Teardowns and Demolitions in Chicago, 2000-2014: A Conditionally Parametric Approach

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December 2014

Abstract

Conditionally parametric (CPAR) probit models are used to estimate the probability that a demolition permit was issued for residential properties in Chicago for 2000-2014. The approach has significant advantages when analyzing demolition permits because the coefficients vary across locations where demolition is followed by construction of a new building and locations where demolition leads to a vacant lot. In prime areas of the city where demolition permits are associated with teardowns, the results indicate that permits are more likely to be issued for small homes on large lots. In contrast, homes on small lots are more likely to be demolished in low-priced areas of the city, and building area has less influence on the demolition probability. All estimated coefficients vary substantially across the sample area, suggesting that a simple, global parametric specification is not sufficient for modeling demolitions in a large city such as Chicago.

1. Introduction

Cities are not static. Traditional urban models emphasize the role of "filtering" as a determinant of neighborhood change. When housing is durable but subject to depreciation and income is increasing over time, the filtering model predicts that high-income households will satisfy their demand for improved housing by building new homes in outlying areas, leaving older homes to lower-income households. The filtering model is consistent with the process of urban decline that characterized much of the United States in the 20th century. Early studies such as Lowry (1960), Muth (1973), and Sweeney (1974), and Brueckner (1977) treated neighborhood change as a one-way process of decline in income as the housing stock aged.[1]

This process of decline has been reversed in many cities since the 1990s. Low-income neighborhoods in central cities offer short commutes for downtown workers, and often have an attractive bundle of amenities such as accessibility to parks, restaurants, stores, and historic buildings. The process of gentrification, which leads to an increase in house prices for centrally located neighborhoods as low-income residents are replaced by high-income households, has been emphasized in studies such as Brueckner and Rosenthal (2009); Brueckner, Thisse, and Zenou (1999); Ellen and O'Regan (2011); Freeman and Braconi (1994); Gleaser, Gottlieb, and Tobio (2012); Guerrieri, Hartley, and Hurst (2013); Hamnett (2003); Lester and Hartley (2014); McKinnish, Walsh, and White (2010); McKinnish and White (2011); McMillen (2003); Smith (1996), and Vigdor (2002). Whether by decline or gentrification, what is clear is that neighborhood change is common. Indeed, in an extensive study of the determinants of neighborhood dynamics,

[1] More recent theoretical contributions include Arnott and Braid (1997) and Bond and Coulson (1989).

Rosenthal (2008, p. 833) concludes "roughly two-thirds of urban neighborhoods in 1950 … were of quite different economics status in 2000."

Renovations are one way to conduct redevelopment; another is to demolish an existing structure and replace it with another. These demolitions – "teardowns" – became quite controversial during the early 2000s. The National Trust for Historic Preservation includes the following on its web site:[2]

> "Across the nation a teardown epidemic is wiping out historic neighborhoods one house at a time. As older homes are demolished and replaced with dramatically larger, out-of-scale new structures, the historic character of the existing neighborhood is changed forever. Neighborhood livability is diminished as trees are removed, backyards are eliminated, and sunlight is blocked by towering new structures built up to the property lines. Community economic and social diversity is reduced as new mansions replace affordable homes. House by house, neighborhoods are losing a part of their historic fabric and much of their character."

Teardowns remain common in desirable older urban neighborhoods despite ordinances designed to delay the permit process and raise the costs of demolitions.[3]

The primary focus of academic studies of teardowns has been to explain the probability of demolitions in prime neighborhoods and to compare hedonic price function estimates for teardown and non-teardown properties. Examples include Charles (2013); Clapp et al. (2012); Clapp, Eichholtz and Lindenthal (2013); Clapp and Jou (2012); Clapp and Salavei (2010); Dye and McMillen (2007); McMillen and O'Sullivan (2013); Munneke (1996); Munneke and Womack (2004); Rosenthal and Helsley (1994); and Weber et al. (2006). These studies suggest that teardowns are more likely to be older, smaller homes, on large lots in attractive neighborhoods. Characteristics of the location have much greater influence than structural characteristics on the

[2] http://www.preservationnation.org/information-center/sustainable-communities/creating/teardowns/#.VICJdzHF_Ct

[3] A survey of tactics that have been employed to slow teardown rates is presented in the following report by the National Trust for Historic Preservation: http://www.preservationnation.org/information-center/sustainable-communities/creating/teardowns/Teardown-Tools-on-the-Web-1.pdf.

sale price of a teardown property. Other empirical studies suggest that renovations are also more likely to occur in desirable urban neighborhoods, but in contrast to teardowns, desirable structural characteristics serve to increase the probability and extent of renovation (Boehm and Ihlanfeldt, 1986; Helms, 2003, 2012; Munneke and Womack, 2014; Plaut and Plaut, 2010).

Teardowns are typically identified as properties for which demolition permits have been issued. A problem with this procedure is that it combines two potentially dissimilar types of properties. Whereas a teardown is defined as a structure that is demolished in order to replace it with a new building, other demolitions are simply demolitions – a structure that is torn down and not replaced. Teardowns are most apt to occur in desirable, high-priced neighborhoods. In contrast, demolitions are likely to take place in older neighborhoods where vacant, dilapidated buildings have become potentially dangerous eyesores. Demolition permits do not distinguish between the two courses of action. In part to avoid the problem of combining two disparate processes, studies such as Dye and McMillen (2007), McMillen and O'Sullivan (2013), and Weber et al. (2006) restricted their analysis to prime housing markets where any demolition could reasonably be assumed to have been issued for teardown purposes. Charles (2013, 2014) restricted her analysis to properties that could be verified as having a change in square footage following the issuance of a demolition permit.

In this study, I use a conditionally parametric (CPAR) approach to model the probability that a demolition permit was issued for residential properties in Chicago for 2000-2014. Following McMillen and Soppelsa (forthcoming), I estimate weighted probit models at a set of target locations, and then interpolate the results to the full sample of nearly 400,000 observations. When estimating the model for a given target location, the weight provided to an observation is a declining function of distance from the observation to the target point. The approach is directly comparable to the estimation procedure that has been referred to as “locally weighted regression”, “local linear estimation”, or “geographically weighted regression” for linear regression models.

The approach has significant advantages when analyzing demolition permits because the coefficients vary across locations. In prime areas of the city where demolition permits are associated with teardowns, the results indicate that permits are more likely to be issued for small homes on large lots. In contrast, homes on small lots are more likely to be demolished in many low-priced areas of the city, and building area has less influence on the demolition probability. All estimated coefficients vary substantially across the sample area. Thus, a simple, global parametric specification is not sufficient for modeling demolitions in a large city such as Chicago.

2. Teardown Timing

Rosenthal and Helsley (1994) expanded on studies by Brueckner (1980), Braid (2001), and Wheaton (1982) to explicitly model an investor’s redevelopment strategy. The marginal benefit of a delay in redevelopment across two time periods is the increase in land rent plus the present discount value of the stream of future rents associated with housing capital. The marginal cost of a delay is the foregone interest earned on structural capital plus the change in capital costs across the two times. The decision rule simplifies considerably when developers do not have perfect foresight: “under myopic expectations, land is redeveloped when the bid rent on newly developed land net of construction costs equals the bid rent on developed land given its existing stock of structural capital” (Rosenthal and Helsley, 1994, p. 186). If developers have an infinite time horizon and demolition is costless, the optimal redevelopment time occurs when the value of the structure has depreciated to zero.

An important implication of this decision rule is that the sale price of a property that is immediately redeveloped – i.e., a teardown – will equal its land value: the current set of structural characteristics will have no influence on its sale price. The empirical portion of the study by Rosenthal and Helsley (1994) tests whether this decision rule explains the probability of redevelopment for a sample of single-family homes in Vancouver. As their data does not include measures of structural characteristics, they were unable to test the prediction that the sales prices of teardown properties are unaffected by characteristics of the current structure.

Using data from suburban Chicago for 1993-2004, Dye and McMillen (2007) find support for the prediction, finding that structural variables do not offer statistically significant explanatory power in a hedonic price function for approximately 1400 teardown properties. However, McMillen and O'Sullivan (2013) find that the estimated standard errors decline sufficiently when the data set is expanded to include sales through 2008 that some coefficients for structural characteristics are statistically significant. The variables that are significant – square footage, the presence of a full basement, and an indicator that the structure has two or more stories – tend to be associated with higher-quality structures and potentially higher demolition costs. The structural variables provide much greater explanatory power in the sample of non-teardown properties than in the teardown sample.

The empirical finding that structural characteristics offer some but reduced explanatory power in the sample of properties that are eventually demolished is consistent with the predictions of McMillen and O'Sullivan's (2013) theoretical model. They explicitly account for the role of uncertainty in the future price of structural capital in the redevelopment decision. The irreversibility of the demolition decision implies that there is a value to delaying decision in order to observe future returns to the structural characteristics. For example, if the current house is small and buyers will pay a premium for larger houses, it may be optimal to demolish the property now. But if there is uncertainty whether the current premium for large houses will be maintained over time, it may be optimal to wait until the future to demolish the home. The model predicts that structural characteristics do not influence the sale price of a home that is demolished immediately after purchase, but otherwise the contribution of structural characteristics will increase with the expected length of time between the purchase and eventual demolition date. The empirical results are consistent with this prediction: the magnitude of the coefficients for structural characteristics declines with the estimated probability of demolition concurrent with the time of sale.[4]

Redevelopment dates are concurrent with demolition in these theoretical models. In practice, buildings are often demolished with no intention of replacing them with new structures in the foreseeable future. In a model with certainty, demolition without replacement will occur when (1) the current demolition cost plus the present value of the holding costs of a building has fallen below present value of the stream of expected rents from the current structure and (2) the expected return from a new building is less than the construction cost.

[4] This result can also be explained in terms of Clapp and Jou's (2012) model of option value in the housing market. They show that the equilibrium hedonic price function reflects the value of the option to redevelop at a higher intensity per unit land value. Structural characteristics can influence the sale price of a home that is eventually demolished if they are correlated with the option value at the time of sale.

3. Empirical Modeling of the Demolition Decision

The fact that demolitions with and without redevelopment can take place in different areas of a city at the same time poses challenges for empirical analysis. It is reasonable to expect variables such as square footage to have different effects on the probability of a demolition permit in different areas of a city. Studies of active teardown markets suggest that demolition permits are more likely for small buildings on large lots. In areas of the city where lots are more likely to be left vacant after a structure is demolished, it is reasonable to expect that large buildings will be more likely to have demolition permits because taxes and maintenance costs tend to be higher for bigger structures. Although teardowns and demolitions could be modeled separately if a clear distinction could be made be made between the two types of redevelopment, mistakes in classification are inevitable and there are bound to be transition areas where neither form of redevelopment is taking place.

A conditionally parametric model has significant advantages in this situation.[5] The idea is simply to allow the coefficients to vary smoothly over space. For a standard linear regression model, the CPAR model is:

$$y_i = \beta(lo_i, la_i)' x_i + u_i \tag{1}$$

where *y* is the dependent variable, *x* is a set of explanatory variables, *u* is the error term, and the location of observation *i* is given by the geographic coordinates, lo_i and la_i. A kernel weighting function specifies the weight given to observation *j* when estimating the coefficients for any target location, including observation *i*. In the urban economics and geography literature, the CPAR

[5] The CPAR approach for standard regression analysis is presented in Cleveland (1994), Cleveland et al. (1992), and Loader (1999). Applications to spatial models of discrete choice include Atkinson et al. (2003), McMillen and McDonald (2004), McMillen and Soppelsa (forthcoming), Wang, et al. (2011), and Wrenn and Sam (2014).

model is often referred to as "geographically weighted regression," and the approach has been developed by Meese and Wallace (1991) and McMillen (1996) as a variant of the more general locally weighted regression procedure proposed by Cleveland and Devlin (1988).

An important advantage of the approach for modeling the probability of demolition is that it does not require the researcher to specify beforehand which areas of the city are locations where a demolition is a teardown. Identifying teardowns requires data on demolition permits and characteristics of the structure before and after demolition. Unfortunately, data on structural characteristics are not readily available at multiple times, and the accuracy of the data is often suspect. Under the reasonable assumption that teardowns and true demolitions are each spatially clustered, the CPAR approach provides accurate estimates of demolition permit probabilities for both types of properties.

Tibshirani and Hastie (1987) and Fan, et al. (1995) show that the locally weighted model can be extended readily to the case of maximum likelihood estimators by weighting the log likelihood function by the kernel weights, w_j. The pseudo log-likelihood function for the target location (*lo*, *la*) is simply $\sum_{j=1}^{n} w_j lnL_j$. The pseudo log-likelihood function for the CPAR probit model is:

$$\sum_{j=1}^{n} w_j \left[y_j ln\Phi\big(\beta(lo,la)'x_j\big) + \big(1-y_j\big) ln\left(\Phi\big(-\beta(lo,la)'x_j\big)\right)\right] \qquad (2)$$

where *y* now represents a discrete variable and Φ is the standard normal distribution function. Following White (1982), a consistent estimate of the covariance matrix for $\hat{\beta}(lo,la)$ is

$$\left(\sum_{j=1}^{n} w_j \frac{\phi_j^2}{\Phi_j\big(1-\Phi_j\big)} x_j x_j'\right)^{-1} \left(\sum_{j=1}^{n} w_j^2 \left(\frac{y_j - \hat{\beta}' x_j}{\Phi_j\big(1-\Phi_j\big)}\phi_j\right)^2 x_j x_j'\right)\left(\sum_{j=1}^{n} w_j \frac{\phi_j^2}{\Phi_j\big(1-\Phi_j\big)} x_j x_j'\right)^{-1} \qquad (5)$$

where ϕ represents the standard normal density function.

Although the coefficients and standard error estimates can be constructed easily using standard statistical software packages that have weight options for the log-likelihood function, the CPAR probit model is computationally intensive. McMillen and Soppelsa (forthcoming) show that the approach becomes feasible for very large data sets by taking advantage of the smoothness of the coefficients over space to estimate the model at a small number of carefully chosen target points and then interpolating to other locations. Following Loader (1999, pp. 215-217), they use an adaptive decision tree approach to identify a small set of target points (122 in their application), and then interpolate to the full set of data points using the modified Shepard algorithm of Franke and Neilson (1980). I again use Loader's approach to identify target points in the empirical section of this paper, but I instead use the Akima (1978) method of interpolation because it provided a better statistical fit in this application.

After interpolation, the CPAR estimation procedure produces very large, *n*x*k* matrices of estimated coefficients and local standard errors, where *n* is the number of observations and *k* is the number of explanatory variables (including the intercept). I use three procedures to summarize the results. First, I present simple kernel density function estimates to show the distribution of coefficient estimates and z-values for each explanatory variables. Second, I use maps to show the variation in the estimates across census tracts. Finally, I adapt an approach developed by McMillen (forthcoming) for spatial quantile models to show how the distribution of predicted demolition probabilities shifts with discrete changes in an explanatory variable, an approach that in turn was based on the counterfactual distribution approached proposed by Machado and Mata (2005).

Let the estimated coefficients for observation i be denoted by $\hat{\beta}_i = \hat{\beta}(lo_i, la_i)$. The estimated probability that $y_i = 1$ is simply $\hat{p}_i = \Phi\left(\hat{\beta}' x_i\right)$. Now suppose we want to illustrate the effect of changing variable from $x_1 = \delta_1$ to $x_1 = \delta_2$, where the matrix of explanatory is now written $x = (x_1 \quad x_2)$. Holding the variables in x_2 to their actual values and setting x_1 to the two discrete values δ_1 and δ_2, we have:

$$\hat{p}_i(x_1 = \delta_1) = \Phi\left(\hat{\beta}_1\delta_1 + \hat{\beta}_2{}'x_{2i}\right) \tag{3}$$

$$\hat{p}_i(x_1 = \delta_2) = \Phi\left(\hat{\beta}_1\delta_2 + \hat{\beta}_2{}'x_{2i}\right) \tag{4}$$

A comparison of kernel density function estimates for equation (3) and (4) provides a simple visual representation of the effect of a discrete change in x_1 on the probability that $y = 1$. Standard errors for the counterfactual distributions can be constructed using the approach presented in Chernozhukov, Fernandez-Val, and Melly (2013).

4. Data

The data for the study are drawn from two sources. Data on various forms of building permits is published online by the Chicago Metropolitan Association for Planning (CMAP). The CMAP files show the address, parcel identification number, and date of issue for demolition permits, renovations and alterations, new construction, and general repairs. For this study, I will focus on demolition permits, which are closely tied to redevelopment. The dependent variable for the CPAR probit models is a discrete variable that equals one if a demolition permit was issued for a property any time during the 2000 – 2014 period covered in the data set.

The parcel identification number makes it possible to merge the permit data with data from the Cook County Assessor's Office on structural characteristics of all properties as of 1997. These structural characteristics include standard explanatory variables in a hedonic price function: building area, lot size, building age in 2000, number of bathrooms, and indicators of a multi-unit building, brick construction, central air conditioning, a basement, a fireplace, and a 1-car or 2+ car garage. I restrict the sample to "Class 2" properties, which are defined for purposes of tax assessment as residential buildings with six units or fewer.

Descriptive statistics for these variables are presented in Table 1. After eliminating observations with missing data, the data set has 367,762 properties, of which 6,548 (1.8%) had demolition permits issued during the 2000-2014 period. The data set also includes the assessed value of the property in 2000. Class 2 properties are typically assessed at between 9-10% of property value. Thus, the mean assessed value of $15,167 translates into an assessed market value of approximately $150,000 across the entire sample.

Figure 1 shows the geographic distribution of demolition permits across census tracts. Of the 864 census tracts in Chicago, 162 (19.0%) had no properties with demolition permits issued during 2000-2014. Figure 1 shows that there are clusters of census tracts with relatively large numbers of demolitions permits just west of Lake Michigan on the north side of the city, in a region on the west side, and in several areas of the south side. For some perspective on these areas, Figure 2 shows the log of median household income from the 2000 US Census. The north-side cluster of demolition permits is located in one of the highest-income areas of Chicago. The cluster on the extreme south side of the city is in a moderately high-income area. In contrast, the two clusters on the west side and the middle of the south side are both in very low-income areas. Thus, there is good reason to expect that a single global parametric probit model will not adequately account for the spatial variation in the determinants of demolition probabilities.

5. CPAR Probit Results

The base parametric probit results are presented in Table 2. The set of results labeled "base model" does not include any controls for location. The "fixed effects" model includes controls for 75 community areas, which is the standard definition of neighborhoods in Chicago. After controlling for location, the results indicate that demolitions are more likely for small buildings on large lots. Lower-priced properties are more likely to be demolished. Brick buildings with garages are less likely to be demolished, most likely because they are both more costly to tear down and of generally higher quality than other structures.

The results of the parametric models are clearly sensitive to the controls for location. Conditionally parametric models can be quite useful in this situation. By allowing the coefficients to vary smoothly over space, the CPAR probit model avoids the somewhat arbitrary nature of the fixed effects approach, which allows for discrete changes at neighborhood boundaries but constant effects within neighborhoods. The fixed effects assumption may be reasonable if the neighborhood definition is correct, but it may be just as reasonable to use census tracts or even blocks as the appropriate unit for the fixed effects. Although the CPAR approach can potentially be modified to allow for discrete boundaries, it is more common to assume that the effects of location vary smoothly over the sample area. The results are essentially a smoothed version of the fixed effects model if only the intercept varies over space. However, the approach is more general since the coefficients for other variables can also vary over space.

I use a tri-cube kernel with a 25% window size for the CPAR probit estimates. The adaptive decision tree algorithm identifies 73 target locations. I then use the Akima (1978) method to interpolate the estimated coefficients to the full set of 367,762 data points. Means and standard deviation for the estimates are presented in Table 2.

Figure 3 presents kernel density estimates for the sets of coefficient estimates. Several of the variables have large numbers of both negative and positive values, including log lot size, log assessed value, central air conditioning, and indictors that the structure has a basement and a fireplace. Although the coefficients for other variables do vary over space, it is clear that higher demolition rates are predicted for smaller, older, multi-unit buildings with more bathrooms, without garages, and with non-brick construction. In contrast, the distribution of coefficients is double-peaked for the indicators that a structure has a basement or a fireplace, with separate peaks on the positive and negative sides of the graphs.

Figure 4 shows the distribution of implied z-values (i.e., the ratio of estimate coefficients divided by local standard errors). Several variables are statistically significant with the same sign in nearly all locations: the probability of having a demolition permit declines significantly with building area, brick construction, and the presence of a garage, while demolition probabilities rise with the age of the structure. The estimated coefficients for the number of bathrooms and multi-unit buildings are nearly all statistically significant and positive or insignificant. The estimates for central air conditioning, a basement, and fireplace are usually statistically insignificant. For several key variables – log lot size, log assessed value, and basements – the estimated coefficients are nearly equally as likely to be either statically significant and positive or significantly negative.

Figures 5 and 6 show the spatial distribution of the estimated coefficients and z-values across the city. The maps show the average value of the estimates by census tract. The colors denote regions based on benchmarks for z-values: -1.96, -1.64, 0, 1.64, and 1.96, with blues representing negative values and reds for positive.[6] The maps reinforce most of the results shown

[6] The map for log age is shown entirely in reds because all estimated coefficients are statistically significant and positive.

in the kernel density graphs. Building area, brick construction, and garages have statistically significant negative coefficients virtually everywhere in the city, while age always has a positive effect on the probability of demolition. In contrast, lot size has a statistically significant positive effect on the probability of demolition in the high-income areas of the city along the lake on the north side and in the northwest side of the city, but it has a statistically significant negative effect in lower-income parts of the city. The pattern of results is similar for log assessed values.

The magnitudes of the estimated effects of discrete changes in the explanatory variables are illustrated in Figure 7. Increasing building area from 1000 to 2000 to 3000 square feet (or log values from 6.91 to 7.60 to 8.01) leads to a large increase in the density of demolition probabilities near zero. Increasing lot size from 3000 to 6000 to 9000 square feet leads to a marked increase in the density of estimated demolition probabilities at higher values, near 0.01. (To keep these figures in perspective, it is important to note that permits were issued for only 1.8% of the observations.) Changes in assessed values have virtually no effect on the overall distribution of demolition probabilities, while increases in age greatly increase the probability of above-zero probabilities. Multi-unit buildings are more likely to be demolished than single-unit properties, and brick buildings are much less likely to be demolished than others. Garages are associated with lower probabilities of demolition.

6. Parametric Probit Models by Region

Nonparametric estimates can help guide the specification of a parametric model by revealing where a simple global model appears to be inadequate. The maps of estimated coefficients suggest that the northeast and northwest sides of Chicago are distinctly different from other parts of the city, particularly the low-priced areas on the west and south sides. This section presents the results of separate parametric models estimated for five different regions of the city. Prior to the 1990s, the five regions comprised separate districts for official property assessments. They correspond roughly to the distinct regions evident in the coefficient maps.

The results for the base parametric specification are shown in Table 3. Table 4 adds fixed effects for the community areas represented within the five districts. The results do suggest that there is significant variation across districts. Whereas demolition probabilities are estimated to be lower for larger buildings for all five districts, larger lot sizes are associated with higher demolition probabilities in the northwest and northeast regions, while the estimated coefficients for log lot size are negative or insignificant in the other three regions. Compared with the simple, global specification in Table 2, the district-level estimates are much more stable across Table 3 and 4 when controls for community area are added to the probit models.

7. Conclusion

The most commonly used spatial econometric models typically assume that a global parametric specification adequately accounts for any spatial heterogeneity in the data. Variants of the spatial autoregressive and spatial error models have been adapted to the case of discrete dependent variables in such studies as Case (1992), McMillen (1992), LeSage (2000), Pinkse and Slade (1998), and Klier and McMillen (2008). Unfortunately, parametric models often produce inconsistent coefficient estimates when a model is misspecified, and misspecification may well be the rule rather than the exception when trying to fit a single model to a large urban area.

This study illustrates some of the advantages of a conditionally parametric approach to modeling spatial data. Teardowns have become widespread in many large urban areas. Though controversial, they also play an important role in the process of urban redevelopment. Yet teardowns are not easily defined using existing data sources. Demolition permits indicate that a property owner plans to demolish the existing structure; they do not automatically imply that the structure is going to be replaced with a new one. Demolition permits are common in high-demand neighborhoods where a teardown is clearly going to be replaced with a new building reflecting current demand conditions, yet they also are common in low-priced, declining neighborhoods where there is no intention of replacing the demolished structure any time soon. How long is the delay between demolition and new construction for a teardown versus a simple demolition? What are the geographic limits of prime teardown markets?

The empirical results suggest that there are clear differences between demolition probabilities in different parts of Chicago. In the high-priced markets in the north side of the city, demolition permits are more likely to be issued for small building on large lots, whereas the probability of a demolition permit is estimated to decline with lot size in much of the rest of the city. Building area has little or no effect on demolition probability in much of the low-priced area on the west side of city, whereas it has a highly significant effect in high-priced northern neighborhoods. The significant variation in all estimated coefficient across the city is strong evidence that a simple, global parametric specification is inappropriate for such a large city. However, the CPAR estimates do serve as a valuable guide to the specification of an acceptable parametric model. Since the estimates differ systematically across various regions of the city, estimating simple parametric models for sub-regions of the city may prove an acceptable alternative to nonparametric modeling.

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Table 1

Descriptive Statistics (367,762 obs.)

	Mean	Std. Dev.	Minimum	Maximum
Demolition Permit Issued	0.018	0.132	0	1
Log of Building Area	7.315	0.486	5.476	9.903
Log of Lot Size	8.255	0.325	3.178	13.312
Log of Assessed Value in 2000	9.437	0.781	0	12.969
Log of Building Age	4.209	0.524	0	5.242
Number of Bathrooms	1.726	0.955	1	43
Multi-Unit	0.309	0.462	0	1
Brick	0.628	0.483	0	1
Central Air Conditioning	0.155	0.362	0	1
Basement	0.759	0.428	0	1
Fireplace	0.086	0.281	0	1
1-Car Garage	0.211	0.408	0	1
2+ Car Garage	0.532	0.499	0	1

Table 2

Probit Results

	Base Model		Fixed Effects		CPAR	
	Coefficient	Std. Error	Coefficient	Std. Error	Mean	Std. Dev.
Intercept	-4.3813	0.2498	-3.4583	0.2659	-3.999	3.178
Log of Building Area	-0.2165	0.0208	-0.3875	0.0226	-0.373	0.260
Log of Lot Size	-0.1573	0.0206	0.1590	0.0234	-0.013	0.315
Log of Assessed Value in 2000	-0.0004	0.0082	-0.0880	0.0083	0.049	0.342
Log of Building Age	1.1778	0.0262	0.7711	0.0288	0.935	0.231
Number of Bathrooms	0.0517	0.0088	0.0354	0.0095	0.051	0.031
Multi-Unit	0.1323	0.0168	0.1659	0.0184	0.180	0.141
Brick	-0.2640	0.0130	-0.2321	0.0143	-0.259	0.088
Central Air Conditioning	0.0664	0.0223	-0.0378	0.0242	-0.043	0.084
Basement	0.0561	0.0140	0.0186	0.0154	0.015	0.070
Fireplace	0.0280	0.0232	-0.0412	0.0250	-0.008	0.092
1-Car Garage	-0.1631	0.0154	-0.1445	0.0163	-0.162	0.050
2+ Car Garage	-0.1322	0.0129	-0.1045	0.0137	-0.161	0.058

Notes. The number of observations is 367,762. The fixed effects model includes controls for 75 community areas.

Table 3
Probit Estimates by Region

	Northwest	Northeast	Central	Southwest	Southeast
Intercept	-8.435 (0.811)	-4.326 (0.608)	-1.977 (0.524)	-0.957 (0.471)	-4.136 (0.698)
Log of Building Area	-0.688 (0.069)	-0.873 (0.063)	-0.245 (0.039)	-0.166 (0.041)	-0.177 (0.061)
Log of Lot Size	0.368 (0.061)	0.244 (0.048)	-0.164 (0.043)	-0.277 (0.044)	-0.024 (0.057)
Log of Assessed Value in 2000	0.514 (0.093)	0.429 (0.051)	-0.034 (0.015)	-0.225 (0.012)	-0.095 (0.019)
Log of Building Age	0.717 (0.072)	0.693 (0.071)	0.791 (0.059)	0.989 (0.043)	1.031 (0.083)
Number of Bathrooms	0.044 (0.033)	0.048 (0.020)	0.025 (0.017)	0.073 (0.021)	0.069 (0.023)
Multi-Unit	0.183 (0.054)	0.336 (0.038)	0.062 (0.032)	0.137 (0.036)	0.216 (0.050)
Brick	-0.245 (0.039)	-0.323 (0.032)	-0.137 (0.026)	-0.274 (0.027)	-0.388 (0.040)
Central Air Conditioning	0.072 (0.046)	-0.006 (0.042)	-0.037 (0.070)	-0.069 (0.052)	-0.271 (0.105)
Basement	-0.096 (0.040)	-0.344 (0.049)	0.068 (0.026)	0.105 (0.026)	-0.150 (0.060)
Fireplace	0.076 (0.060)	-0.140 (0.045)	-0.025 (0.077)	0.009 (0.049)	0.003 (0.059)
1-Car Garage	-0.287 (0.043)	0.018 (0.056)	-0.101 (0.027)	-0.138 (0.027)	-0.143 (0.051)
2+ Car Garage	-0.244 (0.038)	0.075 (0.032)	-0.164 (0.026)	-0.168 (0.025)	-0.192 (0.037)
Number of Observations	62,099	27,717	95,884	53,239	128,823

Note. Standard errors are in parentheses.

Table 4
Probit Estimates by Region with Community Area Fixed Effects

	Northwest	Northeast	Central	Southwest	Southeast
Intercept	-5.900 (0.883)	-4.821 (0.558)	-1.087 (0.537)	-2.030 (0.526)	-3.146 (0.729)
Log of Building Area	-0.543 (0.071)	-0.736 (0.060)	-0.412 (0.041)	-0.259 (0.044)	-0.262 (0.065)
Log of Lot Size	0.528 (0.063)	0.836 (0.057)	-0.038 (0.048)	-0.124 (0.050)	-0.065 (0.061)
Log of Assessed Value in 2000	0.054 (0.100)	-0.020 (0.025)	-0.079 (0.015)	-0.131 (0.016)	-0.099 (0.020)
Log of Building Age	0.609 (0.080)	0.373 (0.050)	0.709 (0.062)	0.759 (0.047)	0.947 (0.092)
Number of Bathrooms	0.040 (0.033)	0.021 (0.022)	0.034 (0.017)	0.069 (0.022)	0.072 (0.023)
Multi-Unit	0.164 (0.057)	0.176 (0.039)	0.098 (0.034)	0.195 (0.039)	0.215 (0.053)
Brick	-0.232 (0.040)	-0.276 (0.033)	-0.136 (0.027)	-0.207 (0.028)	-0.408 (0.044)
Central Air Conditioning	0.056 (0.047)	-0.076 (0.045)	-0.071 (0.072)	-0.044 (0.054)	-0.262 (0.107)
Basement	-0.080 (0.041)	-0.218 (0.050)	0.045 (0.028)	0.040 (0.027)	-0.145 (0.062)
Fireplace	0.060 (0.062)	-0.147 (0.048)	-0.051 (0.079)	-0.032 (0.051)	-0.052 (0.061)
1-Car Garage	-0.272 (0.044)	0.024 (0.059)	-0.123 (0.028)	-0.147 (0.028)	-0.129 (0.053)
2+ Car Garage	-0.226 (0.038)	0.062 (0.034)	-0.122 (0.027)	-0.131 (0.026)	-0.150 (0.039)
Number of Community Areas	19	9	18	22	19
Number of Observations	62,099	27,717	95,884	53,239	128,823

Note. Standard errors are in parentheses.

Figure 1

Log of Number of 1 + Number of Demolition Permits by Census Tract

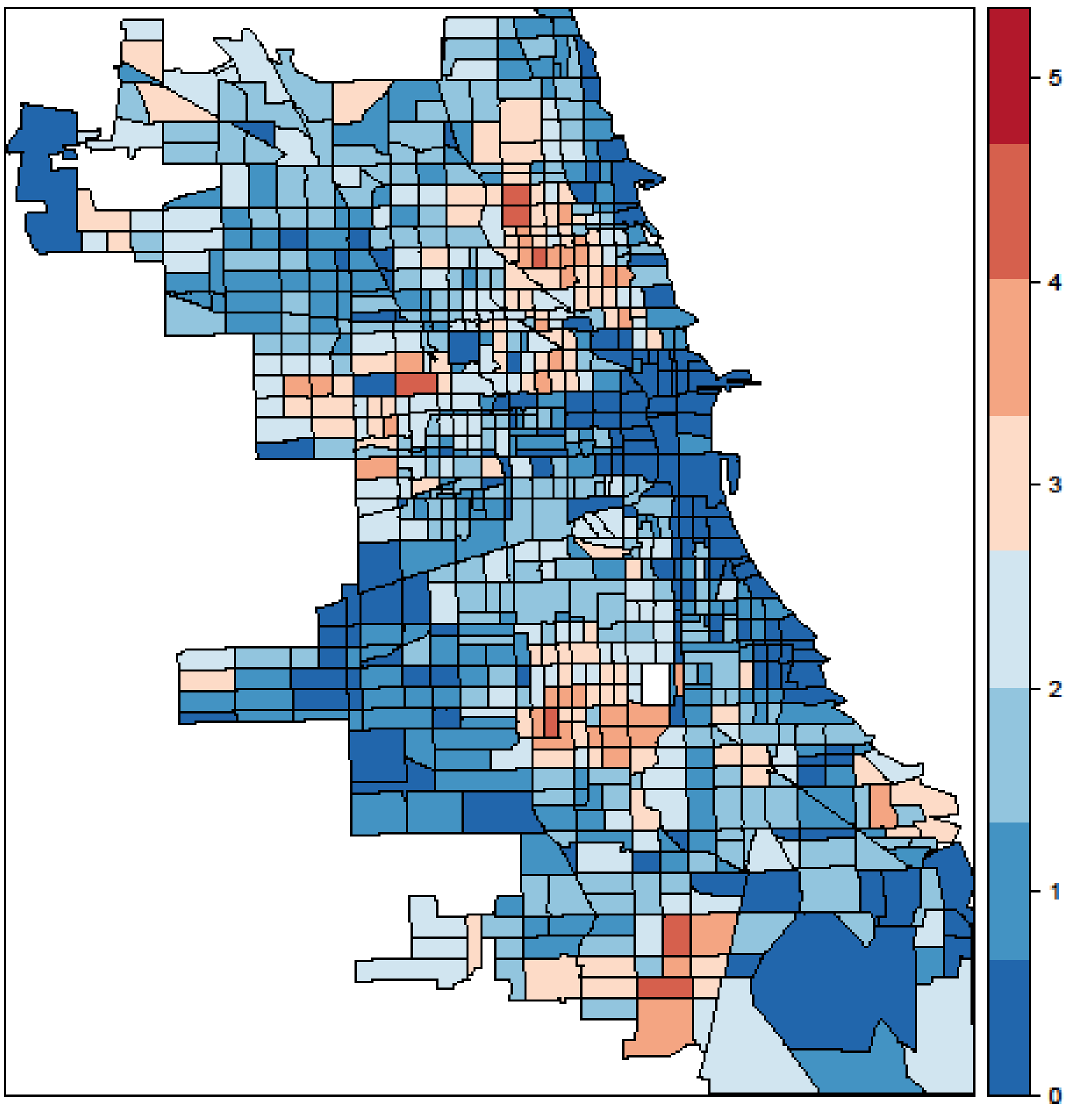


Figure 2

Log of Median Household Income by Census Tract

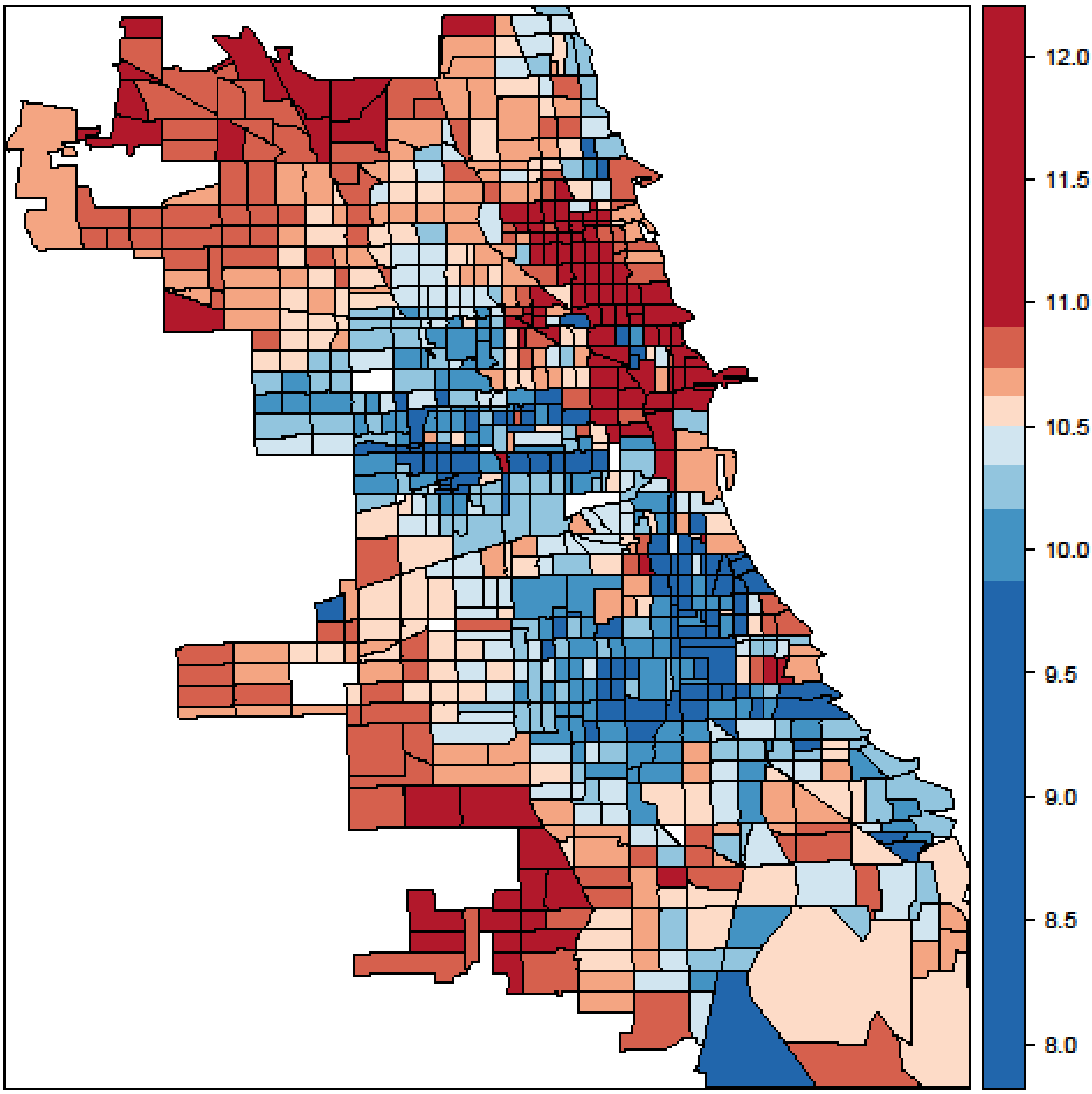
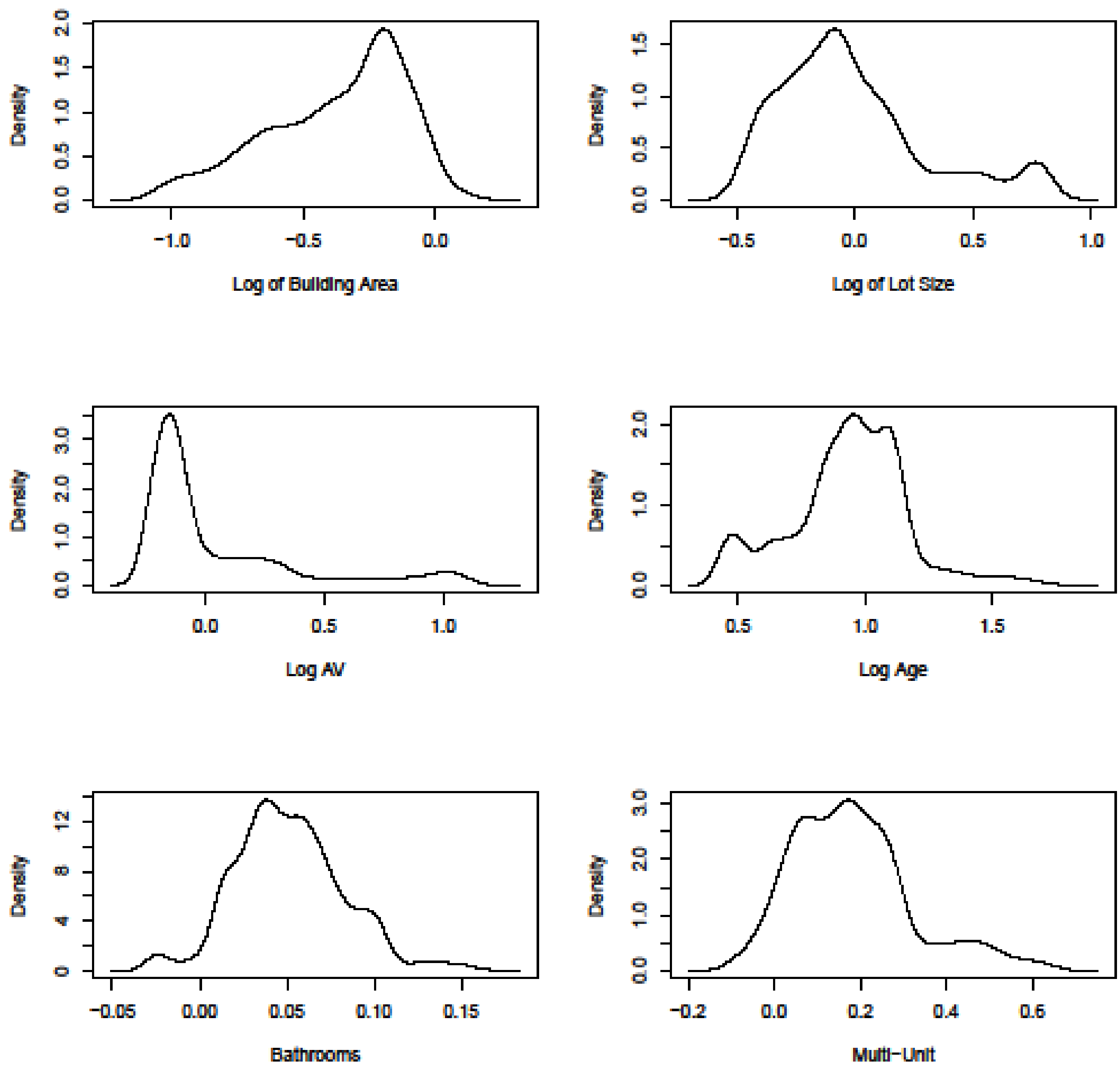


Figure 3

Density of Estimated CPAR Probit Coefficient Estimates



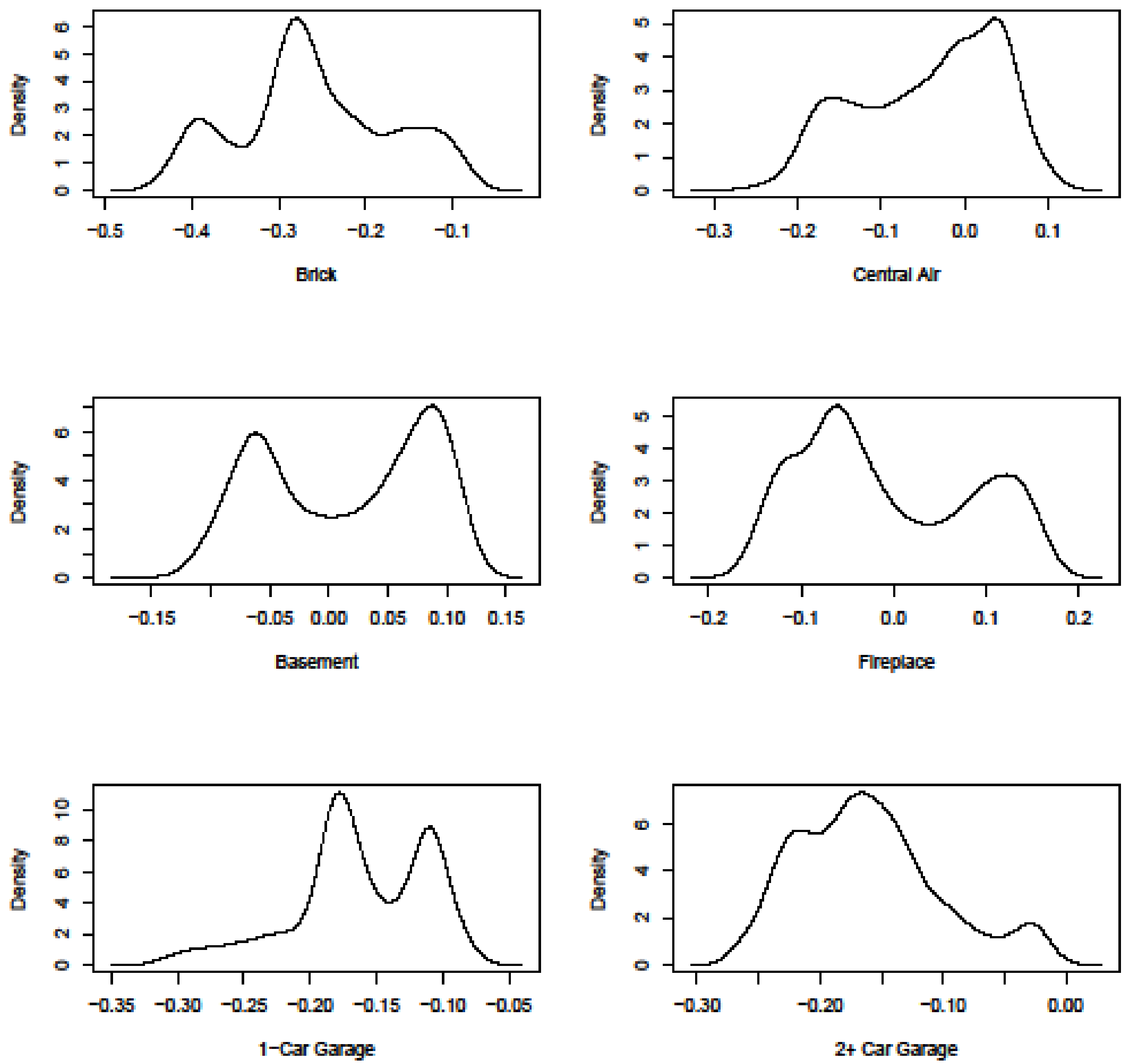
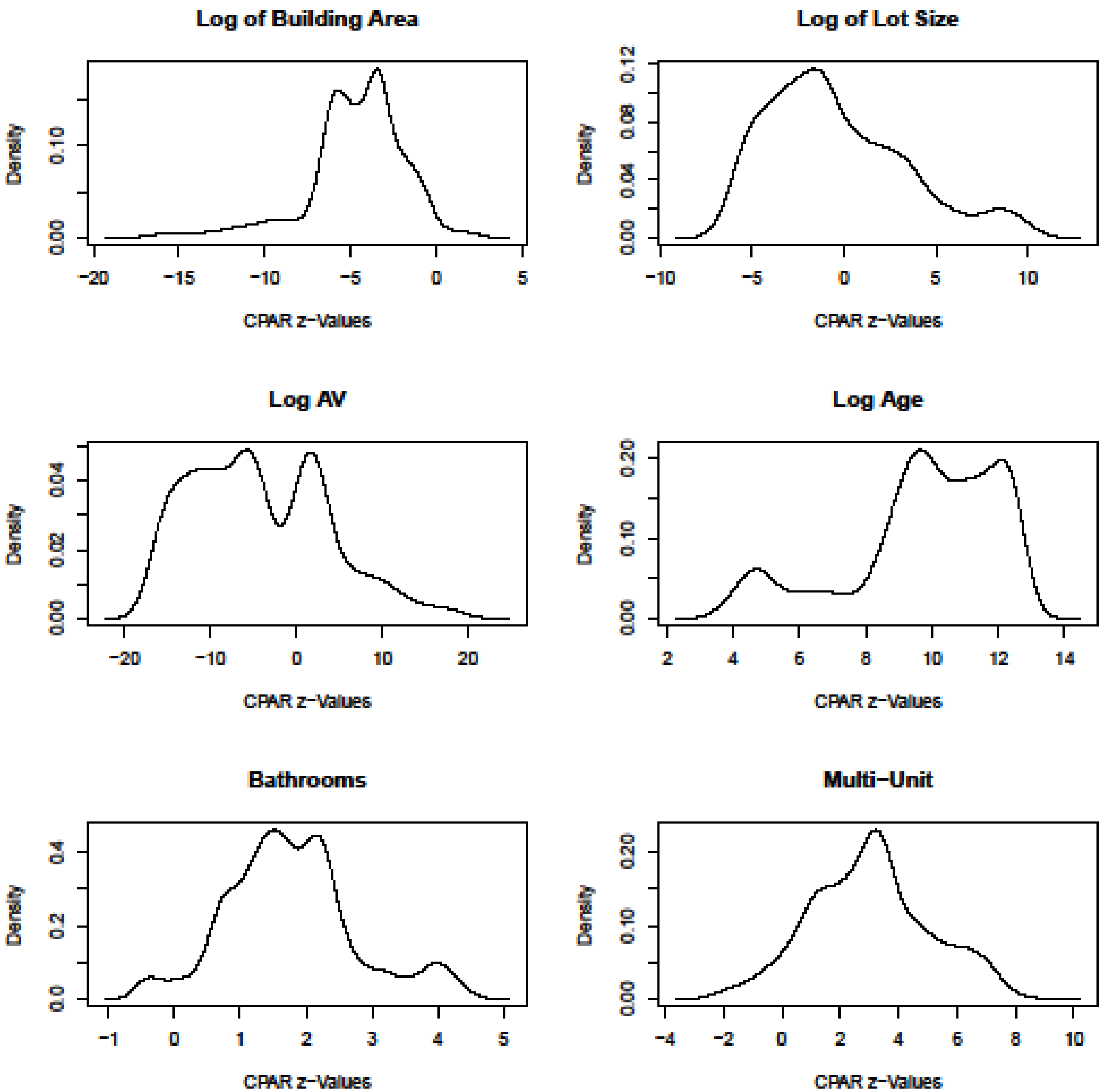

Density
Brick
−0.5
−0.4
−0.3
−0.2
−0.1
Central Air
−0.3
−0.2
−0.1
0.0
0.1
Basement
−0.15
−0.05
0.00
0.05
0.10
0.15
Fireplace
−0.2
−0.1
0.0
0.1
0.2
1−Car Garage
−0.35
−0.30
−0.25
−0.20
−0.15
−0.10
−0.05
2+ Car Garage
−0.30
−0.20
−0.10
0.00

Figure 4

Density of Estimated z-Values



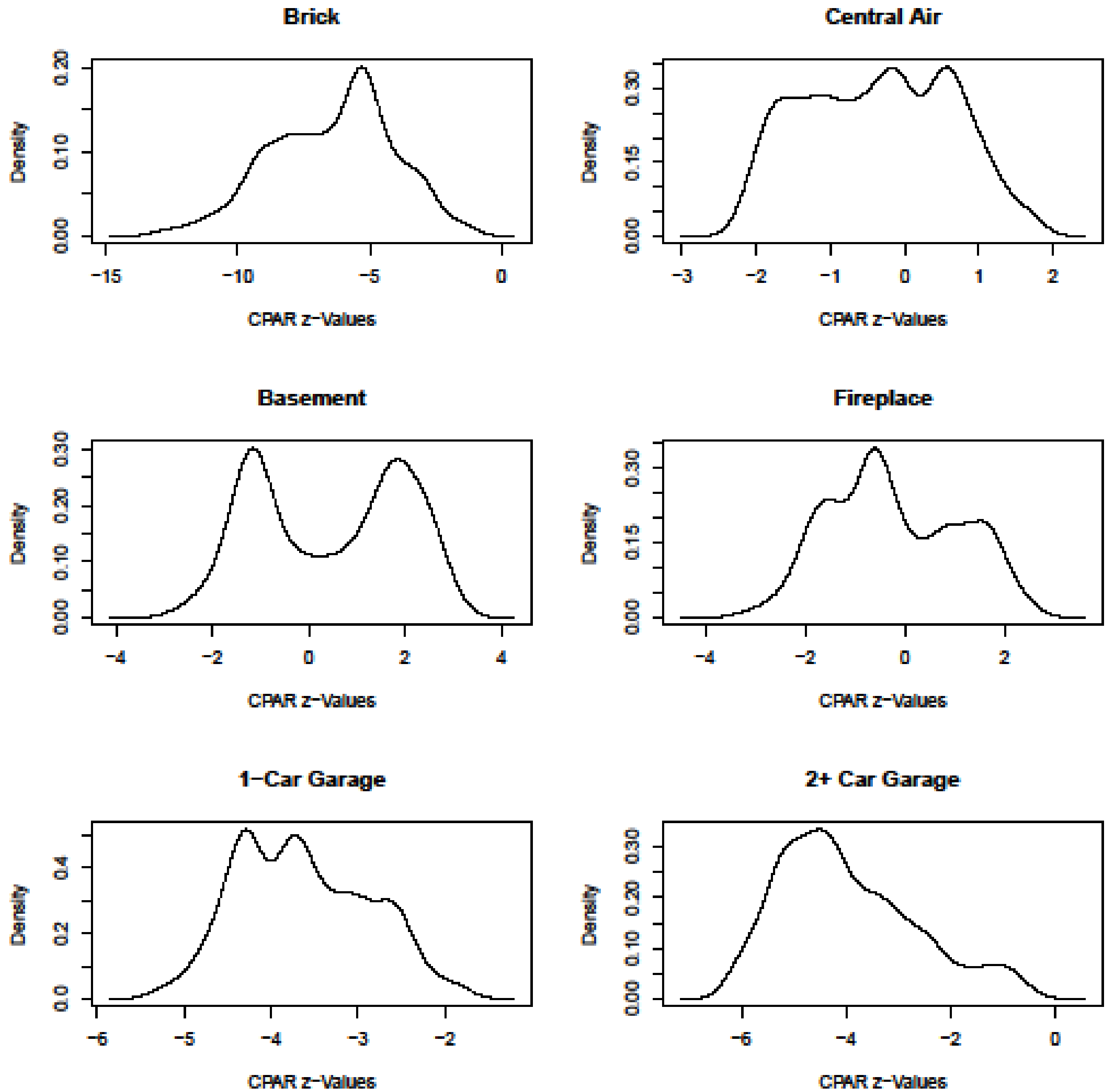
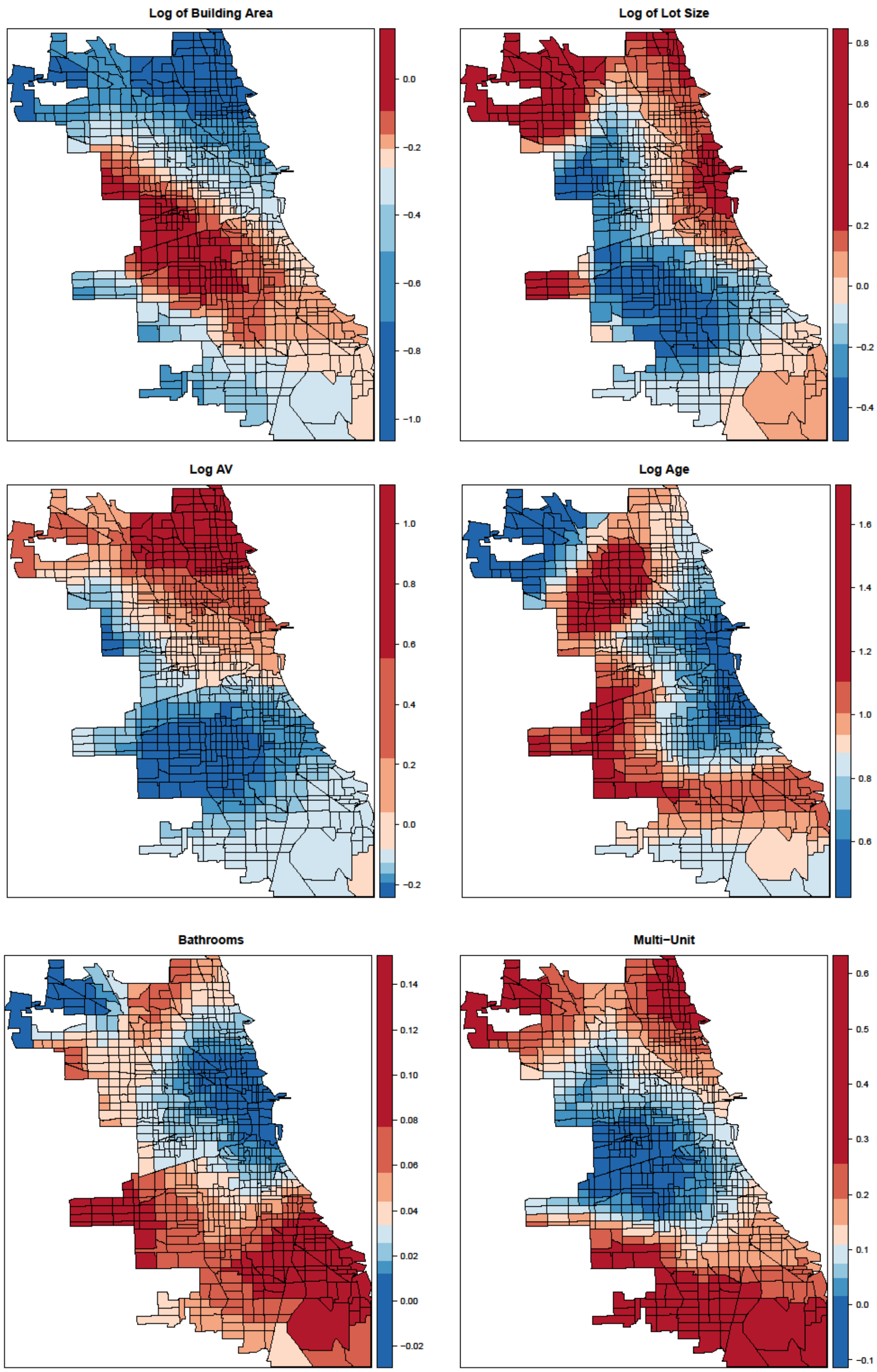

Brick
Density
0.00 0.10 0.20
−15 −10 −5 0
CPAR z−Values
Central Air
Density
0.00 0.15 0.30
−3 −2 −1 0 1 2
CPAR z−Values
Basement
Density
0.00 0.10 0.20 0.30
−4 −2 0 2 4
CPAR z−Values
Fireplace
Density
0.00 0.15 0.30
−4 −2 0 2
CPAR z−Values
1−Car Garage
Density
0.0 0.2 0.4
−6 −5 −4 −3 −2
CPAR z−Values
2+ Car Garage
Density
0.00 0.10 0.20 0.30
−6 −4 −2 0
CPAR z−Values

Figure 5
Average Coefficient Estimates by Census Tract



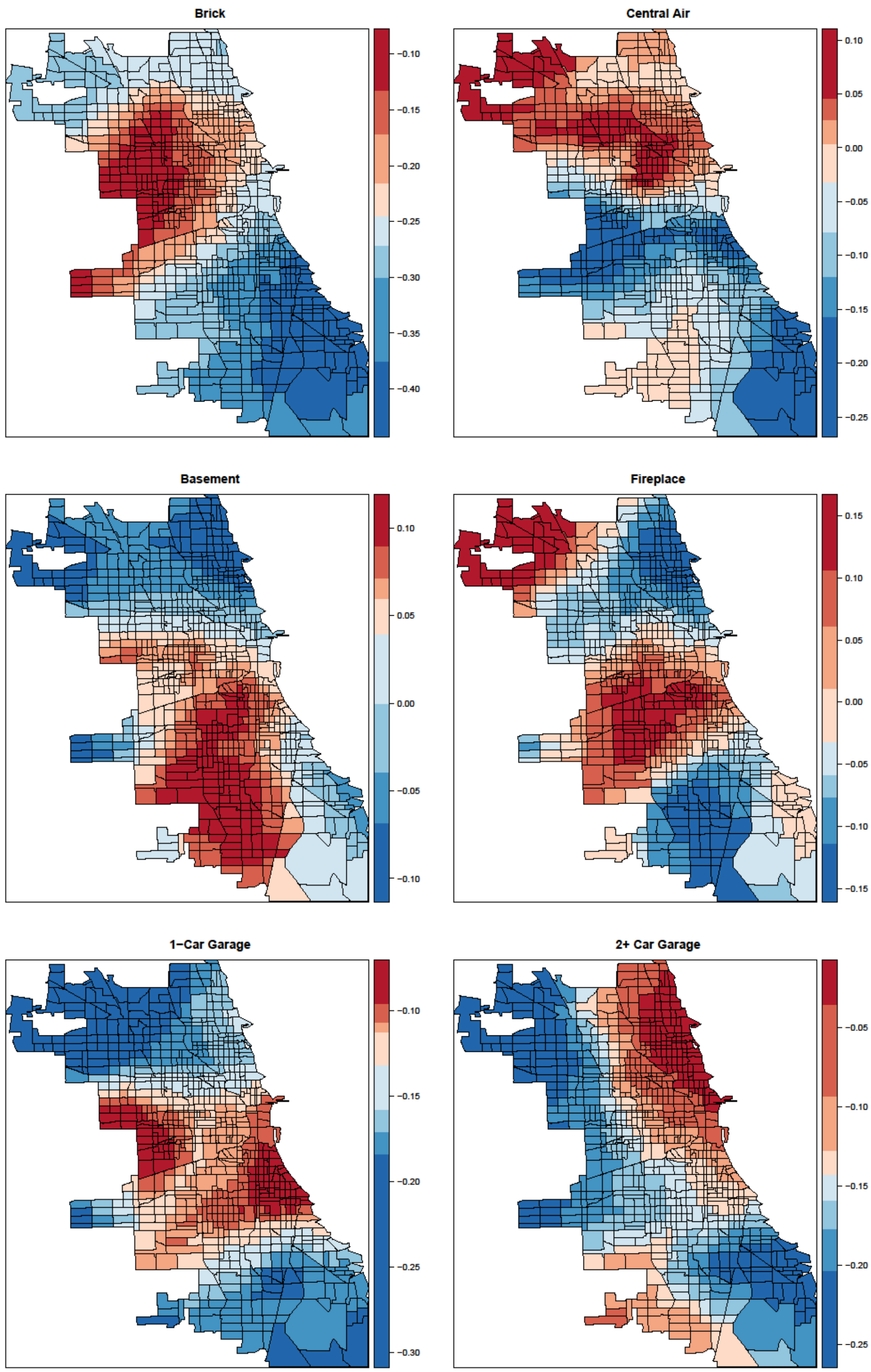
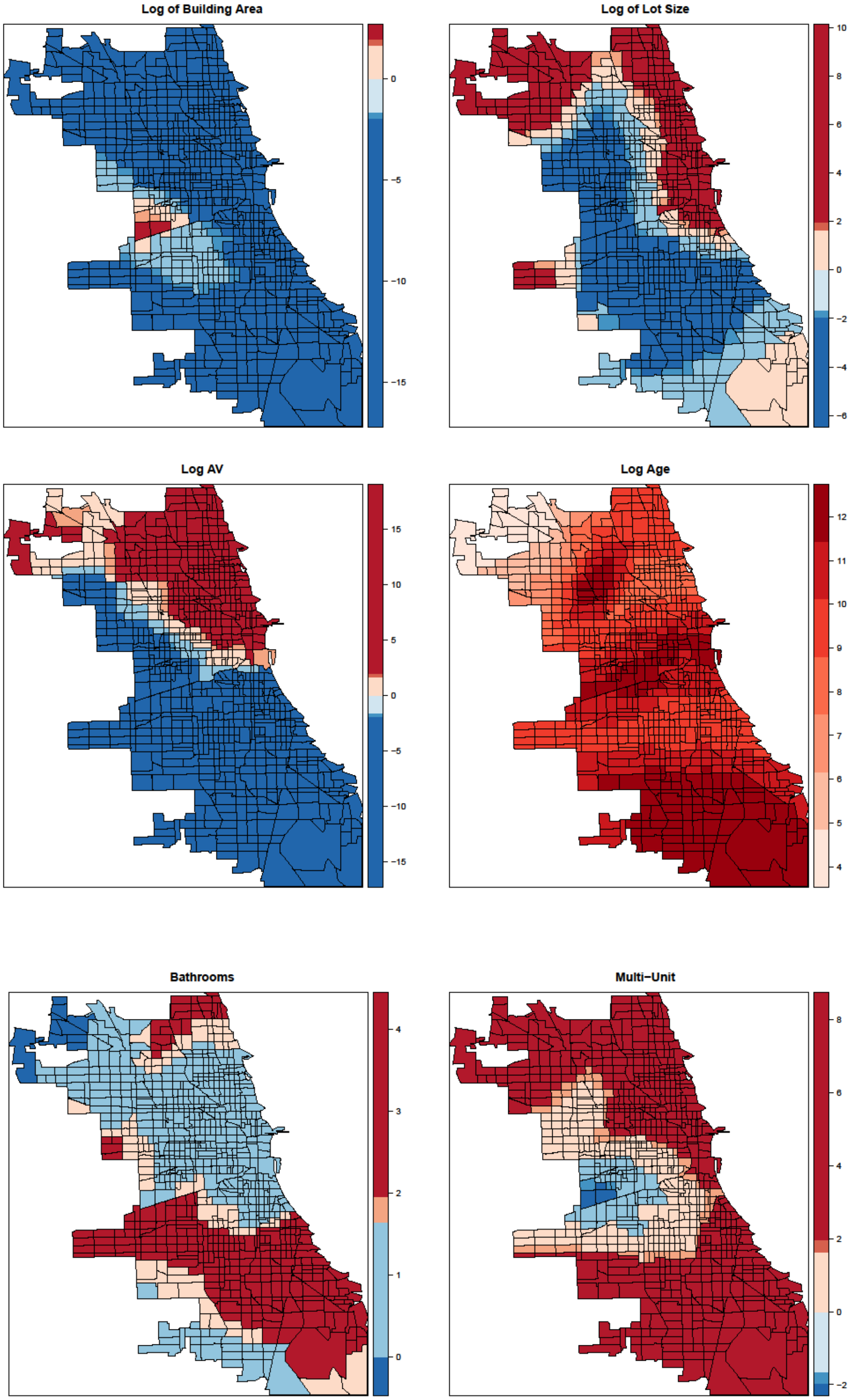

Brick
−0.10
−0.15
−0.20
−0.25
−0.30
−0.35
−0.40
Central Air
0.10
0.05
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
Basement
0.10
0.05
0.00
−0.05
−0.10
Fireplace
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
1−Car Garage
−0.10
−0.15
−0.20
−0.25
−0.30
2+ Car Garage
−0.05
−0.10
−0.15
−0.20
−0.25

Figure 6
Average z-Values Estimates by Census Tract



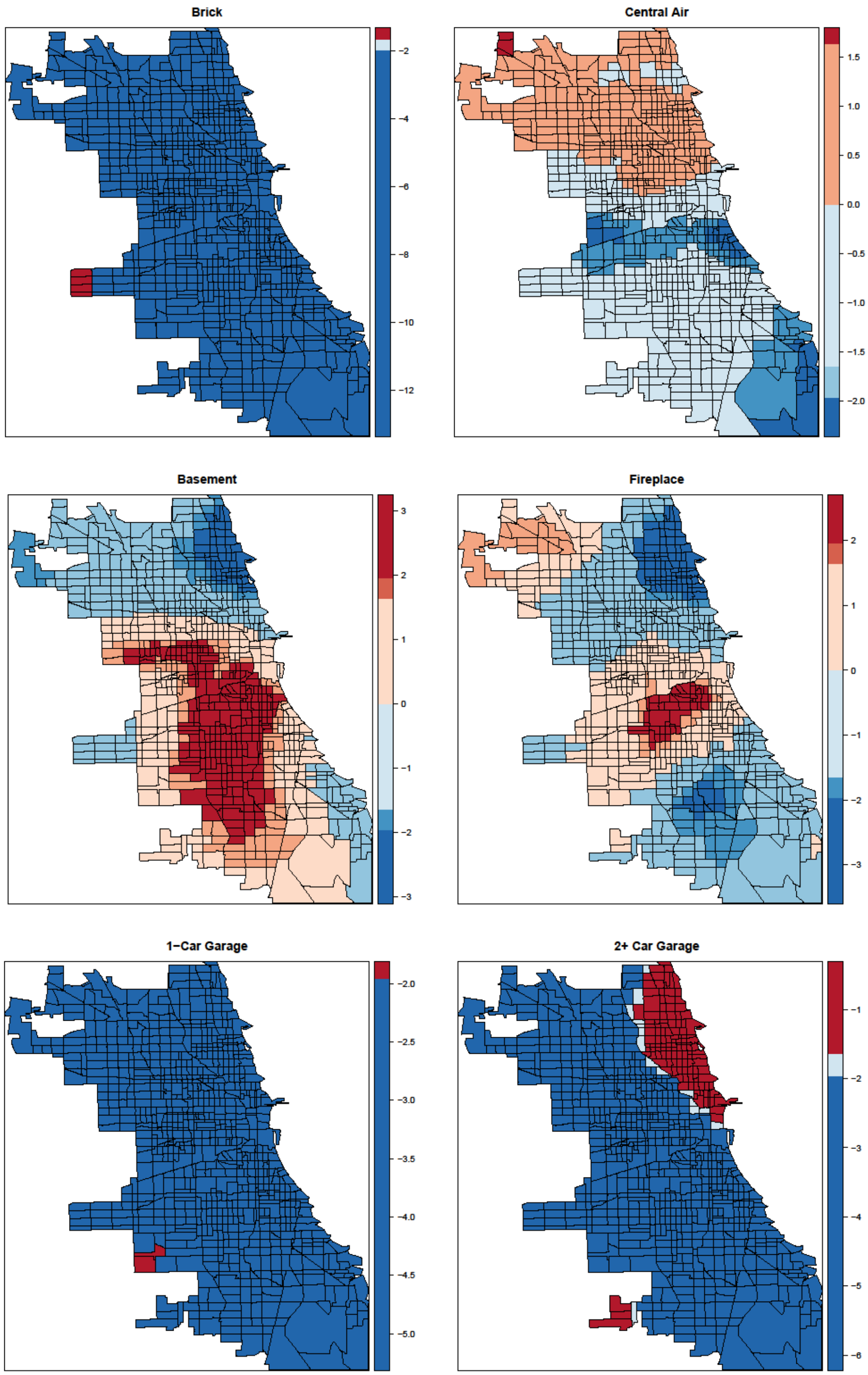
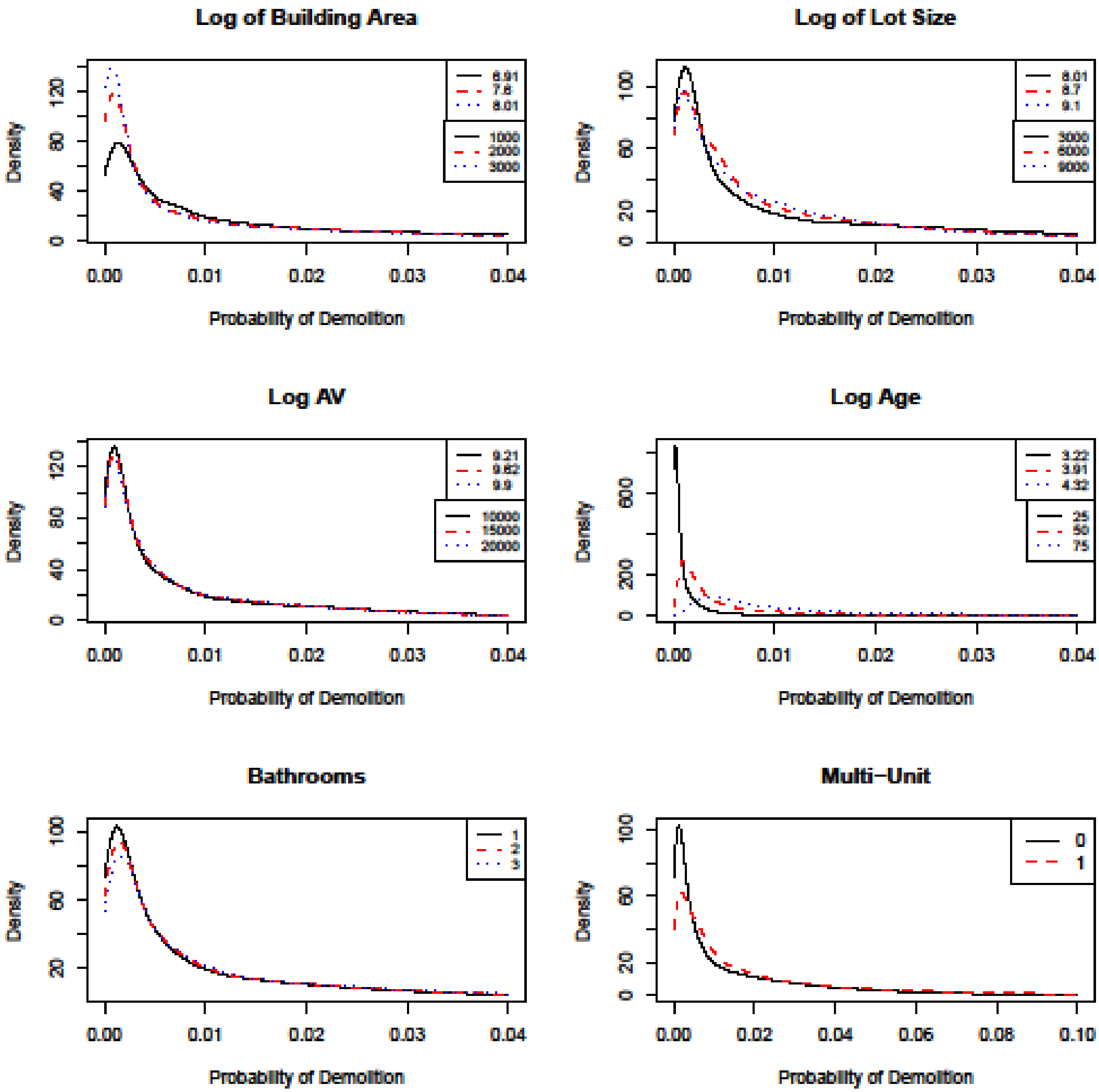
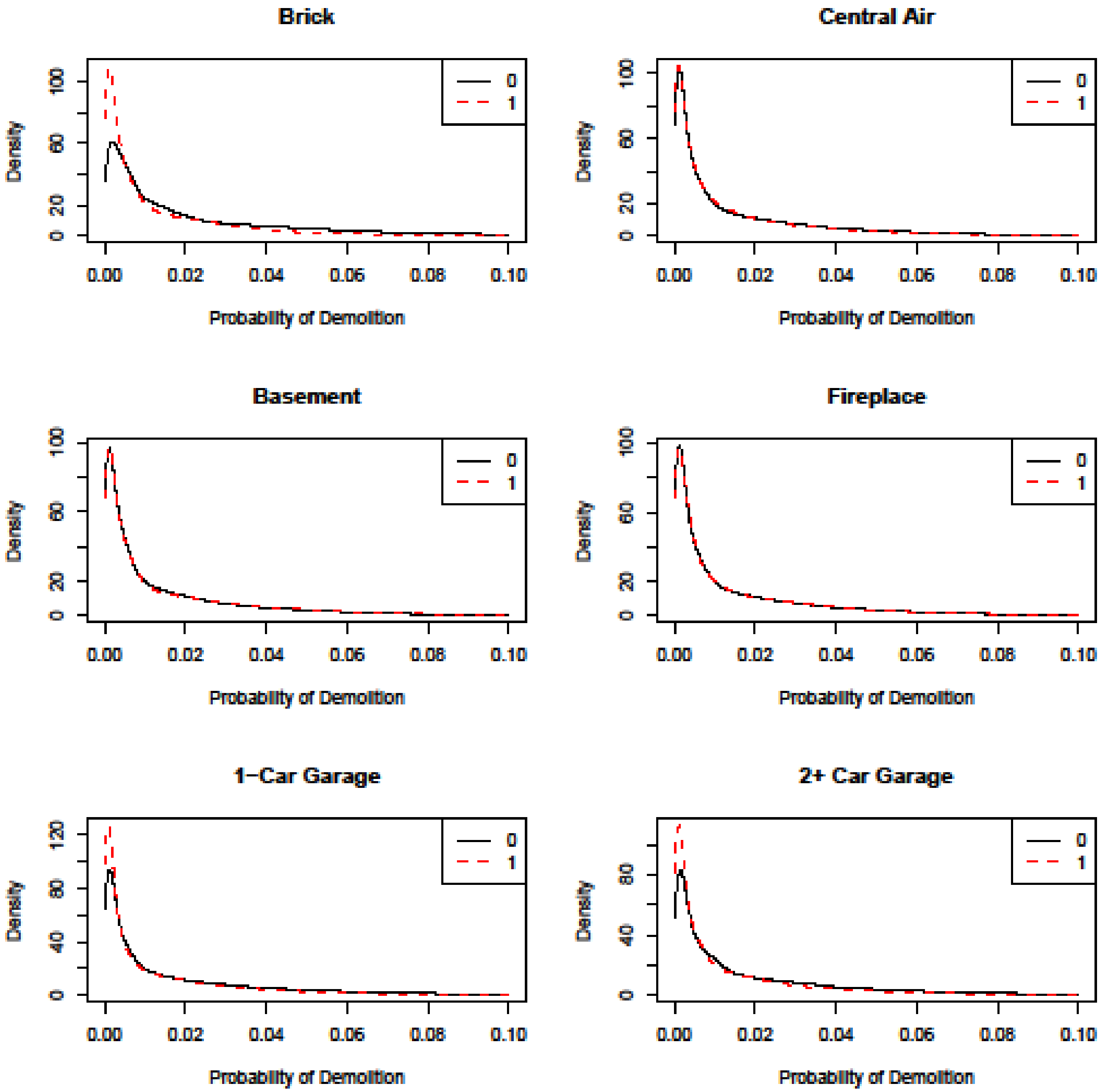

Brick
-2
-4
-6
-8
-10
-12
Central Air
1.5
1.0
0.5
0.0
-0.5
-1.0
-1.5
-2.0
Basement
3
2
1
0
-1
-2
-3
Fireplace
2
1
0
-1
-2
-3
1−Car Garage
-2.0
-2.5
-3.0
-3.5
-4.0
-4.5
-5.0
2+ Car Garage
-1
-2
-3
-4
-5
-6

Figure 7

Discrete Changes in Explanatory Variables




Brick
Central Air
Basement
Fireplace
1−Car Garage
2+ Car Garage
Density
Probability of Demolition
0
1
0.00
0.02
0.04
0.06
0.08
0.10
0
20
60
100
40
80
120