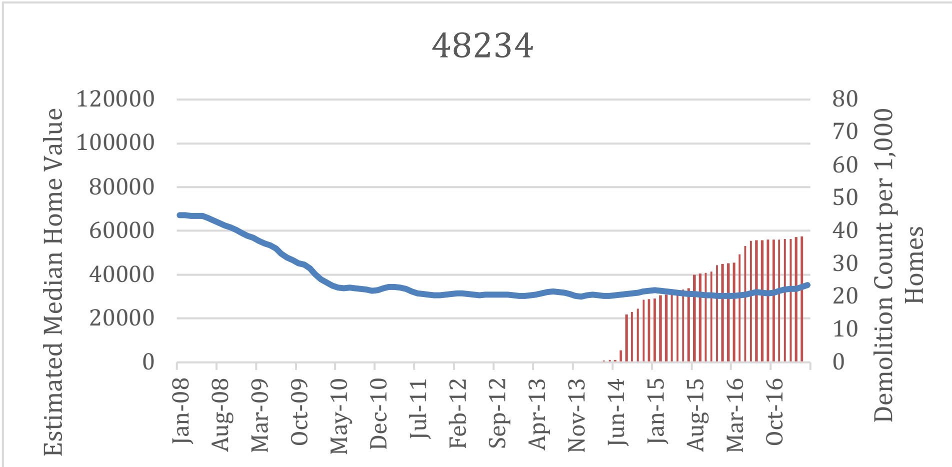

Figure 18. Estimated Median Home Values & Cumulative Demolition Counts per 1,000 Homes: Zip Code 48238, Jan. 2008 – March 2017

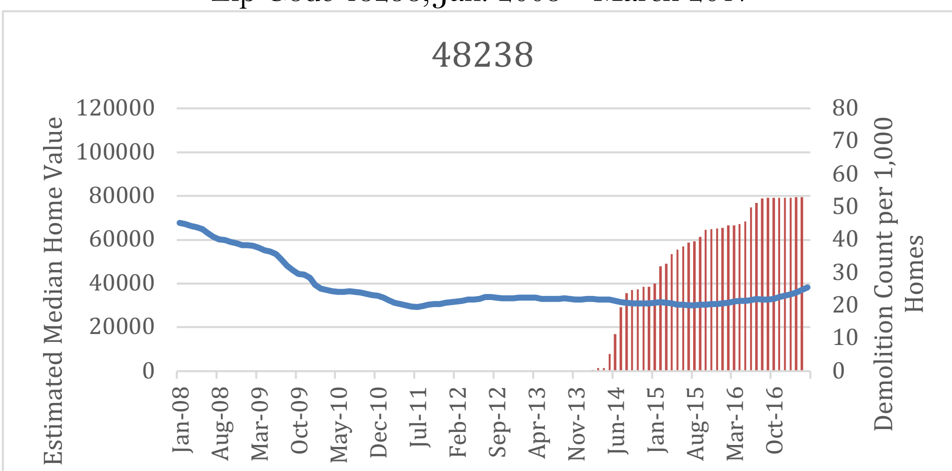

Figure 19. Property Sale & Demolition Counts by Month in Detroit

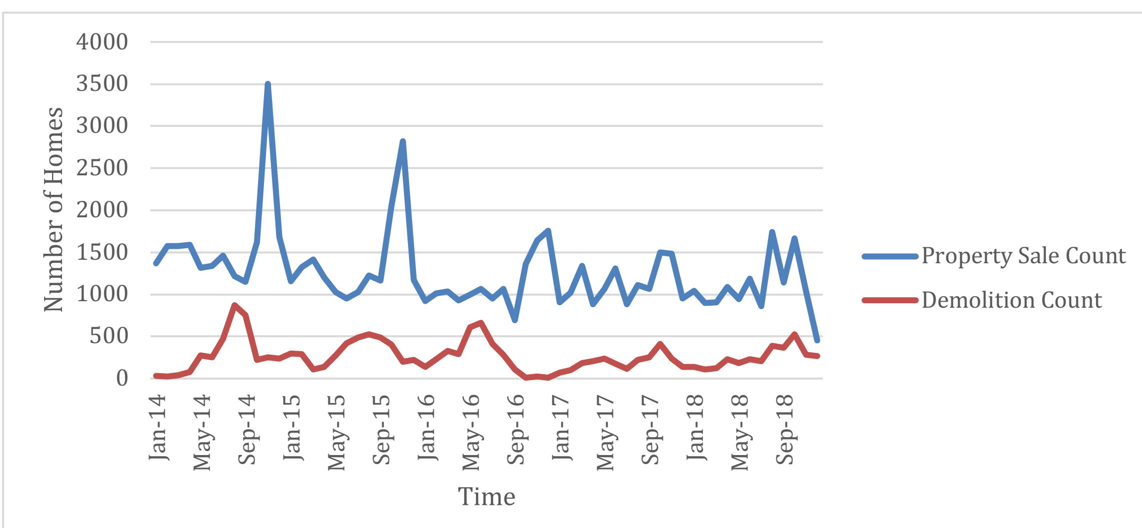

Table 1. Detroit Property Sale Quintile Ranges, 2012 – 2018

Quintile		2012	2013	2014	2015	2016	2017	2018
1	Minimum	$1,000	$1,000	$1,000	$1,000	$1,000	$1,000	$1,000
	Median	$1,700	$2,000	$2,000	$1,840	$1,500	$1,500	$2,100
	Maximum	$3,142	$3,600	$3,600	$3,501	$3,500	$4,200	$6,000
2	Minimum	$3,150	$3,634	$3,601	$3,508	$3,501	$4,206	$6,010
	Median	$5,000	$6,100	$5,750	$6,000	$6,000	$7,500	$11,000
	Maximum	$7,000	$9,999	$8,650	$9,000	$9,400	$12,000	$17,549
3	Minimum	$7,001	$10,000	$8,681	$9,001	$9,410	$12,001	$17,551
	Median	$10,000	$15,000	$13,000	$13,300	$14,463	$18,032	$25,000
	Maximum	$16,350	$25,000	$19,000	$18,900	$20,000	$25,000	$33,000
4	Minimum	$16,368	$25,001	$19,001	$18,960	$20,001	$25,100	$33,025
	Median	$31,855	$40,000	$28,332	$28,000	$29,000	$35,000	$43,000
	Maximum	$58,000	$58,103	$42,000	$43,000	$42,000	$48,500	$57,000
5	Minimum	$58,016	$58,148	$42,050	$43,100	$42,168	$48,592	$57,160
	Median	$93,537	$73,342	$69,900	$81,673	$80,000	$84,000	$109,900
	Maximum	$340,000	$342,000	$345,000	$345,000	$345,000	$345,000	$345,000
Overall	Minimum	$1,000	$1,000	$1,000	$1,000	$1,000	$1,000	$1,000
	Median	$10,000	$15,000	$13,000	$13,300	$14,463	$18,032	$25,000
	Maximum	$340,000	$342,000	$345,000	$345,000	$345,000	$345,000	$345,000

Quintile 1 refers to the lowest 20% of residential property sale prices in Detroit during the given year.
Quintile 2 refers to the middle 21-40% of residential property sale prices in Detroit during the given year.
Quintile 3 refers to the middle 41-60% of residential property sale prices in Detroit during the given year.
Quintile 4 refers to the middle 61-80% of residential property sale prices in Detroit during the given year.
Quintile 5 refers to the highest 20% of residential property sale prices in Detroit during the given year.

Table 2. Estimated Percent Change in Home Property Sale Prices due to the Common Time Trend within a Zip Code: January 2012 – November 2018

Zip Code	Estimate	Standard Error
48201	2.02**	0.90
48202	2.35***	0.43
48204	1.34***	0.21
48205	1.05***	0.12
48206	1.61***	0.25
48207	2.35***	0.43
48208	2.59***	0.66
48209	1.24***	0.20
48210	1.07***	0.21
48211	1.73**	0.69
48213	0.55*	0.30
48214	2.41***	0.51
48215	1.95***	0.45
48216	1.50**	0.58
48217	0.78**	0.31
48219	1.06***	0.10
48221	1.20***	0.10
48223	0.88***	0.17
48224	1.03***	0.10
48227	1.27***	0.11
48228	0.82***	0.10
48234	0.83***	0.14
48235	0.94***	0.09
48238	0.57***	0.21

Note: Sample period is January 2012 through March 2017.
Dependent Variable: 100 * log sale price
Regressor: number of months passed since January 2012
***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 3. Predicting Percent Change in Estimated Median Home Values Due to Demolitions Using Fixed Effect Least Squares Regressions

		(1)	(2)	(3)	(4)
demo		0.11		-0.35*	-0.31
		(0.19)		(0.19)	(0.19)
cum_demo			0.13***	0.14***	0.12***
			(0.02)	(0.02)	(0.02)
green_light					0.15**
					(0.07)
	48204	-74.75***	-75.60***	-75.54***	-75.47***
		(1.18)	(1.14)	(1.14)	(1.14)
	48205	-96.11***	-98.36***	-98.22***	-98.04***
		(1.19)	(1.17)	(1.17)	(1.17)
	48208	-40.92***	-42.09***	-41.96***	-41.80***
		(1.18)	(1.15)	(1.15)	(1.15)
	48209	-92.94***	-94.07***	-94.00***	-93.91***
		(1.18)	(1.15)	(1.14)	(1.14)
	48210	-95.92***	-97.83***	-97.69***	-97.45***
		(1.18)	(1.16)	(1.16)	(1.16)
	48211	-86.34***	-88.36***	-88.23***	-87.94***
		(1.18)	(1.16)	(1.16)	(1.17)
	48212	-87.50***	-88.52***	-88.44***	-88.29***
		(1.18)	(1.14)	(1.14)	(1.14)
	48213	-79.28***	-80.42***	-80.34***	-80.20***
		(1.18)	(1.15)	(1.14)	(1.14)
zip	48215	-49.72***	-51.37***	-51.25***	-51.13***
		(1.18)	(1.15)	(1.15)	(1.15)
	48217	-94.30***	-95.70***	-95.56***	-95.39***
		(1.18)	(1.15)	(1.15)	(1.15)
	48221	-68.97***	-69.43***	-69.41***	-69.42***
		(1.18)	(1.14)	(1.14)	(1.14)
	48224	-85.16***	-87.63***	-87.61***	-88.99***
		(1.18)	(1.17)	(1.17)	(1.34)
	48226	-48.20***	-48.20***	-48.20***	-48.19***
		(1.18)	(1.14)	(1.14)	(1.13)
	48227	-86.59***	-87.27***	-87.23***	-87.30***
		(1.18)	(1.14)	(1.14)	(1.14)
	48234	-94.37***	-95.67***	-95.59***	-95.44***
		(1.18)	(1.15)	(1.15)	(1.15)
	48238	-91.19***	-93.07***	-92.97***	-92.72***
		(1.18)	(1.16)	(1.16)	(1.16)
Constant		1129.65***	1129.65***	1129.65***	1129.64***
		(0.83)	(0.80)	(0.96)	(0.80)
Observations		1071	1071	1071	1071
R^2		0.9374	0.9416	0.9418	0.9420
Root MSE		0.0660	0.0638	0.0638	0.06364

Note: Sample period is January 2012 through March 2017.
Standard errors are displayed in parentheses.
Dependent Variable: 100 * log estimated median home value
Regressors: demolitions per 1,000 homes, cumulative demolitions per 1,000 homes, number of green light locations, dummy variable for each zip code other than 48201
***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 4. Predicting Cumulative Percent Change in Estimated Median Home Values Due to Demolitions: January 2012 – March 2017

Zip Code	Cum. Number of Demolitions /1,000 Homes	(2)	(3)	(4)
48204	20.55	2.67	2.88	2.47
48205	51.11	6.64	7.16	6.13
48208	35.40	4.60	4.96	4.25
48209	25.52	3.32	3.57	3.06
48210	47.54	6.18	6.66	5.70
48211	46.94	6.10	6.57	5.63
48212	25.61	3.33	3.59	3.07
48213	27.29	3.55	3.82	3.27
48215	40.66	5.29	5.69	4.88
48217	41.50	5.40	5.81	4.98
48221	9.61	1.25	1.35	1.15
48224	32.75	4.26	4.59	3.93
48227	15.58	2.03	2.18	1.87
48234	29.73	3.87	4.17	3.57
48238	40.04	5.21	5.61	4.80
Overall	28.40	3.69	3.98	3.41

Note: Sample period is January 2012 through March 2017.
Dependent variable: estimated percent change in estimated median home value.
Independent variable: cumulative number of demolitions per 1,000 homes.
The "overall" estimates are weighted averages of across all of the sampled zip codes.

Table 5. Predicting Total Dollar Increase in Estimated Median Home Values Due to the Demolition Program: January 2012 – March 2017

Zip Code	(2)	(3)	(4)
48204	$991	$1,067	$915
48205	$2,073	$2,232	$1,914
48208	$2,623	$2,825	$2,421
48209	$989	$1,065	$913
48210	$1,817	$1,957	$1,677
48211	$2,124	$2,287	$1,960
48212	$1,112	$1,198	$1,026
48213	$1,270	$1,368	$1,172
48215	$2,627	$2,829	$2,425
48217	$1,565	$1,685	$1,444
48221	$496	$534	$458
48224	$1,465	$1,577	$1,352
48227	$695	$748	$641
48234	$1,181	$1,272	$1,090
48238	$1,718	$1,850	$1,586
Overall	$1,269	$1,367	$1,171

Note: Sample period is January 2012 through March 2017.
Dependent variable: estimated total dollar increase in estimated median home values.
Independent variable: cumulative number of demolitions.
The "overall" dollar increase is a weighted average of the price increases across all of the sampled zip codes.

Table 6. Median Cost per Demolition: January 2012 – March 2017

Zip Code	Demos Primarily Funded by HHF	Demos Primarily Funded by Non-HHF	All Demos
48204	$17,870	$11,175	$14,241
48205	$12,700	$11,235	$12,137
48208	$13,377	$11,199	$13,213
48209	$10,834	$11,600	$11,200
48210	$13,500	$10,080	$12,914
48211	$12,560	$10,210	$12,195
48212	$11,765	$10,909	$11,500
48213	$14,278	$11,684	$12,873
48215	$12,222	$12,405	$12,300
48217	$14,485	$8,257	$14,200
48221	$12,599	$12,357	$12,489
48224	$11,759	$10,150	$11,517
48227	$14,018	$10,572	$12,190
48234	$11,896	$10,753	$11,633
48238	$13,424	$12,331	$13,061
Overall	$12,336	$12,223	$12,336

Note: Sample period is January 2012 through March 2017.
Column (2) provides the median cost per demolition for demolitions that were primarily funded by the U.S. Treasury's Hardest Hit Fund (HHF) Program.
Column (3) provides the median cost per demolition for demolitions that were primarily funded by sources other than the Hardest Hit Fund Program; most notably, these demolitions were funded by the city of Detroit for the emergency demolition of homes that posed an immediate threat to public safety.
Column (4) provides the median cost per demolitions for all demolitions in the zip code. The "overall" median costs are the median values across all 15 zip codes that were selected for my first round of analysis.

Table 7. Predicting Percent Change in Home Sale Prices due to the Number of Demolitions Within 500 Feet

	Quintile				
	(1)	(2)	(3)	(4)	(5)
num_demos	0.49	-4.27***	-7.94***	-15.99***	-22.88***
	(0.93)	(0.82)	(0.79)	(0.85)	(1.86)
Constant	97.9***	47.0***	18.7***	-17.16***	-53.17***
	(2.59)	(1.82)	(1.42)	(1.66)	(3.31)
Observations	2,750	3,214	3,864	3,094	1,063
R^2	0.0001	0.0085	0.0252	0.1036	0.1248
Root MSE	1.2132	0.9517	0.8319	0.8764	1.0210

Note: Sample period is January 2012 through November 2018.
Standard errors are displayed in parentheses.
Dependent Variable: 100 * log detrended change in sale price
Regressor: number of demolitions that occurred within 500 ft of the property and between the initial and final sale dates
The quintile of a home is defined by the initial sale price of the home relative to all other homes that sold in the same year.
***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 8. Demolition Counts by Quintile

	Quintile					
	(1)	(2)	(3)	(4)	(5)	Total
demos_curr	80	76	46	47	5	254
demos_1_6	644	728	515	421	104	2,412
demos_7_12	487	434	358	296	87	1,662
demos_over_12	2,018	1,295	1,125	1,148	359	5,945
Total	3,229	2,533	2,044	1,912	555	10,273

Note: Sample period is January 2012 through November 2018.
demos_curr is the total number of demolitions that occurred (1) within 500 feet of at least one home in the given quintile and (2) during the month of the final sale date of that home.
demos_1_6 is the total number of demolitions that occurred (1) within 500 feet of at least one home in the given quintile and (2) 1-6 months prior to the final sale date of that home.
demos_7_12 is the total number of demolitions that occurred (1) within 500 feet of at least one home in the given quintile and (2) 7-12 months prior to the final sale date of that home.
demos_over_12 is the total number of demolitions that occurred (1) within 500 feet of at least one home in the given quintile and (2) over 12 months prior to the final sale date of that home.
The quintile of a home is defined by the initial sale price of the home relative to all other homes that sold in the same year.

Table 9. Predicting Percent Change in Home Sale Prices due to the Number of Demolitions Within 500 Feet and Timing of Demolitions

	Quintile				
	(1)	(2)	(3)	(4)	(5)
demos_curr	25.57***	-1.54	-16.24	2.15	-51.87
	(8.59)	(8.01)	(10.87)	(8.77)	(45.65)
demos_1_6	1.68	-5.04***	-13.76***	-12.98***	-40.94***
	(3.40)	(1.93)	(2.51)	(2.84)	(6.99)
demos_7_12	0.23	-8.65***	-11.87***	-9.68***	-50.66***
	(3.88)	(3.00)	(2.61)	(3.04)	(8.08)
demos_over_12	-0.32	-2.67**	-5.47***	-18.73***	-18.90***
	(1.14)	(1.16)	(1.09)	(1.19)	(2.34)
Constant	97.56***	46.74***	18.79***	-18.47***	-51.78***
	(2.60)	(1.81)	(1.42)	(1.66)	(3.27)
Observations	2,750	3,214	3,864	3,094	1,063
R^2	0.0033	0.0083	0.0265	0.0997	0.1509
Root MSE	1.2119	0.9523	0.8317	0.8687	1.0071

Note: Sample period is January 2012 through November 2018.
Standard errors are displayed in parentheses.
Dependent Variable: 100 * log detrended change in sale price
Regressors: number of demolitions that occurred within 500 ft of the property and between the initial and final sale dates
The quintile of a home is defined by the initial sale price of the home relative to all other homes that sold in the same year.
***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.