The Many Dimensions of Historic Preservation Value: National and Local Designation, Internal and External Policy Effects

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This analysis examines the internal and external policy effects of national and local register programs for historic preservation. Robust hedonic pricing models are crucial to informing policy proposals and understanding how property markets relate to urban heritage. Estimating a repeat-sales hedonic model with neighborhood trends and spatial mixed models, novel to this literature, offers a marked improvement in terms of jointly identifying internal and external policy effects, comparing national and local designations, separating policy from heritage effects, and estimating models robust to spatial dependence and trends in hedonic prices. Historic designation variables, while often individually insignificant in the model, are always jointly significant in explaining varying appreciation rates. Local districts exhibit no consistent price impacts across the models. Being located inside a national district confers a price premium that increases over time in the preferred model specification, while prices fall in national districts' buffers after designation. The sensitivity of results to model specification raises questions about alternative approaches to spatial dependence in the data in the urban historic preservation context. Evidence of the influence of historic district designation on property turnover and renovation investments is also examined.

Keywords: Historic Preservation, National and Local Register Programs, External Policy Effects, Repeat-Sales Hedonics, Spatial Econometrics

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1. Introduction

a. Background

The designation program is widely accepted as a standard historic preservation tool. The United States introduced two broad types of designation programs to help preserve historic properties: one at a national level and the other at a local level. The former is the National Register of Historic Places (NRHP) based on the 1966 National Historic Preservation Act. As of March 2015, 90,540 buildings, districts, sites, structures, and objects are registered as historic properties in the NRHP. The second type of program is the designation programs based on various state and local ordinances around the country. Unlike the largely voluntary federal NRHP, these programs often have a direct effect on preservation as they limit owners' rights through zoning and renovation review. Using national or local designations to preserve districts can affect properties inside districts as well as their neighbors. We analyze how property prices capture these impacts in Atlanta, a major metropolitan capital in the southern U.S. with active designation programs at both the local and national levels.

A number of researchers have already examined these designation programs for historic preservation and attempted to measure the price impact of historic designations on property values by using hedonic regression analysis. (See literature reviews in Heintzelman and Altieri (2013), Licciardi and Amirtahmasebi. eds. (2012), and Noonan (2013).) These findings examine the magnitude of historic designation impacts, the designation type (national / local), resource type (historic districts / historic buildings) and expression area of effects (internal effect / external effect). However, previous studies (Noonan and Krupka, 2011; Heintzelman and Altieri, 2013; Noonan, 2013) also revealed issues that must be addressed, such as identifying the policy effect (i.e., the effect of historic designation) separate from the effect of heritage or historic quality. Other methodological issues should be addressed to credibly estimate the results not only in the cross-sectional hedonic pricing method, which is the norm in many previous studies, but also in the repeat-sales hedonic pricing method and spatial hedonic approach, which are becoming more popular. Although previous studies confirmed the significance of the specified estimation model with test statistics, only a few have comprehensively checked the robustness of the results across different types of estimation models and responses to bias. Thus, promoting historic preservation policies relies on robust results relevant to policy impacts.

b. Purpose

Our primary contribution comes in the robust estimation of price effects of preservation policies along multiple dimensions. Because these are correlated elements, we advance the literature by combining several critical elements in the same empirical analysis: (1) comparing national and local designation, (2) identifying both direct designation effects and spillovers to neighboring properties, and (3) separating policy/designation effects from pre-existing heritage quality effects. All of this is estimated with in a robust spatial econometric model for a major metropolitan in the southern United States, Atlanta, as-yet unstudied in the literature. Previous works fail to incorporate all of these critical elements, leaving it open for criticism for incompletely addressing these several essential elements affecting the price effects of historic preservation efforts. To our knowledge, ours is the only the second historic preservation hedonic analysis to use a spatial mixed model (after Lazrak et al., 2014), and the first to apply a repeat-sales approach in this model. This analysis assesses the specific changes in designating historic landmarks (buildings) and historic districts over the eleven years from 2000 to 2010 using a rich and original geo-database, built by merging the repeat-sales property dataset containing both pre-designation and post-designation observations with contemporaneous neighborhood and demographic characteristics. We compare several models to explicitly examine the robustness of the estimation results, where most price effects are not robust except for certain spillover effects.

2. Literature Review

The cross-sectional hedonic pricing method is used to obtain the implicit price of a property's attributes by regressing the prices of a property onto its attribute. As established by Rosen (1974), it has been the standard method for previous studies since Ford (1989), which was one of the first papers addressing property sales premiums due to historic designations. Many studies have quantitatively identified a positive impact (price premium) of historic designation in varying degrees. These studies typically identify the price effects of designations on homes themselves or contained inside districts (e.g., Asabere et al., 1994; Cebula, 2009; Thompson et al., 2011), although several have also estimated price effects on properties just outside designated districts (e.g., Clark and Herrin, 1997; Coulson and Leichenko, 2001). The net policy effect on designated properties themselves is theoretically ambiguous depending on the loss from restricting property rights and the gains from possible preservation externalities, subsidies, and neighborhood stabilization (Angjellari-Dajci and Cebula, 2016; Heintzelman and Altieri, 2013). Nearby undesignated properties, however, may enjoy many of the preservation externalities without offsetting regulations. Though earlier studies tend to show positive neighbor price effects to accompany premiums in districts, more recent work with more sophisticated approaches reveals more mixed results with insignificant internal (Noonan, 2009; Ahlfeldt and Maennig, 2010; Noonan and Krupka, 2011) or external (Heintzelman and Altieri, 2013) effects.

Another important dimension of historic designation policies involves the preservation program itself. Most studies examine national-level designations (e.g., Asabere and Huffman, 1994; Angjellari-Dajci and Cebula, 2016) or local-level designations (e.g., Noonan, 2007; Narwold, 2008; Heintzelman and Altieri, 2013; Been et al., 2016) separately. Some examine both national and local designations in the same model. Studies comparing local and national designation effects have found smaller premiums (Haughey and Basolo, 2000) or even discounts (Schaeffer and Millerick, 1991) for local designations. Conversely, Coulson and colleagues (Coulson and Leichenko, 2001; Leichenko et al., 2001; Coulson and Lahr, 2005) find strong premiums for local designations and insignificant effects for national designation. Rarely, if ever, do hedonic studies include these multiple dimensions (national vs. local, internal vs. external) in the same empirical model.

Important challenges remain for applying hedonic price models in the historic preservation context, especially in disentangling policy effects from historic quality (Ahlfeldt and Maennig, 2010; Noonan, 2013). In particular, the policy effect (the effect of official historic landmark or district designation) cannot be distinguished from the heritage effect (the effect of underlying historic quality of the property or neighborhood) when designations are correlated with (often unobserved in hedonics) historic quality. More recent studies have focused on using pre-designation information by applying the repeat-sales hedonic pricing method instead of the cross-sectional hedonic pricing method to find the price impact of a historic designation. This helps mitigate endogeneity and omitted variable bias concerns. Noonan (2007, 2009), Noonan and Krupka (2011), Thompson et al. (2011), Heintzelman and Altieri (2013) incorporate the repeat-sales hedonic pricing method and report insights that differ from (or even oppose) many previous studies based on the traditional cross-sectional hedonic pricing method.

Historic preservation efforts may have other, related effects on real estate markets, although the evidence is sparser. How quickly markets react to historic designation remains an open question (Thompson et al., 2011), as designation's impacts may be more gradual as preserved housing stock becomes more outdated or special over time. Zahirovic-Herbert and Gibler (2014) report on marketing duration after designation, and Been et al. (2016) examine new construction activity after designations. Thus, there is concern that sampling only (residential) properties sold, or sold multiple times, may not capture the impacts of historic preservation on the value of other properties. Furthermore, better addressing the spatial complexities of urban real estate markets remains a serious challenge in this literature. Accordingly, more recent studies have attempted to verify the robustness of their estimation results by applying the multiple hedonic pricing models to address these methodological issues (e.g., Diaz III et al., 2008; Noonan and Krupka, 2011; Ahlfeldt and Mastro, 2012; Heintzelman and Altieri, 2013; Been et al., 2016).

3. Data Description

a. Study Area

This study analyzes historic preservation and home sales in the City of Atlanta. Data are collected on all home sales in Fulton County and all historic districts and buildings in the city. The sales sample is restricted to the overlapping areas (i.e., the part of the city contained in Fulton County) to capture most of the city and keep consistent governing policies. (See Figure 1 to see the small portion of the city that extends eastward into Dekalb County.)

b. Historic Designation Data

Atlanta has two primary registration programs to preserve historic properties: the NRHP (national) and the City of Atlanta Historic Preservation Ordinance (local). The

Historic Preservation Division of Georgia's Department of Natural Resources (DNR) manages NRHP programs in the state.[1] Listing on the NRHP does not restrict private property rights but can bring some economic benefit, including eligibility for tax credits when renovating. The City of Atlanta's Urban Design Commission, established in 1975, nominates, registers, regulates, and reviews historic buildings and districts for local designation. Any exterior alterations of locally registered historic properties require permission from the Urban Design Commission. Furthermore, commitments of time and effort by the neighborhood and an open hearing process whereby all opinions can be heard are required. On the other hand, economic incentives for historic preservation are also in place as preservation tools including a property tax abatement program (for locally or nationally designated properties), a federal and state income tax credit program, and a transfer of development rights.

This study incorporates GIS data on historic designation for districts and buildings from both the NRHP and the City of Atlanta Designated Properties (CADP) list. The Georgia DNR assisted in building this dataset at the parcel level with detailed maps, time of designation, and related information. Historic districts spanning Fulton and Dekalb counties are included, along with four districts whose boundaries changed between 2000 and 2010 due to a review of the designated areas. Compiling these information sources allows the manual construction of 48 time-varying district boundaries in Atlanta. Buildings located outside the City of Atlanta are excluded. The City of Atlanta provided data to map 16 districts and 61 buildings locally classified as either landmark or historic

[1] DNR also manages a state-level Georgia Register of Historic Places, which uses the same criteria as the NRHP and automatically lists properties listed on the NRHP. Neither the state nor national register restricts rights of private property owners. Owners of properties on the state register may be eligible for some subsidies from the state.

as of 2010. (By comparison, 48 districts and 133 buildings were listed on the NRHP in Atlanta at the end of 2010.) Figure 1 shows the locations of the local and national districts in Atlanta in both 2000 and 2010, as well as the areas that are cross-listed on both the national and the local registries. Figure 1 also shows considerable changes as new districts are created and boundaries are altered over the decade. Similarly, the set of individual buildings listed at the local and national levels also differs and changes over time with new listings. As shown in Figure 1, NRHP listings appear more extensive than local designations in Atlanta.

c. Property Records Data

The study used the Tax Parcel Data and the Property Record Data from 2000 to 2010 provided by the Fulton County Board of Assessors.[2] These data consist of a tax parcel map, the assessor's appraisal data, and sales records for properties sold during this time. The study develops an extensive geo-dataset by matching data from tax parcel maps and the assessor's sales records. This panel of houses sold during the 2000s of course includes the date of sale and the transaction price. This study extracts arm's-length single-family detached housing sales following methods in Noonan (2012). (The sample area in Figure 1 is outlined in black.) The assessor's data also include several basic property characteristics recorded at the time of sale: construction year, stories, lot size, indoor living area, construction style, location, and numbers of rooms, bedrooms, and bathrooms. Thus, while detailed property characteristics in the assessor's data are somewhat limited, this dataset of property sales has updated characteristics at the time of sale. For properties

[2] This was the longest period of time for which they would provide data. Spanning a decade has advantages in containing many instances of the same property selling more than once, variations in macroeconomic conditions, and numerous changes to the inventory of historic landmarks and districts.

sold multiple times in the dataset, some characteristics (e.g., square footage rather than location) can and do change between sales.

d. Neighborhood Characteristics Data and Demographic Characteristics Data

For neighborhood characteristics data, this study uses data from the Census and the City of Atlanta GIS Data Catalog provided by Atlanta's Office of Planning. This study adds transportation data (e.g., highways, public rail transit), available from the Atlanta Regional Commission.

e. Original Geo-database including Historic Designation Status Data

This study uses proxy variables for historic status by introducing multiple indicators for designation status, distance, count, and proportion variables. Additionally, the type of designation (national / local) and the resource type (historic districts / historic buildings) are distinguished to explicitly consider the features of historic properties and the historic designation policy. We create variables for buffer areas around properties at different distances for inside/outside of the boundaries of historic districts as well as distances to historic buildings in order to consider the spatial spillovers. The variables in the final model reflect an interest in multidimensional characterization of historic status balanced with an interest in parsimony and consistency with prior literature.[3]

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[3] Recent studies employing a similar buffer approach to measuring external effects include Noonan and Krupka (2011), Lazrak et al. (2014), Ahlfeldt and Mastro (2011), and Zahirovic-Herbert and Chatterjee (2012). Distance to nearest landmark building also compares conveniently to Moro et al. (2010), Ahlfeldt and Mastro (2011), and Zahirovic-Herbert and Chatterjee (2012). Buffers at greater distances than 100 meters did not add explanatory power in our models, and smaller buffers risked too few observations.

4. Method

A repeat-sales hedonic regression forms the base empirical model for this analysis of the market price effects of historic designation and historic districts. Repeat-sales estimators are sometimes used in hedonic analysis and offer advantages in robustness as described below. Further, the analysis emphasizes several features that, combined in the same empirical specification, address many shortcomings of previous research and provide a rich characterization of market effects or historic preservation. Several alternative specifications are estimated, where comparison across cases allows for robustness checks as the models allow for different price effects within and adjacent to historic districts, of preexisting historic quality and official designation, and locally and nationally designated districts – all with varying approaches to controlling for spatial dependence in the data.

A standard in previous historic designation hedonic studies represents a linear regression model as:

$$lnP_{it} = \alpha + \beta x_{it} + \delta H_{it} + \mu_{it} \tag{1}$$

Here, lnP_{it} represents the log of the property price of house *i* in period *t*. x_{it} represents property and neighborhood characteristics, H_{it} includes measures of historic designation status, and μ_{it} is the error term. α is the constant term, while β and δ are coefficients.

Greenstone and Gayer (2009) recommend a fixed-effects model (FEM) as an approach to overcome omitted variable bias:

$$lnP_{it} = \alpha + \beta x_{it} + \delta H_{it} + \nu_i + \varepsilon_{it} \tag{2}$$

In the FEM, the error term μ_{it} in equation (1) is categorized into the unobservable effect specific to sales property (ν_i) and its error term (ε_{it}) in equation (2). Estimation using the FEM addresses simultaneity or endogeneity biases that may arise from time-invariant omitted variables.

Repeat-sales hedonic pricing models offer many advantages over traditional cross-sectional hedonic models (Kiel and Zabel, 1997). These advantages are especially important in the context of historic preservation and designation, where separating unobservable quality characteristics of properties and neighborhoods is crucial in identifying the effects of formal designation apart from preexisting quality (Heintzelman and Altieri, 2013). Controlling for time-invariant unobservables will not, of course, control for time-varying unobserved quality, but it should substantially reduce the endogeneity bias in designations (Coulson and Lahr, 2005). This advantage over cross-sectional hedonics comes at the expense of a smaller sample, discussed further below.

One concern still present in repeat-sales estimators is that spatial dependence in the data, even when time-invariant variables are controlled for, may impact the estimation results. These spatial effects (Anselin, 1988) include spatial nuisance that affects the error term and serial correlation due to spatial proximity as well as spatial dependence and peer effects that can influence parameter estimates. These problems also affect cross-sectional hedonic models. Some previous studies, including Noonan (2007), Diaz III et al. (2008), and Ahlfeldt and Mastro (2012), apply the spatial autoregressive model or the spatial error model to the cross-sectional dataset in an attempt to address these problems. Because spatial dependence in *y* may leave OLS estimators inconsistent, explicitly addressing spatial dependence is critical. A spatially explicit model can account for different types of spatial effects (e.g., spatially correlated errors, spatial lags affecting price), and our spatial mixed model addresses both, unlike previous spatially explicit models in this hedonics of historic preservation literature. Our repeat-sales estimates include cases of OLS, a neighborhood trends model, and spatial mixed models (SMM). Two SMM cases estimate a model with explanatory variables for historic districts only and another model with additional historic building variables.

Case 1 ∶ Ordinary Least Squares Model

The OLS model (equation 2) is the base model from which we obtain our repeat-sales hedonic estimator that allows for time-varying x as in Noonan (2007). Our approach also follows Coulson and Lahr (2005) by relaxing the assumption that coefficient δ is time-invariant. The constant α in equation (2) becomes a set of parameters for Y_{it}, the vector of T dummy variables for each time period to indicate when the sale occurred.(i.e., $\alpha Y_{it} = \sum_{j=1}^{T} \alpha_j Y_{it}^{j}$). This more flexible model (equation 3) allows the hedonic price of designation, δ, to change over time from period s to period t ($t > s$):

$$lnP_{it} = \alpha Y_{it} + \beta x_{it} + \delta_t H_{it} + \nu_i + \varepsilon_{it} \tag{3}$$

$$lnP_{is} = \alpha Y_{is} + \beta x_{is} + \delta_s H_{is} + \nu_i + \varepsilon_{is}$$

$$lnP_{it} - lnP_{is} = \Delta lnP_{it} = \alpha \Delta Y_{it} + \beta \Delta x_{it} + \delta_t \Delta H_{it} + \Delta\delta H_{is} + \theta_{it} \tag{4}$$

where $\theta_{it} = \varepsilon_{it} - \varepsilon_{is}$

The unobservable individual effects and time-invariant missing variables (ν_i) can be removed by first-differencing. Thus, estimating equation (4) mitigates omitted variable bias for repeat-sales properties.[4] Furthermore, relaxing the assumption that the hedonic price of designation is fixed in time offers a richer characterization of the price effects of historic preservation in (4). Including historic landmark status at the time of the initial sale (s) allows identification of any price change in the designation attribute. In other words, the coefficient for the initial landmark status represents the change in premium

[4] Following Bailey et al. (1963), the set of time controls ΔY_{it} takes values of –1 for the period of initial sale, +1 for the period of the final sale, and 0 otherwise. The data include 11 years and 4 quarters for time and seasonal controls. The coefficients for the year and seasonal controls reflect price changes relative to the omitted times (2000 and winter, respectively). We keep a constant term in the model to allow for a nonzero intercept, essentially capturing the effect of the final sale.

between sales – something that might be substantial if historic preservation becomes scarcer, if regulatory constraints bind more as development pattern change, or demand changes (Noonan and Krupka, 2011). The coefficient on the change in historic designation status still identifies the price premium (or discount) associated with official status changes.

Case 2：Neighborhood Trends Model

The neighborhood trends case extends the OLS case to allow for each neighborhood (i.e., census tract here) to have its own price trend. This guards against the possibility that changes in historic preservation status correlate with prevailing price trends at the neighborhood level. We extend the model from (3) to allow for neighborhood-specific time trends by adding tract-level dummy variables (N_i) interacted with sales date (d_{it}), as shown in (5). Estimating (5) in first-differences yields a repeat-sales model as shown in (6):

$$lnP_{it} = \alpha Y_{it} + \beta x_{it} + \delta_t H_{it} + \nu_i + \tau N_i d_{it} + \varepsilon_{it} \tag{5}$$

$$lnP_{is} = \alpha Y_{is} + \beta x_{is} + \delta_s H_{is} + \nu_i + \tau N_i d_{is} + \varepsilon_{is}$$

$$\Delta lnP_{it} = \alpha \Delta Y_{it} + \beta \Delta x_{it} + \delta_t \Delta H_{it} + \Delta \delta_t H_{is} + \tau N_i \Delta d_{it} + \Delta \varepsilon_{it} \tag{6}$$

By interacting tract-level dummy variables with a time variable, differencing the equations lets the repeat-sales model control for tract-specific trends. The model in equation (6) thus includes J-1 neighborhood time trend parameters (τ) based on Δd_{it}, which is the time elapsed between sales, and T-1 time parameters (α) based on ΔY_{it}, which takes values of (-1, 0, 1) for the periods of initial sale, no sales, and final sale.

Case 3 : Spatial Mixed Model

This study introduces the SMM following Anselin (1988) to explicitly examine both the spatial lag and the spatial error. Representing the base model from equation (6) in the vector format, the SMM can be expressed as equation (7).

$$\mathbf{\Delta lnP} = \rho \boldsymbol{W} \mathbf{\Delta lnP} + \boldsymbol{\Delta Y \alpha} + \mathbf{\Delta x \beta} + \mathbf{\Delta H \delta} + \mathbf{H_s \Delta \delta} + \mathbf{u}\ ,\ |\rho| < 1 \qquad (7)$$

$$\text{with}\ \ \mathbf{u} = \lambda \mathbf{W u} + \boldsymbol{\theta}\ ,\ |\lambda| < 1,\ \boldsymbol{\theta} \sim \mathrm{N}(0, \sigma^2 \boldsymbol{I})$$

where $\mathbf{\Delta lnP}$ is the n×1 vector of price changes; $\mathbf{W}$ is the n×n spatial weight matrix; $\boldsymbol{\Delta Y}$, $\Delta\mathbf{x}$, $\mathbf{\Delta H}$, and $\mathbf{H_s}$ are matrices of regressors (corresponding to ΔY_{it}, Δx_{it}, ΔH_{it}, and H_{is} in equation (4)); and $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\delta}$, and $\boldsymbol{\Delta\delta}$ are the vectors of the coefficients (corresponding to α, β, δ_t, and $\Delta\delta_t$). Parameters ρ and λ are both spatial autoregression parameters that represent the influence relationship between the dependent variables and error terms, while $\boldsymbol{\theta}$ is the n×1 vector of errors (with a normal distribution assuming homoscedasticity and zero covariance) and $\boldsymbol{I}$ is the identity matrix of n×n. This study estimates the spatial autoregressive parameters using the maximum likelihood estimation method. The spatial weight matrix is defined by weights normalized to make the rows sum to 1 by using $1/distance_{ij}$ as the inverse distance between 2,451 locations. Here, all the elements on the diagonal are 0.

Case 4 : Spatial Mixed Model with historic building variables

Case 4 extends the SMM case to include historic designation of individual buildings or properties (distinct from buildings designated because they are located in districts) in the hedonic model. This provides a richer characterization of historic designation's price effects. While too few sales of individual building landmarks appear in the data to allow identification of direct price effects of individual designation on that property, the indirect or spillover effects on prices of nearby properties can still be detected. Case 4 tests for these spillovers by including distances to the closest individual building designations at the local and national levels separately. Also, by explicitly including initial building landmark status as well as changes, Case 4 can estimate the premium associated with proximity to historic landmark buildings as well as changes in that amenity value between sales.

5. Analysis

a. Definitions and Descriptive Statistics for Variables

Although the final models estimated are repeat-sales hedonics, the underlying data include a larger information set that informs the final models. Table1 lists and defines many of the variables that contextualize this analysis. In addition to property attributes, like sales price and parcel area, and locational characteristics, the data incorporate key local demographic characteristics at the Census block-group level from 1990, which is prior to the analysis period (thus avoiding the endogeneity that arises as current or future demographic shifts respond to local price trends). A dummy variable, *preWWII*, indicates whether the property's block group is entirely located inside a pre-World War II neighborhood to reflect traditionally organized local communities' importance in historic preservation. The set of historic designation variables includes dummy variables indicating whether the property is located inside a national (NRHP) or local (CADP) historic district at the time of sale, and whether the property is inside a 100-m buffer area around a national or local historic district at the time of sale. Year and quarter dummy variables are also included in the Y vector as controls to capture time trends in sales prices. Thus, year and quarter variables for timing of sale take the values of [-1, 0, 1] for initial sales periods, other periods, and the final sales periods in the repeat-sales model (Bailey et al., 1963). In light of equation (3), year and quarter variables are interpreted as differences from the omitted category (i.e., the year 2000 and winter).

The full dataset has 24,613 unique property sales, while the repeat-sales dataset has 2,451 unique properties. Figure 2 maps all those sales, indicating the repeat-sales sample with black. Overall, the spatial pattern of sales conforms to the housing density in Atlanta, and repeat-sales observations spread over those locations. Although most sales were well outside historic districts, local and national districts – and their buffers – hosted a considerable number of transactions. In Table 1, *NRHPdistrict*, *CADPdistrict*, *NRHPdist100*, and *CADPdist100* means reveal that more than one in six homes sold were in national historic districts, almost half as many in local districts, and smaller fractions of home sales occurred just outside those districts.

Although many important attributes (e.g., construction year, distance to airport) do not vary over time, some variables in Table 1 are time-varying for individual properties. Variables marked with an asterisk (*) in Table 1 have substantial variation between sales and are thus candidates for entering final repeat-sales hedonic models. Table 2 provides the descriptive statistics for the variables used in the repeat-sales models. The differenced variables all take a 'Δ' prefix and are defined as the value at the time of the last sale minus the value at the first sale. This $\Delta x = x_t - x_s$ construction follows Noonan's (2007) repeat-sales approach to mitigate problems arising for properties with numerous sales, such as serial correlation of the error terms (Bertrand et al., 2004). These differenced variables generally include the sales price and the historic preservation status of the property. In addition, the property's sales date enters the repeat-sales model as the number of days elapsed between sales (*Δsalesdate*, appearing as Δd_{it} in equation (6)). Further, the estimated models include a constant term, equivalent to a dummy variable for the final sale. The repeat-sales model in equation (4) also allows for including (undifferenced) variables at their value at initial sale (H_{is}), thus identifying time-trends in the hedonic price for initial or time-invariant attributes. Table 2 shows the descriptive statistics for these property and neighborhood characteristics. This flexible repeat-sales approach allows for a variable like *BldgYr* to partly capture differential appreciation for older and newer structures while *Δsalesdate* identifies the price effects of additional age.

Table 2 shows descriptive statistics for the repeat-sales sample. This list contains some differenced variables (Δx, ΔH) as well as some initial values (x_s) as included in the models. (For time-varying variables from Table 1, the 'f' prefix indicates the value at the time of the first sale.) Missing values limit the usefulness of the room count variables. Although *Bedrooms* goes unreported for 30% of the cross-section, *ΔBedrooms* is missing from over 56% of the repeat-sales sample. Thus, Table 2 and the hedonic models estimated here omit them.[5] Unsurprisingly, the initial value of the historic designation variables (*fNRHPdistrict*, *fCADPdistrict*) have very similar means to the corresponding variables' (*NRHPdistrict*, *CADPdistrict*) means for the full sample. Importantly, many properties not initially in historic districts became included in new district boundaries before their final sale. 3.5% and nearly 1% of repeat-sales properties saw their designation status change for national and local districts, respectively. The corresponding frequencies for sales in the district buffers tell a similar story, although these 'just outside' properties are rarer. Not many properties see their buffer status change between sales. In fact, fewer repeat-sales properties are within 100 meters of a CADP district at their final sale than at their initial sale because of shrinking local district boundaries. Also included in Table 2

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[5] When these (*ΔRooms*, *ΔBedrooms*, *ΔFamRooms*, *ΔBaths*, *ΔHalfBaths*) variables have missing values imputed using other independent variables from the model, comparable hedonic models can be estimated. Results for the coefficients of interest (δ) are essentially unchanged.

are descriptive statistics for initial and changes in (log) distance to the closest historic landmark building (nationally or locally designated). That the mean and maximum values for the changes in those distances are nonpositive reflects the growing number of historic landmark buildings tending to shrink the distance-to-closest measures over time.

b. Evaluation by Repeat-Sales Hedonic Pricing Method

Table 3 summarizes the repeat-sales hedonic pricing method estimation results for the four cases. Across cases, the models explain substantial variation in home price changes. Case 2 includes numerous neighborhood trends, thus showing a higher adjusted R^2. Case 4, which nests Case 3, does not appear to be a much better fit, and neither of the SMMs demonstrate better fits than the neighborhood trends model (with the lowest AIC and higher log likelihood in Table 3). As expected, time trends are observed and consistent across models, reflecting the housing market boom that preceded the crash of the Great Recession starting in 2007. A spring sales date seasonal penalty also appears. Across the models, prices consistently appreciate faster for homes that were surrounded by older housing stock, higher incomes, more vacancies, and fewer whites and blacks. Including tract-level time effects in Case 2 effectively removes these demographic-based price trends. Interestingly, each case shows growing premiums for newer construction. Newer homes surrounded by older homes tended to experience greater appreciation. The *Δsalesdate* coefficients suggest some small but insignificant depreciation with age across all of the cases (except Case 2, where it is significant).

Case 1：Ordinary Least Squares Model

In terms of the historic designation variables, only *fCADPdist100* and *ΔNRHPdist100* exhibited significant effects (at the 5% and 10% level, respectively). Thus, although the premium for being near-but-not-in local districts was rising, homes nearby NRHP districts saw price declines after designation. This negative spillover for NRHP districts contrasts with the positive (but insignificant) hedonic price estimated for properties within districts. The generally positive effects associated with CADP districts and negatives association with NRHP buffers should be interpreted with caution, however, considering the noise in the estimates in Case 1 and the potential for spatial dependence in the data to bias these estimates.

Case 2：Neighborhood Trends Model

The neighborhood trends model in Case 2 removes the time trend unique to each of 84 census tracts. As expected, better spatial controls significantly change the estimated coefficients for the locational variables for neighborhood demographics and historic districts. The building age coefficient is largely unaltered while the Census demographics explain little at the block-group level once tract-specific trends are introduced. The neighborhood trends model shows homes joining national districts between sales tend to experience large price gains (+13%) while homes initially in NRHP districts appreciate much faster (+11%). Importantly, while the negative spillover for national districts from Case 1 remains, the positive effect of *fCADPdist100* is no longer significant (p=0.26). The introduction of better spatial controls for price trends in the broader community substantially influences estimated historic designation price effects. Yet the neighborhood trends model still lacks robustness to spatial dependence in other forms, such as spatially correlated errors or the possibility that nearby price spillovers might render the neighborhood trends model estimates inconsistent.

Case 3：Spatial Mixed Model (SMM)

The SMM explicitly considers spatial dependence in the dependent variable and in the error term. The positive spatial lag term (ρ=0.35) is statistically insignificant at conventional levels (p=0.28) while the spatial autocorrelation of error terms parameter (λ=0.05) is statistically insignificant (similar to Lazrak et al., 2014). This, and a significant ρ if a simple spatial lag model were estimated (by restricting λ=0), hints at a spatial lag model, where sales prices positively impact prices of homes through the spatial weights matrix, rather than spatially correlated unobservables. But, ultimately, accounting for the spatial dependence in the SMM adds little to OLS and results in parameter estimates in Case 3 that closely resemble those in Case 1. For the historic designation variables, the positive effect of *fCADPdist100* remains but is now estimated with more precision (standard error = 0.10), which might be expected as OLS models are inefficient in the presence of spatial autocorrelation. The negative effect of *ΔNRHPdist100* remains imprecisely estimated (standard error = 0.19). The hypothesis that the other historic designation variables have no price effect cannot be rejected at even the 10% level for each of them individually. That said, however, the hypothesis that all of them (i.e., the *H* vector) jointly have no price effect can be rejected at the 1% level (χ^2 = 24.5). Thus, while most historic designation variables individually explain little of the price changes, they collectively play a significant role in characterizing Atlanta's hedonic price gradient. Care should be taken in comparing coefficients between OLS and SMM models in light of the spatial lag model's estimating spillover effects through a spatial weights matrix (LeSage and Pace, 2010). In the SMM, a new designation would impact a home's price as that, in turn, ripples out to surrounding areas. The partial derivative of equation (7) with respect to *H* is a matrix, rather than a scalar δ as in OLS, composed of direct and indirect effects. In this application, however, the small and insignificant lag parameter ρ indicates that indirect effects might not be sizeable on average.

Case 4：SMM with historic building variables

Case 4 builds on Case 3 by adding historic building variables to the *H* vector that previously only contains historic district-related measures. This allows identification of the effects of designating individual historic landmark buildings in addition to designated larger neighborhoods or bundles or parcels. Adding measures for distances to the nearest nationally or locally designated building only very slightly improves the hedonic model's explanatory power measured by log likelihood. Otherwise, it does little to alter the hedonic prices estimated in Case 3 or to affect the key SMM parameters (ρ and λ). None of the four variables representing proximity to historic buildings are statistically significant at conventional levels – individually or collectively. In short, previously or recently designated historic buildings are not shown to affect nearby home prices in this repeat-sales model. (The same holds if they were added to the Case 2 model, except that the *ΔlnCADPdisB* coefficient becomes positive.) This finding contrasts with Ahlfeldt and Mastro's (2012) finding sizeable price premiums for proximity to Frank Lloyd Wright houses. The generally negative-yet-insignificant coefficients for building distance variables in Case 4 is consistent with a possible positive spillover that is harder to detect for less prominent landmarks.

6. Discussion and Extensions

a. Many dimensions of preservation policy effects

The results in Table 3 offer a broad perspective on several dimensions of Atlanta's historic preservation policy impacts on housing prices. The findings allow comparing price effects – internal vs. external and national vs. local – across a set of alternative approaches to handling spatial dependence. At first blush, the only robust result is the large, negative coefficient for *ΔNRHPdist100*. This effect indicates a substantial discount for houses after having a national NRHP district designated within 100 meters. Furthermore, the lack of substantial improvement in fit for cases 3 or 4 over Case 2, coupled with the easier interpretation of coefficients in the neighborhood trends model, recommends Case 2 as the preferred model. Case 2 results show that the large, positive effect of being initially inside a local CADP district buffer is no longer statistically significant, while the positive price effects of *fNRHPdistrict* and *ΔNRHPdistrict* grow larger. Houses in national districts appreciate much faster, whether they were located there initially or joined the district between sales. Being located inside local districts, however, shows no significant price effects. This positive effect of NRHP district designation compares well to the national district price effects in Schaeffer and Millerick (1991) of 24% and in Haughey and Basolo (2000) of 33%. They generally fall between Leichenko et al.'s (2001) estimates of 5-20% and Angjellari-Dajci and Cebula's (2016) estimates of 27-79%. The weak local district effects resemble Ahlfeldt and Maennig (2010) and Noonan (2009). The difference in local and national district results may owe to national designation's more prominent signal – all recognition and no limitations – and local designation's advantages being roughly offset by property restrictions. The negative effect of national designation on neighbors is consistent with displacing demand from some areas and concentrating it within districts. That neighbors of local districts might appreciate faster is consistent with some positive spillovers, possibly from improved local amenities or from displaced demand. The insignificant distance-to-landmark-building coefficients likely reflect the landmarks' lack of prominence or acclaim in the local market in Atlanta. Individual landmark building price impacts may vary widely across landmarks and local markets, which should limit generalizations from a single study's price impacts to another historic context

Naturally, other limitations may apply. Even within a city like Atlanta, there may be heterogeneity across districts and landmarks. Prior research has shown considerable variation in price effects across districts (e.g., Angjellari-Dajci and Cebula, 2016) and landmark types (Moro et al., 2013) even in the same housing market. Moreover, results can be sensitive to different definitions of distance. Additional data and analysis can better map out distance gradients around historic resources. Alternative spatial models may warrant exploration. A simpler spatial lag model would yield results similar to Case 3 (with ρ=0.38, p-value=0.07), but Spatial Durbin Error models or Spatial Lag of X may fit the data well while being easier to interpret. Of course, changing unobservables (e.g., renovations that we cannot detect) may correlate with designations, which could bias our results. If unobservable quality improved more (less) for houses that tended to get placed into districts, the price effects may be biased upward.

b. Model Specification

Although the SMM offers a more flexible fit than the OLS model, the estimated coefficients (β, δ) in Cases 3 and 4 are very similar to Case 1. Much of the recent historic preservation hedonic literature either employs a spatial autoregressive model (e.g., Noonan, 2007; Diaz III et al., 2008) or a spatial FEM (e.g., Noonan and Krupka, 2011; Heintzelman and Altieri, 2013; Zahirovic-Herbert and Chatterjee, 2012; Moro et al., 2013). Similar to our neighborhood trends model in Table 3, spatial FEMs typically correct biases in estimated price effects of designation (δ). Yet these approaches emphasize addressing the nuisance of spatially correlated unobservables, and the SMM has the potential to identify the more substantive price spillovers of a spatial lag rather than spatial autocorrelation as the significant source of spatial dependence. The models in Table 3 thus represent a contrast and the results depict sensitivity to model specification. The neighborhood trends model indicates some positive price effects of historic designations and a better fit to the data, whereas the SMM results do not point to spatially correlated unobservables and fail to confirm some positive price effects. Perhaps the only consistent results across the models are that homes inside local districts do not tend to enjoy price premiums and that national district designation may lead to discounts for nearby homes.

The strength of the neighborhood trends model (Case 2) relative to the other models in Table 3 is particularly interesting in this context. The SMM (Cases 3 and 4) and the OLS model (Case 1) yield nearly identical estimates, despite the SMM's allowing for spatial dependence in the data. Spatial autocorrelation and spatial lag concerns fade in the repeat-sales approach that differences out v_i. Yet controlling for tract-specific time trends in Case provides a substantial improvement in fit (measured by log-likelihood or AIC). Thus the main distinction across models in Table 3 rests in how the model characterizes the underlying spatial patterns in price changes. Tract-specific time trends perform better than a weights matrix that does little to account for different timing, and time elapsed between sales, of nearby sales. As a result, controlling for tract-specific price trends reveals a stronger positive price trend in local districts while reducing the possibly overstated positive price increases associated with local district neighbors.

c. Sample Selection and Renovations

A major advantage in repeat-sales hedonics – controlling for time-invariant unobservables – usually comes at a cost of substantially reducing sample size. Houses that sell more frequently may not be representative of the housing market, inviting a sample selection bias. Further, houses in or near historic districts may experience different turnover rates. District status may cause more or less sales, perhaps by providing a shopping externality (by attracting more buyers) or altering transaction costs, just as designation may be a reaction to high turnover in a gentrifying area or low turnover in a declining neighborhood. Concerns about too much or too little owner turnover often manifest in historic preservation policy discussions. Thus, investigating turnover has both importance for policy as well as sample selection concerns. House sale frequencies in these Atlanta data appear roughly independent of district designation. In the full dataset, houses that sold only once appear in national or local districts with the same frequency (17.6% and 7.6%, respectively) as those that sold multiple times (18.2% and 7.7%). The same holds for being in the 100-meter buffer of local districts, but a t-test (t=3.1) shows that being in a national district buffer is significantly more common among one-time sellers (6.4%) than it is among repeat-sales houses (4.8%).

Houses with multiple sales may differ from those only sold once in terms of their other attributes. To explore this, a series of t-tests are performed on the variables in Table 1 for the subsamples with just one sale and with multiple sales. Although mean sale prices look the same, many structural and geographic features differ. Repeat-sales houses tend to be significantly larger (by over a third), older (by almost a decade), more minority, and farther from transportation infrastructure. Even a repeat-sales model that controls for observed and other unobserved attributes can still suffer from sample selection bias if the hedonic price gradient estimated does not generalize to the broader housing market. The results in Table 3 may hold for repeat-sales houses in Atlanta, but extending them to other housing samples warrants caution.

Another major concern in historic preservation policy is the extent to which designations and policy tools catalyze rehabilitation or discourage investment in improvements to the housing stock (e.g., Licciardi and Amirtahmasebi, 2012; Cyrenne et al., 2006; Coulson and Lahr, 2005). Examining the repeat-sales sample can shed light on the empirical question for Atlanta. Major renovation work can be detected in the data by noting whether key structural features change between sales, notably square footage or the numbers of rooms in the home. Houses in buffers or inside national districts, which do not impose private property restrictions, might be expected to renovate at similar rates as those elsewhere. Square footage increased between sales for 0.7% (1.5%) of repeat-sales houses that were (not) in NRHP districts at their first sale, an insignificant difference (t=1.35). There is also no difference in *Δlnsf* by first sale's local district status or by buffer status. Renovations indicated by changes in the room composition can also be examined, although here the missing values problem greatly reduces the sample. Still, some houses altered the composition of rooms (9.2%) and some increased total *Rooms* (3.9%) between sales. Houses initially in a national district buffer, however, were more than twice as likely to change their room counts (20%) or increase *Rooms* (8.6%). These renovation frequencies do not differ significantly by other initial historic status (e.g., *fNRHPdist*, *fCADPdist100*). Overall, historic districts do not appear to discourage resales, nor do they discourage renovations among those that turnover. This finding may be unexpected, especially for local districts, if major renovations are discouraged or restricted in districts. Non-price effects of designations, like national district buffers hosting more renovations or other renovations not measured here, warrant additional research.

7. Conclusion

The many dimensions of historic preservation value include internal and external price effects from local and national designation programs, rarely robustly captured in the same empirical analysis. This study builds a rich and original geo-database, including more property sales transactions and more historic districts and buildings listed on the NRHP and the CADP than earlier studies. It then analyzes the evidence of a policy effect for historic districts and historic buildings, considering both internal effects (i.e., on properties inside districts) and external effects in four repeat-sales hedonic models to illustrate the robustness of the estimation. Altogether, the results offer a marked improvement in terms of jointly identifying internal and external policy effects, comparing national and local designations, separating policy from heritage effects, and estimating models robust to spatial dependence and trends in hedonic prices. The analysis combines these advantages in an application to a major city in the U.S. south, providing the first robust estimates of historic preservation policy's impacts in Atlanta.

Each of these contributions to the literature helps show both the importance of rigorously identifying policy effects and evaluating alternative modelling choices. Addressing the unobserved historic quality that plagues the earlier literature (Noonan, 2013) with a repeat-sales approach greatly improves the results. The robust spatial mixed model approach – in this context – offer little evidence of spatial lags or spatial autocorrelation. The neighborhood trends models mitigate potential bias in the repeat-sales OLS model, particularly for the estimated price increase associated with being in national districts (*ΔNRHPdistrict*) and for differential appreciation rates inside national districts (*fNRHPdistrict*) and local district buffers (*fCADPdist100*). The neighborhood trends model substantially narrows the national district's price increase's 95% confidence interval to -0.01 – 0.25, better supporting a positive price impact than other models. Shifting from OLS or SMM to a neighborhood trends model produces other changes, as local districts' positive spillovers are no longer significant and as national districts are estimated to bring significant, substantial, and rising price premiums. The contrast in results across models lends support for neighborhood trends models (as prior hedonics literature often supports spatial FEMs) and raises questions about the adequacy of using spatial mixed models, especially lacking strong evidence of a spatial lag. The spatial dependence may be captured better by including neighborhood fixed effects (or neighborhood-specific trends in repeat-sales contexts) than simply adding a spatial error and spatially lagged price term.

Despite the sensitivity to model specification choice, the results show some consistent patterns that can guide policy. The effects of building age and time trends persist across alternative spatial models. Historic designation variables, while often individually insignificant in the model, are always jointly significant in explaining varying appreciation rates. Across all models, having a national district designated nearby may tend to reduce prices. In our preferred model, being located inside a national district tends to confer a price premium that increases over time. Proximity to historic landmark buildings is not captured in market prices. Locating inside local districts is never shown to significantly impact prices, despite the stronger property restrictions and incentives accompanying local district designations. Local policymakers may opt to tip the balance, toward more support or more regulation, or reconsider where they target for their next designation. These local districts may have some positive external effects, while national districts may have stronger positive internal effects (and possibly negative external effects) in the study area.

Finally, policies to promote and shape urban development in the U.S. often feature historic preservation. Yet historic preservation policies affect property and markets in complex ways. Highlighting the many dimensions of the values at stake in historic preservation involves more than better data and improved methodology. It also involves appreciating the endogeneity of designations and prices as equilibrium concepts. The endogeneity concern, implicitly evident here in the importance of repeat-sales approach and controlling for neighborhood trends, involves policymakers "picking winners" in preservation (Noonan and Krupka, 2011). Broadly speaking, picking winners may bring diminishing returns to more designations, or it may lead to preserving resources that we might not otherwise prefer. The equilibrium price concern follows from the occasionally negative price effects detected here, raising questions about the mechanisms behind price changes. Supply-side effects, like influencing renovation decisions, influence property values. Rather than just cast district designation as a demand shifter, the supply side needs more attention. After all, the regulators typically focus on renovations, demolitions, construction, and other supply aspects. Additional research is needed to disentangle the potentially concurrent investment and designation decisions associated with historic preservation. Urban redevelopment strategies using historic preservation could benefit from a better understanding of how they will affect supply as well.

The analysis here shows the importance of addressing several dimensions of historic preservation policies in understanding their property price impacts in complex urban settings. Empirical results are sensitive to how we control for properties' historic quality, neighborhood quality and trends. Looking inside *and* next to historic districts, designated under different and overlapping preservation policies, leads to a richer depiction of how property values evolve around historic districts. Insofar as national designation is more symbolic and local designation carries greater regulatory restrictions, the results show how stronger preservation policies may not have stronger price effects. From this study, preservation advocates might not just add another arrow to their quiver of studies finding a premium, but they can make more precise claims about which type of designation. Overall, the stronger effects from national designation points to the power of signalling and information asymmetries in property markets, rather than limiting property rights, in enhancing property values in historic areas. This finding can be useful in other contexts, especially outside of the United States, where other policy instruments or institutions for preservation may be available.

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Table 1. Variable Descriptions

	Variable	Definition [unit]	N	Mean	Std.dev.
*	lnP	Log market sale price [$]	24,613	12.282	0.874
	lnsf	Log square footage [sq ft]	24,613	8.668	1.142
*	salesdate	Serial number value for sales date	24,613	16765.86	1191.031
	lnParcelArea	Log parcel area [sq m], 2010	24,613	6.240	2.640
	BldgYr	Construction year	24,613	1968.153	31.033
	BldgFloors	Number of floors	24,613	1.276	0.451
	Rooms	Number of total rooms	17,123	6.066	2.009
	Bedrooms	Number of bedrooms	17,117	2.649	1.071
	FamRooms	Number of family rooms	20,542	0.249	0.460
	Baths	Number of bathrooms	20,542	1.476	1.034
	HalfBaths	Number of half-bathrooms	20,542	0.256	0.477
	lnAirport	Log distance to ATL airport [m]	24,613	9.643	0.335
	lnMARTA	Log distance to nearest MARTA station [m]	24,613	7.424	0.871
	lnHwy	Log distance to highway [m]	24,613	6.819	0.948
	lnHydro	Log distance to nearest lakes and ponds [m]	24,613	6.835	0.896
	lnCBD	Log distance to CBD [m]	24,613	8.588	0.597
	lnHHincome	Log median household income [$] in BG, 1990	24,613	10.189	0.620
	lnMedValue	Log median house value [$] in BG, 1990	24,613	11.361	0.787
	lnPopDens	Log population density [person/sq km] in BG, 1990	24,613	7.106	0.691
	MedYearBlt	Median year of house construction in BG, 1990	24,613	1955.108	10.938
	%Vacant	Percent of housing units that are vacant in BG, 1990	24,613	0.141	0.087
	%White	Percent of population that is white in BG, 1990	24,613	0.484	0.404
	%Black	Percent of population that is black in BG, 1990	24,613	0.497	0.410
	preWWII	BG is wholly inside pre-WWII neighborhood	24,613	0.343	0.475
*	NRHPdistrict	Property is inside a NRHP District	24,613	0.181	0.385
*	CADPdistrict	Property is inside a CADP District	24,613	0.077	0.266
*	NRHPdist100	Property is inside a NRHP District 100-m buffer area	24,613	0.060	0.237
*	CADPdist100	Property is inside a CADP District 100-m buffer area	24,613	0.020	0.141
*	lnNRHPdisB	Log distance to nearest individually designated NRHP Building [m]	24,613	6.994	1.092
*	lnCADPdisB	Log distance to nearest individually designated CADP Building [m]	24,613	7.402	1.077
*	spring	Sold in spring, March - May	24,613	0.299	0.458
*	summer	Sold in summer, June – August	24,613	0.288	0.453
*	fall	Sold in fall, September - November	24,613	0.208	0.406
*	saleyear	Year of the sale	24,613	2005.426	3.248

Note: * indicates the variable is treated as time-varying.

Table 2. Descriptive Statistics (Repeat-Sales)

Variable	Mean	Std. dev.	Min	Max
ΔlnP	0.063	0.793	-3.894	6.982
BldgYr	1960.525	29.788	1900	2009
Δsalesdate	1576.997	950.238	30	3974
lnHHincome	10.173	0.635	8.517	11.827
lnMedValue	11.314	0.782	8.304	13.122
lnPopDens	7.146	0.667	4.654	8.506
MedYearBlt	1953.944	10.157	1925	1984
%Vacant	0.138	0.088	0	0.505
%White	0.450	0.414	0	1
%Black	0.532	0.420	0	1
fNRHPdistrict	0.180	0.385	0	1
fCADPdistrict	0.076	0.265	0	1
ΔNRHPdistrict	0.035	0.184	0	1
ΔCADPdistrict	0.009	0.094	0	1
fNRHPdist100	0.048	0.214	0	1
fCADPdist100	0.022	0.147	0	1
ΔNRHPdist100	0.002	0.070	-1	1
ΔCADPdist100	-0.001	0.083	-1	1
flnNRHPdisB	7.090	0.950	-0.600	8.887
flnCADPdisB	7.446	0.932	3.465	9.413
ΔlnNRHPdisB	-0.046	0.182	-2.557	0
ΔlnCADPdisB	-0.015	0.094	-1.241	0
Δspring	-0.027	0.641	-1	1
Δsummer	0.011	0.638	-1	1
Δfall	0.014	0.581	-1	1
Δsaleyear=2001	-0.165	0.422	-1	1
Δsaleyear=2002	-0.109	0.439	-1	1
Δsaleyear=2003	-0.051	0.328	-1	1
Δsaleyear=2004	-0.047	0.403	-1	1
Δsaleyear=2005	-0.014	0.454	-1	1
Δsaleyear=2006	0.037	0.436	-1	1
Δsaleyear=2007	0.103	0.460	-1	1
Δsaleyear=2008	0.081	0.340	-1	1
Δsaleyear=2009	0.094	0.323	-1	1
Δsaleyear=2010	0.266	0.442	0	1

Note: N=2,451

Table 3. Results of Repeat-Sales Hedonic Pricing Method

Variable	Case1 OLS	Case2 Neighborhood Trends	Case3 SMM	Case4 SMM - historic buildings
BldgYr	0.0029 ***	0.0024 ***	0.0029 ***	0.0029 ***
	5.24	4.26	6.24	6.30
Δsalesdate	0.0000	-0.0010 **	0.0000	0.0000
	-0.02	-2.31	-0.03	-0.06
lnHHincome	0.1053 **	0.1019 *	0.1019 **	0.1059 **
	2.17	1.80	2.11	2.17
lnMedValue	0.0217	-0.0761	0.0148	0.0169
	0.52	-1.36	0.32	0.37
lnPopDens	-0.0114	0.0174	-0.0090	-0.0116
	-0.50	0.56	-0.37	-0.45
MedYearBlt	-0.0070 ***	-0.0082 ***	-0.0067 ***	-0.0069 ***
	-4.92	-4.44	-4.17	-4.09
%Vacant	0.5028 **	0.3292	0.4478 **	0.4702 ***
	2.48	1.27	2.51	2.59
%White	-0.7527 **	-0.3496	-0.8099 *	-0.9268 **
	-2.29	-0.74	-1.87	-2.12
%Black	-1.0071 ***	-0.1138	-1.0299 **	-1.1388 ***
	-3.29	-0.25	-2.55	-2.80
fNRHPdistrict	0.0547	0.1011 ***	0.0564	0.0581
	1.44	2.58	1.33	1.36
fCADPdistrict	0.0744	-0.0220	0.0828	0.0834
	1.41	-0.31	1.44	1.45
ΔNRHPdistrict	0.0787	0.1211 *	0.0873	0.0701
	1.38	1.82	1.18	0.88
ΔCADPdistrict	0.0186	-0.0502	0.0305	0.0366
	0.10	-0.26	0.19	0.23
fNRHPdist100	-0.0690	-0.0010	-0.0633	-0.0619
	-1.00	-0.01	-0.96	-0.93
fCADPdist100	0.3327 **	0.1918	0.3222 ***	0.3263 ***
	2.14	1.13	3.31	3.35
ΔNRHPdist100	-0.3532 *	-0.2942 *	-0.3461 *	-0.3500 *
	-1.88	-1.87	-1.86	-1.88
ΔCADPdist100	0.1583	0.1173	0.1568	0.1731
	0.91	0.61	0.84	0.93
flnNRHPdisB				0.0349
				1.38
flnCADPdisB				-0.0282
				-1.00
ΔlnNRHPdisB				-0.0709
				-0.96
ΔlnCADPdisB				-0.1322
				-0.87
Δspring	-0.0481 *	-0.0251	-0.0466 *	-0.0471 *
	-1.84	-1.02	-1.79	-1.81
Δsummer	-0.0085	-0.0013	-0.0064	-0.0054
	-0.30	-0.05	-0.23	-0.20
Δfall	-0.0201	0.0049	-0.0180	-0.0161
	-0.55	0.14	-0.52	-0.46
Δsaleyear=2001	0.0157	0.0518	0.0150	0.0170
	0.26	0.88	0.25	0.28
Δsaleyear=2002	0.0545	0.1355	0.0497	0.0491
	0.53	1.33	0.49	0.48
Δsaleyear=2003	0.1052	0.1767	0.1020	0.1070
	0.71	1.22	0.70	0.73
Δsaleyear=2004	0.2233	0.3317 *	0.2185	0.2218
	1.13	1.69	1.14	1.16
Δsaleyear=2005	0.4342 *	0.5165 **	0.4270 *	0.4320 *
	1.76	2.12	1.80	1.82
Δsaleyear=2006	0.3872	0.4973 *	0.3813	0.3840
	1.30	1.69	1.34	1.35
Δsaleyear=2007	0.1922	0.3340	0.1870	0.1892
	0.56	0.99	0.57	0.57
Δsaleyear=2008	0.1131	0.2869	0.1099	0.1141
	0.29	0.74	0.29	0.30
Δsaleyear=2009	-0.1944	-0.0394	-0.1995	-0.1936
	-0.44	-0.09	-0.47	-0.46
Δsaleyear=2010	-0.7152	-0.4493	-0.7193	-0.7135
	-1.45	-0.93	-1.53	-1.51
constant	7.7435 ***	11.3502 ***	7.3384 **	7.7050 **
	2.81	3.24	2.27	2.31
rho(ρ)			0.3504	0.3475
			1.08	1.07
lambda(λ)			0.0452	-0.0023
			0.10	-0.01
sigma(σ)			0.6200 ***	0.6195 ***
			70.00	69.99
Statistics				
Number of Groups		84		
Adjusted R Squared	0.380	0.452		
RMSE	0.625	0.587		
chi2			1406.3998 ***	1411.9852 ***
AIC	4678.5826	4457.3915	4681.3538	4685.3181
Log Likelihood	-2308.2913	-2113.6958	-2306.6769	-2304.6590
Number of Fitted Parameters	31	115	34	38

Notes: N=2,451. Upper values mean coefficients, and lower values mean t-value of OLS and neighborhood trends or z-value of SMM. Case 2 includes 84 tract dummies interacted with *Δsalesdate*. Estimations of OLS and neighborhood trends use robust standard errors. * p<.1; ** p<.05; *** p<.01

Figure 1. NRHP, CADP, and Overlapped Designation Map (Districts 2000, 2010)

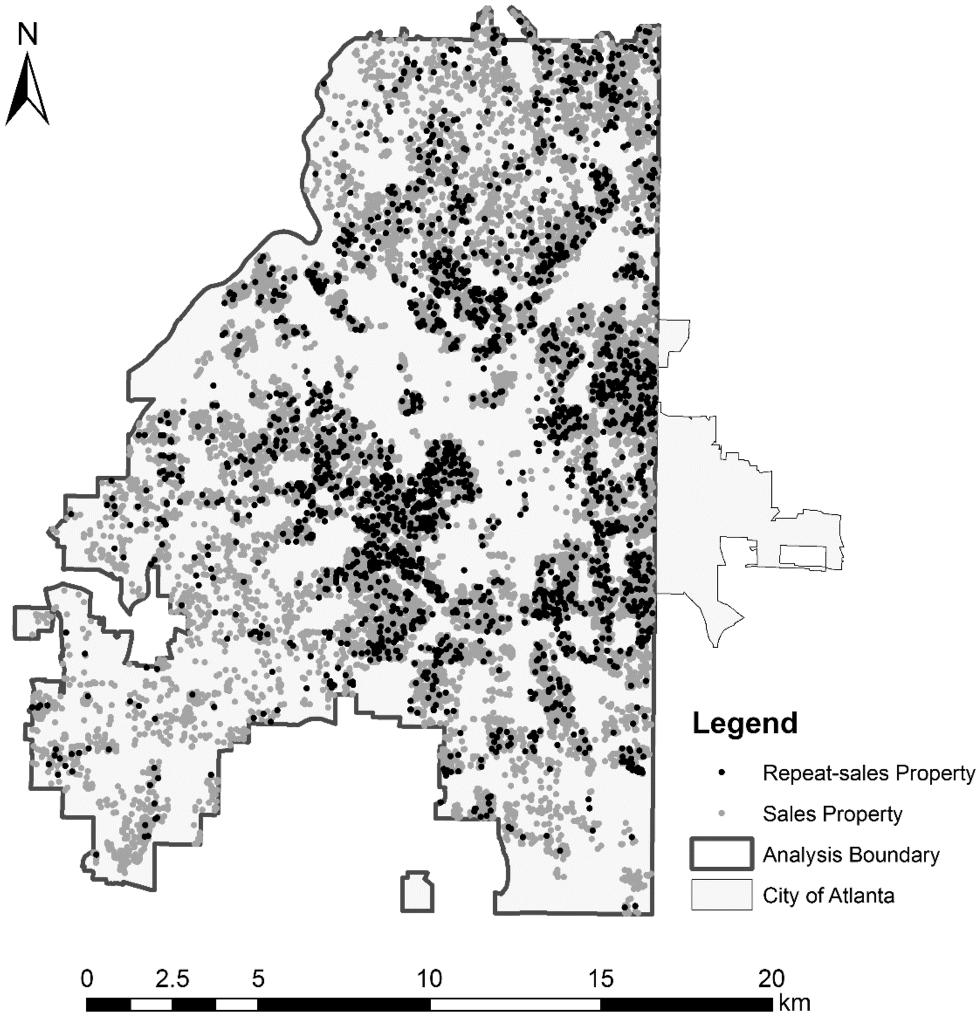

Figure 2. Sales Property and Repeat Sales Property Locations