IMPACTS OF TRANSPORTATION INFRASTRUCTURE PROXIMITY AND ACCESSIBILITY ON REAL PROPERTY VALUES

Analysis of Single-family Properties with Geographic Weighted Regression

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ABSTRACT
Investments in public infrastructure such as highways, airports, mass transit, and stadiums can increase adjacent property values, generating a value premium for private developers and adjacent property owners. A portion of this value can be "captured" as public revenue via property taxes to assist financing such improvements. States and local governments aim to anticipate and capture the economic value created by transportation accessibility. While value capture (VC) represents an opportunity for regional agencies to recapture some transportation infrastructure costs, it is not clear how much value is added by the infrastructure in a particular region. This research applies geographic weighted regression (GWR) to quantify the impacts of transportation infrastructure accessibility on real property values in El Paso, Texas. The presence of spatial nonstationarity and heterogeneity confirms that transportation infrastructure proximity and accessibility might generate a premium on real property values, but that such premium is not always positive, and is even negative in some areas. GWR shows that benefits from a transportation facility can be capitalized by parcels even if they are located away from the facility. Finally, GWR maps can assist to better VC policy development by estimating how much value is added by infrastructure projects throughout particular locations.

Keywords: value capture, VC, tax increment financing, TIF, land-based finance, econometrics, spatial econometrics, geoanalytics, spatial analytics, geographic weighted regression, GWR, transportation funding, transportation finance, innovative finance, public-private partnerships, P3, PPP.
INTRODUCTION

Investments in public infrastructure such as highways, airports, mass transit, and stadiums can increase adjacent property values, generating a value premium for private developers and adjacent property owners. A portion of this value can be "captured" as public revenue via property taxes to assist financing such improvements. States and local governments aim to anticipate and capture the economic value created by transportation accessibility to fund capacity expansions. Value capture (VC) allows public agencies to recoup the private benefits on real properties from investments in public infrastructure via the tax mechanism.

Infrastructure expenditures are financed primarily in three ways: (i) local government revenues (tax and non-tax), (ii) borrowing, and (iii) using funds from higher levels of government. As more vehicles with advanced fuel economies (e.g. hybrids) enter public and private fleets, fuel tax revenues and the Federal Highway Trust Fund will continue to decline, limiting the funds provided to each state. Texas is no exception. Historically, Texas has been a “donor” state, a state that receives less revenue than what it pays to the Highway Trust Fund. Losses are expected through 2050 (1). If the trends for declining fuel tax revenues, increasing transportation needs, and higher infrastructure costs continue, the funding required to satisfy mobility needs is clearly beyond what traditional sources, like the dated fuel tax, can supply.

Most of the non-roadway mechanisms for capturing the value premium are used by local governments, with a few being used by state departments of transportation (DOT). While VC represents an opportunity for regional agencies to recapture some transportation infrastructure costs, it is not clear how much value is added by infrastructure projects in a particular region.

OBJECTIVE

This research applies geographic weighted regression (GWR) to quantify the impacts of transportation infrastructure proximity and accessibility on real property values in El Paso, Texas. The hypothesis tested is that transportation infrastructure proximity and accessibility impact real property values in El Paso. The next section provides a review of the literature. Next, a discussion of the data and methodology is presented. The fifth section reports empirical results. This paper concludes with key findings and suggestions for future research.

LITERATURE REVIEW

Historically, land has been a mechanism to finance urban infrastructure (2). Value capture (VC) is the process by which increments in land values attributed to community efforts are recovered by the public sector. VC financing has attracted more attention due to issues with traditional funding sources (3-5). Tax increment financing is a VC technique that generates cash flows from increases in real property values in a development or redevelopment project via the property tax mechanism. The expected cash flow is used to finance the project costs (7). Texas is one of the first states to develop a legislative framework that allows municipalities to set up Transportation Reinvestment Zones (TRZ), a VC technique similar to TIFs, but specifically designed to fund transportation. Texas law defines a TRZ as a designated continuous zone around a transportation improvement where a local government can commit a portion of the property tax revenue increases to fund an improvement (8). A TRZ improvement should (i) promote public safety; (ii) facilitate the development or redevelopment of property; (iii) facilitate the movement of traffic; and (iv) enhance the local entity’s ability to sponsor transportation projects.
Studies report evidence that investments in public infrastructure can increase adjacent property values, generating a value premium for adjacent property owners. In El Paso, Fullerton and Villalobos apply a hedonic pricing model to a random sample of 562 housing units, and test the significance of 22 variables related to structural and locational features. Results indicate that housing prices are negatively impacted by distances from employment centers and international bridges. A similar effort for Juarez, Mexico indicates that major avenues and accessibility do not always improve housing values. Assessing estimates of cadastral values, forecasting methods, and their accuracy is an essential step to quantify VC, TIF, and municipal revenues. Arnold Cote et al. compare four typical econometric techniques to forecast property taxaton with a random walk and a random walk with drift. The random walk with drift outperformed all four techniques. Martínez and Viegas document 25 hedonic price studies for residential and commercial properties in the U.S. Using walking time and distance to transit stations as accessibility measures, they apply spatial hedonic models and conclude that proximity to metro lines leads to significant impacts on property values. Anselin and Lozano-Gracia note that by considering spatial variables, in the form of distance to amenities, the predictive performance of models used in real property valuation improves significantly.

Spatial econometric techniques have proven useful in studies where spatial dependence is present. Such techniques allow modeling and testing spatial autocorrelation and spatial heterogeneity to assess spillover effects and dependence between observations that are in close geographic proximity (e.g. real property parcels). The evolution of spatial econometrics in recent years is extensive. By applying spatial econometric models, Zhang and Wang find that housing prices in Beijing capitalize positive premia from distances to the nearest metro station. Concasa applies a spatial autoregressive (SAR) estimator, and finds that houses near limited access roadways exhibit greater price resilience during and after market downturns. These price differentials persisted 4 to 5 years subsequent to opening the roadway. Several studies quantify accessibility using distance-based and driving time variables. Results indicate that the premium diminishes as the distance increases, and that prior to the opening, distance from the highway was not statistically significant. Also, the premium fades away in years subsequent to opening the highway to the public. Siethoff and Kockelman analyze parcel values along the U.S. 183 corridor in Austin, Texas using: (i) a total value model, (ii) an improvement value model, and (iii) a land value model. Freeway proximity, corner parcels, and timing of completion are found to significantly impact parcel values.

Geographic Weighted Regression (GWR) accounts for spatial heterogeneity by generating individual regression equations in subsamples of a geographic dataset. Unlike the average coefficients estimated by ordinary least squares OLS (i.e. global coefficients), GWR estimates location-dependent distributions for coefficients around a particular point or epicenter (i.e. local coefficients). GWR assumes that observations closer to the epicenter of each subset have greater weights in parameter estimation than more distant ones. Efthymiou et al. apply OLS, SAR, and GWR to determine the locations for transportation mobility centers. Results show that the GWR model fits the data best, and it is the only model that solves the spatial autocorrelation of the residuals. Number of residents, bus routes, vehicle speed, and length of the road network were the most significant coefficients. Löchl and Axhausen also apply OLS, SAR, and GWR to model residential asking rent prices in Zürich, Switzerland. Spatial explanatory variables include distance-based and driving time accessibility measures. Du and Mulley analyze the impact of transportation accessibility on land values using GWR for VC purposes in the United Kingdom. The findings indicate that accessibility generally has a positive effect on land value. In some areas, however, the effect was either negative or null,
suggesting that indiscriminately applied VC policies would be inappropriate. In Michigan, GWR shows a premium for lots located closer to downtown and farther from rural towns (35).

Spatial spillover effects and spatial dependence between observations also impact the marginal prices of structural housing characteristics (e.g. the price of an additional bedroom in two different neighborhoods) particularly within large metropolitan regions. GWR has proven useful to address such spatial effects (36-41). One of the critiques of GWR is that multivariate parameter estimates might be intrinsically correlated, making the interpretation of map patterns for individual coefficients difficult. However, spatial dependence remains an issue even after including spatial independent variables in OLS (42). Getis suggests several tests to check for spatial autocorrelation and discusses their main advantages: assessing the strength of the spatial effects on any variable; evaluating spatial stationarity, spatial heterogeneity, and distance decay; and allowing spatial hypothesis testing (43). All these advantages represent improvements to the efficiency and accuracy of modeling cadastral values; hence, better quantification of VC, TIF, and municipal revenue gains.

METHODOLOGY AND DATA

The hypothesis tested is that transportation infrastructure proximity and accessibility impact real property values in El Paso, Texas. The procedure involves the application of hedonic price models using least squares regression analysis. Hedonic studies have been widely used to analyze the impact of transit on property values (44). Prior empirical evidence indicates that the magnitude of the impacts on property values vary over space (12, 13). Tests for spatial autocorrelation and heterogeneity assess spillover effects and dependence among close parcels.

Global and Local Regressions: OLS and GWR

The methodology starts by estimating three hedonic equations: (i) a total-value model, (ii) an improvement-value model, and (iii) a land-value model (27). These three specifications are then assessed with GWR using GIS. Data collected include 2013 certified cadastral parcel records for real property for El Paso County, with transportation accessibility and socioeconomic characteristics obtained from GIS. The total-value model consists of all land-value and improvement-value variables and a constant, as shown in Equation 1. The improvement-value model includes all attributes related to structural characteristics of improvements or buildings as shown in Equation 2. The land-value model employs characteristics exclusively related to land parcels, as shown in Equation 3.

1. Total-value model:

$$\text{TotValue}_i = \beta_0 + \sum_{i}^{n} \beta_{i,Impr} X_{i,Impr} + \sum_{j}^{n} \beta_{j, Land} X_{j, Land} + \epsilon_i \quad (1)$$

where

- $\text{TotValue}_i$ = dependent variable related to the total taxable value of a parcel (i.e. the taxable value for the land plus the improvement);
- $X_{i,Impr}$ = vector of variables related to the characteristics of the improvement;
- $X_{j, Land}$ = vector of variables related to the characteristics of the land; and
- $\epsilon_i$ = error term at point $i$.

2. Improvement-value model:
where

\[ \text{ImprValue}_i = \beta_0 + \sum_{l}^{n} \beta_{l \text{Impr} \ X_l \text{Impr}} + \epsilon_i \] (2)

\[ \text{LandValue}_i = \beta_0 + \sum_{j}^{n} \beta_{j \text{Land} \ X_j \text{Land}} + \epsilon_i \] (3)

\[ y_i = \beta_0(u_i, v_i) + \sum_{k}^{k} \beta_k(u_i, v_i)X_{ik} + \epsilon_i \] (4)

The GWR method is an enhancement of the weighted least-squares technique. It accounts for spatially varying relationships by generating individual regression functions in subsets of a specific location with coordinates \((u_i, v_i)\). GWR incorporates a spatial weights matrix, which varies by location, estimating a local regression for each observation in the dataset, as shown in Equation 4 (31). In Equation 4, observations located closer to the epicenter \((u_i, v_i)\) of each subset have greater weights in parameter estimation than more distant ones.

The spatial weights matrix is determined including observations for the dependent and explanatory variables falling within the bandwidth around a specific point \((u_i, v_i)\). The bandwidth can be determined by distance, number of neighbors, or by a Gaussian kernel process. Kernel bandwidths can be fixed or adaptive depending on the density of observations at a particular location. The weights of the estimator used in this model are conditioned on the location coordinates \((u_i, v_i)\):

\[ \hat{\beta}(u_i, v_i) = (X^TW(u_i, v_i)X)^{-1} X^TW(u_i, v_i)Y_i \] (5)
\( \hat{\beta}(u_i, v_i) = \) vector of estimated parameters at location coordinates \((u_i, v_i)\);

\( X^T = \) the transpose of matrix \(X\) number of variables;

\( W(u_i, v_i) = \) \( n \times n \) spatial weight matrix, which varies by location \((u_i, v_i)\);

\( X = n \times k \) matrix of covariates; and

\( Y = n \times 1 \) vector of dependent values (across \( n \) observations).

Adaptive kernel bandwidths are typically preferred when some of the regression points are not uniformly distributed over space (i.e. the data are sparse). When the data are sparse, the spatial weight matrix is estimated using a small number of data points resulting in fairly large standard errors for the parameters. In order to minimize the standard errors, adaptive kernels adjust the bandwidth to include the same number of observations in a consistent manner regardless of their density variation across space. Kernel bandwidths are determined by minimizing a corrected Akaike Information Criterion (\( AIC_c \)) or a cross validation (\( CV \)) score regardless of the type of kernel bandwidth selected (i.e. fixed or adaptive). The formula for the \( AIC_c \), as applied in Hurvich et al. is (45):

\[
AIC_c = 2n \log_c(\hat{\sigma}) + n \log_c(2\pi) + n \left[ \frac{n + tr(S)}{n - 2} - tr(S) \right]
\]  
(6)

where

\( AIC_c = \) information distance between the true and the fitted models;

\( n = \) number of data points;

\( \hat{\sigma} = \) estimated standard deviation of the residuals; and

\( tr(S) = \) trace of hat matrix \( S \) (also called projection matrix, which maps the vector of observed values to the vector of fitted values); and

\( S = X(X^TX)^{-1}X^T \).

The formula for the \( CV \) score, as applied in Fotheringham et al. is (30):

\[
CV = \sum_{n=1}^{N_{obs}} \sum_{j=0}^{J} (I_{\neq n,j} - \hat{p}_{\neq n,j}(b))^2
\]  
(7)

where

\( CV = \) cross-validation score minimized to find the optimal bandwidth value or number of nearest neighbors;

\( I_{\neq n,j} = \) indicator variable for data points other than \( n \), which equals 1, if parcel \( n \) is of land use type \( j \), and 0 otherwise; and

\( \hat{p}_{\neq n,j} = \) estimated probability for parcel \( n \) with land use type \( j \).

The lower the \( AIC_c \) and the \( CV \) score, the closer the fitted model is to the true model. However, problems with local multicollinearity might prevent both the \( AIC_c \) and \( CV \) methods from resolving an optimal distance or number of neighbors. In such instance, the calculation needs to be done manually using the following kernel estimator (32):

\[
\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K \left( \frac{x - X_i}{h} \right)
\]  
(8)

where
\[ \hat{f}(x) = \text{density}; \]
\[ n = \text{number of data points}; \]
\[ h = \text{bandwidth}; \text{ and} \]
\[ K = \text{kernel}. \]

Finally, the Getis and Ord's \( G_i \) test is applied to check for spatial autocorrelation in the residuals as suggested by Getis (43).

Data Collection and Study Area

El Paso County consists of a polycentric surface (i.e. multiple economic and urban centers) of 1,015 square miles with a population of 827,398 according to the 2012 Census estimate. El Paso Central Appraisal District (EPCAD) maintains parcel records and their taxable values, which account for exemptions. Only real property is allowed to be within a TRZ. Given that, all personal property is excluded such as mobile homes or inventory. Non-taxable parcels (e.g. government, churches, etc.) are classified as TRZ not eligible (46). The predominant land use is Single-family, which is the focus of this paper. Single-family consists of 198,574 parcels and includes homes on tracts of land or platted lots for residential purposes. Proximity for each parcel is determined as the distance from the front edge of each parcel to the centerline of the nearest interstate, freeway, and major arterial measured in feet. Accessibility for each parcel is determined as the driving-time measured in minutes from the geometric centroid of each parcel to the nearest port-of-entry (POE) and shopping centers (47). The driving times are estimated calculating driving-time areas using the actual street network also in GIS. El Paso County has 145 miles of interstates, 216 miles of freeways, and 482 miles of major arterials, as measured at the centerline of each link of a transportation facility. There are four international POEs in the County: 1) Bridge of the Americas, 2) Paso Del Norte Bridge, 3) Ysleta International Bridge, and 4) Stanton International Bridge. Fullerton and Villalobos find that proximity to such POEs positively impacts housing prices (9). Distance to job centers was not considered since most of them are located adjacent or very close to the interstates (likely to raise multicollinearity issues) or in tax-exempt land not eligible for VC (i.e. Fort Bliss). Table 1 illustrates the descriptive statistics for the variables considered.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Min</th>
<th>Max</th>
<th>Median</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TotValue, i</td>
<td>Total value</td>
<td>$0.00</td>
<td>$18,135,362</td>
<td>$94,367</td>
<td>$108,824</td>
<td>$116,147</td>
</tr>
<tr>
<td>ImprValue, i</td>
<td>Improvement value</td>
<td>$0.00</td>
<td>$15,425,252</td>
<td>$86,234</td>
<td>$95,665</td>
<td>$87,796</td>
</tr>
<tr>
<td>LandValue, i</td>
<td>Land value</td>
<td>$0.00</td>
<td>$7,607,537</td>
<td>$17,199</td>
<td>$23,520</td>
<td>$63,880</td>
</tr>
<tr>
<td><strong>Explanatory variables common in all models</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PopDens_CY</td>
<td>Population density per block</td>
<td>0.00</td>
<td>26,171</td>
<td>5,115</td>
<td>4,892</td>
<td>3,412</td>
</tr>
<tr>
<td>Renter_CY</td>
<td>Housing units occupied by renters</td>
<td>0.00</td>
<td>1,436</td>
<td>145</td>
<td>184</td>
<td>165</td>
</tr>
<tr>
<td>Vacant_CY</td>
<td>Number of improvements not occupied (empty buildings) per block</td>
<td>0.00</td>
<td>182</td>
<td>27</td>
<td>37</td>
<td>34</td>
</tr>
<tr>
<td>Unemp_CY</td>
<td>People 16/older unemployed per block</td>
<td>0.00</td>
<td>374</td>
<td>42</td>
<td>61</td>
<td>63</td>
</tr>
<tr>
<td>PCI_CY</td>
<td>Income per-capita per block</td>
<td>0.00</td>
<td>$54,598</td>
<td>$14,802</td>
<td>$16,502</td>
<td>$9,628</td>
</tr>
<tr>
<td>MP35003a,B</td>
<td>People with 3 or more air trips per yr.</td>
<td>0.00</td>
<td>510</td>
<td>70</td>
<td>92</td>
<td>82</td>
</tr>
<tr>
<td>DistInterst</td>
<td>Distance to nearest interstate (ft.)</td>
<td>28.2</td>
<td>120,171</td>
<td>11,544</td>
<td>16,928</td>
<td>15,271</td>
</tr>
<tr>
<td>DistFreeways</td>
<td>Distance to nearest freeway (ft.)</td>
<td>0.00</td>
<td>137,610</td>
<td>5,561</td>
<td>8,938</td>
<td>12,293</td>
</tr>
<tr>
<td>DistMajArter</td>
<td>Distance to nearest major artery (ft.)</td>
<td>0.00</td>
<td>59,501</td>
<td>1,240</td>
<td>1,856</td>
<td>2,562</td>
</tr>
</tbody>
</table>
EMPIRICAL ANALYSIS

This section presents the empirical analysis for the three hedonic equations: (i) the total-value model, (ii) the improvement-value model, and (iii) the land-value model for single-family. First, a statistically significant OLS model (i.e. a global model) is identified, and then its GWR version is developed (i.e. a local model). Results for each coefficient also include robust standard errors (Robust SE), t-statistics (Robust t), and probabilities (Robust Prob). Robust estimators are accurate even in the presence of nonstationarity or heteroskedasticity, and they are used to determine if an explanatory variable is significant (48). Variables that are not significant in the OLS estimation are excluded from the GWR estimation. A statistically significant Koenker Bruesch-Pagan (BP) test indicates that problems with nonstationarity or heteroskedasticity are present (49). To counter local multicollinearity issues associated with insufficient variation of observations neighboring the epicenter \( u_i, v_i \), adaptive kernels are determined setting the bandwidth to 1,000 neighbors, as Wang et al. (37). When the variance inflation factor (VIF) is larger than 7.5 for a variable, local multicollinearity is a problem, and such variables are excluded from the GWR estimation. Dummy variables and variables with spatial clustering of identical values are also removed in the GWR estimation. The diagnostics from GWR include results from a baseline global model (i.e. residual squares, sigma, \( \text{AdjR}^2 \), \( AIC_c \)); furthermore, a summary that defines the extent of the variability in the local coefficients and their standard errors (i.e. minimum, mean, and maximum). In GWR, it is necessary to visualize the local coefficients in maps to better interpret nonstationarity. Local coefficient maps are presented for each of the variables testing the hypothesis to better understand the local variation of the impacts.

Total Value Models

The total value model for single-family consists of 198,574 observations (56.4% of the total population) where the dependent variable is \( \text{TotValue} \). Table 2 presents the results for the 21 independent variables plus the intercept term, from which 17 are significant according to their robust 95% confidence interval. Results for \( \text{Mp35003a}_B \) indicate an increase of $37.50 in...
**Bujanda & Fullerton**

*Total Value* for every additional person with 3 or more air-trips/year. *DistInterstate* indicates that *Total Value* decreases $0.66 for every foot a parcel is located away from the nearest interstate. *DistFreeways* indicate a similar decrease of $0.72 per foot. *DistMajorArteries* is not significant. *POE_DrivingTime* indicates that *Total Value* increases $1,297 for every driving minute a single-family property is located away from the nearest POE. This is counterintuitive to the results in the random sample of Fullerton and Villalobos, which imply that as distance to a POE increases, the list price of a housing unit decreases (9). *ShopC_DrivingTime* indicates that *Total Value* decreases $884 for every minute it takes to drive to the nearest shopping center. Adjusted $R^2$ indicates that the model explains 47.6% of the variation. The Jarque-Bera statistic indicates that residuals are not normal. Nonstationarity and heteroskedasticity are confirmed by a significant Koenker BP statistic. The Joint Wald Statistic indicates that the overall model is significant.

**TABLE 2 Total Value Model OLS Estimation Results**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>Std. Error</th>
<th>t-Stats.</th>
<th>Prob.</th>
<th>Robust SE</th>
<th>Robust t</th>
<th>Robust Prob.</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1203.06</td>
<td>4123.42</td>
<td>0.29</td>
<td>0.77</td>
<td>22619.90</td>
<td>0.05</td>
<td>0.96</td>
<td>-----</td>
</tr>
<tr>
<td>ImpAge</td>
<td>-105.95</td>
<td>17.55</td>
<td>-6.04</td>
<td>0.00*</td>
<td>21.26</td>
<td>-4.98</td>
<td>0.00*</td>
<td>4.80</td>
</tr>
<tr>
<td>Air</td>
<td>-2285.74</td>
<td>759.16</td>
<td>-3.01</td>
<td>0.00*</td>
<td>1209.19</td>
<td>-1.89</td>
<td>0.06</td>
<td>2.22</td>
</tr>
<tr>
<td>Baths²</td>
<td>1858.36</td>
<td>49.96</td>
<td>37.20</td>
<td>0.00*</td>
<td>193.23</td>
<td>9.62</td>
<td>0.00*</td>
<td>1.30</td>
</tr>
<tr>
<td>Bedrooms²</td>
<td>1083.94</td>
<td>36.05</td>
<td>30.07</td>
<td>0.00*</td>
<td>89.58</td>
<td>12.108</td>
<td>0.00*</td>
<td>1.52</td>
</tr>
<tr>
<td>Garage</td>
<td>1545.81</td>
<td>1198.30</td>
<td>1.29</td>
<td>0.20</td>
<td>1015.83</td>
<td>1.52</td>
<td>0.13</td>
<td>1.26</td>
</tr>
<tr>
<td>Depreciable</td>
<td>867.51</td>
<td>30.75</td>
<td>28.22</td>
<td>0.00*</td>
<td>25.67</td>
<td>33.79</td>
<td>0.00*</td>
<td>3.88</td>
</tr>
<tr>
<td>LandAcres</td>
<td>7313.27</td>
<td>62.06</td>
<td>117.83</td>
<td>0.00*</td>
<td>1886.81</td>
<td>3.88</td>
<td>0.00*</td>
<td>1.03</td>
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<tr>
<td>ImpSize</td>
<td>34.39</td>
<td>0.12</td>
<td>285.58</td>
<td>0.00*</td>
<td>2.19</td>
<td>15.67</td>
<td>0.00*</td>
<td>1.30</td>
</tr>
<tr>
<td>Stories</td>
<td>-70389.95</td>
<td>2582.89</td>
<td>-27.25</td>
<td>0.00*</td>
<td>20495.23</td>
<td>-3.43</td>
<td>0.00*</td>
<td>11.56</td>
</tr>
<tr>
<td>Vacant</td>
<td>-51719.14</td>
<td>2609.16</td>
<td>-19.82</td>
<td>0.00*</td>
<td>20969.16</td>
<td>-2.47</td>
<td>0.01*</td>
<td>11.94</td>
</tr>
<tr>
<td>PopDens_CY</td>
<td>-0.58</td>
<td>0.07</td>
<td>-8.82</td>
<td>0.00*</td>
<td>0.13</td>
<td>-4.28</td>
<td>0.00*</td>
<td>1.40</td>
</tr>
<tr>
<td>Renter_CY</td>
<td>4.28</td>
<td>1.37</td>
<td>3.13</td>
<td>0.00*</td>
<td>2.53</td>
<td>1.69</td>
<td>0.09</td>
<td>1.43</td>
</tr>
<tr>
<td>Vacant_CY</td>
<td>42.00</td>
<td>7.47</td>
<td>5.62</td>
<td>0.00*</td>
<td>13.38</td>
<td>3.14</td>
<td>0.00*</td>
<td>1.87</td>
</tr>
<tr>
<td>Unemp_CY</td>
<td>-50.84</td>
<td>3.66</td>
<td>-13.90</td>
<td>0.00*</td>
<td>4.90</td>
<td>-10.37</td>
<td>0.00*</td>
<td>1.51</td>
</tr>
<tr>
<td>PCI_CY</td>
<td>1.40</td>
<td>0.03</td>
<td>55.33</td>
<td>0.00*</td>
<td>0.07</td>
<td>20.41</td>
<td>0.00*</td>
<td>1.67</td>
</tr>
<tr>
<td>Mp35003a_B</td>
<td>37.50</td>
<td>3.18</td>
<td>11.78</td>
<td>0.00*</td>
<td>3.2</td>
<td>11.85</td>
<td>0.00*</td>
<td>1.94</td>
</tr>
<tr>
<td>DistInterstate</td>
<td>-0.66</td>
<td>0.02</td>
<td>-40.84</td>
<td>0.00*</td>
<td>0.03</td>
<td>-22.80</td>
<td>0.00*</td>
<td>1.69</td>
</tr>
<tr>
<td>DistFreeways</td>
<td>-0.72</td>
<td>0.02</td>
<td>-32.37</td>
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<td>0.03</td>
<td>-23.15</td>
<td>0.00*</td>
<td>2.11</td>
</tr>
<tr>
<td>DistMajorArteries</td>
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<td>0.09</td>
<td>-1.32</td>
<td>0.19</td>
<td>0.10</td>
<td>-1.21</td>
<td>0.23</td>
<td>1.52</td>
</tr>
<tr>
<td>POE_DrivingTime</td>
<td>1297.10</td>
<td>54.42</td>
<td>23.83</td>
<td>0.00*</td>
<td>104.17</td>
<td>12.45</td>
<td>0.00*</td>
<td>2.47</td>
</tr>
<tr>
<td>ShopC_DrivingTime</td>
<td>-883.99</td>
<td>55.81</td>
<td>-15.84</td>
<td>0.00*</td>
<td>82.31</td>
<td>-10.74</td>
<td>0.00*</td>
<td>2.41</td>
</tr>
</tbody>
</table>

AICc: 5066953  
Adjusted R-Squared: 0.476

Joint F-Statistic: 8595  
Prob(>F), (21,198552) degrees of freedom: 0.00*

Joint Wald Statistic: 143016  
Prob(>chi-squared), (21) degrees of freedom: 0.00*

Koenker (BP) Statistic: 3197  
Prob(>chi-squared), (21) degrees of freedom: 0.00*

Jarque-Bera Statistic: 601884996105  
Prob(>chi-squared), (2) degrees of freedom: 0.00*

*Statistically significant probabilities have an asterisk next to them.

The GWR total value model estimation yields 177,450 regression points with invertible matrices, 89.4% from the single-family sample (Table 3). *DistInterstate* indicates that *Total Value* decreases $5.52 per foot according to the mean. Local coefficients for *DistInterstate* range from a negative $909 per foot to a positive $200 per foot depending on their location, as shown in Figure 2(a). *DistFreeways* indicates that *Total Value* decreases $5.98 per foot according to the mean. Local coefficients for *DistFreeways* range from a negative $596 to a positive $345 per
foot depending on their location, as shown in Figure 2(b). According to the mean, \( \text{POE} \_\text{DrivingTime} \) indicates that \( \text{TotValue} \) increases $2,036 for every additional minute required to drive to the nearest international crossing. \( \text{POE} \_\text{DrivingTime} \) ranges from a negative $220,522 per minute to an increase in \( \text{TotValue} \) of $584,558 per minute, shown in Figure 2(c). Results indicate a higher premium for \( \text{DistInterstate} \), \( \text{DistFreeways} \), and \( \text{POE} \_\text{DrivingTime} \). \( \text{POE} \_\text{DrivingTime} \) indicates a higher \( \text{TotValue} \) premium in parcels more distant to the POEs, in the west and north outskirts of the county, as indicated by the dark parcels distant to the POEs.

### Table 3 Total Value Model GWR Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Local coefficient estimates</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Mean</td>
</tr>
<tr>
<td>Intercept</td>
<td>-20119734</td>
<td>-73885</td>
</tr>
<tr>
<td>Bedrooms(^2)</td>
<td>-17383</td>
<td>955</td>
</tr>
<tr>
<td>Baths(^2)</td>
<td>-50256</td>
<td>5597</td>
</tr>
<tr>
<td>Depreciable</td>
<td>-44896</td>
<td>2720</td>
</tr>
<tr>
<td>PCI_CY</td>
<td>-486</td>
<td>0.766</td>
</tr>
<tr>
<td>DistInterstate</td>
<td>-909</td>
<td>-5.52</td>
</tr>
<tr>
<td>DistFreeways</td>
<td>-596</td>
<td>-5.98</td>
</tr>
<tr>
<td>( \text{POE} _\text{DrivingTime} )</td>
<td>-220522</td>
<td>2036</td>
</tr>
<tr>
<td>Residual Squares:</td>
<td>43854883988</td>
<td></td>
</tr>
<tr>
<td>Sigma</td>
<td>53146.6</td>
<td></td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.430</td>
<td></td>
</tr>
<tr>
<td>Effective Number:</td>
<td>0.4737</td>
<td></td>
</tr>
<tr>
<td>AICc:</td>
<td>396</td>
<td></td>
</tr>
</tbody>
</table>

The GWR global diagnostics show improvement over OLS for the AICc from 5,066,953 to 396, but not for the \( \text{AdjR}^2 \) which decreased slightly from 0.476 in OLS to 0.450 in the GWR baseline model. Figure 3 illustrates the spatial autocorrelation results using a Getis and Ord’s \( G_i \) (Hot Spot) test on the standard residuals from a) OLS and b) GWR. The \( G_i^* \) statistic for each observation in the figure is a Z score. The larger a significant positive Z score, the more intense the clustering of high values (i.e. a hot spot). The smaller negative Z scores, the more intense the clustering of low values (i.e. cold spot). Spatial autocorrelation is confirmed in the residuals from OLS with hot spots predominantly in the west and north sides of the county and cold spots in the east. Spatial autocorrelation is eliminated in the residuals from GWR.
FIGURE 2 Total Value GWR Model Coefficient Estimates.
Improvement Value Models

The improvement value model for single-family consists of 198,574 data points where the dependent variable is ImpValue. Table 4 presents the results for the 20 independent variables, from which 19 are robust significant. Results indicate ImpValue increases $17.30 for every additional person in Mp3503a B. DistInterstate indicates a decrease in ImpValue of $0.45 per foot. DistFreeways indicate a similar decrease of $0.49 per foot. DistMajorArteries indicates an increase in ImpValue of $0.38 per foot. POE_DrivingTime indicates that for every additional minute, ImpValue increases $853. ShopC_DrivingTime indicates that ImpValue increases $449 per driving minute to the nearest shopping center. The improvement value model explains 61.8% of the variation. The Jarque-Bera statistic indicates that residuals are not normally distributed. The Koenker BP statistic is significant indicating nonstationarity or heteroskedasticity. The Joint Wald Statistic indicates that the overall model is significant.

TABLE 4 Improvement Value Model OLS Estimation Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>Std. Error</th>
<th>t-Stats.</th>
<th>Prob.</th>
<th>Robust SE</th>
<th>Robust t</th>
<th>Robust Prob.</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-92069.58</td>
<td>2153.63</td>
<td>-42.75</td>
<td>0.00*</td>
<td>4266.78</td>
<td>-21.58</td>
<td>0.00*</td>
<td>----</td>
</tr>
<tr>
<td>ImpAge</td>
<td>52.20</td>
<td>11.32</td>
<td>4.61</td>
<td>0.00*</td>
<td>19.68</td>
<td>2.65</td>
<td>0.01*</td>
<td>4.80</td>
</tr>
<tr>
<td>Air</td>
<td>5798.42</td>
<td>483.96</td>
<td>11.98</td>
<td>0.00*</td>
<td>657.99</td>
<td>8.81</td>
<td>0.00*</td>
<td>2.17</td>
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<tr>
<td>Baths²</td>
<td>1811.24</td>
<td>32.21</td>
<td>56.23</td>
<td>0.00*</td>
<td>221.86</td>
<td>8.16</td>
<td>0.00*</td>
<td>1.29</td>
</tr>
<tr>
<td>Bedrooms²</td>
<td>872.03</td>
<td>23.22</td>
<td>37.56</td>
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<td>107.64</td>
<td>8.10</td>
<td>0.00*</td>
<td>1.52</td>
</tr>
<tr>
<td>Garage</td>
<td>2050.83</td>
<td>771.90</td>
<td>2.66</td>
<td>0.01*</td>
<td>665.66</td>
<td>3.08</td>
<td>0.00*</td>
<td>1.25</td>
</tr>
<tr>
<td>Depreciable</td>
<td>863.87</td>
<td>19.82</td>
<td>43.58</td>
<td>0.00*</td>
<td>23.14</td>
<td>37.33</td>
<td>0.00*</td>
<td>3.87</td>
</tr>
<tr>
<td>LandAcres</td>
<td>481.09</td>
<td>40.04</td>
<td>12.02</td>
<td>0.00*</td>
<td>403.29</td>
<td>1.19</td>
<td>0.23</td>
<td>1.03</td>
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</table>
Table 5: Improvement Value Model GWR Summary Statistics

<table>
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<tr>
<th>Variable</th>
<th>Local coefficient estimates</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>Min</td>
<td>Mean</td>
</tr>
<tr>
<td>Intercept</td>
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<tr>
<td>Bedrooms²</td>
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<td>Depreciable</td>
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<td>ImpSize</td>
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<tr>
<td>DistFreeways</td>
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<td>1.29</td>
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<tr>
<td>DistMajorArteries</td>
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<td>-0.163</td>
</tr>
<tr>
<td>POE_DrivingTime</td>
<td>-128320</td>
<td>347</td>
</tr>
</tbody>
</table>

*Statistically significant probabilities have an asterisk next to them.

The GWR improvement value model estimation yields 177,450 regression points with invertible matrices, 87.6% from the single-family sample (Table 5). DistInterstate indicates that ImpValue increases $1.25 per foot according to the mean. Local coefficients for DistInterstate range from a negative $343 per foot to a positive $241 per foot depending on their location, shown in Figure 4(a). DistFreeways indicates that ImpValue increases $1.29 per foot according to the mean. Local coefficients for DistFreeways range from a negative $218 to a positive $341 per foot, as shown in Figure 4(b). DistMajorArteries indicates that ImpValue decreases $0.16 per foot according to the mean. Local coefficients for DistMajorArteries range from a negative $548 to a positive $116 per foot, as shown in Figure 4(c). POE_DrivingTime indicates that ImpValue increases $347 per minute according to the mean. Local coefficients for POE_DrivingTime range from a negative $128,320 to a positive $418,682 per minute, as shown in Figure 4(d). In general, Figure 4 indicates a higher premium for DistInterstate and DistFreeways for properties on the west and a smaller portion on the east side of the county, south from the interstate. The premium for DistMajorArteries seems sparser through the county. POE_DrivingTime shows the highest premium on properties located in areas with high ImpValues. GWR shows improvement over their OLS counterpart for the AICc from 4,892,903 to 2,778 and for the AdjR² which increased from 0.618 in OLS to 0.953 in the GWR baseline model. Spatial autocorrelation practically disappears in the residuals from GWR.
Bujanda & Fullerton

Residual Squares: 30651063734
Sigma: 15945
\( R^2: 0.954 \)
Effective Number: 4.44
AICc: 2778
\( \text{AdjR}^2: 0.953 \)

FIGURE 4 Improvement Value GWR Model Coefficient Estimates.
The land value model consists of 198,574 data points where the dependent variable is \( \text{LandValue} \). Table 6 presents the results for the 6 independent variables plus the intercept term; all statistically significant. \( \text{DistInterstate} \) indicates an increase in \( \text{LandValue} \) of $0.29, \( \text{DistFreeways} \) an increase of $0.40, and \( \text{DistMajorArteries} \) indicates an increase of $0.53 per foot. \( \text{POE\_DrivingTime} \) indicates that \( \text{LandValue} \) increases $1,276 for every additional minute required to drive from a parcel to a POE, which implies that as distance to a POE increases, the \( \text{LandValue} \) increases. Similarly, as \( \text{ShopC\_DrivingTime} \) increases, \( \text{LandValue} \) is $186 higher per minute. The land value model explains 12.6% of the variation. The residuals are not normally distributed. Nonstationarity and heteroskedasticity are confirmed by the Koenker BP statistic.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>Std. Error</th>
<th>t-Stats.</th>
<th>Prob.</th>
<th>Robust SE</th>
<th>Robust t</th>
<th>Robust Prob.</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
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<td>22.86</td>
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<td>763.71</td>
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</tr>
<tr>
<td>LandAcres</td>
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<td>161.50</td>
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<td>1852.62</td>
<td>3.81</td>
<td>0.00*</td>
<td>1.01</td>
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<td>0.01</td>
<td>26.54</td>
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<td>0.02</td>
<td>15.21</td>
<td>0.00*</td>
<td>1.54</td>
</tr>
<tr>
<td>DistFreeways</td>
<td>0.40</td>
<td>0.02</td>
<td>26.12</td>
<td>0.00*</td>
<td>0.02</td>
<td>17.19</td>
<td>0.00*</td>
<td>2.00</td>
</tr>
<tr>
<td>DistMajorArteries</td>
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<td>0.06</td>
<td>8.56</td>
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<td>0.10</td>
<td>5.29</td>
<td>0.00*</td>
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</tr>
<tr>
<td>POE_DrivingTime</td>
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<td>38.17</td>
<td>0.00*</td>
<td>61.34</td>
<td>20.81</td>
<td>0.00*</td>
<td>1.85</td>
</tr>
<tr>
<td>ShopC_DrivingTime</td>
<td>186.17</td>
<td>36.86</td>
<td>5.05</td>
<td>0.00*</td>
<td>73.26</td>
<td>2.54</td>
<td>0.01*</td>
<td>2.08</td>
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</tbody>
</table>

| AICc                     | 4931181 | Adjusted R-Squared: 0.125 |

Joint F-Statistic: 4765
Prob(>F), (21,198552) degrees of freedom: 0.00*
Joint Wald Statistic: 2164
Prob(>chi-squared), (21) degrees of freedom: 0.00*
Koenker (BP) Statistic: 17576
Prob(>chi-squared), (21) degrees of freedom: 0.00*
Jarque-Bera Statistic: 18224193886
Prob(>chi-squared), (2) degrees of freedom: 0.00*  

*Statistically significant probabilities have an asterisk next to them.

The GWR land value model estimation also yields invertible matrices for 87.6% of the sample (Table 7). As \( \text{DistInterstate} \) increases, \( \text{LandValue} \) decreases $0.98 per foot according to the mean. Local coefficients for \( \text{DistInterstate} \) range from a negative $467 per foot to an increase of $526 per foot depending on their location, as shown in Figure 6(a). As \( \text{DistFreeways} \) increases, \( \text{LandValue} \) increases $0.59 per foot according to the mean. Local coefficients for \( \text{DistFreeways} \) range from a negative $133 to an increase of $532 per foot, as shown in Figure 6(b). As \( \text{DistMajorArteries} \) increases, \( \text{LandValue} \) decreases $0.82 per foot according to the mean. Local coefficients for \( \text{DistMajorArteries} \) range from a negative $320 to an increase of $153 per foot, as shown in Figure 6(c). \( \text{POE\_DrivingTime} \) indicates \( \text{LandValue} \) decreases almost $50 per minute on average. This is in line with the findings from Fullerton and Villalobos (9). This indicates that the premium is mainly capitalized by the land rather than the improvement. Nonetheless, \( \text{POE\_DrivingTime} \) coefficients range from a negative $144,729 per minute to an increase of $222,070 per minute depending on their location, as shown in Figure 6(d). \( \text{ShopC\_DrivingTime} \) indicates that \( \text{LandValue} \) decreases $96 per minute according to the mean. Local coefficients for \( \text{ShopC\_DrivingTime} \) range from a negative $155,053 to a positive $216,636 per minute, as shown in Figure 6(e). A higher premium for \( \text{DistInterstate, DistFreeways, and POE\_DrivingTime} \) dominate the west side and, of less magnitude but still positive, on the east side of the county in Figure 6. The premia for \( \text{DistMajorArteries} \) seem quite limited for most parcels. \( \text{POE\_DrivingTime} \) shows the highest premia. GWR shows better predictive performance than OLS. The \( \text{AICc} \) decreased from 4,931,181 to 1,223 respectively, and
the AdjR\(^2\) increased from 0.125 in OLS to 0.836 in the GWR baseline model. Spatial autocorrelation practically disappears in the residuals from GWR.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Local coefficient estimates</th>
<th>Std. Error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Mean</td>
</tr>
<tr>
<td>Intercept</td>
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<td>25590</td>
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<tr>
<td>LandAcres</td>
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<td>60894</td>
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<tr>
<td>DistInterstate</td>
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<td>-0.978</td>
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<td>DistFreeways</td>
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<td>-0.824</td>
</tr>
<tr>
<td>POE_DrivingTime</td>
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</tr>
<tr>
<td>ShopC_DrivingTime</td>
<td>-155053</td>
<td>-96.3</td>
</tr>
</tbody>
</table>

Residual Squares: 490882289661  Sigma: 104479  R\(^2\): 0.839
Effective Number: 2.03  AICc: 1223  AdjR\(^2\): 0.836
FIGURE 6 Land Value GWR Model Coefficient Estimates.
CONCLUSION AND FURTHER RESEARCH

Traditional hedonic models that are global in nature could be deceptive in examining the impacts of transportation infrastructure proximity and accessibility on real property values. Koenker BP tests confirmed that problems with spatial nonstationarity and heteroskedasticity are present in all models. The significant large values of the Jarque-Bera statistic in all models indicate that residuals are not normally distributed. \( \text{AIC}_c \) was lower for GWR than OLS in all models, and \( \text{AdjR}^2 \) reports improvement for GWR in almost all models. The relationship between real property values and transportation infrastructure proximity and accessibility is highly localized and varies significantly over space. The presence of spatial nonstationarity and heterogeneity confirms that transportation infrastructure proximity and accessibility might generate a premium on real property values, but that a positive premium is not always present and is even negative in some areas.

This research demonstrates the importance of spatial dependence and spatial heterogeneity in econometric models. This research shows that GWR is a practice-ready alternative that allows visualizing the diverse spatial relationships between transportation infrastructure and real properties values. GWR confirms that the different impacts from a specific transportation facility can swing from positive to negative regardless of its proximity. Benefits from a transportation facility can be capitalized by parcels even if they are located away from the facility. Furthermore, the local coefficients indicate, for this sample, that not always the parcels that are adjacent to the facility necessarily have a premium. Such is the case of \( \text{POE}_\text{DrivingTime} \) which showed a lower premium in parcels located closer to the international crossings than more distant ones. While results for the El Paso are similar to those reported in the literature, replication of the analysis for other like-sized cities may provide additional insights. In general, GWR maps can translate into better VC policy development. This represents an opportunity for regional agencies to estimate how much value is added by infrastructure projects throughout particular locations to recapture some infrastructure costs in the form of VC.

As described in this paper, this methodology focused on a single cross-sectional dataset for 2013 allowing the identification of a premium in property clusters and at the parcel level. However, it is not possible to explore how the relationship between property values and transportation infrastructure changes over time. When a transportation facility is built, the real estate market capitalizes such benefits, positive or negative, into a new equilibrium price, which has an impact on the assessed values. Further research includes calculating elasticity values, adding the time dimension to this study, and shifting the focus from estimation and hypothesis testing to forecasting. This would allow to incorporate variables such as bank lending practices, inflation, and the local economy (e.g. local property tax rates). Spatial autoregressive approaches as in Anselin, 1988 and spatial panel data methods similar to Baltagi et al. (50) emerge as natural candidates to advance the models in this paper. Having the time dimension would allow to identify not only the short-term, but also the long-term impacts of transportation infrastructure on real property values, which are crux of VC.

ACKNOWLEDGEMENTS

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