REBUILDING THE MOTOR CITY: EXPLORING DEMOLITION, NEIGHBORHOOD STABILIZATION, AND LAND VALUATION

By

Camila Gabriela Alvayay Torrejón

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food, and Resource Economics – Doctor of Philosophy

2023

ABSTRACT

The City of Detroit, once the symbol of industrial prosperity, is an example of a declining city. Urbanized areas that have experienced population loss, reduced employment opportunities, and continued economic decline. For decades, these cities have been in a downward spiral characterized by deteriorating infrastructure and urban residential decay. "Is Detroit Dead?" asked Peter Eisinger in his 2014 essay. In this dissertation, I provide a partial answer to that question and show that Detroit is not dead, but rather in transition. By examining the city's urban policies and their impact on the housing market, I illuminate Detroit's potential for urban renewal and offer important insights into the successes and failures of these efforts, as well as possible alternatives to property taxation. The city's efforts serve as a case study for other shrinking cities around the world.

In the first essay, titled "Impact of Demolitions on Neighboring Property Values in Detroit", I evaluate the impact of demolitions on neighboring property values using a Repeat Sales (RS) regression approach. The Detroit Demolition Program began in 2014 and has since demolished more than 20,800 properties at a cost of over $250 million. In addition, the city demolished 11,400 buildings containing hazardous materials such as asbestos from 2009-2015. I use information on property sales prices from 2009 to 2019, and information from the 2009 Detroit Residential Survey to differentiate by the level of dilapidation prior to the start of the program. I find that, on average across the city, the removal of disrepair through the demolition program does not appear to have affected residential transaction prices. However, when I differentiate the effect by the ex-ante characteristics of the properties, I find that the demolitions have a positive effect on property prices in areas where there was a low level of decay prior to the demolitions.

In the second essay, titled "Revitalization in Shrinking Cities: Impact of the Neighborhood Stabilization Program in Detroit", I evaluate the effectiveness of the Neighborhood Stabilization Program (NSP) in terms of housing valuation, foreclosure decline, and rehabilitation projects. The Great Recession led to the largest housing market collapse in US history. During this time, many homeowners suffered the consequences of the crisis, accumulating unpaid property tax bills and foreclosures. This problem was concentrated primarily in cities that were experiencing long-term economic decline, such as Detroit. In an effort to address the housing crisis, Congress provided funding for emergency assistance to rehabilitate abandoned and foreclosed homes under the NSP, a $7 billion program. In Detroit's case, nine neighborhoods were identified as those most affected by the housing crisis. Overall, the results indicate that the NSP had a stabilizing effect on the housing market in treated neighborhoods, preventing further declines, but did not stimulate pronounced revitalization.

In the third essay, titled "Valuing Land in Detroit Using the Option Value Approach", I present empirical evidence for the option value of residential properties in Detroit and use this to estimate their land values. This is particularly relevant as Detroit considers adopting a split-rate property tax (City of Detroit, 2023), a policy where land is taxed more than improvements, known for its efficiency and equity benefits. Using the option value technique, a novel approach in land valuation, I analyze data from the Zillow ZTRAX database and employ land use intensity variables to construct hedonic models incorporating option value. This method, which considers the relative volume of the structure of the property, reveals that option value positively correlates with property depreciation, increasing sales prices significantly. These findings not only offer a new perspective in measuring option value but also demonstrate the importance of including it in land value assessments, particularly for higher-priced properties, to avoid underestimation.

ACKNOWLEDGEMENTS

I am profoundly grateful to my advisor, Dr. Mark Skidmore. His vast experience, patience, and unwavering support were pivotal in crafting this thesis. More than just technical and disciplinary knowledge, he imparted human skills and lessons on how to be both a good person and a researcher. My heartfelt thanks also go to the members of my committee: Dr. Dusan Paredes, Dr. Scott Loveridge, Dr. Frank Lupi, and Dr. Justin Kirkpatrick. Their invaluable advice and time significantly contributed to the refinement of this work.

I extend my appreciation to the faculty and colleagues from the AFRE and Economics departments. The lessons learned and the curiosity kindled through years of classes have greatly enriched my journey. A special acknowledgment is due to my fellow students. Navigating our PhD journey during a pandemic, we thrived on mutual support and camaraderie, creating an environment of warmth and motivation.

I am also thankful for the financial and resource support provided by the Lincoln Institute of Land Policy, the MSU College of Agriculture and Natural Resources, and the Institute for Public Policy and Social Research. Their backing was crucial in my research endeavors.

Above all, my deepest gratitude is reserved for my wife, family, and friends. Their relentless support and unwavering belief in my capabilities have been the cornerstone of my pursuit of academic and personal goals. This achievement is as much theirs as it is mine

TABLE OF CONTENTS

INTRODUCTION

This thesis delves into the transformative dynamics of urban renewal in Detroit, a city grappling with the consequences of population decline and economic shifts. Owens et al. (2020) have highlighted the inefficiencies arising from these changes: “Large declines in population over several decades have resulted in a city structure that is clearly inefficient and that severely inhibits positive economic outcomes in the city” (pp. 1, Owens et al., 2020). This observation sets the stage for a deeper exploration of urban renewal strategies, including the Detroit Demolition Program and the Neighborhood Stabilization Program (NSP), both of which are central to the discussions in this thesis. In the following paragraph I explain the main contribution of these three essays to our field.

In the first essay, I explore the critical question: How do demolitions impact the value of neighboring properties in Detroit, and to what extent? The methodology employed combines Repeat Sales (RS) analysis, spatial regression techniques, and time series analysis. This comprehensive approach assesses the influence of demolitions on property values while accounting for variables such as the level of dilapidation and temporal changes.

This work contributes to the understanding of urban blight by quantitatively analyzing the effect of property demolitions on the value of neighboring properties in Detroit. This analysis is significant given the scale of the program and the investment involved, offering insights into the effectiveness of such initiatives in urban revitalization efforts. Additionally, another significant contribution of this essay is likely the differentiation of the impact by levels of dilapidation and blight before the start of the demolition program. This approach allows for a more detailed understanding of how the benefits of demolition programs may vary across different neighborhood contexts. Such insights are valuable for policymakers and urban planners in designing targeted interventions for neighborhood improvement and could influence how future programs are structured to maximize their positive effects on property values and community well-being.

The second essay is guided by the following set of research questions: To what extent does the Neighborhood Stabilization Program (NSP) intervention correlate with changes in the real estate market dynamics in treated neighborhoods compared to control neighborhoods in Detroit? And in being able to estimate this effect, I furthermore queried: How does the rehabilitation of neighborhoods impacted by property demolition due to abandonment and urban decay affect residential property sale prices within a 0.1-mile radius? The Neighborhood Stabilization Program (NSP) was established by the U.S. Department of Housing and Urban Development (HUD) to respond to the nationwide crisis in housing markets, primarily triggered by the foreclosure boom that accompanied the Great Recession starting in 2008. The goal of the program was to stabilize communities that had suffered from foreclosures and abandonment. In Detroit, a city that was particularly hard-hit by the housing crisis and economic downturn, the NSP aimed to address the issues of vacant and abandoned properties and to revitalize neighborhoods that were experiencing decline.

This essay holds pivotal importance in urban economics by providing empirical insights into the long-term effects of programs like Detroit's NSP, filling a gap in urban renewal literature. It introduces a methodological framework, utilizing the synthetic control method, setting a benchmark for evaluating urban interventions in the absence of randomized trials. The findings not only refine existing urban economic theories but also offer broader economic implications, potentially guiding efficient public expenditure and managing urban sprawl.

Finally, in the third essay, I answer the following questions: 1) How can accurate valuations of land and structures be obtained separately to facilitate the implementation of a split-rate tax in

Detroit, 2) Does option value, as derived from real options theory, have an empirical presence in Detroit's property transactions, and how can it be measured effectively?, 3)How does redevelopment potential, as captured by property intensity measures, affect residential property values in Detroit?, and 4)What is the impact of including option value in the estimation of land values, particularly in terms of predicting land values and understanding redevelopment potential?

The importance of this study lies in its contribution to the ongoing discourse on property tax reform, particularly within the context of Detroit's urban renewal efforts. By tackling the intricacies of accurately separating the valuations of land and improvements, the paper addresses a critical bottleneck in implementing a split-rate tax system, which has the potential to encourage investment and equitable growth. The innovative use of option value theory from financial economics to real estate valuation represents a significant interdisciplinary approach that could refine property tax assessments, leading to a more fair and efficient tax system.

These essays collectively paint a picture of a city in transformation, one where economic, social, and policy dimensions intersect to shape its future.

ESSAY 1: IMPACT OF DEMOLITIONS ON NEIGHBORING PROPERTY VALUES IN DETROIT

Introduction

Urban blight is the "critical stage in the functional or social depreciation of real property beyond which its existing condition or use is unacceptable to the community" (p.372, Breger, 1967). After the Great Recession, major metropolises in the United States (US) faced an urban blight epidemic characterized by dilapidated residential structures, abandoned buildings, and neglected vacant lots that did not meet the minimum health and safety requirements (Leon & Schilling, 2017). As evidenced by the literature, blighted properties in residential neighborhoods constitute an environmental disamenity and can reduce the value of nearby properties, and thus be a financial burden to a city directly and indirectly through reduced tax revenues (Johnson, 2008). Additionally, these dilapidated properties are a potential risk to 1) health, with blight negatively associated with the health of individuals living in or near these types of properties (Leon & Schilling (2017), Pearson et al. (2019)); and 2) safety, where studies have found a relationship between blighted properties and increased crime in neighborhoods (see, for example, Spelman (1993), Ellen et al. (2013), Kondo et al. (2018), and Larson et al. (2019)).

Among the large cities that are experiencing blight challenges, Detroit has been particularly hard hit. This city, with 365,000 housing units in 2014, had 40,077 blighted structures with a projected additional 38,429 emerging blighted structures (Detroit Future City, 2017). In addition, blight takes various forms, including vacant lots that become illegal landfills or lots with neglected grass growth, contribute to the deterioration of neighborhoods. In over a decade, the number of vacant lots in the City of Detroit increased 106% from 38,668 to 79,725 (Mallach, 2012). This trend is especially grave and has resulted in a substantial economic burden for the city that spends an average of $800,000 annually cleaning vacant lots (Johnson, 2008). To curb urban blight, the city implemented the largest demolition program in the nation. Funded through the Federal Hardest Hit Fund (HHF)[1], the Detroit Demolition Program started in 2014, and it has demolished 21,299 properties[2] to date at the cost of more than $250 million (C. Williams, 2020). Additionally, there are previous efforts by the city to eliminate blight through demolitions registered through National Emission Standards for Hazardous Air Pollutants (NESHAP) Compliance Monitoring. The combined efforts to eliminate blight has translated into almost thirty thousand demolitions in over a decade.

This essay aims to assess whether there is an impact from demolitions on the value of neighboring properties in the city of Detroit. For cities characterized by chronic population and employment decline, dilapidated housing demolition activity is a response to address a mismatch between supply and demand in the housing market to deal with vacant and abandoned blighted structures that negatively impact neighborhoods (Mallach, 2012). Therefore, demolition policy is one approach to eliminate the blight and generate urban renewal. According to the nonmarket valuation theory (Champ et al., 2017), economic benefit individuals generated from blight elimination is capitalized into the price of properties. The main idea is that when buying or acquiring property, individuals prefer places with fewer nearby blighted properties, holding other factors constant. Thus, buyers are willing to pay more to avoid this disamenity, which allows us to calculate the implicit price of blight elimination through demolition activity. Hence, there could

[1] According to the government web page, "President Obama established the Hardest Hit Fund in February 2010 to provide targeted aid to families in states hit hard by the economic and housing market downturn. As part of the Administration's overall strategy for restoring stability to housing markets, HHF provides funding for state HFAs to develop locally-tailored foreclosure prevention solutions in areas that have been hard hit by home price declines and high unemployment." One of the goals of the program is to provide funds for blight elimination. The following link provides additional information about the program: https://bit.ly/3jcYGt6.

[2] This figure corresponds to the demolitions carried out through May 24, 2021.

potentially be a revaluation in property prices in the places that were the focus of the demolition policy.

To test our hypothesis, we used property transaction data from 2009 to 2019 and a combined demolition database with geolocated information. Moreover, we used several control variables from other databases to account for modifications over time, and to address possible selection bias issues. All this information came from publicly available databases, which is accessible for replication in future studies. One of the challenges in conducting this evaluation is that we did not have all the variables required for a standard hedonic pricing model, such as individual property characteristics. To address this issue, we used a repeat sale (RS) regression approach that allows us to evaluate the policy over several years. This method is a well-established alternative to and extension of the standard hedonic regression analysis and is especially valuable when there is limited information for estimating complete hedonic regressions (Case & Shiller (1987), Palmquist (2005)). Using a modified version of the model proposed by Palmquist (1982), we estimated repeat sales regressions with property and year fixed effects, controlling for *ex-ante* dilapidation levels, income levels, and housing occupancy status, we determined the marginal impact of demolitions in different types of Detroit neighborhoods.

The main findings indicate that blight removal through the demolition program does not appear to have been capitalized into residential prices on average across the entire city. By differentiating the effect by neighborhood characteristics, we find a positive effect of demolitions on property prices in areas where there was low level of blight before the demolitions. Specifically, an additional nearby demolition in a 0.06-mile radius increases property prices by 0.61%. In dollars, this marginal effect translates to $180, on average. Furthermore, without restricting distance to a specific value, we find that this effect occurs in the range of 0.044 to 0.084 miles, with an impact that decreases with distance, and with minimum and maximum values of 0.23% and 1.22%, respectively. Our results are robust to different specifications, to a subsample of properties without modifications during the analysis period, and to a two-step Heckman sample selection correction procedure. Furthermore, when we disaggregate the effect by type of demolition program, we find that the results remain consistent with those properties that were affected by both types of demolitions. Finally, properties affected by demolitions between 2009 and 2015 have higher and positive impacts than those affected later in the program.

Our study is closely related to the literature that evaluates the relationship between foreclosures and nearby property values. Research has shown that the intensity of foreclosed and potentially distressed properties is associated with lower nearby housing prices (Lee (2008), Harding, Rosenblatt, & Yao (2009), Campbell, Giglio, & Pathak (2011), Anenberg & Kung (2014), Hartley (2014), Gerardi, Rosenblatt, Willen, & Yao (2015), Zhang & Leonard (2014) and Zhang, Leonard, & Murdoch (2016)). In many cases, these properties in foreclosure are proxying for low quality properties. Therefore, this disamenity is negatively capitalized in the price of neighboring properties. The conclusions of these investigations focus on the premise that eliminating this negative externality will positively affect the value of neighboring properties, with the same magnitude but opposite sign. This can be referred to as an indirect approach to evaluating demolition performance.

There is also a branch of literature related to our work where authors directly evaluate demolition activity and its impact on the value of neighboring properties. This type of research uses demolitions as an explanatory variable that explains its impact through the removal of low-quality or blighted properties. The results from the two approaches may differ even in similar contexts. For example, Whitaker & Fitzpatrick (2016) explore the impact of land bank properties on surrounding property values in the Cuyahoga County, Ohio. They apply a spatial hedonic model where the key variable is the count of land bank properties within 500 feet of a given property. Land banks buy low-value properties with the goal of returning them to productive use. In the case of Cuyahoga County, many of these blighted properties are demolished, which results in vacant lots. The authors indirectly evaluate the removal of a blighted property due to a land bank purchase. The results indicate that land bank properties within 500 feet of properties increased the sales price of such properties by 3.4%. Niemesh *et al*. (2020) replicate this study for Butler County, Ohio using a direct approach. While they found that an additional demolition increased the sale's price by 1.64%, the estimate is not statistically significant. The authors attribute this null impact to two factors: the low number of demolitions and the lack of redevelopment of the land after a demolition.

In the case of Detroit, there are two studies that use an indirect approach. Paredes & Skidmore (2017) evaluate the costs and benefits of demolitions in Detroit. They estimate the impact of dilapidated housing and empty lots on nearby properties in a cross-sectional analysis, finding that dilapidated housing has a larger negative effect than empty lots. Since the estimated negative impacts of dilapidated housing are larger than empty lots, they conclude that demolitions will result in a 3.8% increase in sales prices.[3] Additionally, the authors conclude that the net positive effect is too small to cover the costs of the demolitions. Using a similar approach, a non-peer-reviewed report produced by Dynamo Metrics estimated a spatial hedonic regression to evaluate the effect of blight structures inside and outside the Hardest Hit Fund (HHF) Zones on property sale prices (Dynamo Metrics, 2015). They found that blighted structures have a negative

[3] The key variables in the study correspond to the count of dilapidated structures and vacant lots within a 0.05-mile radius. One additional unit of a dilapidated structure decrease the price by 8.7%, while an additional unit of a vacant lot in the radius decreases the sale price by 4.9%. Hence, the difference that it is attribute to a possible demolition that becomes a vacant lot is an increase of 3.8% in the sale price.

impact of 4.2% on sale prices inside the HHF Zones, and 2.8% outside the HHF Zones. On the basis of these findings, they conclude that elimination of these properties will have a positive net effect on the price of neighboring properties. Both studies indirectly evaluate the impact of demolitions by using information on dilapidated structures and vacant lots. Also, both studies use a hedonic regression approach with cross-sectional data.

With these points in mind, this research contributes to literature in two ways. First, we contribute to the second type of study by directly evaluating the effect of demolitions on housing prices, and we attribute this effect to the elimination of blighted properties that should be capitalized on the price of neighboring properties. We believe this approach provides more direct and thus accurate estimates to assess this public policy. Second, while the two papers evaluate the same research question, the methods, approaches, and analysis periods are very different. Cross-sectional and spatial approach may capture longer-run impacts, while the present research uses a dynamic approach in repeat sales framework that can capture short to medium-run impacts.

The remainder of this paper is organized as follows. Section II includes a discussion of the context of the City of Detroit and the Detroit Demolition Program. Section III presents the theoretical model, and in Sections IV and V, we provide the data and the proposed identification strategy for the estimation. In Section VI, we present the estimated price effects of demolition on nearby residential properties. Finally, Section VII offers a brief discussion and a conclusion.

The Detroit Demolition Program

Detroit is a shrinking deindustrialized city characterized by ongoing population loss, reduced employment, and extended economic decline, which began in the middle of the twentieth century (Reckien & Martinez-Fernandez, 2011). These difficult circumstances are reflected in a weak real estate market, with low market prices for residential housing, high rates of property tax delinquency (Alm et al., 2014), and a slow recovery from a bankruptcy with an estimated $18 billion debt (Sands & Skidmore, 2015). These factors are occurring in conjunction with a real estate market with an excess supply of housing where a substantial number of abandoned and dilapidated properties are part of the current urban infrastructure landscape.

In 2014, Detroit Mayor Mike Duggan provided strong support for the Detroit Demolition Program to counteract the real estate crisis. This program was funded through the Federal Hardest Hit Fund[4] (HHF) to remove blight while considering the following: "minimizing adverse environmental health impacts, promoting reuse of salvaged materials and safe disposal of hazardous materials, supporting compliance with asbestos regulations, and leaving sites in a condition suitable for redevelopment, including reuse for green infrastructure and urban agriculture" (p.12, United States Environmental Protection Agency, 2014). Thus, safety and suitability for redevelopment play an important role in the process. Figure 1.1 illustrates demolition in Detroit. Until now, there have been 20,867 demolished structures with an average cost per demolition between $12,616 and $20,000[5], plus all other costs associated with managing a program of this scale. The total HHF investment is $263 million (C. Williams, 2020), one of the country's largest demolition programs (Larson et al., 2019). The program mission contains an explicit statement regarding the goals of increasing the value of neighboring properties following safety measures, contracting with the local demolition companies, complying with environmental standards, and to removing all the blight from the city.[6] With large-scale programs such as this, it

[4] More information about the Detroit Demolition Program is available at https://bit.ly/2EU2gqB.

[5] Larson *et al*., (2019) indicate the average cost corresponds to $12,616, however, Paredes & Skidmore (2017) considered additional costs such as shutting off gas, water, electricity, asbestos removal, etc., which tallies to $20,000 per demolition.

[6] See Footnote 3.

is important to analyze whether these objectives were achieved and what things can be learned and improved for future public policy.

Figure 1. 1: Demolition Detroit Program, before and after demolition

Source: Retrieved August 6, 2020, from https://detroitmi.gov/departments/detroit-demolition-department. Note: figure shows the before and after a demolition of a property. This illustration was promoted by the city to explain how demolitions work.

We also have information on demolitions conducted by the city that are registered through the National Emission Standards for Hazardous Air Pollutants (NESHAP) Compliance Monitoring. NESHAP provides public health standards to minimize the release of asbestos fiber during demolition activity. Importantly, advanced notification of demolitions is required to ensure all precautions are being taken to minimize asbestos emissions (Michigan Department of Environment, Great Lakes, and Energy (EGLE)). The NESHAP information, which predates but overlaps with the Demolition Detroit Program, is also important to consider.

We also provide a brief commentary on the controversy surrounding the Detroit Demolition Program. Over the years, there have been various inquiries regarding the performance of the program; however, the debate intensified in 2020, when the city ran out of the HHF fiscal budget, and citizens voted to pass Proposal N, a $ 250 million plan that included Neighborhood

Improvement Bonds (debt instruments) to continue blight elimination. Questions about the program focused on the high cost of demolitions, and on the secondary negative effects on people's health. A study indicated that "demolitions may also release lead-containing dust into the environment, which may lead to acute (short-term) lead exposure, even while the removal of lead from the environment may reduce exposures to lead in the long run" (p.2, Detroit Health Department, 2017). While the conclusion of the study was that the program was in compliance with environmental standards, there are also negative effects from the activity. More studies are needed to provide more information regarding the costs and benefits of this public policy.

Theoretical Background

The housing market is a clear example of a market where differentiated products are traded, reflected in the nonexistence of a unique sale price. Rosen (1974), in his seminal paper, modeled the pricing by indicating that property value is a function of its own characteristics, which is now widely known as the hedonic price model. The Repeat Sales (RS) regression is one approach that has been adapted from the general hedonic modeling framework. The RS technique has mainly been used to construct real estate price indices as an alternative to hedonic price indices. Bailey, Muth, & Nourse (1963) developed the RS technique to address the issue of the substantial variation in quality among properties. The idea, though simple, is powerful: calculate the variation in property prices using sales information from the same property at two different points in time. This approach is now widely recognized as a valuable alternative to the hedonic price index. It requires far less data than hedonic regressions since the RS model does not require the inclusion of time-invariant property characteristics. Two decades later, Case & Shiller (1987) modified the index, arguing that the constant variance of the error term assumption did not always hold. The technique, therefore, needed to address this problem by using weighted regression.[7] This new approach is called the Weighted Repeat Sales (WRS) method, which was one of the first steps in constructing the now widely used S&P CoreLogic Case–Shiller U.S. Price Index (S&P Dow Jones Indices LLC, 2021).

The RS method has also been used in environmental economics literature to value environmental externalities. Palmquist (2005), in his survey of property value models, links the literature on real estate price indices and environmental valuations by using RS methods to show that changes in the environmental quality surrounding a property, positive or negative, should be capitalized and reflected in the sales price of that property over time, which enables the appropriate estimation of the effect. Palmquist (2005) references the seminal paper wherein he developed an RS theoretical framework and then empirically tested it using data from a residential area north of Seattle, Washington (Palmquist, 1982). In this work, the environmental variable is the noise pollution that comes from installing a new highway in the residential zone, a negative environmental externality that resulted in property price decline. Part of his theoretical model is presented below to motivate the functional form and the variables we use in our empirical analysis. Following Palmquist (1982), the market price of property i at time t is a function of the following variables,

$$P_{it} = f(m_{i1}^{j}, \dots, m_{it}^{j}, \dots, m_{iT}^{j}, B_{it}, t) \tag{1}$$

[7] Note that the procedure to obtain the coefficients do not change, but rather the treatment of the error term and the efficiency of the method. Bailey, Muth, & Nourse (1963) assumed that the error term had a constant variance over time because it consisted of the unobserved part of the same property. However, Case & Shiller (1987) indicated that the term error could be a function of the time between the first and second sale of a property. Therefore, properties that are sold over a shorter period of time should be of greater importance than those sold over a longer period of time since the latter had a greater probability of being modified during the time interval.

where m_{it}^{j} represents the jth characteristic of property i at time t with $j = 1, \ldots, N$ ($\boldsymbol{M}$ attribute matrix); B_{it} represents the blight level to which property i is subject at time t.[8] Note that this variable corresponds to a negative externality that affects the property price, hence, $\frac{\partial P_{it}}{\partial B_{it}} < 0$. Finally, t indicates the year of sale. Although the choice of the functional form of (1) is an empirical question, any functional form chosen must comply with the restriction that general changes in housing prices are in percentage terms, as are changes due to the environmental variable (Palmquist, 2005). Taking this restriction into account, we use the functional form proposed by Case et al. (2006), which is similar to the original Palmquist (1982) model, except this specification is more flexible and allows the inclusion of the environmental variable in the equation in two ways. Let $\boldsymbol{x_{it}}$ and $\boldsymbol{y_{it}}$ be $Jx1$ subset vectors of the $\boldsymbol{M}$ attribute matrix (not necessarily mutually exclusive sets). Each of these vectors comprises prototypical attributes that define the price of property i as equation (2) shows. Equation (3) defines d_{it}, a dummy variable representing the sale year from equation (1).

$$P_{it} = \gamma \boldsymbol{x_{it}}^{\alpha_1} e^{\alpha_2 Y_{it} + \delta_1 d_{i1} + \cdots + \delta_t d_{it} + \cdots \delta_T d_{iT} + u_{it}} \tag{2}$$

$$d_{it} = \begin{cases} 1 \; if \; t = sale \; year \; of \; property \; i \\ 0 \; if \; t \neq sale \; year \; of \; property \; i \end{cases} \tag{3}$$

The error term u_{it} follows the classical assumptions that $E(\boldsymbol{u}) = \boldsymbol{0}$ and $E(\boldsymbol{uu'}) = \sigma^2 I$.[9] Since we use the RS framework, we define $\tilde{t}$ as the first sale price and t as the second sale price

[8] In terms of Rosen's classic (1974) model, B_{it} corresponds to one of the jth attributes that define the price of a property. The attributes correspond to physical characteristics of the property as well as amenities or disamenities that exist in the place where the property is located.

[9] In the empirical section we take into account that this assumption may not hold and, therefore, we use a robust variance-covariance matrix to heteroskedasticity and serial correlation.

with $\tilde{t} \neq t$. Therefore, equation (2) repeated for a sale in time $\tilde{t}$ is shown in equation (4). We construct the relative price ratio by dividing equation (2) by equation (4) to obtain equation (5).

$$P_{i\tilde{t}} = \gamma \boldsymbol{x}_{i\tilde{t}}^{\alpha_1} e^{\alpha_2 \boldsymbol{Y}_{i\tilde{t}} + \delta_{\tilde{1}} d_{i\tilde{1}} + \cdots + \delta_{\tilde{t}} d_{i\tilde{t}} + \cdots \delta_T d_{i\tilde{T}} + u_{i\tilde{t}}} \tag{4}$$

$$\frac{P_{it}}{P_{i\tilde{t}}} = \frac{\gamma \boldsymbol{x}_{it}^{\alpha_1} e^{\alpha_2 Y_{it} + \delta_1 d_{i1} + \cdots + \delta_t d_{it} + \cdots + \delta_T d_{iT} + u_{it}}}{\gamma \boldsymbol{x}_{i\tilde{t}}^{\alpha_1} e^{\alpha_2 Y_{i\tilde{t}} + \delta_{\tilde{1}} d_{i\tilde{1}} + \cdots + \delta_{\tilde{t}} d_{i\tilde{t}} + \cdots + \delta_T d_{i\tilde{T}} + u_{i\tilde{t}}}} \tag{5}$$

To assumptions enable the cancelling out of terms in the equation (5) ratio: 1) the coefficients in the characteristics function are relatively stable between the sales ($\delta_t = \delta_{\tilde{t}}$); and 2) the set of attributes that defines the property price remains constant over time ($\boldsymbol{x_{it}} = \boldsymbol{x_{i\tilde{t}}}$, $\boldsymbol{y_{it}} = \boldsymbol{y_{i\tilde{t}}}$). Later, we will relax this last assumption. Equation (6) shows the price ratio with the two assumptions, and equation (7) shows the linearized version of equation (6) by using the natural logarithm.

$$\frac{P_{it}}{P_{i\tilde{t}}} = e^{\delta_1(d_{i1} - d_{i\tilde{1}}) + \cdots + \delta_t(d_{it} - d_{i\tilde{t}}) + \cdots + \delta_T(d_{iT} - d_{i\tilde{T}}) + (u_{it} - u_{i\tilde{t}})} \tag{6}$$

$$ln\frac{P_{it}}{P_{i\tilde{t}}} = \delta_1(d_{i1} - d_{i\tilde{1}}) + \cdots + \delta_t(d_{it} - d_{i\tilde{t}}) + \cdots + \delta_T(d_{iT} - d_{i\tilde{T}}) + v_{it\tilde{t}} \tag{7}$$

From equation (7), notice that $v_{it\tilde{t}} = u_{it} - u_{i\tilde{t}} \sim N(0, 2\sigma^2)$ and $(d_{it} - d_{i\tilde{t}})$ is a variable that can take three values depending on the first and last sale price of the property (see equation 8).

$$(d_{it} - d_{i\tilde{t}}) = \begin{cases} 1 \quad if\ d_{it} = 1 \\ -1\ if\ d_{i\tilde{t}} = 1 \\ 0\ otherwise \end{cases} \tag{8}$$

Therefore, the vector of parameters, $\boldsymbol{\delta}$, is the true unknown real estate price index reflecting how prices changed over time. We estimate this equation to visualize the price trend and confirm that the sample follows a similar pattern as the official price indices for Detroit. However, in our case, the main objective is to obtain the marginal impact of demolition on nearby housing prices. Hence, we begin by relaxing one of the assumptions and allow certain attributes to change over time. Define $\boldsymbol{x}_{it}^{s} \subset \boldsymbol{x}_{it}, \boldsymbol{x}_{i\tilde{t}}^{s} \subset \boldsymbol{x}_{i\tilde{t}}, \boldsymbol{y}_{it}^{s} \subset \boldsymbol{y}_{it}, \boldsymbol{y}_{i\tilde{t}}^{s} \subset \boldsymbol{y}_{i\tilde{t}}$ as all subsets from the original vectors. With this information, we further redefine previous equations as follows.

$$\frac{P_{it}}{P_{i\tilde{t}}} = \frac{\gamma(\boldsymbol{x}_{it}^{s})^{\alpha_1} e^{\alpha_2 \boldsymbol{y}_{it}^{s} + \delta_1 d_{i1} + \cdots + \delta_t d_{it} + \cdots + \delta_T d_{iT} + u_{it}}}{\gamma(\boldsymbol{x}_{i\tilde{t}}^{s})^{\alpha_1} e^{\alpha_2 \boldsymbol{y}_{i\tilde{t}}^{s} + \delta_{\tilde{1}} d_{i\tilde{1}} + \cdots + \delta_{\tilde{t}} d_{i\tilde{t}} + \cdots + \delta_T d_{i\tilde{T}} + u_{i\tilde{t}}}} \tag{9}$$

$$ln\frac{P_{it}}{P_{i\tilde{t}}} = \alpha_1 ln\frac{x_{it}^{s}}{x_{i\tilde{t}}^{s}} + \alpha_2 \Delta \boldsymbol{y}_{it\tilde{t}}^{s} + \delta_1(d_{i1} - d_{i\tilde{1}}) + \cdots + \delta_t(d_{it} - d_{i\tilde{t}}) + \cdots + \delta_T(d_{iT} - d_{i\tilde{T}}) + v_{it\tilde{t}} \tag{10}$$

Equation (10) is a modified version of the model that Case et al. (2006) called *changing attributes*. In this case, we define $\Delta \boldsymbol{y}_{it\tilde{t}}^{s} = \boldsymbol{y}_{it}^{s} - \boldsymbol{y}_{i\tilde{t}}^{s}$ as the variation of the attributes between the first and second sale of a property which gives us a measure of semi-elasticity. The second input form of a variable is through the logarithm of the ratio of the characteristics in the second sale compared to the situation in the first sale, which provides an elasticity measure. Notice that both forms only consider the variation that occurs between the two sales. In this work, we use the first form to construct the key independent variable.[10] Thus, let $\Delta B_{it\tilde{t}} = B_{it} - B_{i\tilde{t}}$ be the variation between the initial and final level of blight surrounding a property (see equation 11)[11] where β represents the marginal impact of additional blight near to a property between the first and second sale, approximately defined as $\%\beta \approx \frac{\partial ln\frac{P_{it}}{P_{i\tilde{t}}}}{\partial \Delta B_{it\tilde{t}}}$.

$$ln\frac{P_{it}}{P_{i\tilde{t}}} = \alpha_1 ln\frac{x_{it}^{s}}{x_{i\tilde{t}}^{s}} + \alpha_2 \Delta \boldsymbol{y}_{it\tilde{t}}^{s-1} + \beta \Delta B_{it\tilde{t}} + \delta_1(d_{i1} - d_{i\tilde{1}}) + \cdots + \delta_t(d_{it} - d_{i\tilde{t}}) + \cdots + \delta_T(d_{iT} - d_{i\tilde{T}}) + v_{it\tilde{t}} \tag{11}$$

[10] This flexibility is required in this case because we cannot calculate the logarithm of the number of demolitions around a property since there are observations with zero demolitions recorded near it.

[11] In equation 11 we define $\Delta y_{it\tilde{t}}^{s-1} = y_{it}^{s-1} - y_{i\tilde{t}}^{s-1}$, where y_{it}^{s-1} correspond to the y_{it}^{s} vector without B_{it}. The same logic applies to $y_{i\tilde{t}}^{s-1}$.

According to our hypothesis, β should have a negative effect since blight constitutes a negative externality that decreases the value of a property. Consequently, a demolition that removes blighted property should have the opposite effect, or a positive effect on property prices. Over time, the number of demolitions near the property reduces the level of blight in the surroundings, which increases property value. In the next sections, we treat demolitions as a proxy for the decline of the blight that each residential property is subject to. Hence, the expected sign of the coefficient is positive. However, it is important to note that the effect of demolitions is not necessarily of an equivalent magnitude and opposite sign to the effect of blighted properties due to the adverse and unintentional consequences that the demolition activity can have on nearby properties mentioned in the Literature Review section. Nevertheless, we hypothesize that the positive effects on property prices are greater than negative effects, generating a positive net effect. In the following section, we discuss how we measure this effect and the construction of the key independent variable.

Data

The following three sections provide information about the main data sources and the descriptive statistics of the variables that we use to measure the impact of demolitions on neighboring property sales prices in Detroit. We also offer a discussion of the key independent variable and its calculation. Additionally, we provide a detailed explanation of our identification strategy and the underlying assumptions embedded therein. Finally, we address possible sources of endogeneity and the additional databases we use to address this potential problem.

Sales Data

The data on property sales prices come from the Office of the Assessor of the City of Detroit.[12] In addition to the information about sales prices, the publicly available database includes information on the parcel number (which is an identifier that helps us add more information to the main database), grantee and grantor for each transaction, a term-of-sale variable, and geolocated information through the geographic coordinates, and the address of each property. While this core database does not contain many variables, it has many observations with sales dating back to the beginning of the 20th century. From the total number of registered sales, we focus on properties sold between 2009 and 2019. Likewise, we narrow the focus to sales within the "Valid Arm's Length" category. We merge these data with information regarding the property class code for each of the parcels in Detroit and further narrow to residential properties.[13] After deleting observations with missing data for the sale price and sale date variable, we eliminate observations with sales prices below the 1st percentile and above the 99th percentile.[14] The last filter eliminates sales of properties sold more than five times during the analysis period, resulting in a database with a mean transaction value of $34,279. All of these filters are common in hedonic price and repeat sales analyses to help ensure that we are using market transactions (see Table A1.1 in the appendix for details of all these filters).

[12] This database is provided by the Office of the Assessor of the City of Detroit and can be obtained from https://bit.ly/3iEJtye. This database is continually updated.

[13] The property class code, required by law, is a property classification system for tax purposes. The database containing this information can be found at http://bit.ly/3sD2OVy.

[14] This is common practice among hedonic regressions. For example, Case et al. (2006) set a minimum price of $10,000 when studying the effect of groundwater contamination on condo prices in Scottdale, Arizona. Likewise, Cheung et al. (2018) set the same minimum price, but they also corrected the data in the upper distribution by setting a maximum price of $1,000,000 to study the effect of earthquakes on property values in Oklahoma. In this case, we follow Cheung et al. (2018) but we take into consideration the fact that the housing market in Detroit has experienced a decline in recent years. Therefore, we decided that instead of arbitrarily setting a minimum price, removing the distribution in the range of the lowest and highest percentile was a reasonable approach to remove relatively low prices that are unlikely represent market transactions.

Table 1.1 summarizes the type of sale and properties in the database after filtering as mentioned above were made. This table indicates how many properties were used in the regression analysis. The database contains properties that have been sold only once during the entire study period and properties that were sold up to five times (column 1). Some of these properties will be used in the final regressions, while others will not (column 2). There are two reasons why a property is excluded from the final database. First, the RS regression requires each property to be sold at least twice during the study period. Therefore, 26,723 properties that were only sold once are excluded. Second, as Case et al. (2006) explain in their work, it is common practice to eliminate any consecutive pair of transactions that have occurred during the same time interval. Since the analysis is by year, we eliminate all properties sold more than once in the same year. Therefore, 4,629 properties are included in the analysis (total in column 3), which is also equal to the number of clusters in the standard errors. However, this is not the final number of observations.

Table 1. 1: Usable and Unusable Number of Properties, Transactions, and Transactions-pair in the Database

Number of Times a property was Sold	Usable?	Properties	Transactions	Transaction-Pairs	Mean Sale Price
(1)	(2)	(3)	(4)	(5)	(6)
1	*No*	26,723	26,723	0	$33,166
2	*Yes*	4,149	8,298	4,149	$35,131
2	*No*	2,148	4,296	2148	$36,024
3	*Yes*	450	1,350	900	$35,423
3	*No*	272	816	544	$37,936
4	*Yes*	27	108	81	$39,284
4	*No*	35	140	105	$38,362
5	*Yes*	3	15	12	$36,740
5	*No*	5	25	20	$45,134
Total	***No***	**29,183**	**32,000**	**2,817**	**$38,124**
	Yes	**4,629**	**9,771**	**5,142**	**$36,644**

Source: Authors' own calculations. Note: this table is a modified version of Table 1 in Case et al. (2006). Column (1) shows the number of times a property was sold between 2009 and 2019. Column (2) indicates the *usable* properties

Table 1. 1 (cont'd)
and transactions, those that were used in the repeat sale specification, and *non-usable*, those that were not used in the repeat sale regression. There are two reasons for the existence of this last type of property. First, the first row is not included because these properties were sold only once in the period. Second, the following rows are not included because these properties were sold more than two times in the same year. As the analysis is on a yearly basis, it cannot be included. Column (3) indicates the number of properties according to the number of times it was traded. Column (4) indicates the total number of transactions. This column is obtained by multiplying (1) by (3). For example, a property sold twice has two transactions in the database. Column (5) indicates the pairs of transactions, which enter as an observation in the final regression. A property sold three times has two pairs of transactions because the sale of the medium acts as a second sale and as a first sale simultaneously (more details, please read the main text). Finally, column (6) shows the average sale price calculated with the number of transactions.

To obtain the total number of observations, we first calculate the transactions by the number of times the property was sold (column 4). Note that this column is the result of the multiplication of column 1 by column 3. For instance, the second row corresponds to the properties that were sold twice and that entered in the RS regression (4,149 properties). Because they were sold twice, this means 8,298 transactions. Then we obtain the pairs of transactions that correspond to the total number of observations from this information. Column 5 would be identical to column 3 if we were only working with properties sold twice. However, as in previous work, we also used those properties sold more than twice in different years.[15] This is possible by using the same sale as the initial and final record for different pairs of transactions. For example, for properties that have been sold three times in different periods, let P_a, P_b, and P_c represent the first, second, and third sale prices, respectively, with $a, b, c \in \{2009, 2010, \ldots, 2019\}$ and $a < b < c$. In this case, one transaction pair is constructed with the sale occurred at time a and the sale occurred at time b, with the sale price ratio being P_b/P_a.[16] The second transaction pair corresponds to the sale in time b and the sale in time c, with the price ratio being P_c/P_b. Hence, the sale in time b acts as a second

[15] From the beginning, this has been a common practice among papers that use the repeat sale method, those where the main objective is to build the real estate price index (Bailey et al. (1963), Case & Shiller (1987), Clapp & Giaccotto (1992), Guo et al. (2014), among others) and also those papers that seek to evaluate an environmental variable (Palmquist (1982), Mendelsohn et al. (1992), Case et al. (2006), Cheung et al. (2018), Fernandez et al. (2018), among others).

[16] It should be noted that a transaction pair is the observation that enters the regression, since the dependent variable will be the natural logarithm of the ratio between the final price and the initial price.

sale in the first ratio and as a first sale in the second ratio, simulating two different sales. Generalizing this fact on properties sold more than twice, a property sold four times generates three pairs of transactions. A property sold five times generates four pairs of transactions, which is presented in column 5 of Table 1.1. Therefore, the final number of observations that enter the regression is 5,142 transaction pairs that occurred between 2009 and 2019 in Detroit.

Demolition Data

The second data source that we used contains information on demolitions during the period of interest. This information comes from two different sources. Firstly, the State of Michigan Department of Environmental Quality (MDEQ) provided data that contain Notifications Tied to Demolition Activity information (NESHAP)[17], which includes detailed information about property demolitions within the city over the 2009-2015 period. According to Data Driven Detroit's description, this portal is constructed through the notification of structures that contain a hazardous substance, such as lead or asbestos, that are required to be demolished by the city. To our knowledge, these demolitions are not part of the city's official demolition program. However, there are two reasons we believe that this information should be included to treat the entire demolition period as a continuous intervention: 1) this database contains about 11,500 demolitions, which represents a nontrivial figure that, through the same causal channel, can have effects on the sale prices of neighboring properties; and 2) the two databases that we are using with demolition information overlap in some years, which makes it difficult to unravel the effects separately. The second data source on demolitions is from the City of Detroit. This source provides information on demolitions managed by the Detroit Land Bank Authority and the Detroit Building Authority

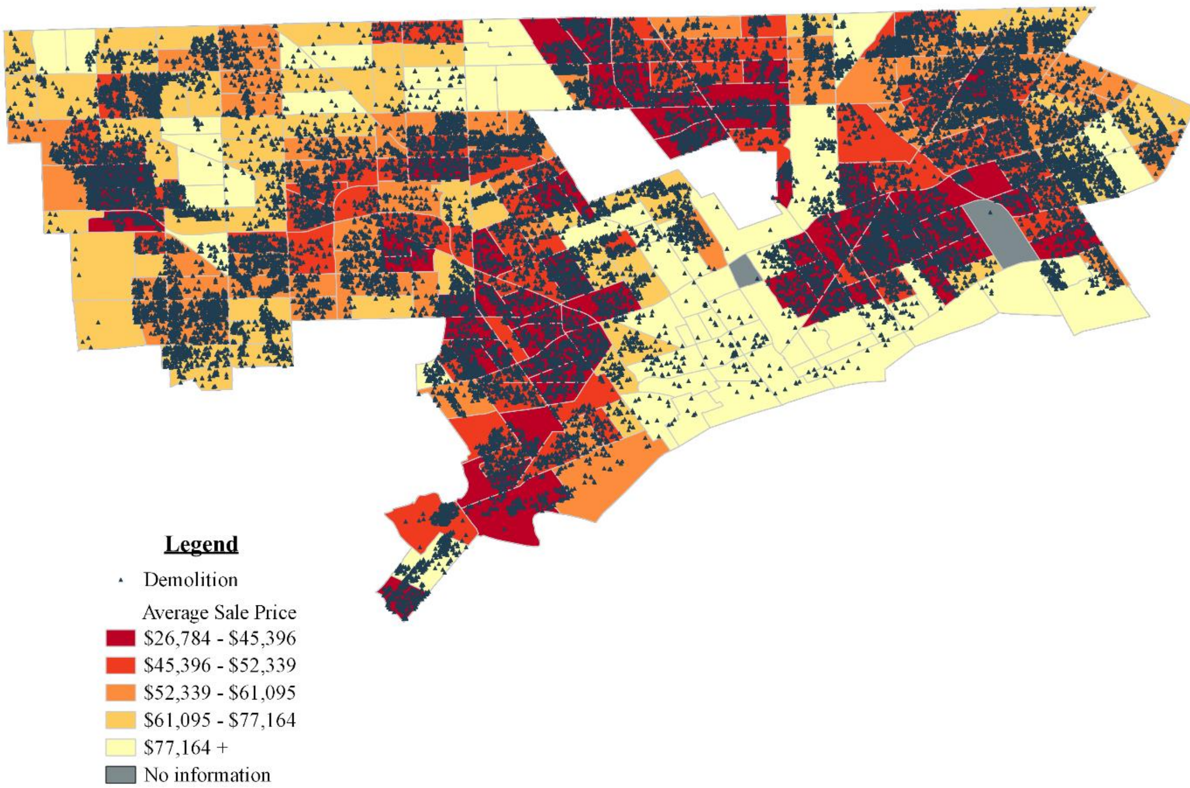
[17] This database is provided by Data Driven Detroit and can be obtained from the following web page https://portal.datadrivendetroit.org/datasets/D3::neshap-notifications-tied-to-demolition-activity-january-2009-to-april-2015/explore?location=42.353737%2C-83.100581%2C12.04.

since January 1, 2014.[18] This source provides information about 21,000 demolitions over the 2014-2019 period. Together, these data sources provide geolocated information from each of the 32,354 demolitions in the city of Detroit over the 2009-2019 period. Although the main analysis aggregates all demolitions, we also provide differentiated results by type of program.

With the dataset in place, we generate a map which offers a visual on the spatial elements of our analysis. Figure 1.2 shows the locations of all demolitions in the city and the quantile distribution of the average sales prices of the census tract. The map in Figure 1.2 shows a pattern between census tracts with low sales price levels and the number of demolitions that have occurred in those places or neighboring census tracts. This positive correlation is consistent with our expectation: neighborhoods with a greater number of blighted properties also have relatively low sales prices and are the areas in the focus of the policy intervention. Hence, the blighted neighborhoods have a greater number of demolitions over the period. Figure 1.2 is central to understanding the challenge of inferring causality with respect to the effect of demolitions on the price of neighboring properties because demolitions are not randomly distributed throughout space. Therefore, we must consider the pre-intervention neighborhood characteristics to understand the scope of the effect. In the following sections, we discuss this challenge and the steps we have taken to address it.

[18] This database is provided by the Detroit Land Bank Authority and the Detroit Building Authority and can be obtained from the following web page https://data.detroitmi.gov/datasets/detroitmi::completed-residential-demolitions/explore?location=42.352877%2C-83.100004%2C11.06.

Figure 1. 2: Location of demolitions and property sales prices in Detroit



Source: Authors' calculations. Note: The map uses the average sales price by census tract to create a quantile map with five classes. The average sales price corresponds to residential property sales from 2009-2019. The triangles represent the exact locations of all the demolitions in Detroit during the period of analysis. The white area within the city corresponds to the cities of Hamtramck and Highland Park, which are enclaves of the City of Detroit.

Detroit Residential Survey, Building Permits Databases, and ACS

We also use three additional data sources to help us causally identify the effect of demolitions on property sales prices. First, we use information from the 2009 Detroit Residential Parcel Survey (DRPS), which is the result of a collaborative effort between the Detroit Office of Foreclosure Prevention and Response (FPR), the Community Legal Resources (CLR), and Data Driven Detroit (3D). In their words, "equipped with maps and lists of individual parcels, the teams drove on every residential street, indicating parcels that were vacant lots and reporting the primary characteristics of each house that was present" (p.5, Detroit Residential Parcel Survey, 2010). Therefore, we have a rich database containing georeferenced data and dilapidation levels for all residential lots in Detroit in 2009. This information is very useful for our analysis because it provides an assessment of neighborhood conditions before the demolitions that we examined.

Another data source provides support for the assumption the property attributes are constant over time. This information comes from the City of Detroit and contains data on all building permits issued during the 2010-2019 period. According to the Construction Codes in Michigan, building permits are required for any of the following reasons: construction or alteration of a structure, construction of an addition, demolition or movement of a structure, a change of occupancy, installation or alteration of any equipment that is regulated by the code and moving a lot line which affects an existing structure.[19] Thus, this information is very useful because it enables us to control for any reported modifications or alterations that the properties had during the period of analysis, before and/or after the sale. Additionally, to control for neighborhood-level characteristics that change over time, we use data from the American Community Survey (ACS) at the census tract level. Specifically, information on Median Household Income (MHI), occupancy rates, and percentage of white people at the census tracts level. Finally, we also use information on the individual property characteristics that do not change over time, such as distances to parks, the Central Business District (CBD), among others. We use GIS tools and property coordinates to generate the distance measures.

Identification Strategy

Construction of the Independent Variable

The model explained in the theoretical section provides a guideline for determining the explanatory variables to include in the RS regression. The key variable that measures blight elimination, the demolitions, has to represent the variation between the first and the second sale,

---

[19] See in https://bit.ly/35LG8co.

which implies that each observation will be unique due to the diverse combinations between the initial and final years of sale.[20] This last point is important because it implies the non-inclusion of variables that do not vary over time.[21] Two additional questions remain to be answered before we can conduct the empirical analysis: 1) how are we going to measure the demolition activity nearby a property? and 2) what do we mean by "nearby"? In the first case, we measure the elimination of blight by the number of demolitions around a property between the first and second sales. In the second case, we offer a discussion below.

Following Alvayay Torrejón et al. (2020), we create the key independent variable that provides information on property's proximity to demolitions. Figure 1.3 summarizes the general framework. First, we consider that the distribution of demolitions across the city changes over time, making it difficult to use a distance measure. Therefore, we use a measure of the number of demolitions. We calculate a ring with a radius of 0.06 miles (96.5 meters) for each residential property in a specific year t. Then, the total number of demolitions that occurred within that ring and for that specific year is calculated (there are ten demolitions in the Figure 1.3 example). To abbreviate the above information, we define $D_{it}^{0.06}$ as the total number of demolitions within a 0.06-mile radius for property i in year t. Once this information is determined for each residential property, we only include demolitions between the first and the second sale. Hence, we further define $\Delta D_{it}^{0.06} = \sum_{t=2009}^{t=seconsale} D_{it}^{0.06} - \sum_{t=2009}^{t=firstsale} D_{it}^{0.06}$, where $\sum_{t=2009}^{t=seconsale} D_{it}^{0.06}$ is the sum of demolitions within a radius of 0.06 miles between the year 2009 (initial year of the policy) and the

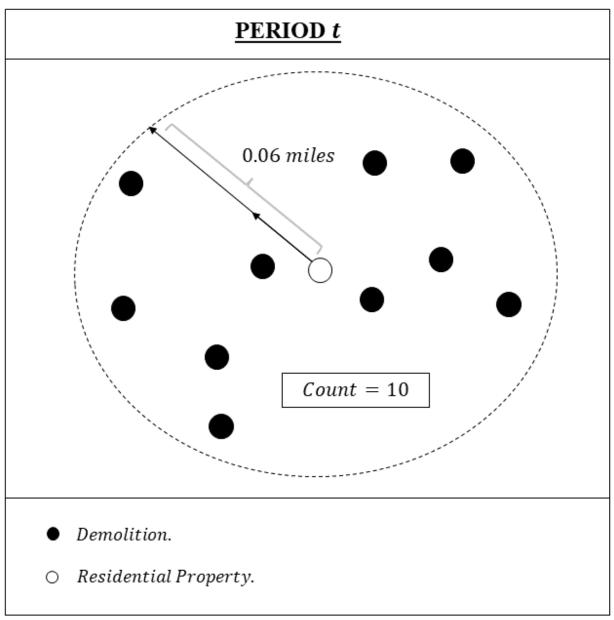
[20] To be precise, there are 55 combinations of year pairs between initial sale and final sale that may exist. For example, 2009 has ten possible sales pairs (2009-2010, 2009-2011, etc.). Likewise, 2010 has nine possible sales pairs, 2011 has eight, and so on. Considering that the last year of analysis in our research is the year 2019 all possible combinations that can exist can be calculated through this logic.

[21] Since we use OLS to calculate the repeat sales regressions, the statistical program will allow us to include these types of variables. Therefore, it is the responsibility of the author not to include them due to theoretical restriction.

second year sale of property i. A similar interpretation occurs in the case of $\sum_{t=2009}^{t=firstsale} D_{it}^{0.06}$.[22] Thus, $\Delta D_{it}^{0.06}$, our key independent variable, is the total number of demolitions within 0.06 miles that occurred between the first and second sale of property i.

This variable allows us to estimate the marginal effect of an additional demolition on the sales price. A distance of 0.06 miles was chosen because previous research examining the effect of demolitions on property tax delinquency in Detroit demonstrated that distances between 0.05 and 0.1 miles are empirically reasonable (Alvayay Torrejón et al., 2020). In addition, we explore the sensitivity of our results to different distances.

Figure 1. 3: Creation of the Independent Key Variable



Source: Authors' illustration. Note: This illustration helps to explain the creation of the independent variable. Each black circle represents a demolition in period t, with $t = \{2009, 2010, \dots, 2019\}$. Each white circle represents a

[22] Note that the minimum window between the first and the second sale is one year. For example, for a property that was sold for the first time in 2009 and for the second time in 2010 $\Delta D_{it}^{0.06}$ would be defined as $\Delta D_{it}^{0.06} = \sum_{t=2009}^{t=2010} D_{it}^{0.06} - \sum_{t=2009}^{t=2009} D_{it}^{0.06} = D_{i2010}^{0.06} + D_{i2009}^{0.06} - D_{i2009}^{0.06} = D_{i2010}^{0.06}$, which becomes the number of demolitions between the first and the second sale within a 0.06-mile ring.

Figure 1. 3 (cont'd)
residential property never demolished in period t. For each of the residential properties, we have calculated a ring with a radius of 0.06 miles. Once this ring has been calculated, the number of demolitions carried out in year t is counted within this radius of 0.06 miles. In this example, the final count is ten demolitions in a radius of 0.06 miles in year t for that specific residential property. This procedure is repeated for each of the residential properties for all the years of study.

Repeat Sales Specifications

In this section, we present our approach to identifying causal impacts. Following the framework proposed by Case et al. (2006), several steps and specifications range from the simplest to refined, depending on the availability of information. First, we calculate the real estate price index and perform a descriptive analysis of the trends of the values of property prices in Detroit. Following equation (7) from the Theoretical Model section, the first specification is illustrated in equation (12).

First Specification: Traditional Repeat Sale Housing Price Index

$$ln\frac{P_{it}}{P_{i\tilde{t}}} = \delta_1(d_{i2009} - d_{i\widetilde{2009}}) + \cdots + \delta_t(d_{it} - d_{i\tilde{t}}) + \cdots + \delta_T(d_{i2019} - d_{i\widetilde{2019}}) + v_{it\tilde{t}} \qquad (12)$$

The left-hand side of equation (12) is the natural logarithm of the price ratio between the second sale and the first sale of property i. Furthermore, the appreciation or depreciation in the property value is explained by the sale year variables that we describe in equation (8) in the Theoretical section (right-hand side). For estimation, we use an OLS estimator with standard errors robust to heteroskedasticity and autocorrelation.[23] Additionally, we do not include the constant term in the estimation in order to construct the index classically because the theory does not support inclusion (Palmquist, 1982). After calculating the coefficients, we construct the index in accordance with equation (13). Then we plot the estimate $\hat{I}^t$ for each $t = 2009, \ldots, 2019$ to obtain a graph of the price index.

[23] Note that for a correct inference we need to take into account the fact that the error term is not independent between observations because a property appears twice in the database if it is sold more than twice during the study period, as explained in the Data section.

$$\hat{I}^t = \exp(\hat{\delta}_t)\,100 \quad (13)$$

In the following specifications, we continue to use the same estimator with the difference that now we include a constant term for two reasons: 1) the coefficient in the environmental variable is unaffected by any type of adjustment to the year variables or the constant term; and 2) in equation (9) from the Theoretical Model, the gammas do not necessarily cancel out, which means the constant term should be included. As Case *et al*. (2006) indicate, this constant term represents the existence of a nontemporal component that affects property value, i.e., modifications that are made before or after the purchase of a property. Therefore, the inclusion of the constant term allows us to control for physical improvements to the houses during the analysis period. Note that we later offer an additional approach to control for physical improvements.

Second Specification: RS with environmental variable

$$ln\frac{P_{it}}{P_{i\tilde{t}}} = \alpha + \beta\Delta D_{it}^{0.06} + \delta_1(d_{i2009} - d_{i\widetilde{2009}}) + \cdots + \delta_t(d_{it} - d_{i\tilde{t}}) + \cdots + \delta_T(d_{i2019} - d_{i\widetilde{2019}}) + v_{it\tilde{t}} \quad (14)$$

The second specification includes the demolitions of blighted properties ($\Delta D_{it}^{0.06}$). We expect $\hat{\beta}$ to be positive; that is, an additional demolition within a 0.06-mile radius between the first and second sale of a property will positively affect nearby property's prices, as we stated in our hypothesis. Nevertheless, this specification represents a naive approach to estimation because it assumes that all properties share the same characteristics before the policy intervention as if they were located in the same neighborhood. However, the level of dilapidation in the neighborhoods differs greatly across the city. Below, we describe other approaches to address this challenge and increase confidence that we causally identify the β coefficient.

An approach to include the heterogeneity arising from the different neighborhood characteristics where the properties are located is to include interaction effects with the demolition variable since we cannot directly include variables that do not change over time. The variables generally used to estimate neighborhood effects are well known in the literature, such as census tracts or census blocks. However, the inclusion of 292 census tracts as interactions generates a loss of efficiency, considering the number of observations with which we are working. Therefore, we group census tracts across the dilapidation/blight level to generate categories from the lowest to the highest level.

Specifically, we first identify the 33,107 dilapidated structures from the 2009 Detroit Residential Parcel Survey (Paredes & Skidmore, 2017). Then we merge this information to the repeat sales sample and divide the distribution into quartiles to generate four categories of dilapidation levels: 1) Low (L), 2) Medium Low (ML), 3) Medium High (MH), and 4) High (H). Once the categories are created, we generate the third and last specification. Equations (15) and (16) show the RS specifications including $DilapidationLevel_i$, a variable that contains information about the level of dilapidation/blight to which the property i was subject before the demolitions.

Additionally, $\boldsymbol{x_{ic}}$, includes two control variables that vary across i, property, and across c, census tract. The first variable is the percentage change in median household income at the census tract level, between the first and second sale of the property ($\Delta\% MHI_{ijt} = \frac{MHI_{ijt} - MHI_{ij\tilde{t}}}{MHI_{ij\tilde{t}}} \times 100$).[24] The second variable is the percentage variation in housing occupancy at the census tract level, between the first and the second sale of the property ($\Delta\% Occupied_{ijt} = \frac{Occupied_{ijt} - Occupied_{ij\tilde{t}}}{Occupied_{ij\tilde{t}}} \times 100$). We expect these variables to reflect quality changes in the neighborhood that affect the sale price of the property and are closely related to the demolition activity.

[24] Notice that MHI_{ijt} is the median household income in census tract j and in time t (second sale), and $MHI_{j\tilde{t}}$ is the median household income in census tract j and in time $\tilde{t}$ (first sale). Therefore, $\Delta\% MHI_{ijt}$ corresponds to the percentage change in income at the census tract level between the first and second sale of property i. It varies across i because each combination of first sale and second sale years is different for each property.

Third Specification: RS with environmental variable and ex ante Dilapidation Levels

$$ln\frac{P_{it}}{P_{i\bar{t}}} = \alpha + \boldsymbol{\beta_1}\Delta D_{it}^{0.06} + \boldsymbol{\beta_2}\Delta D_{it}^{0.06} * \boldsymbol{DilapidationLevel_i} + \phi \boldsymbol{x_{ic}} + \delta_1(d_{i2009} - d_{i\widehat{2009}}) + \cdots + \delta_t(d_{it} - d_{i\bar{t}}) + \cdots + \delta_T(d_{i2019} - d_{i\widehat{2019}}) + v_{it\bar{t}} \quad (15)$$

$$DilapidationLevel_i \begin{cases} 1) Low\ (L) \\ 2)\ Medium\ Low\ (ML) \\ 3) Medium\ High\ (MH) \\ 4)\ High\ (H) \end{cases} \quad (16)$$

According to our main hypothesis, all $\widehat{\boldsymbol{\beta}}$ estimates should be positive. However, there should be a hierarchy regarding the strength of the policy impact. As mentioned previously, some studies link the capitalization of negative externalities in property prices using the number of nearby foreclosure properties. Recent studies on the same topic have added to their conclusions a degree of relativity on the effect of foreclosure properties on nearby property values: negative externalities are not going to have as a large an impact in poor neighborhoods as in higher income neighborhoods due to the lack of frequency of the problem in high income neighborhood, especially when the likelihood of foreclosure depends on the financial status of the owners (see, for example, Rogers & Winter (2009) and Zhang & Leonard (2014)). A similar logic can be extrapolated in this study: in those more dilapidated neighborhoods, blighted properties are more frequent and, therefore, the elimination of a property may not mean a great difference compared to the elimination of blight in a neighborhood with less dilapidation and higher income. Therefore, we hypothesize that the program's effect will be relatively greater in the higher quality neighborhoods. Hence, the estimated coefficient of the interaction between demolitions and low dilapidation level, $\widehat{\beta}_L$, is hypothesized to be positive and of highest impact. On the contrary, the coefficient of interaction between demolitions and high dilapidation level, $\widehat{\beta}_H$, are hypothesized to be positive and of lowest impact.

Finally, in the regression estimations, we indicate when the specifications are estimated using the total sample of repeat sales and a subsample of only those properties that did not issue any building permits during the period.

Limitations Regarding RS Model

As previously stated, the RS model controls for property attributes that do not change over time by using the transaction prices of a property at two different points in time. In a context of limited information, this procedure can be very useful and powerful. However, this simplicity comes at a cost, and the literature is clear on the disadvantages and risks of using this approach. First, there is an inefficient use of information. Table 1.1 shows the properties that were sold only once and cannot enter the regression (26,723 properties). Second, and perhaps more importantly, there are studies that show evidence of a selection bias (Jud & Seaks (1994), Gatzlaff & Haurin (1997)). These studies are mainly focused on the construction of a real estate price index, and therefore, on the coefficients of the year effects. The conclusion is that the set of properties that are sold twice or more is inherently different from the set of properties that are sold only once.[25] This can lead to an overrepresentation of properties that are not in optimal condition or have poor quality infrastructure. However, this bias decreases the more years are incorporated into the sample (Clapp et al., 1991).

Using the information from Table 1.1 on the usable and non-usable samples, we present Table 1.2 that shows the results of differences in means of key variables across both groups (see Table A1.2 to see the disaggregated analysis by year).

[25] Interestingly, it has also been shown that traditional hedonic models can also be biased in the same way (Gatzlaff & Haurin, 1998). The properties that are sold in the market are different from those that are never sold (analogous to the labor market and those who participate in it).

Table 1. 2: Difference in means by group of Usable and Non-usable

	Non-usable	Usable	Difference	(p-value)
Variation across property and years				
Sale Price	$33,892.3465	$35,546.2089	$-1,653.8624	0.0000
Mean[a] Distance to Demolition (miles)	0.2747	0.2804	-0.0057	0.0002
Mean[a] Demolitions within 0.06 miles	1.1544	0.7476	0.4068	0.0000
Variation across properties				
Total Square Footage	4,946.7658	4,943.6211	3.1447	0.8896
Distance to CBD (miles)	7.7657	8.2065	-0.4409	0.0000
Distance to Main Roads (miles)	3.5968	3.7323	-0.1355	0.0000
Distance to Secondary Roads (miles)	2.9521	3.0641	-0.1120	0.0000
Distance to Parks (miles)	0.3758	0.3920	-0.0163	0.0000
Variation across Census Tract and years				
Mean[a] Median Household Income	$31,762.0974	$32,342.6959	$-580.5985	0.0000
Mean[b] % White	12.2628	10.7852	1.4776	0.0000
Mean[b] % Occupied	74.7938	75.8559	-1.0621	0.0000

Source: Authors' own calculations. Note: this table presents a t test for differences in means, by group of observations (t test with equal variances). The categories, Usable and Non-usable, come from Table 1.1, where column (2) specifies the classification of each property and transaction. We use as observations the transactions (column 4, Table 1.1). Notice that 32,000 transactions fall into the non-usable category, while 9,771 fall into the usable category.

[a] Mean across years 2009 to 2019.

[b] Mean across years 2010 to 2019.

First, the group of properties with at least two sales during the period has a higher average sale price compared to those properties with only one sale, with a difference of $1,654. Second, in terms of the minimum distance to a demolition or the average number of demolitions within a radius of 0.06-miles, the difference is not large in magnitude. It can be indicated that the group of properties that were sold only once is relatively closer to a demolition and has on average more exposure to it. Third, properties in the non-usable category are on average closer to the Central

Business District (CBD), to main and secondary roads, and to parks. Finally, in terms of the census tracts where these properties are located, usable properties are located in the census tracts with higher median household income, with lower percentage of white people, and have a higher average occupancy rate in the neighborhoods. These differences are statistically significant at 1% but are not large in magnitude.

This evaluation provides an overview of the differences between both groups. To address potential sample selection in the repeat regression we use a two-step Heckman procedure adapted for repeat sales proposed by Vecco et al. (2021). First, we calculate a probit model with the following specification.

$$prob(I_{it} = 1) = \Phi(\gamma_0 + \boldsymbol{\gamma Z_{it}}) \tag{17}$$

Where I_{it} is an indicator variable with a value of 1 if the repeat-sale property is sold at time t and 0 otherwise. $\boldsymbol{Z_{it}}$ is the set of characteristics in Table 1.4. Hence, for each year we calculate the inverse Mills ratio as $\lambda_{it} = \emptyset(\gamma Z_{it})/\Phi(\gamma Z_{it})$, where $\emptyset(.)$ Is the standard normal density and $\Phi(.)$ is the cumulative distribution of standard normal distribution. The second step is to include λ_{it} as an independent variable in the repeat sales regressions. As we do with the other independent variables, lambda enters the equation as $\lambda_{it} - \lambda_{i\tilde{t}}$, where λ_{it} is calculated for property i in the second sale year t, and $\lambda_{i\tilde{t}}$ is calculated for property i in the first sale year $\tilde{t}$. In the next section, we include this procedure in the third specification.

Results

Descriptive Statistics

Table 1.3 shows the descriptive statistics of the variables entering the repeat sale regressions. We highlight a few of them. First, the complete sample contains 5,142 observations, the number of transaction pairs calculated in Table 1.1 (see column 5). The subsample, composed of properties that never issued a building permit, contains 4,774 observations, meaning that approximately 7% of the repeat sale sample has reported modification or alteration to the property's structure. According to theory, analysis without these properties will result in more robust coefficients because we are more fully controlling for attributes that do not change over time. Additionally, Table 1.3 provides information on the ratio between the second sale price and the first. Note that the mean value is 1.844, which indicates that, on average, the value of the properties in the sample increased by 84.4% between the first and second sale. In the subsample, this percentage decreases to 82.2%. Regarding the key independent variable, there are 3.4 demolitions on average with a standard deviation of almost 21 for the subsample. These demolitions occurred within a 0.06-mile radius between the first and second sale of a property.

Furthermore, Table 1.3 shows the variables that represent the sale year effects. For our analysis, 2009 is the base year. Note that the maximum value that 2009 takes is 0 and not 1 because there cannot be second sales in 2009 (the first year of our sample). Likewise, the 2019 variable cannot have a minimum value of -1 because there cannot be first sales in that year. Interestingly, there are no records of second sales for 2010, which occurred by chance and not by construction.

We also show descriptive statistics for the variable we use to control for the pre-demolition trends. Table 1.3 shows the dilapidation quartiles levels, indicating the four categories and their composition. While these are categorical variables, we show the distribution of the number of blighted properties within each category to give context from the census tract where these properties were located. The *Low* category corresponds to those properties located in census tracts with an average of almost 50 blighted properties before the demolition program. In comparison, the *High* category corresponds to properties located in census tracts with an average of 231 blighted properties. Therefore, belonging to the *High* category implies properties that, before the demolitions, were more exposed to urban blight.

Finally, we offer comments on the three control variables that we use. Firstly, regarding the percentage variation of Median Household Income (MHI), on average, the census tracts where the properties are located experienced an increase in income of 6.6% between the first and second sale. However, there is large variation in this variable, with properties located in places where income decreased by 58% and properties living in places where income increased by up to 130% approximately. For the percentage variation in housing occupancy, the census tracts in which properties are located experienced an increase of around 1.8% between the first and the second sale with a standard deviation of 8.8%. Finally, we show the lambda distribution that we computed from the first stage of the Heckman correction. We discuss the details of this procedure in the following subsection.

Table 1. 3: Summary Statistics

Variables (1)	Description (2)	*Entire Sample (3)*					*Without Building Permit Issued (4)*				
		Observations	**Mean**	**Std. Dev.**	**Min**	**Max**	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
$\frac{P_t}{P_{\tilde{t}}}$	Ratio between the second sale price and the first sale price of the property.	5,142	1.844	1.650	0.126	12.923	4,774	1.822	1.636	0.126	12.923
$ln\frac{P_t}{P_{\tilde{t}}}$	Natural logarithm of the ratio between the price of the second sale of a property and the first sale price.	5,142	0.298	0.804	-2.069	2.559	4,774	0.285	0.805	-2.069	2.559
$\Delta D_t^{0.06}$	Number of demolitions within a radius of a 0.06-mile radius between the first and second sale of a property	5,142	3.363	20.244	0	546	4,774	3.492	20.941	0	546
$(d_{2009} - d_{\widetilde{2009}})$	$(d_{it} - d_{i\tilde{t}})$ is a variable that can take three values depending on the property's first and last year sale $(d_{it} - d_{i\tilde{t}}) = 1$ if t is the second sale price. $(d_{it} - d_{i\tilde{t}}) = -1$ if $\tilde{t}$ is the first sale price. $(d_{it} - d_{i\tilde{t}}) = 0$ otherwise.	5,142	-0.053	0.223	-1	0	4,774	-0.052	0.222	-1	0
$(d_{2010} - d_{\widetilde{2010}})$		5,142	-0.007	0.085	-1	0	4,774	-0.007	0.084	-1	0
$(d_{2011} - d_{\widetilde{2011}})$		5,142	-0.010	0.108	-1	1	4,774	-0.009	0.104	-1	1
$(d_{2012} - d_{\widetilde{2012}})$		5,142	-0.018	0.150	-1	1	4,774	-0.016	0.144	-1	1
$(d_{2013} - d_{\widetilde{2013}})$		5,142	-0.187	0.411	-1	1	4,774	-0.191	0.411	-1	1
$(d_{2014} - d_{\widetilde{2014}})$		5,142	-0.214	0.530	-1	1	4,774	-0.215	0.532	-1	1
$(d_{2015} - d_{\widetilde{2015}})$		5,142	-0.057	0.468	-1	1	4,774	-0.060	0.467	-1	1
$(d_{2016} - d_{\widetilde{2016}})$		5,142	0.000	0.455	-1	1	4,774	-0.001	0.456	-1	1
$(d_{2017} - d_{\widetilde{2017}})$		5,142	0.049	0.549	-1	1	4,774	0.051	0.546	-1	1
$(d_{2018} - d_{\widetilde{2018}})$		5,142	0.168	0.533	-1	1	4,774	0.168	0.533	-1	1

Table 1. 3 (cont'd)

$(d_{2019} - d_{\widetilde{2019}})$		5,142	0.329	0.470	0	1	4,774	0.332	0.471	0	1
$\Delta\%MHI_{ijt}$	Percent change in Median Household Income (MHI) between first and second sale, in the census tract where the property is located.	5,142	6.581	19.834	-57.735	129.655	4,774	6.634	19.903	-57.735	129.655
$\Delta\%Occupied_{ijt}$	Percentage variation in the number of occupied properties ($Occupied$), between the first and the second sale, in the census tract where the property is located.	5,142	1.832	8.794	-68.362	51.658	4,774	1.840	8.815	-68.362	51.658
$\lambda_{it} - \lambda_{i\tilde{t}}$	Percentage variation in the number of occupied properties ($Occupied$), between the first and the second sale, in the census tract where the property is located.	5,142	0.030	0.126	-0.853	0.500	4,774	0.032	0.121	-0.847	0.442
Distribution of dilapidated properties according to quantiles [a]											
		Distribution of blighted properties by category									
Low	Categorical variable that has four values depending on the number of dilapidated properties in the tract where the property was located before the demolitions: low number of dilapidated properties	1,327	49.662	16.992	2	74	1,188	50.038	17.028	2	74
Medium Low		1,313	91.739	10.672	76	109	1,229	91.666	10.649	76	109
Medium High		1,222	125.062	12.973	110	153	1,150	124.958	12.905	110	153
High		1,280	230.763	52.361	154	450	1,207	231.194	52.585	154	450

Source: Author's calculations.

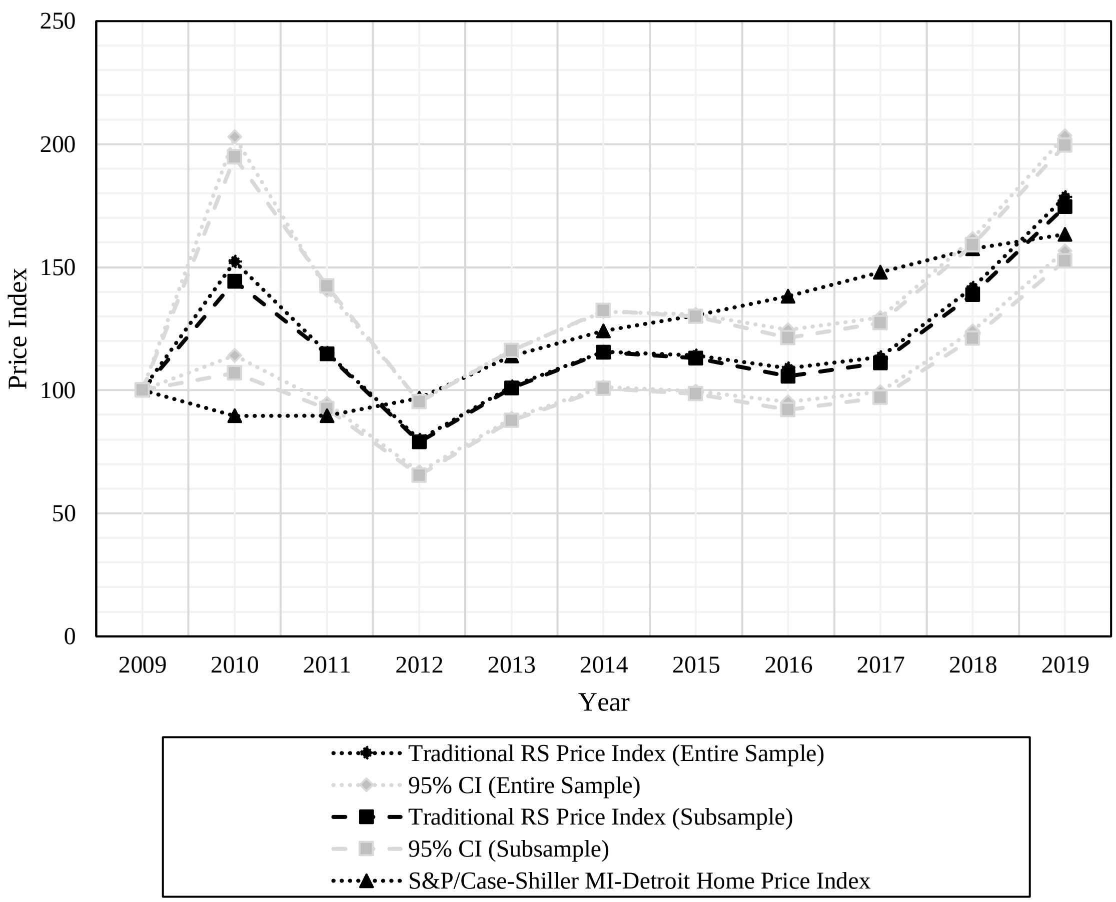
[a] This is a categorical variable with four categories. The purpose of this panel is to indicate what it means for a property to be in one of these categories. We indicate the distribution of the blighted properties in each of these categories to give context. For example, a property located in a neighborhood in the *Low* category implies that this census tract had on average almost 50 blighted properties, while a property located in the *High* category implies a location in a census tract with around 225 blighted properties on average (for the full sample).

Results from the First and Second Specification

We start by analyzing the results of the first specification, where we construct a traditional real estate price index. Columns 1 and 2 from Table 1.4 show the results of these regressions, while Figure 1.4 plots these coefficients after the reverse transformation of the natural logarithm (for the entire sample and the subsample). This figure also includes the S&P/Case-Shiller MI-1 as a reference point. We include this last index to compare the Detroit market with the overall Detroit Metropolitan region, including Lapeer, Livingston, Macomb, Oakland, Saint Clair, and Wayne counties, which is very different from the Detroit urban core. We offer this comparison because the direct comparison between our calculations and the S&P/Case-Shiller index for the City of Detroit is not feasible. We are also using sales between 2009 and 2019, while the S&P/Case-Shiller index is built with the base year of 2000, and its construction includes properties sold before that date. To plot both indices together, we modified the base year to 2009. Finally, the S&P / Case-Shiller index includes a weighting of the aggregate value of housing stock, which is the product of the average housing price of properties in the metropolitan area and the number of houses that exist from the census information (S&P Dow Jones Indices LLC, 2021). We do not include this estimate in our index results. Figure 1.4 shows us the pattern of property prices for our sample. Note that although there has been a trend towards an increase in prices in recent years, this is reflected to a lesser extent in the index built by us. Additionally, there is a greater fluctuation due to the smaller number of observations included in our analysis.

Table 1.4 (columns 3 and 4) shows the results of the regressions. The objective is to determine the blighted discount effect through its elimination by using the demolitions over a ten-year period, which can be considered a medium-term analysis. The results indicate that an additional demolition between the first and second sales within a 0.06-mile radius does not significantly affect a property's valuation, but it is positive in magnitude. However, is not overly surprising due to the naive approach used in this specification. As we mentioned in the previous sections, some properties in Detroit have a higher probability of having nearby demolitions. Therefore, this heterogeneity must be addressed in the evaluation. Note that this result is consistent along with the two samples.

Figure 1. 4: Traditional Repeat Sale Housing Price Index



Source: Author's calculations. Note: Traditional Repeat Sale Price Index series for the entire sample and the subsample. The coefficients and the 95% confidence intervals (CI) come from the reverse logarithmic transformation in the coefficients of columns 1 and 2 of Table 1.3. The third series is from S&P Dow Jones Indices LLC, S&P/Case-Shiller MI-Detroit Home Price Index [DEXRSA], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/DEXRSA, June 24, 2021. All the indices shown in this figure have the year 2009 as their base year (2009=100).

Table 1. 4: The effect of demolitions of blighted properties in nearby property values (within a 0.06-mile radius)

	First Specification		*Second Specification*			*Third Specification*	
	Entire Sample	Without Building Permit Issued	Entire Sample	Without Building Permit Issued	Entire Sample	Without Building Permit Issued	Without Building Permit Issued
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$(d_{2010} - d_{\widetilde{2010}})$	0.420***	0.367**	0.424***	0.378**	0.428***	0.380**	0.374**
	(0.147)	(0.153)	(0.152)	(0.161)	(0.150)	(0.158)	(0.161)
$(d_{2011} - d_{\widetilde{2011}})$	0.143	0.137	0.120	0.102	0.122	0.0971	0.0599
	(0.101)	(0.110)	(0.101)	(0.109)	(0.101)	(0.108)	(0.110)
$(d_{2012} - d_{\widetilde{2012}})$	-0.224**	-0.236**	-0.256***	-0.267***	-0.256***	-0.270***	-0.260***
	(0.0911)	(0.0957)	(0.0912)	(0.0962)	(0.0911)	(0.0961)	(0.0952)
$(d_{2013} - d_{\widetilde{2013}})$	0.0157	0.00907	-0.0237	-0.0217	-0.0267	-0.0272	-0.110
	(0.0695)	(0.0714)	(0.0694)	(0.0714)	(0.0694)	(0.0712)	(0.0833)
$(d_{2014} - d_{\widetilde{2014}})$	0.145**	0.144**	-0.00292	0.00758	-0.00340	0.00417	-0.0611
	(0.0673)	(0.0693)	(0.0681)	(0.0701)	(0.0681)	(0.0701)	(0.0771)
$(d_{2015} - d_{\widetilde{2015}})$	0.133*	0.123*	-0.142**	-0.130*	-0.138*	-0.129*	-0.211**
	(0.0691)	(0.0708)	(0.0712)	(0.0729)	(0.0714)	(0.0730)	(0.0838)
$(d_{2016} - d_{\widetilde{2016}})$	0.0850	0.0546	-0.287***	-0.292***	-0.285***	-0.293***	-0.341***
	(0.0684)	(0.0704)	(0.0718)	(0.0738)	(0.0719)	(0.0738)	(0.0777)
$(d_{2017} - d_{\widetilde{2017}})$	0.126*	0.106	-0.293***	-0.288***	-0.293***	-0.291***	-0.337***
	(0.0674)	(0.0695)	(0.0723)	(0.0747)	(0.0723)	(0.0746)	(0.0784)
$(d_{2018} - d_{\widetilde{2018}})$	0.348***	0.328***	-0.202***	-0.187**	-0.204***	-0.192**	-0.254***
	(0.0674)	(0.0693)	(0.0756)	(0.0777)	(0.0756)	(0.0776)	(0.0841)
$(d_{2019} - d_{\widetilde{2019}})$	0.579***	0.557***	-0.126	-0.106	-0.132	-0.114	-0.153*
	(0.0665)	(0.0684)	(0.0806)	(0.0830)	(0.0807)	(0.0831)	(0.0855)
$\Delta D_t^{0.06}$			0.0000852	0.000165	0.000241	0.000249	0.000270
			(0.000685)	(0.000687)	(0.000625)	(0.000627)	(0.000631)
$\Delta D_t^{0.06} * ML$					0.00273**	0.00301***	0.00302***
					(0.00115)	(0.00111)	(0.00113)
$\Delta D_t^{0.06} * MH$					-0.00558*	-0.00539*	-0.00540*
					(0.00290)	(0.00287)	(0.00289)
$\Delta D_t^{0.06} * H$					-0.000790	-0.000775	-0.000732
					(0.00124)	(0.00124)	(0.00125)
$\Delta \% MHI_{ijt}$					0.000427	0.000398	0.000395
					(0.000615)	(0.000637)	(0.000636)
$\Delta \% Occupied_{ijt}$					0.00180	0.00171	0.00167
					(0.00131)	(0.00136)	(0.00136)
$\lambda_{it} - \lambda_{i\tilde{t}}$							-0.289*
							(0.148)
$Constant$			0.374***	0.355***	0.372***	0.352***	0.353***
			(0.0227)	(0.0236)	(0.0227)	(0.0236)	(0.0236)
Property Fixed Effects	YES^{a}	YES	YES^{a}	YES	YES^{a}	YES	YES
Observations	5,142	4,774	5,142	4,774	5,142	4,774	4,774
R^2	0.113	0.110	0.040	0.043	0.043	0.046	0.046
Adjusted R^2	0.111	0.109	0.038	0.040	0.040	0.043	0.043

Source: Author’s calculations. Note: The table reports OLS to repeat sale regression coefficients from six separate regressions. The dependent variable in all regressions is the natural logarithm of the ratio between an observation's first and second sale price. The observations correspond to the transaction pairs (see Table 1.1) for the entire sample case, and only those without building permits between 2010 and 2019 for the subsample case. The key independent

Table 1. 4 (cont'd)
variable is $\Delta D_t^{0.06}$, which corresponds to the total number of demolitions between the first and second sale within a radius of 0.06-miles. An interaction term is included to account for the context before the demolitions: dilapidation levels in quantiles. All regressions control for property fixed effects and year effects ($(d_t - d_{\tilde{t}})$ variables). Standard errors are clustered at the property level.
[as] It is important to note that although there are characteristic attributes of a property that do not change over time and that we are controlling due to the nature of the repeat sale regression, it is only when we use the subsample of properties with no building permits issued that we are making sure that we control for all those time-invariant attributes.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
- Significant at the 10 percent level.

Results from the Third Specification

The next step is to include the neighborhood the dilapidation level that existed before demolitions. As we explained in the previous section, four levels of dilapidation are obtained in the creation of quartiles of the number of dilapidated properties at the tract level. These variables represent the physical and socioeconomic conditions to which properties were subjected prior to demolitions. In addition, we incorporate the change in relative income and in house occupancy. Change in income at the census tract level may be positively related to demolitions if there is an urban renewal process after demolition. This implies that intervention in a neighborhood to eliminate blight may encourage new investment in real estate, but it may also attract people with higher incomes to buy the new vacant lots. Furthermore, higher household income is related to higher capital gains in property prices. However, the relationship between occupancy and demolitions is more mechanical. Higher occupancy rate means fewer demolitions of abandoned and dilapidated properties, and vice versa.

Columns 5 and 6 of Table 1.4 show the results of the third specification that includes these variables. We focus on column 7, where we use the subsample of properties without building permits issued and where we include the variation of the lambda generated from the first step of the Heckman correction. This coefficient is statistically significant and negative, implying an upward bias when we do not include this correction. The results of the probit of the first stage are shown in Table A1.3 of the Appendix. From these results we conclude that total square footage is significant in some years and positively related to the probability that a transaction will be a repeat sale. The distance from the CBD, main roads, and parks are also positively related to the probability of a repeat sale. Additionally, building permits and the percentage of white people in the neighborhood are negatively related to being a repeat sale. Therefore, there is a difference between the usable and the non-usable sample of transactions that must be considered when generating the regressions.

Focusing our analysis on the last column of Table 1.4, Figure 1.5 shows the calculation of the marginal effects, that is, the effect of an additional demolition on the value of neighboring properties according to the level of dilapidation of the neighborhood and controlling for all the other variables. Importantly, the vertical axis of Figure 1.5 shows the Average Marginal Effect (AME) of an additional demolition in the expected price ratio. Note that we transform percentage approximations to predicted ratios in this case, which can be interpreted in percentage values.[26] The estimates with the interaction term reveal an interesting finding that is supported by theory.

Firstly, there is a positive effect of demolitions in those neighborhoods that were less dilapidated before the demolitions. The marginal effect of an additional nearby demolition is positive in the Low (L) and Medium Low (ML) categories of the dilapidation quartiles. However, only in the ML category, the effect is statistically significant at the 1% level. In these areas of the city, an additional nearby demolition increases property prices by 0.61% (statistically significant at a 1% level), a finding that is consistent with our hypothesis, which provides some evidence that

[26] Reversing the logarithmic transformation in a traditional hedonic price regression leads to obtaining the AME in dollars. However, the dependent variable in this specification is the natural logarithm of the price ratio. Therefore, reversing the logarithmic transformation provides us with the predicted price ratio. The marginal effect is on this price ratio, which also has a percentage interpretation. For example, if the price ratio is 1.2 it implies that the prices of that property increased 20% between the first and the second sale. To obtain unbiased prediction after the reverse transformation (Wooldridge, 2010), we use Generalized structural equation model estimation, the following link provides more information on the calculation https://bit.ly/3CaUYqw.

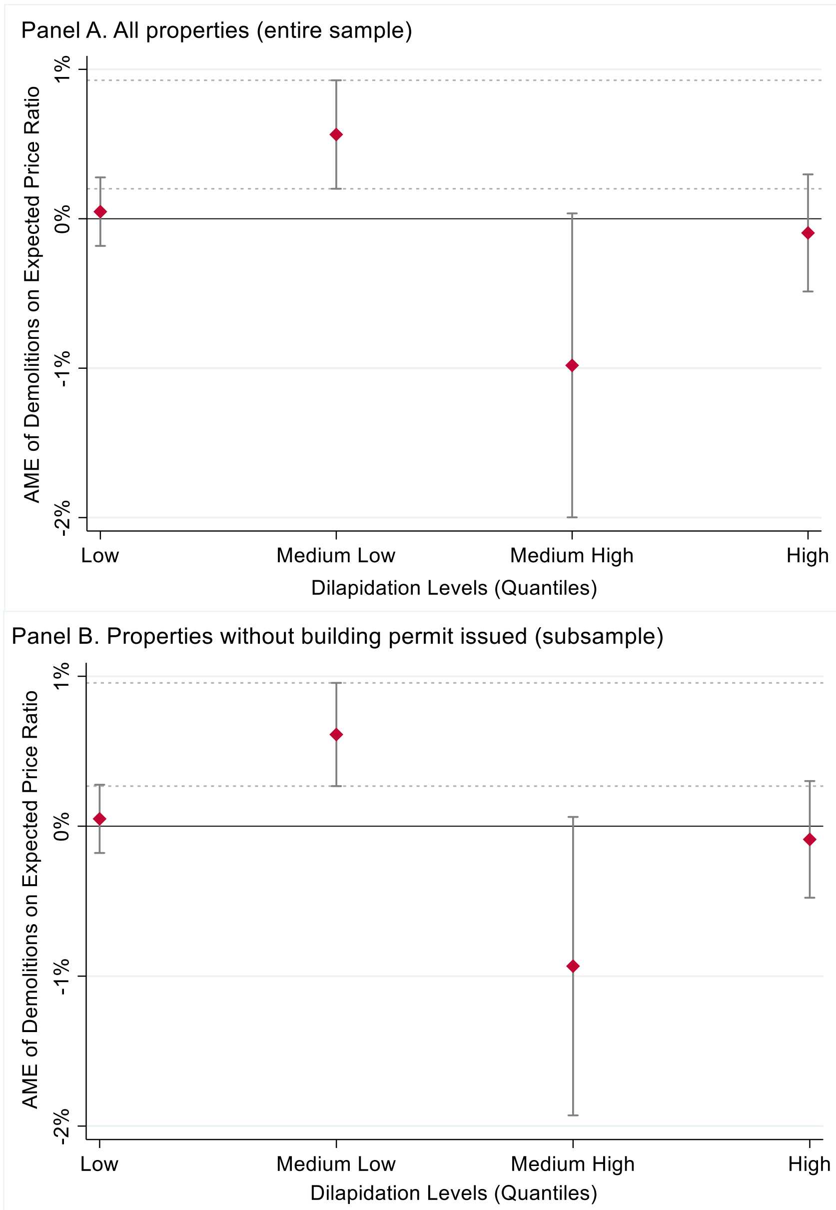
the demolition program generates a benefit that is capitalized on the value of properties. The interpretation from the perspective of the environmental variable is that blight has a negative effect, and its elimination has a positive impact.

Nonetheless, this positive effect is restricted to specific areas within the city (those neighborhoods with a low level of dilapidation prior to the policy). It has a relatively small magnitude compared to the other studies (Paredes & Skidmore (2017) and Dynamo Metrics (2015)). Second, in those neighborhoods with a high level of dilapidation before the policy, the marginal effect of an additional demolition is negative for nearby properties. As Figure 1.5 shows, this effect is statistically non-significant for the Medium-High (MH) and High (H) categories.

Additionally, we use the coefficient calculated for the ML category to measure the effect in dollars. Note that the estimated AME is the average effect of an additional nearby demolition. Therefore, we can multiply this percentage by the first sale price of the properties in the ML category to get an approximate dollar effect. Figure 1.6 shows the histogram of the effect calculated in dollars, where the red line identifies a mean of \$180, with a minimum of almost \$3 and a maximum of approximately \$1,750. This is the effect of an additional demolition within a radius of 0.06-miles, between the first and second sale, for properties in relatively less dilapidated neighborhoods before the program.

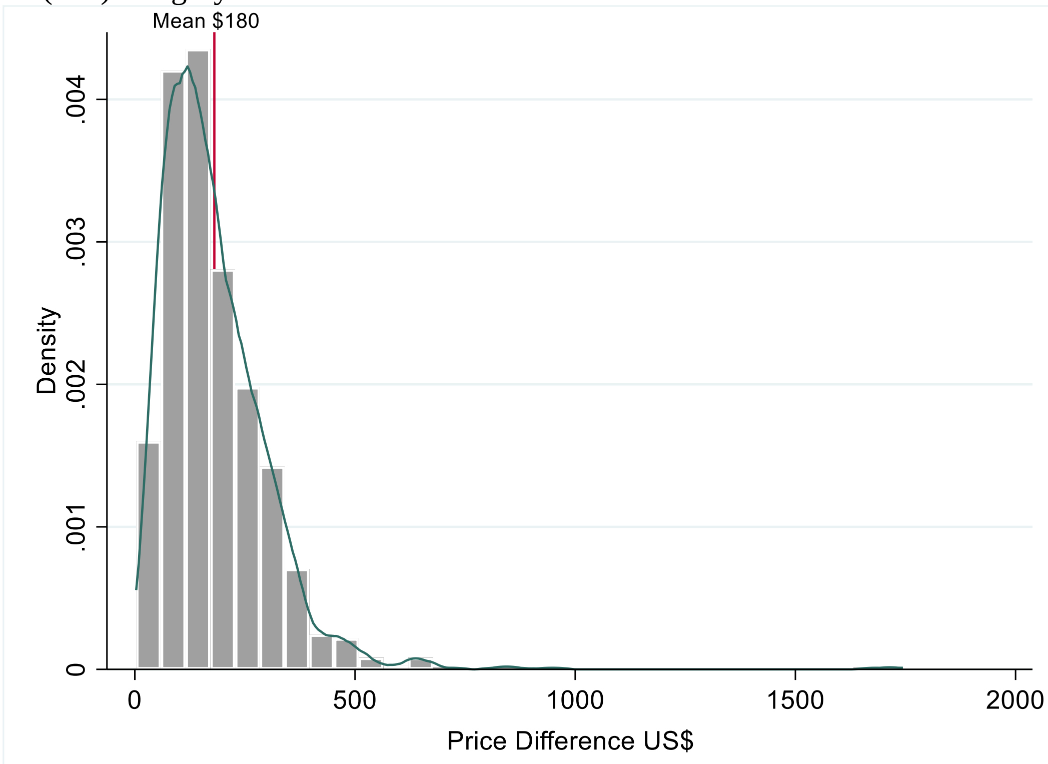
Figure A1.1 provides a map of where these properties are located. These results provide evidence regarding the performance of the demolition program and are helpful to city officials. However, because the regressions may be sensitive to methods and empirical decisions, we examine the robustness of these results in the next section.

Figure 1. 5: Marginal effect of demolitions on property prices by Dilapidation Levels



Source: Authors' calculations. Note: figure shows the average marginal effect of the number of demolitions, within a 0.06-mile radius and between the first and second sale, on the value of properties by dilapidation levels before demolitions (quantiles). Calculations of the average marginal effects come from regressions in Table 1.3 (column 7) and the reverse logarithm transformation is explained in Footnote 30. Each panel shows a separate repeat sale regression according to the sample size. The sample size in panel A is 5,142, and in the panel B is 4,774. Standard errors are clustered at the property level, and the lines display 95 percent confidence intervals through each coefficient. The dotted line highlights the confidence intervals of those coefficients that are statistically significant at the 1 percent level.

Figure 1. 6: Effect in the Price Difference of one additional demolition within a 0.06-mile, Medium Low (ML) category



Source: Authors' calculations. Note: this figure uses the AME of demolitions in the property price calculated for the ML dilapidation category and multiplies this effect with the first sale price of the properties in this category. This shows, in dollar amounts, the part of the price increase between the first and second sale associated with blight elimination due to the proximity to a demolition.

Redefining What We Understand by "Close"

All results presented thus far are subject to the decision to create an initial radius of 0.06 miles to calculate the demolitions that we consider close to the property. Therefore, it is necessary to examine what happens to the estimates if we change the distance. Instead of choosing other distances and obtaining the results for a discrete function, we allow the distance to vary continuously until we find the threshold where the results become statistically insignificant. Specifically, let ΔD_{it}^{x} be the total number of demolitions between the first and second sale of property i, within a radius of x miles, where $x \in [a, b]$. In this case, the parameter a indicates the minimum distance where the properties begin to register demolitions around them. Parameter b indicates the maximum distance where we find a statistically significant effect of demolitions on the price of neighboring properties.[27] Hence, for each distance $x \in [a, b]$, we calculate equation (4) with a 0.001-mile variation between each regression. Note that by changing the radius, we change the number of demolitions that we consider near a property, and therefore the marginal effect becomes a function of distance. The result of this evaluation for each of the dilapidation categories is presented in Figure 1.7.

Figure 1.7 is made up of four charts for each of the dilapidation levels. In each of these graphs, a black continuous line is plotted in the middle of the gray area. Each point that makes up that black line represents one of the hundreds of regressions estimated to generate each graph in Figure 1.7. The black line is the effect of demolitions on the value of neighboring properties (left vertical axis) that changes through distance (horizontal axis). The gray area represents the 95% confidence intervals of these coefficients. We also plot the number of observations included in the regression by interaction term (right vertical axis). Note that the number of observations varies by both the dilapidation quartile and the distance chosen to generate the radius of the independent variable because there are distances that are too short for there to be a positive number of demolitions around residential property.

There are several points to highlight. First, in the L category, the coefficients remain statistically insignificant, even at higher distance levels. This implies consistency in the non-significant impact that demolitions have in these areas of the city. We believe that this result is related to the fact that these neighborhoods were the ones that were initially *healthier* and did not become the primary focus of the demolition program. Therefore, these are the areas that had the least number of blighted properties demolished. The number of demolitions in these neighborhoods is lower than the other categories (see the right vertical axis). Second, demolitions

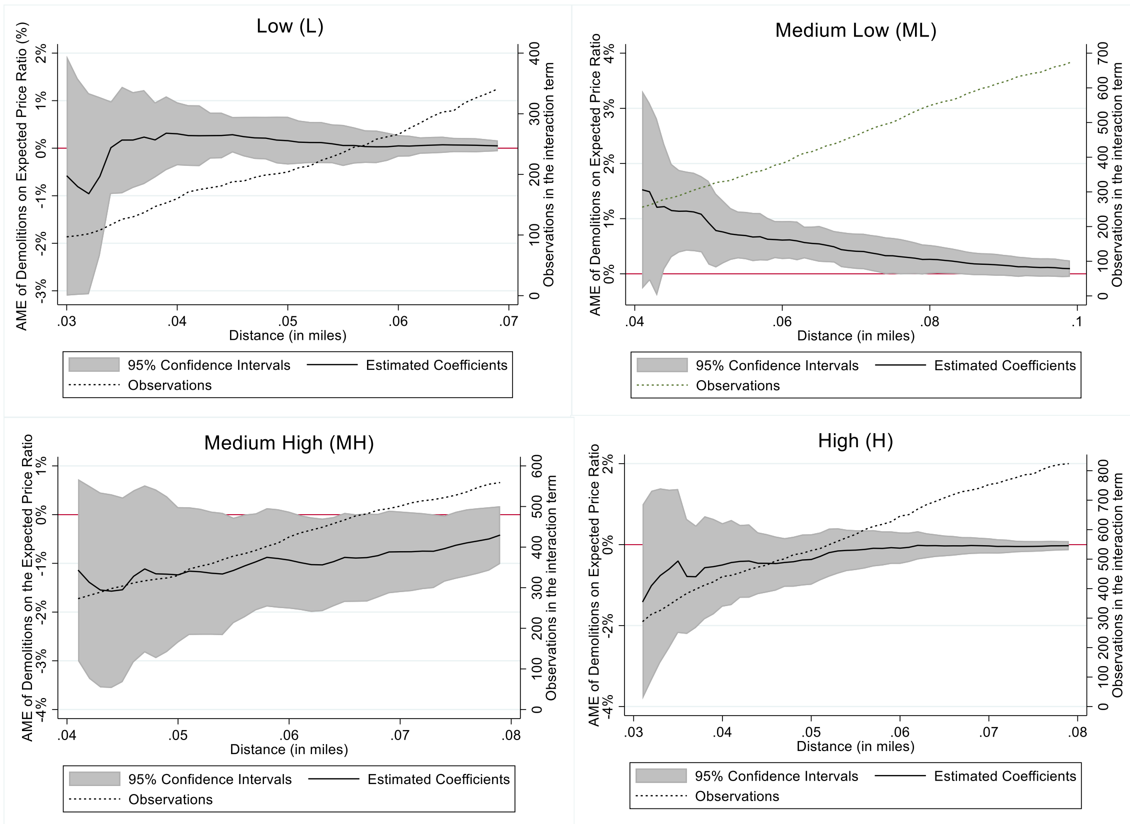
---

[27] It should be noted that for the Low (L) category we have ignored this restriction in the realization of Figure 5, because it is statistically non-significant in all distance variations.

have a negative effect on the value of neighboring properties in MH and H categories that are persistent over a certain distance range.

Specifically, between 0.061 and 0.064 miles, this effect is statistically significant for the MH category. In this range, the minimum marginal effect of demolitions is -1.03%, while the maximum value is -0.97%, with an average value of -1.00%. Hence, in areas that were most devastated before the program, we find a negative effect of additional demolition at close distances and in relatively short ranges. On the other hand, there is a positive effect of demolitions in the less devastated places with the lower amount of blight before demolitions. Starting at 0.044 miles, an additional demolition positively impacts the value of neighboring properties, and this impact fades with distance. The upper bound is 0.084 miles. This result is consistent with Tobler's first law, where closer demolitions have a greater effect than more distant ones (indicated by the negative slope) (Tobler, 1970). The marginal impact threshold occurs at 0.083 miles; beyond this point, the effect of an additional demolition becomes virtually zero. Furthermore, the minimum value effect is 0.23% in this range, while the maximum is 1.22%, with an average of 0.59%. This result indicates that the marginal impact calculated in the previous section is much more conservative compared with the effects of higher values. These additional findings suggest that the results reported earlier are reasonably consistent with all distance measurements.

Figure 1. 7: Results of the first robustness analysis: the impact of distance on the marginal effects of demolitions



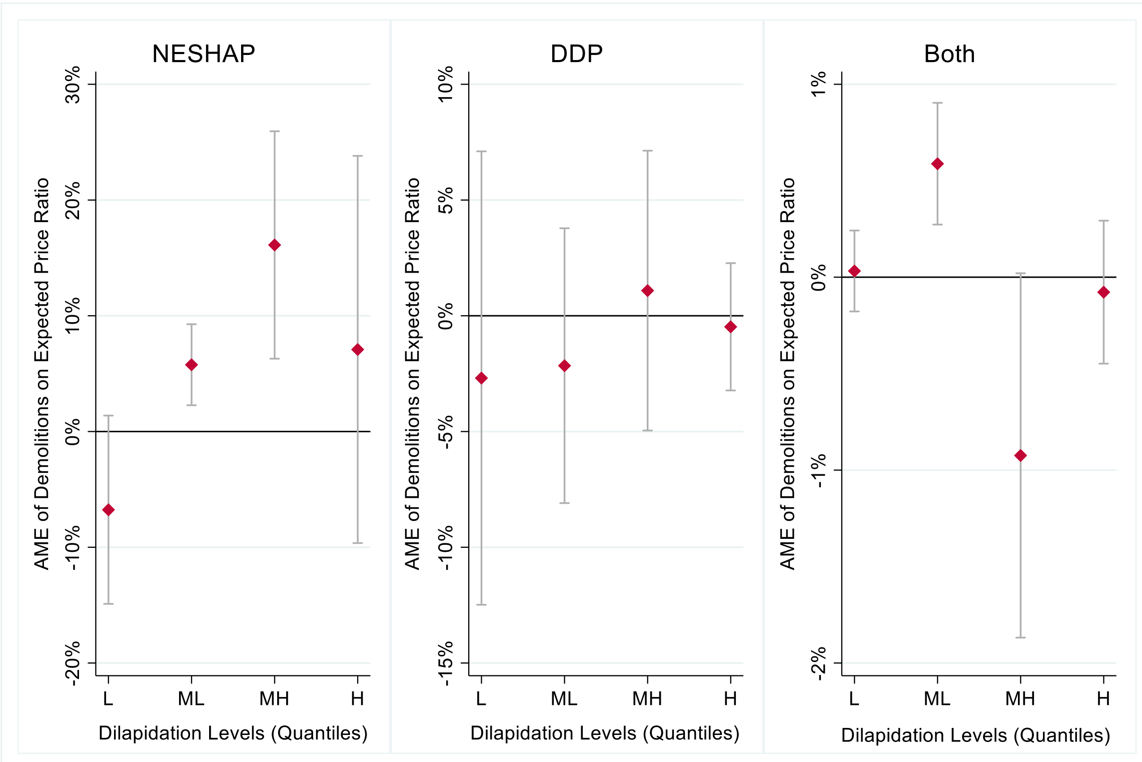
Source: Authors' calculations. Note: these figures plot the marginal effects obtained from the interaction term coefficients in equation 15 (see Identification Strategy section). The marginal effects vary because in this opportunity, the interaction term is $\Delta D_{it}^{x} * DilapidationLevel_i$, where $x \in [a, b]$ (see main text for the explanation of the a and b parameters). That implies that the radius to calculate the number of demolitions around a residential property varies with the distance. In each plot, the left vertical axis corresponds to the magnitude of the marginal effect of demolitions on the value of neighboring properties (% approximation), the horizontal axis is the distance measured in miles. The right vertical axis is for the observations pertaining to the interaction term which vary according to the dilapidation quantile category and the minimum distance where properties start having demolitions around. Each of the hundreds of regressions uses the subsample of properties with no building permit issued. Standard errors are clustered at the property level, and 95 percent confidence intervals are displayed through the gray areas.

Effect of Demolition by Program

Thus far, we have used the information from the demolitions in a data pool. However, we have two sources of demolition information. From NESHAP and the Detroit Demolition Program (DDP). Based on the date of the first sale and the date of the second sale, we identify which properties were primarily affected by NESHAP-registered demolitions, DDP demolitions, and both.

Figure 1.8 shows the results of this exercise (Table A1.4 in the appendix provides the details of these regressions). These estimates indicate that for the subsample of properties affected mainly by demolitions at the beginning of the analysis period (NESHAP), the effect of an additional demolition is positive and statistically significant. This occurs at both levels of dilapidation, ML category, where the effect is approximately 5.4%, and MH category, where the effect is 15.7%. This effect is of high magnitude, however, the number of observations for this subsample is only 321. In the case of the properties affected only by the DDP, the results indicate no statistically significant effects. Finally, those properties affected by both types of demolition provide results similar to those shown in the previous sections. This may indicate that in the short-term, demolitions have a positive effect for both categories (ML and MH) and that in the longer-term this effect is only maintained for the ML category. However, the low number of observations may make it difficult to draw conclusions from these results.

Figure 1. 8: Marginal effect of demolitions on property prices by Dilapidation Levels and by Type of Program



Source: Authors' calculations. Note: figure shows the average marginal effect of the number of demolitions, within a 0.06-mile radius and between the first and second sale, on the value of properties by dilapidation levels before demolitions (quantiles) and by type of program. *NESHAP* represents the column of the subsample of properties affected only by the demolitions registered through the NESHAP. *DDP* is the subsample column for properties only affected by Detroit Demolition Program demolitions. Finally, *both* is the column with the properties affected by both types of demolitions. All regressions consider the subsample of properties without building permit issued and we include the two-steps Heckman correction in all specifications.

Finally, we investigate whether the results are sensitive to the number of quantiles chosen to generate the dilapidation levels. This figure shows a consistent positive impact of demolitions on neighboring property values for those located in low-dilapidation zones before the program began. The level of statistical significance is maintained in most cases for the category with the lowest dilapidation level. Additionally, the negative magnitude of the impact of demolitions in areas with a high level of dilapidation also remains. However, in all cases there is no statistical significance in this effect.

Discussion and Conclusion

Blight is a risk to the health, safety, and economic development in a city. This problem is embedded in post-industrial cities that once stood out for their productive capacity and that today are struggling with the challenges of depopulation. In an effort to address these challenges, Detroit has conducted the largest demolition program in the country. However, this program is not without controversy, especially regarding costs and the potential adverse effects that demolitions can have on neighborhoods. This analysis adds to the evaluation of the Detroit Demolition Program by providing evidence on the effect of demolitions on the neighboring properties prices.

This article uses various publicly available data sources. Nevertheless, a challenge is limited information needed to conduct hedonic price analysis. Repeat Sales (RS) and the environmental economics literature have much to offer in addressing the challenge of limited information. Using data on property sales from 2009 through 2019, and a RS specification, we estimate regressions within *ex-ante* dilapidation levels to determine the marginal impact of demolitions in different types of neighborhoods across the city.

The main findings are as follows: 1) on average, blight elimination through the demolition program does not appear to have been capitalized into residential prices across the entire city; 2) by differentiating the effect by *ex-ante* neighborhood characteristics, we find a positive effect of demolitions on property prices in some areas of the city. Specifically, an additional nearby demolition increases property prices by 0.61% in areas of the city that had a *Medium Low* (ML) dilapidation level before the demolition program; 3) on average, this effect is about $180 of the price of properties in census tracts included in the ML category; 4) this effect is in the range from 0.044 to 0.084 miles, with an impact that decreases with distance and with minimum and maximum values of 0.23% and 1.22%, respectively; and 5) we find negative impacts in those neighborhoods that were most dilapidated before the policy, but magnitude is smaller than the positive impact, and in most cases statistically non-significant. These results agree with recent studies related to externalities, wherein in more dilapidated neighborhoods, blighted properties are more frequent and therefore the elimination of a property may not mean a great difference compared to the elimination of blight in neighborhoods with less dilapidation and higher income. Therefore, the effect of the program will likely be greater in the second type of neighborhood. Our findings support this idea.

According to our evaluation, the average marginal increase in property values due to nearby is $180. If we assume that the demolitions affect all the properties in the neighborhoods that benefit from the policy, we calculate a back-of-the-envelope aggregate impact assessment. From the universe of residential parcels, we know that 25.5% are located in the census tracts belonging to the ML category; these are the parcels that are positively affected by demolitions. Therefore, the total residential parcels multiplied by 25.5% results in about 65,897 parcels. Multiplying $180 by 61,601 residential parcels generates a total increase in property values of $11,861,460 due to demolitions per year, and almost $119 million in the entire period, which offsets a small portion of the total demolition costs. According to Paredes and Skidmore (2017) the average cost of demolitions in Detroit is $20,000, which includes additional costs such as shutting off gas, water, and electricity services, asbestos removal, as well as the costs of dumpsters and landfill space. Multiplying this average by the number of demolitions undertaken over the period of evaluation, the total cost amounts to about $630 million. Without taking into consideration other types of benefits such as spillover effects, crime reduction, health impacts, reduced law enforcement costs, among others, the costs far exceed the benefits we estimate. However, this is a restricted analysis that does not consider other types of benefits.

In summary, our research shows that the demolition of blighted properties is a potentially useful tool that policymakers can use to address urban blight and promote renewal and redevelopment across the city, if it is used in targeted ways. Future research should direct efforts to inform cost-benefit analysis through the effect of demolitions on other key variables related to other aspects of well-being and quality of life such as safety and health, reduction in crime and enforcement cost, implicit effects on tax revenues, urban renovation, among others.

BIBLIOGRAPHY

Alm, J., Hodge, T. R., Sands, G., & Skidmore, M. (2014). Detroit Property Tax Delinquency: Social Contract in Crisis. *Public Finance and Management, 14*(3), 280–305.

Alvayay Torrejón, C., Paredes, D., & Skidmore, M. (2020). Housing demolition and property tax delinquency: Evidence from Detroit. *Journal of Urban Affairs, 00*(00), 1–22. https://doi.org/10.1080/07352166.2019.1697183

Anenberg, E., & Kung, E. (2014). Estimates of the size and source of price declines due to nearby foreclosures. *Finance and Economics Discussion Series, 104*(8), 2527–2551. http://ideas.repec.org/p/fip/fedgfe/2012-84.html

Bailey, M. J., Muth, R. F., & Nourse, H. O. (1963). A Regression Method for Real Estate Price Index Construction. *Journal of the American Statistical Association, 58*(304), 933–942. https://doi.org/10.1080/01621459.1963.10480679

Breger, G. E. (1967). The Concept and Causes of Urban Blight. *Land Economics, 43*(4), 369–376. https://doi.org/10.1017/CBO9781107415324.004

Campbell, J. Y., Giglio, S., & Pathak, P. (2011). Forced Sales and House Prices. *American Economic Review , 101*(5), 2108–2131. https://doi.org/10.1257/aer.101.5.2108

Case, B., Colwell, P. F., Leishman, C., & Watkins, C. (2006). The impact of environmental contamination on condo prices: A hybrid repeat-sale/hedonic approach. *Real Estate Economics, 34*(1), 77–107. https://doi.org/10.1111/j.1540-6229.2006.00160.x

Case, K. E., & Shiller, R. J. (1987). Prices of single-family homes since 1970: new indexes for four cities. *New England Economic Review*, September, 45–56. http://www.nber.org/papers/w2393.pdf

Champ, P. A., Boyle, K. J., & Brown, T. C. (2017). A Primer on Nonmarket Valuation. https://doi.org/10.1007/978-94-007-7104-8_4

Cheung, R., Wetherell, D., & Whitaker, S. (2018). Induced earthquakes and housing markets: Evidence from Oklahoma. *Regional Science and Urban Economics, 69*(February), 153–166. https://doi.org/10.1016/j.regsciurbeco.2018.01.004

Clapp, J. M., & Giaccotto, C. (1992). Estimating Price Trends for Residential Property: A Comparison of Repeat Sales and Assessed Value Methods. *Journal of Real Estate Finance and Economics, 5*(4), 357–374.

Clapp, J. M., Giaccotto, C., & Tirtiroglu, D. (1991). Housing Price Indices Based on All Transactions Compared to Repeat Subsamples. *Real Estate Economics, 19*(3), 270–285. https://doi.org/10.1111/1540-6229.00553

Detroit Future City. (2017). 139 Square Miles. Detroit Future City, 1–41. https://detroitfuturecity.com/wp-content/uploads/2017/11/DFC_139-SQ-Mile_Report.pdf

Detroit Health Department. (2017). *Task Force Recommendations for Improving Demolition Safety and Health Standards Introduction*. http://www.bridgemi.com/sites/default/files/task_force_recommendations.pdf

Detroit Residential Parcel Survey. (2010*). The Power of Partners: The Detroit Residential Parcel Survey and Neighborhood Reporting System Project*. https://datadrivendetroit.org/files/DRPS/Detroit Residential Parcel Survey OVERVIEW.pdf

Dynamo Metrics. (2015). *Estimating Home Equity Impacts from Rapid, Targeted Residential Demolition in Detroit, MI: Application of a Spatially-Dynamic Data System for Decision Support*. www.dynamometrics.com

Ellen, I. G., Lacoe, J., & Sharygin, C. A. (2013). Do foreclosures cause crime? *Journal of Urban Economics, 74*(1), 59–70. https://doi.org/10.1016/j.jue.2012.09.003

Fernandez, L., Cutter, B., Sharma, R., & Scott, T. (2018). Land preservation policy effect or neighborhood dynamics: A repeat sales hedonic matching approach. *Journal of Environmental Economics and Management, 88*, 311–326. https://doi.org/10.1016/j.jeem.2018.01.001

Gatzlaff, D. H., & Haurin, D. R. (1997). Sample Selection Bias and Repeat-Sales Index Estimates. *Journal of Real Estate Finance and Economics, 14*(1–2), 33–50. https://doi.org/10.1023/a:1007763816289

Gatzlaff, D. H., & Haurin, D. R. (1998). Sample Selection and Biases in Local House Value Indices. *Journal of Urban Economics, 43*(2), 199–222. https://doi.org/10.1006/juec.1997.2045

Gerardi, K., Rosenblatt, E., Willen, P. S., & Yao, V. (2015). Foreclosure externalities: New evidence. *Journal of Urban Economics, 87*, 42–56. https://doi.org/10.1016/j.jue.2015.02.004

Guo, X., Zheng, S., Geltner, D., & Liu, H. (2014). A new approach for constructing home price indices: The pseudo repeat sales model and its application in China. *Journal of Housing Economics, 25*, 20–38. https://doi.org/10.1016/j.jhe.2014.01.005

Harding, J. P., Rosenblatt, E., & Yao, V. W. (2009). The contagion effect of foreclosed properties. *Journal of Urban Economics, 66*(3), 164–178. https://doi.org/10.1016/j.jue.2009.07.003

Hartley, D. (2014). The effect of foreclosures on nearby housing prices: Supply or dis-amenity? *Regional Science and Urban Economics, 49*, 108–117. https://doi.org/10.1016/j.regsciurbeco.2014.09.001

Johnson, C. (2008). (2008). Fight blight: Cities sue to hold lenders responsible for the rise in foreclosures and abandoned properties. *Utah Law Review, 3*, 1169–1254. https://heinonline.org/HOL/Page?handle=hein.journals/utahlr2008&div=39&g_sent=1&casa_tok

en=cCh_s6k__h4AAAAA:YlNIpelXQTDwfZ7Un735laZHv1djVArlVDemV3m6JOte5Oav6yVLimGnBW0EZl84Hmq_r_CVF-A&collection=journals#

Jud, D., & Seaks, T. (1994). Sample Selection Bias in Estimating Housing Sales Prices. Journal of Real Estate Research, 9(3), 289–298. https://doi.org/10.1080/10835547.1994.12090753

Kondo, M. C., Morrison, C., Jacoby, S. F., Elliott, L., Poche, A., Theall, K. P., & Branas, C. C. (2018). Blight abatement of vacant land and crime in New Orleans. *Public Health Reports, 133*(6), 650–657. https://doi.org/10.1177/0033354918798811

Larson, M., Xu, Y., Ouellet, L., & Klahm, C. F. (2019). Exploring the impact of 9398 demolitions on neighborhood-level crime in Detroit, Michigan. *Journal of Criminal Justice, 60*(November 2018), 57–63. https://doi.org/10.1016/j.jcrimjus.2018.11.002

Lee, K. (2008). Foreclosure's Price-Depressing Spillover Effects on Local Properties: A Literature Review. *Community Affairs Discussion Paper*, 14.

Leon, E. De, & Schilling, J. (2017). *Urban Blight and Public Health* (Issue April). https://www.urban.org/research/publication/urban-blight-and-public-health

Mallach, A. (2012). Laying the Groundwork for change: Demolition, urban strategy, and policy reform. In *Brookings Metropolitan Policy Program* (Issue September).

Mendelsohn, R., Hellerstein, D., Huguenin, M., Unsworth, R., & Brazee, R. (1992). Measuring hazardous waste damages with panel models. *Journal of Environmental Economics and Management, 22*(3), 259–271. https://doi.org/10.1016/0095-0696(92)90032-R

Niemesh, G. T., Jones-Farmer, L. A., Hart, J., Holmes, W., & Soundappan, N. (2020). The impact of land bank demolitions on property values. *Economics Bulletin, 40*(1), 217–233.

Owens, R., Rossi-Hansberg, E., & Sarte, P. D. (2020). Rethinking Detroit. *American Economic Journal: Economic Policy, 12*(2), 258–305. https://doi.org/10.1257/POL.20180651

Palmquist, R. B. (1982). Measuring environmental effects on property values without hedonic regressions. *Journal of Urban Economics, 11*(3), 333–347. https://doi.org/https://doi.org/10.1016/0094-1190(82)90079-1

Palmquist, R. B. (2005). Chapter 16 Property Value Models. *Handbook of Environmental Economics, 2*(05), 763–819. https://doi.org/10.1016/S1574-0099(05)02016-4

Paredes, D., & Skidmore, M. (2017). The net benefit of demolishing dilapidated housing: The case of Detroit. *Regional Science and Urban Economics, 66*(November 2016), 16–27. https://doi.org/10.1016/j.regsciurbeco.2017.05.009

Pearson, A. L., Rzotkiewicz, A., Pechal, J. L., Schmidt, C. J., Jordan, H. R., Zwickle, A., & Benbow, M. E. (2019). Initial Evidence of the Relationships between the Human Postmortem

Microbiome and Neighborhood Blight and Greening Efforts. *Annals of the American Association of Geographers, 109*(3), 958–978. https://doi.org/10.1080/24694452.2018.1519407

Reckien, D., & Martinez-Fernandez, C. (2011). Why do cities shrink? *European Planning Studies, 19*(8), 1375–1397. https://doi.org/10.1080/09654313.2011.593333

Rogers, W. H., & Winter, W. (2009). The impact of foreclosures on neighboring housing sales. *Journal of Real Estate Research, 31*(4), 455–479. https://doi.org/10.1080/10835547.2009.12091261

Rosen, S. (1974). Hedonic Prices and Implicit Markets : Product Differentiation in Pure Competition. *Journal of Political Economy, 82*(1), 34–55. https://doi.org/http://dx.doi.org/10.1086/260169

S&P Dow Jones Indices LLC. (2021). S & P CoreLogic Case-Shiller Home Price Indices Methodology. In *S&P Dow Jones Indices* (Issue April). https://www.spglobal.com/spdji/en/documents/methodologies/methodology-sp-corelogic-cs-home-price-indices.pdf

Sands, G., & Skidmore, M. (2015). *Detroit and the Property Tax*.

Spelman, W. (1993). Abandoned buildings: Magnets for crime? *Journal of Criminal Justice, 21*(5), 481–495. https://doi.org/10.1016/0047-2352(93)90033-J

Tobler, W. R. (1970). A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography, 46*, 234–240. https://doi.org/https://doi.org/10.2307/143141

United States Environmental Protection Agency. (2014). Developing Practical Land Revitalization Tools for Communities: Green Demolition Practices. *In Land Revitalization Success Stories* (Issue October, p. 12). https://www.epa.gov/sites/production/files/2015-07/documents/green_demolition_practices.pdf

Vecco, M., Chang, S., & Zanola, R. (2021). The more you know, the better: A Heckman repeat-sales price index. *Quarterly Review of Economics and Finance, xxxx*. https://doi.org/10.1016/j.qref.2021.01.005

Whitaker, S., & Fitzpatrick, T. J. (2016). Land bank 2.0: An empirical evaluation. *Journal of Regional Science, 56*(1), 156–175. https://doi.org/10.1111/jors.12206

Williams, C. (2020). DuggaWilliams, C. (2020). Duggan pitches revised $250M bond plan to save more Detroit homes from demolition. The Detroit News. https://www.detroitnews.com/story/news/local/detroit-city/2020/07/14/plan-n-bond-proposal-would-save-some-detroit-homes-demolish-others/5436775002/

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data. In *MIT press*. https://doi.org/10.1515/humr.2003.021

Zhang, L., & Leonard, T. (2014). Neighborhood impact of foreclosure: A quantile regression approach. *Regional Science and Urban Economics, 48*, 133–143. https://doi.org/10.1016/j.regsciurbeco.2014.06.004

Zhang, L., Leonard, T., & Murdoch, J. C. (2016). Time and distance heterogeneity in the neighborhood spillover effects of foreclosed properties. *Housing Studies, 31*(2), 133–148. https://doi.org/10.1080/02673037.2015.1070794

APPENDIX

Table A1. 1: Description of the steps to filter the database and identify market transactions

St ep Number	Description	Obs.	Mean Sale Price
0	All transactions in Detroit	1,012,623	$50,870
1	Select transaction from 2009-2019	330,795	$69,162
2	Remove observations with missing values in coordinates and sale year	330,151	$68,709
3	Keep only "Valid Arm's Length" sales	49,098	$85,712
4	Keep only Residential properties	45,446	$44,751
5	Drop observations below the 1st percentile and above the 99th percentile	44,553	$35,930
6	Drop observations that sold more than 5 times	44,367	$35,927
7	Mismatch between the Main database and the Secondary databases that we use in the analysis	41,771	$34,279

Source: Author's calculations.

Table A1. 2: Difference in means by group of Usable and Non-usable (Extended by year)

	Non-usable	Usable	Difference	(p-value)
Sale Price	33,892.3465	35,546.2089	-1,653.8624	0.0000
Distance to Demolition 2009	0.6677	0.6588	0.0089	0.0466
Distance to Demolition 2010	0.3398	0.3559	-0.0161	0.0000
Distance to Demolition 2011	0.2627	0.2828	-0.0201	0.0000
Distance to Demolition 2012	0.4026	0.4151	-0.0125	0.0001
Distance to Demolition 2013	0.2831	0.2806	0.0025	0.3646
Distance to Demolition 2014	0.1629	0.1638	-0.0009	0.5818
Distance to Demolition 2015	0.1507	0.1554	-0.0047	0.0020
Distance to Demolition 2016	0.1718	0.1761	-0.0043	0.0065
Distance to Demolition 2017	0.1908	0.1975	-0.0066	0.0001
Distance to Demolition 2018	0.1771	0.1793	-0.0023	0.2208
Distance to Demolition 2019	0.2125	0.2190	-0.0065	0.0039
Demolitions within 0.06 miles 2009	0.0358	0.0111	0.0248	0.1642
Demolitions within 0.06 miles 2010	0.1375	0.0729	0.0646	0.0000
Demolitions within 0.06 miles 2011	0.2855	0.2252	0.0603	0.0577
Demolitions within 0.06 miles 2012	0.7723	0.1170	0.6553	0.0002
Demolitions within 0.06 miles 2013	2.2577	0.4437	1.8141	0.0000

Table A1. 2 (cont'd)

Demolitions within 0.06 miles 2014	4.7906	3.8820	0.9086	0.0013
Demolitions within 0.06 miles 2015	1.9549	1.6176	0.3373	0.0264
Demolitions within 0.06 miles 2016	0.6121	0.4566	0.1555	0.0001
Demolitions within 0.06 miles 2017	0.4280	0.2944	0.1336	0.0000
Demolitions within 0.06 miles 2018	0.6886	0.5736	0.1149	0.0024
Demolitions within 0.06 miles 2019	0.7353	0.5297	0.2056	0.0000
Median Household Income 2009	32,950.6210	33,643.6603	-693.0393	0.0000
Median Household Income 2010	33,932.6099	34,712.8887	-780.2787	0.0000
Median Household Income 2011	32,950.6210	33,643.6603	-693.0393	0.0000
Median Household Income 2012	31,532.8380	32,155.4439	-622.6059	0.0000
Median Household Income 2013	30,593.2373	31,159.5630	-566.3257	0.0000
Median Household Income 2014	30,221.9557	30,743.1934	-521.2377	0.0001
Median Household Income 2015	29,302.0892	29,781.5244	-479.4352	0.0002
Median Household Income 2016	29,836.9340	30,158.5015	-321.5675	0.0168
Median Household Income 2017	31,296.9988	31,848.1863	-551.1875	0.0001
Median Household Income 2018	32,663.0640	33,251.5777	-588.5137	0.0000
Median Household Income 2019	34,108.2343	34,671.4540	-563.2197	0.0001
% White 2010	11.2910	10.2033	1.0877	0.0000
% White 2011	11.7440	10.5640	1.1799	0.0000
% White 2012	11.7189	10.4948	1.2241	0.0000
% White 2013	11.5355	10.1734	1.3620	0.0000
% White 2014	12.1114	10.6478	1.4636	0.0000
% White 2015	12.5569	10.9065	1.6503	0.0000
% White 2016	12.6921	10.9880	1.7040	0.0000
% White 2017	12.8398	11.1749	1.6649	0.0000
% White 2018	13.0488	11.3110	1.7379	0.0000
% White 2019	13.0949	11.3887	1.7061	0.0000
% Occupied 2009	76.2740	77.3762	-1.1022	0.0000
% Occupied 2010	77.8636	79.0577	-1.1941	0.0000
% Occupied 2011	76.2740	77.3762	-1.1022	0.0000
% Occupied 2012	74.6288	75.6552	-1.0264	0.0000
% Occupied 2013	73.9333	74.9173	-0.9841	0.0000
% Occupied 2014	73.1691	74.1607	-0.9917	0.0000

Table A1. 2 (cont'd)

% Occupied 2015	72.8997	73.8466	-0.9469	0.0000
% Occupied 2016	73.0987	74.0880	-0.9893	0.0000
% Occupied 2017	73.8260	74.8398	-1.0138	0.0000
% Occupied 2018	74.6869	75.8043	-1.1174	0.0000
% Occupied 2019	76.0775	77.2925	-1.2150	0.0000

Source: Authors' own calculations. Note: this table presents a t test for differences in means, by group of observations (t test with equal variances). The categories, Usable and Non-usable, come from Table 1.1, where column (2) specifies the classification of each property and transaction. We use as observations the transactions (column 4, Table 1.1). Notice that 32,000 transactions fall into the non-usable category, while 9,771 fall into the usable category.

Table A1. 3: Probit results of the first step of the Heckman correction

	(1) 2009	(2) 2010	(3) 2011	(4) 2012	(5) 2013	(6) 2014	(7) 2015	(8) 2016	(9) 2017	(10) 2018	(11) 2019
Dependent Variable	I_{i2009}	I_{i2010}	I_{i2011}	I_{i2012}	I_{i2013}	I_{i2014}	I_{i2015}	I_{i2016}	I_{i2017}	I_{i2018}	I_{i2019}
Variation across properties											
Total Square Footage	-0.00000812 (0.0000238)	-0.0000159 (0.0000431)	-0.0000167 (0.0000292)	-0.0000502 (0.0000337)	0.0000336** (0.0000143)	-0.0000196* (0.0000108)	-0.00000843 (0.0000126)	-0.0000211 (0.0000140)	-0.0000126 (0.0000106)	-0.0000203 (0.0000131)	-0.0000115 (0.00000995)
Distance to CBD	0.0228 (0.0180)	-0.0410 (0.0529)	0.0314 (0.0381)	-0.00384 (0.0266)	0.0661*** (0.0117)	0.0308*** (0.00945)	0.0389*** (0.0116)	0.0520*** (0.0119)	0.0402*** (0.00993)	0.0403*** (0.0105)	0.0370*** (0.00937)
Distance to Main Roads	0.00467 (0.0229)	0.0846 (0.0625)	0.0785 (0.0503)	-0.0108 (0.0342)	0.0216 (0.0141)	0.0218** (0.0109)	0.0305** (0.0135)	0.0311** (0.0130)	0.0318*** (0.0110)	0.0358*** (0.0111)	0.0351*** (0.0103)
Distance to Secondary Roads	-0.00599 (0.0283)	-0.0446 (0.0745)	-0.00519 (0.0635)	0.0781* (0.0415)	0.00893 (0.0181)	0.00127 (0.0137)	-0.00652 (0.0172)	-0.00165 (0.0168)	0.0263* (0.0140)	0.00282 (0.0147)	0.0134 (0.0131)
Distance to Parks	0.0471 (0.171)	0.312 (0.456)	0.237 (0.453)	0.198 (0.262)	0.339*** (0.103)	0.185** (0.0819)	0.132 (0.104)	0.244** (0.100)	0.162** (0.0823)	0.107 (0.0833)	0.110 (0.0735)
Variation across properties, census tracts and years											
Distance to Demolition 2009	0.0327 (0.0942)										
Median Household Income 2009	-0.00000431 (0.00000384)										
% Occupied 2009	0.0122** (0.00477)										

Table A1. 3 (cont'd)

Distance to Demolition 2010	-0.503 (0.515)		
1 = if Building Permit 2010	-		
Median Household Income 2010	0.00000935 (0.00000813)		
% Occupied 2010	0.00309 (0.0138)		
% White 2010	0.00306 (0.00619)		
Distance to Demolition 2011		-1.067** (0.513)	
1 = if Building Permit 2011		-	
Median Household Income 2011		-0.00000260 (0.00000780)	
% Occupied 2011		-0.00415 (0.0109)	
% White 2011		0.00848** (0.00424)	
Distance to Demolition 2012			0.457** (0.193)
1 = if Building Permit 2012			-0.251 (0.370)
Median Household Income 2012			-0.00000108 (0.00000509)
% Occupied 2012			0.00539 (0.00671)
% White 2012			-0.00158 (0.00295)

Table A1. 3 (cont'd)

Distance to Demolition 2013	-0.0247		
	(0.0930)		
1 = if Building Permit 2013	-0.892***		
	(0.221)		
Median Household Income 2013	-0.00000158		
	(0.00000226)		
% Occupied 2013	0.00434		
	(0.00275)		
% White 2013	-0.00423***		
	(0.00153)		
Distance to Demolition 2014		-0.124	
		(0.124)	
1 = if Building Permit 2014		-0.185	
		(0.149)	
Median Household Income 2014		-0.000000946	
		(0.00000189)	
% Occupied 2014		0.00110	
		(0.00237)	
% White 2014		-0.00380***	
		(0.00110)	
Distance to Demolition 2015			-0.0460
			(0.167)
1 = if Building Permit 2015			0.0278
			(0.168)
Median Household Income 2015			-0.000000221
			(0.00000239)
% Occupied 2015			0.00410
			(0.00274)
% White 2015			-0.00248*
			(0.00133)

Table A1. 3 (cont'd)

Distance to Demolition 2016	-0.164			
	(0.167)			
1 = if Building Permit 2016	-0.231			
	(0.150)			
Median Household Income 2016	0.00000415**			
	(0.00000204)			
% Occupied 2016	0.000750			
	(0.00258)			
% White 2016	0.000533			
	(0.00130)			
Distance to Demolition 2017		0.173		
		(0.126)		
1 = if Building Permit 2017		-0.211*		
		(0.115)		
Median Household Income 2017		-0.00000102		
		(0.00000186)		
% Occupied 2017		0.00123		
		(0.00205)		
% White 2017		0.000251		
		(0.00107)		
Distance to Demolition 2018			0.271**	
			(0.124)	
1 = if Building Permit 2018			-0.0708	
			(0.112)	
Median Household Income 2018			0.000000961	
			(0.00000172)	
% Occupied 2018			0.00261	
			(0.00194)	
% White 2018			0.000461	
			(0.00107)	
Distance to Demolition 2019				0.122
				(0.0872)
1 = if Building Permit 2019				-0.493
				(0.513)
Median Household Income 2019				-0.00000139
				(0.00000153)
% Occupied 2019				-0.000366
				(0.00168)
% White 2019				0.000809
				(0.00103)

Table A1. 3 (cont'd)

Constant	- 1.946*** (0.341)	-1.406 (0.978)	-0.912 (0.706)	- 1.579*** (0.504)	- 1.762*** (0.200)	- 0.955*** (0.164)	- 1.261*** (0.187)	-1.423*** (0.180)	-1.369*** (0.142)	-1.360*** (0.143)	-1.198*** (0.124)
Observations	1,650	244	338	848	3,844	6,250	3,805	4,380	6,511	6,107	7,794

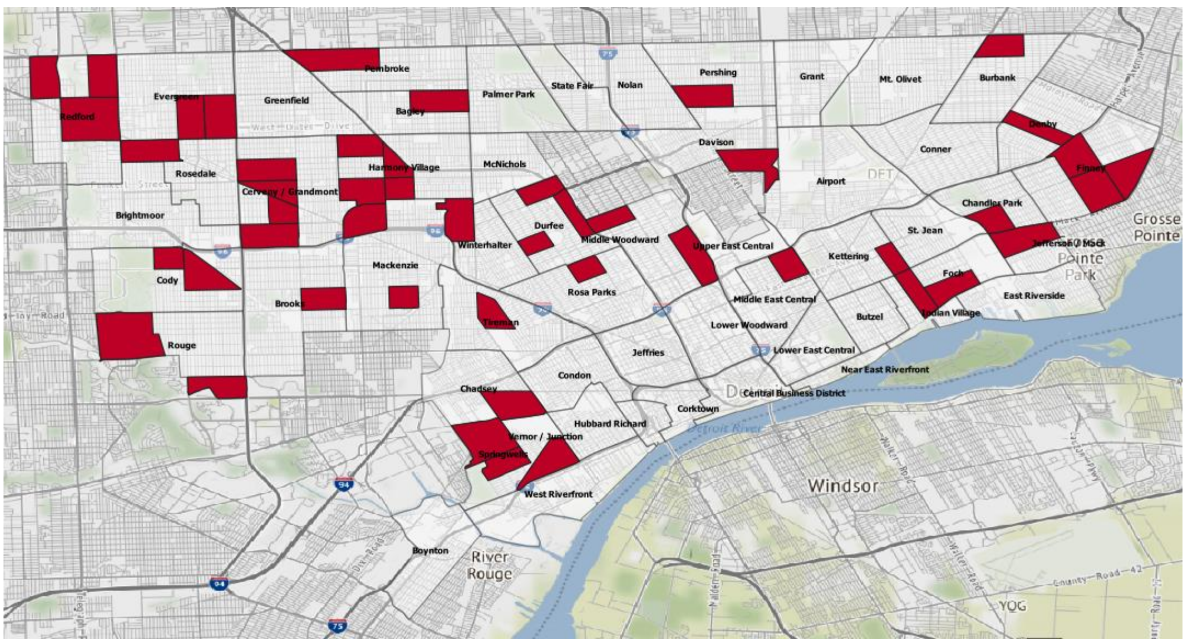
Source: Author's calculations. Note: Table reports probit results from the first stage of the Heckman correction. The dependent variable is I_{it}, which is an indicator variable taking the value of 1 when it is a transaction that falls into the *usable* category (properties sold at least twice in the sample) and it is sold in time t. Note that the sum of the observations in all the years corresponds to 41,771, which is the total number of transactions that appears in Table 1.1.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Figure A1. 1: Census tracts of the properties that belong to the ML category, hence, the ones affected by the Demolition Program



Source: Authors' own calculations. Note: this map highlights the census tracts for properties in the ML category that were affected by the demolition program.

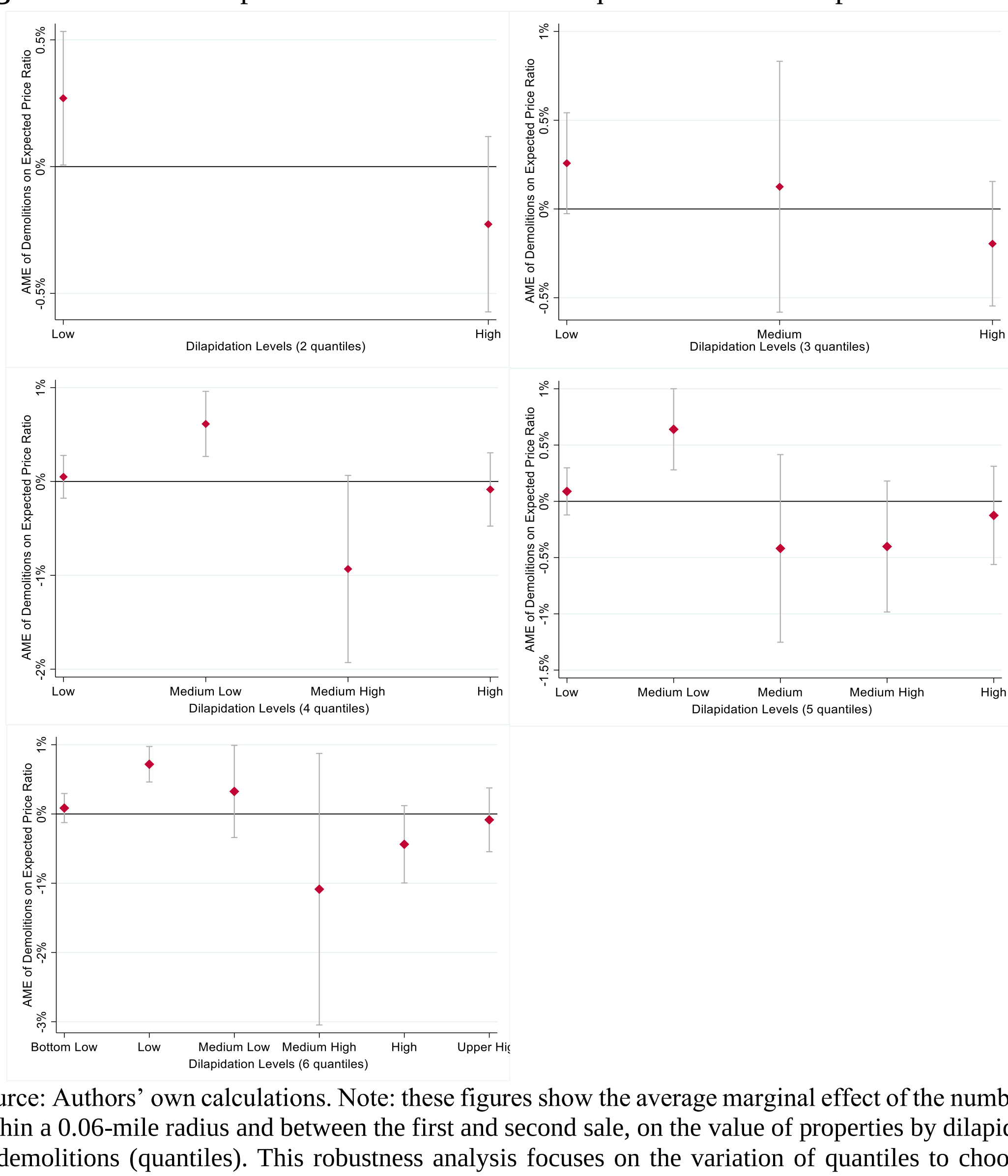
Table A1. 4: The effect of demolitions of blighted properties in nearby property values by program (within a 0.06-mile radius)

	NESHAP		*DDP*		*Both*	
	Second Specification (1)	Third Specification (2)	Second Specification (3)	Third Specification (4)	Second Specification (5)	Third Specification (6)
$(d_{2010} - d_{\widetilde{2010}})$	0.515**	0.595**			0.291	0.300
	(0.228)	(0.232)			(0.201)	(0.199)
$(d_{2011} - d_{\widetilde{2011}})$	-0.0849	-0.0390			0.104	0.0935
	(0.163)	(0.161)			(0.142)	(0.142)
$(d_{2012} - d_{\widetilde{2012}})$	-0.514***	-0.534***			-0.217*	-0.227*
	(0.179)	(0.181)			(0.120)	(0.120)
$(d_{2013} - d_{\widetilde{2013}})$	-0.476***	-0.519***			-0.000931	-0.0165
	(0.179)	(0.185)			(0.101)	(0.101)
$(d_{2014} - d_{\widetilde{2014}})$	-0.584**	-0.649**			0.00864	-0.00724
	(0.283)	(0.291)			(0.0923)	(0.0921)
$(d_{2015} - d_{\widetilde{2015}})$					-0.130	-0.141
					(0.100)	(0.100)
$(d_{2016} - d_{\widetilde{2016}})$			0.415***	0.414***	-0.340***	-0.352***
			(0.0808)	(0.0806)	(0.105)	(0.105)
$(d_{2017} - d_{\widetilde{2017}})$			0.252***	0.253***	-0.241**	-0.246**
			(0.0672)	(0.0673)	(0.105)	(0.105)
$(d_{2018} - d_{\widetilde{2018}})$			0.185***	0.187***	-0.182*	-0.185*
			(0.0553)	(0.0555)	(0.109)	(0.109)
$(d_{2019} - d_{\widetilde{2019}})$					0.0232	0.0212
					(0.105)	(0.105)
$\Delta D_t^{0.06}$	0.00481	-0.0367	-0.00192	-0.0130	0.000190	0.000189
	(0.0245)	(0.0228)	(0.00609)	(0.0243)	(0.000703)	(0.000629)
$\Delta D_t^{0.06} * ML$						
$\Delta D_t^{0.06} * MH$		0.0671***		0.00260		0.00320***
		(0.0256)		(0.0282)		(0.00110)
$\Delta D_t^{0.06} * H$		0.118***		0.0181		-0.00575*
		(0.0325)		(0.0283)		(0.00300)
$\Delta\%MHI_{ijt}$		0.0739		0.0107		-0.000647
		(0.0506)		(0.0251)		(0.00128)
$\Delta\%Occupied_{ijt}$	-0.00798	-0.00755	0.00557*	0.00572**	0.00132	0.00108
	(0.00658)	(0.00668)	(0.00287)	(0.00290)	(0.00157)	(0.00157)
$\lambda_{it} - \lambda_{i\tilde{t}}$	0.0828	0.00356	0.176	0.185	-0.343*	-0.344*
	(0.284)	(0.288)	(0.407)	(0.408)	(0.182)	(0.182)
$Constant$	0.596***	0.618***	0.691***	0.692***	0.337***	0.332***
	(0.162)	(0.164)	(0.0496)	(0.0496)	(0.0518)	(0.0518)
Property Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	321	321	1,441	1,441	3,012	3,012
R^2	0.103	0.121	0.022	0.023	0.031	0.036
Adjusted R^2	0.077	0.087	0.018	0.016	0.026	0.030

Source: Author's calculations. Note: Table reports OLS to repeat sale regression coefficients from six separate regressions. The dependent variable in all regressions is the natural logarithm of the ratio between an observation's first and second sale price. The observations correspond to the transaction pairs (see Table 1.1) for the entire sample case, and only those without building permits between 2010 and 2019 for the subsample case. The key independent variable is $\Delta D_t^{0.06}$, which corresponds to the total number of demolitions between the first and second sale within a

Table A1. 4 (cont'd)
0.06-mile radius. An interaction term is included to account for the context before the demolitions: dilapidation levels in quantiles. NESHAP represents the column of the subsample of properties affected only by the demolitions registered through the NESHAP. DDP is the subsample column for properties only affected by Detroit Demolition Program demolitions. Finally, Both is the column with the properties affected by both types of demolitions. All regressions control for property fixed effects and year effects ($(d_t - d_{\bar{t}})$ variables). Standard errors are clustered at the property level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Figure A1. 2: The impact of different number of quantiles in the dilapidation distribution



Source: Authors' own calculations. Note: these figures show the average marginal effect of the number of demolitions, within a 0.06-mile radius and between the first and second sale, on the value of properties by dilapidation levels prior to demolitions (quantiles). This robustness analysis focuses on the variation of quantiles to choose the number of categories per level of dilapidation. Although the statistical significance varies according to the number of categories of dilapidation, the pattern is clear that in neighborhoods with a lower level of dilapidation, the effect of an additional demolition is positive, while the opposite occurs in neighborhoods with a high level of dilapidation.

ESSAY 2: REVITALIZATION IN SHRINKING CITIES: IMPACT OF THE NEIGHBORHOOD STABILIZATION PROGRAM IN DETROIT

Introduction: Foreclosure Crisis and Detroit's Housing Market

The Great Recession resulted in the most significant collapse in the US housing market since the Great Depression (Wang & Immergluck, 2018a). During this time, property values decreased 31 percent, mortgages with more than 90 delinquent days increased threefold relative to previous record highs, and properties in the early stages of the foreclosure process increased from 0.5 to 1.4 percent nationwide (Joice, 2011). A large number of homeowners suffered the consequences of the crisis, with accumulating unpaid property tax bills and mortgage debts. This problem was especially concentrated in cities experiencing long-term economic decline such as Detroit. The foreclosure rate of the city ranked the second highest among the nation's 100 largest metropolitan areas by the end of 2007, with 1 foreclosed property for every 31 households (RealtyTrac, 2007). According to a report by the Committee on Financial Services from the US House of Representatives, 139,699 of Detroit's 384,672 property foreclosures were the result of mortgage defaults or unpaid taxes, and fifty-six percent of these units became blighted properties in a very short period (Committee on Financial Services, 2019). The accumulation of deteriorated properties plus excess housing supply resulting from long-term declines in employment and population (Alm et al., 2014), exacerbated the complex problem of urban blight in the city.

In an effort to help address the real estate crisis, Congress passed the Housing and Economic Recovery Act (HERA) in July 2008, which allocated funding for emergency assistance to redevelop abandoned and foreclosed homes through the Neighborhood Stabilization Program (NSP). According to a GAO report to Congressional Committees, the key mission of the NSP program was to "'help reduce the number of foreclosed and abandoned properties and restore depressed local housing markets" (pp.2, U.S. General Accountability Office, 2010). This $7 billion program was allocated to grantees in three distinct stages, designated as NSP1, NSP2, and NSP3. Unlike other policies and programs that the federal government offered to alleviate the consequences of the crisis, the NSP is a place-based policy that directly targets the neighborhoods most affected by the crisis. In the case of Detroit, nine neighborhoods were identified as NSP Target Zones. These funds were allocated in five different type of activities: 1) establishing financial assistance for the purchasers of foreclosed properties, 2) rehabilitating residential properties that have been abandoned or foreclosed upon, 3) establishing and managing land banks, 4) demolishing blighted structures, and 5) redeveloping demolished or vacant properties as housing (Spader et al., 2015). Detroit allocated its funds primarily to demolition of blighted structures and rehabilitation.

More than a decade has passed since the NSP policy was put into place in Detroit, with total of nearly $70 million allocated in the geographically selected zones (US Department of Housing and Urban Development Detroit Field, 2016).[28] Hence, it is essential to assess the impact of this policy with regard to its key mission: 1) did the program succeed in decreasing the number of property foreclosures in Detroit?, and 2) did it manage to restore depressed neighborhood housing markets by increasing property values within them? Addressing these questions is the main goal of our research. However, conducting policy impact evaluation such as this poses a challenge in causally identifying the effect of the program, because the target areas are neighborhoods that are different from untargeted neighborhoods due to selection parameters used

[28] As of 2023, the NSP program has formally concluded by the HUD (Neighborhood Stabilization Program | HUD.gov / U.S. Department of Housing and Urban Development (HUD)). However, while federal financial support has ceased, grant recipients, such as the City of Detroit, continue to carry out development activities using the remaining funds. Although this will inevitably come to an end as the funds deplete (US Department of Housing and Urban Development Detroit Field, 2016).

by authorities. Hence, causal identification must control for observable and unobservable variables that make up the neighborhood selection parameters.

In an attempt to mitigate this issue, our empirical evaluation relies on two steps. First, we evaluate the effect of the policy in the neighborhoods where the NSP actions were implemented using a hedonic pricing model in conjunction with a Difference-in-Differences estimator (diff-in-diff). Acknowledging the significant advancements in the diff-in-diff literature in recent years—particularly in modeling and integrating treatment heterogeneity at different points in time—we employ specialized techniques tailored for the context of staggered intervention, such as the NSP program. This process helps us find an overall effect in the city. The second step involves finding a local effect by differentiating between demolitions that were accompanied by rehabilitation projects and demolitions that did not end in real estate development or construction projects on the available land. To execute this step, we construct a counterfactual using Synthetic Control Method (SCM).

Using rich residential property-level information from several sources, our results indicate that the NSP had a stabilizing effect on the housing market in treated neighborhoods, preventing further declines, but did not stimulate pronounced revitalization. In terms of demolitions with NSP-rehabilitation projects versus demolitions without rehabilitation, we found different results across the three study cases. There are some signs of urban renewal in some places, but overall effects are not statistically significant. However, great lessons can be obtained from analyzing each of the cases, to investigate unobservable characteristics that made rehabilitation in some places more successful than in others.

Our contribution is two-fold. First, our research provides useful information for policymakers, in particular for local officials of the City of Detroit. Although the NSP program has concluded, in 2020, Proposal N was passed in a city-wide referendum, which approved $250 million in Neighborhood Improvement Bonds (debt instruments) to continue blight elimination. The proposal was passed, and the demolition program continues in the city (but no longer through the NSP). Therefore, our research will shed light on whether concentrating resources in more devastated areas is more effective than a less concentrated strategy. As the city continues efforts to eliminate blight through demolition, this evaluation informs policy decisions. Second, we aim to evaluate this policy on an aggregate basis, using advanced staggered differences-in-differences techniques that allow us to model the NSO heterogeneity, as well on the possible localized effects from demolitions plus rehabilitation projects, versus only demolitions.

Neighborhood Stabilization Program (NSP): A place-based policy

General Features

By mid-2007, in anticipation of a significant crisis in the financial and real estate sectors, policy measures were put in place to mitigate the impending challenges. In July 2008, the Housing and Economic Recovery Act was enacted, which authorized the first stage of the Neighborhood Stabilization Program (NSP1). This was followed by the implementation of the American Recovery and Reinvestment Act in 2009, which authorized NSP2. Lastly, in 2010, the Dodd-Frank Wall Street Reform and Consumer Protection Act was established, authorizing NSP3 (Immergluck, 2013). The strategy of this federal initiative was to allocate funding to states, local governments, and non-profit organizations for the acquisition and rehabilitation of foreclosed and abandoned properties. The goal was two-fold: first, to curb the rapidly escalating foreclosure crisis, and second, to reverse patterns of devaluation in affected neighborhoods. The United States Department of Housing and Urban Development (HUD) was responsible for the allocation of the program's funds. These funds were distributed across three stages, NSP1, NSP2, and NSP3, allocating \$3.9 billion, \$2 billion, \$1 billion, respectively (Fraser & Oakley, 2015). This multi-stage approach reflected the magnitude and urgency of the challenge, and the determination to fight against the consequences of the financial crisis.

A key aspect of this policy is its placed-based feature. This implies that geographical areas impacted by the foreclosure crisis were the main targets for the allocation of funds. The spatial dimension of the policy aims to identify that certain areas are or have historically been more vulnerable than others but at the same time have the potential to reverse the economic decline. The final outcome is to reduce economic, social, and environmental disparities that arise between places (Fainstein & Markusen, 1993). In the words of Joice (2011), “HUD staff believe that local officials have a tendency to spread community development funding across a town like peanut butter on bread […] In the case of NSP, HUD believed that such a geographically dispersed strategy would be extremely inappropriate. HUD wanted NSP to be used like a defibrillator – a forceful government intervention to brace a neighborhood before its heart stops for good” (p.139, Joice, 2011). Therefore, it is interesting to evaluate this policy emphasizing this spatial dimension, with respect to a counterfactual scenario where resources would have been spread throughout a community in a random spatial allocation.

To allocate the funds in the first round, a two-step identification procedure is used: a statewide and sub-state formula allocation. The statewide formula considers the number and percentage of foreclosures, subprime loans, loans in default or delinquency, and vacancy rates.[29]

---

[29] Specifically, the statewide allocation is calculated with the following formula:

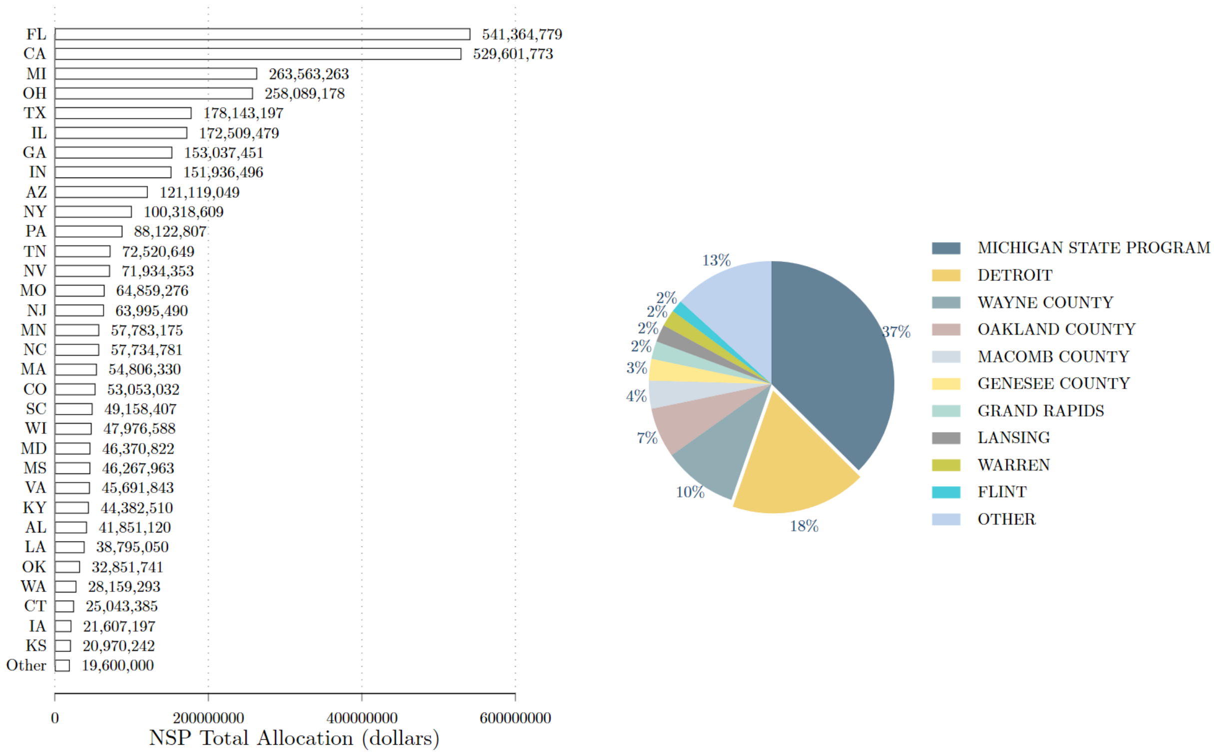
$$
\begin{aligned}
Statewide\ Allocation = {} & Appropriation \\
& * \Bigg[\Bigg(0.7 * \frac{State's\ foreclosure\ starts\ in\ last\ 6\ quarters}{National\ foreclosure\ starts\ in\ last\ 6\ quarters} * \frac{State\ foreclosure\ rate}{National\ foreclosure\ rate} + 0.15 * \frac{State's\ Number\ of\ subprime\ loans}{National\ number\ of\ subprime\ loans} \\
& * \frac{State\ subprime\ rate}{National\ subprime\ rate} + 0.10 * \frac{State's\ number\ of\ loans\ in\ default}{National\ number\ of\ loans\ in\ default} * \frac{State\ default\ rate}{National\ default\ rate} + 0.05 * \frac{State's\ loans\ 60\ to\ 89\ days\ delinquent}{National\ loans\ 60\ to\ 89\ days\ delinquent} \\
& * \frac{State\ 60\ to\ 89\ day\ delinq\ rate}{National\ 60\ to\ 89\ day\ delinq\ rate}\Bigg) * \frac{State\ vacancy\ rate\ in\ Census\ Tracts\ with\ more\ than\ 40\%\ of\ the\ loans\ High-cost}{National\ vacancy\ rate\ in\ Census\ Tracts\ with\ more\ than\ 40\%\ of\ the\ loans\ High-cost}\Bigg]
\end{aligned}
$$

This formula indicates the importance of each item to calculate allocation funds. The most important value is foreclosure status, while the least important is delinquency rates. All of it is weighted by relative vacancy rates.

For sub-state allocations, the funds are divided among Community Development Block Grant (CDBG)-eligible grantees within each state using a similar formula as the statewide allocation. Grantees used information from private sources as well as local data provided by HUD to identify NSP target zones (United States Department of Housing and Urban Development (HUD), 2008). NSP1 and NSP3 use a similar methodology for the allocation process. However, NSP2 deviates from the other two stages as funds are provided through a competitive application process rather than a formula-based methodology (Spader et al., 2015). This discrepancy led to grantees who received funds during the first stage not being selected for the subsequent second stage under similar economic conditions, as exemplified by Detroit. Since the competitive application process was employed, other variables, such as prior experience managing federal funds and administrative capacity, played more significant roles in the selection process (Immergluck, 2013).

Figure 2.1 displays the allocation of funds of both the state level and within the state of Michigan. This figure indicates that HUD identified Michigan as the third most in need of NSP funds, surpassed only Florida and California. This implies that in 2008, Michigan experienced the highest rates of foreclosure properties, sub-prime loan, default rate, tax delinquency rate, and vacancy rate among the great majority of states. In the first round, HUD awarded nearly $264 million to Michigan. Additionally, within the state of Michigan, Detroit received the largest share of funds (excluding the Michigan State Program, which represents resources for managing policy at the state level, rather than a specific location) (Figure 2.1, right side). Detroit and Wayne County, where Detroit is situated, jointly obtained 28% of the state's NSP funds. This information highlights the severity of the urban blight issue and the foreclosure crisis in Michigan, particularly in Detroit.

Figure 2. 1: Allocation of NSP funds at the state level and within the state of Michigan



Source: Authors' calculations using information from the United States Department of Housing and Urban Development (HUD). Note: bar chart on the left presents the distribution of the NSP funds from the first round by state. The "Other" category does not imply that the remaining states collectively received $19.6 million, but that each remaining state received that amount, which is the minimum NSP fund that HUD established for each state. A pie chart showing the distribution of NSP funds within the state of Michigan is presented in the figure to the right.

Once the areas in greatest need were identified, a decision had to be made on the use of the funds. Across the nation, the funds could be used in five different activities according to the needs of each community. Eligible activities are 1) establishing financial assistance for the purchasers of foreclosed properties, 2) rehabilitating residential properties that have been abandoned or foreclosed upon, 3) establishing and managing land banks, 4) demolishing blighted structures, and 5) redeveloping demolished or vacant properties as housing (Spader et al., 2015). A key fact is that each local government chose the weight given to each activity. Therefore, the emphasis on certain activities or the final combination depended on the assessment of local governments.

NSP in Detroit

In describing the NSP program, the city's website indicated that, in 2008, Detroit was a city in crisis, grappling with challenges such as a shrinking population scattered across a large land mass, an oversupply of housing, a dwindling tax base, aging housing stock, and outdated infrastructure.[30] Consequently, the city received about $47 million in NSP1 and almost $22 million in NSP3 funds (US Department of Housing and Urban Development Detroit Field, 2016). Local officials quickly prioritized areas of greatest need to receive these funds, guided by the goal of stabilizing neighborhoods heavily impacted by the foreclosure crisis.

Figure 2.2 illustrates the NSP target zones in Detroit, classified by round type, as well as the administrative boundaries within the city based on the 2000 Census block groups. These boundaries are particularly significant as they guided the city with the selection of target areas and serve as the unit of analysis for our research, providing the empirical definition of a "neighborhood".[31] In NSP1, nine neighborhoods were selected based on five factors (see Table 2.1), a similar process was employed for NSP3. Part of these criteria draws from HUD's general guidelines and data, including the designation of low, moderate, and middle-income (LMMH) areas, zones with high foreclosure rates, and areas with a high percentage of homes financed by a subprime mortgage related loan. The remaining criteria align with citywide policies from the Master Plan, ensuring coherence with the city's broader development objectives (Planning and Development Department, 2009). This is an important point in our research, because even though we lack data pertaining to the Master Plan policies and their application, we have extensive HUD-

---

[30] See https://detroitmi.gov/departments/housing-and-revitalization-department/hud-programs-and-information/neighborhood-stabilization-program.

[31] This is evidenced in the detailed maps with information regarding the selection variables that the city makes available to the public. See: https://detroitmi.gov/departments/housing-and-revitalization-department/hud-programs-and-information/neighborhood-stabilization-program/nsp-maps.

provided data at the census block group level. This information is instrumental in understanding the selection process for target zones, and it strengthens our identification strategy by comparing census block groups that were initially similar in selection characteristics, presenting a robust method for assessing the impact of the NSP. A detailed discussion of this approach will be presented in the methodology section.

Figure 2. 2: NSP Target Zones in Detroit

Source: Authors' calculations. Note: "NSP1" refers to the Neighborhood Stabilization Program (NSP) first round, and "NSP3" correspond to third round.

Table 2. 1: Criteria for Defining NSP Target Zones in the City of Detroit

Criteria	*Description*
1) Low/Moderate/Middle Income Area	Properties benefiting from NSP must be in low, moderate, and middle-income (LMMH) areas, where over 51% of people have incomes less than 120% of the Area Median Income (calculated at the census block level).

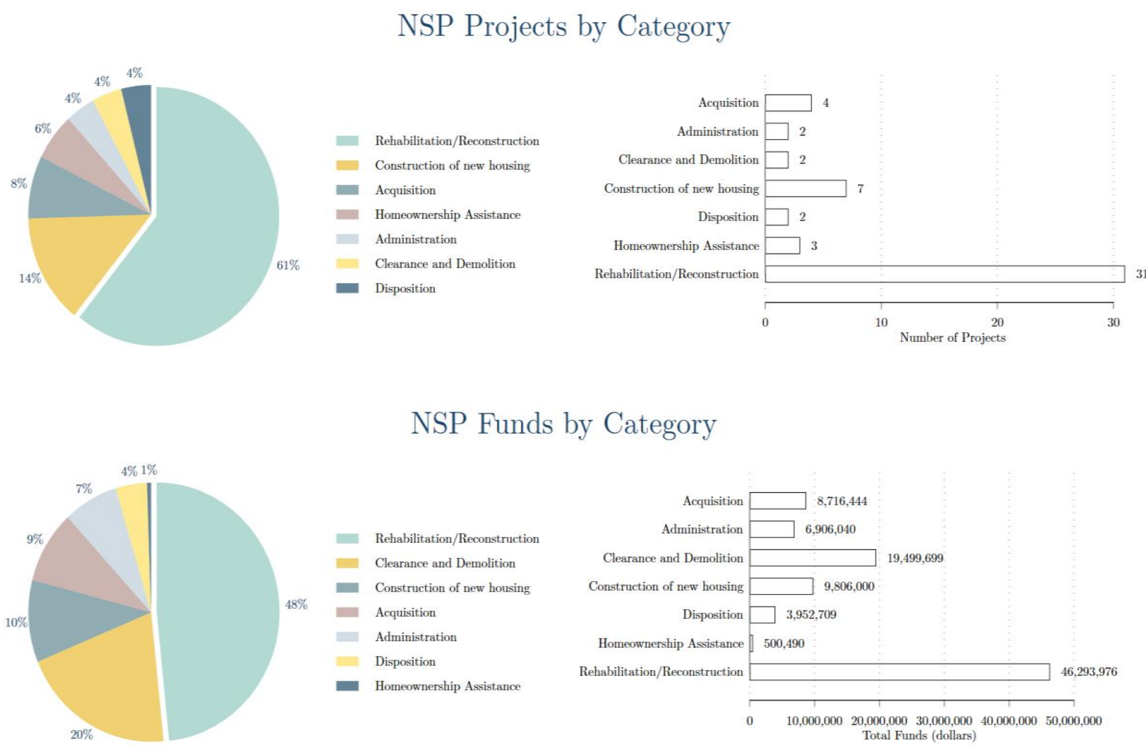
Table 2. 1 (cont'd)

2) NSP HUD Data	Properties that benefit from NSP must be in areas with: • Highest percentage of foreclosures. • Highest percentage of homes financed by a subprime mortgage relates to loan. • Identified as likely to face a significant rise in the rate of home foreclosures. This information is available from HUD at the census block and census tract levels.
3) Foreclosure Data	Properties benefiting from NSP must have high rates of mortgage foreclosures in 2006 and 2007. This information was adjusted by the city.
4) Local Target Areas	In addition to HUD information, local officials also prioritized areas with: 1. High private sector investment (measured by building permit activity). 2. Allocation of Block Grant activity. 3. Urban renewal activity. 4. Prior local designation (such as Next Detroit Neighborhood Initiative). 5. Federally designated Empowerment Zone and Renewal Community activity. 6. Identified by the Master Plan od=f Policies of the city. 7. Investment by certain foundations.
5) City Wide Policies	Benefited areas had to be congruent with certain citywide policies from the Master Plan.

Source: Authors' own elaboration based on information from the report "Neighborhood Stabilization Plan" by the Planning and Development Department of the City of Detroit (Planning and Development Department, 2009). Note: for specific information regarding the specific policies related to the Master Plan that were used to select the NSP target zones, see page 14 of the report.

The figure reveals that, to date, the majority of NSP projects are associated with the rehabilitation or reconstruction of selected properties in the target zones, with 31 projects in this category. Each of these projects involve multiple properties that benefit from the process. The construction of new housing is in second place, with 7 projects. In terms of funding distribution, 48% is allocated to the rehabilitation or reconstruction category, and 20% to clearance and demolitions. This indicates that approximately $46 million has been designated to return these properties to productive and social use. Despite the high number of rehabilitation projects, demolition ranks second in terms of dollars spent. This can be explained by the externalization of demolition through the Detroit Land Bank or other private contractors. Unfortunately, we do not have specific information on the number of demolitions funded by NSP; we only have data on the total number of demolitions within the city.

Figure 2. 3: NSP number of projects and NSP funds by category of activity in Detroit



Source: Authors' calculations based on the individual quarterly NSP performance reports provided by the City of Detroit.

Previous Work

The central premise of NSP implementation is that foreclosure properties contribute to negative externalities within neighborhoods (Spader et al., 2015). These externalities manifest as urban blight, caused by the accumulation of vacant, abandoned, and dilapidated properties, which in turn impacts surrounding properties through various causal pathways. The causal mechanisms include: 1) the visual aspect of decay, creating a perception, among buyers and sellers, of an abandoned neighborhood and thereby decreasing neighboring property values; 2) the consequential increase in the supply of properties due to foreclosures and subsequent vacancy, leading to an overall decline in market prices (Schuetz, 2015); 3) a negative perception of neighborhood safety as the number of foreclosed, abandoned, and deteriorated properties grows, which impacts the social infrastructure that can prevent criminal activity (broken window hypothesis) (Spader et al., 2016); and 4) a reduction in property tax revenues caused by lower assessed values, which subsequently impacts the provision of public goods and services for the neighborhood, further lowering property values and perpetuating the vicious cycle (Johnson, 2008).

Empirical evidence supports all the aforementioned hypotheses. Studies have identified decrease in property values (Lee (2008), Harding et al. (2009), Campbell et al. (2011), Anenberg & Kung (2014), Hartley (2014), Gerardi et al. (2015), Zhang & Leonard (2014)), increase in crime rates (Spelman (1993), Ellen et al., (2013), Kondo et al., (2018), Stacy (2018) and Larson et al., (2019)), and health implications for local residents (Leon & Schilling (2017), Wang & Immergluck (2018b), Pearson et al. (2019)), as consequences of foreclosures. Therefore, NSP policymakers aim to mitigate the adverse effects of foreclosed properties and revitalize the neighborhoods most severely affected during the crisis through demolitions, clearance, construction of new housing, and rehabilitation and redevelopment of foreclosed, abandoned, or blighted structures. However, a key challenge lies in the gap between the first hypothesis of the policy - that foreclosures generate negative externalities - and the second one - elimination of these externalities will be positively capitalized in neighbors, such as improved property values or reduced crime rates. The effectiveness of the policy relies on a multitude of factors identified in previous studies, and it is crucial to recognize that the mere eradication of foreclosure-related negative externalities does not automatically guarantee a corresponding positive impact of equal magnitude in the surrounding properties (Alvayay Torrejón et al., 2023).

This question is reflected in the mixed evidence regarding the performance of the NSP. Table 2.2 summarizes three studies that are closely related to ours in methodological terms. Schuetz et al. (2016) conducted an evaluation of the NSP2 program at the census tract level for 28 grantees across various counties. To assess the program's success in neighborhood recovery, they proposed using regression analysis for three different outcome variables, employing a dummy variable for treated and control census tracts, and controlling for idiosyncratic attributes using baseline information. The study focused solely on NSP2 information, and although Detroit was not included in this round, Wayne County did receive funds from NSP2.

An initial examination of Wayne County suggests that the NSP program had no effect on any of the three outcome variables (growth rate in annual property sales volume, growth rate in vacant properties, and growth rate in distressed properties). The results for other counties were mixed; for example, Cuyahoga County exhibited consistently positive effects on the growth rate in sales volume, while Miami showed negative and statistically significant results. The growth rate of vacant properties decreased for Cuyahoga and Cook counties but remained unchanged for the others. Furthermore, there is evidence of an increase in distressed properties in Cuyahoga and Maricopa counties. The authors attribute the inconsistent results to factors such as the small scale of NSP activity within tracts, the omitted variable problem arising from unobservable information related to each grantee's unique policy implementation, and the possibility that the study was conducted too early to detect a significant impact (Schuetz et al., 2016).

Table 2. 2: Studies on the impact of NSP on different Outcomes

Study	Outcome Variable	Unit of Analysis	Period	Location	Results	NSP Round
Schuetz, Spader, & Cortes (2016)	_Growth rate in annual sales volume. _Growth rate in vacant properties. _Growth rate in distressed properties.	Census Tract	2009-2013	IL, Cuyahoga OH, Los Angeles CA, Maricopa AZ, Miami-Dade FL, Philadelphia PA, and Wayne MI (counties)	No significant results for Wayne County.	NSP2
Spader, Schuetz, and Cortes (2016)	Number of crimes	Property	March 2008 – February 2013	Cleveland, Chicago, and Denver	NSP demolitions in Cleveland: reduction of 0.08 (0.027 standard error) property crimes per quarter. No significant effect from NSP activity in Chicago or Denver.	NSP1 and NSP2
Bak & Hewings, (2017)	log(sale price)	Property	2008-2014	Chicago	Homes with at least one NSP project within 0.1 mile increased by 14.3% (mean 0.134, standard error 0.061)	NSP1, NSP2, NSP3 (rehabilitations only)

Source: Authors' own elaboration.

The following two studies are designed at the property level, using a common approach to create geographically close counterfactuals. They construct two rings (buffers) of different radios around a property, with the inner ring serving as the treatment zone and the outer ring as the control zone. This method aims to ensure that unobservable characteristics within the treatment and control zones are as similar as possible. Spader et al. (2016) investigate the impact of NSP on crime in Cleveland, Chicago, and Denver, and they find that NSP demolitions within 0.05 miles in Cleveland led to a reduction of 0.08 property crimes per quarter. However, they found no statistically significant results for Chicago or Denver. Conversely, Bak & Hewings (2017) discover that average sale prices within 0.1 miles of NSP projects in Chicago increased by 14.3%, which implies an average capitalization of $12,016 in property values for treated properties. Thus, in Chicago, positive effects on property prices were observed, but there was no evidence of an effect on crime.

We now proceed to identify critical insights from previous studies that must be accounted for in our evaluation of the NSP policy. The mentioned studies differ in two main aspects, aside from the variation in key outcome variables. First, Bak & Hewings (2017) consider all three rounds of NSP and use a longer time frame to estimate the effect. Time is a critical factor when evaluating such policies, as urban revitalization processes may take years to materialize (Galster et al. (2006), Schuetz (2015)). Second, Bak & Hewings (2017) focus on the effects of NSP projects that resulted in property rehabilitation, whereas Spader et al. (2016)'s analysis also includes demolitions. Rehabilitation, which aims to restore a property to productive use (Collins & Shester, 2013), is observed to have a positive impact on neighboring property values (Leonard et al., (2017), Ganduri & Maturana, (2021)). On the other hand, the impact of demolition on neighborhood dynamics is more ambiguous. For example, research on the Detroit Demolition Program provides an interesting contrast. According to Alvayay Torrejón et al. (2023), the program, which was applied nearly citywide, shows no overall positive impact on property prices. Only when accounting for ex-ante blight heterogeneity, the study found that in areas with less initial blight, demolitions did yield a positive effect on property values. However, using the same information on demolitions, Alvayay Torrejón et al. (2020) found positive short-term effects on tax compliance in surrounding properties. Given that the Detroit Demolition Program is not a place-based initiative like the NSP, the outcomes of these different types of interventions, even when applied in same urban contexts, might diverge. Therefore, it is important to recognize the different activities of the NSP program, and their expected effects.

In line with this idea, even though the NSP activities were the same across grantees, the emphasis on each activity varied significantly across urban contexts. As Spader et al. (2016) notes, the heterogeneous nature of NSP treatment across grantees complicates the estimation of an average treatment effect for the policy. The flexibility afforded to grantees in selecting activities most relevant to their needs, coupled with the unique local conditions (such as housing market conditions, declining economic markets, expertise, and resources), makes comparisons across areas challenging. However, this also presents an opportunity for research within the same counties or cities to individually assess how these differences impact the final outcomes (Schuetz et al., 2016). Moving forward, an increased understanding of the distribution of NSP effects in various contexts will provide urban economists with valuable insights for policy design and implementation. Cases of success should not be the only source of evidence, since instances where the policy had less impact than expected also offer crucial lessons. In this way, we can continue to refine our understanding of urban renewal and revitalization.

Finally, central to our study is the recognition of the staggered implementation of the NSP policy across different rounds. No study we have encountered thus far has explicitly considered this temporal variation, which significantly affected the selection and potential impact of targeted neighborhoods. NSP1 selected areas were largely influenced by the pressing time constraints set by HUD, as noted by Immergluck (2013). Immergluck (2013) identified several challenges with the policy's design and implementation, one of which was the short 18-month timeline to obligate NSP funds. This tight deadline proved overly ambitious for the execution of complex local redevelopment programs. As a result, many NSP1 recipients were forced to rush their decisions, often committing a large proportion of their grant funds in the last few months of the obligation period. Consequently, the selection process became more about meeting deadlines than effectively identifying and intervening in areas that could benefit most from the NSP. Due to this rushed process, the first-round beneficiaries were substantially different from those of the third round. The staggered nature of NSP, therefore, presents a key consideration for understanding its impacts.

Hence, in this research we contribute to the existing literature in four ways. First, we extend the time frame of the policy analysis, which helps us understand the long-term impacts of the NSP. Second, we provide an evaluation of the NSP's overall impact, and specific effects of rehabilitation projects. This two-fold approach acknowledges the nature of NSP activity heterogeneity. Third, we focus on the unique context of Detroit, a city grappling with economic decline and a shrinking housing market. This provides insights into how such policies play out in cities with similar challenges and offers potential lessons for urban renewal efforts in comparable contexts. Finally, we use advanced difference-in-differences estimators in staggered settings, allowing us to effectively explore and exploit the staggered nature of the NSP intervention.

Identification Strategy

First Step: NSP Overall Effect

Traditional Two-Way Fixed Effects (TWFE)

In this section we provide the econometric strategy to identify the effect of the overall effect of NSP policy on different outcomes. We define Y_{bt} as the dependent variable in census block groups b for year t. We evaluate the effects of the policy on three key variables: 1) the average residential property sale price, 2) the number of foreclosure properties, and 3) the foreclosure rate, variables identified by census block group b for year t. Census blocks group are categorized in control group (never treated), NSP1 zones (first treated in 2009), and NSP3 zones (first treated in

2011). The effect of the NSP policy on a set of outcomes is initially examined using the conventional two-way fixed effects (TWFE) OLS estimator, as shown in equation (1).

$$Y_{bt} = \alpha + \beta^{DD} NSP_{bt} + \boldsymbol{X'_{bt}\theta} + \sigma_b + \tau_t + \epsilon_{bt} \tag{1}$$

In this equation, NSP_{bt} is a binary treatment variable that takes the value of 1 if a census block implements NSP activities in year t, and 0 otherwise. Additionally, the variation in our dependent variables are a function of time-variant control variables related to average structural characteristics of housing in each census block by time (X_{bt}), census block group fixed effects (α_b), year fixed effect (μ_t), and a random error term component that follows the classical assumptions (ϵ_{ct}). When estimating, we cluster the errors at the census block level to adjust for serial correlation and heteroscedasticity. The estimated coefficient, $\widehat{\beta^{DD}}$, allows us to examine whether the census blocks treated by the NSP, present higher property sales prices, fewer foreclosed properties, and lower foreclosure rates, on average. This could suggest a hypothetical scenario where the policy had a beneficial effect on treated NSP census blocks, reversing their decline patterns even more than those of untreated blocks. However, another scenario where the policy might be effective is when there are no differences in key outcome variables between treated and control census blocks over time, implying that, on average, treated census blocks did not deteriorate further after policy implementation.

Due to potential bias that may exist when using TWFE in the setting when the treatment effect is heterogenous across time (Callaway & Sant'Anna (2021), de Chaisemartin & D'Haultfœuille (2020), Goodman-Bacon (2021), Roth et al. (2023)), we proceed to test the NSP policy under more robust estimators. The existence of temporal treatment heterogeneity potentially jeopardizes the consistency of the TWFE estimator, especially since it is recognized in the literature that the selection of block groups in the first round was very different from the third round. In the first round, local governments did not have much time to meticulously assess those places that were going to be selected. On the other hand, in the third round, greater importance was given to the fact that the selected places were effectively capable of reversing their patterns of economic decline.

Nonlinear Staggered Difference-in-Differences – Wooldridge (2002) Estimator

Recent advances in the field of difference-in-difference estimators allow us to account for the staggered nature of the policy. However, it is important to remember that these estimators only provide useful results under the assumption that the mean function is linear. This can complicate matters when we transform the dependent variable—for instance, using logarithms for positive variables could disrupt the parallel trend assumption in the case of the original variable (Wooldridge, 2022). Because of these potential distortions and given the nature of the outcome variables we use, the estimator proposed by Wooldridge (2022). This estimator allows for a non-linear mean function within the context of difference-in-difference in staggered settings. Specifically, we assume an exponential mean function to model outcome variables that follows $Y_{bt} \geq 0$.

In terms of potential outcome notation, $Y_t(g)$ is the potential outcome at time t, and g indicates the first time subjected to the intervention. Notice that in our case, $g \in \{2009, 2011, \infty\}$ and $t \in \{2006, 2007, \dots, 2019\}$. $g = \infty$ indicates potential outcome in the never treated state. A key fact is that, in any post-intervention period, census block groups treated initially at time 2009 will have been exposed to the intervention longer than the census block treated in 2011. This is an important fact for a policy evaluation because it implies a longer exposure to treatment. We are interested in estimating the Average Treatment Effect on the Treated (ATT), which is defined in equation (2).

$$ATT_{gr} = E\left[Y_r(g) - Y_r(\infty)\middle|D_g = 1\right] \quad for\, r = g, \dots, T; g = q, \dots, T \tag{2}$$

Hence, ATT_{gr} it is the expected value of the difference between the outcome in year r for the cohort treated in year g, $Y_r(g)$, and the outcome in year r if the same cohort would never have been treated, $Y_r(\infty)$, given that the cohort did received treatment ($D_g = 1$). Since we can only observe one of the states of the world, the main idea is to construct a counterfactual using baseline (pre-treatment) information from the outcome of the treated group and the average change in the control group. This is a key difference with respect to the traditional TWFE: we open theβ^{DD} in equation (1) to include high degree of heterogeneity in the effect of the policy that models the staggered application. In the words of Wooldridge (2022), "there is nothing inherently wrong with two-way fixed effects estimation: One simply needs to apply the method to a suitably flexible equation" (pp.4 Wooldridge, 2022). To estimate the ATT, we assume an exponential mean function (equation (3)).

$$E(Y_{bt}|X) = exp\left[\alpha + \beta_g + \gamma_t + \sum_{g=2009}^{G=\{2009,2011\}} \sum_{t=2006}^{T=2019} \lambda_{gt}\, Tr_c \cdot 1[NSPyear_g \ = g] \cdot 1[year_t \ = t]\right] \tag{3}$$

Where $NSPyear_g$ indicates the first treatment year for cohort g, $year_t$ is the calendar year, Tr_c is an indicator for being treated currently or in the future, and if the block is never treated. Specifically:

$$Tr_c = \begin{cases} = 1\ if\ year_t \geq {}_{NSPyear_g}\ and\ {}_{NSPyear_g} > 0 \\ \quad = 1\ if\ never \neq 1 \\ \quad\quad = 0\ otherwise \end{cases} \tag{4}$$

The coefficient λ_{gt} captures the treatment effect. We estimate the parameters of the mean function in (1) and use them to construct the counterfactual outcomes under no treatment (imputation). First, we construct the output in the state of the world without treatment (equation (5)).

$$\widehat{Y_{ct}(\infty)} = exp\left[\hat{\alpha} + \hat{\beta}_g + \hat{\gamma}_t\right] \tag{5}$$

Then we calculate the output for the treated units and for each cohort and time (equation (6)).

$$\widehat{Y_{ct}(g)} = exp\left[\hat{\alpha} + \hat{\beta}_g + \hat{\gamma}_t + \sum_{g=2009}^{G=\{2009,2011\}} \sum_{t=2006}^{T=2019} \hat{\lambda}_{gt}\right] \tag{6}$$

Then the estimated ATT is calculated for each observation as follows:

$$\widehat{ATT_{ct}} = \widehat{Y_{ct}(g)} - \widehat{Y_{ct}(\infty)} \tag{7}$$

Interestingly, the control group can change depending on the units we use for comparison. Just as Callaway & Sant'Anna (2021) estimator, we consider two control groups: 1) Never-treated census blocks and 2) Not-yet treated census blocks. In the case of the not-yet treated block groups we modify the definition of Tr_c in equation for as follows.

$$ETr_c = \begin{cases} = 1\ if\ year_t \geq {\scriptstyle NSPyear_g}\ \wedge\ {\scriptstyle NSPyear_g} > 0 \\ \quad = 0\ otherwise \end{cases} \tag{8}$$

This is the key difference between the two control groups. $Tr_c = 1$ is identifying as treated the block groups that have been treated or that will be treated in the future, leaving out the block groups that will be never treated. Hence, $Tr_c = 0$, the control group, will be the census blocks that will be never treated by the NSP program. Instead, $ETr_c = 1$ is identifying as treated if the current year is greater than or equal to the year in which treatment was received, and the census block did received treatment at some point. Hence, $ETr_c = 0$, the control group, will be the census blocks that both were never treated and that are not-yet treated. Notice that defining both control sets as $\Psi_{never} = \{c \mid Tr_c = 0\}$ and $\Psi_{notyet} = \{c \mid ETr_c = 0\}$, it implies that $\Psi_{never} \subset \Psi_{notyet}$.

Note that the chosen control group for counterfactual construction may affect the outcome of the study. Selecting the most suitable group for a given context is an empirical task. However, in the results section, we illustrate results using both control groups. What factors may cause these estimates to vary? The "never-treated" group only includes block groups that will never experience the intervention. This could lead to the exclusion of blocks that more closely resemble the treated areas. On the other hand, the "not-yet treated" group includes both types of blocks: those that will never be treated and those that will be treated in the future. By including both, this control group might have a higher chance of containing blocks that align more closely with the pre-treatment trends of the treated blocks. However, due to the previously mentioned implementation issues, this may not necessarily be the case in this context.

Overall Estimated ATT (averaging across all treated units)

To summarize the estimated ATT across units, we calculate the following aggregate indicators. First, we calculate the overall estimated ATT, which is interpreted as the effect of the

NSP policy on the outcome variable, in the intervened census blocks. We treat t as fixed, and we calculate the aggregate estimated ATT as follows.

$$\widehat{ATT} = \frac{1}{N_{tr}} \sum_{c=1}^{N_{tr}} \widehat{ATT_c} \tag{9}$$

Where N_{tr} correspond to the sample where $year_t \geq NSPyear_g \wedge NSPyear_g > 0$. Notice that even though we use the same N_{tr} for both control groups, the individual $\widehat{ATT_c}$ are calculated different based on the control group we choose, as explained before.

Estimated ATT by cohort g.

We disaggregate the $\widehat{ATT}$ by cohort treated and calculate averages as follows.

$$\widehat{ATT_g} = \frac{1}{N_g} \sum_{c=1}^{N_g} \widehat{ATT_c} \quad for\ g = \{2009, 2011\} \tag{10}$$

Where N_g correspond to the sample for each cohort. N_{2009} are the census blocks treated in 2009 and N_{2011} are the census blocks treated in 2011.

Estimated ATT by years relative to treatment (Event Study)

Additionally, we calculate the estimated $\widehat{ATT}$ in a given relative year (the time relative to when the event occurred (the event being the treatment)). In this case, the relative time is calculated as follows.

$$relative_t = year_t - NSPyear_g \quad for\ NSPyear_g > 0 \tag{11}$$

Hence,

$$relative_t \in \{-5, -4, \dots, 0, \dots, 10\} \tag{12}$$

We can define $N_{relative_t}$ that corresponds to the sample for each relative time value. For example, N_{-5} is the sample of census tracts treated in 2011 but in the year 2006. Hence, we calculate the estimated ATT event study coefficients by disaggregating by relative time sample groups.

$$\widehat{ATT_{relative_t}} = \frac{1}{N_{relative_t}} \sum_{c=1}^{N_{relative_t}} \widehat{ATT_c} \quad for\ relative_t = \{-5, -4, \dots, 0, \dots, 10\} \tag{13}$$

In the case of the not-yet treated control group, since it is formed by never treated plus the not-yet treated, the relative time in this case only starts when the treatment begins. Hence $relative_t \in \{0, \dots, 10\}$. Additionally, same as before, we define $N_{relative_t}$ that corresponds to the sample for each relative time period. Hence, we calculate the estimated ATT event study coefficients by disaggregating by relative time sample groups.

$$\widehat{ATT_{relative_t}} = \frac{1}{N_{relative_t}} \sum_{c=1}^{N_{relative_t}} \widehat{ATT_c} \quad for\ relative_t = \{0, \dots, 10\} \tag{14}$$

As per Wooldridge (2022), with random sampling across c (and treating T as fixed), we apply the delta method to obtain standard errors of $\widehat{ATT}$ and the other estimates (clustered at the census block group level).

Importantly, ATT_{gr} can be identified under two assumptions: 1) Conditional No Anticipation, staggered (CNAS) and 2) Conditional Independence Parallel Trends, Staggered (CIPTS) (Wooldridge, 2022). The CNAS assumption requires that prior to treatment, block groups did not anticipate and react to their future treatment assignment. While we cannot directly test this assumption empirically, the rapid timeline of the NSP program selection makes anticipation unlikely for the first round of treatments in 2009. However, some anticipation may have occurred for the second round in 2011. We examine changes in pre-treatment demographic characteristics between rounds to assess this possibility.

The CIPTS assumption states that in the absence of treatment, outcomes in the treated and control census blocks would have followed parallel trends over time. This assumption is central for difference-in-differences designs but may be violated in our setting because declining neighborhoods were specifically targeted for NSP. To strengthen the plausibility of parallel trends, we construct a refined control group of census blocks based on a selection of a subsample. Event study plots will provide more information regarding the CIPTS assumption.

Propensity Score and Subsample Creation

The key motivation behind creating a subsample is to generate a more specific control group that more closely resembles the treatment group prior to the intervention. This adjustment strengthens the assumptions needed for a difference-in-differences analysis, particularly the parallel trends assumption.

Certain neighborhoods in Detroit were chosen for the NSP treatment because of their long-standing economic decline. However, some stable neighborhoods were also included in the program. If we compare the treated neighborhoods with all untreated neighborhoods, the control group would include many areas in better economic condition. These areas might not have followed the same trajectory as the declining neighborhoods if they had not received treatment, thereby violating the parallel trends assumption. In this environment subsampling is useful in that allows us to narrow the control group to include only those neighborhoods similar to the treated ones. Several steps were executed to create the subsample.

Steps for the Creation of the Subsample

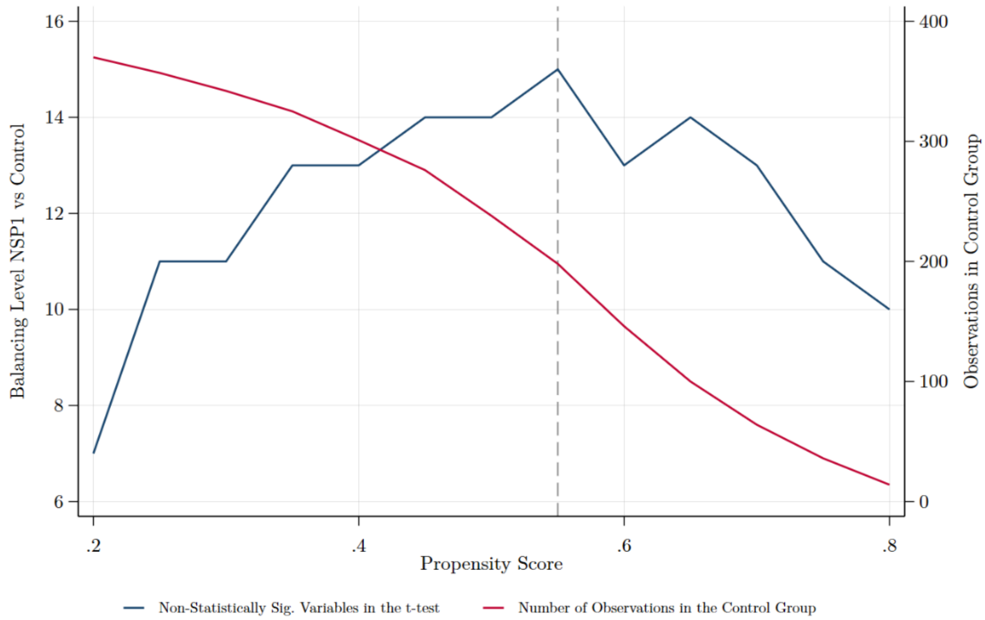
1. The first step is to select pre-treatment variables related to NSP selection criteria. For our analysis, we choose 15 variables available in the pre-treatment period. Notice that we include specific information from the HUD that Detroit local officials use to select the target zones. Other variables include demographics, housing conditions, income, dilapidated houses, among others (see Table A2.2 in the Appendix, "Time-invariant variables (Propensity Score)" panel for a description of all the variables used in this part of the analysis.
2. Next, we estimate propensity score models separately for each treatment group. In our case, NSP1 and NSP3 targeted different types of neighborhoods, so it's important to create separate models for each. This means, two samples are used to calculate the propensity scores: 1) NSP1 vs the block groups never treated, without the NSP3 blocks groups, and 2) NSP3 vs the block groups never treated, without the NSP1 blocks groups. These samples are used to predict treatment status based on our 15 selected variables (see Table A2.1 in the Appendix for the results of the logistic regressions).
3. We calculate propensity scores. Notice that these scores represent the likelihood of a neighborhood being selected for treatment. Importantly, after calculating the scores we modify the scores such that treated census blocks automatically receive a score of 1, while untreated blocks receive scores ranging from 0 to 1 based on their predicted likelihood of receiving treatment.
4. The next step involves segmenting the control groups based on propensity score thresholds. By incrementally raising the threshold, we can progressively refine our control group and test the mean differences between controls and treated neighborhoods on all 15 variables.

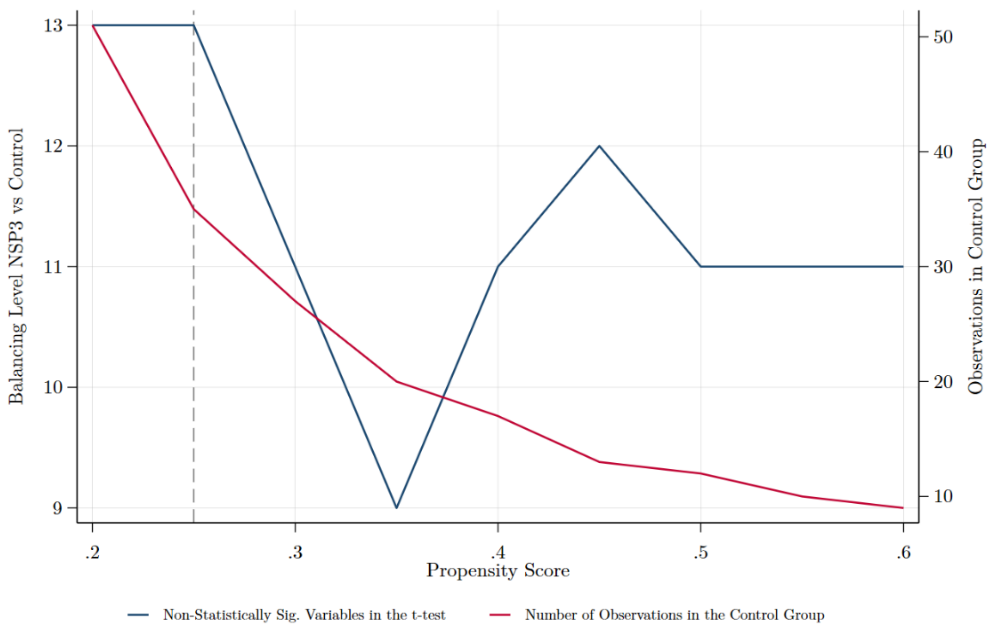
Through this process, we track the sample size and the balance of our groups (see Figure 2.4 that shows the results of these iterations).

5. The penultimate step is choosing the optimal threshold. We aim to select a threshold that strikes a balance between maximizing pre-treatment balance and retaining a reasonable sample size for the control group. Based on the observation of Figure 2.4, we have concluded that this balance is achieved at the level of the propensity score of 0.55 for the case of the NSP1 group, and the level of propensity score of 0.25 for the case of the NSP3 (vertical lines in both graphs).
6. The final step is to apply these thresholds to create our final subsample. This refines the control group for each treatment wave, increasing the similarity with the treated groups in terms of pre-treatment characteristics. Through this approach, we manage to find a balance between improving the internal validity of our study with a more comparable control group, and the potential trade-off in external validity that comes from narrowing the sample. Our final subsamples exhibit substantially better balance in pre-treatment characteristics when compared to the full control groups. Table 2.3 and Table 2.4 provide evidence of this balance through a mean t-test in the ex-ante policy covariates.

A final comment regarding this procedure is that the subsample will be composed of all block groups treated NSP1 and NSP3, and control block groups selected for both types of treatment. While we expect that there will be an overlap between the selected controls, we also expect that certain controls may only have been selected based on the unique characteristics of the treatment cohort. This is evidenced in the Venn Diagram of Figure 2.5. Finally, comment that the selected pool of controls (N=215) will be used in the regression to build the counterfactuals.

Figure 2. 4: Choice of subsample: tradeoff between balancing the groups and the number of observations





Source: Authors' calculations. Note: The chart shows our methodology for selecting a cut-off point in the propensity score to generate a subsample. This subsample allows us to compare the treatment group NSP1 (first chart) and group NSP3 (second chart), with a control group highly similar in pre-treatment characteristics, specifically regarding the selection criteria. Each point plotted on the graph corresponds to a distinct iteration, with the sample varying based on the specific propensity score utilized. For instance, a point marked 0.2 on the x-axis indicates a subsample where the propensity score equals or surpasses 0.2. The blue line on the graph illustrates the outcome of a mean test conducted between the treatment group and the control group, using all variables employed in the logit. After calculating the mean test, we incorporate all variables that exhibit no significant average difference (p-value>0.05) between the control and treatment groups. These non-significant variables serve as indicators of the balance between the two

Figure 2. 4 (cont'd)

groups before the implementation of the policy. With a total of 15 variables used, the maximum number of non-significant variables attainable is 15. The greater the number of statistically non-significant variables in the difference in mean test, the greater the pre-treatment similarity between the two groups. One crucial consideration is the trade-off between achieving a balanced sample and losing the number of observations. While the treatment group size remains constant, the control group size varies. As the red line in the chart indicates, an increase in balance results in a decrease in the number of comparative observations in the control group. The cut-off point for choosing the control group from the census blocks first treated (NSP1) is a propensity score of 0.55. The cut-off point for choosing the control group of the census blocks treated after (NSP1=3) is a propensity score of 0.25 (vertical lines in both graphs).

Table 2. 3: Comparison of Control and NSP1 Treated Census Blocks before and after Subsample Selection

	Entire Sample				Subsample			
Variables	*Control*	*Treated*	*Diff*	*p-value*	*Control*	*Treated*	*Diff*	*p-value*
Population 2009	3266.69	3205.46	-61.22	0.3888	3121.50	3205.46	83.96	0.2714
Loan Rate	66.80	71.45	4.65	0.0000	71.21	71.45	0.24	0.7962
Predicted Foreclosures	15.89	16.67	0.77	0.0000	16.65	16.67	0.01	0.9462
USPS Vacancy	16.49	19.18	2.69	0.0000	18.12	19.18	1.06	0.0589
Distance to CBD	6.91	7.15	0.24	0.2000	7.21	7.15	-0.06	0.7715
Percentage Residential Zoning Area	54.24	56.02	1.77	0.1257	55.78	56.02	0.23	0.8484
If Contains Dilapidated Houses 2009	0.92	0.97	0.05	0.0004	0.97	0.97	0.00	0.9314
Total Houses in 2009	1423.31	1364.87	-58.44	0.0168	1355.86	1364.87	9.02	0.7391
MHI 2009	30162.40	29734.88	-427.52	0.4349	30094.06	29734.88	-359.17	0.5463
Percentage White 2009	13.34	11.39	-1.96	0.0323	9.99	11.39	1.40	0.1368
Percentage Black 2009	79.25	84.01	4.76	0.0007	85.99	84.01	-1.98	0.1299
If Contains Demolitions 2009	0.08	0.16	0.08	0.0004	0.09	0.16	0.06	0.0143
If Middle Low Area	0.93	0.97	0.04	0.0030	0.98	0.97	-0.01	0.4407
Risk Score	9.83	9.89	0.06	0.3244	9.91	9.89	-0.02	0.7871
Percentage under 120	79.69	82.38	2.69	0.0117	82.39	82.38	-0.01	0.9947
Observations	**399**	**599**			**276**	**599**		

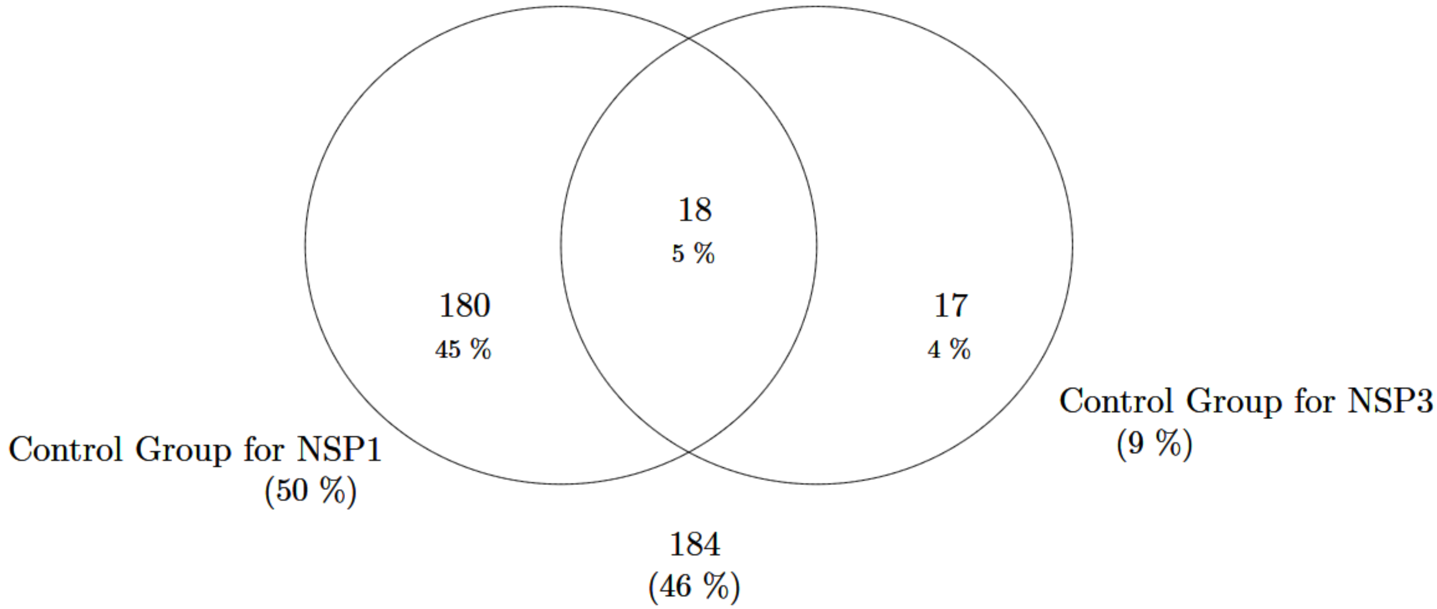
Source: Authors' calculations. Note: The table presents the results of the *t*-test (mean comparison), comparing the control group with the group treated first (NSP1) in two different samples. Sample A includes the total sample without the census blocks treated later (NSP3), while Sample B represents the subsample obtained after selecting controls with a propensity score greater than 0.55 (also without the NSP3 census blocks). The variables used for comparison are the same as those employed in the logit model to calculate the propensity score. These socioeconomic variables characterize the census blocks prior to the implementation of the NSP intervention.

Table 2. 4: Comparison of Control and NSP3 Treated Census Blocks before and after Subsample Selection

	Entire Sample (A)				Subsample (B)			
Variables	*Control*	*Treated*	*Diff*	*p-value*	*Control*	*Treated*	*Diff*	*p-value*
Population 2009	3266.69	3183.72	-82.97	0.5486	2980.91	3183.72	202.81	0.3459
Loan Rate	66.80	59.98	-6.81	0.0013	51.01	59.98	8.98	0.0044
Predicted Foreclosures	15.89	14.72	-1.17	0.0014	13.17	14.72	1.55	0.0043
USPS Vacancy	16.49	13.63	-2.86	0.0024	11.25	13.63	2.39	0.0644
Distance to CBD	6.91	7.39	0.48	0.2387	6.56	7.39	0.84	0.2552
Percentage Residential Zoning Area	54.24	53.46	-0.79	0.7709	44.86	53.46	8.59	0.1028
If Contains Dilapidated Houses 2009	0.92	0.94	0.02	0.5423	0.91	0.94	0.03	0.6117
Total Houses in 2009	1423.31	1404.54	-18.77	0.6707	1358.79	1404.54	45.75	0.4530
MHI 2009	30162.40	39235.14	9072.74	0.0000	44199.11	39235.14	-4963.97	0.1377
Percentage White 2009	13.34	17.26	3.91	0.0655	22.68	17.26	-5.43	0.1473
Percentage Black 2009	79.25	76.21	-3.05	0.3861	69.47	76.21	6.74	0.2347
If Contains Demolitions 2009	0.08	0.09	0.01	0.8232	0.14	0.09	-0.05	0.4002
If Middle Low Area	0.93	0.84	-0.10	0.0063	0.74	0.84	0.10	0.2507
Risk Score	9.83	9.88	0.05	0.6884	9.86	9.88	0.03	0.8856
Percentage under 120	79.69	69.44	-10.25	0.0001	63.48	69.44	5.96	0.2388
Observations	399	68			35	68		

Source: Authors' calculations. Note: The table presents the results of the *t*-test (mean comparison), comparing the control group with the group treated later (NSP3) in two different samples. Sample A includes the total sample without the census blocks treated first (NSP1), while Sample B represents the subsample obtained after selecting controls with a propensity score greater than 0.25 (also without the NSP1 census blocks). The variables used for comparison are the same as those employed in the logit model to calculate the propensity score. These socioeconomic variables characterize the census blocks prior to the implementation of the NSP intervention.

Figure 2. 5: Venn diagram to compare the set of controls selected for NSP1 and the set selected for NSP3



Source: Authors' calculations. Note: This Venn diagram illustrates the comparison between the sets of controls selected for NSP1 and NSP3. The initial sample of controls (N=399) was reduced by applying a propensity score cutoff, resulting in a selected set of controls (N=215). Among these controls, 198 were chosen for the census blocks treated first (NSP1), while 35 controls were chosen for the census blocks treated later (NSP3). Notice that 18 census blocks correspond to controls selected for both NSP1 and NSP3, indicating an overlap in the chosen controls for these treatment groups.

Second Step: NSP Localized Effects

Synthetic Control Method (SCM)

Initially, local governments designed this policy based on available data, using the most disaggregated administrative divisions such as census block groups or census tracts, to define a geographic area as a neighborhood. However, the spatial effects of urban policies are not subject to these geographical limits, and can have spillover effects that either diminish or amplify over varying spatial scales and directions, making the initial geographical definitions less accurate in capturing the real impact (Clapp & Wang, 2006). Therefore, a second stage of this NSP analysis consists of looking at localized effects, comparing NSP specific actions carried out within the target zones: demolitions with rehabilitation and demolitions without rehabilitation.

Our strategy to identify these localized effects is twofold. First, we reconceptualize the definition of a neighborhood, moving away from the census block groups boundaries. Instead, we introduce a buffer approach, wherein the neighborhood is determined by the proximate geographical space surrounding a property, a similar approach used in Bak & Hewings (2017). Nevertheless, our strategy diverges from theirs in its second characteristic. Conventional urban economics research typically employs the buffer method, by designating a direct surrounding area (or buffer) around a property as the treated zone, while demarcating a larger, non-overlapping outer buffer as the control zone. While this methodology holds intuitive appeal, it poses a potential pitfall. The very proximity of the control zone to the treated zone, meant to enhance comparability, could blur the lines between the two. Specifically, if the effects of the treatment inadvertently extend to the control zone, distinguishing genuine impacts becomes challenging.[32]

[32] This is known as a violation of the Stable Unit Treatment Value Assumption (SUTVA) (Holland, 1986).

To address the issue of potential spillover effects, we adopt a straightforward approach: we compare demolitions that incorporate a neighborhood rehabilitation component with demolitions without rehabilitation. We choose demolitions from different parts of the city to make this comparison. It is important to note that in this setting, the parallel trends assumption is not guaranteed. Comparing demolitions from distant areas means we are potentially dealing with neighborhoods that have different inherent traits and trajectories. Given this challenge, for the rehabilitation projects, we employ a Synthetic Control Method (SCM) (Abadie et al. (2010), Klößner et al. (2018), Abadie (2021)). SCM constructs a unique counterfactual for each project, drawing from data on other demolitions. To clarify, for each demolition with rehabilitation project, we are simulating a scenario where a demolition that culminated in rehabilitation instead resulted in undeveloped land.

Our treated units consist of demolitions that took place between 2009 and 2019 and were accompanied by urban rehabilitation under the NSP policy. From the geolocated data, we identified 331 rehabilitation or reconstruction undertakings backed by NSP funds. Crossing these data with the demolition records from the same timeframe, 6 out of these 331 projects involved demolitions. Additionally, half of these demolitions, i.e., 3 projects, were executed recently in 2019.[33] Furthermore, for each treated demolition, we construct a synthetic control using a donor pool of demolitions without rehabilitations. This donor pool comprises demolitions that: 1) occurred in the same year as the treated unit, 2) are situated more than 0.1 miles from a demolition/rehab project and a separate rehabilitation project, 3) have the same funding source, 4) currently do not have any building constructed on them (empty land)[34], and 5) are part of a cluster of demolitions, defined

[33] This fact reinforces our choice of using SCM since other causal inference methods relies heavily on a sizable cohort of treated units.

[34] We used publicly available information from current building footprints in Detroit and cross-referenced it with geolocated information from demolitions. Therefore, we chose only those that did not currently have a

as being in the top 25% in the distribution of demolitions within 0.1 miles occurring in the years prior to the demolition itself.[35]

We analyze the impact of the NSP rehabilitation on three primary outcomes: 1) the average sale price within a 0.1-mile radius from the demolition site, spanning from 2006 to 2019, 2) the number of foreclosure properties within a 0.1-mile radius from the demolition site, from 2006 to 2019, and 3) the number of issued building permits within a 0.1-mile radius from the demolition site, observed from 2010 to 2019. This last variable could indicate whether these rehabilitation projects generate incentives for private investment in land development and construction projects. Additionally, we use as control variables several pre-intervention characteristics. Specifically, for years leading up to the intervention, we include total population, number of houses, Median Household Income (MHI), racial composition (percentages of white and black populations), and the percentage of occupied properties. All these characteristics are sourced from the census block group where the demolition occurred.

The effect is calculated as follows. Let $n = 1, 2, \ldots, N$ be all the demolitions in our data. Without loss of generality, we assume that the first unit ($n = 1$) is the treated unit, that is, the demolition intervened by the NSP policy through the rehabilitation project. The donor pool, $n = 2, \ldots, N + 1$ is the set of all the untreated demolitions. In terms of potential outcome notation, our objective is to estimate the average treatment effect on the treated (ATT) defined as equation (15) (Abadie, 2021).

$$\tau_{1t} = Y_{1t}^{1} - Y_{1t}^{0} \quad (15)$$

construction. For a small sample we verified that this was the case by inspecting the latitude and longitude on Google Map.

[35] We realized that rehabilitation projects follow cluster patterns. For example, the three projects that include demolition and rehabilitation cover an entire block of houses.

Where Y_{1t}^{1} is the outcome of the treated unit in time t, and Y_{1t}^{0} denotes the hypothetical outcome the treated unit would have exhibited at time t had it not undergone any treatment (in this case, rehabilitation). SCM constructs this counterfactual by solving an optimization problem where the objective is to minimize the mean squared prediction error between the treated unit and the synthetic control for the pre-intervention period. The result are optimal weights to construct a synthetic control made of different parts of the control units that most resemble the treated unit based on pre-treatment information (as shown in equation 16).

$$\hat{Y}_{1t}^{0} = \sum_{n=2}^{N+1} \omega_n Y_{nt} \tag{16}$$

Hence, the estimated effect corresponds to $\hat{\tau}_{1t} = Y_{1t}^{1} - \hat{Y}_{1t}^{0}$. Statistical inference is achieved by using placebo tests (Hahn & Shi, 2017). Instead of applying the treatment to the actual treated unit, the treatment is "falsely" applied to each of the control units, one at a time. For each of these "placebo treatments", a synthetic control is constructed, and the post-intervention gap (or treatment effect) is calculated as if that control unit was the treated unit. By iterating this action for each control unit, we build a distribution of treatment effects under the null hypothesis that the treatment has no effect. The actual treatment effect of the truly treated unit is then compared to this distribution. If the actual effect is notably larger (in absolute value) than the bulk of the placebo effects, it suggests that the treatment had a significant effect.

We hypothesize that rehabilitation positively impacts areas where properties have been demolished due to abandonment and urban decay. Consequently, in the immediate vicinity of such rehabilitated neighborhoods (within a radius of 0.1 miles), we anticipate observing increased property sale prices, a reduction in foreclosures, and possibly a surge in private investment, as evidenced by a rise in building permits issued nearby.

Data

Data Sources

The observation unit in this analysis is census block groups. There are 1,066 block groups in Detroit, based on the 2000 census map. The analysis time is from 2006 to 2019, with the NSP policy starting in 2009, generating a panel of 14,924 observations. Table A2.2 in the Appendix describes all the variables used in the analysis, the span of time available, the geographic level and the source.

The sale price represents the average sale value of residential properties within a specific census block in a given year, calculated using property sales data with geographical coordinates. The foreclosure count is the number of foreclosures within a census block each year, which is calculated through foreclosure data with geographic coordinates. Foreclosure rate represents the number of foreclosures divided by the number of houses per census block. The data for these dependent variables come from ZTRAX (Zillow, 2020) and Data Driven Detroit.[36]

Furthermore, key independent variables are derived from GIS calculations and data from the City of Detroit. Time-variant control variables include the mean age of properties sold, the mean lot size, the average number of stories, the average number of full bathrooms, and the average garage area of properties sold per census block per year. To construct the propensity scores, we include variables such as predicted foreclosures, USPS vacancy, the eligibility of an area for Low-Moderate-Middle-Income area benefit, risk score, and the percentage of persons estimated to earn less than 120 percent of the median income (HUD data). Other geographic variables such as the

[36] We are grateful to the City of Detroit for making high-quality data publicly available to conduct these analyses. For more information visit the following webpage: https://portal.datadrivendetroit.org/.

distance to the Central Business District (CBD) and the percentage of residential zoning area were also included. The data for these variables were generated from GIS calculations, and other sources like the Detroit Residential Survey from 2009.

For extended analysis, time-variant variables such as population, total houses, median household income, and percentage of white and African American people per census tract were taken into account. These variables are only available from years from 2009 to 2019 and were primarily sourced from the American Community Survey (ACS) - IPUMS NHGIS (Manson et al., 2023), and Logan et al. (2014). Having these variables implied an extra interpolation effort because the policy is based on 2000 geographic administrative limits, and the information was based on 2010 census geography.

Data Description: NSP Overall Effect

Note that the block groups treated first are very different from those that were treated later. Figure 2.6 provides a visual comparison of the three key housing market outcome variables (sales prices, foreclosures, and foreclosure rates) over time across the treatment and control groups. The graphs in Figure 2.6 show that prior to treatment in 2009 and 2011, the trends in these outcomes were relatively similar between treated block groups and those never treated. However, the trajectories diverge in the post-treatment period. What is interesting is that the trajectories are contradictory between both treatment groups versus the control group. In the case of the NSP1 census blocks, the sale prices of the properties have always remained below those never dealt with. The exact opposite occurs in the case of NSP3 block groups.

Table 2.5 provides a set of summary statistics. The mean sale price of residential properties is $28,791, across all units and years, and has substantial variance. We contrast these data with those of other studies in different geographic locations. For instance, in the study by Bak &

Hewings (2017), where NSP policy has a positive effect in the City of Chicago, the mean sale price was $171,885. Additionally, in the study by Schuetz et al. (2016), where there was a positive effect in Cook County, Illinois, the mean sale price was $98,478. Compared to these figures, the mean sale price in Detroit appears significantly lower, suggesting the unique challenges and dynamics within Detroit's housing market.

Furthermore, Table 2.5 indicates that the average number of foreclosures per year for these blocks is approximately 10, with a foreclosure rate of 0.86%. This figure shows a significant variability, with certain blocks experiencing a foreclosure rate of up to 21%. Almost half of the census blocks within the sample, as represented by a 0.48 mean, were benefits of the NSP intervention. Among the houses sold, it is evident that the average residential building was relatively old, constructed around 1950, and modest in size, at approximately 1,200 square feet.

Table 2. 5: Summary Statistics

Variable	Observations	Mean	Std. dev.	Min	Max
Sale Price ($)	13,973	28791.06	48364.57	200.0	844333.3
Foreclosures	14,924	9.91	12.30	0	185.0
Foreclosure Rate	14,924	0.86	1.21	0	21.4
NSP	14,924	0.48	0.50	0	1.0
NSP1	14,924	0.56	0.50	0	1.0
NSP3	14,924	0.06	0.24	0	1.0
Age	13,966	78.54	15.15	0	137.0
Lot Size SqFt.	13,942	5609.26	5280.30	1742.4	44431.2
Number of Stories	13,902	2.92	1.20	1	7.0
Number of Full Baths	13,973	1.20	0.39	1	5.3
Garage Area SqFt	13,973	205.79	107.20	0	1693.3

Source: Authors' calculations.

Figure 2. 6: Key Dependent Variables Over Time: A comparison across first-treated (NSP1), later-treated (NSP3), and never-treated (non-NSP) blocks

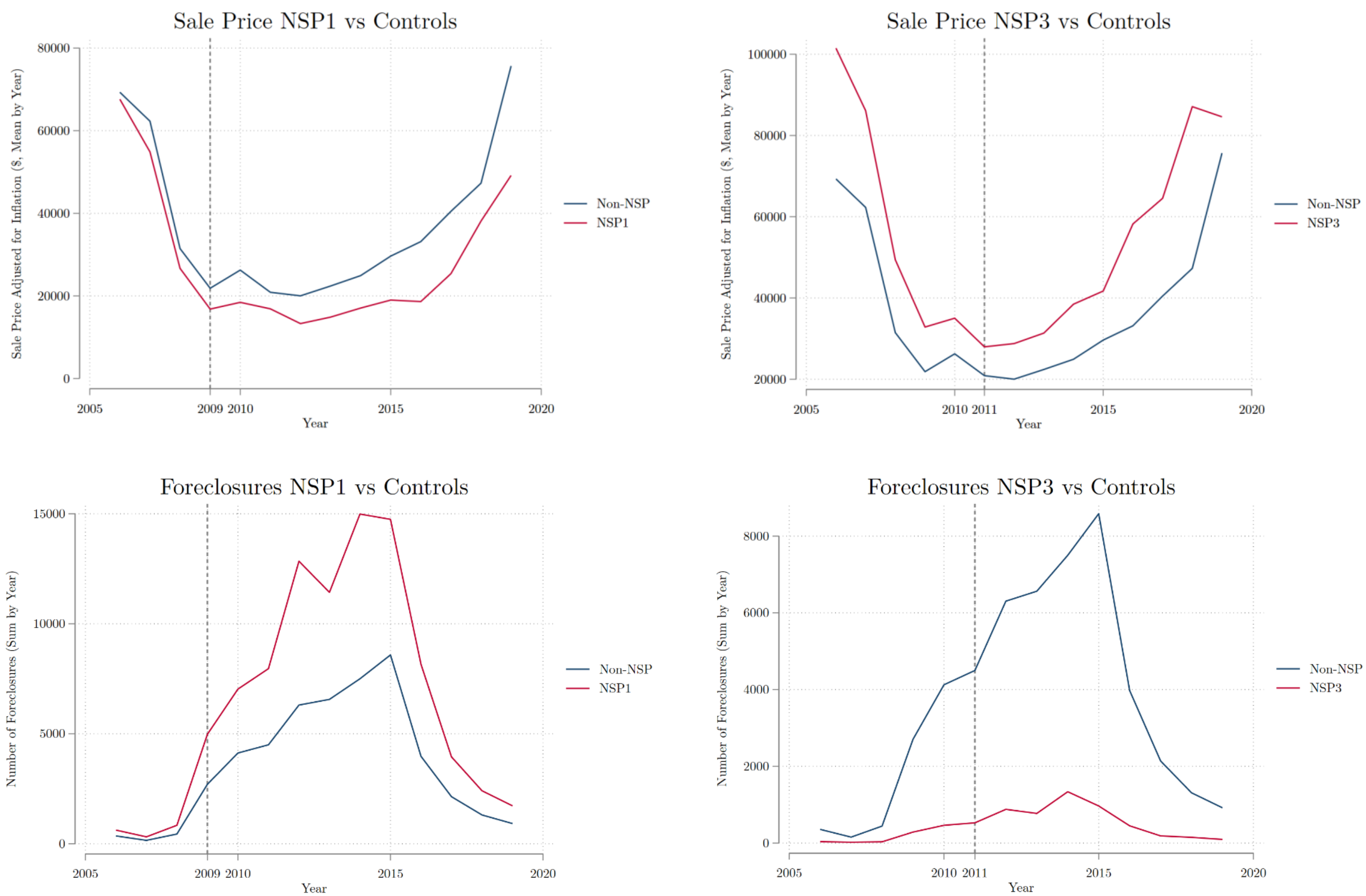
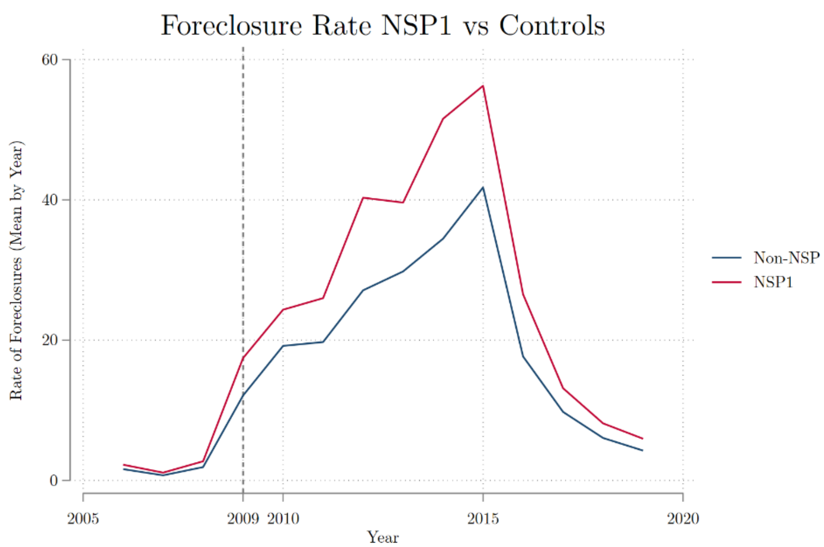
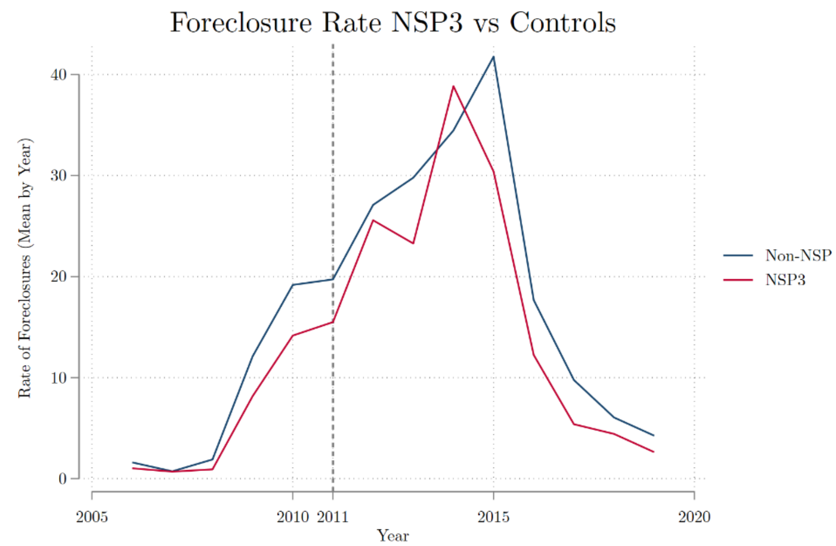


Figure 2. 6 (cont'd)





Source: Authors' calculations. Note: The figure presents a comparative visualization of our dependent variables over time, segmented by treatment groups. Each line graph represents trend trajectories for census blocks that received treatment in 2009 (NSP1), those treated in 2011 (NSP3), and census blocks that never received treatment (controls), represented by red and blue lines respectively. The top row of graphs provides a comparative overview of the average residential property sales prices for each group, on a year-by-year basis. The middle row offers a parallel comparison of the total number of property foreclosures annually for each group. The bottom row displays the comparative evolution of the average foreclosure rate annually for each group. Sale prices have been adjusted for inflation to reflect 2006 price levels using the S&P/Case-Shiller MI-Detroit Home Price Index (https://fred.stlouisfed.org/series/DEXRSA). The index is set to a base of 100 for the year 2006. To adjust for inflation, the nominal sale price of each year is multiplied by the ratio of the base year index value (100) to the index value of that year. This calculation provides the sale price in constant dollars, allowing for a comparison of property values over time without the confounding effects of general price level changes.

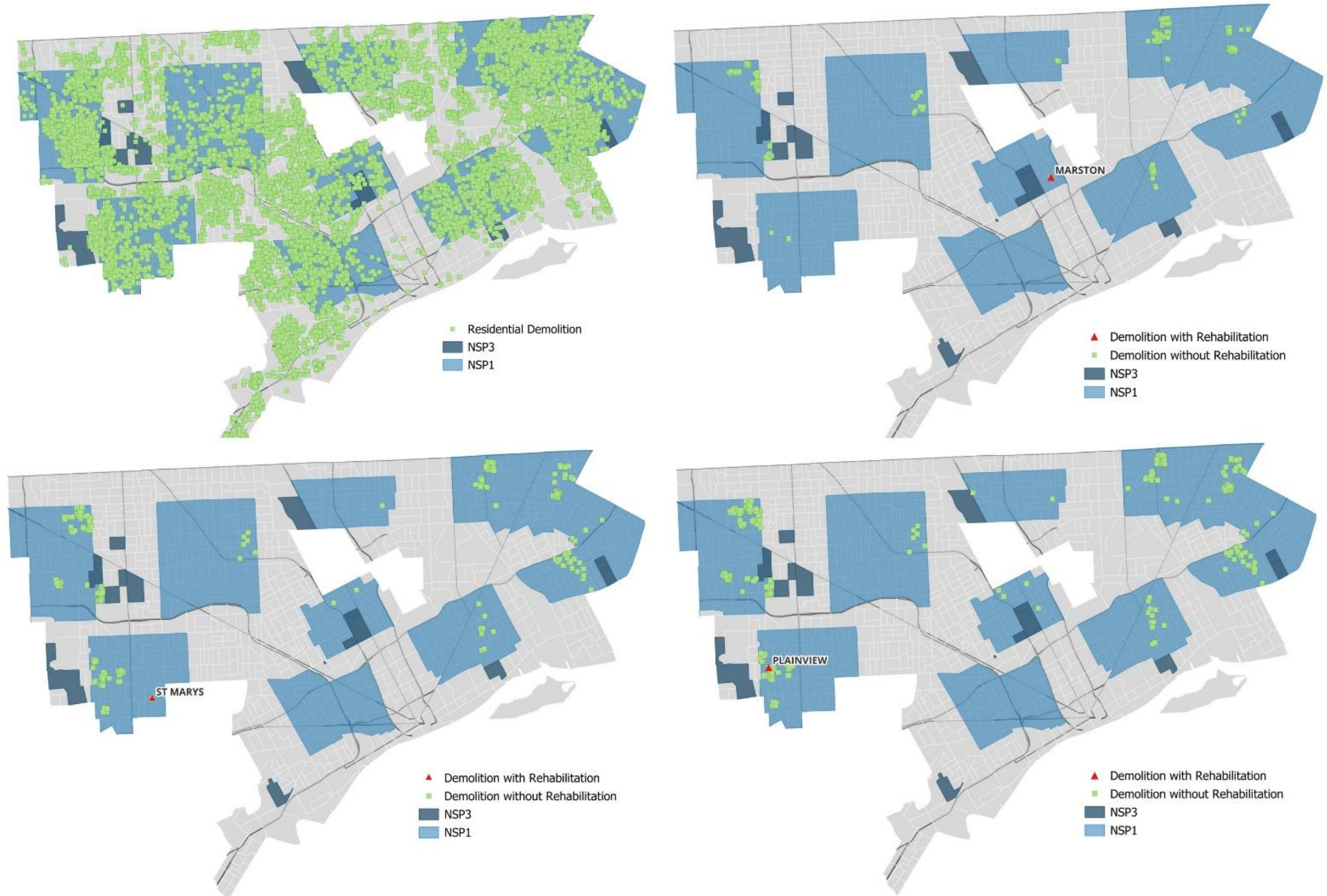
Data Description: NSP Localized Effects

Figure 2.7 depicts the specific NSP-funded demolitions followed by rehabilitation projects. These three projects are located in Marston, St. Marys, and Plainview streets in Detroit. They serve as our treated units for the Synthetic Control Method (SCM) analysis. Additionally, we identified corresponding donor pools for each of these locations (see Figure 2.8). These pools are comprised of demolitions without subsequent NSP rehabilitation but match certain criteria discussed in the previous section, ensuring a more reliable counterfactual for our treated sites. Furthermore, Table 2.6 offers summary statistics of the outcome variables in the vicinity of the three projects and describes the behavior of the outcome variable for the donor pool of demolitions for each project (control group). These represent characteristics in ex-ante treatment. By comparing each treated demolition with its respective donor pool, we illustrate the potential variations across the neighborhoods surrounding these units. The objective with the SCM is to minimize these differences to construct an accurate counterfactual.

Figure 2. 7: Location of the Demolition with NSP Rehabilitation Projects in Detroit

Source: Authors' calculations. Note: This visualization highlights three key rehabilitation projects in Detroit that followed demolitions, serving as our treated units for the Synthetic Control Method analysis. Each zoomed-in section displays a specific street, emphasizing that the rehabilitation extends across the entire block.

Figure 2. 8: Location of Demolitions with NSP Rehabilitation Projects, and Demolitions without Rehabilitation, in Detroit



Source: Authors' calculations. Note: The maps provide a comprehensive view of demolitions and associated rehabilitation projects under the NSP policy between 2009 and 2019. Top left shows the overview of all demolitions in the city, which constituted the group of potential controls. Top right shows "Marston", a representative demolition followed by NSP rehabilitation, with the surrounding donor pool of demolitions without rehabilitation. Bottom left shows "St Marys", a similar NSP-backed rehabilitation post-demolition, alongside its corresponding donor pool. Bottom Right shows "Plainview", the third project showcasing NSP-induced rehabilitation after demolition, and the respective donor pool. Each donor pool consists of demolitions that meet stringent criteria to ensure comparability, including the timing of demolition, distance from rehab projects, funding source, current land status, and being part of a significant demolition cluster in the area (more details in the Identification Strategy section).

Table 2. 6: Pre-Treatment Characteristics of NSP-Funded Demolitions with Rehabilitation vs. Their Respective Donor Pools

	Demolition with Rehab **Marston**	Demolition without Rehab **Marston's donor pool**	Demolition with Rehab **St. Marys**	Demolition without Rehab **St. Marys's donor pool**	Demolition with Rehab **Plainview**	Demolition without Rehab **Plainview's donor pool**
Demolition Year	2014	2014	2015	2015	2015	2015
Average Sale Price within 0.1 miles	$16,426	$18,963	$19,410	$18,258	$18,145	$18,130
Standard Deviation	$9,172	$24,255	$18,488	$22,370	$24,558	$22,149
Number of Demolitions (N)	1	263	1	192	1	299
Number of Foreclosures within 0.1 miles	3.13	6.83	3.78	6.82	5.11	6.850615
Standard Deviation	2.95	7.43	4.12	7.00	7.13	6.98
Number of Building Permits within 0.1 miles	0.63	1.77	1.89	0.82	0.89	0.82
Standard Deviation	0.75	1.36	3.22	1.41	1.45	1.45
Number of Demolitions (N)	1	457	1	406	1	659.00

Source: Authors' calculations. Note: This table contrasts the characteristics of specific demolitions that underwent subsequent NSP rehabilitation with those of their respective donor pools (demolitions without rehabilitation). Each demolition with rehabilitation ("Marston", "St. Marys", and "Plainview") is paired with its donor pool, comprising demolitions that align with specific criteria to ensure robustness in the Synthetic Control Method analysis. Metrics include the demolition year, average sale price within 0.1 miles, number of foreclosures within 0.1 miles, and the number of building permits issued within the same radius. Standard deviations for each group. Note that the number of demolitions composing the pool of donor for the synthetic control method changes according to the outcome variable we are using. In the case of sale prices, the sample size is smaller due to balance in the panel structure of data to perform the SCM.

Results

Overall Effect of NSP on Residential Property Sale Prices

Table 2.7 provides estimates of the effect of the NSP policy on average residential sale prices in Detroit. The first two columns present the results for the TWFE specifications. The traditional TWFE model on the full sample in column 1 shows no significant price effect. Including block group-specific quadratic trends in column 2 does not change the result. The results are consistent among the other estimators. In the case of the Wooldridge Poisson model, the full sample estimates conflict: negative but insignificant with never-treated controls, but significantly negative at -$2,766 using not-yet-treated blocks. The final specifications (columns 5 and 6) on the matched subsample indicate no effect using the never control group and significantly reduced sale prices using the not-yet control group.

To assess the plausibility of the parallel trend and the results dynamically, we plotted the results of the event plot of the regressions in columns 5 and 6 of Table 2.7 (see Figure 2.9). This figure indicates that although there is no significant difference between the treated and control groups in the three years prior to the implementation of the policy, there is a difference in the fourth year before the policy, indicating that the treated block groups had an average of property prices higher than the control group. Post-treatment effects indicate slightly different history based on the control groups chosen (which is consistent with the results in Table 2.7). That is, in the first years after the implementation of the policy, the difference between block groups does not seem to be significant. However, after nine years there are patterns indicating a divergence between treated and controls.

Finally, Figure 2.10 shows the effects of the NSP policy over time differentiated by cohort or treated group. Using the never treated controls there is no statistical difference between the two groups. While using the not-yet-treated controls, the first ones to be treated have a negative effect on property prices, but the second ones have a large variation in effect.

.

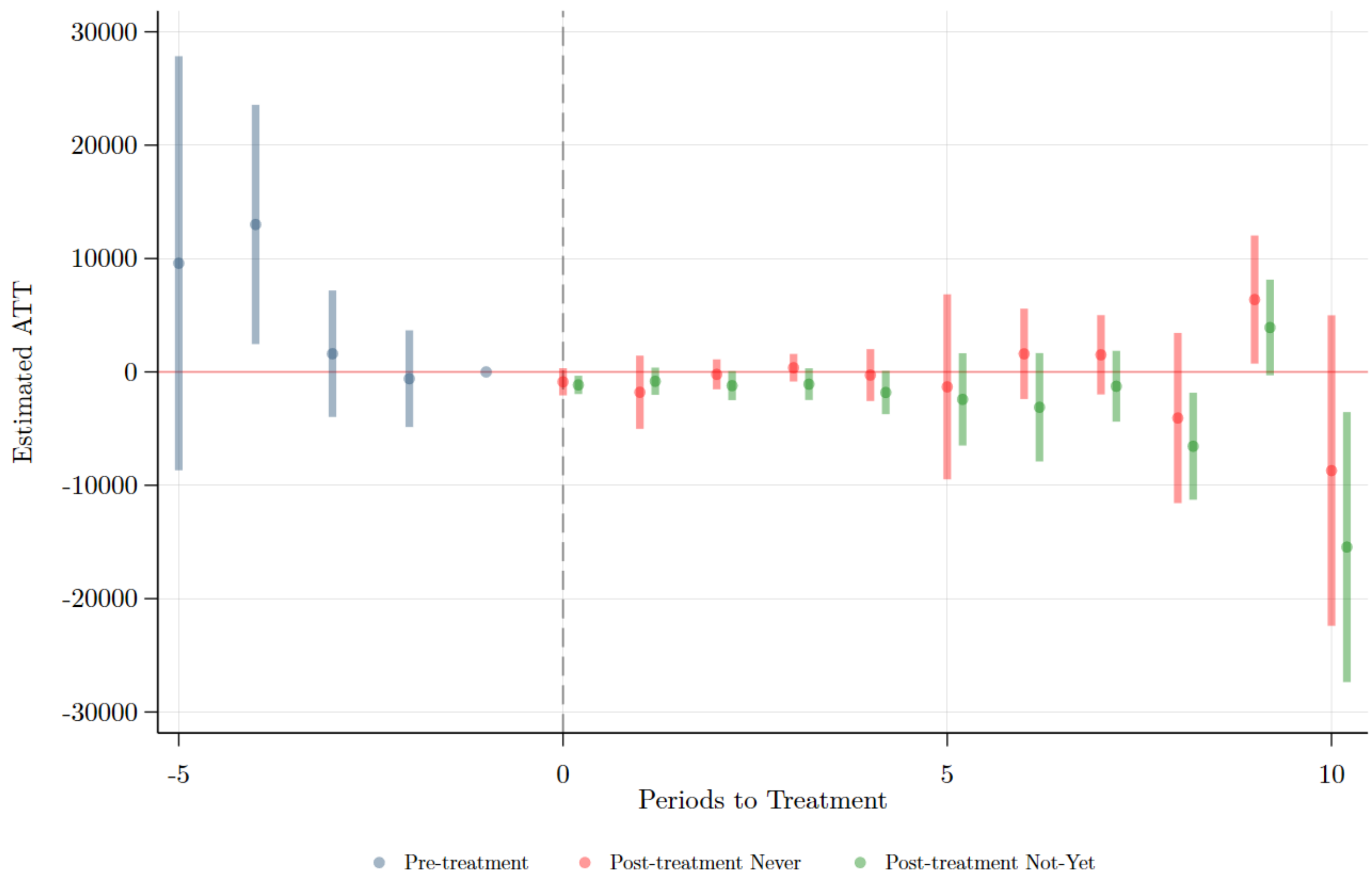
Table 2. 7: Estimated Average Treatment Effect on the Treated (ATT) of NSP on Average Residential Sale Price using Different Models and Samples

	Entire Sample				*Subsample*	
	(1) TWFE	(2) TWFE	(3) TWFEP Never	(4) TWFEP Not-Yet	(5) TWFEP Never	(6) TWFEP Not-Yet
$\widehat{ATT}$	-1136.9	1536.9	-661.3	-2766.9**	-2372.7	-5225.6**
	(1247.5)	(1617.6)	(1773.526)	(1126.293)	(2511.021)	(2344.733)
Constant	77870.5***	-9.1821e+09***				
	(9212.5)	(62450324.2)				
Observations	13,894	13,894	13,873	13,873	11,599	11,599
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Block Group Fixed Effects	Yes	Yes	No	No	No	No
Cohort Fixed Effects	No	No	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Block Group-specific quadratic time trends	No	Yes	No	No	No	No
R^2	0.490	0.660				
Adjusted R^2	0.449	0.601				

Source: Author's calculations. Note: This table presents regression results estimating the effect of NSP treatment on the average price of residential property sales in census block groups in Detroit. Specifications include Two-Way Fixed Effects (TWFE) models on the full sample with and without block group-specific linear time trends, as well as Wooldridge Two-Way Fixed Effects Poisson (TWFEP) models on the full and propensity score matched subsamples. In the case of the TWFE, $\widehat{ATT}$ correspond to the estimated β^{DD} from equation (1). In the case of TWFEP, ATT is calculated as shown in equation (10) after using a Poisson two-way fixed effects regression (Wooldridge, 2022). The dependent variable is the average price of residential property sales, hence $\widehat{ATT}$ is interpreted in dollars. Models control for year fixed effects, cohort fixed effects, and the following time-varying housing characteristics: mean age of properties sold, mean lot size of properties sold, average number of stories, average number of full bathrooms, and average garage area. Standard errors clustered at the block group level are reported in parentheses.

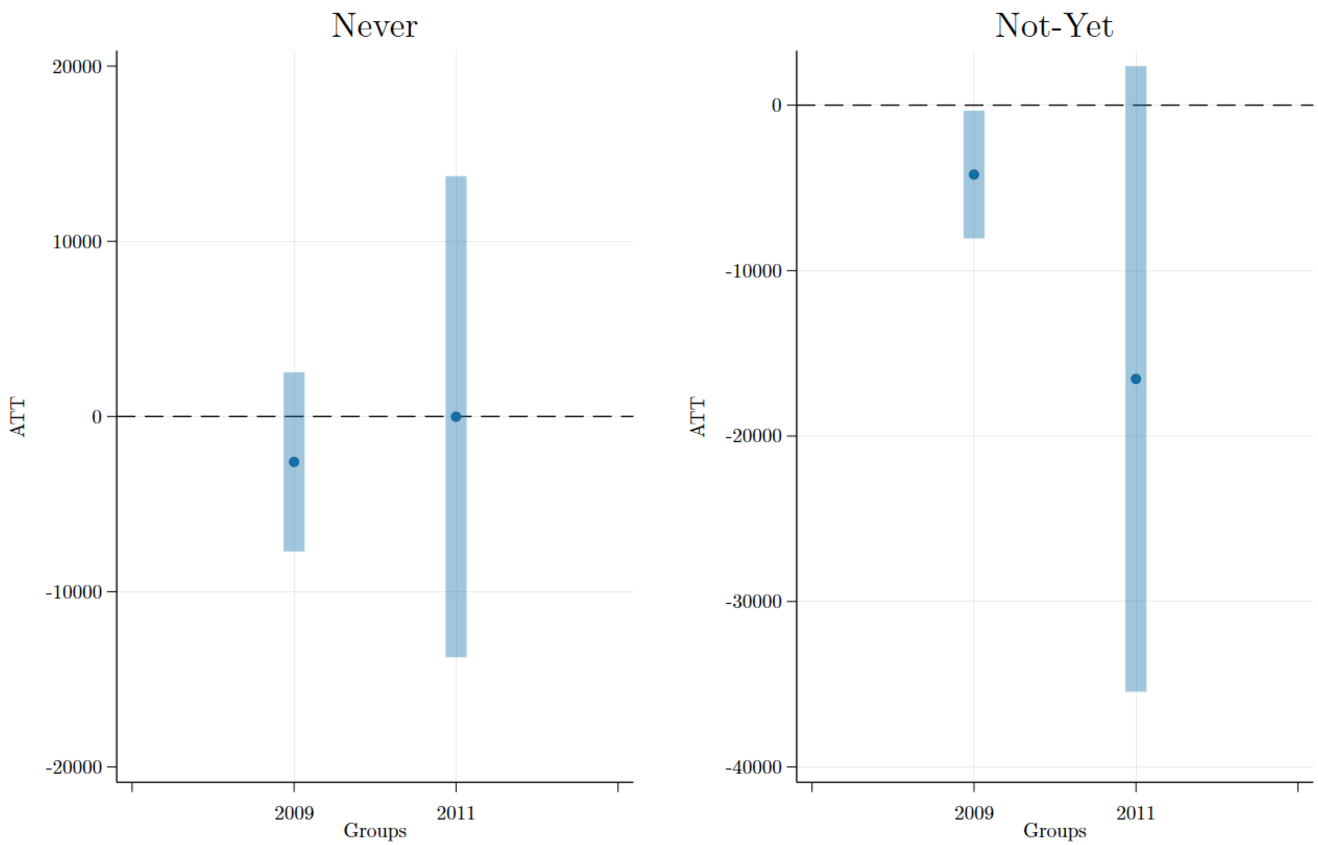
*** Significant at the 1 percent level.

Figure 2. 9: Estimated Average Treatment Effect on the Treated (ATT) of NSP on Average Residential Sale Price – Event Study Results (Subsample)



Source: Author's calculations. Note: this figure presents the event study results described in equations (14) (never treated control group) and equation (15) (not-yet treated control group). These are the aggregated results from the output Two-Way Fixed Effects Poisson (TWFEP) regression used in column (5) and (6) of Table 2.7. Estimated ATT is interpreted in dollars. Point estimated in red are the effect of the NSP policy on residential sale prices for the block groups treated using the never treated control group. Point estimated in green are the effect of the NSP policy on residential sale prices for the block groups treated using the not-yet treated control group. Standard errors are clustered at the block group level, and the estimated coefficients are at a 95% confidence interval.

Figure 2. 10: Estimated Average Treatment Effect on the Treated (ATT) of NSP on Average Residential Sale Price by Cohort (Subsample)



Source: Author's calculations. Note: this figure presents the cohort effects results described in equation (11) using never treated control group and not-yet treated control group. These are the aggregated results from the output Two-Way Fixed Effects Poisson (TWFEP) regression used in column (5) and (6) of Table 2.7. Groups or Cohorts are two census block groups treated in 2009 and those treated in 2011. Estimated ATT is interpreted in dollars. Standard errors are clustered at the block group level, and the estimated coefficients are at a 95% confidence interval.

Overall Effect of NSP on Number of Foreclosed Properties

Table 2.8 provides estimates of the effect of the NSP policy on the number of foreclosed properties in Detroit. Unlike the previous case, the TWFE results in the first two columns are consistent. Both indicate that, on average, treated block groups experienced an increase from around 1.4 to 1.9 properties in foreclosure. However, when analyzing the results of the Wooldridge Poisson estimator, none is statistically significant, using the entire sample and the subsample.

These results coincide with the results of the event study (see Figure 2.11). Before the policy, and thus, before the foreclosure crisis, the number of properties in foreclosure on average per census block group was very low. After policy implementation this number increased for both groups, but there is no significant difference between treated block groups versus controls. Using the not-yet controls there are certain periods where the difference is positive and significant, but the magnitude is too small to influence the overall ATT. The results of the estimated ATT by cohort in Figure 2.12 indicate that the group of census blocks that was treated in 2011 experienced an increase in foreclosure properties. This result is consistent for both types of control groups.

Table 2. 8: Estimated Average Treatment Effect on the Treated (ATT) of NSP on Number of Foreclosed Properties using Different Models and Samples

	Entire Sample				*Subsample*	
	(1) TWFE	(2) TWFE	(3) TWFEP Never	(4) TWFEP Not-Yet	(5) TWFEP Never	(6) TWFEP Not-Yet
$\widehat{ATT}$	1.431***	1.943***	-8.066	0.130	0.152	1.125
	(0.385)	(0.571)	(41.276)	(0.891)	(2.381)	(0.858)
Constant	0.724	-0.883				
	(1.472)	(1.627)				
Observations	13,894	13,894	13,873	13,873	11,599	11,599
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Block Group Fixed Effects	Yes	Yes	No	No	No	No
Cohort Fixed Effects	No	No	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Block Group-specific linear time trends	No	Yes	No	No	No	No
R^2	0.550	0.571				
Adjusted R^2	0.549	0.536				

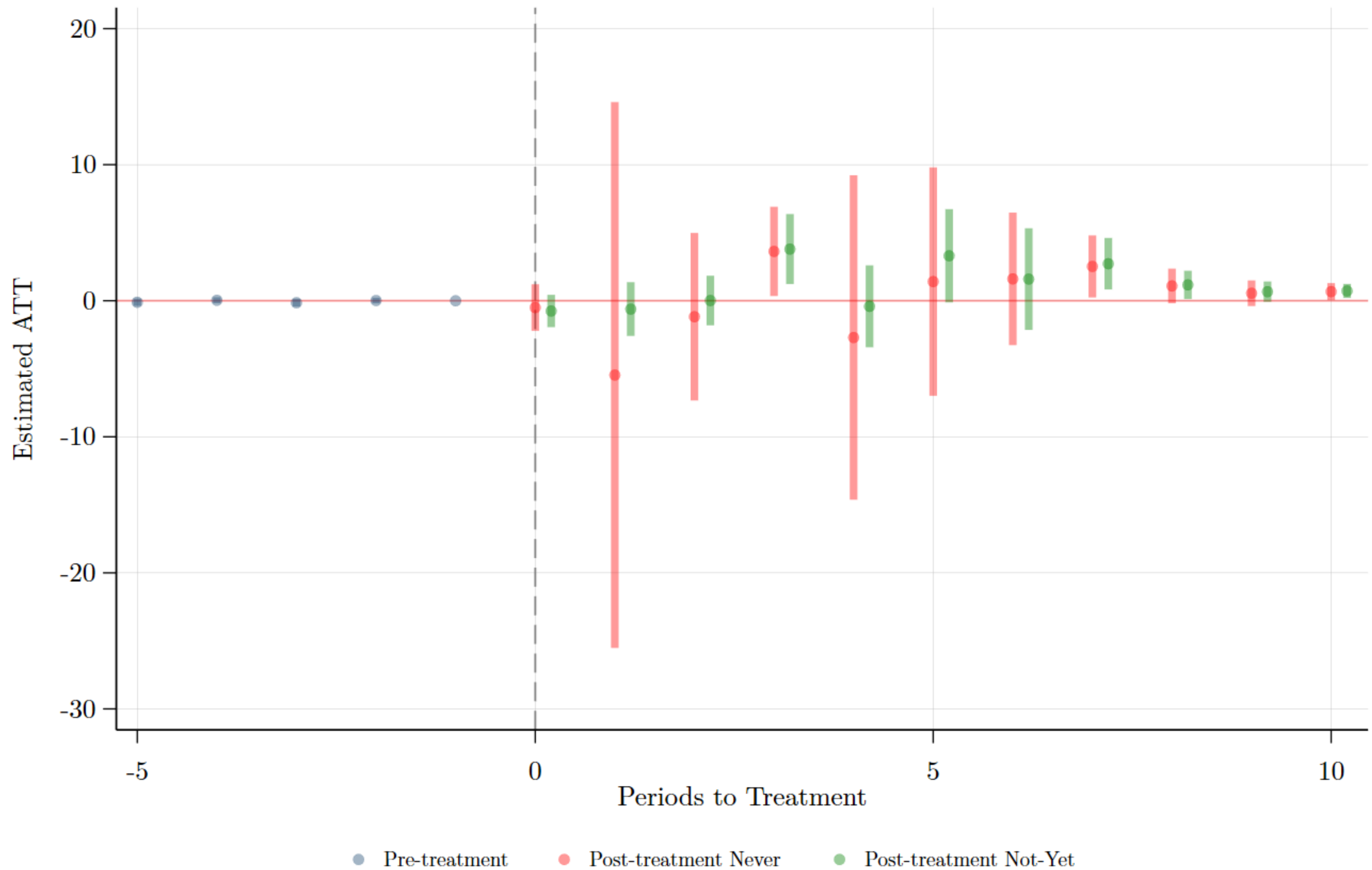
Source: Author's calculations. Note: This table presents regression results estimating the effect of NSP treatment on the number of foreclosure properties in census block groups in Detroit. Specifications include Two-Way Fixed Effects (TWFE) models on the full sample with and without block group-specific linear time trends, as well as Wooldridge Two-Way Fixed Effects Poisson (TWFEP) models on the full and propensity score matched subsamples. In the case of the TWFE, $\widehat{ATT}$ correspond to the estimated β^{DD} from equation (1). In the case of TWFEP, ATT is calculated as shown in equation (10) after using a Poisson two-way fixed effects regression (Wooldridge, 2022). The dependent variable is number of properties in foreclosure, hence $\widehat{ATT}$ is interpreted in average number of foreclosures. Models control for year fixed effects, cohort fixed effects, and the following time-varying housing characteristics: mean age of properties sold, mean lot size of properties sold, average number of stories, average number of full bathrooms, and average garage area. Standard errors clustered at the block group level are reported in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

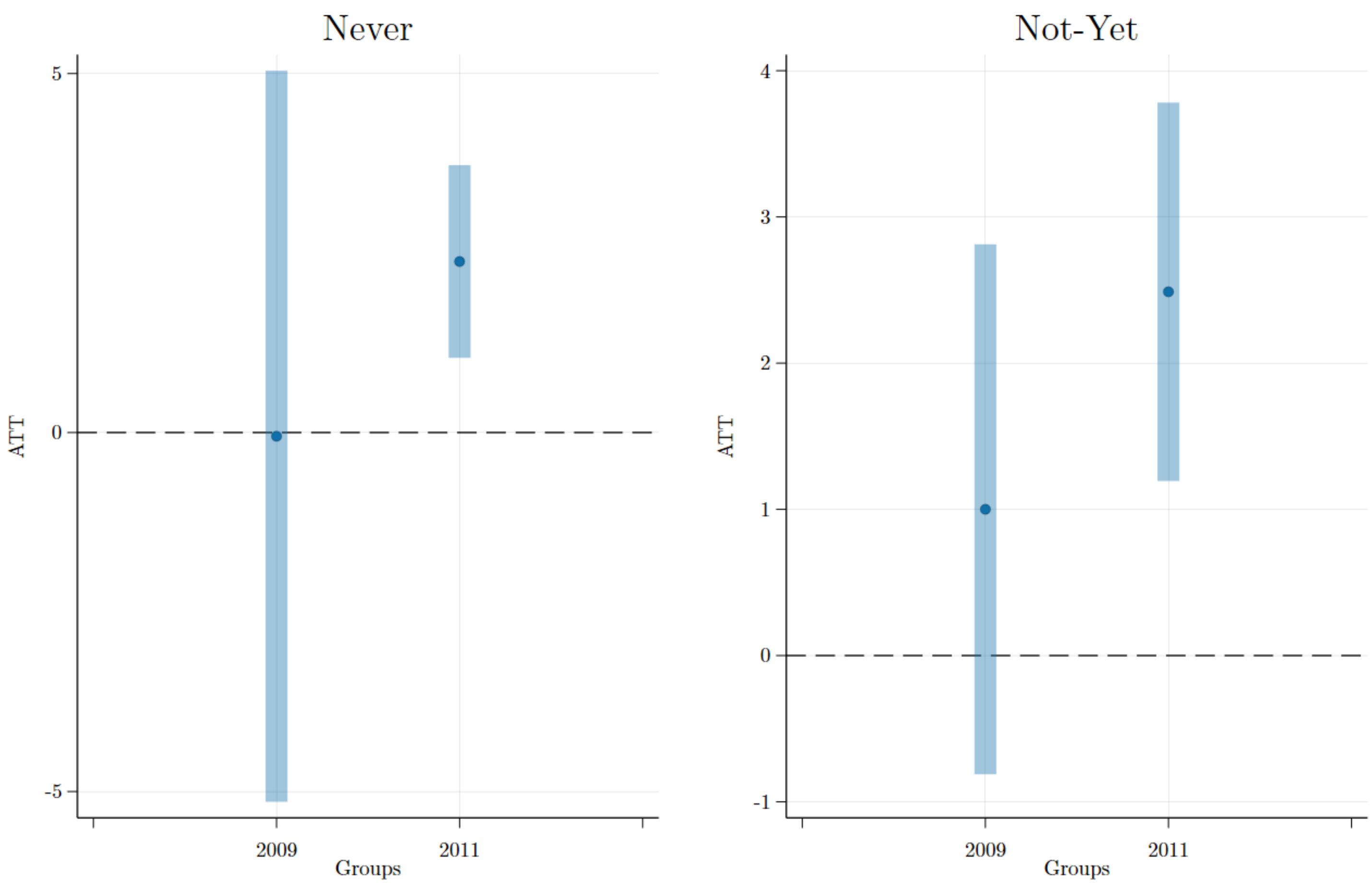
* Significant at the 10 percent level.

Figure 2. 11: Estimated Average Treatment Effect on the Treated (ATT) of NSP on Number of Foreclosed Properties – Event Study Results (Subsample)



Source: Author's calculations. Note: this figure presents the event study results described in equations (14) (never treated control group) and equation (15) (not-yet treated control group). These are the aggregated results from the output Two-Way Fixed Effects Poisson (TWFEP) regression used in column (5) and (6) of Table 2.8. Estimated ATT is interpreted in average number of foreclosures. Point estimated in red is the effect of the NSP policy on the number of foreclosed properties for the block groups treated using the never treated control group. Point estimated in green are the effect of the NSP policy on the number of foreclosed properties for the block groups treated using the not-yet treated control group. Standard errors are clustered at the block group level, and the estimated coefficients are at a 95% confidence interval.

Figure 2. 12: Estimated Average Treatment Effect on the Treated (ATT) of NSP on Number of Foreclosed Properties by Cohort (Subsample)



Source: Author's calculations. Note: this figure presents the cohort effects results described in equation (11) using never treated control group and not-yet treated control group. These are the aggregated results from the output Two-Way Fixed Effects Poisson (TWFEP) regression used in column (5) and (6) of Table 2.8. Groups or Cohorts are two census block groups treated in 2009 and those treated in 2011. Estimated ATT is interpreted in number of foreclosures. Standard errors are clustered at the block group level, and the estimated coefficients are at a 95% confidence interval.

Overall Effect of NSP on the Foreclosure Rate

The effects on the foreclosure rate do not deviate much from the effects on the number of foreclosures (see Table 2.9). In the case of the TWFE, the results indicate an increase of 0.14 to 0.19 percentage points. However, these effects become statistically insignificant when we use the Wooldridge Poisson estimator. The results of the event study and of the effects by cohorts are interpreted in the same way as with the number of properties in foreclosure.

In general, this may be indicating that after the policy the number of properties in foreclosure and the foreclosure rate did not diverge between the treated and control groups. This may be because the policy effectively maintained this balance, or because the increase in foreclosure properties was spread around the city, similarly affecting both groups. Since there are no pre-trends indicating that the treated groups were worse than the controls, it is difficult to interpret these results.

Table 2. 9: Estimated Average Treatment Effect on the Treated (ATT) of NSP on the Foreclosure Rate using Different Models and Samples

	Entire Sample				*Subsample*	
	(1) TWFE	(2) TWFE	(3) TWFEP Never	(4) TWFEP Not-Yet	(5) TWFEP Never	(6) TWFEP Not-Yet
$\widehat{ATT}$	0.140***	0.196***	-3.912	-0.003	-0.496	0.119
	(0.0407)	(0.0599)	(21.734)	(0.089)	(2.445)	(0.086)
Constant	0.111	-0.0191				
	(0.176)	(0.198)				
Observations	13,894	13,894	13,873	13,873	11,599	11,599
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Block Group Fixed Effects	Yes	Yes	No	No	No	No
Cohort Fixed Effects	No	No	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Block Group-specific linear time trends	No	Yes	No	No	No	No
R^2	0.461	0.482				
Adjusted R^2	0.461	0.440				

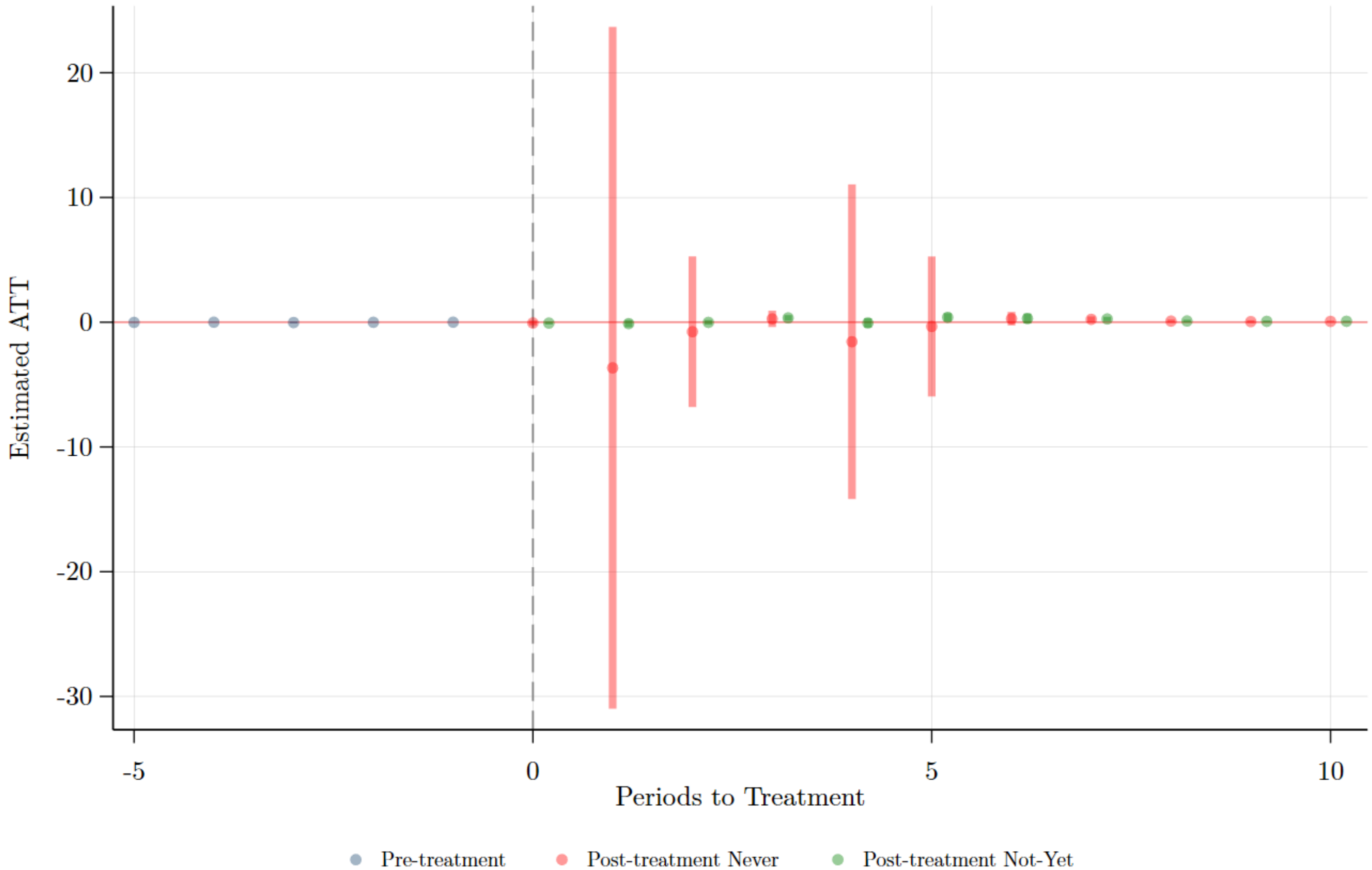
Source: Author's calculations. Note: This table presents regression results estimating the effect of NSP treatment on the foreclosure rate in census block groups in Detroit. Specifications include Two-Way Fixed Effects (TWFE) models on the full sample with and without block group-specific linear time trends, as well as Wooldridge Two-Way Fixed Effects Poisson (TWFEP) models on the full and propensity score matched subsamples. In the case of the TWFE, $\widehat{ATT}$ correspond to the estimated β^{DD} from equation (1). In the case of TWFEP, ATT is calculated as shown in equation (10) after using a Poisson two-way fixed effects regression (Wooldridge, 2022). The dependent variable is foreclosure rate in percentage, hence $\widehat{ATT}$ is interpreted in foreclosure rate percentage points. Models control for year fixed effects, cohort fixed effects, and the following time-varying housing characteristics: mean age of properties sold, mean lot size of properties sold, average number of stories, average number of full bathrooms, and average garage area. Standard errors clustered at the block group level are reported in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

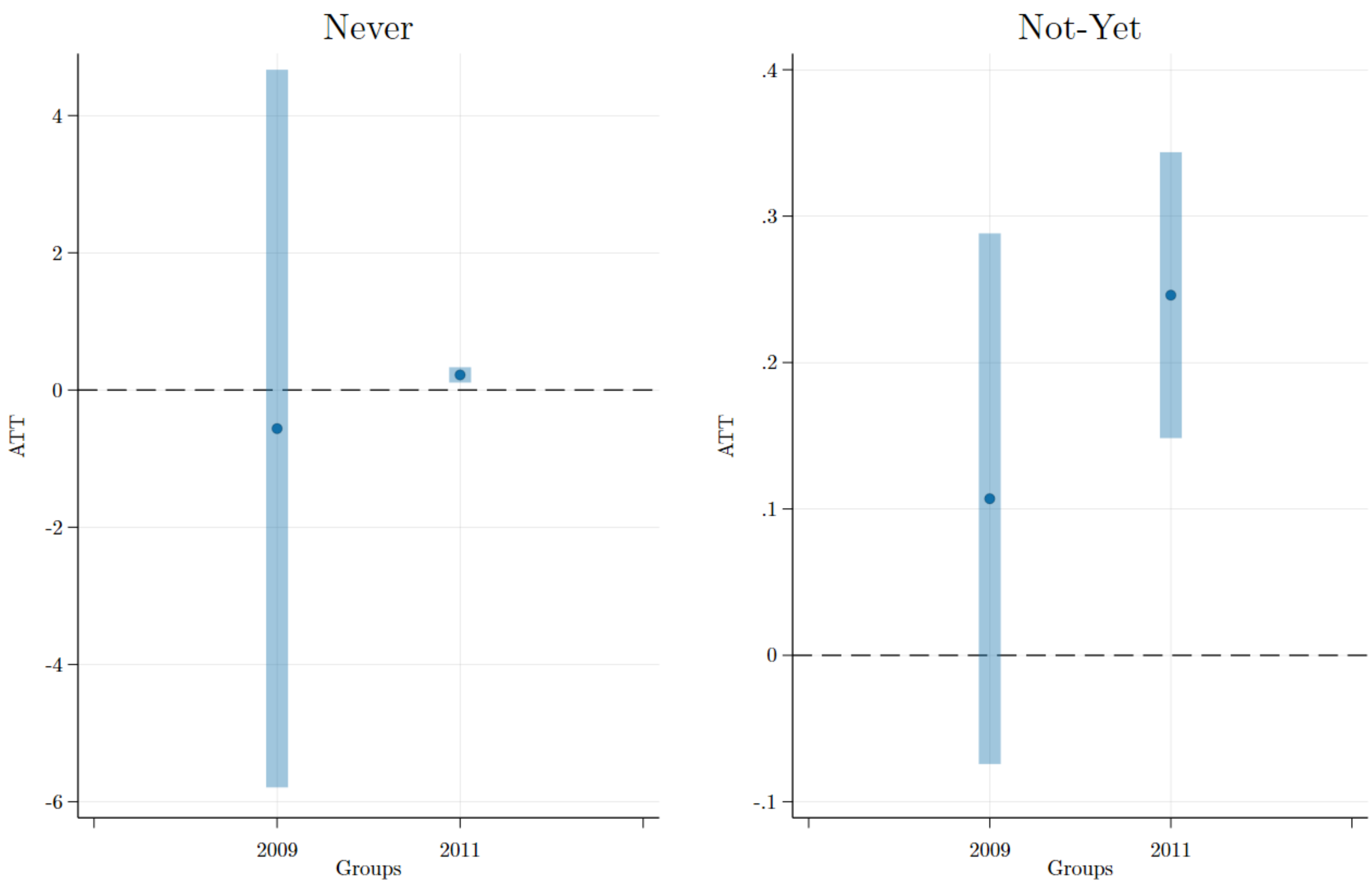
* Significant at the 10 percent level.

Figure 2. 13: Estimated Average Treatment Effect on the Treated (ATT) of NSP on Foreclosure Rate – Event Study Results



Source: Author's calculations. Note: this figure presents the event study results described in equations (14) (never treated control group) and equation (15) (not-yet treated control group). These are the aggregated results from the Two-Way Fixed Effects Poisson (TWFEP) regression used in column (5) and (6) of Table 2.9. Estimated ATT is interpreted in percentage points of foreclosure rate. Point estimated in red are the effect of the NSP policy on the foreclosure rate for the block groups treated using the never treated control group. Point estimated in green are the effect of the NSP policy on the foreclosure rate for the block groups treated using the not-yet treated control group. Standard errors are clustered at the block group level, and the estimated coefficients are at a 95% confidence interval.

Figure 2. 14: Estimated Average Treatment Effect on the Treated (ATT) of NSP on Foreclosure Rate by Cohort (Subsample)



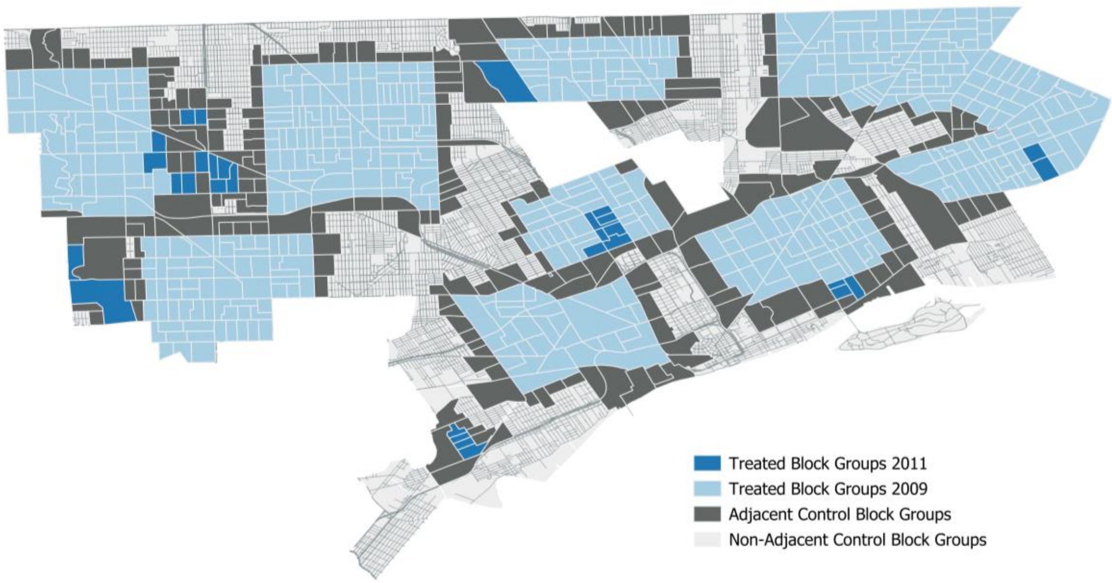
Source: Author's calculations. Note: this figure presents the cohort effects results described in equation (11) using never treated control group and not-yet treated control group. These are the aggregated results from the output Two-Way Fixed Effects Poisson (TWFEP) regression used in column (5) and (6) of Table 2.9. Groups or Cohorts are two census block groups treated in 2009 and those treated in 2011. Estimated ATT is interpreted in percentage points of the foreclosure rate. Standard errors are clustered at the block group level, and the estimated coefficients are at a 95% confidence interval.

Assessing Spillover Effects: Excluding Adjacent Control Block Groups in Robustness Analysis

The Stable Unit Treatment Value Assumption (SUTVA) implies that the NSP treatment status of one unit (in this case, a census block group) should not affect the outcome of another unit. This assumption is crucial in causal inference to ensure that the estimated effect is solely due to the treatment and not due to external influences or interactions between units. However, in this context, spillover effects may occur if the NSP policy implementation in one block group affects adjacent block groups that are technically in the control group. This can happen through various channels such as economic activities, social networks, or environmental factors. For example, NSP rehabilitation and reconstruction activities often affected an entire street. If new construction is also funded through NSP in the same sector, this can easily signal the market for private investment in adjacent sectors, trying to get ahead of capturing the added value that will be generated in the neighborhood. If spillover effects are present, they can bias the estimated coefficients of the treatment effect.

This robustness check involves excluding census block groups adjacent to treated ones from the control group, to isolate the effect of the NSP policy. This step helps to uphold the SUTVA by minimizing the interference between treated and control units, providing a more precise estimation of the impact of the policy. We recalculate the results leaving out of the sample the adjacent block groups (see Figure 2.15). For this robustness check, we use only the never treated group because it remains unaffected by the NSP policy throughout the observation period, offering a clean comparison without the confounding effect of anticipated future treatment.

Figure 2. 15: Robustness check: Spatial Distribution of Treated, Adjacent, and Non-Adjacent Census Block Groups



Source: Author's calculations. Note: Adjacent Control Blocks (color dark grey) are those in close proximity to treated areas but did not receive NSP treatment, crucial for analyzing potential spillover effects. Non-Adjacent Control Blocks (color light grey) are distant from treated blocks and serve as a baseline to assess the NSP policy's impact without neighboring influences. The map aims to provide a clear understanding of the spatial dynamics involved in the NSP's implementation and its broader effects on urban areas.

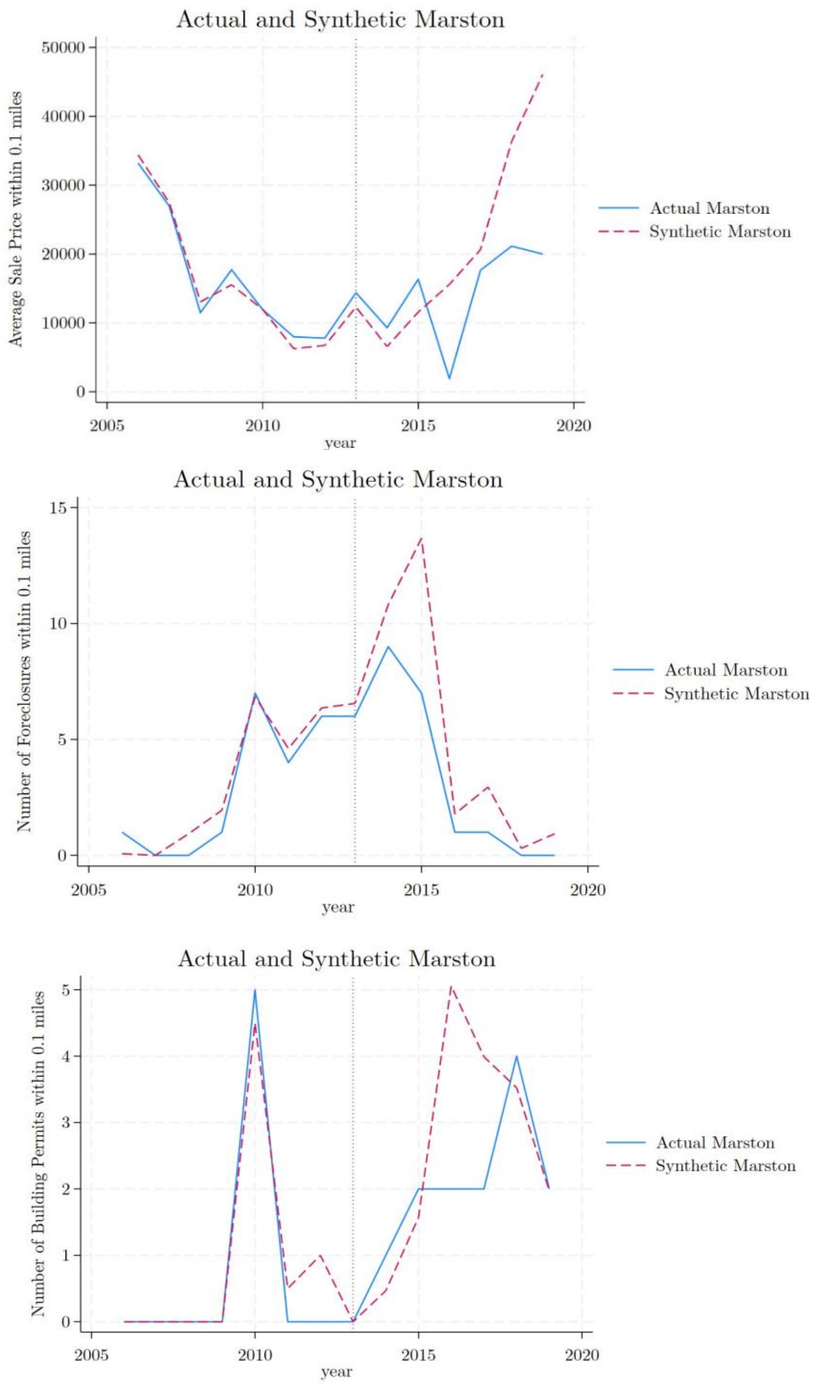
The results are shown in Table A2.3 in the Appendix. The calculations indicate that the effect in the three outcomes remain non-statistically significant, even when we do not include the adjacent census block groups. This analysis strengthens the validity of our findings by showing that they hold even under conservative assumptions about treatment spillovers.

Localized Effects of NSP

In this section, we present the results for the SCM analysis for Marston, St. Mary's and Plainview rehabilitation projects in Detroit, and how this NSP action can affect the surrounding neighborhoods around these projects.

Figure 2.16 presents the results for Marston on the three outcome variables. Figure 2A.1 in the Appendix presents the results of the inference process. In terms of sale prices, Figure 2.16 indicates that there is a decline in actual sale price for Marston post-intervention when compared to the predicted values. This suggests that NSP rehabilitation in Marston might not have contributed to an increase in property sale prices in the immediate aftermath of the intervention. However, according to in-place placebo test (Figure 2A.1), this effect is not statically significant when compared to a distribution of placebo effects, which is contrary to the result in terms of foreclosures around Marston post-NSP rehabilitation. According to Figure 2.16, there is a decrease in foreclosures in Marston post-intervention and it is statistically significant (see Figure 2A.1). This effect represents about 6 less foreclosures on average within 0.1 miles after the NSP rehabilitation. The NSP rehabilitation appears to have had a positive impact on housing stability in the Marston area. Post-NSP rehabilitation, Marston exhibited an upward trend in the issuance of building permits. However, when comparing with its synthetic control, the volume of permits was less than expected, falling short of anticipated levels. Interestingly, while the pace of construction and development in Marston has not rebounded to the expected magnitude, the trajectory suggests a gradual revitalization. It is important to note that the observed disparity between Marston and its synthetic counterpart is not statistically significant when evaluated against the backdrop of placebo effects.

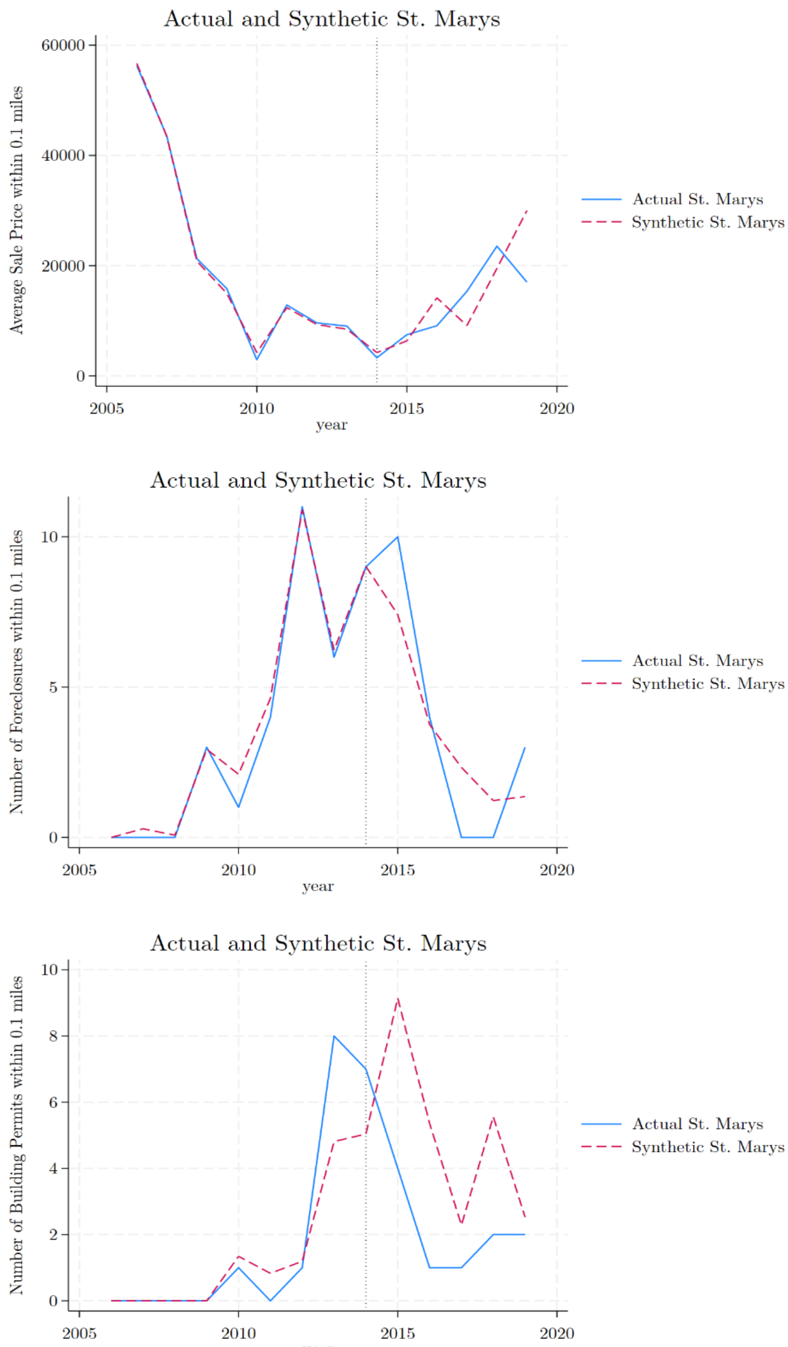
Figure 2. 16: Estimated Effect of NSP Demolition-Rehabilitation projects on Sale Price, Foreclosures and Building Permits – Synthetic Control Results (Marston)



Source: Author's calculations. Note: The figures show the outcomes of Marston, a unit undergoing demolition coupled with NSP rehabilitation, in comparison to its synthetic control. The synthetic control represents the expected outcomes of Marston if it had only experienced a demolition without the subsequent NSP intervention. The outcomes of interest are: average sale price within 0.1 miles, number of foreclosed properties within 0.1 miles, and number of building permits issued within 0.1 miles. Differences between the observed outcomes for Marston and its synthetic control provide insights into the added value of NSP rehabilitation in shaping the local environment post-demolition.

Figure 2.17 presents the results for St. Mary's on the three outcome variables. Figure A2.2 in the Appendix presents the results of the inference process. In terms of sale prices, Figure 2.17 indicates that prior to the intervention, sale prices in St. Mary's align very closely with its synthetic counterpart, which is a good indicator on how reliable the estimator is. Post-2015, St. Mary's experiences a decline in sale prices relative to its synthetic control. This suggests that post-intervention, the property valuations around St. Mary's have not kept pace with those predicted by the synthetic control. However, this reversed quickly in the following year, maintaining prices higher than the synthetic control (about $5,000 higher on average). However, in the last year prices decline again with respect to synthetic St. Mary's. However, both trends are very close, indicating a non-statically significant effect that is corroborated with the p-values in Figure A2.2. Regarding the building permits, it is difficult to interpret results since that trends between actual St. Mary's and synthetic St. Mary's were different prior to the treatment, indicating that the control group is not composed of demolitions that make a good match based on building permits issued prior to the intervention. Finally, the number of foreclosures around St. Mary's post-NSP rehabilitation indicates a decline compared to its synthetic control, especially noticeable after 2015. However, this decline is not statistically significant when contrasted with the distribution of placebo effects.

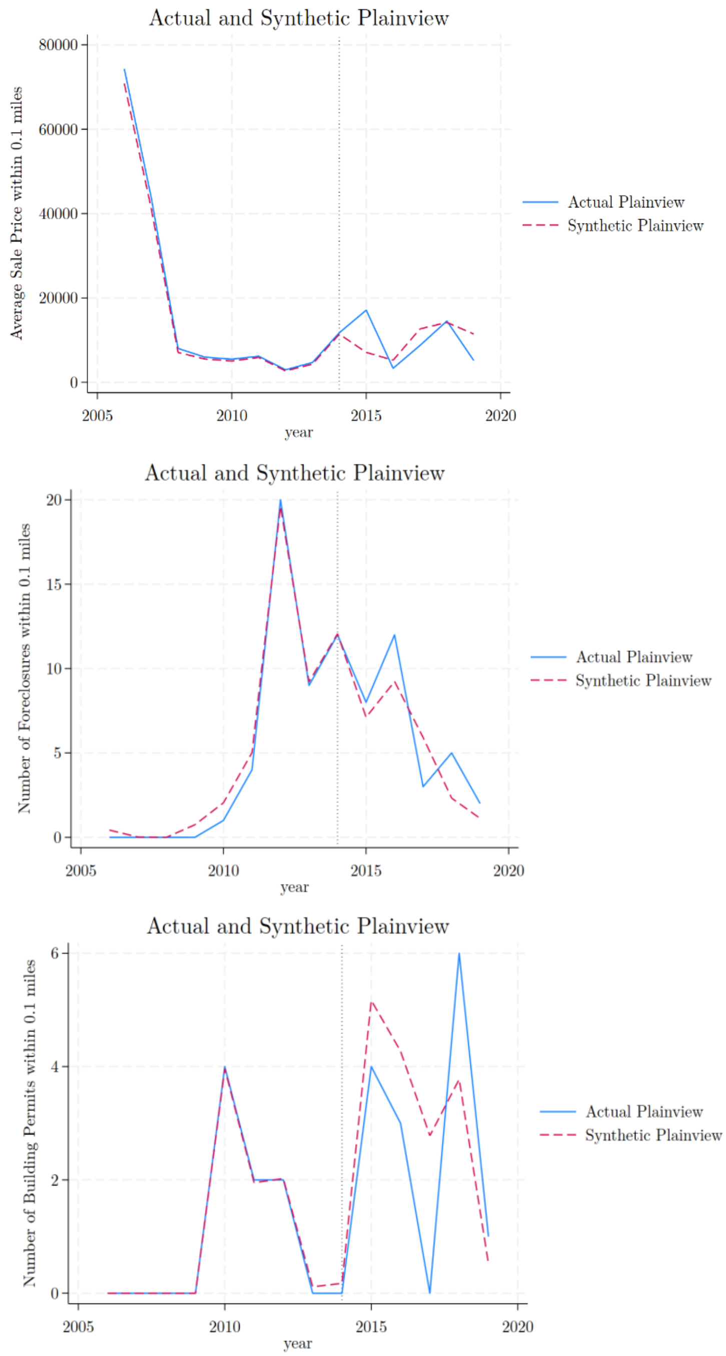
Figure 2. 17: Estimated Effect of NSP Demolition-Rehabilitation projects on Sale Price, Foreclosures and Building Permits – Synthetic Control Results (St. Mary's)



Source: Author's calculations. Note: The figures show the outcomes of St. Mary's, a unit undergoing demolition coupled with NSP rehabilitation, in comparison to its synthetic control. The synthetic control represents the expected outcomes of St. Mary's if it had only experienced a demolition without the subsequent NSP intervention. The outcomes of interest are the average sale price within 0.1 miles, number of foreclosed properties within 0.1 miles, and number of building permits issued within 0.1 miles. Differences between the observed outcomes for St. Mary's and its synthetic control provide insights into the added value of NSP rehabilitation in shaping the local environment post-demolition.

Figure 2.18 presents the results for Plainview on the three outcome variables. Figure A2.3 in the Appendix presents the results of the inference process. In terms of sale prices post-NSP rehabilitation, sales prices around Plainview increase up to $10,000, on average, compared to the synthetic Plainview. This point is very close to being statistically significant at a 10% level. The number of foreclosures around Plainview post-NSP rehabilitation declined compared to its synthetic control, especially noticeable after 2016. However, this decline is not statistically significant when contrasted with the distribution of placebo effects. Finally, while there were noticeable variations in building permits for Plainview compared to its synthetic counterpart immediately after the intervention, recent years have witnessed a positive shift. The number of building permits around Plainview has been on the rise, exceeding the expected values based on its synthetic control. This upward trend signals a rejuvenation in development activities in the vicinity of Plainview, indicating a promising phase of growth and revitalization.

Figure 2. 18: Estimated Effect of NSP Demolition-Rehabilitation projects on Sale Price, Foreclosures and Building Permits – Synthetic Control Results (Plainview)



Source: Author's calculations. Note: The figures show the outcomes of Plainview, a unit undergoing demolition coupled with NSP rehabilitation, in comparison to its synthetic control. The synthetic control represents the expected outcomes of Plainview if it had only experienced a demolition without the subsequent NSP intervention. The outcomes of interest are: average sale price within 0.1 miles, number of foreclosed properties within 0.1 miles, and number of building permits issued within 0.1 miles. Differences between the observed outcomes for Plainview and its synthetic control provide insights into the added value of NSP rehabilitation in shaping the local environment post-demolition.

Conclusions

This study evaluated the impact of the Neighborhood Stabilization Program (NSP) in Detroit, focusing on key housing market outcomes including residential property sales prices, number of foreclosures, and foreclosure rates. Using a difference-in-differences approach along with specialized estimators to account for the staggered implementation of the NSP, our analysis provides nuanced insights into the effects of this place-based policy. Additionally, using Synthetic Control Method, we provide evidence on the localized effects of the NSP rehabilitation activities.

Overall, the results indicate that the NSP had a stabilizing effect on the housing market in treated neighborhoods, preventing further declines, but did not stimulate pronounced revitalization. In terms of sales prices, we find suggestive evidence that the NSP may have halted downward trajectories, particularly for later treatment cohorts. However, effects on foreclosure numbers and rates were insignificant, implying policy-maintained balance between treated and untreated areas but did not reduce foreclosures. These conclusions in general align with the key goals of the NSP - to mitigate housing decline. In the face of Detroit's structural challenges of high vacancy, weak demand, and oversupply, stemming the tide of abandonment constitutes an important achievement. Nonetheless, more transformational change would require interventions beyond the scope of this program.

The localized effects of the NSP rehabilitation, when compared against demolitions without subsequent development, manifest differently across different areas in Detroit. For Marston, the post-intervention period saw a decline in property sale prices, suggesting that NSP rehabilitation did not immediately bolster the property market. However, this effect was not statistically significant. In stark contrast, housing stability in the area seems to have benefited from the NSP rehabilitation, as evidenced by a significant reduction in foreclosures. In the case of St.

Mary's, the immediate post-intervention phase saw a dip in property valuations. But this trend was reversed swiftly in the subsequent year, with prices outpacing the synthetic control. Nevertheless, this effect, as well as the observed decline in foreclosures post-2015, was not statistically significant. Plainview, on the other hand, showcased promising signs of urban rejuvenation post-NSP rehabilitation. The area also experienced a decline in foreclosures post-2016, though this effect was not statistically significant. Notably, in recent years there has been a surge in building permits, indicating burgeoning development activities and pointing towards a promising phase of urban renewal.

Our analysis demonstrates the value of data-driven program evaluation, both for accountability and to inform policy decisions. As Detroit continues to combat blight, lessons from the NSP should shape how resources are targeted going forward. This study also highlights the complexities of policy evaluation using causal inference tools. Contending with issues like staggered adoption, interactive treatment effects, anticipation, and shifting comparators underscores the need for rigorous analysis.

BIBLIOGRAPHY

Abadie, A. (2021). Using synthetic controls: Feasibility, data requirements, and methodological aspects. *Journal of Economic Literature, 59*(2), 391–425. https://doi.org/10.1257/jel.20191450

Abadie, A., Diamond, A., & Hainmueller, A. J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's Tobacco control program. *Journal of the American Statistical Association, 105*(490), 493–505. https://doi.org/10.1198/jasa.2009.ap08746

Alm, J., Hodge, T. R., Sands, G., & Skidmore, M. (2014). Detroit Property Tax Delinquency: Social Contract in Crisis. *Public Finance and Management, 14*(3), 280–305.

Alvayay Torrejón, C., Paredes, D., & Skidmore, M. (2020). Housing demolition and property tax delinquency: Evidence from Detroit. *Journal of Urban Affairs, 00*(00), 1–22. https://doi.org/10.1080/07352166.2019.1697183

Alvayay Torrejón, C., Paredes, D., & Skidmore, M. (2023). *Impact of demolitions on neighboring property values in Detroit. September* 2022, 1–27. https://doi.org/10.1111/jors.12654

Anenberg, E., & Kung, E. (2014). Estimates of the size and source of price declines due to nearby foreclosures. *Finance and Economics Discussion Series, 104*(8), 2527–2551. http://ideas.repec.org/p/fip/fedgfe/2012-84.html

Bak, X. F., & Hewings, G. J. D. (2017). Measuring foreclosure impact mitigation: Evidence from the Neighborhood Stabilization Program in Chicago. *Regional Science and Urban Economics, 63*(December 2016), 38–56. https://doi.org/10.1016/j.regsciurbeco.2016.12.002

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-Differences with multiple time periods. *Journal of Econometrics, 225*(2), 200–230. https://doi.org/10.1016/j.jeconom.2020.12.001

Campbell, J. Y., Giglio, S., & Pathak, P. (2011). Forced Sales and House Prices. *American Economic Review , 101*(5), 2108–2131. https://doi.org/10.1257/aer.101.5.2108

Clapp, J. M., & Wang, Y. (2006). Defining neighborhood boundaries: Are census tracts obsolete? *Journal of Urban Economics, 59*(2), 259–284. https://doi.org/10.1016/j.jue.2005.10.003

Collins, W. J., & Shester, K. L. (2013). Slum Clearance and Urban Renewal in the United States. *American Economic Journal: Applied Economics, 5*(1), 239–273. https://doi.org/10.1257/app.5.1.239

Committee on Financial Services. (2019). An Examination of the Housing Crisis in Michigan, 11 years after the Recession.

de Chaisemartin, C., & D'Haultfœuille, X. (2020). Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review, 110*(9), 2964–2996. https://doi.org/10.1257/aer.20181169

Ellen, I. G., Lacoe, J., & Sharygin, C. A. (2013). Do foreclosures cause crime? *Journal of Urban Economics, 74*(1), 59–70. https://doi.org/10.1016/j.jue.2012.09.003

Fainstein, S. S., & Markusen, A. (1993). The Urban Policy Challenge: Integrating Across Social and Economic Development Policy' (1993) 71(5) North Carolina Law Review. *North Carolina Law Review, 71*(5), 1463–1486. https://heinonline.org/HOL/License

Fraser, J. C., & Oakley, D. (2015). The neighborhood stabilization program: Stable for whom? *Journal of Urban Affairs, 37*(1), 38–41. https://doi.org/10.1111/juaf.12159

Galster, G., Tatian, P., & Accordino, J. (2006). Targeting investments for neighborhood revitalization. *Journal of the American Planning Association, 72*(4), 457–474. https://doi.org/10.1080/01944360608976766

Ganduri, R., & Maturana, G. (2021). Do Property Rehabs Affect Neighboring Property Prices? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3794796

Gerardi, K., Rosenblatt, E., Willen, P. S., & Yao, V. (2015). Foreclosure externalities: New evidence. *Journal of Urban Economics, 87*, 42–56. https://doi.org/10.1016/j.jue.2015.02.004

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics, 225*(2), 254–277. https://doi.org/10.1016/j.jeconom.2021.03.014

Hahn, J., & Shi, R. (2017). Synthetic control and inference. *Econometrics, 5*(4), 1–12. https://doi.org/10.3390/econometrics5040052

Harding, J. P., Rosenblatt, E., & Yao, V. W. (2009). The contagion effect of foreclosed properties. *Journal of Urban Economics, 66*(3), 164–178. https://doi.org/10.1016/j.jue.2009.07.003

Hartley, D. (2014). The Effect of Foreclosures on Nearby Housing Prices: Supply or Disamenity? (No. 10; 11R).

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association, 81*(396), 945–960. https://doi.org/10.1080/01621459.1986.10478354

Immergluck, D. (2013). Too Little, Too Late, and Too Timid: The Federal Response to the Foreclosure Crisis at the Five-Year Mark. *Housing Policy Debate, 23*(1), 199–232. https://doi.org/10.1080/10511482.2012.749933

Johnson, C. (2008). (2008). Fight blight: Cities sue to hold lenders responsible for the rise in foreclosures and abandoned properties. *Utah Law Review, 3*, 1169–1254. https://heinonline.org/HOL/Page?handle=hein.journals/utahlr2008&div=39&g_sent=1&casa_token=cCh_s6k__h4AAAAA:YlNIpelXQTDwfZ7Un735laZHv1djVArlVDemV3m6JOte5Oav6yVLimGnBW0EZl84Hmq_r_CVF-A&collection=journals#

Joice, P. A. (2011). Neighborhood Stabilization Program. *Cityscape: A Journal of Policy Development and Research, 13*(1), 135–141. https://doi.org/10.4135/9781452218380.n176

Klößner, S., Kaul, A., Pfeifer, G., & Schieler, M. (2018). Comparative politics and the synthetic control method revisited: a note on Abadie et al. (2015). *Swiss Journal of Economics and Statistics, 154*(1). https://doi.org/10.1186/s41937-017-0004-9

Kondo, M. C., Morrison, C., Jacoby, S. F., Elliott, L., Poche, A., Theall, K. P., & Branas, C. C. (2018). Blight abatement of vacant land and crime in New Orleans. *Public Health Reports, 133*(6), 650–657. https://doi.org/10.1177/0033354918798811

Larson, M., Xu, Y., Ouellet, L., & Klahm, C. F. (2019). Exploring the impact of 9398 demolitions on neighborhood-level crime in Detroit, Michigan. *Journal of Criminal Justice, 60*(November 2018), 57–63. https://doi.org/10.1016/j.jcrimjus.2018.11.002

Lee, K. (2008). Foreclosure's Price-Depressing Spillover Effects on Local Properties: A Literature Review. *Community Affairs Discussion Paper, 14*.

Leon, E. De, & Schilling, J. (2017). Urban Blight and Public Health (Issue April). https://www.urban.org/research/publication/urban-blight-and-public-health

Leonard, T., Jha, N., & Zhang, L. (2017). Neighborhood price externalities of foreclosure rehabilitation: an examination of the Neighborhood Stabilization Program. *Empirical Economics, 52*(3), 955–975. https://doi.org/10.1007/s00181-016-1194-1

Logan, J. R., Xu, Z., & Stults, B. J. (2014). Interpolating U.S. Decennial Census Tract Data from as Early as 1970 to 2010: A Longitudinal Tract Database. *Professional Geographer, 66*(3), 412–420. https://doi.org/10.1080/00330124.2014.905156

Manson, S., Schroeder, J., Van Riper, D., Knowles, K., Kugler, T., Roberts, F., & Ruggles, S. (2023). *IPUMS National Historical Geographic Information System: Version 18.0* [dataset]. IPUMS. https://doi.org/http://doi.org/10.18128/D050.V18.0

Pearson, A. L., Rzotkiewicz, A., Pechal, J. L., Schmidt, C. J., Jordan, H. R., Zwickle, A., & Benbow, M. E. (2019). Initial Evidence of the Relationships between the Human Postmortem Microbiome and Neighborhood Blight and Greening Efforts. *Annals of the American Association of Geographers, 109*(3), 958–978. https://doi.org/10.1080/24694452.2018.1519407

Planning and Development Department. (2009). Neighborhood Stabilization Program Plan. In City of Detroit.

RealtyTrac. (2007). Q3 2007 Metropolitan Foreclosure Market Report. http://online.wsj.com/public/resources/documents/WSJ-foreclosure-rates071114.pdf

Roth, J., Sant'Anna, P. H. C., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics, 235*(2), 2218–2244. https://doi.org/10.1016/j.jeconom.2023.03.008

Schuetz, J. (2015). Investing in Distressed Communities: Outcomes from the Neighborhood Stabilization Program. *Cityscape: A Journal of Policy Development and Research, 17*(2), 279–306. http://www.huduser.org/periodicals/cityscpe/prev_iss/cspast.html%0Ahttp://search.ebscohost.com/login.aspx?direct=true&db=eoh&AN=1544821&site=ehost-live

Schuetz, J., Spader, J., & Cortes, A. (2016). Have distressed neighborhoods recovered? Evidence from the neighborhood stabilization program. *Journal of Housing Economics, 34*, 30–48. https://doi.org/10.1016/j.jhe.2016.07.003

Spader, J., Cortes, A., Burnett, K., Buron, L., DiDomenico, M., Jefferson, A., Whitlow, S., Buell, J. L., Redfearn, C., & Schuetz, J. (2015). The Evaluation of the Neighborhood Stabilization Program. In *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3055189

Spader, J., Schuetz, J., & Cortes, A. (2016). Fewer vacants, fewer crimes? Impacts of neighborhood revitalization policies on crime. *Regional Science and Urban Economics, 60*, 73–84. https://doi.org/10.1016/j.regsciurbeco.2016.07.005

Spelman, W. (1993). Abandoned buildings: Magnets for crime? *Journal of Criminal Justice, 21*(5), 481–495. https://doi.org/10.1016/0047-2352(93)90033-J

Stacy, C. P. (2018). The effect of vacant building demolitions on crime under depopulation. *Journal of Regional Science, 58*(1), 100–115. https://doi.org/10.1111/jors.12350

U.S. General Accountability Office. (2010). GAO-11-48 Neighborhood stabilization program: HUD and grantees are taking actions to ensure program compliance but data on program outputs could be improved. (Issue December). https://www.gao.gov/products/gao-11-48

United States Department of Housing and Urban Development (HUD). (2008). Methodology for Allocation of $3.92 billion of Emergency Assistance for the Redevelopment of Abandoned and Foreclosed Homes. https://www.huduser.gov/portal/datasets/NSP_Allocation_Methodology.doc

US Department of Housing and Urban Development Detroit Field. (2016). NSP is coming to an End (MiHUDdle). https://www.hud.gov/sites/documents/MI-NEWSLETTER-Q4.PDF

Wang, K., & Immergluck, D. (2018a). The Geography of Vacant Housing and Neighborhood Health Disparities After the U.S. Foreclosure Crisis. *Cityscape, 20*(2), 145–170. https://doi.org/https://www.jstor.org/stable/26472173?seq=1

Wang, K., & Immergluck, D. (2018b). The Geography of Vacant Housing and Neighborhood Health Disparities After the U . S . Foreclosure Crisis. *Cityscape, 20*(2), 145–170. https://scholarworks.gsu.edu/urban_studies_institute/41/

Wooldridge, J. M. (2022). Simple Approaches to Nonlinear Difference-in-Differences with Panel Data. *SSRN Electronic Journal*, 1–72. https://doi.org/10.2139/ssrn.4183726

Zhang, L., & Leonard, T. (2014). Neighborhood impact of foreclosure: A quantile regression approach. *Regional Science and Urban Economics, 48*, 133–143. https://doi.org/10.1016/j.regsciurbeco.2014.06.004

Zillow. (2020). ZTRAX Zillow [data]. http://www.zillow.com/ztrax

APPENDIX

Table A2 1: Logit Regression Results for NSP1 and NSP3 Selection Probability

	(1) NSP1 = 1	(2) NSP3 = 1
Population 2009	0.000623***	-0.00111**
	(0.000216)	(0.000439)
Total Houses 2009	-0.00212***	0.00168*
	(0.000528)	(0.00100)
MHI 2009	-0.00000219	0.0000727***
	(0.0000116)	(0.0000188)
Percentage White 2009	0.0761***	0.0695*
	(0.0195)	(0.0393)
Percentage Black 2009	0.0501***	0.0128
	(0.0131)	(0.0278)
If contains Demolitions 2009=1	0.370	0.347
	(0.242)	(0.557)
If Middle Low Area=1	1.225**	0.935
	(0.561)	(0.790)
Risk Score	-0.0356	0.162
	(0.138)	(0.209)
Percentage under 120	-0.0123	-0.0242*
	(0.00761)	(0.0133)
Loan Rate	0.214**	-1.021
	(0.0992)	(0.910)
Predicted Foreclosures	-1.099*	5.849
	(0.575)	(5.274)
USPS vacancy	0.0397***	0.0109
	(0.0130)	(0.0317)
Distance to CBD	-2.106***	-0.0501
	(0.390)	(0.620)
Distance to CBD # Distance to CBD	0.319***	0.0187
	(0.0560)	(0.0907)
Distance to CBD # Distance to CBD # Distance to CBD	-0.0142***	-0.00137
	(0.00247)	(0.00410)
Percentage Residential Zoning Area	0.00479	0.00611
	(0.00480)	(0.00858)
If contains Dilapidated Houses=1	1.449***	1.621**
	(0.478)	(0.784)
Constant	1.116	-32.55
	(2.690)	(23.55)
Observations	998	467

Source: Authors' calculations. Note: This table presents the results of two logit regression models estimating the probabilities of census blocks being selected for the first round of the NSP (NSP1) and the third round of the NSP (NSP3). The variables included in the models are ex-ante policy indicators, some of which were explicitly utilized for selecting census blocks in the years 2008-2009. The coefficients and standard errors are reported for each variable in the models. These regression results are used to generate separate propensity scores, which aid in the selection of a subsample comprising comparable census blocks. The subsampling process aims to create a subset of census blocks that share similar characteristics based on the calculated propensity scores. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2 2: Comprehensive Guide to Variables: Descriptions, Timelines, Geographical Levels, and Sources

Variable	Description	Year	Geographic Level	Source
Key Dependent Variables				
Sale Price ($)	The mean sale price of residential properties for a specific census block in a specific year, calculated from property sales data with geographic coordinates.	2006 - 2019	Census Block	ZTRAX (Zillow, 2020)
Foreclosures (#)	The number of foreclosures per census block for each year, calculated from foreclosure data with geographic coordinates.	2006 - 2019	Census Block	Data Driven Detroit
Foreclosure Rate (%)	The number of foreclosures divided by the number of houses per census block multiplied by 100. The number of houses is estimated by dividing the total number of houses per census tract by the number of census blocks in that tract, using data from 2009.	2006 - 2019	Census Block	Data Driven Detroit / ACS - IPUMS NHGIS
Key Independent Variables				
NSP	Binary treatment variable that takes the value of 1 if a census block implements NSP activities in year t and 0 otherwise. Notice that before year 2009 (for the NSP1 treated) this variable takes values 0, and then only 1s. Same happens for the NSP3 treated, only that it takes values of 0 until 2010, and then only 1s.	2006 - 2019	Census Block	GIS Calculations / City of Detroit
NSP1	Dummy variable that takes the value of 1 if census block was treated in 2009 (first round), zero otherwise.	2006 - 2019	Census Block	GIS Calculations / City of Detroit
NSP3	Dummy variable that takes the value of 1 if census block was treated in 2011 (second round), zero otherwise.	2006 - 2019	Census Block	GIS Calculations / City of Detroit
Time-variant controls				
Age	The mean age of residential properties that were sold in a specific census block in a specific year.	2006 - 2019	Census Block	ZTRAX (Zillow, 2020)
Lot Size SqFt.	The mean lot size of properties sold, measured in square feet, per census block per year.	2006 - 2019	Census Block	ZTRAX (Zillow, 2020)
Number of Stories	The average number of stories of residential properties sold per census block per year.	2006 - 2019	Census Block	ZTRAX (Zillow, 2020)
Number of Full Baths	The average number of full bathrooms in residential properties sold per census block per year.	2006 - 2019	Census Block	ZTRAX (Zillow, 2020)
Garage Area SqFt.	The average garage area, in square feet, of residential properties sold per census block per year.	2006 - 2019	Census Block	ZTRAX (Zillow, 2020)

Table A2. 2 (cont'd)

Time-invariant variables (Propensity Score)				
Predicted Foreclosures	The HUD model's estimated count of foreclosure starts over 18 months through June 2008.	2008	Census Block	HUD
USPS vacancy	The ratio of residential addresses vacant for 90-days or longer to total residential addresses, based on USPS data from June 2008.	2008	Census Block	HUD
If Middle Low Area	A binary variable indicating if an area qualifies for Low- Moderate- Middle-Income area benefit.	2008	Census Block	HUD
Risk Score	A score from 0 to 10 indicating foreclosure and abandonment risk, based on the estimated foreclosure rate and percent of vacant addresses.	2008	Census Block	HUD
Percentage under 120	The percentage of persons estimated to earn less than 120 percent of the median income.	2008	Census Block	HUD
Loan Rate	The percentage of loans made between 2004 and 2006 that were high cost, according to HMDA data.	2008	Census Block	HUD
Distance to CBD	The distance in miles from the centroid of each census block to the Central Business District of Detroit.		Census Block	GIS Calculations / Koordinates
Percentage Residential Zoning Area	The percentage of the total area of the census block allocated to residential zoning.	2009	Census Block	GIS Calculations /ArcGIS Hub
If contains Dilapidated Houses	A binary variable indicating whether a census block had a dilapidated house prior to the policy, based on 2009 residential survey data.	2009	Census Block	GIS Calculations / Detroit Residential Survey 2009
Population 2009	Total population per census tract in 2009, interpolated from 2010 to 2000 geographic boundaries.	2009	Census Tract	ACS - IPUMS NHGIS / Logan et al. (2014)
Total Houses in 2009	Total housing per census tract in 2009, interpolated from 2010 to 2000 geographic boundaries.	2009	Census Tract	ACS - IPUMS NHGIS / Logan et al. (2014)
MHI 2009	Median Household Income per census tract in 2009, interpolated from 2010 to 2000 geographic boundaries.	2009	Census Tract	ACS - IPUMS NHGIS / Logan et al. (2014)
Percentage White 2009	Percentage of white people per census tract in 2009, interpolated from 2010 to 2000 geographic boundaries.	2009	Census Tract	ACS - IPUMS NHGIS / Logan et al. (2014)
Percentage Black 2009	Percentage of African American people per census tract in 2009, interpolated from 2010 to 2000 geographic boundaries.	2009	Census Tract	ACS - IPUMS NHGIS / Logan et al. (2014)
Time-variant variables for extended analysis				
Population	Total population per census tract, interpolated from 2010 to 2000 geographic boundaries.	2009 - 2019	Census Tract	ACS - IPUMS NHGIS / Logan et al. (2014)
Total Houses	Total housing per census tract, interpolated from 2010 to 2000 geographic boundaries.	2009 - 2019	Census Tract	ACS - IPUMS NHGIS / Logan et al. (2014)

Table A2. 2 (cont'd)

MHI	Median Household Income per census tract, interpolated from 2010 to 2000 geographic boundaries.	2009 - 2019	Census Tract	ACS - IPUMS NHGIS / Logan et al. (2014)
Percentage White	Percentage of white people per census tract, interpolated from 2010 to 2000 geographic boundaries.	2009 - 2019	Census Tract	ACS - IPUMS NHGIS / Logan et al. (2014)
Percentage Black	Percentage of African American people per census tract, interpolated from 2010 to 2000 geographic boundaries.	2009 - 2019	Census Tract	ACS - IPUMS NHGIS / Logan et al. (2014)
Building Permits	The number of building permits issued for a specific census block in a specific year, calculated from data with geographic coordinates.	2010 - 2019	Census Tract	City of Detroit / Data Driven Detroit

Source: Author's own elaboration. Note: Column "Sources" make references to the following information:

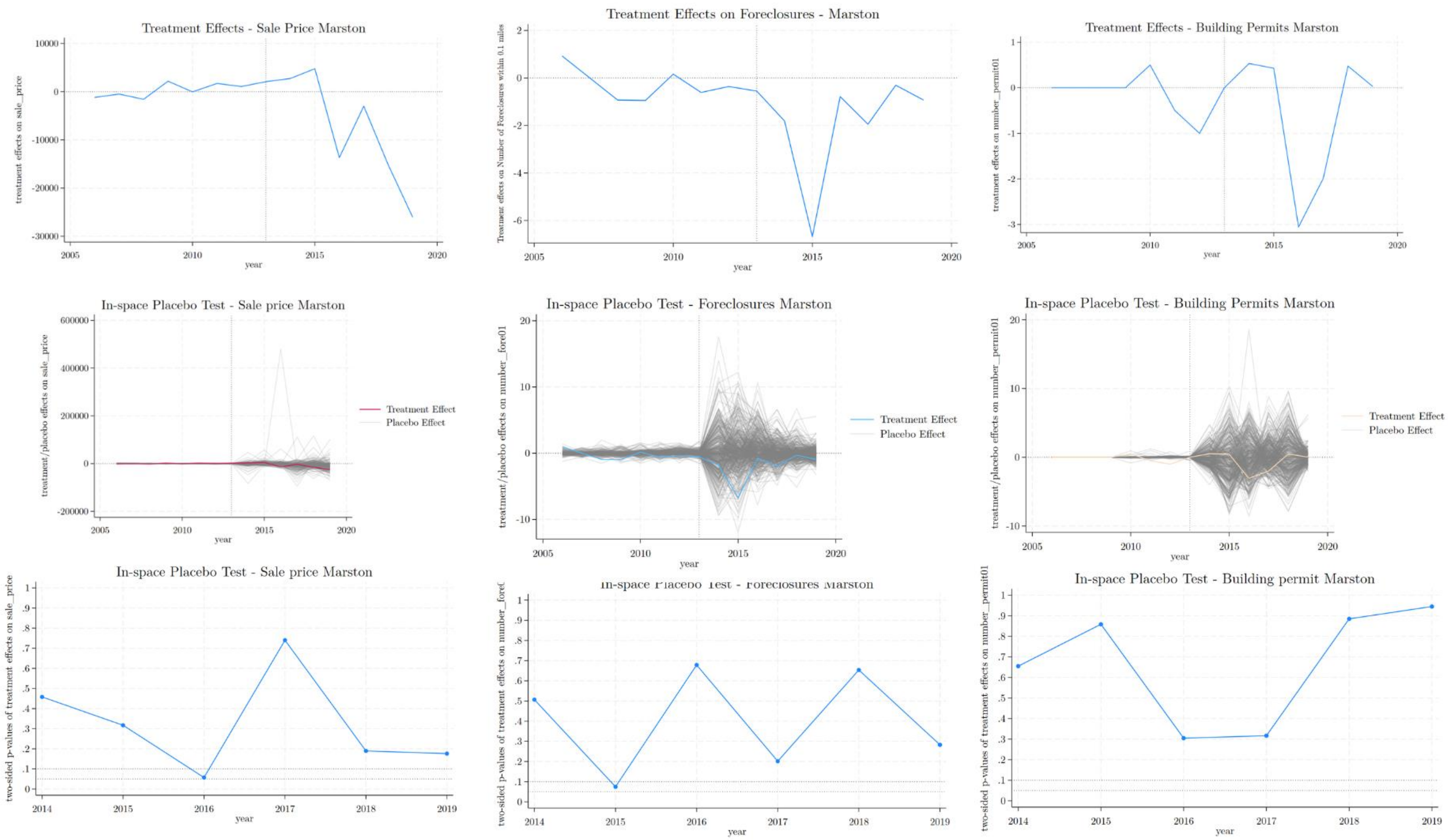
1) ZTRAX (Zillow, 2020): Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group.
2) GIS Calculations / City of Detroit: The City of Detroit provides public information regarding the NSP in Detroit, from design to performance reports. We use all the information available to create these variables and to know the census blocks treated and the census blocks controls. Information can be found in the following link: https://detroitmi.gov/departments/housing-and-revitalization-department/hud-programs-and-information/neighborhood-stabilization-program.
3) Data Driven Detroit: Foreclosure data was acquired from Data Driven Detroit. The dataset can be accessed publicly at this link https://portal.datadrivendetroit.org/datasets/detroit-tax-foreclosures-2002-2019/about (Accessed: June 22, 2023).
4) HUD: Information related to the U.S. Department of Housing and Urban Development (HUD) pertains to the Neighborhood Stabilization Program (NSP) grantees data at the census block level. For additional details, please visit https://www.huduser.gov/portal/datasets/NSP.html#:~:text=HUD's%20Neighborhood%20Stabilization%20Program%20(www,and%20blight%20within%20their%20communities (Last access June 23, 2023).
5) GIS Calculations / Koordinates: Geographic calculations, including distances to the Central Business District (CBD), were based on the 2000 Census Block Groups shapefile of City of Detroit, Michigan. Available at: https://koordinates.com/layer/101455-city-of-detroit-michigan-2000-census-block-groups/ (Last access June 23, 2023).
6) GIS Calculations /ArcGIS Hub: The Detroit zoning codes (2010) shapefile, obtained from ArcGIS Hub, was used to compute the residential zoning area in each census block. This data is significant in the context of the Neighborhood Stabilization Program (NSP). The file can be downloaded in the following link: https://koordinates.com/layer/101455-city-of-detroit-michigan-2000-census-block-groups/ (Last access June 23, 2023).
7) GIS Calculations / Detroit Residential Survey 2009: As in Paredes & Skidmore (2017) and Alvayay Torrejón et al. (2023a), we identify, through the information the Detroit Residential Survey 2009 (Detroit Residential Parcel Survey, 2010), all properties that had some degree of dilapidation based exterior damage, degree of repair needed, and if the property was structurally sound. We calculated the number of dilapidated properties per census block using the coordinates information from the survey.
8) City of Detroit / Data Driven Detroit: Building permit data was provided by the City of Detroit upon request through Data Driven Detroit.
9) ACS - IPUMS NHGIS / Logan et al. (2014): Manson et al. (2022) make available American Community Survey (ACS) data at the geographic census tract level but using the 2010 boundaries (https://www.nhgis.org/). Therefore, we used the codes provided by Logan et al. (2014) to interpolate the ACS information in the 2010 census tract to the 2000 census tracts (information and Stata code can be found in the following webpage: https://s4.ad.brown.edu/Projects/Diversity/researcher/LTDB.htm

Table A2. 3: Robustness Check: Regressions without including adjacent census block groups (Spillover effects)

	Sale Prices		*Foreclosures*		*Foreclosure Rate*	
	(1) TWFEP Never Full Sample	(2) TWFEP Never Subsample	(3) TWFEP Never Full Sample	(4) TWFEP Never Subsample	(5) TWFEP Never Full Sample	(6) TWFEP Never Subsample
$\widehat{ATT}$	393.3 (1460.8)	-3146.8 (6867.2)	0.502 (1.365)	1.314 (1.352)	0.020 (0.135)	0.104 (0.132)
Observations	11,098	9,256	11,098	9,256	11,098	9,256
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Block Group Fixed Effects	No	No	No	No	No	No
Cohort Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Block Group-specific quadratic time trends	No	No	No	No	No	No

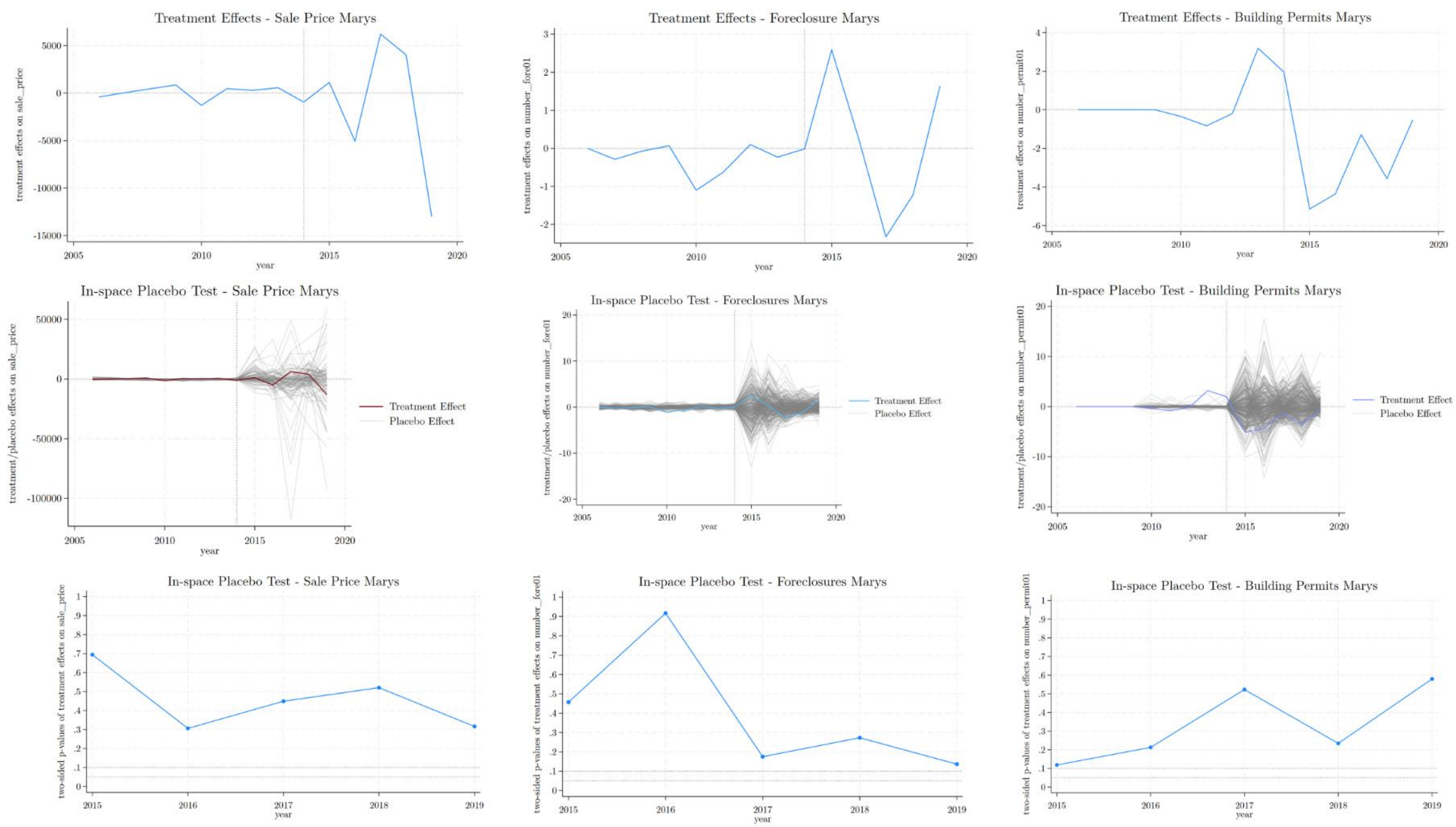
Source: Author's calculations. Note: This table presents regression results estimating the effect of NSP treatment on the average price of residential property sales in census block groups in Detroit excluding the adjacent census block groups. ATT is calculated using a Poisson two-way fixed effects regression (Wooldridge, 2022). The dependent variable is the average price of residential property sales (columns 1 and 2), number of foreclosures (columns 3 and 4), and foreclosure rate (columns 5 and 6). Models control for year fixed effects, cohort fixed effects, and the following time-varying housing characteristics: mean age of properties sold, mean lot size of properties sold, average number of stories, average number of full bathrooms, and average garage area. Standard errors clustered at the block group level are reported in parentheses.
*** Significant at the 1 percent level.

Figure A2. 1: Synthetic Control Analysis of the NSP Treatment Effect with Placebo-Based Inference – Marston



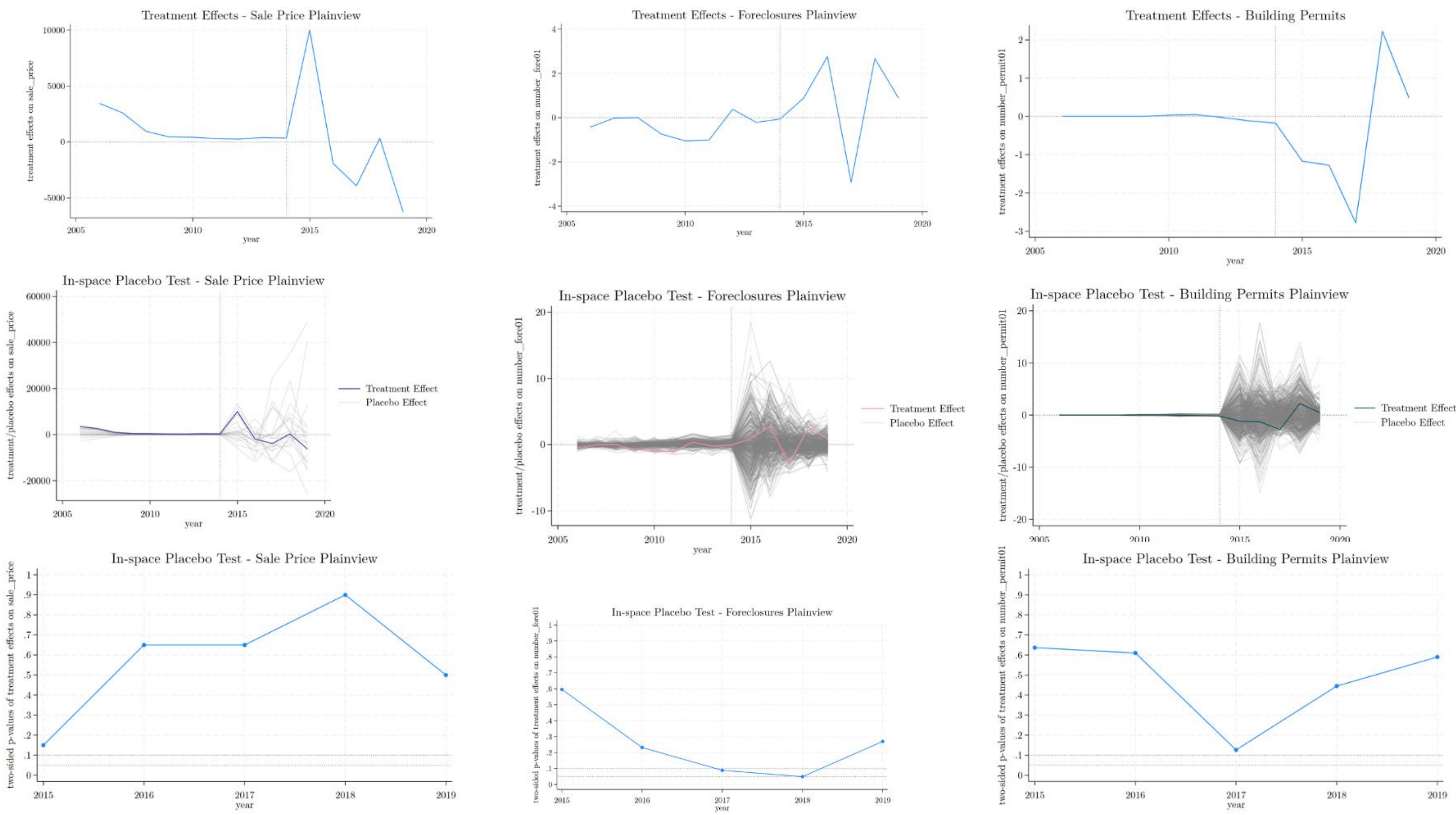
Source: Author's own elaboration using "synth2" command (Yan & Chen, 2021). Note: These are the results of the inference process for the SCM estimation for Marston on the three outcome variables: 1) average sale prices within 0.1 miles, 2) number of foreclosures within 0.1 miles, and 3) number of building permits within 0.1 miles (each column in the figure). The first row shows the effect of the NSP on the selected outcome (difference between the observed outcome for the treated unit alongside its synthetic counterpart over time). The second row illustrates the placebo effects for each control unit, assuming it was treated. The last row shows the two-sided p-value for each control unit under the hypothetical treatment scenario. For the inference, an in-space placebo test was conducted: each control unit was hypothetically "treated", and a synthetic control was constructed for it. The treatment effect for the primary treated unit was compared against the distribution of these placebo effects. The two-sided p-value was calculated by determining the proportion of placebo effects that were more extreme (in either direction) than the actual effect observed for the treated unit.

Figure A2. 2: Synthetic Control Analysis of the NSP Treatment Effect with Placebo-Based Inference – St. Mary’s



Source: Author's own elaboration using “synth2” command (Yan & Chen, 2021). Note: These are the results of the inference process for the SCM estimation for St. Marys on the three outcome variables: 1) average sale prices within 0.1 miles, 2) number of foreclosures within 0.1 miles, and 3) number of building permits within 0.1 miles (each column in the figure). The first row shows the effect of the NSP on the selected outcome (difference between the observed outcome for the treated unit alongside its synthetic counterpart over time). The second row illustrates the placebo effects for each control unit, assuming it was treated. The last row shows the two-sided p-value for each control unit under the hypothetical treatment scenario. For the inference, an in-space placebo test was conducted: each control unit was hypothetically "treated”, and a synthetic control was constructed for it. The treatment effect for the primary treated unit was compared against the distribution of these placebo effects. The two-sided p-value was calculated by determining the proportion of placebo effects that were more extreme (in either direction) than the actual effect observed for the treated unit.

Figure A2. 3: Synthetic Control Analysis of the NSP Treatment Effect with Placebo-Based Inference – Plainview



Source: Author's own elaboration using "synth2" command (Yan & Chen, 2021). Note: These are the results of the inference process for the SCM estimation for Plainview on the three outcome variables: 1) average sale prices within 0.1 miles, 2) number of foreclosures within 0.1 miles, and 3) number of building permits within 0.1 miles (each column in the figure). The first row shows the effect of the NSP on the selected outcome (difference between the observed outcome for the treated unit alongside its synthetic counterpart over time). The second row illustrates the placebo effects for each control unit, assuming it was treated. The last row shows the two-sided p-value for each control unit under the hypothetical treatment scenario. For the inference, an in-space placebo test was conducted: each control unit was hypothetically "treated", and a synthetic control was constructed for it. The treatment effect for the primary treated unit was compared against the distribution of these placebo effects. The two-sided p-value was calculated by determining the proportion of placebo effects that were more extreme (in either direction) than the actual effect observed for the treated unit.

ESSAY 3: VALUING LAND IN DETROIT USING THE OPTION VALUE APPROACH

Introduction

In 2010, the flaws in the property tax system in Detroit came to light when properties in lower-value neighborhoods, with an average sale price of $1,700, were taxed based on an assessment of $41,000—representing an overassessment of up to 30 times the actual sale price (Hodge et al., 2017). Through time, tax overassessment has been covered by multiple studies and media reports[37], providing evidence of a broken property tax system and the need to compensate affected homeowners. Additionally, current discussions aim to find a sustainable solution through property tax reform. Among the recommendations, Sands & Skidmore (2015) noted that it is possible under current statutes to implement a citywide land-based special assessment tax that could improve the efficiency of the overall property tax system. A land value tax or a split-rate tax applies a higher tax rate on land than on improvements,[38] and it is intended to foster growth and urban renewal. The rationale behind a split-rate tax is to lower the relative cost of capital versus land, thereby attracting more investments and fostering growth. The split-rate tax model has been adopted in over 30 jurisdictions globally (Dye & England, 2010), including Pennsylvania and Hawaii, with beneficial outcomes such as increased downtown job opportunities (Hartzok, 1997), more efficient use of urban infrastructure, a rise in the capital/land ratio aiding in combating urban sprawl (Banzhaf & Lavery, 2010), increment in the number of business establishments (Hanson, 2021), and an expanded tax base (Yang & Hawley, 2021). This idea merits discussion, especially

[37] See, for example, the studies and media coverage by Coalition for Property Tax Justice (https://www.illegalforeclosures.org/research)

[38] If taxes only apply to land value, then the tax regime moves from a split rate tax to a land value tax. In the literature, both terms are interchangeable because it is assumed that a land value tax comprises a tax combination with greatest emphasis on land value.

in light of the completion of the legislative proposal and the anticipation of a city council decision by November 2023 to potentially present the Land Value Tax Plan to Detroit voters in the February 2024 primary (City of Detroit, 2023).This highlights the urgency of informed discourse and analysis on property tax reform as the voting approaches.

However, there are challenges that must be resolved in order to implement a split-rate tax. First, changes to the institutional framework may be needed to implement split-rate or land value taxation because most states would require new statutory authority (Sands & Skidmore, 2015). Second, and most relevant to this study, practitioners must be able to provide accurate and timely assessment of land value separate from improvements (Dye & England, 2010). The contribution of this study is to evaluate a simple method using Option Value (OV) theory, and to provide predicted land values based on this indicator. The call option model of land value indicates that land ownership gives the owner the right without obligation to develop or redevelop the property. Hence, there is an underlying decision to either develop the property and incur construction costs now or delay development to some point in the future (Titman (1985), Capozza & Helsley (1989)) Consequently, the value of a property is the sum of use value (the value of the land and existing structures in current use) and the option value, which is a function of the unrealized development potential of the parcel.

In this chapter we present two sets of findings. First, we report empirical evidence for the existence of option value in Detroit property transactions. Using information from the Zillow ZTRAX database and constructing different intensity variables to compare predictions from theory, we estimate hedonic regression models of residential property value that include a measure of option value as an explanatory variable. We contribute to the current literature with a new way of measuring option value through an intensity measure that uses the relative volume of the property built through building footprint information. Results indicate that option value increases with property depreciation, as theory predicts. Having 100 percent option value increases sales prices by 18 percent, in our more conservative estimates. Second, we use these findings to calculate land values, and provide a simple and straightforward method to accomplish this. Results indicate that excluding option value from predicted land values under-estimates values, especially for higher priced properties.

In recent years, researchers have worked to develop approaches that allow land to be estimated separately from improvements. The approaches to measure land values include the residual land valuation approach, where the land value is equal to the sale price minus the replacement cost of the depreciated structure (Davis & Heathcote (2007), (Davis & Palumbo (2008). This method is computationally easy to implement, but it is demanding in terms of the information needed to calculate land values, particularly regarding the information needed on replacement costs. Researchers have also used vacant lot sales to calculate land values (Dye & Mcmillen, 2007). The main idea in this approach is that the lack of improvements creates an opportunity to measure the transaction price as the value of the land. Hodge et al. (2015) implemented this approach in Detroit where they found that land values were high near the central business district (CBD) of the city and in the periphery, compared to land value in between. They were also able to generate a land value gradient for the entire city. The disadvantages of this approach are that the vacant lot sales are relatively few in comparison to the total number of transactions, and usually the spatial distribution of this type of lot is not random across the city.

Hybrid methods or methods that are generalizations of the aforementioned approaches have also been developed. Of relevance to the present work has been the visualization of the decision to redevelop a property as an action similar to the call option in the option pricing framework.

Clapp & Salavei (2010), Clapp, Salavei, et al. (2012), Clapp et al. (2021) contribute to the literature by: 1) theoretically justifying the inclusion of option value in traditional hedonic pricing models (Rosen, 1974); 2) proposing empirical functional forms for measuring option value; and 3) offer different variables that capture option value and empirical evidence through studies using data in cities in the United States as well as in Germany. In this work, the redevelopment option value is separated from the value of the property in its current use. This approach is particularly relevant and useful for our work. In recent years, these authors have developed a land valuation method including the option value implicitly by relying on the assumption of irreversibility in the decision to redevelop. However, a drawback of these approaches is that these models also require information regarding the replacement cost.

Our contribution to the literature is as follows. First, we propose two empirical measures of property structural intensity to calculate the option value in Detroit transactions, and we compare this measure with one already used in the literature. To our knowledge, this is the first chapter to present evidence of option value for the city of Detroit and to use a combined three-dimensional intensity variable with neighborhood quality, that capture the potential to redevelopment. Second, using the notion of option value as discussed above, we propose a simple method to measure land values: the use of hedonic models where measures of option value and current land use value are used to estimate the value of land. We include in our results a subsample of teardown properties (McMillen & O'Sullivan, 2013).

The remainder of this chapter is organized as follows. Section II presents the theoretical framework. In section III, we present the specifications that identify the option value in hedonic regression models. Section IV provides the sources of data and discusses modifications we made to the original database. In section V, we present empirical evidence of the option value in Detroit using three types of intensity variables and the predicted land values. Finally, section VI concludes.

Real Options and Urban Land Valuation: Literature Review

The concept of real options comes from the finance literature related to asset investment decisions (Geltner et al., 2001). The evaluation of an investment decision involves making calculations regarding the expected net profit that the asset will grant in the future. The real option approach is a method that improves the prediction of the standard net present value (NPV), by including in this evaluation the opportunity cost for a lost option value (McDonald & Siegel, 1986). This option value arises from two important characteristics of an investment: irreversibility and the possibility of delay (Dixit & Pindyck, 1994). Hence, in each investment decision, the investor is holding an option (analogous to the call option), where she has the right but not the obligation to invest (or modify) an asset. The value of this option is embedded in the total value of the asset.

Real options framework were first applied to the context of real estate decision analysis by Titman (1985). In this environment, the investor is the landowner who owns a property as an asset. In each period, the landowner has the option to develop or modify her assets to another scale, or to do nothing depending on the net benefits perceived from this action. This option is embedded in the total value of the property, which has allowed us to identify the real option value from property transactions information. We offer a compilation and analysis of empirical literature. To our knowledge, this is the first attempt to organize the literature in a systematic way, which is in itself a contribution.[39]

[39] Womack (2015) provides a survey paper of the literature on real options and urban land values. However, the author does not delve into the results of the empirical studies, since the main objective is to cover all the literature on these topics, including theoretical research and gentrification. Our section elaborates on the subsection Womack (2015) calls "Redevelopment Option" in his article.

Real option theory implies the existence of 1) *development option*, when the landowner of undeveloped (raw) land has the option to develop to an optimal scale and in the optimal time, and 2) *redevelopment option*, when the landowner of a developed land can redevelop the property to a higher and best use (Womack, 2015).[40] Table 3.1 presents a summary of the empirical papers that study these decisions and identify what percentage of a property's market value is attributable to option value. The table is divided into two sections depending on the type of option being studied.

Quigg (1993) is the first empirical work that calculates the development option of vacant land. She uses the framework proposed by Williams (1991), where the optimal date and optimal intensity of a vacant depends on the expectation of future rents of the asset, that is not yet built, minus the construction costs. Using improved land transactions, she estimates the non-observable optimal developed property for vacant land (option model price). Additionally, she uses vacant land transaction prices and several parameters to calibrate the model to calculate the intrinsic value. Option value premium is then defined as the division between the difference of option value minus intrinsic value, divided by intrinsic value. Their results indicate that this option premium is equivalent, on average, to 6% of the value of vacant properties.

A very similar study by Grovenstein et al. (2011), but conducted in a different city and time, found that the option value is 6.6% of the total value of the vacant land. Unlike the study by Quigg (1993), Grovenstein et al. (2011) estimates the elasticity cost, one of the parameters that most affects the variation in the results. Both studies rely on construction cost information, something that is not necessarily available in all contexts. Additionally, both studies construct a counterfactual of the vacant property as if it were developed at its optimal scale with data from the

[40] There is a third option, the *abandonment option*, when the owner of either undeveloped or developed land can sell or abandon the property. In this work we do not focus on this option, but it would be interesting to study it in future research.

already developed properties. This methodological decision, although very creative, can cause bias if the properties developed are inherently different (in unobservable variables) from those that are not yet developed.

Ooi et al. (2006) addresses this issue with a different approach. The authors exploit a natural experiment from Singapore Government Land Sales (GLS), where two types of auctions are held. Private auctions where vacant land is traded without restrictions, and GLS auctions where vacant land is traded but must be developed immediately after purchase. In this sense, this second type of transaction is stripped of any type of option, because development becomes mandatory. Therefore, the difference between both types of transaction should be equal to the value of the option value, *ceteris paribus*. Authors find a 45% option value in vacant properties, and they indicate that the main factor driving this effect is uncertainty of future prices. These results agree with those found by Cunningham (2006), where he estimates that price uncertainty reduces the likelihood of development and increases vacant land prices.

All previous studies focus on the development option, using vacant land. However, recent studies have also focused on expanding the sample of transactions to study the redevelopment option (see second section of Table 3.1). Pioneers in this area are the work from Clapp & Salavei (2010), Clapp, Salavei, et al. (2012) and Clapp et al. (2013). Our interest is on the empirical variables to measure the redevelopment option through hedonic pricing models. Clapp & Salavei (2010) conducts a study for Greenwich, Connecticut, where they propose (and test) intensity, a scalar aggregation index for the amount of structure per unit of land, as a proxy variable for the option to redevelop. Intensity moves in the opposite direction to the option value, i.e., the higher the capital intensity of a property, the higher the opportunity cost of modifying or changing the structure to a new optimal level, because demolition costs increase.

The authors propose measuring intensity in three different ways. The first variable is constructed using information from the city assessor and corresponds to the ratio between assessed structure value and assessed land value. The second variable is the ratio between the interior square footage and the average interior square footage of nearby new construction. Additionally, they propose a variable that they do not test in the paper, which is the percentage of neighboring sales recently torn down or having teardown potential where teardowns are identified by the town assessor. This contribution is essential for our present work, since our first objective is to measure the option to redevelop from a complete sample of property transactions in Detroit.

Two of the three mentioned variables use information from the assessor office. Clapp, Salavei, et al. (2012) also use the first variable in their study. This kind of information is useful because "[…] it has been shown that assessors add information through careful inspection of the property and the use of hedonic regressions that include numerous location factors… [and they are] able to observe whether the lot is suitable for development and assigns land value accordingly" (p.366, Clapp & Salavei, 2010). However, this may not be the case for Detroit. Skidmore and Sands (2015) present evidence that assessed valuations do not reflect market prices. Further, Hodge, et al. (2017) shows that properties with lower market values are significantly over assessed. Note, however, that the city underwent a citywide residential reassessment in 2016, which improved the situation. Nevertheless, we do not prioritize assessed value information for our intensity estimators, nor for land value predictions.

Alternatives consist of using a comparison between the current scale of the property, and relatively new and recently sold properties in the neighborhood (as the second variable proposed by Clapp & Salavei (2010)). That is, it is assumed that this last type of property is sold at its highest and best use (HBU). Büchler et al. (2020) follows this logic. The methodology they used to estimate redevelopment option in commercial properties consists of a three-step procedure. First, construction of a continuous variable reflecting option value. Second, a first stage probit, using the continuous variable to instrument a redevelopment dummy variable. A third consideration relates to the second-stage hedonic model. To instrumentalize the redevelopment option, they build three proxies that attempt to measure the difference between a property in its current use versus the same property in its HBU, through the matching with a second sample (not used in the hedonic regression) of recently built properties. These variables consist of the difference in ratios between Net Operating Income (NOI)[41] and land size, the ratios between structure size and land size, and the comparison between the land use (residential, retail, industrial and office) of the HBU properties and the land use of the property. Munneke & Womack (2020) follow a similar approach, using the ratio of land value to property value, the concentration of teardown activity, and a measured intensity variable such as the floor-to-area ratio as instruments for the redevelopment option. Both studies propose a key contribution by modeling the redevelop decision first, and then create an index or instrument to be use in the hedonic regression. At the same time both studies require knowing ex-ante which properties are effectively those that have the redevelop option.[42]

Let us summarize some empirical considerations when using option value proxies: 1) Development option is usually studied through the separation of the sample, between vacant properties and similar properties with improvements; 2) Redevelopment option is studied from the idea of intensity of the property; 3) Intensity moves in the opposite direction of option value; 4) Usually, the intensity proxy variable enters the hedonic regression in polynomials (to model the

[41] NOI is a calculation used to determine the profitability of commercial real estate investment (Büchler et al., 2020). Not available for residential properties.

[42] In the case of Büchler et al. (2020), this information was within the data from a third-party evaluation. In the case of Munneke & Womack (2020), they divide the sample between teardown and non-teardown property through property characteristics and demolition permit information.

curvature of the option value) (Clapp & Salavei (2010), Clapp, Salavei, et al. (2012), Clapp et al. (2013)); 5) Zoning restrictions can also be important when empirically modeling this variable (Clapp et al., 2013); 6) Redevelopment option can have a high degree of spatial clustering (Munneke & Womack, 2020); 7) Finally, the option value varies with the periods of the economic cycle. In periods of expansion, the option value will have a greater weight in the value of the property, while the opposite happens in periods of recession (Clapp et al., 2013). In the next section, we offer a theoretical explanation of why this happens.

Table 3. 1: Overview of the empirical works analyzing development and redevelopment option in Hedonic Models

Authors & Year	Key Characteristics	Option Value Variable	Results
Development Option			
Quigg (1993)	Transaction type: unimproved land parcels (vacant lots). Land use type: business, commercial, industrial, low-density residential and high-density residential transactions. Location: City of Seattle. Time: 1976 to 1979. Sample Size: 2,700	$OV\ Premium = \frac{Option\ Model\ Price - Intrinsic\ Value}{Option\ Model\ Price}$	Option Value Premium is calculated as a 6% of the average across all sample observations. For residential properties effect ranges from 1.1% to 11.2%, depending on the year of sale and the density of residential (low or high).
Ooi et al. (2006)	Transaction type: Land transactions by auctions (vacant lots). Land use type: Residential only. Location: Singapore Time: 1994 to 2004. Sample size: 273.	Dummy variable for Singapore Government Land Sales (GLS) transactions.	Option Value is 45% of the market value of vacant land.
Grovenstein et al. (2011)	Transaction type: Unimproved land parcels. Land use type: Commercial, Industrial and Residential. Location: City of Chicago. Time: 1986 to 1993. Sample size: 836.	$OV\ Premium = \frac{Option\ Model\ Price - Intrinsic\ Value}{Option\ Model\ Price}$	Option Value Premium is calculated as a 6.6% average across all properties. 10.4% for residential properties. Magnitude of the option premium varies greatly across the individual land use types.
Redevelopment Option			
Clapp & Salavei, (2010)	Transaction type: Improved parcels. Land use type: Single-family residential houses. Location: Greenwich, Connecticut. Time: 1995 to 2007. Sample size: Ranges from 4,557, to 5,218.	(1) $Intensity_{Assessor} = \frac{Assessed\ Structure\ Value}{Assessed\ Land\ Value}$ (2) $Intensity_{Const} = \frac{Interior\ Square\ Footage\ (ISF)}{Average\ ISF\ Nearby\ New\ Construction}$ (3) Percent of neighboring sales recently torn down or having teardown potential where teardowns are identified by the town assessor. [a]	Using Intensity (Assessor): The value of the option to redevelop an old, low intensity is 5.8% (10.5% for larger lots). The value to redevelop median property is only 1.8% in the entire sample (3.5% for larger lots and 1.1.% for small lots). Using Intensity (Construction): 32% of market price is option value.

Table 3.1 (cont'd)

Clapp et al. (2012)	Transaction type: Improved properties. Land use type: Single-family residential properties. Location: 53 towns in Connecticut. Time: 1994 to 2007. Sample size: 162,454.	$Intensity_{Assessor} = \frac{Assessed\ Structure\ Value}{Assessed\ Land\ Value}$ $LINT = \ln(Intensity_{Assessor})$ $LINT' = Detrended\ component\ of\ LINT.$ $LINTZ' = \begin{cases} 10 \text{ if LINT}' \text{ is at its bottom 2\% values} \\ 0\ Otherwise \end{cases}$ $LINT25' = \begin{cases} 10 \text{ if LINT}' \text{ is at its bottom 25\% values} \\ 0\ Otherwise \end{cases}$ $LINT75' = \begin{cases} 10 \text{ if LINT}' \text{is at its upper 75\% values} \\ 0\ Otherwise \end{cases}$	20% of towns have significantly positive option value, with a mean value of 29%-34% for properties most similar to vacant land. Average town has option value of about 6%.
Clapp et al. (2013)	Transaction type: Improved properties. Land use type: Single-family homes. Location: West Berlin. Time: 1978 to 2007. Sample size: 19,825.	$D(Development\ Potential) = \frac{Maximum\ Size\ of\ a\ Property}{Size\ of\ existing\ Property}$ They use the natural logarithm of D. Additionally, they have two dummy variables: fully developed (1 for all observations for which development potential is 0), and high development potential: 1 for all observations with development potential > 0.58.	The elasticity of house value with respect to development potential is 15% on average over the full sample period. For high development potential properties, the elasticity is 23%.
Munneke & Womack (2020)	Transaction type: Improved properties. Land use type: Single-family residential properties. Location: City of Miami, Dade County, Florida. Time: 1999 to 2002. Sample size: 5,493.	First stage: probit where the redevelopment decision is evaluated. Explanatory variables are a measure of the ratio of land value to property (Value Ratio), a concentration of teardown activity measure (Percent Teardowns) and a variable physical intensity (FAR) which is measured by a property's floor-to-area ratio. Second Stage: consists of incorporating the predicted probability (*option value variable*) in a traditional hedonic price model.	Spatial Model: option value accounts for 4% of property's selling price on average for all the properties in the sample. For properties exhibiting option value (38% of the sample), the average option value is approximately 12% of a property's selling price and about 25% of a property's land value. Non-spatial model: the average redevelopment option value ranges from 8% to 18% of the sales price.

Table 3.1 (cont'd)

Büchler et al. (2020)	Transaction type: Improved properties. Land use type: Commercia properties only. Location: 30 American cities. Time: 2001 to 2018. Sample size: 46,000.	Proxies for redevelopment: $N = \left(\frac{\overline{NOI}^{hbu}}{\overline{LS}^{hbu}}\right) - \left(\frac{NOI^{current}}{LS^{current}}\right)$ $F = \left(\frac{\overline{SS}^{hbu}}{\overline{LS}^{hbu}}\right) - \left(\frac{SS^{current}}{LS^{current}}\right)$ $HBU\ Property\ Type\ Similarity$ Where NOI is Net Operating Income, SS is Structure Size, LS is Land Size and hbu is High and Best Use.	100% of redevelopment potential increases property values between 9% to 17%.

Source: Authors' own calculations.

[a] This variable is proposed by the authors, but they do not use it explicitly in their calculations.

[b] Mean across years 2010 to 2019.

Theoretical Considerations

In this section we present the theoretical foundations for the inclusion of option value in traditional hedonic models. Additionally, we relate these concepts to the valuation of land and the use of option value to determine it.

The Option to Redevelop in Hedonic Models

Rosen's model of market equilibrium for differentiated products explicitly abstracts from the representation of properties as assets, but rather as consumption goods (Rosen, 1974). However, the dynamics in the housing market related to urban renewal processes are explained by process of deterioration and consequent redevelopment, where owners make decisions to partially redevelop (renovate) or fully redevelop (tear down) their existing properties (Munneke & Womack, 2015). Consequently, these types of decisions can be studied from the point of view of investment projects and be included in equilibrium models of the housing market.

Clapp et al. (2012) propose a framework that builds on Rosen (1974) by incorporating Option Value Theory (OVT) in the hedonic price model, and specifically from the framework of real options. The call option model of land value is based on the idea that land ownership gives the owner the right without obligation to develop or redevelop her property. Hence, there is an underlying decision to either develop the property and incur in construction costs now, or delay development to some point in the future (Titman, 1985). The strength of this model lies in the determination of the option value as an additive term in the hedonic price function, which is very useful at the time of its estimation. Below, we provide a brief summary of the model and its theoretical consequences.

The first assumption of Clapp's model is to treat the option to redevelop as a single irreversible call option.[43] This assumption implies that once the land redevelopment investment has been made, the structure cannot return to the initial state due to nonzero demolition and construction costs (Clapp et al., 2021). The historical context of Detroit, marked by profound economic shifts and urban decay, further substantiates this irreversibility assumption. This assumption indicated that once redevelopment has occurred, the option to revert to the previous state is typically off the table, due to sunk costs. With the average cost of demolitions in Detroit being \$20,000 (Paredes & Skidmore, 2017), and the prevalence of vacant lots, blighted neighborhoods, and underdeveloped land (Owens et al., 2020), it is clear that redevelopment decisions have enduring consequences and that reversal of such decisions is not readily accomplished. Finally, it is worth noting that while we do not observe all individual choices of redevelopment, we have an opportunity to observe one from one agent: the local government. In the context of an urban policy, where the local government has been faced with a choice between demolition and redevelopment, the government's actions have led to a far greater number of demolitions compared to redevelopments (Alvayay Torrejón & Skidmore, 2023). This provides an indication of how costly the redevelopment option can be.

In this model, the landowner (and developer) is risk-neutral and that at time t, she has a unit of land ($L = 1$) and an initial scale of housing ($\bar{Q}$). Then, at any time $s \geq t$, the landowner is able to redevelop land on a scale equal to Q. The functions of cost of redevelopment and rent per unit of the redeveloped property are given by equations (1) and (2), respectively.

[43] The single irreversible call option has the following investment characteristics: 1) Irreversibility, 2) Uncertainty, and 3) Timing. From the real option approach to investment, these characteristics are also present in the landowner's decision to develop his property. Irreversibility, because the initial investment cost is at least partially sunk, especially when construction and demolition costs are high. Uncertainty because there is an option to wait based on future rewards. And timing because there is a control of when the investment will be made.

$$C(Q,\bar{Q}) = Q^{\eta_2}\bar{Q}^{\eta_1} \tag{1}$$

$$R\big(Q,x(t)\big) = Q^b x(t) \tag{2}$$

Costs depend on the initial structure ($\bar{Q}$) and the scale or density of the new structure to be invested (Q). Costs are assumed to increase with Q ($\eta_2 > 0$), but there is no restriction for the case of $\bar{Q}$. However, for our case it is probable that costs increase with initial structure ($\frac{\partial C}{\partial \bar{Q}} > 0$) due to positive demolition costs. Also, we assume that rent per unit of the redeveloped property decreases with Q, at a decreasing rate ($0 > b > -1$). Likewise, the rent per unit of the existing property is giving by $R\big(Q,x(t)\big) = \bar{Q}^b x(t)$.

The developer's problem is to find the optimal time to execute the option and the optimal redevelopment scale that maximizes the expected net present value of the existing property (Poterba, 1984). Equation (3) summarizes the problem mathematically, where the first term is the expected present value of rents up to the redevelopment time T, the second term is the expected present value of rents since redevelopment time, and the third term corresponds to the expected present value of redevelopment costs. A risk-free interest rate that also corresponds to the discount rate, ρ, is assumed.

$$z(x,\bar{Q}) = \max_{T,Q} E_t\left\{\int_t^T \bar{Q}^{b+1}x(s)e^{-\rho(s-t)}ds + \int_T^\infty Q^{b+1}x(s) - Q^{\eta_2}\bar{Q}^{\eta_1}e^{-\rho(T-t)}\right\}$$

$$st \qquad dx(t) = \alpha x(t)dt + \sigma x(t)dz(t) \tag{3}$$

Notice that the landowner's maximization problem is subject to the shocks on the demand side, $x(t)$ (x from now on). Unlike Quigg (1993) who introduces uncertainty in the cost function, Clapp et al. (2012) includes uncertainty in x. Therefore, the constraint in equation (3) indicates that the demand shocks follow a Geometric Brownian motion, where α is the constant growth rate, σ^2 is the variance of the growth rate, and $z(t)$ follows a standard Wiener process where $E[dz(t)] =$

0 and $E[dz(t)]^2 = dt$. Note that the Geometric Brownian motion is a special case of an Ito Processes to model the behavior of a non-stationary stochastic variable (Dixit & Pindyck, 1994).

The solution to the optimization problem determines an optimal development density and a critical demand level above which redevelopment becomes the preferable choice (see details of this calculation in the appendix section of (Clapp, Jou, et al., 2012). This optimization balances the present value of the existing property against the potential upside of redevelopment, inherently factoring in the option value. The insights of the model are particularly relevant in markets like the one of Detroit, where historical economic volatility and urban blight underscore the permanence of redevelopment decisions.

To map the option value to the hedonic characteristics space, x must be held constant at time t. We define $\bar{Q}_0$ as the lowest intensity level such that $x = x^*(\bar{Q}_0)$, and we focus on the case where $\bar{Q} > \bar{Q}_0$, that is, where it is better to delay the redevelop option of the existing property because the current state x still does not reach the critical optimal value. In this case, the value of the existing ($F(\bar{Q}) = P(\bar{Q})$) is a function of the current development intensity, as indicated by equation (4)

$$F(\bar{Q}) = P(\bar{Q}) = B_0\bar{Q}^{b+1} + B_1\bar{Q}^{\alpha_0} \tag{4}$$

Where $B_0\bar{Q}^{b+1}$ represents the base value of the property, which is influenced by factors like the property size and the intrinsic value of the land without redevelopment, and $B_1\bar{Q}^{\alpha_0}$, captures the added value from potential redevelopment, reflecting the premium that the market is willing to pay based on the property development prospects[44] (Clapp, Jou, et al., 2012). Note that

[44] The parameters represented by B_i and α_0 in equation (4) are functions of the level of scale $\bar{Q}_0$, the constant rate of interest, the rate of depreciation, the stochastic parameters, the parameters from the cost function, and solution to the fundamental quadratic equation. Within the valuation model, B_0 and B_1 serve as fixed parameters that encapsulate several economic and property-specific factors. B_0 is influenced by the intrinsic characteristics of the property, such as its location, land area, and current usage, which determine the baseline value of the property irrespective of redevelopment potential. It reflects the worth derived from the property's existing utility and the income

$\alpha_0 < 0$, which implies that the option value will decrease with increasing intensity. Intensity can be understood as a scalar aggregation index of the amount of structure per unit of land value (Clapp, Salavei, et al., 2012). Second, $B_1 \geq 0$ because property owners have the right but not the obligation to redevelop. Therefore, the option value term cannot be negative.

Furthermore, the value of a property is the sum of use value, the value of the land and existing structures in current use, and the option value, which is a function of the unrealized development potential of the property (see equation 5).

$$Market\ Value = Use\ Value + Option\ Value \tag{5}$$

There are two theoretical implications from equation (4) that can be tested empirically. First, notice that the first part of equation (4) is the classic hedonic model specification that includes factors that determine value under the current use of the asset. The second part, which measures option value, enters the equation in an additive form. The additive nature of the equation implies that models that do not directly measure option value assume that this second part is equal to zero. In practical terms, the option value is zero or close to zero in markets that are fully developed with relatively new properties (Clapp, Jou, et al., 2012).

The second implication is that equation (4) indicates that the option value is measured by the inclusion of a non-linear function of intensity, which is the size of the structure relative to land on a property. The literature offers several alternatives proxy measures for intensity (as shown in the next section). However, it is important to understand the interpretation of each measure. In this context, a larger structure relative to the size of the land suggests a higher intensity. Properties with

---

it can generate in its current form. Conversely, B_1 represents the option value parameter. It is shaped by expectations of future market conditions, zoning regulations, and the potential for an increase in property value due to possible improvements or changes in land use. This parameter quantifies the additional value that the market assigns to the property based on its redevelopment potential—essentially, the financial advantage of holding onto a property until the optimal moment for redevelopment.

such a characteristic might be close to optimal intensity, especially if they are newer. This near-optimal intensity implies a higher opportunity cost if the redevelopment option is exercised, as it would involve forgoing the income generated by the current structure. Consequently, the option value is lower for properties at or near optimal intensity because the benefits of redeveloping are not as pronounced relative to the costs.

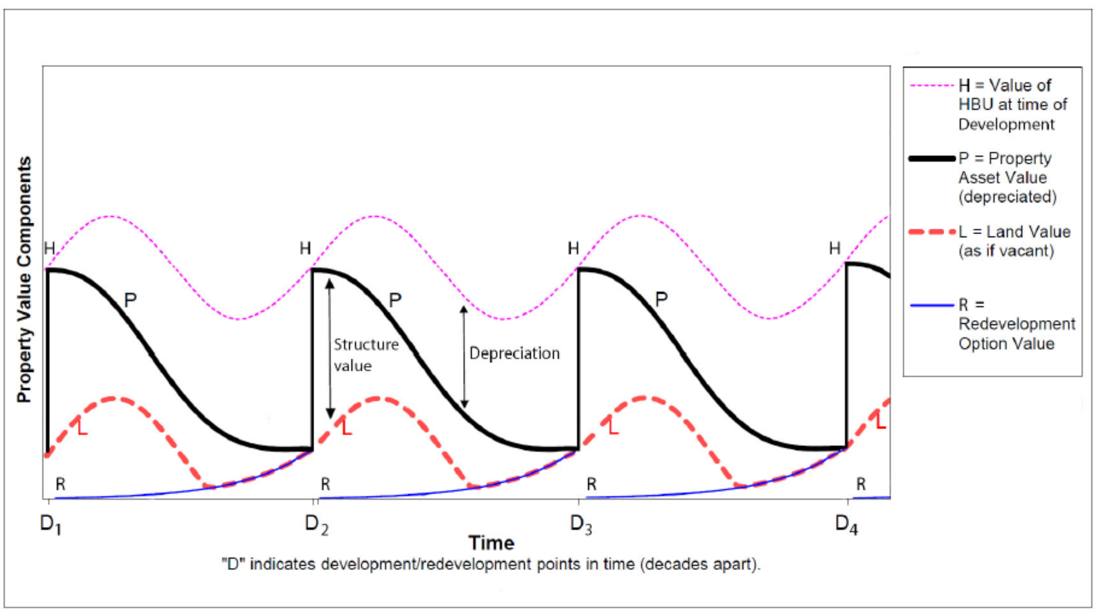
Conversely, a smaller structure relative to the size of the land indicates a lower intensity. Older properties that are smaller in scale may be further from optimal intensity, which can increase the option value. These properties, being further from the optimal point, carry a higher option value since the potential income from redevelopment, relative to the cost of redevelopment, is greater. This relationship is justified by the second part of equation (4), which is a function of the intensity scalar and the depreciation rate effects. Note that this relationship is simplified as long as factors such as demand shocks, uncertainty, interest rates, depreciation rate, costs, and economic cycle factors are held constant.

Land Value and Option Value

The option value component in the hedonic model represents the value of the potential to redevelop a property in the future (see Figure 3.1). As a property approaches the optimal time for redevelopment, the option value gets close to the underlying land value. This occurs because just before redevelopment, the existing structure has little remaining useful life and therefore minimal value. Thus, the opportunity cost of redeveloping is low, and the redevelopment option value approximates the land value Büchler et al. (2020). In contrast, for a property that is far from the redevelopment point and at peak use value, the land value exceeds the option value. In this case, the current use of the land and improvements adds significant value above the raw land value. Therefore, the option to redevelop has a higher opportunity cost.

This framework suggests two potential empirical approaches to estimate land value using the hedonic model with option value. First, for properties near the redevelopment point, the estimated option value provides an approximation of land value. Second, for properties at peak use value, the combined estimated use value and option value provide an upper bound estimate of land value. The use value component measures the gross value added from existing structures. Subtracting use value from total value yields an estimate of land value. In summary, the relationship between option value and land value established in the theoretical model can be leveraged to empirically estimate land values for properties at different points in their lifecycle. This provides useful insights for the next section.

Figure 3. 1: Relationship between land value and redevelopment option value



Source: Büchler et al. (2020).

Identification Strategy

This section describes our approach to calculate land values in Detroit. We first estimate hedonic regressions to identify/measure option value. We then explain how we use these estimates to compute land values.

Step One: Estimate Option Value for Detroit Residential Properties

According to Clapp & Salavei (2010), equation (6) can be estimated using several potential functional forms, starting with the logarithmic transformation. As a benchmark, the first specification that we estimate is the classic hedonic pricing model.

Standard Hedonic Model

$$lnP_i = \boldsymbol{\alpha}' \boldsymbol{q_i} + \varepsilon_i \tag{6}$$

In equation (7), $\boldsymbol{q_i}$ is the vector of the typical variables that measure property characteristics, location attributes, dummies variables indicating the year of sale, and a constant term. Of these variables, the greatest relevance are the intensity proxy variables: $InteriorFootage_i$ (interior area or building square footage), $Lotsize_i$ (lot size in square feet), and Age_i and Age_i^2, (polynomial function of building age as a proxy for depreciation).

Let $Intensity_i$ represent the intensity of land use as measured by the relative size of the structure land area for each property i, and $\ln Intensity_i$ as the natural logarithm of this variable. Equation (7) shows the first specification to be estimated, which is the standard hedonic model with the option value. Usually, this variable is measured as a ratio between structure and land which implies that $Intensity_i \geq 0$. The upper bound depends on the relative sizes of the numerator and denominator. However, if the structure is equal to zero (vacant properties) the logarithmic transformation may not be the most appropriate to measure the effect of the option value.[45]

First Specifications: Hedonic Model including the Option Value

$$lnP_i = \boldsymbol{\alpha}'\boldsymbol{q_i} + \beta_1 \ln Intensity_i + \varepsilon_i \tag{7}$$

The option value increases the market value of the property by discounting the future net benefits at the present value. At the same time, the option value is inversely related to the intensity of the property. Therefore, the hypothesis we test is $\beta_1 < 0$. Hence, the marginal effect will be multiplied by (-1) to obtain the interpretation of the option value effect (see equation 10).

$$\frac{\%\Delta Price}{\%\Delta Option\ Value} \approx \frac{lnP}{\ln Option\ Value} = -\hat{\beta}_1 \tag{8}$$

The second specification we estimate is intended to capture the theoretically predicted relationship between option value and the depreciation rate. Older and, therefore, more deteriorated property will tend to have a higher option value. This effect occurs via the component in the cost of developing the option value, which is a function of the current value of the property. A high depreciation implies a lower structural value and thus a lower opportunity cost to exercise the option to redevelop. One approach to capture this effect is through the interaction of the intensity variable with the age of the structure. This specification is illustrated in equation (9):

Second Specification: Hedonic Model including the Option Value and Depreciation Effect

$$lnP_i = \boldsymbol{\alpha}'\boldsymbol{q_i} + \beta_1 \ln Intensity_i + \beta_2 \ln Intensity_i \times Age_i + \beta_3 \ln Intensity_i \times Age_i^2 + \varepsilon_i \tag{9}$$

---

[45] In this chapter, the sample does not contain vacant lots, so we have no problem with the logarithmic transformation.

Equation (10) captures the marginal effect of the intensity variable, which is now a function of age. The interpretation is that older structures have higher depreciation, and thus we expect a higher option value (or lower intensity).

$$\frac{\%\Delta Price}{\%\Delta Option\ Value} \approx \frac{lnP}{\ln Option\ Value} = \{-(\hat{\beta}_1 + \hat{\beta}_2 \times Age_i + \hat{\beta}_3 \times Age_i^2)\} \tag{10}$$

Finally, our last specification is shown in Equation (11).

Third Specification: Hedonic Model including the Option Value, Depreciation Effect and Neighborhood Housing Quality

$$lnP_i = \boldsymbol{\alpha}'\boldsymbol{q_i} + \beta_1 \ln Intensity_i + \ \beta_2 nhood_{quality_i} + \beta_3 \ln Intensity_i \times nhood\_quality_i \times nhood\_quality_i \times Age_i \ + \beta_4 \ln Intensity_i \times nhood\_quality_i \times Age_i^2 + \varepsilon_i \tag{11}$$

Equation (12) captures the marginal effect of the intensity variable, which is now a function of age and neighborhood quality.

$$\frac{\%\Delta Price}{\%\Delta Option\ Value} \approx \frac{lnP}{\ln Option\ Value} = \{-(\hat{\beta}_1 + \hat{\beta}_3 \times nhood\_quality_i \times Age_i + \hat{\beta}_4 \times nhood\_quality_i \times Age_i^2)\} \tag{12}$$

The neighborhood quality in our study is quantified through the construction of a blight index. Thanks to a newly rich publicly available data from the City of Detroit, we have geolocated information on blight infractions within the city of Detroit, from 2008 to 2019. For each sale, we count the number of blighted properties within a 0.5 miles radius, within the three years prior to the sale year. To add depth to this count, we calculate the average fine amount reflecting on the severity of the infraction. Additionally, for each property we multiply the number of blight infractions times the average fine (Blight Intensity Score, BIS) amount that reflects both the prevalence of blight and the financial weight of its impact. To ensure comparability across different neighborhoods, we normalize this score by dividing it by the maximum BIS observed within each neighborhood, resulting in our final Blight Index measure.[46] This index serves as a nuanced indicator of neighborhood quality, capturing not just the presence of blight, but its economic significance as well.

To our knowledge, this is the first attempt to include neighborhood quality as an interaction effect with intensity. The hypothesis is that a neighborhood with higher blight scores (indicating more violations and potentially lower quality) could reduce the option value of a property. Investors might perceive properties in such areas as less desirable due to the potential for higher costs to address these issues or because they expect less appreciation in property values. Combining intensity with neighborhood quality adds another dimension to the redevelopment decision. A high-intensity score in a neighborhood with a poor blight index might be less favorable than the same score in a neighborhood with a better blight index. This can affect the interpretation of option value because the potential for redevelopment might be curbed by negative neighborhood factors.

Summarizing, the three hypothesis that we are testing (and the ones that will shed light on how good we are measuring option value) are the following ones:

- H1: There is a negative impact of the intensity measure on property sale prices, suggesting evidence of option value in property transactions.
- H2: The devaluing effect of land use intensity on price intensifies with property age, indicating a greater option value for older properties.
- H3: Higher neighborhood blight scores diminish the option value, with the impact of intensity on price being less adverse in areas with more blight.

[46] Hence, blight score ranges from 0 to 1, with 1 indicating areas with more blight infractions and more serious ones as well.

Construction of the Intensity variables

In this section, we present the methods we use to construct the two measures of option value. The database we are using contains information on assessed values in Detroit. Specifically, we have information on the assessed land value and the assessed value of improvements. Several papers in the literature use this information from the Office of the Assessors to create the intensity variables because, "…it has been shown that assessors add information through careful inspection of the property and the use of hedonic regressions that include numerous location factors… [and they are] able to observe whether the lot is suitable for development and assigns land value accordingly"(p.366, Clapp & Salavei, 2010). However, this may not be the case for Detroit. Skidmore and Sands (2015) present evidence that assessed valuations do not reflect market prices. Further, Hodge, et al. (2017) shows that properties with lower market values are significantly over assessed. Note, however, that the city underwent a citywide residential reassessment in 2016, which improved the situation. Nevertheless, in this chapter we do not use assessment data to estimate the impact of intensity on property values, and particularly to estimate the value of land. Recall that our ultimate objective is to develop methods for improving land value assessments for tax purposes. However, the results of this exercise are available upon request, though the estimates are contrary to theoretical predictions.

1) Relative 2D Intensity measure (neighbors within 0.5 miles)

The first variable we use to examine option value is $Intensity_{2D\_05,i}$ (see equation 13). This variable measures the interior square footage of property i relative to the average interior square footage of neighbors j. This is a relative measure of the condition of the property with respect to the neighborhood.

$$Intensity_{2D\_05,i} = \frac{Interior\ Square\ Footage_i}{\frac{1}{J}\sum_{j \neq i}^{J} Interior\ Square\ Footage_j} \tag{13}$$

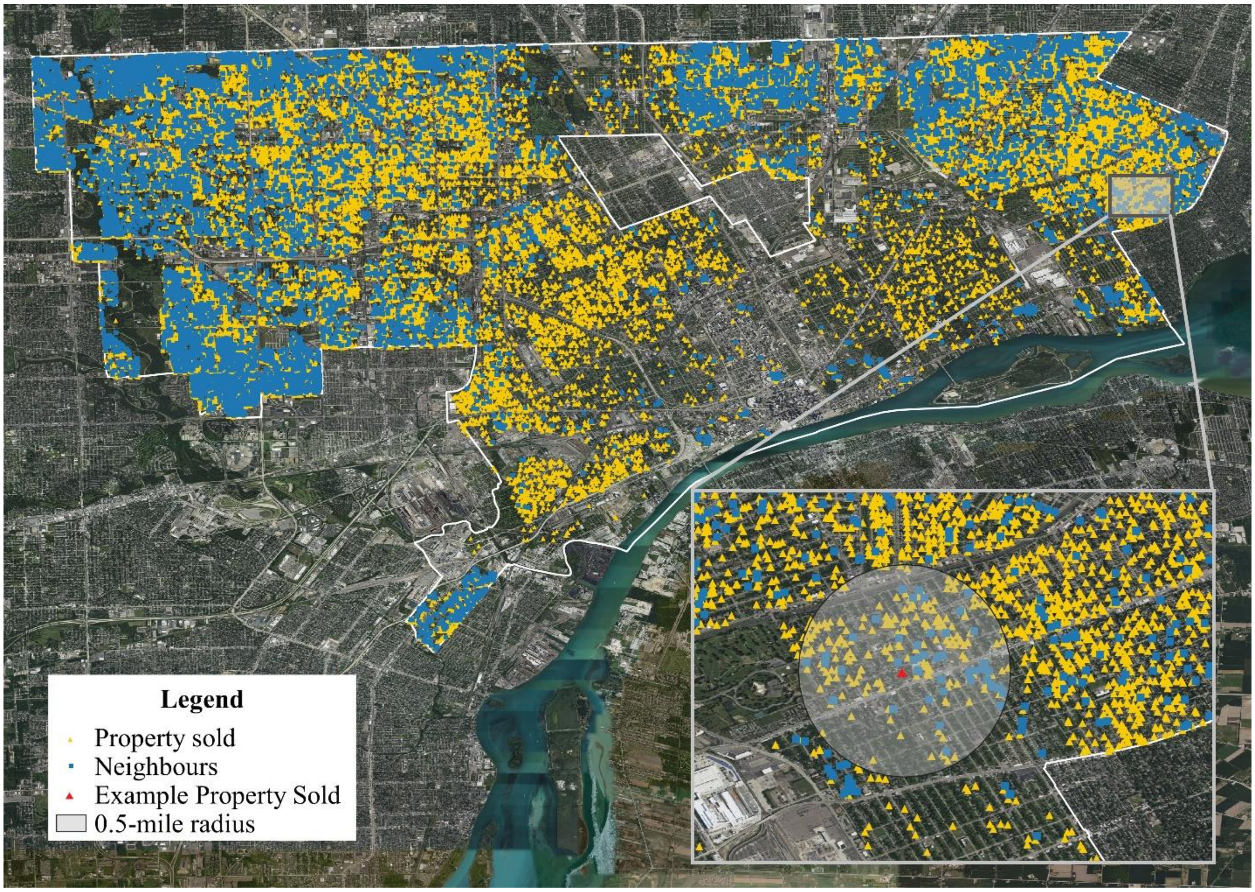
It is important to indicate that neighbors j of property i must meet certain conditions to fall into the category of neighbors and be included in the comparison group. First, the neighbors are all those properties that are within a radius of 0.5 miles around property i.[47] Second, we only include properties with an age of structure equal to or less than 60 years. Third, the comparison group only includes properties that were sold within three years of the year of sale of property i, including the present year.[48] For example, if a property was sold in 2015, neighbors are those properties around property i that were sold in 2015, 2014, 2013, and 2012. These conditions ensure that the comparison group in the denominator of equation (13) are relatively new properties that were recently sold.

Figure 3.2 presents a geographic representation of this process using 2012 data as an example. Figure 3.2 shows the mapping of two types of properties across Detroit. The first group are all those properties that sold in 2012 (marked with a yellow triangle). The second group includes all the properties that constitute potential neighbors according to the requirements discussed above. The map shows that for each of the properties sold that year, a radius of 0.5 miles is calculated (the property marked with the red triangle is an example). Then the interior square footage of each of the neighboring properties within that radius (those properties marked with blue) is averaged. Finally, the ratio is the interior square footage of the property divided by the average of its neighbors within a 0.5-mile radius. This procedure is repeated for each of the properties marked in yellow for all the years of the sample.

[47] In the case of Clapp & Salavei (2010), they chose a radius of 1.25 miles. We chose a smaller radius based on the size of the city.

[48] In addition to these requirements, the filters made to the properties in the complete sample are added, which are detailed in the following Data section.

Figure 3. 2: Example of the construction of the variable $Intensity_{2D_{05},i}$



Source: Authors' calculations. Note: This map presents an example of the construction of the $Intensity_{neighbor05,i}$ variable for 2012. The geographic location of properties sold that year is indicated with yellow triangles, while neighbors or comparison group is indicated with blue squares (read the main text for more detail regarding the construction of this group). Additionally, we provide a zoom to the map to show the construction process of the variable. For each property sold (as an example the property highlighted with a red triangle) a radius of 0.5 miles is set and the interior square footage of the structure as marked with blue squares is averaged. This procedure is repeated for each of the properties marked with yellow triangles. Note: The two areas within the city are the separate jurisdictions of Hamtramck and Highland Park.

2) <u>Relative 3D Intensity measure (neighbors within 0.5 miles)</u>

The second intensity measure we propose exploits current technological resources to include volume as a three-dimensional measure of the property infrastructure development. Equation (14) shows that the variable$Intensity_{3D_{05},i}$ is equal to the ratio between the volume of property i and the average volume of all properties j located within 0.5 miles from property i. Volume is defined as $interior\_sqft \times building\_height$.

$$Intensity_{3D_{05},i} = \frac{Volume_i}{\frac{1}{J}\sum_{j\neq i}^{J} Volume_j} \tag{14}$$

Similar to the $Intensity_{neighbor05,i}$, neighbors must comply with all the requirements we discussed. A 3D intensity variable provides a more comprehensive measurement by accounting for the volume of structures in addition to area (see Figure 3.3 as an example). This additional dimension could capture the real estate value more accurately, as it reflects the physical reality of structures better than a 2D measure. Certainly, there are still limitations regarding the physical and visual characteristics of the property, or the state of the infrastructure. Although we do not include a measure of infrastructure quality explicitly, the interaction with age allows us to at least control for part of the depreciation. In the Data section we present, discuss and compare the descriptive statistics for the three intensity measures.

Figure 3. 3: Example of the information to construct of the variable $Intensity_{3D_{05},i}$

Source: Building Footprint information from the Southeast Michigan Council of Governments (SEMCOG). Note: This 3D map presents an example of the building footprint information that we use to create $Intensity_{3D_{05},i}$.

Step Two: Estimating Land Value Using Option Value

First, we calculate land values by adding to the option value the use value coming from the current use of the land and its location. We measure the option value and use value components as proposed in equation (15) and (16). We use Poisson regression model to ensure positive predicted values, and to predict values in dollar amounts.

$$P = f(OptionValue, UseValueofLand, Improvements) \tag{15}$$

$$E(P_i|\boldsymbol{X}) = \exp\left[f(\beta_i, Intensity) + \beta_5 Nhood + \boldsymbol{\alpha}'\boldsymbol{q_i} + \varepsilon_i\right] \tag{16}$$

In the first step, we have three specifications to calculate $f(\beta_i, Intensity)$. We use the third specification to simplify the analysis, and to test this new intensity variable that we are including in the option value literature. In equation (16), use value of land depends on lot size and location through a neighborhood categorical variable and a set of distances variables. Notice that the $\boldsymbol{q_i}$ vector is composed of the variables that measure the improvements, such as the interior square footage, number of stories, number of bathrooms, type of heating system and the material of the exterior wall of the property.

We obtain the predicted price values from equation (16), $\hat{P}_i$. Then, we replace the intensity, age and neighborhood quality variables for each property to the maximum intensity, minimum age and best blight index within its neighborhood n, respectively. The idea here is to find the property developed at its Highest and Best Use (HBU) (this means with zero option value). We obtain predicted price values assuming the property its developed to the full potential, $\hat{P}_{maxint,i}$. Finally, the option value is going to be the difference between the actual development of the property and the counterfactual property in its HBU (see equation 17).

$$\widehat{OptionValue_i} = \hat{P}_i - \hat{P}_{maxint,i} \tag{17}$$

To estimate predicted land values, we calculate equation (18), where $P_{nooptionvalue} = P_i - (\widehat{OptionValue_\iota})$. This means $P_{nooptionvalue}$ corresponds to the sale price removing the option value calculated in the previous step.

$$E\left(P_{nooptionvalue_i} \middle| \boldsymbol{X}\right) = \exp\left[+\beta_4 Lotsize\ +\ \beta_5 Nhood\ + \boldsymbol{\alpha}'\boldsymbol{q_i} + \varepsilon_i\right] \tag{18}$$

We conduct the same exercise as before. We adjust property characteristics to their minimum values within each neighborhood, and then predict values from equation (18). The objective here is to predict the sale price for a property with no improvement and without option value, which constitutes the predicted land values without option value, $LV_{\widehat{nooptionvalue}}$. Finally, predicted land prices will be the sum between land value without option value, and option value, as shown in equation (19).

$$\widehat{LV} = LV_{\widehat{nooptionvalue}} + \widehat{OptionValue_\iota} \tag{19}$$

Importantly, we also compute land values using the teardowns property subsample. With this approach we identify those properties that were sold when they had smaller structures compared to their neighbors (low level of intensity, that is, relatively small properties), and we used building permits data to determine which properties were significantly altered after sale as determined by the estimated cost of the modifications. That is, we only included the higher cost modifications as a proxy for teardowns. This approach constitutes our best effort to identify teardowns in the sample.

With this subsample we estimate $\widehat{LV} = \widehat{OptionValue_\iota}$ where the difference is that now we believe that for these properties the transaction occurred closer in time to the redevelopment point (see Figure 3.1), and therefore the option value should be equal to or very close to land value. That is, for this land value calculation we do not include the effects of lot size or location because they are already implicit in the option value.

Data

Data Sources

We use information from the ZTRAX database, which is real estate information provided by Zillow Inc., an American online real estate marketplace company. For the State of Michigan, there are nearly 3.5 million transactions recorded of which 940,805 correspond to transactions made in the City of Detroit.[49] ZTRAX contains two sources of information: 1) ZTrans, which is the property transaction database, and 2) ZAsmt, which is the tax-assessment information. We also use the geolocation of all the properties in combination with GIS to add information regarding neighborhood, and distances to the main database.[50] We also add data on building footprint to construct the three-dimensional measure of intensity.[51] To assess neighborhood quality, we incorporate Blight Violation Notices (BVN), a dataset documenting the issuance of citations to property owners who fail to maintain the exterior of their properties in accordance with City of Detroit ordinances.[52] These blight tickets, issued by city inspectors and other officials, reflect compliance with local property maintenance codes and are processed by the Department of Administrative Hearings. The integration of blight violations contributes to the construction of the blight index, offering a robust indicator of neighborhood quality. We combined these data sources to create the dataset we use to estimate a set of hedonic regressions.

---

[49] This is the number of transactions that have been collected by Zillow. The information includes transactions from the last century.

[50] See Table A2 in the appendix for further details on distances calculations.

[51] The data on Building Footprints is publicly available by the Southeast Michigan Council of Governments (SEMCOG). See here for more information: https://maps-semcog.opendata.arcgis.com/datasets/building-footprints-2020/explore?location=42.445079%2C-83.286436%2C9.44

[52] The data on Blight Violation Notices (BVN) is publicly available by the City of Detroit. See here for more information: https://data.detroitmi.gov/datasets/detroitmi::blight-violations/about.

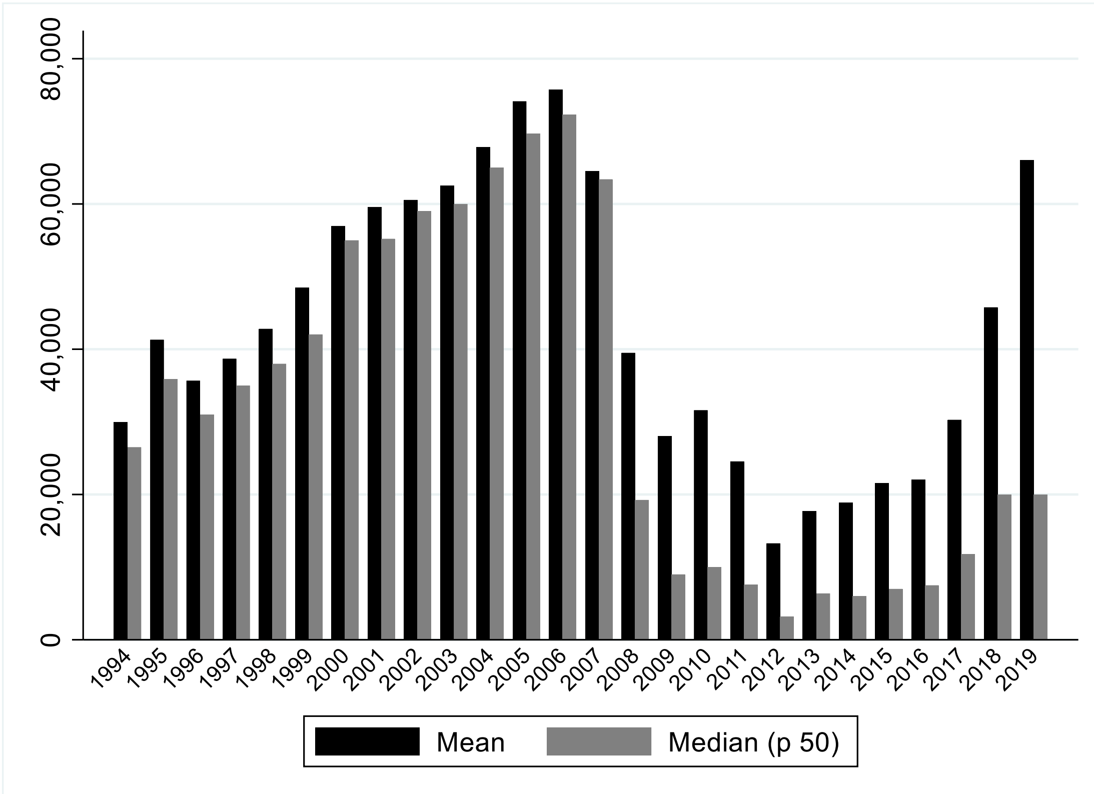
Identification of market transactions

In this subsection we review the filters we used to identify those transactions that are likely to reflect market value. First, we limited the time period of analysis to 2012-2019. The reason for choosing this time frame is that that the rate of redevelopment of a durable asset is affected by the economic cycle and thus is not a constant over time (Clapp et al., 2013). In boom periods, it is expected that the prices of properties with the highest option value will fluctuate the most. Therefore, we examine a period of housing market recovery following the real estate crisis where housing prices were in recovery.

It is important to note that we use sales from 2009 because the intensity variables are constructed with transactions that occurred up to three years prior. Therefore, although the study period begins in 2012, we also used transactions from 2009, 2010, and 2011 to generate the intensity measures. Figure 3.4 shows the fluctuations over time in the mean and median sales prices in Detroit. The graph shows the effect that the real estate crisis had on the housing market, including the slow recovery where the pre-crisis price levels have not yet been reached.

Table A3.1 in the Appendix summarizes the steps we use to identify market transactions. The first step consists of removing observations with incorrect latitude and longitude information. Second, we select sales for the years 2009-2019. The third step is to remove duplicate transactions. For steps five and six, we follow Nolte et al. (2021) to resolve issues with the ZTRAX database where the authors filtered transactions based on type of deed, document type, whether transactions occurred within families, and whether properties were tax exempt. Additionally, we selected residential properties for our evaluation, and we removed properties that sold more than seven times during the study period. We removed these properties because the repeat sales literature suggests that these properties are typically in worse condition relative to other properties. The final step involved selecting only single-family properties. The second part of Table A3.1 presents the effect of each of these steps and filters on the distribution of key variables in our calculations.

Figure 3. 4: Mean and Median Sale Prices in Detroit



Source: Authors' calculations. Note: The calculation of this figure involves all the transactions carried out in Detroit according to the ZTRAX database.

Generally, property characteristics are very similar across all filtered subsamples. In terms of the dependent variable, the sale prices change with subsamples where the mean price decreases from \$31,179 to \$15,845. Although the price difference is notable, it is mainly the result of selecting the sample from sales in the recovery period. The final sample of observations and descriptive statistics are discussed below.

Results

First Step Results: Evidence of Option Value in Detroit

Table 3.2 presents the descriptive statistics for all variables included in our evaluation, of which we discuss several key variables. In Panel A we show the dependent variable, sale price and natural logarithm of the sale price. In this first stage of the analysis, we use the natural logarithm of the dependent variable so that we can more easily compare our results with those in other articles. However, in the second stage of the analysis we use the sale price in dollars in order to predict land values in dollar amount. The mean sale price is $15,634 with a standard deviation of $21,387. Low prices are common in Detroit during this period. Although it does not appear in the table, it is important to point out that the median sales price is $7,000, which implies a high variance. The natural logarithm of the sale price has a mean of 8.7, and the number of observations on sales price is 87,606.

In Panel B we show the key independent variables, which are the two intensity variables that were described in previous sections. First, $Intensity_{2D_{05}}$ has a mean of 1.03, i.e. on average properties have slightly more interior square footage than their neighbors within a 0.5-mile radius. There are properties that have interior square footage as small as 0.08 times that of their neighbors (minimum value), and properties that are almost 7 times larger than their neighbors in terms of interior square footage (maximum value). Furthermore, when we measure intensity with the relative volume of the property, on average, properties are more intense developed using this indicator (mean value of 1.19). This variable presents a greater variance in its distribution, which is why it could be capturing other elements of the infrastructure that the two-dimensional variable does not capture. For both measures, note again that neighbors constitute relatively new properties (less than or equal to 60 years of age) that were sold within three years of the sale of the subject property. The blight index has a mean value of 0.13, indicating that on average properties are located in good quality neighborhoods relative to the worst-case scenario. Figure A3.1 in the Appendix shows the spatial distribution of this variable.

Panel C presents summary statistics for the property attributes. Note that the average age is 74 years. Additionally, the average number of stories is 2.4 and the average garage area is 248 square feet. In Table 3.3 we also include descriptive statistics for the categorical variables. First, as reflected in the year of sale, the highest percentage of properties sold in 2012, and this percentage decreases over the years we include in our evaluation. Second, we include data on heating system type and by exterior wall type. Most transactions have a forced air heating system and have a brick exterior. Finally, we show the distribution of observations across the 53 Detroit neighborhoods.

Table 3. 2: Summary Statistics of the Full Sample (Continuous Variables)

Variable	Definition	N	Mean	SD	Min	Max
Dependent Variables ***(Panel A)***						
$Price$	Sale Price	87,606	15633.75	21386.59	436.00	175830.00
$Ln\ Price$	Natural Logarithm of Sale Price	87,606	8.73	1.51	6.08	12.08
Key Independent Variables ***(Panel B)***						
$Intensity_{2D_{05}}$	$\frac{Interior\ Square\ Footage_i}{\frac{1}{J}\sum_{j\neq i}^{J} Interior\ Square\ Footage_j}$ within a radius of 0.5-mile	87,606	1.03	0.31	0.08	6.51
$Ln\ Intensity_{2D_{05}}$	Natural Logarithm of $Intensity_{2D_{05}}$	87,606	-0.01	0.26	-2.52	1.87
$Intensity_{3D_{05}}$	$\frac{Volume_i}{\frac{1}{J}\sum_{j\neq i}^{J} Volume_j}$ within the census tract	87,606	1.19	0.55	0.11	9.03
$Ln\ Intensity_{3D_{05}}$	Natural Logarithm of $Intensity_{3D_{05}}$	87,606	0.09	0.39	-2.19	2.20
$Blight\_index$	$\frac{No. Blighted\ Properties\ within\ 0.5\ miles\ x\ Avg\ Fine\ Amount\ within\ 0.5\ m}{Maximum\ Blight\ Intensity\ Score\ in\ the\ Nhood}$ This formulation yields a value between 0 and 1, where 0 indicates no blight and 1 indicates the most intense blight within the neighborhood comparison.	87,606	0.13	0.18	0.00	1.00
Property Attributes (Continuous Variables) ***(Panel C)***						
Age	Sale Year - Year Built	87,606	74.36	11.01	1.00	152.00
$Lot\ Size$	Lot Size	87,606	5057.90	1524.30	1960.2	53622.36
$Ln\ Lot\ Size$	Natural Logarithm of Lot Size	87,606	8.50	0.23	7.58	10.89
$Interior\ Sqft$	Interior Square Footage	87,606	1171.71	362.38	90.00	4520.00
$Ln\ Interior\ Sqft$	Natural Logarithm of Interior Square Footage	87,606	7.02	0.28	4.50	8.42
$No. of\ Stories$	Number of Stories	87,606	2.38	1.47	1.00	10.00

Table 3. 2 (cont'd)

$Full\ Baths$	Number of full baths.	87,606	1.04	0.21	1.00	5.00
$Garage\ Area\ SqFt$	Garage square footage area.	87,606	247.78	183.79	0.00	3144.00
$Dist.to\ Primary\ Roads\ (m$	Distance to Primary Roads in miles	87,606	1.02	0.79	0.02	3.96
$Dist.to\ Secondary\ Roads\ ($	Distance to Secondary Roads in miles	87,606	1.04	0.78	0.01	4.54
$Dist.to\ Jails\ (miles)$	Distance to Federal, State or local Jails and/or detention centers in miles	87,606	6.20	2.65	0.03	11.55
$Dist.to\ Airport\ (miles)$	Distance to the Airport in miles	87,606	7.43	3.80	0.03	13.78
$Dist.to\ CBD\ (miles)$	Distance to the Central Business District (CBD) in miles	87,606	8.62	1.88	1.68	14.20
$Dist.to\ Parks\ (miles)$	Distance to the nearest park in miles	87,606	0.38	0.21	0.01	1.54

Source: Author's calculations.

Table 3. 3: Summary Statistics of the Full Sample (Categorical Variables)

Variable	Definition	Observations	Categories	Observations by category	Percentage
Property Attributes (Categorical Variables)					
			2012	14,724	16.8%
			2013	13,356	15.2%
			2014	13,195	15.1%
Sale Year	Year of property sale	87,606	2015	9,821	11.2%
			2016	9,028	10.3%
			2017	9,059	10.3%
			2018	9,306	10.6%
			2019	9,117	10.4%
			Forced Air	79,047	90.23%
			Hot Water	7,926	9.05%
Heating	Heating System Type	87,606	Floor/Wall	558	0.64%
			Electric	34	0.04%
			Baseboard	40	0.05%
			None	1	0.00%
			Brick	58,975	67.3%
			Shingle	13,461	15.4%
Exterior Wall	Exterior Wall Type	87,606	Wood Siding	5,677	6.5%
			Asbestos Shingle	9,487	10.8%
			Siding (Alum, Vinyl)	6	0.0%
			Airport	253	0.3%
			Bagley	2,852	3.3%
			Boynton	1,164	1.3%
			Brightmoor	2,152	2.5%
Neighborhood	53 Neighborhoods	87,606	Brooks	6,016	6.9%
			Burbank	3,364	3.8%
			Butzel	31	0.0%
			Cerveny / Grandmont	7,037	8.0%

Table 3.3 (cont'd)

	Chandler Park	107	0.1%
	Cody	3,005	3.4%
	Conner	2,048	2.3%
	Davison	130	0.1%
	Denby	5,312	6.1%
	Durfee	979	1.1%
	East Riverside	395	0.5%
	Evergreen	5,651	6.5%
	Finney	4,401	5.0%
	Foch	12	0.0%
	Grant	747	0.9%
	Greenfield	4,566	5.2%
	Harmony Village	4,387	5.0%
	Indian Village	32	0.0%
	Jefferson / Mack	45	0.1%
	Jeffries	1	0.0%
	Kettering	170	0.2%
	Mackenzie	4,087	4.7%
	McNichols	459	0.5%
	Middle Woodward	415	0.5%
	Mt. Olivet	4,995	5.7%
	Nolan	1,568	1.8%
	Palmer Park	206	0.2%
	Pembroke	3,089	3.5%
	Pershing	3,835	4.4%
	Redford	3,420	3.9%
	Rosa Parks	351	0.4%
	Rosedale	3,039	3.5%

Table 3.3 (cont'd)

	Rouge	6,120	7.0%
	State Fair	95	0.1%
	Tireman	519	0.6%
	Winterhalter	551	0.6%

Source: Author's calculations.

Table 3.4 shows the results of the hedonic regressions, all of which include a measure of option value. In the first column, we show the results for the standard hedonic model where the estimated coefficients are consistent with and similar to previous research. For example, a 1% increase in lot size increases the selling price by almost 0.4%, while a 1% increase in interior square footage increases the average selling price by 0.7%. Both variables are statistically significant at a 1% significance level. Additionally, the age variable also has the expected negative sign, indicating that older homes are less valuable, other things being equal. Calculating the marginal impact of age, on average an additional year decreases the sale price by approximately 0.14% (statistically significant at 1%).

Additionally, the coefficients on property attributes have the expected signs. An additional story increases the sale value by 0.4%, and this coefficient is statistically significant. A large number of bathrooms have a positive effect on prices, specially three bathrooms compared to one bathroom. Regarding the heating system, the base category is forced air, which implies, for example, that properties with a baseboard heating system have sale prices that are 23% lower than properties with forced air heating, when other factors are held constant. The base category for exterior wall material is brick. Hence, properties with shingle exterior walls are associated with a 79% decrease in sale price compared to properties with brick exterior walls, holding all other factors constant. Finally, the signs of the year effects coefficients and the neighborhood indicator variables behave as expected (the full table is available upon request).

Columns 2 to 5 of Table 3.4 present the results of the first and second specifications in the Identification Strategy section. Column 2 presents the results for the first specification using $Ln\ Intensity_{2D_{05}}$. The estimated coefficient is negative and statistically significant at the 1% level.

Table 3. 4: Hedonic regressions with option value measured as intensity

		First Specification	*Second Specification*	*First Specification*	*Second Specification*	*Third Specification*	*Third Specification*
	(1) Standard Hedonic	(2) Option Value (2D Int O.5)	(3) Option Value with Depreciation (2D Int 0.5)	(4) Option Value (3D Int 0.5)	(5) Option Value with Depreciation (3D Int 0.5)	(6) Option Value (3D Int 0.5x nhood quality)	(7) Option Value with Depreciation (3D Int 0.5 x nhood quality)
$Ln\ Lot\ Size$	0.380***	0.352***	0.345***	0.359***	0.351***	0.356***	0.352***
	(0.0291)	(0.0223)	(0.0223)	(0.0223)	(0.0223)	(0.0223)	(0.0223)
$Ln\ Interior\ Sqft$	0.656***	1.245***	1.235***	0.856***	0.857***	0.849***	0.862***
	(0.0331)	(0.0442)	(0.0450)	(0.0338)	(0.0341)	(0.0339)	(0.0340)
Age	0.0377***	0.0345***	0.0405***	0.0390***	0.0427***	0.0391***	0.0440***
	(0.00489)	(0.00401)	(0.00418)	(0.00401)	(0.00435)	(0.00401)	(0.00412)
Age^2	-0.000351***	-0.000328***	-0.000369***	-0.000353***	-0.000375***	-0.000354***	-0.000386***
	(0.0000334)	(0.0000272)	(0.0000284)	(0.0000272)	(0.0000297)	(0.0000272)	(0.0000280)
$No.of\ Stories$	0.0408***	0.0376***	0.0384***	0.0508***	0.0497***	0.0503***	0.0498***
	(0.00540)	(0.00433)	(0.00433)	(0.00445)	(0.00445)	(0.00445)	(0.00445)
$Full\ Baths = 2$	-0.00349	0.00287	0.00976	0.000688	0.0191	0.00217	0.00493
	(0.0364)	(0.0272)	(0.0277)	(0.0272)	(0.0275)	(0.0273)	(0.0273)
$Full\ Baths = 3$	0.314*	0.331***	0.321***	0.322***	0.342***	0.323***	0.322***
	(0.137)	(0.0957)	(0.0969)	(0.0958)	(0.0965)	(0.0958)	(0.0959)
$Full\ Baths = 4$	0.105	0.149	0.101	0.114	0.132	0.115	0.121
	(0.489)	(0.332)	(0.334)	(0.333)	(0.334)	(0.333)	(0.333)
$Full\ Baths = 5$	1.065***	1.433	1.478	1.176	1.327	1.188	1.222
	(0.100)	(1.237)	(1.237)	(1.238)	(1.238)	(1.238)	(1.238)
Heating System= Base Category: Forced Air							
$Hot\ Water$	-0.0190	-0.0283	-0.0178	-0.0210	-0.00439	-0.0197	-0.0135
	(0.0236)	(0.0174)	(0.0176)	(0.0174)	(0.0175)	(0.0174)	(0.0175)
$Floor/Wall$	-0.233***	-0.232***	-0.223***	-0.253***	-0.249***	-0.254***	-0.248***
	(0.0550)	(0.0535)	(0.0536)	(0.0536)	(0.0537)	(0.0536)	(0.0537)
$Electric$	-0.765***	-0.753***	-0.843***	-0.730***	-0.919***	-0.730***	-0.808***
	(0.116)	(0.213)	(0.214)	(0.214)	(0.214)	(0.214)	(0.214)
$Baseboard$	-0.783**	-0.759***	-0.773***	-0.792***	-0.805***	-0.793***	-0.798***
	(0.270)	(0.195)	(0.195)	(0.196)	(0.196)	(0.196)	(0.196)
$None$	-1.169***	-1.277	-1.232	-1.294	-1.317	-1.310	-1.276
	(0.158)	(1.241)	(1.241)	(1.242)	(1.242)	(1.242)	(1.242)

Table 3. 4 (cont'd)

Exterior Wall= Based Category: Brick							
Shingle	-0.787***	-0.772***	-0.772***	-0.779***	-0.782***	-0.779***	-0.779***
	(0.0166)	(0.0136)	(0.0136)	(0.0136)	(0.0136)	(0.0136)	(0.0136)
Wood Siding	-0.774***	-0.764***	-0.766***	-0.768***	-0.773***	-0.768***	-0.769***
	(0.0237)	(0.0187)	(0.0188)	(0.0188)	(0.0188)	(0.0188)	(0.0188)
Asbestos Shingle	-0.892***	-0.878***	-0.872***	-0.882***	-0.877***	-0.880***	-0.877***
	(0.0180)	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0153)	(0.0154)
$Siding\ (Alum, Vinyl)$	0.708*	0.656	0.303	0.788	0.206	0.799	0.715
	(0.286)	(0.515)	(0.518)	(0.515)	(0.519)	(0.515)	(0.515)
Garage Area SqFt	0.000409***	0.000404***	0.000398***	0.000403***	0.000396***	0.000404***	0.000400***
	(0.0000305)	(0.0000242)	(0.0000242)	(0.0000242)	(0.0000242)	(0.0000242)	(0.0000242)
$Dist. to\ Primary\ Roads\ (miles)$	-0.0991***	-0.0875***	-0.0870***	-0.0956***	-0.0943***	-0.0974***	-0.0966***
	(0.0133)	(0.0109)	(0.0110)	(0.0109)	(0.0109)	(0.0110)	(0.0109)
$Dist. to\ Secondary\ Roads\ (miles)$	0.0647***	0.0389**	0.0361**	0.0512***	0.0466***	0.0557***	0.0537***
	(0.0148)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)	(0.0120)
$Dist. to\ Jails\ (miles)$	-0.774***	-0.719***	-0.715***	-0.755***	-0.749***	-0.770***	-0.766***
	(0.0310)	(0.0246)	(0.0246)	(0.0245)	(0.0245)	(0.0248)	(0.0248)
$Dist. to\ CBD\ (miles)$	-1.259***	-1.237***	-1.227***	-1.235***	-1.202***	-1.228***	-1.210***
	(0.196)	(0.151)	(0.151)	(0.151)	(0.151)	(0.151)	(0.151)
$Dist. to\ CBD\ (miles)^2$	0.146***	0.140***	0.138***	0.141***	0.137***	0.141***	0.138***
	(0.0218)	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0168)
$Dist. to\ CBD\ (miles)^3$	-0.00460***	-0.00438***	-0.00429***	-0.00441***	-0.00424***	-0.00441***	-0.00433***
	(0.000793)	(0.000611)	(0.000611)	(0.000611)	(0.000611)	(0.000611)	(0.000611)
$Dist. to\ Airport\ (miles)$	0.693***	0.671***	0.669***	0.688***	0.686***	0.703***	0.700***
	(0.0287)	(0.0231)	(0.0231)	(0.0231)	(0.0231)	(0.0234)	(0.0234)
$Dist. to\ Parks\ (miles)$	-0.178***	-0.185***	-0.185***	-0.182***	-0.183***	-0.181***	-0.180***
	(0.0281)	(0.0230)	(0.0230)	(0.0231)	(0.0231)	(0.0231)	(0.0231)

Table 3. 4 (cont'd)

$Ln\ Intensity_{2D05}$		-0.617***	2.360***				
		(0.0369)	(0.500)				
$Age\ x\ Ln\ Intensity_{2D_{05}}$			-0.0727***				
			(0.0128)				
$Age^2\ x\ \ Ln\ Intensity_{2D_{05}}$			0.000435***				
			(0.0000812)				
$Ln\ Intensity_{3D_{05}}$				-0.193***	2.178***	-0.193***	-0.199***
				(0.0200)	(0.312)	(0.0216)	(0.0216)
$Age\ x\ Ln\ Intensity_{3D_{05}}$					-0.0548***		
					(0.00809)		
$Age^2\ x\ Ln\ Intensity_{3D_{05}}$					0.000306***		
					(0.0000521)		
$Blight\_index$						-0.114***	-0.0956**
						(0.0314)	(0.0318)
$Ln\ Intensity_{3D_{05}} xBlight\_index$						0.0400	9.068***
						(0.0613)	(1.343)
$Age\ xLn\ Intensity_{3D_{05}} xBlight\_index$							-0.221***
							(0.0333)
$Age^2\ xLn\ Intensity_{3D_{05}} xBlight\_index$							0.00132***
							(0.000207)
Year Effects	YES	YES	YES	YES	YES	YES	YES
Neighborhoods Effects	YES	YES	YES	YES	YES	YES	YES
Constant	3.043***	-0.765	-0.852	1.694**	1.546**	1.741***	1.477**
	(0.639)	(0.550)	(0.557)	(0.520)	(0.526)	(0.520)	(0.523)
Observations	87606	87606	87606	87606	87606	87606	87606
R Squared	0.330	0.332	0.332	0.331	0.331	0.331	0.331

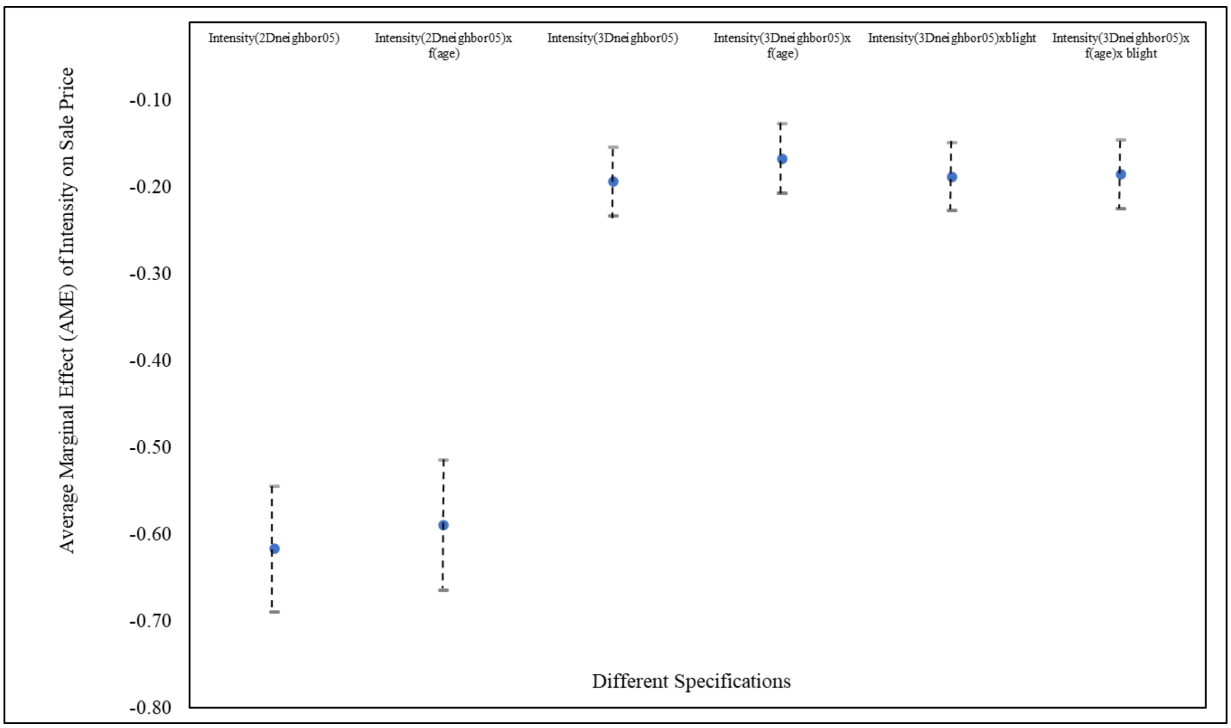
Source: Author's calculations. Note: Table reports OLS hedonic regressions coefficients from five separate regressions. The dependent variable in all regressions is the natural logarithm of the sale price. Column (1) presents the standard hedonic pricing model, columns (2) and (3) we show the models including the option value through the mean $Intensity_{2D_{05}}$, and columns (4) and (5) we show the models including the option value through the mean $Intensity_{3D_{05}}$. Standard errors are clustered at the property level. *** Significant at the 5 percent level. ** Significant at the 1 percent level. * Significant at the 0.1 percent level.

The interpretation of option values is as follows: a 1% increase in the value of the redevelopment option increases the value of the property by 0.62%. To facilitate comparability of the average marginal effect (AME) across the models, consider Figure 3.5. The first point plotted in this figure corresponds to the column 2 coefficient of -0.62. The second coefficient plotted corresponds to the AME calculated from column 3. In this case, including the effect of depreciation, a 1% increase in the value of the redevelopment option increases the price of the property by 0.59%.

Columns 4 and 5 of Table 3.4 present the results of the same specifications as above, but in this case using $Ln\ Intensity_{3D\_05}$. For both specifications, the coefficients are of lesser magnitude than the previous ones but continue to be statistically significant at 1% level. In the case of the first specification, the coefficient is -0.23 and in the case of the second specification the coefficient is -0.21. Finally, using $Ln\ Intensity_{3D\_05}$ interacted with neighborhood quality measured with the blight index we find that the coefficient is -0.23 without the interactions with age, and -0.22 with the age interaction. That is, in our most conservative estimate, having a 100% option value increases the value of the property by approximately 22%. Using the three-dimensional measure of intensity generates a lower impact on price compared to the use of the two-dimensional measure, but including quality neighborhood effects increased the effect.

In summary, these results offer evidence of option value in Detroit (the first hypothesis). In relative terms, our results are similar to other studies in magnitude using the three-dimensional intensity variable. Büchler et al. (2020), for example, in the largest magnitude coefficients, they found that having a 100% redevelopment potential increases the property price by 17%. The sharp difference in results between both measures of intensity is worthy of further research. The potential for redevelopment might vary based on building height. For example, properties with taller existing structures might have more limited redevelopment options compared to shorter structures, leading to a lower option value. Additionally, there might be economic or behavioral factors at play. For instance, developers might perceive properties with larger areas but shorter heights as having greater redevelopment potential due to fewer complications or costs associated with height (for example, lower demolition costs), leading to a stronger relationship in the 2D measure. Spatial patterns related to height is a future work.

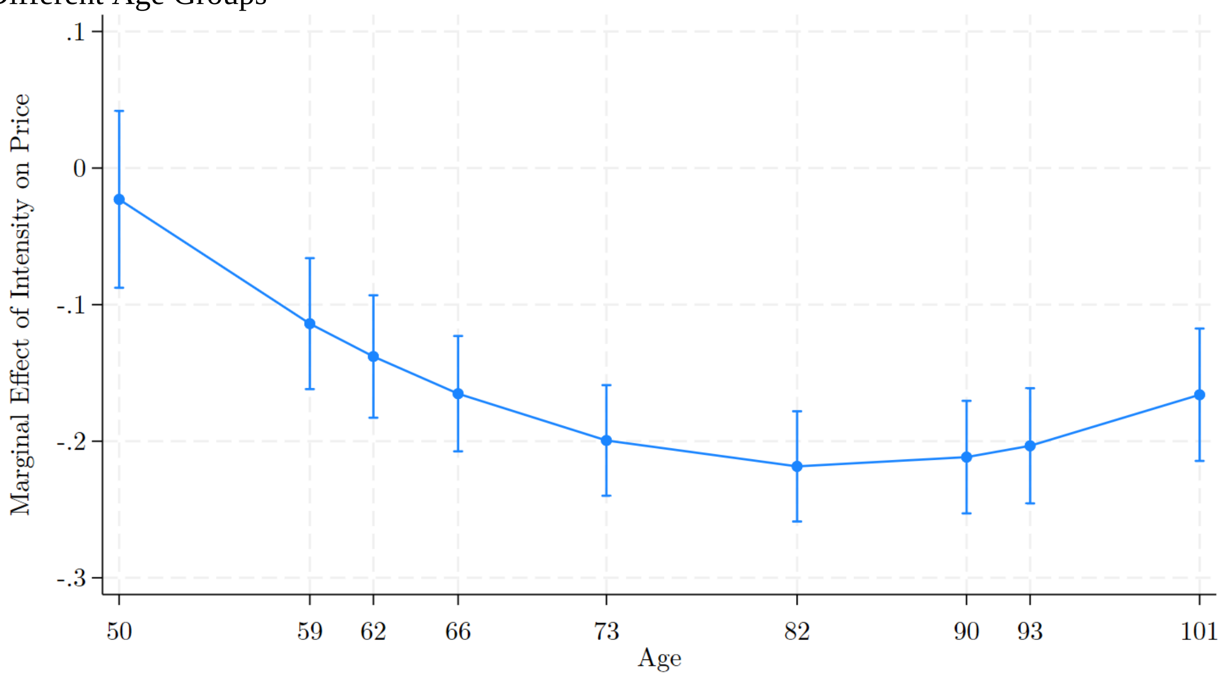
Figure 3. 5: Evidence supporting H1: Average Marginal Effect of Intensity on the value of the property in different specifications



Source: Authors' calculations. Note: figure shows the average marginal effect of intensity on the sale prices. Intensity is measured in two ways: 1) interior square footage of the property divided by the interior square footage of neighbors within a 0.5-mile radius ("Intensity(2Dneighbor05)"), and 2) volume of the property divided by the volume of neighbors within the same census tract ("Intensity(3Dneighbor05)"). For both cases neighbors are properties that constitute new construction sold within the last three years. Calculations of the average marginal effects come from regressions in Table 3.4, columns (2) to (7), which also includes interaction with the age of the property ("Intensityxf(age)"), and interaction with neighborhood quality represented by the blight index. Each point and interval correspond to the estimated coefficient of intensity and to the dotted line display 95 percent confidence intervals through each coefficient. The sample size is 122,117. Standard errors are clustered at the property level.

In terms of our second hypothesis, we present an interesting result in Figure 3.6. This figure captures the main effects of intensity (measure with the three-dimensional intensity variable) and age on property price, respectively, holding all else constant. We use the specification of column 7, which means we are including neighborhood quality as mediating variable with respect to intensity. This figure suggests that the impact of intensity on sale prices is not constant but varies depending on the age of the property. This is in line with theory, indicating that older properties, which are more depreciated, have a different redevelopment potential. Additionally, older properties should have higher redevelopment potential, hence, the negative slope. The older the property, the negative impact of intensity on housing prices, meaning the positive the impact of option value on housing prices. This is consistent with the results found in Clapp & Salavei (2010).

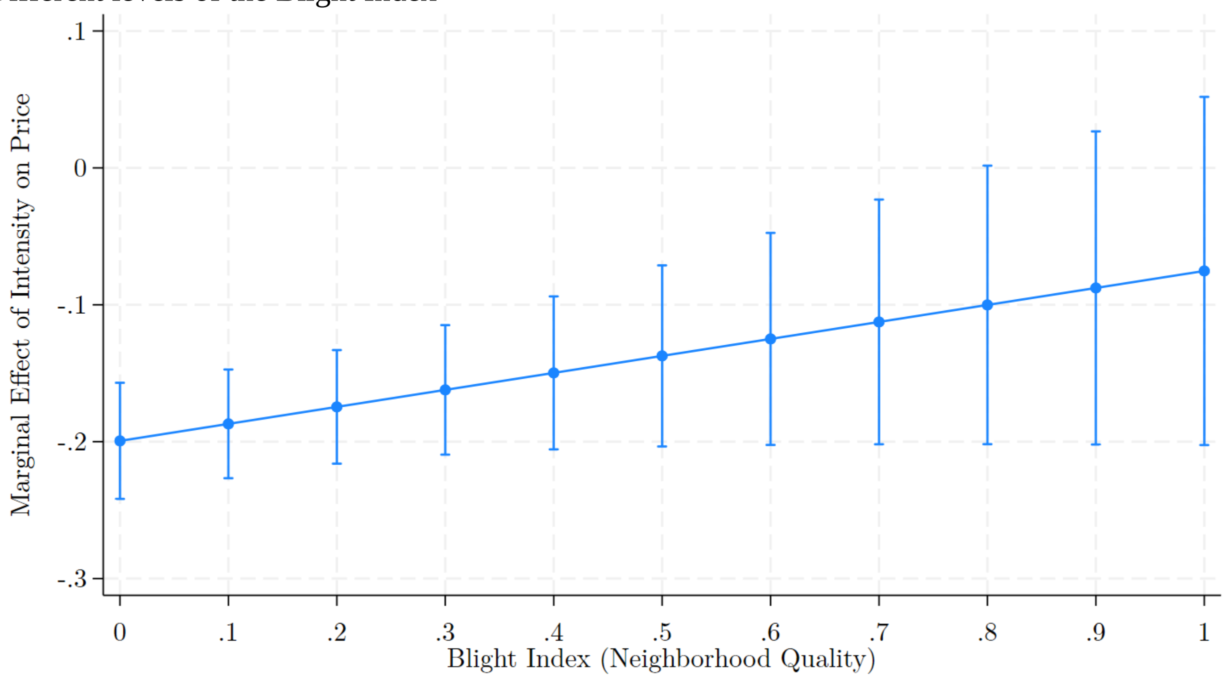
Figure 3. 6: Evidence supporting H2: Average Marginal Effect of Intensity on Price Across Different Age Groups



Source: Authors' calculations. Note: This graph illustrates the average marginal effect of property intensity (a measure of redevelopment potential) on property prices for different age groups. The negative slope suggests that older properties have higher redevelopment potential (measured by the negative significant effect of intensity on property prices). The error bars denote the 95% confidence intervals, indicating statistical significance for all age groups, except the first one. Results follow from the specification in column (7) of Table 3.4.

Finally, in terms of evidence supporting our third hypothesis, we present Figure 3.7. This figure presents the marginal impact of intensity on sale prices varying by different levels of the blight index, holding everything else constant. We observe that worse quality neighborhoods, meaning values of the blight index close to 1, are associated with less impact of intensity on prices. The opposite is true as well, indicating that the marginal impact of intensity reaches a value close to 0.2% for neighborhoods with high quality. This is in line with our hypothesis that the option to redevelop will be a function of the quality of the neighborhood.

Figure 3. 7: Evidence supporting H3: Average Marginal Effect of Intensity on Price Across Different levels of the Blight Index



Source: Authors' calculations. Note: This graph illustrates the average marginal effect of property intensity (a measure of redevelopment potential) on property prices for different blight index levels. The positive slope suggests that properties in good quality neighborhoods have higher redevelopment potential (measured by the negative significant effect of intensity on property prices). The error bars denote the 95% confidence intervals, indicating statistical significance for all age groups, except the first one. Results follow from the specification in column (7) of Table 3.4.

Second Step Results: Calculations of Predicted Land Values using Option Value

The previous analysis tested our three-hypothesis needed to confirm our intensity variable actually reflects option values in Detroit. The second portion of this analysis consists of predicting land values from the option value estimates. Interpretation of the results requires some clarifying discussion. First, we use a Poisson model without logarithmic transformations because we want to predict the sale price and land value, not the natural logarithm of the sale price. The Poisson model helps us predict positive sale prices. Furthermore, we identify the subsample of teardowns properties as much smaller compared to the total sample. The subsample constitutes properties that were: 1) sold when they had a lower intensity than their neighbors (less than .9); 2) issued a building permit after being sold; and 3) have an estimated construction cost of over $15,000.[53] There are 1,264 observations in which $\widehat{LV} = \widehat{OptionValue_i}$. For the rest of the observations, we include the use value of land in the prediction of land values. Table 3.5 shows the descriptive statistics for the prediction.

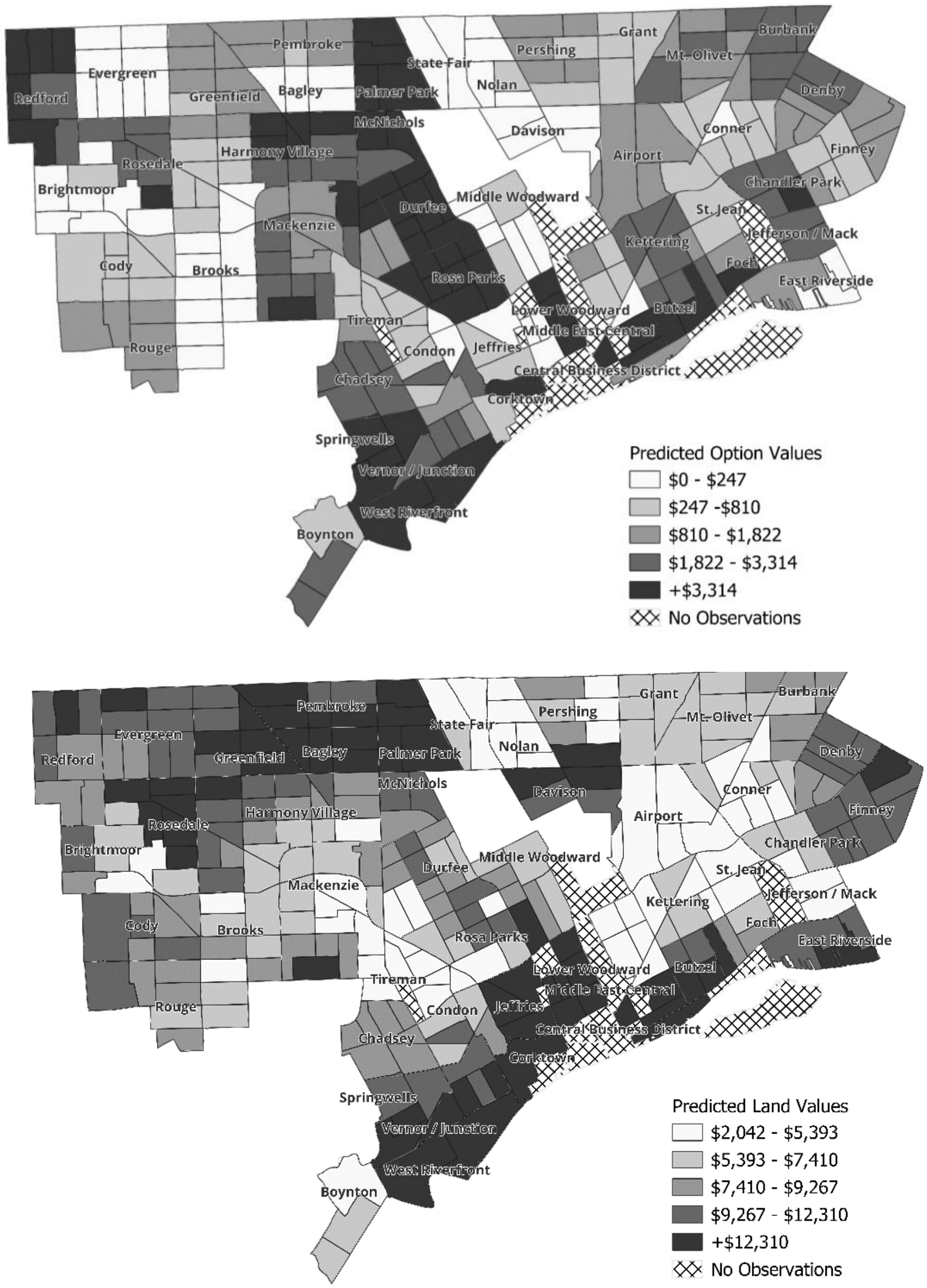
Table 3. 5: Predicted Land and Option Value Statistics from Poisson Regression Analysis

Predictions	Observations	Mean	Std. Dev.	Min	Max
Predicted Land Values	87,606	$10,642	$8,051	$0	$127,377
Predicted Option Value	87,606	$5,133	5657.292	$0	$98,717

Source: Authors' calculations. Note: This table provides summary statistics for predicted land values and option values derived from a Poisson regression model, as per the identification strategy outlined for the study. The predicted land value accounts for the current use and location value, while the predicted option value quantifies the potential value of future property development.

[53] From this value, estimated cost goes up to $244,801.

Figure 3. 8: Quantile Map of Average Predicted Land Values and Predicted Option Values in Detroit

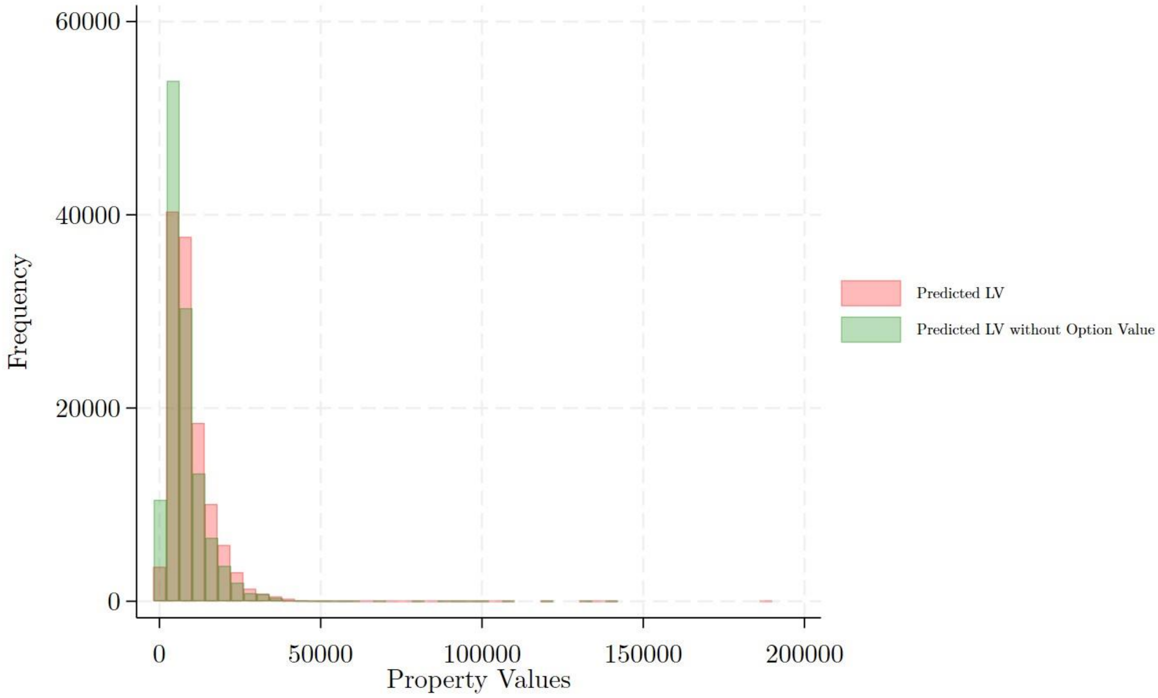


Source: Authors' calculations. Note: The quantile map shows the predicted option values and land values for properties in Detroit, based on the Poisson regression analysis. The map categorizes average option values and land values per census tract into quantiles. Higher option values may suggest areas with greater development potential, while lower values could imply that the current use is closer to the property's perceived best use. This spatial representation provides identification of spatial patterns and potential hotspots for investment and redevelopment.

Figure 3.8 provides a view of the spatial patterns of these predicted values. Neighborhoods such as Rosa Parks, Durfee, and Winterhalter stand out with higher average option values compared to other neighborhoods, suggesting a latent potential for redevelopment not readily apparent from current land values alone. In contrast, the land values themselves do not peak as sharply, indicating that while the present use and improvements do not drive high valuations, there is a significant untapped future value. Moreover, the spatial pattern of predicted land values resonates with the observations made by Hodge et al. (2015), particularly the "donut-shape" distribution where higher values encircle the central business district and spread into the suburbs. Understanding these dynamics is crucial for policymakers and investors alike, as it signals where strategic development could catalyze change and where the market may already be valuing future possibilities.

Finally, Figure 3.9 shows the distribution of predicted land values with and without the option value. Notice that predicting land values without option values can underestimate the land value of properties. Additionally, for higher values properties, option value can account for a large portion of the property price. This is important in terms of policy implications. If a split-tax rate is implemented in Detroit, then calculating land values including the option to redevelop can make a significant difference in the final calculation of property taxes.

Figure 3. 9: Histogram of Predicted Land Values with and without Option Value



Source: Authors' calculations. Note: The histogram shows the distribution of predicted land values with and without the option value.

Conclusion

In the context of proposing an alternative property tax system in the City of Detroit, the idea of the split-rate tax is being considered by policy makers at both the state and local levels in Michigan. However, a key challenge with implementing a split-rate tax is obtaining accurate valuations for both land and structures separately. One approach that could potentially address this challenge is estimation of option value in the context of real options theory. Using this approach, we provide empirical evidence of option value in Detroit through the inclusion of an additive component in hedonic pricing models of residential property values.

Using Zillow's rich ZTRAX database, we constructed two variables that have been used in the option value literature. These variables are based on the relative infrastructure intensity of properties. A higher intensity implies a higher value of construction and improvements relative to land value. A property with relatively less intensity (smaller low-quality structure on a relatively large piece of land) will have a higher option value.

The chapter investigated the impact of redevelopment potential, measured through property intensity, on property values in Detroit from 2012-2019. The analysis was done in two stages. Firstly, hedonic pricing models are used to test if intensity, as a proxy for option value, significantly affects sale prices. The results provide evidence that higher intensity (i.e., lower redevelopment potential) decreases property prices, suggesting the presence of redevelopment option value. This effect is stronger for older properties and those in higher quality neighborhoods. Using a two-dimensional measure of intensity (property interior square footage relative to neighbors), a 1% increase in intensity decreases prices by 0.66% on average, indicating higher redevelopment potential increases prices. Creating a three-dimensional intensity measure (property volume relative to neighbors), a 1% increase in intensity decreases prices by 0.22%, a smaller but still significant effect. The marginal effect of intensity on prices becomes more negative for older properties, aligning with the theory that redevelopment potential increases with depreciation. In higher quality neighborhoods, intensity has a larger negative impact on prices, suggesting redevelopment options are capitalized more in better locations.

Secondly, the chapter used a Poisson regression to predict land values based on the estimated option values. The spatial analysis of predicted values shows neighborhoods like Rosa Parks, Durfee, and Winterhalter have relatively high option values compared to predicted land values, implying redevelopment potential not captured by current use. Including option value significantly increases predicted land values, especially for higher valued properties, versus excluding it.

In summary, the chapter demonstrated that accounting for redevelopment potential through option value theory provides evidence of latent property values not apparent from existing uses. The spatial modeling highlights areas where strategic redevelopment could potentiate revitalization. The results have implications for property valuation, land use policy, and urban planning in Detroit.

BIBLIOGRAPHY

Alvayay Torrejón, C., & Skidmore, M. (2023). *Revitalization in Shrinking Cities: Impact of the Neighborhood Stabilization Program in Detroit*.

Banzhaf, H. S., & Lavery, N. (2010). Can the land tax help curb urban sprawl? Evidence from growth patterns in Pennsylvania. *Journal of Urban Economics, 67*(2), 169–179. https://doi.org/10.1016/j.jue.2009.08.005

Büchler, S., Schöni, O., & van de Minne, A. (2020). Redevelopment Option Value for Commercial Real Estate (Issue 26).

Capozza, D. R., & Helsley, R. W. (1989). The fundamentals of land prices and urban growth. *Journal of Urban Economics, 26*, 295–306. https://doi.org/10.4324/9781315240114-13

City of Detroit. (2023). *Detroit's Land Value Tax Plan*. https://detroitmi.gov/sites/detroitmi.localhost/files/2023-08/DetLandValueTaxPlan_083123.pdf

Clapp, J. M., Cohen, J. P., & Lindenthal, T. (2021). Are Estimates of Rapid Growth in Urban Land Values an Artifact of the Land Residual Model? *Journal of Real Estate Finance and Economics*. https://doi.org/10.1007/s11146-021-09834-4

Clapp, J. M., Eichholtz, P., & Lindenthal, T. (2013). Real option value over a housing market cycle. *Regional Science and Urban Economics, 43*(6), 862–874. https://doi.org/10.1016/j.regsciurbeco.2013.07.005

Clapp, J. M., Jou, J. B., & Lee, T. (2012). Hedonic Models with Redevelopment Options under Uncertainty. *Real Estate Economics, 40*(2), 197–216. https://doi.org/10.1111/j.1540-6229.2011.00323.x

Clapp, J. M., & Salavei, K. (2010). Hedonic pricing with redevelopment options: A new approach to estimating depreciation effects. *Journal of Urban Economics, 67*(3), 362–377. https://doi.org/10.1016/j.jue.2009.11.003

Clapp, J. M., Salavei, K., & Wong, S. K. (2012). Empirical estimation of the option premium for residential redevelopment. *Regional Science and Urban Economics, 42*(1–2), 240–256. https://doi.org/10.1016/j.regsciurbeco.2011.08.007

Cunningham, C. R. (2006). House price uncertainty, timing of development, and vacant land prices: Evidence for real options in Seattle. *Journal of Urban Economics, 59*(1), 1–31. https://doi.org/10.1016/j.jue.2005.08.003

Davis, M. A., & Heathcote, J. (2007). The price and quantity of residential land in the United States. *Journal of Monetary Economics, 54*(8), 2595–2620. https://doi.org/10.1016/j.jmoneco.2007.06.023

Davis, M. A., & Palumbo, M. G. (2008). The price of residential land in large US cities. *Journal of Urban Economics, 63*(1), 352–384. https://doi.org/10.1016/j.jue.2007.02.003

Dixit, A. K., & Pindyck, R. S. (1994). Investment under Uncertainty. *Princeton University Press*. https://press.princeton.edu/books/hardcover/9780691034102/investment-under-uncertainty

Dye, R. F., & England, R. W. (2010). Assessing the Theory and Practice of Land Value Taxation. In *Lincoln Institute of Land and Policy* (Vol. 25, Issue 2). https://doi.org/10.1080/13506129.2018.1474733

Dye, R. F., & Mcmillen, D. P. (2007). Teardowns and land values in the Chicago metropolitan area. *Journal of Urban Economics, 61*, 45–63. https://doi.org/10.1016/j.jue.2006.06.003

Geltner, D., Miller, N. G., Clayton, J., & Eichholtz, P. (2001). Commercial real estate analysis and investments (Vol. 1). South-western Cincinnati, OH.

Grovenstein, R. A., Kau, J. B., & Munneke, H. J. (2011). Development Value: A Real Options Approach Using Empirical Data. *Journal of Real Estate Finance and Economics, 43*(3), 321–335. https://doi.org/10.1007/s11146-010-9277-9

Hanson, A. (2021). *Split-Rate Taxation and Business Establishment Location : Evidence from the Pennsylvania Experience*.

Hartzok, A. (1997). Pennsylvania ' s Success with Local Property Tax Reform : The Split Rate Tax. *American Journal of Economics and Sociology, 56*(2), 205–213.

Hodge, T. R., McMillen, D. P., Sands, G., & Skidmore, M. (2017). Assessment Inequity in a Declining Housing Market: The Case of Detroit. *Real Estate Economics, 45*(2), 237–258. https://doi.org/10.1111/1540-6229.12126

Hodge, T. R., Sands, G., & Skidmore, M. (2015). The Land Value Gradient in a (Nearly) Collapsed Urban Real Estate Market. https://www.lincolninst.edu/sites/default/files/pubfiles/2532_1872_Hodges WP15TH1.pdf

McDonald, R., & Siegel, D. (1986). The Value of Waiting to Invest. *The Quarterly Journal of Economics, 101*(4), 707–728. https://doi.org/https://doi.org/10.2307/1884175

McMillen, D., & O'Sullivan, A. (2013). Option value and the price of teardown properties. *Journal of Urban Economics, 74*(1), 71–82. https://doi.org/10.1016/j.jue.2012.09.004

Munneke, H. J., & Womack, K. S. (2015). Neighborhood renewal: The decision to renovate or tear down. *Regional Science and Urban Economics, 54*, 99–115. https://doi.org/10.1016/j.regsciurbeco.2015.08.001

Munneke, H. J., & Womack, K. S. (2020). Valuing the Redevelopment Option Component of Urban Land Values. *Real Estate Economics, 48*(1), 294–338. https://doi.org/10.1111/1540-6229.12192

Nolte, C., Boyle, K. J., Chaudhry, A. M., Clapp, C., Guignet, D., Hennighausen, H., Kushner, I., Liao, Y., Mamun, S., Pollack, A., Richardson, J., Sundquist, S., Swedberg, K., & Uhl, J. (2021). Studying the Impacts of Environmental Amenities and Hazards with Nationwide Property Data: Best Data Practices for Interpretable and Reproducible Analyses. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3900806

Ooi, J. T. L., Sirmans, C. F., & Turnbull, G. K. (2006). The Option Value of Vacant Land. In *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.952556

Owens, R., Rossi-Hansberg, E., & Sarte, P. D. (2020). Rethinking Detroit. *American Economic Journal: Economic Policy, 12*(2), 258–305. https://doi.org/10.1257/POL.20180651

Paredes, D., & Skidmore, M. (2017). The net benefit of demolishing dilapidated housing: The case of Detroit. *Regional Science and Urban Economics, 66*(November 2016), 16–27. https://doi.org/10.1016/j.regsciurbeco.2017.05.009

Poterba, J. (1984). Tax Subsidies to Owner-Occupied Housing: An Asset-Market Approach. *The Quarterly Journal of Economics, 99*(4), 729–752.

Quigg, L. (1993). Empirical Testing of Real Option-Pricing Models. *The Journal of Finance, 48*(2), 621–640. https://doi.org/https://doi.org/10.2307/2328915

Rosen, S. (1974). Hedonic Prices and Implicit Markets : Product Differentiation in Pure Competition. *Journal of Political Economy, 82*(1), 34–55. https://doi.org/http://dx.doi.org/10.1086/260169

Sands, G., & Skidmore, M. (2015). *Detroit and the Property Tax*.

Titman, S. (1985). Urban land prices under uncertainty. *American Economic Review, 75*(3), 505–514. https://doi.org/10.2307/1814815

Williams, J. T. (1991). Real estate development as an option. *The Journal of Real Estate Finance and Economics, 4*(2), 191–208. https://doi.org/10.1007/BF00173124

Womack, K. S. (2015). Real options and urban land values: A review of the literature. *Journal of Real Estate Literature, 23*(1), 53–63. https://doi.org/10.1080/10835547.2015.12090398

Yang, Z., & Hawley, Z. (2021). Split-Rate Taxation: Impacts on Tax Base. https://www.lincolninst.edu/sites/default/files/pubfiles/yang_wp21zy1.pdf

APPENDIX

Table A3. 1: Description of the steps to filter the database and identify market transactions

Step Number	Description	Observations
0	All transactions in Detroit	387,738
1	Remove observations with coordinates with missing values	387,530
2	Select transaction from 2009-2019	338,841
3	Remove duplicate observations	324,538
4	Identify transactions prices that reflect fair market value	171,479
	4.1 Filter by type of deed (268,405)	
	4.2 Filter by document type (217,969)	
	4.3 Filter by intra family sale (217,784)	
	4.4 Filter by transfer tax exempt (171,479)	
5	Select residential properties	170,667
6	Remove sales price outliers and properties that sold more than seven times	162,222
	6.1 Removing prices below 1st percentile and above 99th percentile (168,044)	
	6.2 Eliminate properties with more than 7 sales (162,222)	
7	Select only Single-Family Residential Properties	87,606

Table 3A.1 (cont'd)

How do the key variables change in each of the filter steps?								
Variable	**Statistics**	**Step 0**	**Step 1**	**Step 2**	**Step 3**	**Step 4**	**Step 5**	**Step 6**
Price	obs.	190,461	190,361	166,061	161,599	133,286	132,658	126,182
	Mean	$31,179	$31,148	$26,478	$20,977	$20,161	$19,976	$15,845
	Sd	$118,757	$118,680	$115,831	$57,599	$58,256	$57,537	$23,139
	p1	$410	$410	$400	$400	$500	$500	$500
	p25	$2,000	$2,000	$1,800	$1,714	$1,500	$1,500	$1,500
	p50	$8,000	$8,000	$6,965	$6,500	$6,873	$6,800	$6,500
	p75	$30,000	$30,000	$25,000	$23,000	$22,000	$22,000	$20,100
	p99	$308,000	$307,000	$271,000	$201,015	$216,000	$210,500	$120,000
Lot Size	obs.	383,091	382,898	335,897	321,677	170,618	169,844	161,770
	mean	5,990.5	5,984.9	5,981.1	5,957.5	5,331.1	5,315.0	5,215.8
	sd	232,441.9	232,500.0	248,222.0	253,643.2	4,486.6	4,414.9	4,015.9
	p1	2,787.8	2,787.8	2,831.4	2,831.4	2,831.4	2,831.4	2,831.4
	p25	4,007.5	4,007.5	4,007.5	4,007.5	4,051.1	4,051.1	4,007.5
	p50	4,660.9	4,660.9	4,660.9	4,660.9	4,660.9	4,660.9	4,617.4
	p75	5,401.4	5,401.4	5,401.4	5,401.4	5,357.9	5,357.9	5,314.3
	p99	43,560.0	43,560.0	43,560.0	43,560.0	43,560.0	43,560.0	19,863.4
Interior Sqft	obs.	387,738	387,530	338,841	324,538	171,479	170,667	162,222
	mean	1,342.2	1,342.2	1,330.2	1,330.6	1,298.5	1,297.8	1,290.5
	sd	615.7	615.7	603.3	600.8	560.2	559.4	540.5
	p1	672.0	672.0	672.0	672.0	672.0	672.0	672.0
	p25	960.0	960.0	960.0	960.0	954.0	954.0	951.0
	p50	1,170.0	1,170.0	1,162.0	1,162.0	1,142.0	1,141.0	1,139.0
	p75	1,529.0	1,529.0	1,513.0	1,514.0	1,479.0	1,478.0	1,473.0
	p99	3,552.0	3,552.0	3,481.0	3,480.0	3,292.0	3,285.0	3,199.0

Table 3A.1 (cont'd)

Age	obs.	387,534	387,326	338,651	324,385	171,393	170,581	162,137
	mean	78	78	78	78	78	78	78
	sd	16	16	16	16	15	15	14
	p1	19	20	21	23	44	44	46
	p25	68	68	67	67	67	67	67
	p50	77	76	76	76	75	75	75
	p75	90	90	89	89	88	88	88
	p99	114	114	113	113	112	112	112
No. of Stories	obs.	381,555	381,389	334,032	320,207	169,476	168,736	160,817
	mean	2.8	2.8	2.8	2.8	2.7	2.7	2.7
	sd	1.6	1.6	1.6	1.6	1.6	1.6	1.6
	p1	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	p25	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	p50	2.0	2.0	2.0	2.0	2.0	2.0	2.0
	p75	5.0	5.0	5.0	5.0	5.0	5.0	5.0
	p99	5.0	5.0	5.0	5.0	5.0	5.0	5.0
No. of Full Baths	obs.	387,731	387,523	338,834	324,533	171,476	170,664	162,219
	mean	1.2	1.2	1.2	1.2	1.1	1.1	1.1
	sd	0.5	0.5	0.5	0.5	0.4	0.4	0.4
	p1	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	p25	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	p50	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	p75	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	p99	3.0	3.0	3.0	3.0	3.0	3.0	3.0
Garage Area Sqft	obs.	387,738	387,530	338,841	324,538	171,479	170,667	162,222
	mean	236.0	236.0	236.0	237.4	229.0	229.0	229.1
	sd	201.6	201.6	200.8	200.1	196.5	196.3	195.7
	p1	0	0	0	0	0	0	0

Table 3A.1 (cont'd)

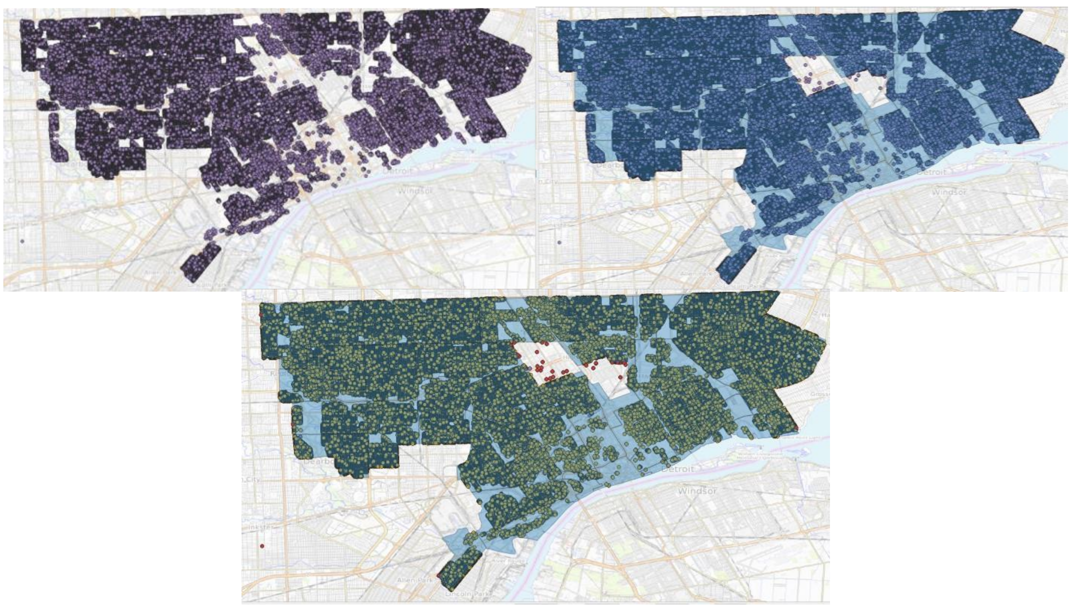
	p25	0	0	0	0	0	0	0
	p50	280.0	280.0	280.0	280.0	280.0	280.0	280.0
	p75	400.0	400.0	400.0	400.0	396.0	393.0	392.0
	p99	672.0	672.0	660.0	662.0	640.0	639.0	624.0

Source: Author's calculations. Note: Summary statistics of Step 7 are shown in Table 3.2.

Table A3. 2: Detailed explanations on Distances Calculations

We have information of longitude and latitude coordinates for all properties in the dataset. This allows us to plot the information for Detroit. Additionally, we eliminate all properties that are spatially outliers using the neighborhood layer information. The following figure shows the identified spatial outliers.

Figure: Spatial outliers identified with the geolocated information of the properties



Main Roads Calculations

We use the information from the United States Census Bureau that provides GIS information across United States.[54] The roads database contains information on various types of roads in a geographic space larger than Detroit. Therefore, we first need to cut the shapefile to the size of Detroit. We do this using Neighborhood information boundaries. The roads database

[54] See https://www.census.gov/cgi-bin/geo/shapefiles/index.php.

Table A3. 2 (cont'd)

contains two important variables: RTTYP code and MFTCC code.[55] Both codes allow us to identify the main roads and the secondary roads. Finally, the shortest distance between the property and the road is calculated as shown in the following figure in miles.

Figure: Identifying the roads in the city of Detroit

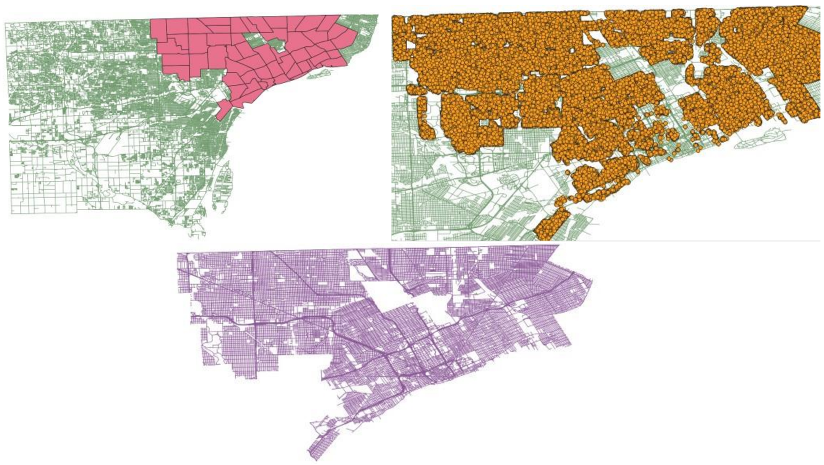
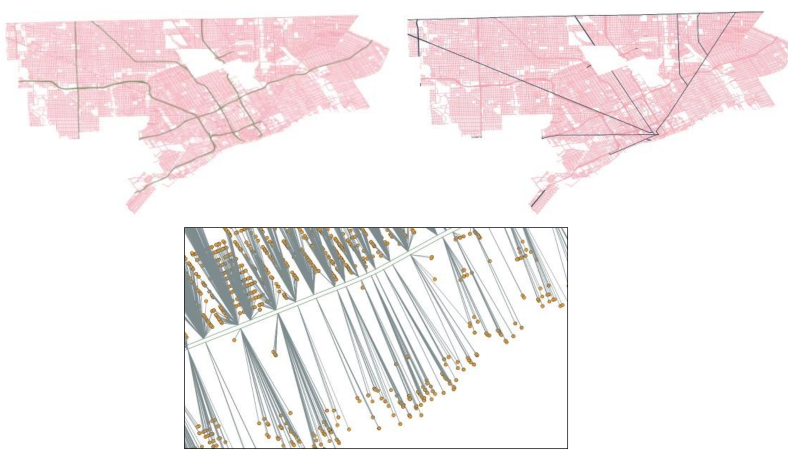


Figure: Main roads, secondary roads, and calculation of the minimum distance from the properties to the roads



[55] The following link contains information regarding the RTTYP code, https://www.census.gov/library/reference/code-lists/route-type-codes.html. The next link contains information regarding the MFTCC code, https://www2.census.gov/geo/pdfs/reference/mtfccs2021.pdf. S1100 and S1200 are used to identify the primary roads and secondary roads, respectively.

Table A3. 2 (cont'd)

Federal, State or local Jails and/or detention centers

We calculate the minimum distance to either of these jails or detention centers. First, we identify all the landmarks in Detroit.[56] Then we did a filter by jail code or detention center. Table A1 shows the selection of the places to which we calculate the minimum distance.

Table: Selection of jails, federal agencies or detention centers according to code

FULLNAME	MTF CC Code	Definition
William Dickerson Detention Faclty	K1236	K1236 Local Jail or Detention Center One or more structures that serve as a place for the confinement of adult persons in lawful detention, administered by a local government (county, municipal, etc.)
Old Wayne County Jail	K1236	K1236 Local Jail or Detention Center One or more structures that serve as a place for the confinement of adult persons in lawful detention, administered by a local government (county, municipal, etc.)
Andrew C Baird Detention Faclty	K1236	K1236 Local Jail or Detention Center One or more structures that serve as a place for the confinement of adult persons in lawful detention, administered by a local government (county, municipal, etc.)
Wayne County Juvenile Detention Faclty	K1235	K1235 Juvenile Institution A facility (correctional or non-correctional) where groups of juveniles reside; this includes training schools, detention centers, residential treatment centers and orphanages.
Mound Corr Faclty	K1237	K1237 Federal Penitentiary, State Prison, or Prison Farm Potential Living Quarters Y N Y An institution that serves as a place for the confinement of adult persons in lawful detention, administered by the federal government or a state government
Ryan Corr Faclty	K1237	K1237 Federal Penitentiary, State Prison, or Prison Farm Potential Living Quarters Y N Y An institution that serves as a place for the confinement of adult persons in lawful detention, administered by the federal government or a state government
Detroit Capstone Acdmy	K1235	K1235 Juvenile Institution A facility (correctional or non-correctional) where groups of juveniles reside; this includes training schools, detention centers, residential treatment centers and orphanages.

[56] The definition with the code of landmarks is in the following link https://www2.census.gov/geo/pdfs/maps-data/data/tiger/tgrshp2009/TGRSHP09AF.pdf.

Table A3. 2 (cont'd)

Other Landmarks

Finally, we calculate the distance to specific landmarks such as the Airport, parks[57], and the Central Business District (CBD).

Figure: Location of Parks in Detroit and calculation of minimum distance to a park

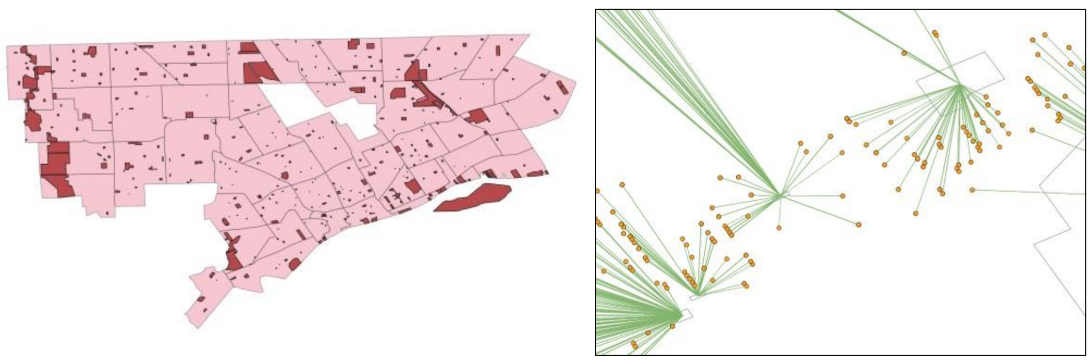
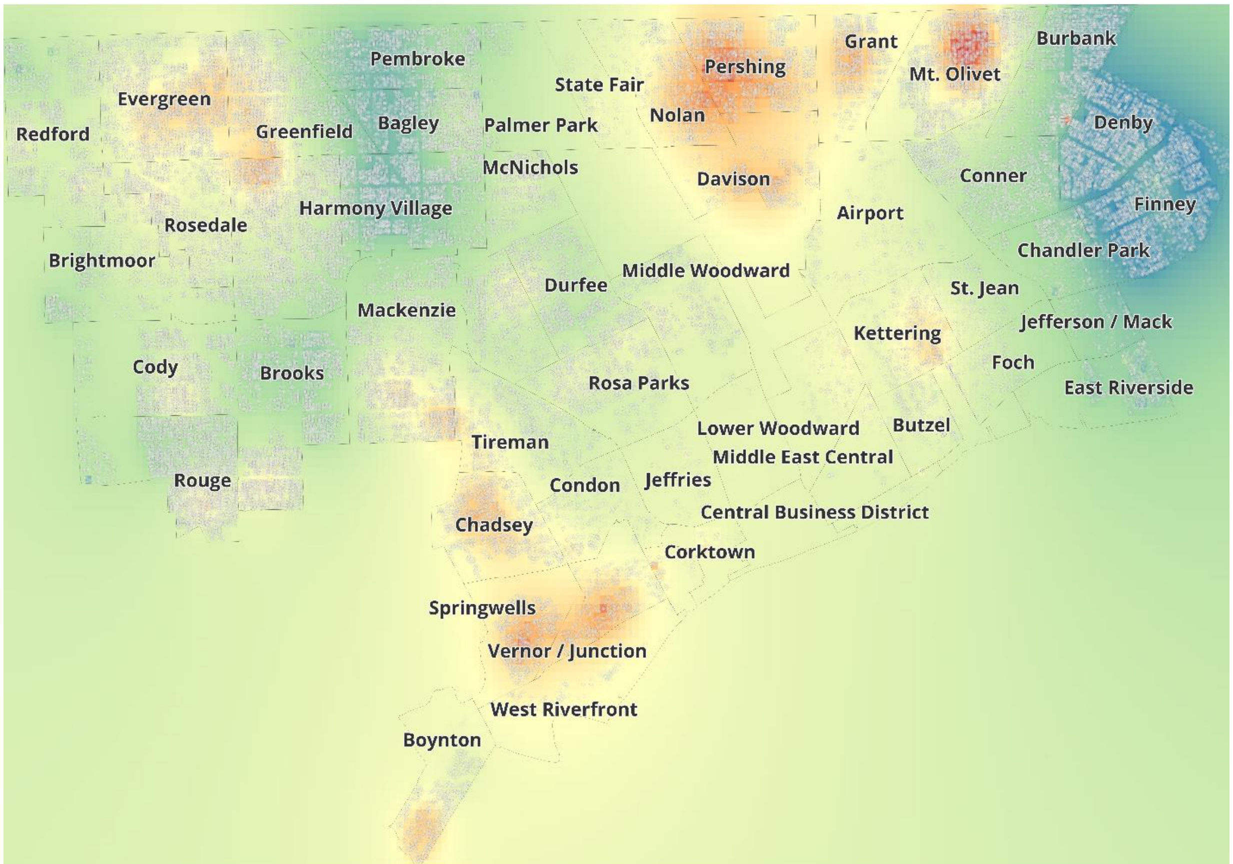


Figure: Identification of the CBD and calculation of the minimum distance

[57] See https://portal.datadrivendetroit.org/datasets/parks-and-landmarks-detroit/explore to obtain the information on parks across the city.

Figure A3. 1: Heat Map of the Blight Index



Source: Authors' calculations. Note: This heatmap was constructed using the Inverse Distance Weighting (IDW) interpolation method. IDW is a deterministic technique for spatial interpolation whereby values at unsampled points are estimated by averaging the values of nearby sampled points, inversely weighted by their distance. Thus, closer points have a higher influence on the interpolated value than those further away. The heatmap provides a visual representation of the neighborhood quality across the studied area (using the blight index). Red Areas represent neighborhoods with a higher blight index, indicating poorer quality areas. Blue Areas represent neighborhoods with a lower blight index, indicating better conditions and higher quality of life.

CONCLUSION

This thesis is structured into three distinct sections, each delving into the dynamics of policy evaluation in the housing market in Detroit. These areas of focus are crucial, especially in the context of ongoing development programs. The ensuing segment presents a summary of each essay, highlighting their individual and collective implications for policy in Detroit and potentially other communities grappling with similar challenges. The current economic climate, marked by rising inflation, underscores the urgency for practitioners and scholars to engage in the vital task of disseminating knowledge and educating communities about these issues.

The first essay discusses the potential impact of demolitions on property values with a focus on neighborhood characteristics, such as the level of dilapidation and median household income. Results indicate that the frequency of blighted properties in more dilapidated neighborhoods could mean that the removal of one such property might not significantly affect the overall neighborhood compared to areas with less blight and higher income. In highly dilapidated neighborhoods with frequently blighted properties, the removal of a single property may not significantly change property values. In contrast, in neighborhoods with less dilapidation and higher income, the removal of blighted properties might have a more substantial positive effect on property values.

The second essay indicated that the NSP had a stabilizing effect on the housing market in treated neighborhoods, preventing further declines, but did not stimulate pronounced revitalization. In terms of sales prices, I find suggestive evidence that the NSP may have halted downward trajectories, particularly for later treatment cohorts. However, effects on foreclosure numbers and rates were insignificant, implying the policy-maintained balance between treated and untreated areas, but did not reduce foreclosures. These conclusions align with the key goals of the

NSP: to mitigate housing decline rather than enable renewal. In the face of Detroit's structural challenges of high vacancy, weak demand, and oversupply, stemming the tide of abandonment constitutes an important achievement. Nonetheless, more transformational change would require interventions beyond the scope of this program.

In the third essay I provide empirical evidence that option value, as predicted by real options theory, is a significant factor in the pricing of residential properties in Detroit. This finding validates the theoretical assertion that the potential for future development influences current property values. Properties with lower infrastructure intensity, which suggests a greater potential for redevelopment, have a higher option value. This indicates that the market recognizes and assigns value to the flexibility or possibility of future improvements to a property. The hedonic pricing models reveal that higher property intensity, implying lower redevelopment potential, is associated with lower property prices. This effect is more pronounced for older properties and in higher-quality neighborhoods, suggesting that the market values the potential for redevelopment more in these areas. Finally, including the option value in land valuations leads to significantly higher predicted land values, especially for properties that are already valued higher. This suggests that current valuation methods may undervalue properties with high redevelopment potential.

In conclusion, the insights garnered from this essay offer a robust foundation for legislative support. They provide empirical evidence for the viability of the Land Value Tax Plan, which could significantly benefit communities like Detroit. Moreover, this research advocates for a nuanced approach to valuing and taxing urban farms and community gardens, balancing development needs with community initiatives. Ultimately, by informing voters and policymakers with data-driven evidence, this study contributes to a more informed and engaged civic discourse, essential for shaping the future of Detroit.