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The Impact of Land Bank Demolitions on Property Values

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1. Introduction

Cities of all sizes in the "Rust Belt" struggle with how to deal with declining population and employment prospects. Cities in decline see falling house prices at the city level and concentrated pockets of deteriorating neighborhoods due to the durable nature of housing. Reductions in the housing stock cannot respond to population declines as quickly as new construction to growth. The relatively inelastic supply of housing when a contraction is needed causes substantial declines in house prices and a rise in vacancy rates (Glaeser and Gyourko, 2005). Governments face a limited amount of policy tools to counteract the deterioration of the housing market, and evidence to their effectiveness remains sparse. In this paper, we evaluate the cost-effectiveness of land banks as a tool to boost the market value of surrounding real estate by using public funds to purchase, demolish, and resell dilapidated housing.

Vacant, abandoned, and tax-delinquent properties impose negative externalities on surrounding properties (e.g. crime, fire and safety hazards, lower property values, and neighborhood destabilization). Under the right conditions, the private market will purchase and redevelop distressed properties. When the private market is unable or unwilling, local governments can use a land bank to redevelop distressed properties and address the negative externalities. Land banks are nonprofit organizations or governmental entities created to purchase abandoned and nonproductive real estate to return them to productive use and generate property tax revenue. As of April 2019, 21 states have at least one land bank in operation.[1]

Whether land banks are effective in reducing the negative externalities imposed on surrounding homes, and are able to recoup the costs involved, is an empirical question. Whitaker and Fitzpatrick (2016) provides the only estimate of land bank effectiveness in the literature; using house prices for the Cleveland area, they find that the demolition activity of the Cuyahoga County Land Bank increased sales prices of nearby homes by 3.4% for a total increase in market value of $200 million. It is an open question whether the impacts found in Cleveland are applicable to the many land banks created across the country. Important dimensions to explore the heterogeneity of effects are the size of the municipality and the scale and density of land bank activity. For instance, the Ohio General Assembly passed land bank authorization legislation in 2009, which led 41 counties and 1 municipality to create land banks. However, only two of the land banks are in municipalities of similar size to Cuyahoga County.[2] Moreover, recent work in the spatial econometrics literature suggests the model used in Whitaker and Fitzpatrick (2016) may be misspecified, and could potentially lead to biased results (LeSage, 2014; Halleck Vega and Elhorst, 2015).

In this paper, we apply multiple spatial correction hedonic price models to housing data for a medium-sized municipality covering the 2012-17 period - Butler County, Ohio (368,000 population). The land bank concentrated its activity in the medium-sized industrial cities of Hamilton and Middletown, with populations in 2017 of 62,000 and 48,000 respectively.

[1] The Center for Community Progress, "National Map of Land Banks and Land Bank Programs." Available at: http://www.communityprogress.net/land-bank-map-pages-447.php. Accessed April 24, 2019.

[2] Cuyahoga County (1.2 million); Hamilton County (Cincinnati) 800 thousand; and Franklin County (Columbus) 1.2 million population. The remainder of land banks are located in counties with population between 24,000 and 504,000, with the majority below 100,000 population.

Population has been on a steady decline in Hamilton since the 1960s, while Middletown experienced a boom and bust cycle.[3] In contrast to the results found in Whitaker and Fitzpatrick (2016), we find increases in sales prices of only half the magnitude (1.4% vs. 3.4%) when using the same model, and modest increases in the surrounding property values and taxes collected. The confidence intervals on the treatment effect of the land bank on house prices are wide. Even when using the most optimistic estimates, it would take the county 39 years to recover its costs through increases in future tax collections. Estimates of the impact of land bank activity on sales prices are even smaller when using the potentially more appropriate spatial correction models suggested in the literature (LeSage, 2014; Halleck Vega and Elhorst, 2015). The evidence suggests that the scale of purchases and demolitions of abandoned houses by the Butler County Land Bank was not a cost-effective policy to reverse neighborhood decline. We comment in the discussion section on the differences in context between the real estate markets in Butler County and Cleveland.

2. Methods

We use hedonic house price models to capture distance-weighted spatial correlations in unobservable amenities and disamenities in the area surrounding a given house (Anselin, 1988). For comparability, our main specifications mimic those of Whitaker and Fitzpatrick (2016) by estimating the spatial autocorrelation model (SAC), which allows for spatial lags in both the dependent variable and the error term. We briefly describe the intuition and estimation. A complete discussion of the model can be found in LeSage and Pace (2009).

$$\mathbf{P} = \lambda \mathbf{W_1 P} + \mathbf{ZB} + \mathbf{e} \tag{1}$$

$$\mathbf{e} = \rho \mathbf{W_2 e} + \mathbf{m} \tag{2}$$

$$\mathbf{m} \sim N(0, \sigma^2 \mathbf{I}). \tag{3}$$

where $\mathbf{P}$ is a matrix of log sales prices, $\mathbf{Z}$ is a matrix of a rich set of property- and sale-specific characteristics.[4] $\mathbf{W_2}$ and $\mathbf{W_2}$ are weight matrices meant to capture the unobserved amenities and disamenities that affect house prices with effects that vary inversely with distance.[5] The remaining error term after the spatial dependence has been removed is $\mathbf{m}$, which is normally distributed with mean zero and variance σ^2.

OLS estimates of the causal effect of land bank demolitions would suffer from omitted variable bias. Land bank demolitions are not randomly distributed across neighborhoods. For instance, the land bank only demolishes homes in neighborhoods where private developers

[3] The population of Middletown increased by 16 percent during the 1960s, fell by 11 percent during the 1970s, increased by 17 percent during the '80s and '90s, and declined by 5.6 percent from 2000-2010. Population has been relatively flat during the last decade.

[4] See Appendix Table A1 for a full list. These include: year of construction, condition, rooms, heating, style, and month of sale indicators, among others.

[5] We use the same weight matrix as Whitaker and Fitzpatrick (2016) based on the inverse distance of the k-nearest neighbors. For a matrix where $k = 3$, sale A is 25 feet from sale B, 50 feet from sale C, and 100 feet from sale D. The weights for sale A would be calculated as:
$\frac{\frac{1}{25}}{\frac{1}{25}+\frac{1}{50}+\frac{1}{100}} Price\ B + \frac{\frac{1}{50}}{\frac{1}{25}+\frac{1}{50}+\frac{1}{100}} Price\ C + \frac{\frac{1}{100}}{\frac{1}{25}+\frac{1}{50}+\frac{1}{100}} Price\ D$

deem entry to be unprofitable, and with elevated levels of tax delinquency and foreclosures. Treated parcels, home sales with land bank activity within 500 feet, are concentrated in neighborhoods with lower initial home prices. Any number of unobservable influences on home price are correlated with land bank treatment. We capture these unobserved location characteristics with a spatial dimension in two ways: a spatial lag of log home prices, $\lambda \mathbf{W_1 P}$, and spatial autocorrelation of the error term, $\rho \mathbf{W_2 e}$. The inclusion of prices of nearby home sales in equation 1 captures the information contained in those prices about all the unobserved location specific amenities, where $\mathbf{W_1}$ places more weight on sales of nearby homes. To the extent that nearby home prices include the same unobservable factors in determining home prices that are correlated with treatment, the adding the spatial lag of the dependent variable to the model reduces the scope for omitted variable bias in the causal estimate of land bank demolitions (Brasington and Hite, 2005; Pace and LeSage, 2010).

Identification relies on a modified selection-on-observables assumption, in that "observables" includes any unobservable factors indirectly measured through neighboring home prices. Thus, our estimate of causal effects are unbiased if treatment with land bank demolitions within 500 feet is as good as randomly distributed across home sales *conditional* on an extensive set of house characteristics and any unobserved factors captured by the spatial lag. To the extent that our model of house price spillovers in the spatial lag term do not capture unobservables correlated with treatment, our estimates will still suffer from omitted variable bias.

Any unobserved spatial heterogeneity uncorrelated with land bank activity reduces efficiency in estimation when using OLS. Thus, equation 2 allows for spatially correlated errors, with $\mathbf{W_2}$ putting more weight on error terms of nearby sales. We estimate the models and spatial parameters using a GMM procedure developed by Kelejian and Prucha (1999), for varying choices of the k nearest neighbors to include in the weighting matrices. Sales further than the k^{th} sale receive zero weight. We choose a model with the lowest residual sum of squares (RSS). Our estimates suggest that the preferred model includes both a spatial lag in the dependent variable and spatial autocorrelation in the error term.

Estimates from spatial interaction models are often sensitive to the choice of specification: a spatial lag in the dependent variable, the independent variables, the error term, or any combination of the three. At the same time, the choice of the spatial lag structure has important implications on the interpretation of the estimated spillovers.[6] These can be separated into *global* and *local*. Global spatial spillovers occur when endogenous interactions between nearby homes imply that changes in one home cause a change in the sales price of a neighboring home, then to the neighbor of that neighbor, and so on. Global spillovers could extend to all homes in a region, even if separated by large distances.[7] *Local* spillovers to do not have this endogenous interaction or feedback effects. In this case, a change in the sales price – or characteristic – of house j has a spillover onto neighbor i. However, the resulting change to the sales price of neighbor i does not affect the sales price of the neighbors of home i (LeSage, 2014).

[6] Note that this paper is concerned with the total causal effect of land bank demolitions, and not the separation of the total effect into direct and spillover effects. The spatial correction to the hedonic house price model is used as a means to potentially account for spatially correlated unobserved amenities.

[7] Global spillovers might appear in a game theoretic setting, where one player makes a change, the second player responds, and the original player reacts until an equilibrium is reached.

The SAC model outlined above contains *global* spillovers because of the inclusion of the spatial lag of the dependent variable. Recent work has argued that a local spillover model is more appropriate to model housing markets, and that spatial lags in the independent variables should be used instead (Gibbons and Overman, 2012; LeSage, 2014; Halleck Vega and Elhorst, 2015). The spatial lag of X model (SLX) consists of a single spatial lag of the independent variables:

$$\mathbf{P} = \mathbf{ZB} + \mathbf{W_1 Z}\theta + \mathbf{e} \tag{4}$$

where θ is a $kx1$ vector measuring the strength of spatial dependence for each of the k explanatory variables. In this model, the direct effects of Z_k would be estimated by β_k and the indirect effects by θ_k. By adding a spatial lag in the error term, equation 2, the model becomes the Spatial Durbin error model (SDEM). We estimate the SDEM model in addition to the SAC model used in Whitaker and Fitzpatrick (2016) in response to recent work that suggests the SLX and SDEM models are more appropriate for housing market analysis (Gibbons and Overman, 2012; LeSage, 2014; Halleck Vega and Elhorst, 2015).[8]

3. Data

Data on sales prices, property characteristics, foreclosures, demolitions, assessment values, taxes paid, and tax delinquencies were provided by the Butler County Auditor's office.[9] Census tract poverty rates and proportion of population with a Bachelor's degree or higher are from American FactFinder (U.S. Census Bureau). In addition to house characteristics, all models include the count of foreclosures within 500 feet over the passed year, and a set of indicators for if the observation is a recent foreclosure, tax delinquent at time of sale, or is a future non-land bank demolition. We limit our sample to only include valid arm's length transactions. Sales to related individuals, to banks holding notes, by sheriff's sale, or of land bank treated parcels are excluded. Table 1 reports summary statistics for the sales prices, taxes assessed, taxes collected, and total market value of all single-family housing in Butler County, OH in 2018. This data is used to estimate value recovery of land bank activity.

Data on land bank purchases and demolitions come directly from the Butler County Land Reutilization Corporation. The solid line in figure 1 plots cumulative land bank demolitions over time. Purchases began in late 2012, with the first demolition occurring in early 2014. The dashed line graphs the stock of parcels purchased by the land bank, but not yet demolished. We measure a sale's exposure to land bank activity within 500 feet by creating three variables: the count of properties that will become land bank demolitions in the future (pre-land bank), the count of properties acquired by the land bank but not yet demolished (land bank acquired), and the count of land bank demolitions.[10] Pre-land bank demolitions

[8]In the appendix, we report results from estimating the SLX and spatial Durbin model (SDM) as well. The SDM includes spatial lags in the dependent and independent variables, but not the error term. Results are quantitatively similar to those of the SDEM.

[9]Butler County Ohio Auditor's Office (2018) http://www.butlercountyauditor.org/GIS_DATA. Accessed on August 30, 2018.

[10]For a given home sale, each land bank parcel within 500 feet is placed into one of these three mutually exclusive variables based on the sales date and the purchase and demolition dates of the land bank parcel.

Table 1: Summary statistics

	Median	Mean	SD	Min	Max
Log Sale Price	12.07	12.02	0.59	6.91	14.31
Sale Price	175,410	194,290	110,430	1,000	1,645,000

Counts in 500-foot buffers	Mean	SD	Min	Max	Sales with counts > 0
Pre-Land Bank	0.02	0.30	0	12	268
Land Bank Acquired	0.01	0.14	0	4	190
Land Bank Demolished	0.03	0.36	0	13	314
Foreclosure	2.30	3.59	0	33	15,330

Aggregate values	$ Millions
Sales Prices (01/2012 - 08/2018)	4,958.3
Taxes Assessed (2018)	317.8
Taxes Collected (2018)	312.7
Market Value (2018 Appraised Value)	16,079.4

Notes: Sales (N=25,520) represent all valid arms-length sales of single-family homes in Butler County, Ohio between January 2012 and August 2018. Counts are of land bank activity or foreclosures within 500 feet of the sale.

Sources: Data on land bank demolition activity provided by the Butler County Land Reutilization Corporation. Sales, foreclosure, tax, and market value data provided by the Butler County Auditor's Office.

capture the negative externality imposed on nearby properties by the parcels that the land bank will eventually purchase and demolish. The count of land bank acquired properties is meant to capture any removal of the negative externalities that occurs without actually demolishing the home. For example, residents might believe the land bank will take better care and upkeep of the distressed property than the previous owners. The main interest of this paper is the difference in the coefficients on the pre-land bank demolitions and the land bank demolitions variables, which captures the reduction in negative externalities associated with land bank demolitions. Table 1 shows that the mean exposure to pre-land bank demolitions is 0.02, with a range from 0 to 12. Exposure to actual land bank demolitions is similar with a mean of 0.03 and a range of 0 to 13. Of the total sales (N=25,520) in the sample period, 268 sales were exposed to at least one pre-land bank demolition and 314 sales were exposed to at least one land bank demolition. Land bank activity was small relative to foreclosure activity, which captures the fact of overall distress in the local housing market during the mid-2010s. Over 15,000 of the sales had at least one foreclosure within 500 feet in the year prior to sale; mean foreclosures was 2.30.

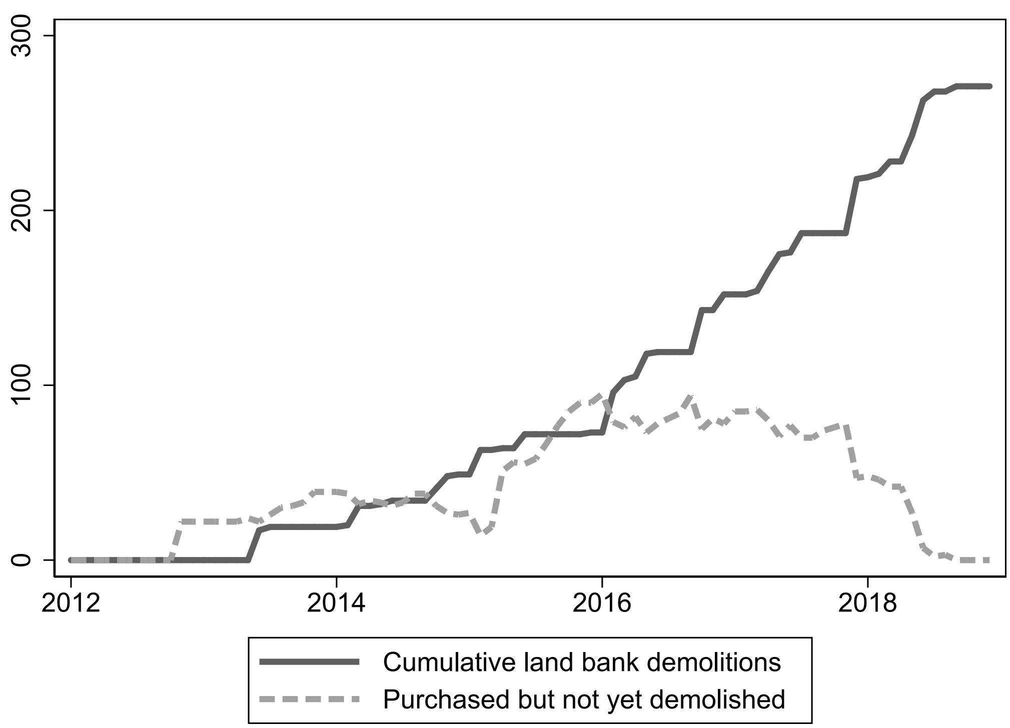

Figure 1: Time series of Butler County land bank demolition activity

For example, suppose that a land bank parcel was purchased by the land bank on March 1, 2015 and the building demolished on August 1, 2015. This parcel would increment the pre-land bank count for any sale prior to March 1, 2015. It would increment the land bank acquired count for any sale between March 1 and August 1, 2015. Finally, any sale occurring after August 1, 2015 would have the land bank demolished count incremented.

4. Results

Table 2 reports estimates of the impact of land bank activity on sales prices allowing for spatial dependence for the SAC model in Panel (A) and the SDEM model in Panel (B). The total impact in Column (3) is separated into the direct effect reported in Column (1) and the indirect spillover effects reported in Column (2). Across all specifications, λ, ρ, and θ are positive and significant, which implies that house prices are spatially dependent, and error terms are spatially correlated; nearby sales contain information about unobserved location specific factors.

We choose the model with a weight matrix that consists of the 15 nearest neighbors based on the smallest RSS. While model selection using the log-likelihood measure is preferred, we estimate the model using GMM to make our results directly comparable to those in (Whitaker and Fitzpatrick, 2016). Estimated impacts for the SAC model come from the matrix of partial derivatives of the reduced-form mean of $\mathbf{P}$. The direct effect of variable k is estimated from the diagonal elements of $(\mathbf{I} - \lambda\mathbf{W})^{-1}\beta_k$ and the indirect effects from the off-diagonal elements (LeSage and Pace, 2009).

The estimated impacts from the SAC model suggest that each property eventually purchased by the land bank imposed a statistically significant 7.5 percent (-0.0747) negative externality on nearby home prices. Direct effects accounted for 80 percent of the externality and spillovers account for the remainder. This is not surprising as the land bank's purpose is to redevelop the worst properties in which private developers are uninterested. However, we do not find strong evidence that land bank purchases or land bank demolitions removed a substantial portion of the negative externality; the estimated total effects of land bank acquisitions and land bank demolitions are both negative and statistically significant. The difference in pre-land bank demo and land-bank acquired total is 0.66%, but is not statistically significant. The point estimates suggest that an additional land bank demolition increased the sale's price by 2.04% $[-.0543 - (-0.0747)]$, but again the difference is not statistically significant. Each additional land bank demolition increases surrounding home values by 1.63% through direct effects and an additional 0.41% through indirect effects.

The last column of Table 2 reports value recovery estimates. In the absence of any land bank activity the negative externality of the distressed properties would have continued. The value recovered in actual sales is estimated by multiplying the point estimate for the total treatment effect of a single demolition by the count of actual land bank demolitions within 500 feet of each sale multiplied by the actual sales price, and summed over the entire dataset of sales from 2012-2017. The remainder of the rows repeat the process using the sample of *all* single-family residential housing in Butler County to estimate the increase in property tax collections and market value recovered for unsold homes.

The estimates from the preferred model suggest that land bank demolitions increased sales prices of nearby homes by a total of \$626 thousand dollars. Assuming that the increased property values were transmitted immediately to assessed values, the county experienced an annual increase in taxes assessed of \$283 thousand. The third row adjusts the estimated increase in taxes assessed by the 2017 proportion of taxes paid for each parcel. Taxes collected are estimated to increase by \$232 thousand annually. Finally, the largest value recovery is in increased market values of unsold nearby properties. Land bank demolitions added an estimated \$11.4 million dollars to the market value of residential property.

Table 2: Spatial Correction Hedonic Price Models

	(1)	(2)	(3)	(4)	
Panel A: SAC model (Eq. 1 & 2)					
	Direct	Indirect	Total	*Value recovery estimates ($1,000s)*	
Pre-Land Bank Demo	-0.0597***	-0.0150***	-0.0747***	Sales Prices	625.6
	(0.0104)	(0.0027)	(0.0131)		
Land Bank Acquired	-0.0533**	-0.0134**	-0.0667**	Taxes Assessed	282.6
	(0.0255)	(0.0064)	(0.0319)		
Land Bank Demo	-0.0434***	-0.0109***	-0.0543***	Taxes Collected	231.6
	(0.0124)	(0.0032)	(0.0155)		
Foreclosures	-0.0131***	-0.0033***	-0.0164***	Market Value	11,400
	(0.0008)	(0.0002)	(0.0010)		
Estimated treatment effect on sales price (in percent)	1.63	0.41	2.04		
Panel B: SDEM Model (Eq. 2 & 3)					
	Direct	Indirect	Total	*Value recovery estimates ($1,000s)*	
Pre-Land Bank Demo	-0.0467***	0.0906***	0.0438**	Sales Prices	-7,208.4
	(0.0051)	(0.0160)	(0.0178)		
Land Bank Acquired	-0.0672***	-0.2071***	-0.2743***	Taxes Assessed	-2,111.1
	(0.0113)	(0.0474)	(0.0512)		
Land Bank Demo	-0.0393***	-0.0690***	-0.1083***	Taxes Collected	-1,730.4
	(0.0047)	(0.0154)	(0.0172)		
Foreclosures	-0.0129***	-0.0100***	-0.0229***	Market Value	-8,490
	(0.0006)	(0.0013)	(0.0016)		
Estimated treatment effect on sales price (in percent)	0.74	-15.96	-15.21		

Notes: Estimated impacts are from regressions of log sales prices on counts of land bank properties with standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Each regression includes controls for distressed status of the property, decade, quality, and style of construction, condition, exterior material, heat type, # of beds, # of baths and half baths, attic, fireplace, size of lot, year and month of sale, and the census tract poverty rate and proportion with a Bachelor's degree or higher. In Panel A for the SAC model, direct effects of variable k are calculated from the diagonal elements of $(\mathbf{I} - \lambda\mathbf{W})^{-1}\beta_k$ and indirect effects are calculated from the off-diagonal elements of the same matrix. In Panel B for the SDEM model, direct effects of variable k are equal to estimates of β_k and indirect effects to θ_k

Sources: Data on land bank demolition activity provided by the Butler County Land Reutilization Corporation. Sales, property characteristics, foreclosure, tax, and other demolition data provided by the Butler County Auditor's Office. Census tract poverty rate and proportion of population with a Bachelor's degree or greater provided by American Fact Finder.

Conclusions drawn from models that include a spatial lag of the independent variable differ immensely from those of the SAC model. Panel B of Table 2 reports estimated impacts from the SDEM model, which includes a spatial lag in the independent variables and the error term, but not the dependent variable. For the k^{th} explanatory variable, direct effects are equal to $\hat{\beta}_k$ and indirect effects equal to $\hat{\theta}_k$. The results imply that each additional pre-land bank demo property within 500 feet of property i *directly* reduces property i's sales price by 4.7 percent, but *increases* the sales price of neighboring properties by 9 percent through spillovers. In total, having a dilapidated property that will be demolished by the land bank at a future date actually increases a home's sale price by 4.4 percent. Not only is there not a negative externality from abandoned housing, but the externality is positive and economically large. These results contradict the idea that the land bank purchases homes with large negative externalities. In the SDEM model, each additional land bank demolition directly reduces the sale price by 3.93 percent. Spillovers reduce the sale price by an additional 6.9 percent. Combined, the total effect is a 10.8 percent reduction in price.

The large differences in estimated spillovers between the SAC and SDEM models explain the reversal in sign of the treatment effect on sale price. The large positive spillover for a pre-land bank property in the SDEM model and the larger negative spillover for a land bank demo work in the same direction to suggest a *negative* 15.2 percent effect of a land bank demolition on sale price. A negative treatment effect implies intervention into the housing market to demolish dilapidated properties reduces home values, as can be seen in the value recovery estimates for Panel B. The realized activity of the land bank led to large estimated reductions in sales prices, taxes assessed and collected, and market value.

To better understand the discrepancies between models, we estimate the spatial Durbin model (SDM), which includes a spatial lag in the dependent variable and independent variables. Appendix Table A2 reports the estimated impacts and they are quantitatively similar in magnitude to those of the SDEM model. The inclusion of spatial lags in the X variables appears to drive the differences in results between specifications. Noting that the recent literature prefers models of local spillovers (Gibbons and Overman, 2012; LeSage, 2014; Halleck Vega and Elhorst, 2015), we conclude that the SDEM is likely misspecified in this case given the unbelievably large negative estimated impacts of land bank activity and the estimated positive spillovers of pre-demolished dilapidated properties.

5. Discussion

At best, we find that land bank demolitions in Butler County caused modest but imprecisely estimated reductions in the negative externalities associated with blighted housing. However, the confidence interval includes both large increases in price and small decreases in price. Estimates from models with spatial lags in explanatory variables imply large reductions in home values and lost taxes. This is a case where conclusions are sensitive to the choice of how to specify spatial interconnections. However, we would argue our results are useful in conducting a cost-benefit analysis despite potential issues with power and model misspecification.

The Butler County Land Bank spent \$7.3 million dollars over the five years included in the sample. Even in the best case when using estimates from the SAC model, it would take the county 39 years to recover the expenditures from the additional taxes collected on an annual basis. The value recovered by unsold homes must be taken into account for the program to pass a cost-benefit analysis.[11] The evidence suggests that the scale of purchases and demolitions of vacant and abandoned houses by the Butler County Land Bank was not a cost-effective policy to reverse neighborhood decline. Further work should try to better understand the specific contexts in which public purchase of abandoned and decaying housing is most effective.

For instance, our results are specific to estimating the effect of land bank activity in a medium-sized county in the "Rust Belt", whereas the only prior study focused on a large city. Whitaker and Fitzpatrick (2016) finds that the Cuyahoga County (Cleveland) land bank *fully* removed the externalities of the blighted housing and increased prices by 3.4%. The difference in estimates might be driven by the fact that Butler County demolished homes with larger estimated externalities (6% vs. 3.4% in Cleveland). Moreover, Cuyahoga County's land bank demolished a larger number of properties and clustered demolitions closer in space. Thus, the positive impacts from land bank demolitions might be larger when contiguous properties are redeveloped together.

The strength of the real estate markets varied between the two counties, as well. The Cuyuhoga County Land Bank operated in the central city and close in suburbs that have experienced population decline over decades. The area was essentially built out, with new housing construction occurring in the outer suburbs. The MSA population was flat over the period. The real estate market of Butler County was dramatically different. The cities of Hamilton and Middletown are rusting small-sized industrial cities of between 42 and 62 thousand people. Population has declined in Hamilton since the 1960s, and Middletown has experienced a boom and bust cycle of decade swings of between 5 and 15 percent of population. Butler County as a whole has seen consistent growth of around 10 percent per decade. The majority of population growth occurred in the southwestern townships that grew into relatively wealthy northern suburbs of Cincinnati. Part of the difference in estimates between the two land banks might be driven by the different context of these real estate markets. Finally, the externality of an empty lot might be different between the two cities. If common, an additional empty lot might not change perceptions of the neighborhood. However, if land bank demolitions created an uncommon occurrence of an empty lot, buyers might view it as negative indication of the future of the neighborhood. However, this is not likely an explanation for the difference in estimates between studies. The Butler County Land Bank was active in census tracts where between 10 and 15 percent of the parcels were vacant residential lots during this period. Land bank activity in the Cleveland area was concentrated in census tracts with between 10 and 60 percent vacant lots (Whitaker and Fitzpatrick, 2016). The change in perception of a neighborhood's price trajectory likely did not differ between the cities for the marginal vacant lot created by the land bank.

We leave to future work to further explore the causes of potential heterogeneous effects of land bank demolitions across metro areas. The growth of land banks as a policy tool and

[11] Our benefit calculations might be understated to the extent that harm reduction from distressed properties is not capitalized into home values within 500 feet, or residents further than 500 feet from land bank demolitions also experience gains.

their use of tens of millions of dollars in public funds to attempt to revitalize neighborhoods requires a better understanding of their effectiveness. We believe that the application of quasi-experimental methods is the most important avenue for future research in the evaluation of land banks (Gibbons and Overman, 2012).

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Supplemental Appendix

Table A1 reports the full results from the SAC model with $k = 15$ nearest neighbor. The table contains the full list of explanatory variables used in all the spatial correction hedonic price models.

Table A1: Full list of coefficients from 15-nearest neighbor mixed model

	Coef.	SE	t-value	p-value
Pre-Land Bank	-0.060***	0.011	-5.696	0.000
Land Bank Acquired	-0.053*	0.025	-2.105	0.035
Land Bank Demolished	-0.044***	0.013	-3.429	0.001
Foreclosures	-0.013***	0.001	-16.939	0.000
House is a Recent Foreclosure	0.025***	0.007	3.445	0.001
House is Tax Delinquent	0.027	0.070	0.389	0.697
House is a Pre-Other Demolition	-0.063***	0.016	-3.906	0.000
Fireplace	0.058***	0.004	15.192	0.000
Pre-1910	-0.023	0.023	-1.039	0.299
1910-1919	0.012	0.027	0.450	0.653
1920-1929	0.075***	0.018	4.259	0.000
1930-1939	0.042*	0.019	2.228	0.026
1940-1949	0.004	0.013	0.323	0.747
1960-1969	-0.022**	0.008	-2.867	0.004
1970-1979	-0.006	0.008	-0.719	0.472
1980-1989	0.027**	0.009	3.040	0.002
1990-1999	0.095***	0.009	10.411	0.000
Post-2000	0.191***	0.010	18.482	0.000
Condition poor	-0.669***	0.073	-9.177	0.000
Condition fair	-0.286***	0.015	-19.086	0.000
Condition good	0.113***	0.005	20.629	0.000
Condition very good	0.236***	0.007	35.390	0.000
Construction AA	0.382***	0.017	22.891	0.000
Construction A+	0.512***	0.020	25.368	0.000
Construction A-	0.329***	0.013	25.534	0.000
Construction B+	0.260***	0.009	28.255	0.000
Construction B	0.176***	0.006	27.441	0.000
Construction B-	0.100***	0.005	19.277	0.000
Construction C	-0.097***	0.005	-20.255	0.000
Construction C-	-0.194***	0.010	-18.936	0.000
Construction below C-	-0.202***	0.018	-11.275	0.000
Exterior brick	0.051***	0.005	9.994	0.000
Exterior wood	0.027***	0.006	4.248	0.000
Exterior other	0.034***	0.004	8.709	0.000
Heat forced air (AC)	0.076***	0.010	7.842	0.000
Heat pump	0.073***	0.011	6.572	0.000

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Table A1 – *Continued from previous page*

	Coef.	SE	t-value	p-value
Heat other	0.191***	0.039	4.962	0.000
Rooms four	0.132	0.119	1.111	0.267
Rooms five	0.204	0.119	1.714	0.087
Rooms six	0.283*	0.119	2.377	0.017
Rooms seven	0.333**	0.119	2.792	0.005
Rooms eight	0.350**	0.119	2.930	0.003
Rooms nine+	0.385**	0.119	3.226	0.001
Baths two	0.125***	0.005	22.870	0.000
Baths three+	0.256***	0.007	35.939	0.000
Half baths one	0.087***	0.004	20.052	0.000
Half baths two+	0.141***	0.007	19.301	0.000
Bedrooms two	-0.046	0.044	-1.040	0.298
Bedrooms three	0.047	0.045	1.048	0.295
Bedrooms four	0.087	0.045	1.954	0.051
Bedrooms five+	0.152***	0.046	3.299	0.001
Attic finished	0.049*	0.023	2.131	0.033
Attic unfinished	0.060***	0.012	5.041	0.000
Style cape cod	0.054***	0.012	4.589	0.000
Style other	-0.022***	0.005	-4.448	0.000
Style ranch	0.079***	0.006	13.219	0.000
Lot small	-0.021***	0.004	-4.807	0.000
Lot large	0.061***	0.004	15.300	0.000
College Degree (% in tract)	-0.000*	0.000	-2.284	0.022
Poverty (% in tract)	-0.001**	0.000	-3.019	0.003
12-Feb	0.025	0.023	1.077	0.282
12-Mar	0.055*	0.028	1.972	0.049
12-Apr	0.048*	0.023	2.112	0.035
12-May	0.110***	0.022	4.900	0.000
12-Jun	0.162***	0.021	7.618	0.000
12-Jul	0.251***	0.023	10.707	0.000
12-Aug	-0.028	0.029	-0.958	0.338
12-Sep	0.016	0.025	0.665	0.506
12-Oct	0.028	0.024	1.181	0.238
12-Nov	0.072**	0.024	2.976	0.003
12-Dec	0.109***	0.025	4.323	0.000
13-Jan	0.155***	0.023	6.591	0.000
13-Feb	0.239***	0.026	9.116	0.000
13-Mar	-0.041	0.027	-1.479	0.139
13-Apr	0.018	0.021	0.870	0.384
13-May	0.046*	0.023	1.995	0.046
13-Jun	0.082***	0.022	3.669	0.000
13-Jul	0.144***	0.020	7.146	0.000

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Table A1 – *Continued from previous page*

	Coef.	SE	t-value	p-value
13-Aug	0.187***	0.020	9.136	0.000
13-Sep	0.223***	0.022	9.968	0.000
13-Oct	0.004	0.021	0.207	0.836
13-Nov	0.040	0.021	1.917	0.055
13-Dec	0.054*	0.022	2.461	0.014
14-Jan	0.088***	0.022	4.064	0.000
14-Feb	0.121***	0.021	5.863	0.000
14-Mar	0.189***	0.021	8.961	0.000
14-Apr	0.248***	0.022	11.465	0.000
14-May	0.013	0.021	0.616	0.538
14-Jun	0.051*	0.020	2.512	0.012
14-Jul	0.076***	0.020	3.765	0.000
14-Aug	0.106***	0.020	5.215	0.000
14-Sep	0.135***	0.020	6.768	0.000
14-Oct	0.196***	0.020	9.719	0.000
14-Nov	0.284***	0.021	13.684	0.000
14-Dec	0.009	0.021	0.436	0.663
15-Jan	0.049*	0.020	2.396	0.017
15-Feb	0.072***	0.020	3.567	0.000
15-Mar	0.104***	0.020	5.207	0.000
15-Apr	0.166***	0.020	8.401	0.000
15-May	0.220***	0.020	11.095	0.000
15-Jun	0.292***	0.021	14.108	0.000
15-Jul	0.016	0.021	0.753	0.451
15-Aug	0.066**	0.020	3.247	0.001
15-Sep	0.075***	0.020	3.790	0.000
15-Oct	0.092***	0.020	4.591	0.000
15-Nov	0.160***	0.020	7.942	0.000
15-Dec	0.233***	0.020	11.416	0.000
16-Jan	0.316***	0.021	15.030	0.000
16-Feb	0.016	0.020	0.780	0.435
16-Mar	0.062**	0.020	3.086	0.002
16-Apr	0.073***	0.021	3.557	0.000
16-May	0.105***	0.021	4.994	0.000
16-Jun	0.152***	0.020	7.419	0.000
16-Jul	0.219***	0.020	10.854	0.000
16-Aug	0.284***	0.022	13.116	0.000
16-Sep	0.038	0.021	1.825	0.068
16-Oct	0.055**	0.021	2.666	0.008
16-Nov	0.084***	0.021	4.045	0.000
16-Dec	0.112***	0.020	5.561	0.000
17-Jan	0.148***	0.021	7.083	0.000

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Table A1 – *Continued from previous page*

	Coef.	SE	t-value	p-value
17-Feb	0.242***	0.021	11.671	0.000
17-Mar	0.018	0.021	0.840	0.401
17-Apr	0.059**	0.022	2.718	0.007
17-May	0.059**	0.021	2.837	0.005
17-Jun	0.109***	0.021	5.071	0.000
17-Jul	0.158***	0.020	7.763	0.000
17-Aug	0.225***	0.021	10.589	0.000
17-Sep	0.029	0.021	1.366	0.172
17-Oct	0.067**	0.021	3.144	0.002
17-Nov	0.086***	0.023	3.759	0.000
17-Dec	0.110***	0.022	5.089	0.000
18-Jan	0.181***	0.021	8.548	0.000
18-Feb	0.267***	0.022	12.387	0.000
18-Mar	0.020	0.023	0.865	0.387
18-Apr	0.065**	0.021	3.074	0.002
18-May	0.071**	0.022	3.253	0.001
18-Jun	0.140***	0.022	6.482	0.000
18-Jul	0.177***	0.021	8.382	0.000
18-Aug	0.251***	0.022	11.461	0.000
Intercept	8.753***	0.163	53.623	0.000
Lambda	0.196***	0.009	22.040	0.000
Rho	0.499***	0.013	39.840	0.000

Notes: Estimated coefficients are from regressions of log sales prices on counts of land bank properties with standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Each regression includes controls for distressed status of the property, decade, quality, and style of construction, condition, exterior material, heat type, # of beds, # of baths and half baths, attic, fireplace, size of lot, year and month of sale, and the census tract poverty rate and proportion with a Bachelor's degree or higher.

Sources: Data on land bank demolition activity provided by the Butler County Land Reutilization Corporation. Sales, property characteristics, foreclosure, tax, and other demolition data provided by the Butler County Auditor's Office. Census tract poverty rate and proportion of population with a Bachelor's degree or greater provided by American FactFinder (U.S. Census Bureau).

Table A2: Alternative Spatial Correction Hedonic Price Models

	(1)	(2)	(3)
Panel A: SDM model ($\mathbf{P} = \lambda \mathbf{W_1 P} + \mathbf{ZB} + \mathbf{W_1 Z}\theta + \mathbf{e}$)			
	Direct	Indirect	Total
Pre-Land Bank Demo	-0.0422***	0.2244***	0.1822***
	(0.0051)	(0.0346)	(0.0358)
Land Bank Acquired	-0.0617***	-0.2936***	-0.3554***
	(0.0114)	(0.1033)	(0.1065)
Land Bank Demo	-0.0394***	-0.2542***	-0.2936***
	(0.0046)	(0.0316)	(0.0327)
Foreclosures	-0.0115***	-0.0141***	-0.0256***
	(0.0006)	(0.0021)	(0.0023)
Estimated treatment effect on sales price (in percent)	0.0028	-0.4786	-0.4758
Panel B: SLX Model ($\mathbf{P} = \mathbf{ZB} + \mathbf{W_1 Z}\theta + \mathbf{e}$)			
	Direct	Indirect	Total
Pre-Land Bank Demo	-0.0533***	0.0548***	0.0015
	(0.0053)	(0.0164)	(0.0169)
Land Bank Acquired	-0.0715***	-0.0619	-0.1333***
	(0.0117)	(0.0496)	(0.0515)
Land Bank Demo	-0.0497***	-0.1511***	-0.2008***
	(0.0048)	(0.0152)	(0.0158)
Foreclosures	-.0119***	-0.0097***	-0.0217***
	(0.0006)	(0.0011)	(0.0011)
Estimated treatment effect on sales price (in percent)	0.0036	-0.2059	-0.2023

Notes: Estimated impacts are from regressions of log sales prices on counts of land bank properties with standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1. Each regression includes controls for distressed status of the property, decade, quality, and style of construction, condition, exterior material, heat type, # of beds, # of baths and half baths, attic, fireplace, size of lot, year and month of sale, and the census tract poverty rate and proportion with a Bachelor's degree or higher. In Panel A for the SDM model, direct effects of variable k are calculated from the diagonal elements of $(\mathbf{I} - \lambda\mathbf{W})^{-1}[\beta_k + \mathbf{W}\theta_k]$ and indirect effects are calculated from the off-diagonal elements of the same matrix. In Panel B for the SLX model, direct effects of variable k are equal to estimates of β_k and indirect effects to θ_k.

Sources: Data on land bank demolition activity provided by the Butler County Land Reutilization Corporation. Sales, property characteristics, foreclosure, tax, and other demolition data provided by the Butler County Auditor's Office. Census tract poverty rate and proportion of population with a Bachelor's degree or greater provided by American Fact Finder.