The Net Benefit of Tearing Down
Dilapidated Housing: The Case of Detroit

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Abstract

We conduct an analysis of the costs and benefits of public investment in demolishing dilapidated residential housing in Detroit. While we estimate a positive net impact of teardowns on nearby property values, we also calculate a low marginal impact on local property tax collections. Under existing housing market conditions in Detroit, demolition costs exceed the present value of additional property tax revenues resulting from demolitions over 50 years. Using efficiency as the criteria for justifying spending public funds on demolition, average property values would have to increase by a factor of five to justify the demolition program.

JEL Codes: R21, R31, R38, R52

Keywords: Detroit, housing market, dilapidated properties, spatial density, hedonic prices, spatial heterogeneity, multilevel regression, spatial econometrics.
I. Introduction

A challenge in declining urban areas is managing an aging and depreciating housing stock. Teardown policies mitigate the negative externalities associated with blighted properties; other benefits are derived from savings in municipal service costs such as police and fire. However, demolitions also have costs that are typically covered by local governments or transfers from state or federal governments. The benefit-cost tradeoff is critical for determining whether tearing down dilapidated structures is an efficient mechanism for revitalizing struggling neighborhoods. While the demolition of a blighted property may generate positive price effects for nearby properties, tearing down a dilapidated structure also generates a new vacant lot, which may have offsetting negative price effects. A deeper empirical analysis is then needed to determine the net effect. In this paper, we use detailed data from Detroit, Michigan to evaluate the net price effects of tearing down dilapidated housing as well as the time it takes to recover the costs through higher property tax collections generated from higher property values resulting from the removal of dilapidated structures.

Our analysis uses parcel level data on sales prices and housing characteristics provided by City of Detroit’s Assessment Division. This data set contains about 336,000 residential parcels of which around 34,000 parcels were sold during the 2009-2012 period. Unique information from the 2009 Detroit Residential Survey, conducted by Data Driven Detroit, is also used in the analysis. This survey records the physical condition of all residential parcels in the city, categorizing each as a vacant lot, dilapidated unoccupied property, or occupied property in varying degrees of dilapidation. At the time of the survey, around 91,000 (27%) residential parcels were vacant and 33,000 were
categorized as dilapidated (10%). We also merge data on demolitions that occurred in the years following the survey as registered by the State of Michigan Department of Environmental Quality. The 6,300 demolitions of dilapidated properties created 6,300 vacant parcels.

As a prelude to the full analysis, we estimate a 3% reduction in the average sales price of a property for an additional dilapidated property within a 0.1 mile radius of a sold property. Negative price effects are found at a distance of up to 0.125 miles, but the impact diminishes with distance. However, after the demolition there is a now a vacant lot, and a vacant lot is estimated to generate a negative price effect of about 1% on the price of a nearby sold property. Using both the dilapidated and vacant lot price elasticities, we evaluate the effect of the teardown policy on city property values and thus the property tax base. These results are robust to controlling for spatial autocorrelation, spatial heterogeneity at neighborhood and census tract levels. We then compare the benefits to the overlying local governments, including city government, of the teardown policy as measured as the present value of increased future tax collections and compare these benefits to the costs of tearing down the dilapidated structures. Our evaluation suggests that it may take more than 50 years to recover the initial costs of demolitions under our most optimistic scenario.

The organization of this paper is as follows. Section I summarizes the literature related with negative price effect derived from blighted properties, as well as the previous works evaluating the benefits and costs of demolition policies. Section II describes our data, and section III analyzes the price effects of dilapidated and vacant units and use these estimations to set tax collection scenarios. Section IV offers a robustness analysis
by testing the existence of spatial autocorrelation in housing market. Section V
concludes.

II. Literature review

For many years local governments in struggling urban areas have used demolition of
distressed properties to mitigate the externalities associated with blighted properties, thus
increasing the value of nearby properties, as well as reducing the public safety costs
associated with criminal activity, arson, and the like (Bass et al., 2012). Demolitions
have a cost, however, that are typically covered by the local government or transfers from
higher levels of government. Measuring these tradeoffs is vital for assessing the validity
of demolition policies as an efficient mechanism to revitalize struggling neighborhoods.
Unlike previous studies, we propose that evaluation must not only consider the expected
positive price effects, but also the time to recover the investment through property tax
collection. In this context, we offer a review of the literature in the context of two crucial
questions:

1) How much is the marginal price benefit of transforming a dilapidated property
to a vacant lot?

2) How much time does it take to recover the demolition costs via increased
property tax collection?

1. Price effect of distressed and vacant properties on nearby houses

Existing research shows that the intensity of foreclosed (and thus potentially
distressed) properties is negatively correlated with nearby housing prices (Anenberg and

1 An example is the U.S Treasury’ Hardest Hit Fund that assigned almost $8 billion for preventing the
foreclosure of residential properties across 18 states.
Kung, 2014; Campbell, Giglio and Pathak, 2011; Girardi, Rosenblatt, Willen and Yao, 2015; Hartley, 2014; Whitaker and Fitzpatrick, 2013). However, researchers such as Whitaker and Fitzpatrick (2013, pp.79-80) argue that the economic mechanism behind this correlation is unclear because, in the context of foreclosures, there is a competition effect and an amenity effect. That is, there is a supply or competition effect through the injection of additional housing properties to the local market. On the other hand, if foreclosed properties are neglected, abandoned or vacant, then negative externalities are responsible for depressing the prices of nearby properties via a negative spillover effect; this is the so called amenity effect.

This empirical controversy has triggered several efforts to disentangle the two effects. Assuming that foreclosed properties are similar to other properties offered in the housing market, Hartley (2014) segments the markets between single-family and multifamily to identify the price effect of new foreclosures. If the new foreclosure is a single-family property, then both the supply and amenity effects are expected. However, only the amenity effect is expected for foreclosed multi-family units because multi-family dwellings are considered to be in a different market than single-family residential. Using this identification strategy for Chicago, Hartley estimates a supply effect of 1.2% on nearby property prices. Anenberg and Kung (2014) corroborate the Hartley’s finding with an analysis using prices listed in Multiple Listing Service for San Francisco, Washington, DC, Chicago and Phoenix. They find that prices fall after the inclusion of a new real estate owned (REO) properties, suggesting that the price drop is evidence of a supply effect.2

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2 Real Estate Owned property is property that goes back to the mortgage company after an unsuccessful foreclosure auction.
However, the literature also provides some support for the amenity effect. Campbell et al. (2011) analyze foreclosures in Massachusetts over the period 1987 through 2009, providing evidence that forced sales reduce prices of nearby properties by 3% to 7%. However, the authors reject the supply effect indicating that, “this evidence suggest ...[low prices]...reflect poor maintenance of houses”. Additional work, such as articles by Leonard and Tammy (2009) and Immergluck and Smith (2009) reach similar conclusions using different data sets and econometric techniques. Although the evidence is mixed regarding the mechanism driving the relationship between foreclosures and nearby property prices, the research clearly demonstrates a negative correlation between foreclosures and nearby property values. While this work is germane to the present study, note these studies focus on foreclosed property and do not directly observe the degree of housing dilapidation.

While studies of foreclosed (and potentially distressed) properties provide statistical evidence to support a negative price effect, less evidence exists on the impact generated by vacant areas. Whitaker and Fitzpatrick (2013) argue this lack of evidence is due to the fact that most of the previous research uses foreclosures as a proxy for distressed properties due to the relatively easy to access property data through banks or local tax offices. However, foreclosure cannot be used as a proxy for vacant lots. Mikelbank (2008) provides one of the few studies that separate the externality effects among vacant, distressed and foreclosed properties using the data from Columbus, Ohio. The author suggests that vacant property has a large negative impact on nearby property values than distressed and foreclosed property; if true, then the foreclosure condition in isolation overestimates the price effect. In a similar vein, Hartley (2014) shows that the
supply effect is the cause of falling nearby property prices, whereas the amenity effect is only a minor factor. Finally, Whitaker and Fitzpatrick (2013) estimate that an additional vacant lot reduces nearby housing prices by 1% to 2% within 500 ft. To our knowledge, Whitaker and Fitzpatrick provide the first estimation of the vacant lot price effect.

In the context of evaluating demolition policy, we argue the we must estimate the externalities associated with dilapidated housing and vacant lots in order to identify the net impact of demolition on nearby property values because demolition a dilapidated structure results in a vacant lot; in the case of Detroit nearly all lots remain vacant with little expectation that a new home will be built. Although our work is closely related to this literature, we provide new information on the price effects of vacant and dilapidated properties, or equivalently, the marginal effect of converting a dilapidated unit into a vacant lot.

2. Cost benefit analysis of demolitions and tax recovery

Our review of the literature did not uncover any published papers evaluating the benefits and costs of housing demolition policy. There is, however, a recent wave of policy reports about this topic. Griswold, Calnin, Schramm, Anselin and Boehnlein (2014) evaluate the effect of residential demolitions on the prices and foreclosure rates in Cleveland, Ohio. The authors evaluate the effect from 6,000 demolitions; indicating that the demolitions generated a $22.6 million net benefit, or equivalently, the analysis generated a cost benefit ratio of 1.4 per dollar spent on demolitions. Schuetz et al., (2014) indirectly assesses the demolition effect through the impact evaluation of Neighborhood
Stabilization Program (NSP) in seven large counties. Although the authors rely primarily on descriptive analyses, they also infer positive net benefits from demolitions.

Perhaps the work that is most relevant to the present study is the recent research by Dynamo Metrics (2015) in which the residential demolition benefits and costs are estimated for Detroit. Specifically, they combine demolition data from Hardest Hit Fund (HHF) between April 1st, 2014 and March 31st, 2015 with the price data between January 1st, 2011 and March 31st, 2015 to evaluate the impacts. The report concludes that demolition activity generates a 4.2% positive impact on value of nearby homes. In aggregate, their work generates a cost benefit ratio of $4.27 per dollar spent on demolitions in the study areas. However, the second round effect generated by newly created vacant lot is not considered.

While we share the same motivation as these previous studies, our approach differs in several respects. First, we think that the demolition process should be framed as a two-step procedure: a demolition of dilapidated property typically generates, particularly for a depressed market like Detroit, a new vacant parcel. According to the previous literature on this issue, vacant areas are considered an undesirable feature at the neighborhood level. This implies that demolition must incorporate two effects: there is a reduction in dilapidated properties, but also an increase in vacant lots, at least in the short- to medium-run. Generally speaking, the previous reports do not take into consideration this double effect estimation to obtain a net effect.

The second issue is with regard to the social benefit versus property tax collection. As an illustration, assume that local government officials allocate $1 million

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3 Cook IL, Cuyahoga OH, Los Angeles CA, Maricopa AZ, Miami-Dade FL, Philadelphia PA, and Wayne, MI.
on demolitions. As a result, we may generate a total price effect greater than $1 million (Griswold et al., 2014; Schuetz et al., 2014). However, from a public finance perspective, this public investment in demolition can be recovered over time primarily through increased property tax revenue generate from the positive price effect. In this scenario, the positive price effect represents the social benefit, but it does not fully consider the cost recovery via increased property tax collection. Our analysis offers a useful addition to existing research by considering both dilapidated teardown and the remaining vacant lot. We also calculate payback period of the public investment by comparing demolition costs to anticipated increases in property tax collection over time resulting from teardowns. Our analysis offers useful insights to better understand the real trade-offs associated with teardown policies.

III. Data

1. House sale prices and characteristics

The data we use in our analysis come from several sources. We first discuss our core data set, which comes from the City of Detroit Assessment Division. Specifically, we use detailed data on more than 336,000 residential parcels in Detroit. For each parcel we know the lot size, square feet of the structure, housing type, neighborhood name, and address. The address allows us to estimate the distance to 51 amenity/disamenity points of the city. This sample also identifies the last registered sales price for sold properties as well as the year when the transaction occurred. Given that sale price and parcel characteristics coincide in real time in our data source only for those transactions that

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4 Additionally details at https://www.michigan.gov/documents/treasury/STC_Recommended_Codes_351268_7.pdf
occurred in 2010, we expect some errors in the matching of prices and characteristics back in years other than 2010. To limit the number of errors in matching while at the same time obtaining a reasonably large set of sold properties, we select transactions that occurred from 2009 through 2012 to be included in our evaluation. We also detect some anomalies in the data such as physically infeasible square feet dimensions or some sale transactions carried out before the year of construction. We clean these inconsistencies from the data to generate out the final sample with 31,259 observations.

We also pay particular attention to the identification of outliers in the dependent variable. Due to economic issues amplified by the nationwide real estate crisis, average residential housing sales prices in Detroit fell from $57,000 to about $7,000 between 2006 and 2010 (Hodge et al., 2014). The long-term eroding of the economic base, in combination with the crisis, ultimately led to the decision by Detroit city leaders to file for bankruptcy. In addition, growing tax delinquency and home mortgage foreclosure pressured many homeowners to either sell at very low prices (less than a $1,000). These unusual housing market circumstances require us to pay special attention to identifying outliers. While some housing studies exclude extreme prices by omitting observations above and below specific percentiles, we use a different approach. Specifically, we use an approach that enables us to distinguish between outliers and leverage prices as discussed in Campbell et al. (2011).

Outliers are extreme values, but they may still represent theoretically expected correlations such as extremely large properties with extremely large prices. On the other hand, leverage-housing prices simply do not correspond with theoretical predictions derived from hedonic framework. For example, distressed properties with extremely high
prices are out of line with theoretical expectations and common sense. In other words, leverage observations do not have unusual values for the dependent or independent variables, but rather they have unusual conditional expectations. To be more specific, leverage observations are those with statistically large predicted errors obtained thorough a linear regression. We use an approach known as the detection of studentized residuals where we estimate initial regressions to identify significant leverage observations. Additional details are reported in Appendix A.

Table 1 shows an average price of $20,193 for the sold property sample, but with an unrealistic standard deviation clearly influenced by observations with extremely high prices. According to the detection of studentized residuals, 6,035 properties, namely the 19% of the sample, are identified as leverages. If we discard these leverages as non-arm’s length transactions, then the mean price falls to $6,991, which is much closer to the mean price reported in the previous literature (Hodge et al., 2014).

Table 1
Summary statistics for property characteristics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observations</th>
<th>Share</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>0.25</th>
<th>Mdn</th>
<th>0.75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price / Total</td>
<td>31259</td>
<td>100%</td>
<td>20193</td>
<td>360000</td>
<td>1</td>
<td>2009</td>
<td>7500</td>
<td>20000</td>
<td>64000000</td>
</tr>
<tr>
<td>Price / Outliers</td>
<td>6035</td>
<td>19%</td>
<td>75373</td>
<td>830000</td>
<td>27250</td>
<td>38000</td>
<td>54300</td>
<td>81095</td>
<td>64000000</td>
</tr>
<tr>
<td>Price / Sample</td>
<td>25224</td>
<td>81%</td>
<td>6991</td>
<td>6732</td>
<td>1</td>
<td>1108</td>
<td>5000</td>
<td>10400</td>
<td>27169</td>
</tr>
<tr>
<td>Floor Area</td>
<td>25224</td>
<td></td>
<td>1081</td>
<td>843</td>
<td>17</td>
<td>799</td>
<td>936</td>
<td>1282</td>
<td>32767</td>
</tr>
<tr>
<td>Lot Size</td>
<td>25224</td>
<td></td>
<td>4806</td>
<td>1770</td>
<td>305</td>
<td>4008</td>
<td>4617</td>
<td>5271</td>
<td>150000</td>
</tr>
<tr>
<td>Sale Year</td>
<td>25224</td>
<td></td>
<td>2010</td>
<td>1</td>
<td>2009</td>
<td>2009</td>
<td>2010</td>
<td>2011</td>
<td>2012</td>
</tr>
</tbody>
</table>

Note: S.D = standard deviation, Min = minimum, 0.25 = 25th percentile, Mdn= median, 0.75= 75th percentile, Max=maximum.
Discarding these 6,035 observations also adjusts the standard deviation and maximum price toward more conventional ranges. The final sample of 25,224 observations reports a standard deviation of 6,732, with a maximum price of $27,000. More than 3,700 properties of the total sample report a price lower than $100, but none of them were detected as outliers. We expected a reduction in the number of these properties, but this statistical procedure also demonstrates that they are not leverage observations and as such these prices may reflect unusual dynamic of this housing market. Our analysis indicates that the real estate crisis resulted lower prices as the standard situation, whereas high price purchases are shown to be unusual events. However, we note that our robustness analysis include estimations using the standard outlier rules to show the robustness of our estimations. As shown in Figure 1, the spatial distribution of sold properties does not exhibit a particular pattern, though most of transactions occur on the outer ring of the city. The map also shows few residential property transactions near the Central Business District where commercial property dominates.
Figure 1. Spatial distribution of sold parcels in Detroit between 2009 and 2012 by price level.

Note: The blue label represents the lowest 33% of transaction prices, the yellow label represents the middle 33% of total transaction prices, while the red label represents the upper 33% of the price distribution. The map also shows the 51 neighborhoods of Detroit. Map built with CartoDB® software.

2. Spatial rings of vacant lots and dilapidated properties

Whitaker and Fitzpatrick (2013, pp.79) indicate that foreclosed properties are generally treated as unoccupied, abandoned and blighted properties. However, in weaker housing markets, such as the case of Detroit, not all foreclosed homes are unoccupied or distressed. Further, a large number of dilapidated properties may not be in a foreclosure process. This clarification motivates us to use more precise information on vacant and dilapidated properties. We exploit the Detroit Residential Survey, which is a unique cross sectional data set with primary information collected by Data Driven Detroit with
partners Living Cities, the Detroit Office of Foreclosure Prevention and Response and Community Legal Resources (Michigan Community Resources) between August and September 2009.5 This survey registers the condition of each parcel in the city; each parcel is identified as a vacant lot or parcel with residential structures rated by degree of dilapidation and occupancy. We merge the Detroit Residential Survey with previously discussed data provided by City of Detroit’s Assessment Division. As shown in Table 2, Detroit had 91,074 vacant parcels (27% of the total) and 33,107 dilapidated properties (9.8% of the total).6

Table 2

| Frequency of vacant lots and dilapidated properties |
|------------------------------|----------------|----------------|
| N          | Frequency | Acum Frequency |
| Not Vacant | 245,629  | 72.95          | 72.95          |
| Vacant     | 91,074   | 27.05          | 100            |
| Total      | 336,703  | 100            |

| Not dilapidated | 303,596 | 90.17 | 90.17 |
| Low dilapidated | 2,607   | 0.77  | 90.94 |
| Medium-Low Dilapidated | 19,775 | 5.87  | 96.81 |
| Medium-High Dilapidate | 7,785  | 2.31  | 99.13 |
| High Dilapidated   | 2,940   | 0.87  | 100   |

Total 336,703 100

Note: N= observations, Acum=Accumulated.

5 http://datadrivendetroit.org
6 Even when all the information is obtained from official data sets, the match of data are imperfect and we lost some information through the process.
We count the number of vacant lots and dilapidated properties to estimate the spatial density of these properties around each of the sold units in our sample as shown in Figure 2. Table 3 shows that the average vacant intensity is higher than the intensity of dilapidated properties. There are about eight vacant lots within a 0.05-mile ring of any given residential property, but there are just three dilapidated properties in the same 0.05-mile ring. As shown in the last two columns of Table 3, vacant lots are always more intense than dilapidated properties with a 95% of confidence. Increasing the size of the ring to 0.125 miles increases the number of vacant lots to 48 units, whereas the number of dilapidated properties increases to 17. The very large number of dilapidated and vacant properties suggests that significant price effects are likely to be present.
Table 3
Spatial ring intensity of vacant lots and dilapidated properties

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std. Err.</th>
<th>[95% Conf. Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Spatial intensity before demolitions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R 0.05v</td>
<td>336,703</td>
<td>8.388</td>
<td>0.016</td>
<td>8.357 - 8.419</td>
</tr>
<tr>
<td>R 0.10v</td>
<td>336,703</td>
<td>31.892</td>
<td>0.056</td>
<td>31.782 - 32.003</td>
</tr>
<tr>
<td>R 0.125v</td>
<td>336,703</td>
<td>48.241</td>
<td>0.084</td>
<td>48.077 - 48.406</td>
</tr>
<tr>
<td>R 0.05d</td>
<td>336,703</td>
<td>2.994</td>
<td>0.005</td>
<td>2.985 - 3.003</td>
</tr>
<tr>
<td>R 0.10d</td>
<td>336,703</td>
<td>11.536</td>
<td>0.015</td>
<td>11.508 - 11.565</td>
</tr>
<tr>
<td>R 0.125d</td>
<td>336,703</td>
<td>17.447</td>
<td>0.021</td>
<td>17.406 - 17.489</td>
</tr>
<tr>
<td><strong>Panel B. Spatial intensity after demolitions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R 0.05v shock</td>
<td>336,703</td>
<td>8.976</td>
<td>0.016</td>
<td>8.945 - 9.008</td>
</tr>
<tr>
<td>R 0.10v shock</td>
<td>336,703</td>
<td>34.167</td>
<td>0.058</td>
<td>34.054 - 34.280</td>
</tr>
<tr>
<td>R 0.125v shock</td>
<td>336,703</td>
<td>51.678</td>
<td>0.086</td>
<td>51.510 - 51.846</td>
</tr>
<tr>
<td>R 0.05d shock</td>
<td>336,703</td>
<td>2.406</td>
<td>0.004</td>
<td>2.398 - 2.413</td>
</tr>
<tr>
<td>R 0.10d shock</td>
<td>336,703</td>
<td>9.262</td>
<td>0.012</td>
<td>9.239 - 9.285</td>
</tr>
<tr>
<td>R 0.125d shock</td>
<td>336,703</td>
<td>14.010</td>
<td>0.017</td>
<td>13.977 - 14.043</td>
</tr>
</tbody>
</table>

Note: R=Ring, v=vacant, d=dilapidated, shock=After demolitions over 2012-2015, N=observations

3. Demolition data

The final set of information we collect are the records of demolitions registered in Detroit by the State of Michigan Department of Environmental Quality (MEDQ). MEDQ is required keep a record of demolitions as part of the National Emission Standards for Hazardous Air Pollutants program, which is supported by United States Environmental Protection Agency. This list contains all the rehabilitations and demolitions on structures where hazardous substances are present. We select the observations tied to demolitions from 2009 through April 2015. Using the Detroit Residential Survey, we match those properties labeled as dilapidated with the demolition list and identify 6,304 demolitions of dilapidated properties. This unique data set allows us to evaluate the monetary impact of transforming 6,304 dilapidated properties into 6,304 vacant areas. The Panel B of Table 3 summarizes the effect to these demolition on the spatial rings previously computed. As we expected, the average number of dilapidated
properties slightly decreases after the demolitions, and the number of vacant lots increases. This is a central element for our estimation because both effects offer opposing price effects and we must consider both to determine the net price effect.

4. Identification strategy

We first estimate the relationship between sales price and the presence of dilapidated and vacant properties. We then use those estimates to evaluate the net price effect generated by the actual teardowns. For this reason, the teardowns are considered to be an exogenous shock to the spatial intensities of vacant and dilapidated parcels. We formalize the discussion using a standard hedonic regression approach as the method for recovering the willingness to pay for housing characteristics in housing markets. These characteristics can be intrinsic features of the property, such as lot size or ground floor area, but they also can be extrinsic characteristics such as the level of pollution, noise, or the spatial intensity of vacant lots and dilapidated properties as in our case. We specify the hedonic regression using \( y_i \) as the log price of parcel \( i \):

\[
y_i = \beta_0 + \beta'X_i + \gamma_d R_{ic}^d + \gamma_v R_{ci}^v + N_i + Y_t + \epsilon_i \tag{1}
\]

where \( X_i \) is a matrix that contains the continuous variables floor area, lot size and distance to 50 amenity locations, as well as dummy variables such as whether or not parcel \( i \) is vacant or dilapidated. \( N_i \) represents 51 neighborhood fixed effects, one for each of the neighborhoods in Detroit. \( Y_t \) represents the year fixed effects for years 2009 through 2012. Our crucial variables, \( R_{ic}^d \) and \( R_{ci}^v \), are the spatial intensities within the radius \( c \), of dilapidated and vacant properties, respectively. Given that the parameters associated with \( R_{ic}^d \) and \( R_{ci}^v \) are the main input for calculating property tax collections
generated from property value changes, we discuss arguments to support its identification.

A key issue we must address is the potential simultaneity between the dependent and independent variables. As we discussed above, we generate the variables $R_{ic}^d$ and $R_{ic}^v$ using the Detroit Residential Survey that was administered in 2009, whereas we use property price data for years 2009 through 2012; thus most sales in our data occurred after the survey was taken. While we acknowledge that panel data is a more ideal approach for examining this issue, we think our data and approach yields a strong causal connection from $R_{ic}^d$ and $R_{ic}^v$ to prices due to the time sequence of data.

In addition, spatial autocorrelation may also affect the consistency and efficiency of the estimation, especially in housing data (Kim, Phipps and Anselin, 2003). To address this issue, we assume that the spatially weighted average could affect nearby housing prices through the imitation effect or the macro spillover effect. This type of spatial dependence transmitted through the dependent variable is called the spatial-lag model, which generates a particular spatially autocorrelated error structure, which we model. However, spatial autocorrelation could rise from unobserved factors that are also spatially correlated. For example, unobserved environmental conditions could affect all parcels in particular neighborhoods, with similar consequences on the error terms. These theoretical elements imply that failure to address spatial dependence may have direct consequences on the consistency of coefficients associated with $R_{ic}^d$ and $R_{ic}^v$. To address this issue, we conduct a spatial exploratory analysis to detect the presence of spatial autocorrelation; if

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7 Note that even when $R_{ic}^d$ and $R_{ic}^v$ are spatially weighted variables, it does not imply that spatial autocorrelation is removed. Assume a spatial price matrix $W$ of $n \times n$ which contains a one if two properties are inside a circle of radius $c$. Then the vector $R$ which contains the spatial ring intensity for all parcels can be represented by $R = Wl$ where $l$ is a column vector with $n$ ones.
detected we must estimate either the Spatial Autoregressive Model (SAR) or the Spatial Error Model (SEM). Additional analysis as presented in Appendix D indicates that there is little evidence of spatial autocorrelation or spatial heterogeneity. However, as shown in Appendix D, estimates that account for spatial autocorrelation and spatial heterogeneity are qualitatively similar to those present in the next section.

IV. Results

1. Hedonic regressions and spatial rings

Table 4 reports a subset of estimated coefficients for Equation (1) using different spatial radii and two different sub-samples of sold properties.\(^8\) The first three columns report the estimations for the sample without the detected outliers, namely with the 25,224 observations previously discussed in Table 1. These results reveal that, using a ring of 0.05 miles, the intensity of vacant lots, as well as dilapidated structures, are negatively correlated with prices. In the case of dilapidated buildings, one additional unit decreases the average price by 8.7%, whereas an increase of one vacant lot reduces the price by 4.9%. These initial results confirm our intuition with respect to demolitions: they generate a net positive price effect by reducing the number of blighted properties. However, the nearly nonexistent redevelopment process that might transform a vacant lot to new housing also generates a negative price effect, which offsets the initial impact. In particular, the ratio of the two effects is around 1.8 and has a magnitude that is different than one with a 99% of significance. This price effect is robust to a large array of control variables as well as different sized rings. For example, the second column reflects the

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\(^8\) We focus the discussion on the relevant variables, but the complete regression outputs are available on request to authors.
same estimation, but using a ring of 0.1 miles instead. While price-ring elasticity is lower than with in column 1, the ratio is still in a similar range. The smaller effects with larger ring size are consistent with the idea that negative externalities resulting from blighted properties are greater the closer they are to the sold properties. If we move to the largest ring, namely 0.125 miles from the transaction, the negative elasticity is still significant. The differences between the coefficients on the dilapidated and vacant variables are also significant. We do not include the different sized rings within the same specification because the rings overlap, thus reducing the efficiency of our estimations.

Our rule for determining outliers might affect the magnitude and efficiency of our estimates. We therefore re-estimate the same set of hedonic regressions, except this time we use the complete sample with 31,259 observations. The results, also displayed in Table 4, are very similar to those discussed above. The magnitudes of the price elasticity coefficients, as well as the significance and ratio between the vacant lots and dilapidated property coefficients, are in similar ranges.

### Table 4

_Hedonic regressions for sold properties in Detroit_

<table>
<thead>
<tr>
<th></th>
<th>Sample no outliers</th>
<th>Total sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.05 M 0.10 M 0.125 M</td>
<td>0.05 M 0.10 M 0.125 M</td>
</tr>
<tr>
<td>Dependent variable</td>
<td>Log price</td>
<td></td>
</tr>
<tr>
<td>Vacant Intensity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dilapidated Intensity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.116 0.118 0.118 0.099 0.101 0.101</td>
<td></td>
</tr>
<tr>
<td>Ratio</td>
<td>1.781 2.402 2.647 1.584 2.206 2.412</td>
<td></td>
</tr>
<tr>
<td>H0: Vacant=Dilapidated</td>
<td>0.000 0.000 0.000 0.001 0.000 0.000</td>
<td></td>
</tr>
<tr>
<td>Neighborhood FE</td>
<td>Yes Yes Yes Yes Yes Yes</td>
<td></td>
</tr>
<tr>
<td>Property Attributes</td>
<td>Yes Yes Yes Yes Yes Yes</td>
<td></td>
</tr>
<tr>
<td>Yearly FE</td>
<td>Yes Yes Yes Yes Yes Yes</td>
<td></td>
</tr>
</tbody>
</table>
Amenities Distance  Yes Yes Yes Yes Yes Yes
Observations     25224 25224 25224 31259 31259 31259

Note: M=Miles. The table shows the estimates and level of confidence are represented by * = p<0.05, ** = p<0.01 and *** = p<0.001.

We now use the coefficients from Table 4 to predict the price effect of demolitions according to the information described in Table 2. The log linear specification allows us to capture the nonlinear price effect along the price distribution: Clearly a 1% of net price effect is different in a depressed neighborhood than in a healthier and well-maintained area of Detroit. Figure 3 shows the density of the price effect using the 0.125 mile ring; similar figures for the 0.05 and 0.10 mile rings are available in Appendix B. Based on the coefficients from the hedonic regressions, demolitions of dilapidated structures increase the sales prices between 0 and 170%. At the same time, a vacant lot decreases price, but range of the effect is between 0 and 60%, which is smaller on average and much narrower.

Figure 3. Price effect after demolitions.
Note: The dashed gray line represents the density of positive price effects to the lower number of dilapidated properties. The black line represents the density of negative price effects due to the higher number of vacant properties.

Figure 4. Price differential measured in dollars.

Note: Left plot uses ring of 0.05 miles, center uses 0.1 miles and right uses 0.125 miles.

Figure 4 converts these percentages in dollars, and Table 5 provides detailed summary statistics for this price effect. For each one of the rings we estimate an upper bound effect between $2,500 and $3,300. However, the average price effect for the complete city is between $64 for the smallest ring to $162 for the largest ring. These magnitudes enable us to better understand the Detroit housing landscape. First, the depressed conditions and thus the very low prices in the Detroit housing market imply a small price effect from demolitions. Thus, the benefits generated via price increases following demolitions are quite small, too small to cover the costs of the demolitions.
However, larger price effects arise when we increase the spatial scope of rings. As Table 5 shows, the average price effect reaches $160 for the largest ring. These estimates provide some intuition about the results described in the next section: Even though demolitions increase housing prices in Detroit, the very low average prices prohibit one from making the case that demolition policy is justifiable based on efficiency alone. We discuss this in greater detail below, along with the potential new property tax collections resulting from the price increases generated by demolition policy.

Table 5
Summary statistics for price effect in dollars for Detroit

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>0.25</th>
<th>Mdn</th>
<th>0.75</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>R 0.05M</td>
<td>235797</td>
<td>64.31</td>
<td>143.72</td>
<td>0</td>
<td>0</td>
<td>65.13</td>
<td>2489.08</td>
<td></td>
</tr>
<tr>
<td>R 0.01M</td>
<td>235797</td>
<td>132.75</td>
<td>216.01</td>
<td>0</td>
<td>0</td>
<td>47.29</td>
<td>176.73</td>
<td>3060.13</td>
</tr>
<tr>
<td>R 0.125M</td>
<td>235797</td>
<td>162.08</td>
<td>245.63</td>
<td>0</td>
<td>0</td>
<td>74.74</td>
<td>213.62</td>
<td>3354.88</td>
</tr>
</tbody>
</table>

Note: S.D = standard deviation, Min = minimum, 0.25 = 25th percentile, Mdn = median, 0.75 = 75th percentile, Max = maximum.

2. Estimation of tax collection after demolition

To evaluate the increased tax collection resulting from demolitions, consider a simple partial equilibrium analysis:

\[ \Delta \pi(\Delta P_i; C, \tau, \phi, r) = \sum_{l=1}^{L} \sum_{t=1}^{T} \frac{\tau \phi \Delta P_i}{(1+r)^t} - (TD \cdot C) \]  

(2)

where \( \Delta \pi \) represents the total change in tax collection after demolitions, \( \Delta P_i \) is the net price effect, considering both the vacant lot and dilapidated structure removal effects resulting from demolitions. To estimate the net new tax collection, we need to specify several parameters: \( C \) represents the demolition cost, \( \tau \) is millage per $1,000 of property value, \( \phi \) delinquency rate, and \( r \) is the interest rate. With respect to demolition costs in
Detroit, base demolition costs are around $15,000. However, additional costs must be considered such as shutting off gas, water, and electricity services, asbestos removal, as well as the costs of dumpsters and landfill space. These additional costs are roughly $5,000. Together, these costs imply that \( C \) is equal to $20,000. The net millage rate is about 80 mills for all taxing jurisdictions and taking in account that State Equalized Value is 50% of market value, on an annual basis. The delinquency rate \( \phi \) has been a severe problem during the housing crisis for Detroit. According to Hodge et al. (2014), the average delinquency rate is more than 35% in Detroit. However, in our calculations we assume a long-run tax delinquency rate of 15%. Finally, we set the interest rate at 3%, which is within a typical range for evaluating public projects.

Panel A of Figure 5 provides a comparison between demolition costs and new tax revenues generated from the estimated increase in property prices generated from the demolitions. In this panel we use the estimate increase using the 0.05 mile spatial ring. The estimated demolition costs for the 6,035 properties we evaluate costs about $120 million, which is depicted by red dashed line at the bottom of the figure. Once the dilapidated structure is eliminated, nearby property values increase: The dotted line labeled “SB (P=1)” represents the estimated net citywide increase in property value resulting from the teardowns under the current housing the price level. The green line labeled “Tax Collection (P=1)” represents an estimate of the new property tax collections for all the overlying tax jurisdictions generated from the increase property values.10 From

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10 This is a stylized property tax collection calculation. In reality, the tax administration environment is more complicated. First, assessments would have to properly capture changes in property values resulting from the teardown activity. Second, depending on the overall growth in property values from year to year the assessment growth cap can potentially prevent the increases from being
these three lines, we can see that: 1) the net property value increases resulting from the demolitions are smaller than the demolition costs; and 2) government will not recover the demolition costs through increased property tax collection over time. In Panel B and C, we present similar scenarios except we base our calculation on the estimates from the 0.10, and 125 mile ring distances, respectively. These cases result in similar conclusions.

The main issue is the property prices are so low in Detroit under current real estate conditions that net social benefit is negative. Consider Figure 5, panels A, B, and C where prices are doubled [“SB (P=2)” and “Tax Collection (P=2)”] and tripled [“SB (P=3)” and “Tax Collection (P=3)”]. Even if we doubled or event tripled housing prices, we do not achieve a positive net social benefit. Our most optimistic scenario is depicted in Panel C with lines “SB (P=3)” and “Tax Collection (P=3)” where we use the largest ring and where prices are triple current values; even here we do not achieve a net social benefit and it takes more than 50 years to fully recover costs.

The last scenario we consider is generated from the model that accounts for spatial autocorrelation, which is found in Appendix D. This analysis results in larger property value and property tax increases than with the estimates presented in the core part of the paper. In Figure 6, we present benefits and property tax calculations using the estimated generated from the 0.12 ring. Under current the housing price scenario labeled “SP(P=1)” we generate a positive net benefit where cost recovery in terms of tax collections falls to about 35 years. Doubling (P=2) and tripling the price (P=3) results even higher net benefits and reduces the time of cost recovery to about 16 and 8 years, respectively. Appendix C offers a set of graphs similar to those presented in Figure 6, captured in assessed value. In such a case, the growth in property taxes would lag behind growth in property values.
except they are generated from the regressions that address spatial autocorrelation as presented and discussed in Appendix D. These graphs are qualitatively similar to those already presented a thus are not discussed here. Though the estimates generated in Appendix D control for spatial autocorrelation, we prefer our core estimates because they are generated from the original parcel level data and are not aggregated. Further, as previously noted, we found little evidence of the presence of spatial autocorrelation. For these reasons, we believe these estimates offer the best overall perspective on the price effects of the teardown policy.

V. Conclusions

In this paper, we use detailed parcel level data for the Detroit to examine the benefits and costs of the city’s dilapidated teardown policies. Our analysis shows that tearing down dilapidated housing generates positive property value effects, where the effects are strongest for nearby properties but the effects are observed up to 0.125 miles. Our analysis offers several contributions to the literature. First, we examine teardown policies in Detroit, a severely stressed real estate market. Second, we consider the both positive effects of blight removal and the negative effect of the remaining vacant lot. Despite the positive effects, we find that the social net benefit is negative, even under very optimistic conditions. We also consider the time to fully recover the costs of teasdowns. Again, even under very optimistic scenarios it may take more than 50 years for costs to be recovered through increased property tax collection. The key issue is that property values are so low that the property value gains from the teasdowns are quite small. Average
prices in the city would have to increase about five-fold in order to generate a positive net social benefit.

The analysis presented in this paper suggests that the teardown policies, under current circumstances, cannot be justified by the efficiency criteria alone. Rather, we must consider other factors. First, equity considerations may play a role; many government expenditures are largely redistributive in nature. It may be that society wishes to help improve quality of life in declining urban areas by helping to pay for the removal of dilapidated structures. Second, removal of blight may be important because it removes barriers to potential future investment. Third, there may be important synergies with other policies such as improving public education and reducing crime; the gains in property values associated with improved public services are enhanced by the removal of dilapidated housing and vice versa. Further, removal of such properties may reduce public services costs (fewer fires, reduced crime, etc.).

In addition, policy makers may be able to increase the benefits of demolition policy. Our estimates show that vacant lots reduced property values on average, but not all vacant lots necessarily reduce property values. For example, lots that are purchased by neighbors and then cared for do not have the same impact as neglected parcels. Policies to encourage the purchase of vacant lots by neighbors can increase the net benefit of teardowns. The City of Detroit currently has this type of policy in place. City officials may want to consider targeting neighborhoods where teardowns generate higher benefits. For example, the prices in neighborhoods surrounding Midtown are relatively high and have recovered in the aftermath of the real estate crisis, whereas other parts of the city such as the East Side, West Side and Southwest continue to languish. One
approach to increasing the benefits of teardowns is to focus efforts in and around these higher value areas. While this approach might lead to concerns about equity, it would help to generate a higher net benefit and reduce the cost recovery time. In summary, our research offers a useful evaluation of teardown policies in Detroit under current conditions, but importantly this analysis can be used to help identify approaches to improve policy effectiveness. More generally, the framework we use to evaluate Detroit’s teardown experience is applicable to other struggling cities across the nation that must deal with unwanted depreciating housing stock.
Figure 5
Benefits and costs demolition policy and time to cost recovery

Panel A

Panel B

Panel C
Figure 6
Benefits and costs demolition policy and time to cost recovery: Spatial autocorrelation model
References


APPENDIX A: BUILDING THE FINAL SAMPLE

To detect the leverage observations we estimated the studentized residuals and we identify those larger than three standard deviations. We run regressions using sale price as dependent variable for the 34,060 sold properties in our working data set. As control variables we use lot size, square feet, age of property, condominium dummy variable and a year sale dummy to control by inflation. We also control for the quality of the property including indicator variables signifying whether a property is occupied, vacant or dilapidated. Finally, we also control for 51 neighborhoods fixed effect to reduce potential bias effects from differences in public goods, amenity provisions and other factors that vary by neighborhood. We also include the distances to 51 amenities points. This regression runs several times until the studentized residual falls below 3 (in absolute value terms). This method identifies 7,306 outliers. It is worth mentioning this procedure does not find the best fitting hedonic regression, but rather efficiently detects the leverage observations.
APPENDIX B: PRICE IMPACTS FOR 0.05 AND 0.1 MILES
APPENDIX C: COST BENEFIT ANALYSIS FOR 0.05 AND 0.1 MILES
APPENDIX D

Robustness analysis for spatial heterogeneity and spatial autocorrelation

The core estimations presented in the paper assumes that hedonic prices are homogenous for each housing sub-market in Detroit, or equivalently, we reject the existence of housing sub-markets. If sub-markets exist, then we should allow hedonic prices to vary across space (Archer, Gatzlaff and Ling, 1996). We label spatial heterogeneity concept simply spatial heterogeneity. This possibility requires us to empirically test whether our assumption is justified, and, indirectly, it also obligates us to identify the spatial extent of the sub-markets in Detroit.

We consider the spatial heterogeneity specifying Equation (1) in a multilevel framework. In this setup we include a second spatial level labeled as sub-market $j$. This implies that the price elasticity associated with the spatial intensity of vacant and dilapidated varies from one market to another. Specifically, we estimate Equation (3):

$$y_{ij} = \left( \beta_0 + u_{o_j} \right) + \beta'X_i + \left( \gamma_d + u_{1dj} \right)R_{ic}^d + \left( \gamma_v + u_{1vj} \right)R_{ci}^v + Y_i + \epsilon_i \quad (3)$$

Note how Equation (3) permits price elasticity to vary across sub-market $j$ using a stochastic error term $u$. Now, the price elasticity is represented by a fixed parameter, $(\gamma_d)$ and $(\gamma_v)$, and a random component represented by $(u_{1vj})$ and $(u_{1dj})$. Note also that Equation (3) and Equation (1) are similar if and only if $\text{var}(u_{1dj}) = 0$ and $\text{var}(u_{1dn}) = 0$. This implies that we can test the spatial heterogeneity using the null hypothesis that both variances are statistically equal to zero. Just as the standard literature of multilevel analysis suggests, we assume these error terms are generated by a normal distribution with expectation equal to zero, but unknown variance (Langford, Leyland, Rasbash and Goldstein, 1999). We estimate both variances $\text{var}(u_{1dn})$ and $\text{var}(u_{1dn})$. We then
compute the Intra-Class Correlation (ICC) that represents the portion of total variance attributed to the spatial level. The ICC is close to zero, and thus less relevant is the hypothesis of spatial heterogeneity.

To estimate Equation 3, we need the spatial scale of \( j \) sub-markets. Given the empirical nature of this decision, we use two spatial scales to evaluate the robustness of our results. The first one corresponds with the Master Plan Neighborhoods, hereafter labeled \( Neighborhoods \), which is a planning and development project in Detroit that divides the city in 51 areas. These 51 neighborhoods share homogeneous features and characteristics that are considered necessary to be considered as a sub-market. The second spatial layers are the 271 census tracks as identified by the U.S. Census Bureau.

We estimate the new hedonic function using a Restricted Maximum Likelihood Estimator assuming a multi-normal distribution that contains the three error terms specified by Equation 3. Due to space considerations, we limit our discussion to the results for spatial intensity with rings of 0.125 miles to make comparisons with the previous estimations. For each spatial scale, namely the 51 neighborhood and 271 census tracks, we assume that spatial heterogeneity exist only in the dilapidated spatial rings and not in the vacant spatial rings. The first column of the Table 6 shows the estimation assuming a random effects approach for the spatial intensity of dilapidated properties. We can see that the fixed part of price elasticity is similar to those reported by Table 4. In other words, the fixed component of both spatial rings does not change in comparison with previous estimations. However, the final decision criteria depends on the estimation of the random component, \( \text{var}(u_{1dn}) \). As we can see, the standard deviation associated with spatial rings of dilapidated properties is 0.07, implying \( \text{var}(u_{1dn}) = 0.005 \), revealing very little if any
spatial heterogeneity in this price elasticity. In fact, the first column also displays the upper and lower bounds for the ICC, which represent \( var(u_{1dn}) \) with respect to the total variance. The confidence interval for this correlation just 2%. In other words, we find no evidence to support the existence of spatial heterogeneity in the dilapidated unit spatial rings under the assumption that neighborhoods are the potential source of this heterogeneity.

The second column of Table 6 now assumes the spatial heterogeneity in both the dilapidated and vacant spatial rings. Again, we observe that the fixed parameters \( \gamma_v \) and \( \gamma_d \) are very similar to those reported by Table 4, rounding to 1.1% and 2.4%, respectively. Using the same reasoning from the first column, we estimate an ICC that is again close to 2%, revealing the no significant role of neighborhoods as the potential scale to explain spatial heterogeneity of hedonic prices. So far, we find little evidence to support the hypothesis of spatial heterogeneity. However, we know this exercise is influenced by the spatial scale selected by the researcher. For example, 51 neighborhoods may not offer enough variability to estimate the parameter \( var(u_{1dj}) \). For this reason, we modify the spatial scale in the third and fourth column using the 271 census tracks with valid information. Again, our results do not change significantly. The price effect remains similar to the original estimates, while the magnitude of the ICC is still low.
The second issue to be tested is the potential existence of spatial autocorrelation. As we discussed in the first section, spatial autocorrelation may result in bias and inefficiency of OLS estimators. In order to test autocorrelation, we need to create the spatial interaction using a $n \times n$ spatial matrix $W$ where the $w_{ij}$ element represents whether or not $i$ and $j$ are considered neighbours. Our first attempt using parcel level data fails because we are not able to build a $W$ matrix with around 30,000 rows and columns. This
large matrix is virtually impossible to invert and be occupied by the Maximum Likelihood (ML) estimator or Generalized Least Squares (GS2SLS) estimator to estimate the model. Our second best attempt consists of aggregating the parcels to neighbourhood and census track levels in order to specify a more malleable $W$ matrix with 51 and 297 rows, respectively. With this matrix we specify the most general specification to test for the existence of spatial autocorrelation using a Spatial Autoregressive Model with Spatial-Autoregressive Disturbances (SARAR):

$$y = \lambda Wy + X\beta + u$$

$$u = \rho Wu + \varepsilon$$

This specification is equivalent to Equation (1), in a matrix form, but it aggregates the information of 30,000 sold parcels to neighbourhood and census track levels. Our strategy consists of making comparisons of price elasticities between Equation 4 and Equation 1. If they were notably different, then we will use the elasticity obtained from Equation 4 to recalculate social benefits and property tax collections defined by Equation 2. Returning to Equation 4, note how this specification makes an explicit consideration of spatial autocorrelation with the incorporation of $\lambda$ and $\rho$. The first parameter captures the spatial autocorrelation as a spatial lag of the dependent variable, while the second parameter $\rho$ indicates the presence of spatial autocorrelation due to an omitted variable with spatial dependence. Table 7 presents two columns, namely Neighborhoods and Census tracks, which represent the spatial models using both specifications. For each spatial scale, we use a Maximum Likelihood estimator, but also a GS2SLS to control for any heteroscedasticity problem. As shown in Table 7, we do not find evidence to support the existence of spatial autocorrelation at the neighborhood level as $\lambda$ and $\rho$ are not
significant even at the 10% level of confidence. In the case of the census track level, both parameters are insignificant at 5%, but some significance appears at the 10% level. Considering the potential for spatial autocorrelation, we turn our attention on the price elasticities to see the differences in comparison to our previous OLS estimations. We do not see a significant difference between Table 7 and Table 4 in the case of vacant intensity. In both cases the parameters are similar in magnitude between 1% and 2%. However, a significant difference is detected for the case of spatial rings for dilapidated properties: The estimates increase from 2.4% in Table 4 to between 5-8% in Table 7. In light of these differences, we present a cost-benefit and tax collection in Figure 6 for comparison with our primary estimates.

Table 7  
SARAR using Ring 0.125 miles

<table>
<thead>
<tr>
<th></th>
<th>Neighborhoods</th>
<th>Census tracks</th>
</tr>
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<tr>
<td></td>
<td>ML</td>
<td>GS2SLS</td>
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<tr>
<td><strong>Vacant Intensity</strong></td>
<td>-0.0151***</td>
<td>-0.0145***</td>
</tr>
<tr>
<td></td>
<td>(-9.19)</td>
<td>(-9.45)</td>
</tr>
<tr>
<td><strong>Dilapidated Intensity</strong></td>
<td>-0.0520***</td>
<td>-0.0510***</td>
</tr>
<tr>
<td></td>
<td>(-9.11)</td>
<td>(-8.75)</td>
</tr>
<tr>
<td><strong>λ</strong></td>
<td>-0.0213</td>
<td>0.0675</td>
</tr>
<tr>
<td></td>
<td>(-0.17)</td>
<td>(0.61)</td>
</tr>
<tr>
<td><strong>ρ</strong></td>
<td>0.199</td>
<td>0.113</td>
</tr>
<tr>
<td></td>
<td>(1.34)</td>
<td>(0.85)</td>
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<tr>
<td><strong>N</strong></td>
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<td>297</td>
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</tbody>
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