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Spatial characteristics of housing abandonment

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A B S T R A C T

This study investigates whether the probability of housing abandonment is influenced by spatial factors. Using indicators of spatial autocorrelation, the study finds that housing abandonment and the predictors of abandonment exhibit statistically significant clustering. More importantly, by comparing a multilevel regression model that does not account for spatial relationships to one that does, the study finds that accounting for spatial relationships significantly improves the ability to predict abandoned housing. Additionally, the study shows that in some cases, conditions in surrounding neighborhoods have a greater influence on the probability of housing abandonment than do conditions in the neighborhood itself.

Introduction

Abandoned houses are a significant problem, especially in cities facing population loss. Among other challenges, these houses decrease property values and harbor crime (Cohen, 2001; Skogan, 1990; Spelman, 1993; Temple University, 2001). As a result, some studies have attempted to assist municipalities in predicting abandoned housing under the notion that if policy makers can predict abandonment, they can better act to prevent it (Bassett, Schweitzer, & Panken, 2006; Hillier, Culhane, Smith, & Tomlin, 2003; Mardock, 1998; Morckel, 2013). This study builds upon existing models by considering the spatial elements of housing abandonment, including whether conditions in surrounding neighborhoods predict the probability of abandonment in a neighborhood of interest.

Using exploratory factor analysis, Morckel (2013) found that three factors predict housing abandonment at the neighborhood level: market conditions, gentrification, and physical neglect. The dataset and factors used in Morckel (2013) were adopted for this study given the utility of factors—the ability to think about abandonment in terms of a small number of constructs. The market conditions factor includes the percentage of foreclosures the year prior, the percentage of properties below the city-wide median property value, and the percentage of properties not sold the year prior. The gentrification factor includes the percentage of properties built prior to 1945, the percentage of residents over 65 years of age, the percentage of residents 25 years and older without a bachelor's degree or higher, and the percentage of residents who are in poverty. Finally, the physical neglect factor includes the percentage of properties that were tax delinquent the year prior, the percentage of properties rated as being in either "poor" or "bad" condition by city officials, the percentage of residents who are unemployed, the percentage of properties demolished the year prior, and the percentage of residents who identify as black alone or in combination. Table 1 shows the variables that comprise the factors, as well as their factor loadings. Morckel (2013) provides a detailed literature review of these variables and factors, and why they are thought to predict abandonment.

Despite a prevailing belief that abandoned houses cluster and spread, there is limited empirical evidence demonstrating this to be the case. A survey study by Accordino and Johnson (2000) found that within ninety-nine cities (two-thirds of their sample) vacant and abandoned properties were confined to specific neighborhoods or areas, rather than scattered throughout the city. While Accordino and Johnson did not test for spatial dependence, the results of their study support the notion that there might be statistically significant hot spots or clusters of abandonment. Wilson, Margulis, and Ketchum (1994), compared the proportion of houses abandoned over two time periods (1980 and 1990) in Cleveland to show evidence of the spreading of housing abandonment. While they did not test for clustering, presumably abandonment has to spread from something—a cluster. Hillier et al. (2003) also acknowledged the likely clustering of abandonment. They randomly sampled 1000 homes for inclusion in their study to reduce the likelihood of a cluster of abandoned homes from appearing in the dataset, thus minimizing the statistical violation of independence of observations.

Since very little work has been conducted on the spatial aspects of abandonment, theories for why abandonment might cluster lack

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Table 1
Factors and rotated factor loadings [new].

Item	Factor		
	1	2	3
% Foreclosures the year prior	.742		
% Properties below the city-wide median property value	.648		
% Properties not sold the year prior	−.482		
% Properties built prior to 1945		.682	
% RESIDENTS over 65 years of age		−.674	
% 25 and older without a bachelor's degree or higher		−.438	
% Residents who are in poverty		.400	
% Properties tax delinquent the year prior			.822
% Properties rated as either "poor" or "bad" condition by city officials			.714
% Residents who are unemployed			.589
% Properties demolished in the year prior			.581
% Residents who identify as black alone or in combination			.433

Note: factor 1 = market conditions, factor 2 = gentrification, factor 3 = physical neglect.

in the literature. This author suspects that abandoned houses cluster because the predictors or causes of abandonment cluster. While no study has specifically examined whether the factors found in Morckel (2013) cluster, there is evidence that some of the variables that comprise the factors cluster. For example, there is emerging spatial research demonstrating that foreclosures cluster and spread (Baumer, Arnio, & Wolff, 2013; Goodstein, Hanouna, Ramirez, & Stahel, 2011). It makes intuitive sense that property values and property ages would cluster, since most of the houses in a neighborhood are built around the same time with similar specifications and styles. Another potential explanation is that abandoned houses cluster due to low location-specific housing demand (Bender, 1979). Scafidi, Schill, Wachter, and Culhane (1998) found that abandoned buildings tend to be located more frequently in distressed neighborhoods with high poverty rates. Since it is well established that social characteristics like unemployment, poverty, and race geographically concentrate, it follows that if these variables predict abandonment, abandonment would also geographically concentrate.

Why characteristics in surrounding neighborhoods would influence the probability of abandonment in a given neighborhood is less intuitive. Perhaps there is an "anticipation effect" whereby property owners anticipate that the neighborhood will decline based on what is happening in nearby neighborhoods; they therefore abandon early in an effort to minimize losses. Such a phenomenon would be similar to white flight in the 1950s and 1960s, where many white homeowners sold their homes in anticipation of an influx of black residents (Frey, 1979). While this study cannot prove that an "anticipation effect" is the cause of abandonment, if surrounding neighborhood conditions impact the probability of abandonment, then this finding would lend support to such a notion.

The Morckel (2013) dataset contains data for 382 neighborhoods in the city of Columbus, Ohio and 80 neighborhoods in the city of Youngstown, Ohio, with neighborhoods operationally defined as census block groups. Columbus neighborhoods in this study average 985 residents, while Youngstown neighborhoods average 838 residents. These population sizes fit one of the "critical membership" ranges of community (400–1500 persons) whereby the size is small enough "… that members can associate with one another on a regular basis, provide mutual aid, and have open and trusting social relations" (Brower, 2011, p. 18). Likewise, block groups are suitable analogs for neighborhoods. However, the reader should keep in mind that there are many different ways to define a neighborhood, with the appropriateness of definition dependent upon the purpose.

Similarly, there is no agreed upon operational definition of abandonment in the literature. Due to data availability, abandonment was operationally defined as follows: For Columbus, an abandoned property is one that appears on the city's Vacant Housing Application (VHA) database maintained by the code enforcement office. Although this database uses the word "vacant," the properties on the list are abandoned properties. Annually, the city code enforcement office documents all of the chronically vacant (i.e. abandoned) properties in the city. A house that is for sale, for rent, or just completed but not occupied would not appear on this list (M. Farrenkopf, personal communication, December 14, 2011). In March 2011, the author received the most recent update of the survey conducted in January 2011. For Youngstown, an abandoned property is a vacant structure rated B–F on the Property Inventory and Condition Survey of 2010, a survey conducted by the Mahoning Valley Organizing Collaborative (MVOC)—a community organization dedicated to improving the quality of life in urban neighborhoods in the Youngstown region. Youngstown identifies structures and lots as vacant if at the time of the survey there are obvious visible signs that a property was not presently occupied or being used and maintained. The survey ratings range from "A" (the structure could easily be reoccupied) to "F" (the structure is an immediate hazard to the neighborhood) (Mahoning Valley Organizing Collaborative, 2011).

Since many cities in Ohio face abandoned property problems (Community Research Partners and Rebuild Ohio, 2008), using data from Ohio cities is appropriate. The City of Youngstown, in particular, received notice in the planning community due to its innovative 2010 plan that embraced the notion of planning for a shrinking city (Pallagst, 2009). Although Columbus' population is growing as a whole, the portions of the city within its 1950 boundary face population losses and accompanying challenges comparable to other cities in Ohio (The Columbus and Franklin County Consortium, 2009). It is useful to consider both of these cities when creating prediction models since one (Youngstown) faces a city-wide abandonment problem, while the other (Columbus) does not. By examining more than one city, generalizability of results is improved.

Thus, building on existing research, this study will use spatial statistics to determine if there is statistically significant clustering of abandoned housing and its predictors. The study will account for spatial relationships by spatially lagging the appropriate variables and adding them as additional independent variables in a multilevel regression model. Among other benefits, adding the spatially lagged terms to the model will provide a metric as to how conditions in nearby neighborhoods influence the probability of abandonment. Finally, the study will determine whether the spatial effects that emerge are the same for the two cities of interest.

Methods

Non-spatial, multilevel models take into account *place*, not space. These models consider the neighborhood affiliation of the individual house, but disregard the spatial connections between neighborhoods (Chaix, Merlo, Subramanian, Lynch, & Chauvin, 2005). Accounting for spatial dependence is important for if there is positive spatial autocorrelation, the regression will tend to underestimate the real variance in the data since the standard errors of the parameter estimates are biased downward. Consequently, decision errors are more likely to be made (Ward & Gleditsch, 2008). In a sense, the model "thinks" it is receiving more information from the observations than it actually is, inflating the value of the R^2 statistic (Voss & Curtis, 2011). Therefore, space should be taken into account in addition to place.

But before adding spatial terms to a regression model, it is necessary to determine whether spatial dependence (i.e. clustering) exists. Spatial dependence is a *functional relationship* between what happens at one point in space and what happens elsewhere (Voss & Curtis, 2011). To see whether neighborhood level abandonment exhibits spatial dependence, Moran's *I* statistics were run in OpenGeoDa: one on the Columbus dataset and one on the Youngstown dataset. Since the global Moran's *I* was statistically significant for both cities, another term—a spatially lagged abandonment variable—was added to the equation to measure and control for some of the effects of neighborhood level spatial dependence. Local Moran's statistics were also conducted to determine exactly where clustering exists.

It is feasible that conditions in nearby neighborhoods—other than neighborhood-level abandonment—influence the probability of a house being abandoned. Therefore, Moran's *I* statistics were run on the independent variables (market conditions, gentrification, and physical neglect), and when appropriate, a spatial lagged version of each variable was added to the regression model. The generic equation is as follows:

$$\text{Level 1 (house):}\quad \ln(P/1-P) = \beta_{0j}$$

$$\text{Level 2 (neighborhood):}\quad \beta_{0j} = \gamma_{00} + \gamma_{01}W_j + \gamma_{02}W_j + \gamma_{03}W_j \ldots + \lambda ZW^*$$

where…

- j is the neighborhood
- W is a level two predictor
- λ is the coefficient for the spatially lagged independent variable. It indicates the degree of spatial dependence, with positive values indicating that neighborhoods are expected to have higher odds of abandonment if, on average, their neighbors have a high value for the variable of interest (in this case, neighborhood-level abandonment).
- Z is the spatial weights matrix.
- ZW^* is the average of the neighbors' values on the variable of interest *W*.

The above equation is a modified version of the Spatial Durbin model. Also note that if Moran's *I* is statistically significant, it does not necessarily mean that the corresponding spatially lagged variable will be significant in the model. A positive, statistically significant Moran's *I* indicates that there is statistically significant clustering of a variable; a statistically significant *lagged* variable in the model indicates that the average of the neighbors on a variable predicts abandonment.

Lagged variables were created using rook contiguity with row standardization for the weights matrices. With this method of weighting, a neighborhood is considered a neighbor if it shares a border with the neighborhood of interest. Likewise, the value for the lagged term is the average of neighbors on a given variable (Crandall & Weber, 2004; Mills, 2010). This method of weighting allows for the results to be interpreted as the change in odds given a one unit change in the average of surrounding neighborhoods.

To see whether the spatial effects of the predictors were the same for Columbus and Youngstown, interaction terms (city by each factor) were added to the model. For the interaction terms that were not statistically significant (meaning that the effect of the variables were the same in both cities), it was concluded that the spatial effects of the predictors generalize between the two cities. For the statistically significant interaction terms, a future study should determine why the predictors differ by city. An analysis of city differences should include data at the city and/or regional level, and likewise the addition of a third or perhaps even a fourth level to the multilevel model. Akaike weights and evidence ratios were used to assess the probability of the final spatial model actually being the best model of those conducted. All statistical tests were performed at the .05 level of significance.

Results

The values of Moran's *I* indicate clustering of abandonment at the neighborhood level. For Youngstown, Moran's *I* was .57. For Columbus, it was .70 (pseudo *p's* = .001 for both cities). However, if policy makers want to know exactly *where* the statistically significant clusters of neighborhood level abandonment are located within the community, it is necessary to run local spatial statistics. The maps below depict the locations with statistically significant local Moran statistics ($p < .05$) and classify those locations by type of association. These maps are commonly referred to as LISA maps (local indicators of spatial autocorrelation). The dark gray and light gray locations indicate clusters (areas of high abandonment surrounded by areas of high abandonment and areas of low abandonment surrounded by areas of low abandonment); whereas the medium gray locations indicate spatial outliers—areas of high surrounded by low, and low surrounded by high respectively (Anselin, Syabri, & Kho, 2004) (Figs. 1 and 2).

Since neighborhood level abandonment exhibits spatial dependence, it should be accounted for in models that predict abandonment. Therefore, to test the impact of accounting for space, the abandonment variable was spatially lagged and added to the final contextual model in Morckel (2013). Doing so revealed that the higher the average value of abandonment for a neighborhood's neighbors, the more likely it is that a house will be abandoned in that neighborhood ($\gamma_{01} = .08$, $p < .001$). Additionally, adding the spatially lagged abandonment variable reduced the model's level two variance (denoted τ_{00}) by 13.3% ($\tau_{00} = .39$; $\tau_{00} = .45$ for the old model). A χ^2 difference test confirmed that the model with the spatially lagged abandonment variable was preferred over the model without ($\chi^2_{(1)} = 391{,}636.28 - 391{,}598.67 = 37.61$; $p = < .001$).

However, it is possible that the model can be further improved by taking into consideration other, nearby neighborhood conditions. Thus, a global Moran's *I* statistic was run on each of the independent variables to test for the presence of spatial dependence. All of the factors exhibited clustering. As shown in Table 2, Moran's *I* is positive and statistically significant for every independent variable in both cities.

Because all of the independent variables exhibit clustering, a spatially lagged version of each variable was added to the model. The resulting model shown in Table 3 reflects a finding that the model with spatially lagged versions of market conditions, gentrification, physical neglect, and neighborhood level abandonment was an improvement over the model with just the spatially lagged abandonment term ($\chi^2_{(3)} = 391{,}598.67 - 391{,}550.86 = 47.81$; $p < .001$). However, since the spatially lagged physical neglect variable was not statistically significant, meaning that the average value of physical neglect for a neighborhood's neighbors does not influence the probability of abandonment in that neighborhood ($\gamma_{03} = .09$, $p = .397$), the model was rerun without the spatially lagged physical neglect term. All variables in the new model (the one shown in Table 3) were statistically significant ($p < .010$). A χ^2 difference test confirmed that the model without lagged physical neglect was preferred over the one with it for parsimony purposes ($\chi^2_{(1)} = 391{,}551.58 - 391{,}550.86 = .72$; $p = .396$). Notably, this model represents a 26.7% decrease in the level two variance over the final

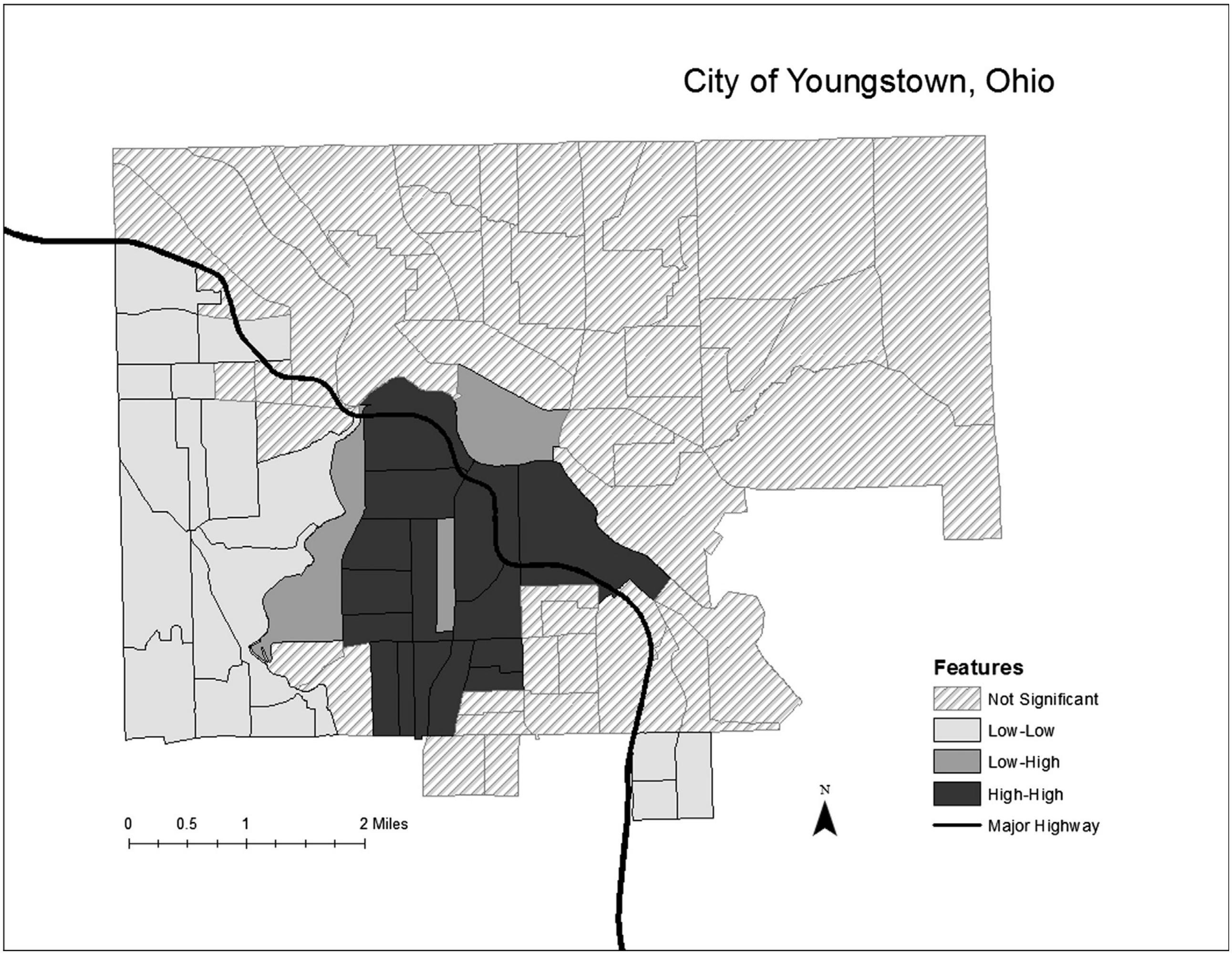

Fig. 1. LISA map of abandonment: Youngstown, 2010.

contextual model not accounting for spatial dependence in the Morckel (2013) study.

Level 1 : $\log[(P/(1-P)]$

Level 2 : $\beta_0 = \gamma_{00} + \gamma_{01}{}^*(\text{City}) + \gamma_{02}{}^*(\text{Lagged\_Market\_Conditions}) + \gamma_{03}{}^*(\text{Lagged\_Gentrification}) + \gamma_{04}{}^*(\text{Lagged\_Neighborhood\_Abandonment}) + \gamma_{05}{}^*(\text{Market Conditions}) + \gamma_{06}{}^*(\text{Gentrification}) + \gamma_{07}^*(\text{Physical\_Neglect}) + \gamma_{08}{}^*(\text{N\_Abandonment}) + u_0$

Another way to compare the model that accounts for spatial dependence to the model that does not is to examine changes in effect sizes using odds ratios. The new model shows that the effect of market conditions and gentrification on abandonment (within the neighborhood itself) decreases once surrounding neighborhood conditions are taken into account. Specially, the odds ratio for market conditions was 2.46 in the non-lagged model (Morckel, 2013; $e^{.90} = 2.46$); now that market conditions in surrounding neighborhoods have been taken into account, the odds ratio is 1.65 (Table 3, $e^{.50} = 1.65$). Similarly, the odds ratio for gentrification was 1.86; now that gentrification in surrounding neighborhoods has been taken into account, it is 1.35. There was little change in the odds ratios for neighborhood level abandonment (1.07 versus 1.05). Yet another way to conceptualize the differences between the models is to convert the odds ratios to the percentage change in odds given a one unit increase in the independent variable, as shown in Table 4.

Table 4 only shows the non-spatial terms since Morckel (2013) did not account for space. The spatial percent changes in odds were as follows from Table 3: there is a 72.0% increase in the odds of abandonment [calculated as 100% *(Odds Ratio − 1.00)] when the average score on market conditions for surrounding neighborhoods increases by one unit (or about one standard deviation since the standard deviation for lagged market conditions is .97, as noted in Appendix A). There is a 57.0% increase in the odds of a house being abandoned when the average score on gentrification for surrounding neighborhoods increases by one unit (or about one standard deviation since the standard deviation for lagged gentrification is .98). Neighborhood level abandonment in surrounding neighborhoods has a weaker effect on the odds since an increase of one unit increases the odds by 4.0%.

Further interpretation of the model

The value of the intercept indicates that a house located in a Youngstown neighborhood:

- With average levels of market conditions, gentrification, and physical neglect

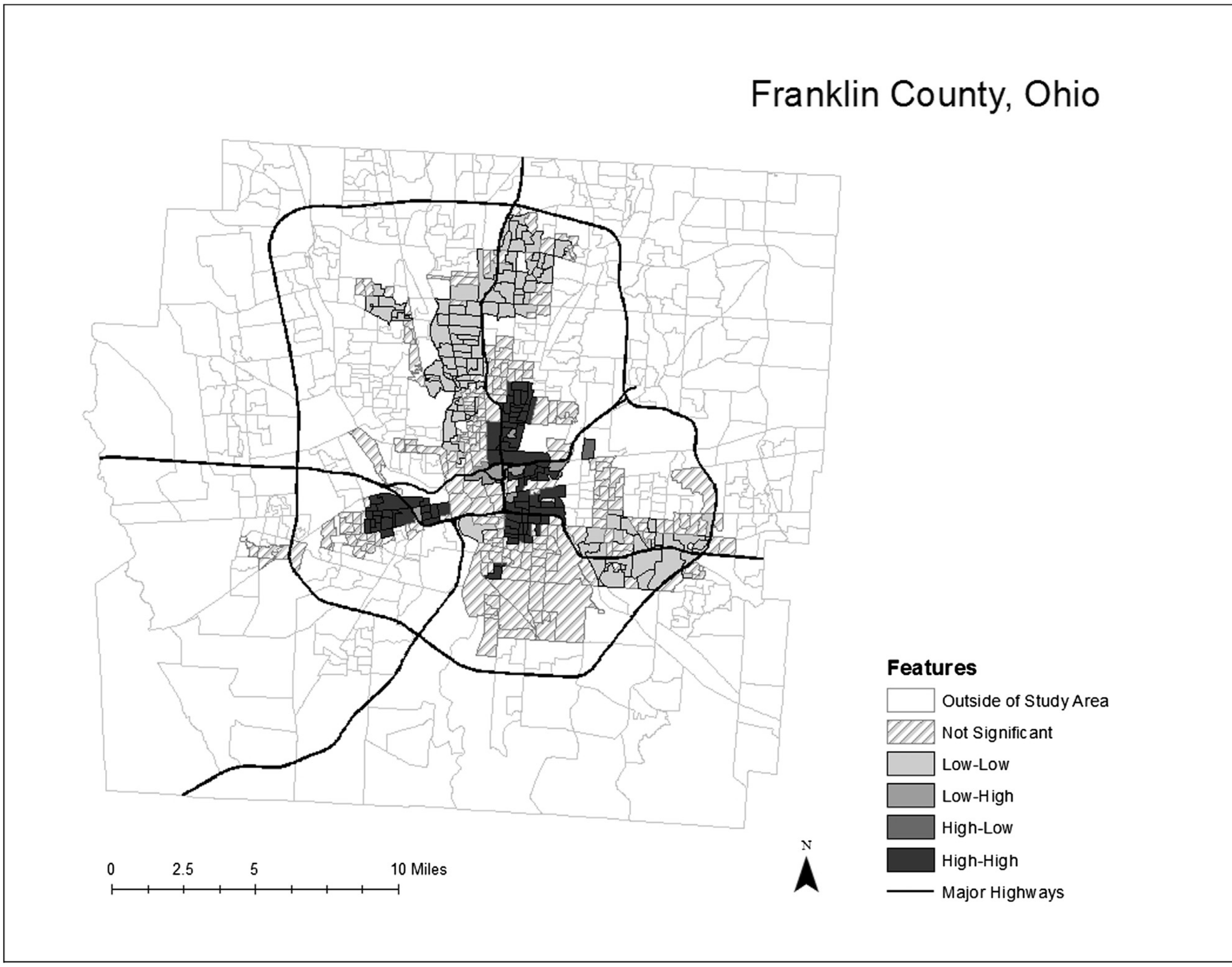

Fig. 2. LISA map of abandonment: Columbus, 2011. No analyses were conducted at the county-level. The maps are at different scales because area wise, the City of Youngstown is much smaller than the City of Columbus. Columbus takes up nearly all of Franklin County, which is why the Columbus map is shown at the county scale.

- With no neighborhood level abandonment
- Surrounded by neighborhoods with average market conditions and average gentrification
- Surrounded by neighborhoods with no neighborhood level abandonment

has a probability of abandonment of 4 out of 100 or 4.0% [$\gamma_{00} = -3.16$; $p < .001$; probability $= (e^{-3.16})/(1 + e^{-3.16})$]. In other words, all of the values except for the intercept are zero. For a similarly situated house in Columbus, the probability of abandonment is 1 out of 100 or 1.0% [logit $= -5.14 = -3.16 + (-1.98)$; probability $= (e^{-5.14})/(1 + e^{-5.14})$]. Following the same methodology, for the extreme—a very high value for every independent variable, meaning two standard deviations above the mean—a house located in such a neighborhood in Youngstown has a probability of abandonment of 93.0%; whereas a house located in a similarly situated neighborhood in Columbus has a probability of abandonment of 64.0%. In terms of neighborhoods, for every 100 houses in a Youngstown neighborhood that is very high on all independent variables, the model predicts that 93 will be abandoned. For a similar neighborhood in Columbus, the model predicts that 64 of 100 houses will be abandoned. This extreme scenario is presented to emphasize the variable effects. However, it is probably unrealistic to think that a neighborhood will have a very high value for all of the independent variables simultaneously. 19 of the 462 neighborhoods in this study had a very high value for 3 of the 7 continuous independent variables. None had 4 or more.

Overall, taking into account space, the odds ratios indicate that city has the strongest effect on the probability of abandonment (OR = .14). Of the factors, market conditions has the strongest effect, with market conditions in surrounding neighborhoods having a stronger effect on the probability than market conditions in the neighborhood itself (OR = 1.72; OR = 1.65). Gentrification has the next strongest effect, with gentrification in surrounding neighborhoods having a stronger effect than gentrification in the neighborhood itself (OR = 1.57; OR = 1.35). The next strongest effect was physical neglect in the neighborhood itself (OR = 1.20), followed by abandonment in the neighborhood itself (OR = 1.05), and abandonment in surrounding neighborhoods (OR = 1.04). Physical neglect in surrounding neighborhoods did not have an effect on the probability of abandonment.

Interaction effects

Morckel (2013) showed that the effects of market conditions and physical neglect differ by city in a contextual model that does not account for spatial dependence. Therefore, it was prudent to test whether these variables would still differ by city once spatial

Table 2
Spatial autocorrelation of independent variables.

	Youngstown		Columbus	
	Moran's *I*	Pseudo *p*	Moran's *I*	Pseudo *p*
Market Conditions	.19	.004	.75	.001
Gentrification	.38	.001	.74	.001
Physical neglect	.62	.001	.73	.001
Neighborhood abandonment	.57	.001	.70	.001

dependence was accounted for. To do so, two interaction terms were added to the model shown in Table 3: city by market conditions and city by physical neglect. Table 5 shows the results.

Even when accounting for space, the effects of market conditions and physical neglect vary by city. The significance for the interaction terms did not change; both terms were still positive and statistically significant ($p < .010$). In other words, even when accounting for spatial dependence, the effect of market conditions and physical neglect on the probability of abandonment is greater in Columbus than it is for Youngstown. The new spatial model with interaction terms was an improvement over the one without them ($\chi^2_{(2)} = 391{,}551.58 - 391{,}511.43 = 40.15$; $p < .001$). Including the interactions in the model reduced the level two variance by 21.0% ($\tau_{00} = .33$ in Table 3; $\tau_{00} = .26$ in Table 5). Additionally, compared to the empty model, the model in Table 5 reduced the level two variance by 92.0%.

Spatial differences by city

Another question that should be examined is whether the effects of the spatially lagged variables generalize from city to city. To state it a different way, are the effects of specific conditions present in surrounding neighborhoods the same for Youngstown and Columbus? To test this, four more interaction terms were added to the model shown in Table 5: city by lagged market conditions, city by lagged gentrification, city by lagged physical neglect, and city by lagged neighborhood level abandonment. The analysis found that the effects of conditions in surrounding neighborhoods on abandonment were the same for both cities since none of the new interactions terms were statistically significant ($p > .100$ for all). To further confirm this result, new terms were eliminated from the model one by one (starting with the least significant) to see whether the significance of the remaining lagged terms would change. It did not. Therefore, the model indicates that the effect of space—that is, the effect of conditions in surrounding neighborhoods on abandonment—generalizes between the two cities of interest. A χ^2 difference test indicated that the model with the new terms was not preferred over the model without them ($\chi^2_{(4)} = 391{,}511.43 - 391{,}507.77 = 3.66$; $p = .454$).

Table 3
Contextual model Accounting for spatial dependence.

Fixed effects	Coefficient *(SE)*	*t (df)*	*p*	Odds ratio
Model for intercept, abandonment (β_0)				
Intercept (γ_{00})	−3.16 (.19)	−16.78 (453)	<.001	
City (γ_{01})	−1.98 (.19)	−10.31 (453)	<.001	.14
L_Market Conditions (γ_{02})	.54 (.09)	5.73 (453)	<.001	1.72
L_Gentrification (γ_{03})	.45 (.09)	4.87 (453)	<.001	1.57
L_Neighborhood Level Aban. (γ_{04})	.04 (.01)	2.98 (453)	.003	1.04
Market Conditions (γ_{05})	.50 (.07)	6.72 (453)	<.001	1.65
Gentrification (γ_{06})	.30 (.07)	4.30 (453)	<.001	1.35
Physical Neglect (γ_{07})	.18 (.06)	3.09 (453)	.002	1.20
Neighborhood Level Aband. (γ_{08})	.05 (.01)	5.13 (453)	<.001	1.05
Random effects (var. components)	Variance	*df*	χ^2	*p*
Var. in intercepts (τ_{00})	.33	453	3103.31	<.001
Deviance = 391551.58				
# of parameters = 10				

Note: An "*L*" in the variable name indicates a lagged version of the variable.

Table 4
Comparison of percent change in odds given a one Unit increase in the IV.

	Model not Accounting for spatial dependence (Morckel, 2013)	Model Accounting for spatial dependence (Table 3)
City (with Columbus coded 1)	−81.00%	−86.00%
Market conditions	146.00%	65.00%
Gentrification	86.00%	35.00%
Physical neglect	31.00%	20.00%
Neighborhood abandonment	7.00%	5.00%

Therefore, of the ten models tested between the two studies (this study and Morckel, 2013), the one that fits the data best is the model shown in Table 5. To confirm, Table 6 was created which shows the Akaike Information Criterion (AIC) and accompanying AIC–based statistics for every model conducted between the two studies. AIC is a model selection index which allows for the ranking or comparison of models with different sets of parameters. It is calculated as $D + 2p$ where D is the model deviance and p is the number of parameters in the model. The model with the lowest AIC value is considered to be the best fitting model of that set (McCoach & Black, 2008). From Table 6, one can see that model 9—the model shown in Table 5 of this study—is preferred.[1]

Using Akaike weights (column 3 of Table 6), one can also assess the probability of a model actually being the best model of those conducted (Burnham & Anderson, 2002; Del Giudice, 2009). For model 9, the Akaike weight is .90. Therefore, the probability of this model being the best is 9 out of 10 or 90.0%. Additionally, one can look at the evidence ratios (the ratio of two model probabilities or Akaike weights) to gage the "relative amount of evidence favouring one model over another" (Del Giudice, 2009, p. 2). Since model 10 (the last row in Table 6) is the only other model that has a practical probability above zero, it will be compared to model 9. The evidence ratio for model 9 versus model 10 is $.90/.10 = 9$. 9 is a relatively high value for an evidence ratio; therefore, there should not be a lot of variation in the selected best model from sample to sample if multiple independent samples are drawn and the study is repeated. In other words, model selection uncertainty is likely to be low (Burnham & Anderson, 2002).

Discussion and conclusions

Since the results for the non-spatial variables are consistent with Morckel (2013), this discussion will focus on the spatial results. However, before discussing the results, it is important to note that this study does prove that any one variable or set of variables *cause* abandonment. To infer causality, the following requirements must be met: that cause precedes effect, that cause covaries with effect, that alternative explanations can be ruled out, and that knowledge is available of what would have happened in the absence of the cause (Shadish, Cook, & Campbell, 2001). Due to limited data availability, this study

[1] Despite this outcome, it is important to note that the results of Table 3 are emphasized over Table 5 since main effects in this type of interaction model are not practically interpretable.

Table 5
Interaction model accounting for spatial dependence.

Fixed effects	Coefficient *(SE)*	*t (df)*	*p*
Model for intercept, abandonment (β_0)			
Intercept (γ_{00})	−3.42 (.18)	−19.14 (451)	<.001
City (γ_{08})	−1.65 (.18)	−8.98 (451)	<.001
L_Market Conditions (γ_{01})	.34 (.09)	3.75 (451)	<.001
L_Gentrification (γ_{02})	.41 (.09)	4.76 (451)	<.001
L_Neighborhood Level Aban. (γ_{03})	.05 (.01)	4.08 (451)	<.001
Market Conditions (γ_{07})	.08 (.13)	.62 (451)	.533
Gentrification (γ_{06})	.27 (.06)	4.14 (451)	<.001
Physical Neglect (γ_{05})	−.02 (.06)	−.32 (451)	.746
Neighborhood Level Aband. (γ_{04})	.05 (.01)	5.25 (451)	<.001
City by Market Conditions (γ_{10})	.41 (.14)	2.92 (451)	.004
City by Physical Neglect (γ_{09})	.54 (.09)	6.17 (451)	<.001
Random effects (var. components)	Variance	χ^2 *(df)*	*p*
Var. in intercepts (τ_{00})	.26	2355.00 (451)	<.001
Deviance = 391511.43			
# of parameters = 12			

could not be designed to meet these conditions. Nonetheless, the study is significant because it finds new, spatial *relationships* between variables that are worthy of further, more methodologically rigorous investigation.

Although practitioners and scholars have long assumed that abandonment clusters and spreads (Sternlieb, Burchell, Hughes, & James, 1974; Wilson et al., 1994), this study empirically demonstrates statistically significant clustering of abandoned homes. The study found that neighborhoods with high abandonment are located near other neighborhoods with high abandonment, while neighborhoods with low abandonment are located near other neighborhoods with low abandonment. While the study cannot directly demonstrate spreading since the dataset is not longitudinal, the finding of clustering is a step towards spreading since abandonment would have to spread from something—presumably a cluster. The finding that abandonment in surrounding neighborhoods predicts abandonment in the neighborhood itself provides additional support for the notion of spreading.

But although the study demonstrates clustering, it also provides some evidence that the influence of abandoned homes on future abandonment may not be as strong as previously thought. Though statistically significant, the effect that other abandonments—both in the neighborhood itself and in surrounding neighborhoods—have on the probability of abandonment is not strong compared to most of the other variables in the models. This finding might help to dispel the belief that abandonment begets abandonment.

Notably, the LISA maps may provide policy makers with insight on where to spend resources—a critical question for shrinking cities. In addition to showing statistically significant clusters of abandonment, the maps also indicate neighborhoods of statistically significant high abandonment surrounded by statistically significant low abandonment (high-low), and neighborhoods of statistically significant low abandonment surrounded by statistically significant high abandonment (low-high). Considering that cities in decline do not have the resources to invest significantly in every neighborhood in need, policy makers might choose to invest in these spatial outliers—either high-low or low-high areas as indicated by the maps. It would be useful to know whether it is more effective to focus resources on the high abandonment neighborhoods in order to stop abandonment from spreading into stable areas, or whether it is more effective to invest resources in the low abandonment neighborhoods to use them as areas of strength from which to tackle the abandoned housing problem. This question is one for future research, as is the question of what exactly should be done with the abandoned housing such as demolition, rehabilitation, or creative reuse.

This study finds that the predictors of abandonment cluster and, more importantly, that conditions in surrounding neighborhoods impact the probability of a house being abandoned in a neighborhood of interest. The model in Table 3 shows that for both market conditions and gentrification, the odds ratios for the lagged variables are higher than the odds ratios for the non-lagged variables. In other words, certain conditions *around* the neighborhood have a stronger effect on the probability of abandonment than do conditions *in* the neighborhood itself. This finding is very important for policy makers who are trying to prevent abandonment; it indicates that rather than focus resources in one neighborhood, it may be necessary to allocate resources in several, adjacent neighborhoods.

Of the independent variables, the study found that market conditions in surrounding neighborhoods have the greatest impact on the probability of abandonment, followed by market conditions in the neighborhood itself. To help explain this outcome, Fig. 3 shows three hypothetical cities with twelve neighborhoods (i.e. cells), with the colors of the cells indicating market conditions. Darker colors indicate more favorable market conditions (i.e. "good" or higher demand neighborhoods), while lighter colors indicate less favorable market conditions (i.e."bad" or lower demand neighborhoods). Focus on the two neighborhoods in the middle of the cities. In city one, neighborhoods one and two have the same internal demand since they are the same color, but different surrounding market conditions. Neighborhood one is surrounded by more "bad" neighborhoods; therefore, its probability of housing abandonment is higher than the probability of abandonment for neighborhood two, even though the two neighborhoods have the same level of internal demand. In city two, neighborhood one is a "good" neighborhood mostly surrounded by "bad" neighborhoods, while neighborhood two is the opposite. Under this scenario, the results of this study indicate that neighborhood one would have a higher probability of abandonment than neighborhood two (despite its internal conditions) since it is surrounded by "bad" neighborhoods. However, whether neighborhood one actually has a higher probability than neighborhood two is dependent upon the level of conditions in each respective neighborhood, as shown in city three. In city three, neighborhood one is a "great" neighborhood mostly surrounded by "bad" neighborhoods. Since neighborhood one is so well-off, it might be able to counteract the effects of the surrounding neighborhoods.

Nonetheless, this explanation does not entirely answer the question of why external conditions matter more than internal. Why neighborhood one could have a higher probability *at present* is puzzling, but why it would have a higher probability *in the future* is perhaps less so. Neighborhood one might become less desirable over time as more residents and prospective residents become discouraged by conditions in surrounding neighborhoods. It is also plausible that the probability of future abandonment is higher in neighborhood one than two because neighborhood one has farther to fall. Neighborhood two might already be in such a poor state that everyone who could leave has already left; therefore, the probability of future abandonment is low since it is already mostly abandoned. Given the cross-section data used in this study, the author can only speculate. A longitudinal dataset would certainly help to answer these questions.

The results also indicate that as gentrification in surrounding neighborhoods increases, abandonment in the neighborhood of interest increases. This result should not be interpreted as gentrification *causes* abandonment. Instead, it is more likely that

Table 6
Summary of model building, model comparison, and model fit.

Model (in the order in which they were run)	$AIC = D + 2p$	$\Delta_i = AIC_i - AIC_{min}$	Akaike weights $w_i\ \exp(-½\Delta_i)/\Sigma\ \exp(-½\Delta_r)$
[a]1. Empty model	392,318.94	783.51	.00
[a]2. Non-spatial model with the four factors, a city dummy-code, and a variable representing neighborhood level abandonment	391,651.87	116.44	<.001
[a]3. Final contextual model not accounting for spatial dependence. Table shown in Morckel, 2013. (Same as model 2 above, but with the social factor dropped.)	391,650.28	114.85	<.001
[a]4. Model 3 above, but with four interaction terms added (city by physical neglect, city by gentrification, city by market conditions, city by neighborhood level abandonment)	391,605.71	70.28	<.001
[a]5. Final interaction model not accounting for spatial dependence. Table shown in Morckel, 2013. (Same as model 4 above, but with city by gentrification and city by neighborhood level abandonment removed.)	391,604.24	68.81	<.001
6. Final contextual model shown in Morckel, 2013 with a spatially lagged neighborhood level abandonment term added to it.	391,614.67	79.24	<.001
7. Model 6 above, but with spatially lagged versions of each factor added.	391,572.86	37.43	<.001
8. Contextual model accounting for spatial dependence. Shown in Table 3 of this study. (Same as model 7 above, but with spatially lagged physical neglect removed.)	391,571.58	36.15	<.001
9. Interaction model accounting for spatial dependence. Shown in Table 5 of this study. [Same as model 8 above, but with two interaction terms added (city by physical neglect and city by market conditions.)]	391,535.43	.00	.90
10. Interaction model accounting for spatial dependence (model 9 above), but with four new interaction terms (city by lagged market conditions, city by lagged gentrification, city by lagged physical neglect, city by lagged neighborhood level abandonment.)	391,539.77	4.34	.10

[a] Indicates that the model was run in Morckel, 2013.

abandonment is a precondition for first-wave gentrification; therefore, gentrifying areas tend to be located near areas of abandonment. This finding is consistent with Marcuse (1985) who theorized that "Gentrifying areas and declining areas are linked in a process of spatial restructuring of the city as a whole, which must of necessity have different consequences for different neighborhoods" (p. 217). Future research should carefully examine the connections between gentrification and abandonment, especially longitudinally. Future models should also account for recursive relationships and mediating variables. Furthermore, it is important to keep in mind that the interpretation of factor 2 in Table 1 drives this discussion. While this author believes that factor 2 is a gentrification factor since it is characterized by young, educated people living in poor neighborhoods with older homes, others may disagree.

Another interesting finding is that physical neglect in surrounding neighborhoods does not influence the probability of abandonment in the neighborhood itself. This finding may suggest that efforts to improvement the physical conditions of neighborhoods (such as painting homes) may not have positive spill-over effects into other neighborhoods, at least as far as abandonment is concerned. However, one would think that by improving the physical conditions, housing demand (i.e. market conditions) would improve. Other methods, like structural equation modeling, might be able to show if such indirect relationships are present.

It is important to note that for Columbus and Youngstown, the effects of surrounding market conditions, gentrification, physical neglect, and abandonment were the same. Likewise, the spatial effects found in this study may be generalizable to other cities in Ohio or other cities facing an abandoned housing problem at the urban core. To confirm, a future study could examine spatial effects across multiple cities and contexts.

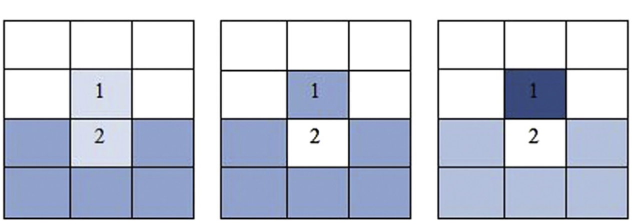

Fig. 3. Market conditions in three hypothetical neighborhoods.

There is also a need for more refined spatial models. Future studies should determine how far spatial effects extend—both in terms of abandonment's effects on other houses or neighborhoods, and the effects of other variables on abandonment. This study spatially lagged the variables and used an equal weight for all neighbors, but other methods of capturing spatial effects like geographically weighted regression could prove to be more fruitful. It might also make sense for future analyses to account for "how much of a neighbor" a contiguous neighborhood actually is. For example, if neighborhood B borders neighborhood A for 1000 feet, but neighborhood C border neighborhood A for 250 feet, one could argue that when calculating spatially lagged variables for neighborhood A, neighborhood B should have more weight in the equation than neighborhood C. But perhaps an inverse distance function should have been used. Perhaps the effects of neighborhood level abandonment on the probability only extend a quarter of a mile or a half of a mile. We do not know. The intensity of the border might also affect the results. Some borders (such as a railroad or interstate highway) create a strong edge such that the character of one area, regardless of the length of the edge, would have no effect on its neighbor. Other borders (such as a narrow road with light traffic) would allow conditions in one neighborhood to affect its neighbors. Since spatial modeling of vacancy and abandonment is lacking in the literature, the possibilities for future research in this area are robust.

Overall, accounting for the clustering of abandonment and for surrounding neighborhood conditions improved the prediction models. The new, spatial models resulted in a significant decrease in the percentage of unexplained variance compared to the non-spatial models. Therefore, future studies will likely benefit from accounting for space when creating models that are meant to predict abandoned housing. Furthermore, by understanding the spatial nature of abandonment and its predictors, planners and other policy makers will be able to make more informed decisions about where to target scare resources.

Appendices

Appendix A. Descriptive statistics for variables entered in the regression models (Combined dataset, post factor analysis)

Variable name	*N*	Mean	SD	Min	Max
Level 1					
Abandonment (House-Level)	181,899			.00	1.00
Level 2					
Neighborhood_Abandonment	462	4.75	6.96	.00	30.98
City	462	.83	.38	.00	1.00
Physical_Neglect	462	-.01	1.05	−1.36	5.41
Gentrification	462	.00	1.12	−3.87	3.82
Market_Conditions	462	.00	1.13	−2.89	3.80
Level 2 Lagged terms					
Lagged_Physical_Neglect	462	.01	.93	−1.13	3.63
Lagged_Gentrification	462	-.01	.98	−2.53	2.98
Lagged_Market_Conditions	462	.01	.97	−1.88	2.44
Lagged_Neighborhood_Abandonment	462	4.84	5.91	.00	26.78

Appendix B. Descriptive statistics for Youngstown (Post factor analysis)

Variable name	*N*	Mean	SD	Min	Max
Level 1					
Abandonment (House-Level)	61,190			.00	1.00
Level 2					
Neighborhood_Abandonment	80	10.54	8.63	.00	30.98
Physical_Neglect	80	1.18	1.56	−1.06	5.41
Gentrification	80	-.83	.83	−3.21	.72
Market_Conditions	80	-.60	.56	−2.89	.46
Level 2 Lagged Terms					
Lagged_Physical_Neglect	80	1.21	1.26	-.92	3.63
Lagged_Gentrification	80	-.87	.61	−2.53	.16
Lagged_Market_Conditions	80	-.61	.29	−1.28	.09
Lagged_Neighborhood_Abandonment	80	10.87	6.70	.21	26.78

Appendix C. Descriptive statistics for Columbus (Post factor analysis)

Variable name	*N*	Mean	SD	Min	Max
Level 1					
Abandonment (House-Level)	120,709			.00	1.00
Level 2					
Neighborhood_Abandonment	382	3.53	5.89	.00	29.73
Physical_Neglect	382	-.26	.69	−1.36	1.86
Gentrification	382	.17	1.10	−3.48	2.84
Market_Conditions	382	.12	1.18	−2.44	3.80
Level 2 Lagged terms					
Lagged_Physical_Neglect	382	-.25	.59	−1.13	1.36
Lagged_Gentrification	382	.17	.95	−2.06	2.98
Lagged_Market_Conditions	382	.14	1.01	−1.88	2.44
Lagged_Neighborhood_Abandonment	382	3.58	4.88	.00	18.28

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