1-2018

Infrastructure Impacts on Commercial Property Values Across El Paso in 2013

Arturo Bujanda  
Mercator International, arturobujar@gmail.com

Thomas M. Fullerton Jr.  
University of Texas at El Paso, tomf@utep.edu

Follow this and additional works at: https://digitalcommons.utep.edu/border_region
Part of the Infrastructure Commons, Real Estate Commons, and the Regional Economics Commons

Comments:
Technical Report TX18-1
A revised version of this study is forthcoming in Asia-Pacific Journal of Regional Science

Recommended Citation
https://digitalcommons.utep.edu/border_region/55

This Article is brought to you for free and open access by the Department of Economics and Finance at DigitalCommons@UTEP. It has been accepted for inclusion in Border Region Modeling Project by an authorized administrator of DigitalCommons@UTEP. For more information, please contact lweber@utep.edu.
Technical Report TX18-1

INFRASTRUCTURE IMPACTS ON COMMERCIAL PROPERTY VALUES ACROSS EL PASO IN 2013

Produced by University Communications, January 2018
Cover image: Loop 375-Interstate 10 interchange in far East El Paso
THE UNIVERSITY OF TEXAS AT EL PASO
UTEP BORDER REGION MODELING PROJECT

Technical Report TX18-1

INFRASTRUCTURE IMPACTS ON COMMERCIAL PROPERTY VALUES ACROSS EL PASO IN 2013
This technical report is a publication of the Border Region Modeling Project and the Department of Economics & Finance at the University of Texas at El Paso. For additional Border Region information, please visit the www.academics.utep.edu/border section of the UTEP web site.

Please send comments to:
Border Region Modeling Project - CBA 236
Department of Economics & Finance
500 West University
El Paso, TX 79968-0543.

**UTEP does not discriminate on the basis of race, color, national origin, sex, religion, age, or disability in employment or the provision of services.**

**The University of Texas at El Paso**
Diana Natalicio, President
Carol Parker, Provost
Roberto Osegueda, Vice Provost

**UTEP College of Business Administration**
*Border Economics & Trade*
Bob Nachtmann, Dean
Steve Johnson, Associate Dean
Erik Devos, Associate Dean
Tim Roth, Templeton Professor of Banking & Economics
Special thanks are given to the corporate and institutional sponsors of the UTEP Border Region Econometric Modeling Project. In particular, El Paso Water Utilities, Hunt Communities, and The University of Texas at El Paso have invested substantial time, effort, and financial resources in making this research project possible.

Continued maintenance and expansion of the UTEP business modeling system requires ongoing financial support. For information on potential means for supporting this research effort, please contact:

Border Region Modeling Project - CBA 236
Department of Economics & Finance
500 West University
El Paso, TX 79968-0543
INFRASTRUCTURE IMPACTS ON COMMERCIAL PROPERTY VALUES ACROSS EL PASO IN 2013*

Arturo Bujanda\textsuperscript{a} and Thomas M. Fullerton, Jr.\textsuperscript{b}

\textsuperscript{a} Transportation Economist, Mercator International, 4040 Lake Washington Boulevard, Kirkland WA 98033, Email: arturobujar@gmail.com, Telephone: (915) 637-9537

\textsuperscript{b} Professor & Trade in the Americas Chair, Department of Economics & Finance, University of Texas at El Paso, El Paso, TX 79968-0543, Email: tomf@utep.edu, Telephone: (915) 747-7747, Facsimile: (915) 747-6282

* A revised version of this study is forthcoming in \textit{Asia-Pacific Journal of Regional Science}.

\textbf{ABSTRACT}  
Real estate property value analysis is used for municipal taxation and budgeting. Commercial properties make up a large percentage of the property tax base in many, if not most, taxing jurisdictions. Data constraints limit the number of analyses conducted on commercial property value patterns. This study employs a fairly extensive data set to address that problem in the context of El Paso in 2013. The sample contains data for 105,611 commercial real estate parcels. Empirical analysis is conducted using geographically weighted regression analysis. Results confirm that parameter estimation for the commercial property data in this sample should be conducted using methodologies that allow for spatial autocorrelation and heteroscedasticity.

\textbf{ACKNOWLEDGEMENTS}  
The authors thank David Stone and Howard Johnson from the El Paso County Central Appraisal District for invaluable support in facilitating access to the data required to conduct this research. The efforts of Beatriz Mesta, who assisted with editorial data processing, are greatly appreciated. Special thanks are extended to the Texas A&M Transportation Institute where Bujanda was previously employed. Partial funding support for Fullerton was received from El Paso Water, Hunt Communities, City of El Paso Office of Management & Budget, UTEP Center for the Study of Western Hemispheric Trade, National Science Foundation Grant DRL-1740695, and UTEP Hunt Institute for Global Competitiveness. Helpful comments were provided by Adam Walke, AlDouri Raed, and two anonymous referees.

\textbf{JEL Classification:} R15, Regional Econometrics; R33, Nonresidential Real Estate Markets; R53, Public Infrastructure

\textbf{Keywords:} Transportation Accessibility; Geographically Weighted Regression; Commercial Property Values

\textbf{Acknowledgements:} The authors thank David Stone and Howard Johnson from the El Paso County Central Appraisal District for invaluable support in facilitating access to the data required to conduct this research. The efforts of Beatriz Mesta, who assisted with editorial data processing, are greatly appreciated. Special thanks are extended to the Texas A&M Transportation Institute where Bujanda was previously employed. Partial funding support for Fullerton was received from El Paso Water, Hunt Communities, City of El Paso Office of Management & Budget, UTEP Center for the Study of Western Hemispheric Trade, National Science Foundation Grant DRL-1740695, and UTEP Hunt Institute for Global Competitiveness. Helpful comments were provided by Adam Walke, AlDouri Raed, and two anonymous referees.

\textbf{JEL Classification:} R15, Regional Econometrics; R33, Nonresidential Real Estate Markets; R53, Public Infrastructure

\textbf{Keywords:} Transportation Accessibility; Geographically Weighted Regression; Commercial Property Values
INTRODUCTION

Investments in public infrastructure such as highways, airports, and mass transit facilities tend to improve productivity. Not surprisingly, these types of investments can increase adjacent property values, generating value premia 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 generally attempt to anticipate and capture the economic value created by transportation accessibility as a means for funding capacity expansions. Value capture (VC) on real properties from investments in public infrastructure has historically been achieved via the tax mechanism.

In the United States, regional infrastructure expenditures are financed using three basic sources: (i) local government revenues (tax and non-tax), (ii) borrowing, and (iii) funding from higher levels of government. As more fuel efficient vehicles such as gasoline-electric hybrids enter public and private fleets, fuel tax revenues and the Federal Highway Trust Fund will continue to decline, reducing funding amounts 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. Reduced funds are expected through 2050 (Hall, 2012). If the trends for declining fuel tax revenues, increasing transportation needs, and higher infrastructure costs continue, the funding required to address mobility needs is clearly beyond what traditional sources, like the dated fuel tax, can supply.

Because of the aforementioned revenue pressures, accurate valuation of taxable properties is important. Most of the non-roadway mechanisms for capturing value premia are used by local governments, with a few being employed 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.

This study applies geographically weighted regression (GWR) analysis to quantify the impacts of transportation infrastructure proximity and accessibility on commercial real property values in El Paso, Texas. The analysis takes advantage of a sample that contains data on 105,611 commercial property parcels in El Paso, Texas. It is an example of the types of data sets that are quickly becoming more prevalent in transportation and real estate settings (Sánchez-Martínez and Munizaga, 2016). The hypothesis tested is that transportation infrastructure proximity and accessibility impact commercial property values in El Paso. The next section provides a review of related literature. After that, a discussion of the data and methodology is presented. The fifth section reports empirical results. The paper concludes with key findings and suggestions for future research.
LITERATURE REVIEW

Real estate valuation questions have received substantial attention due to issues involving public finance and urban infrastructure (George 1920; Batt 2001; Peterson 2009; Levinson and Istrate 2011; Rybeck 2004; Vadali et al. 2009; Zhao et al. 2011). While many studies have examined residential property valuation issues, commercial properties have received comparatively less attention. Those that do analyze commercial property buildings generally document favorable effects of transportation facilities on such properties (Carey and Semmens 2003; Debrezion et al. 2007; Golub et al. 2012). Data scarcity is generally cited as the culprit behind the relative paucity of commercial property valuation studies (Montero-Lorenzo and Larraz-Iribas, 2012).

A small number of studies have examined property value issues for border metropolitan economies. For El Paso, Fullerton and Villalobos (2011) employ a hedonic pricing approach to analyze 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 Ciudad Juarez, Mexico indicates that major avenues and accessibility do not always improve housing values (Fierro et al., 2009). One study examines the predictability of both commercial and industrial property cadastral values in El Paso (Arnold Cote et al., 2010). Results in that study indicate that structural econometric model forecasts compare well to other time series and random walk alternatives for predictive accuracy.

Spatial econometric techniques have proven useful in studies where spatial dependence is present (Dubin, 1988; Basu and Thibodeau, 1998). 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 such as real property parcels or tax jurisdictions (Paelinck and Klaassen 1979; Anselin 1988; Anselin 2010; and Elhorst 2010). By applying spatial econometric models, Zhang and Wang (2013) finds that housing prices in Beijing capitalize positive premia from distances to the nearest metro station. Concas (2013) applies a spatial autoregressive (SAR) estimator, and finds that houses near limited access roadways exhibit greater price resilience during and after market downturns. Several studies quantify accessibility using distance-based and drive-time variables (Chernobai et al. 2011; Diao and Ferreira, 2010; Shin et al. 2007; Vadali, 2008; and Srour et al. 2002). Results indicate that the premium diminishes as the distance increases. Siethoff and Kockelman (2002) analyzes 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.

GWR allows 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 (Brunsdon et al. 1996; Brunsdon et al. 1998; Fotheringham et al. 2002;). Efthymiou et al. (2013) apply OLS, SAR, and GWR to determine the locations for transportation mobility centers. Results indicate that GWR modeling fits the data best and generates residuals that are random. Similar outcomes are reported in a variety of other studies that examine residential property and tax policy issues (Bujanda and Fullerton 2017; Du and Mulley 2007; Legg and Bowe 2009; Löchl and Axhausen 2010).

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 in allowing for such spatial effects (Bitter et al. 2007; Wang et al. 2012; Páez et al. 2007, Yu et al. 2007, Farber and Yeates, 2006, and Kestens et al. 2006). 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 (Löchl, 2007). Getis (2007) proposes several tests to check for spatial autocorrelation. Advantages provided include assessment of the strength of spatial effects on any variable; evaluation of spatial stationarity, spatial heterogeneity, and distance decay; and accommodation of spatial hypothesis testing. All of the latter potentially improve the efficiency and accuracy of cadastral value modeling, thus providing better quantification of municipal revenue gains associated with regional transportation and infrastructure investments.

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 (Rosen, 1974). Prior empirical evidence indicates that the magnitude of the impacts on property values vary over space (Martinez and Viegas 2009; Anselin and Lozano-Gracia 2008; Lozano-Gracia and Anselin 2012). Tests for spatial autocorrelation and heterogeneity are used to assess spillover effects and dependence among close parcels.

GLOBAL AND LOCAL REGRESSION METHODS: OLS AND GWR
The methodology involves estimating three hedonic equations: (i) a total-value model, (ii) an improvement-value model, and (iii) a land-value model (Siethoff and Kockelman, 2002). GWR is used to test each specification using geographic information system (GIS) data. Data collected include 2013 certified cadastral parcel records for real property in El Paso County, with transportation accessibility and socioeconomic characteristics obtained using GIS and ESRI Business Analyst (Bujanda, 2014). 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 and 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:

\[ \text{TotValue}_i = \beta_0 + \sum_{i}^{n} \beta_i \text{Impr} X_{i, \text{Impr}} + \sum_{j}^{n} \beta_j \text{Land} X_{j, \text{Land}} + \epsilon_i \]

where

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

2. Improvement-value model:

\[ \text{ImprValue}_i = \beta_0 + \sum_{i}^{n} \beta_i \text{Impr} X_{i, \text{Impr}} + \epsilon_i \]

where

- \( \text{ImprValue}_i \) = dependent variable related only to the value of improvements on parcel i; and
- \( X_{i, \text{Impr}} \) = vector of variables related to specific characteristics of the improvements.

3. Land-value model:

\[ \text{LandValue}_i = \beta_0 + \sum_{j}^{n} \beta_j \text{Land} X_{j, \text{Land}} + \epsilon_i \]

where

- \( \text{LandValue}_i \) = dependent variable related only to the taxable value of the land corresponding to a parcel i; and
- \( X_{j, \text{Land}} \) = vector of variables related to specific characteristics of that land.

GWR represents an enhanced version of the weighted least-squares approach of parameter estimation. It accounts for spatially varying relationships by generating individual regression functions for subsets of data at a specific location with coordinates \((u_i, v_i)\). GWR incorporates a spatial weights matrix, which varies by location, and estimates a local regression for each
observation in the dataset as shown in Equation 4 (Brunsdon et al. 1996). In Equation 4, observations located closer to the epicenter \((u_i, v_i)\) of each subset are assigned greater weights in estimation than are more distant ones.

\[
y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)X_{ik} + \epsilon_i
\]

where

- \(y_i\) = dependent variable for a specific model (i.e. total values, improvement values, and land values);
- \((u_i, v_i)\) = spatial coordinates of a point \(i\) (i.e. geometric centroid of each parcel);
- \(k\) = number of variables;
- \(\beta_k(u_i, v_i)\) = realization of function \(\beta_k(u,v)\) at point \(i\), and
- \(X_{ik}\) = value of explanatory variable \(k\) at point \(i\).

The spatial weights matrix is determined including observations for the dependent and explanatory variables falling within a specific bandwidth around a given 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 each model are conditioned on the location coordinates \((u_i, v_i)\):

\[
\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) Y_i
\]

where

- \(\hat{\beta}(u_i, v_i)\) = vector of estimated parameters at location coordinates \((u_i, v_i)\);
- \(X^T\) = the transpose of matrix \(X\) containing explanatory variables;
- \(W(u_i, v_i)\) = \(n\) by \(n\) spatial weight matrix, which varies by location \((u_i, v_i)\);
- \(X\) = \(n\) by \(k\) matrix of covariates; and
- \(Y\) = \(n\) by \(1\) 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 (AICc) or a cross validation (CV) score, regardless of the type of kernel bandwidth selected (i.e. fixed or adaptive). The formula for the AICc, as applied in Hurvich et al. (1998) is:
where

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

where

- \(AICc\) = 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 matrix S hat (also called the 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. (2002) is:

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

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 AICc and the CV score, the closer the fitted model is to the true model. However, problems with local multicollinearity might prevent both the AICc and CV methods from calculating an optimal distance or number of neighbors. In such instances, the calculation must be completed manually using the following kernel estimator (Efthymiou et al. 2013):

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

where

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

Finally, the Getis and Ord Gi test is used to check for spatial autocorrelation in the residuals as suggested by Getis (2007).
DATA COLLECTION AND STUDY AREA

El Paso County is a polycentric surface 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 taxable values plus any exemptions. This paper focuses on parcels with a Commercial land use classification. Commercial includes land and improvements associated with businesses selling goods or services (e.g., office buildings, hotels, gas stations, retail stores, utilities, railroads, multi-family rentals, and vacant lots for sale still owned by developers). All personal property is excluded, including mobile homes and inventory. Non-taxable parcels (e.g., government properties, churches, etc.) are also excluded (Combs, 2013). The 2013 EPCAD certified cadastral roll included a total of 105,611 Commercial parcels (30.0% of the total parcel population), which occupy 62,423 acres of land within El Paso County. Although the Commercial land use classification does contain some multi-family rental properties, the majority of what are commonly considered as multi-family housing units are excluded from these data. That is because the State of Texas, and EPCAD, has a separate parcel category denominated as Multi-family in which most apartments, duplexes, and other multi-family units are included (Combs, 2013).

Proximity to transportation infrastructure for each parcel is determined as the distance from the front edge of each parcel to the centerline of the nearest interstate highway, freeway, and major arterial, respectively, 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 center, respectively. The driving times are estimated by calculating driving-time areas using the actual street network using 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. Table 1 provides descriptive statistics for the variables included in the sample. Figure 1 maps the transportation network, POEs, and shopping centers utilized in the analysis.

EMPIRICAL ANALYSIS

Three hedonic specifications are employed: (i) the total-value model, (ii) the improvement-value model, and (iii) the land-value model for Commercial. 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 heteroscedasticity, and they are used to determine if an explanatory variable is significant (White, 1980).

Variables that do not render significant OLS coefficient estimates are excluded from the GWR specifications. A Koenker Bruesch-Pagan (BP) test is used to examine whether problems with nonstationarity or heteroscedasticity are present (Koenker, 1981). To counter local multicollinearity issues associated with insufficient variation of observations neighboring the epicenter \((u_i, v_i)\), adaptive kernels are determined by setting the bandwidth to 1,000 neighbors as Wang et al. (2012). When the variance inflation factor (VIF) is larger than 7.5 for any variable, local multicollinearity is problematic and that variables is excluded from the GWR specification. Dummy variables and variables with spatial clustering of identical values
Table 1 | Descriptive Statistics for 2013 Commercial Data: 105,611 Parcels

<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>TotValuei</td>
<td>Total value</td>
<td>$0.00</td>
<td>$142,824,129</td>
<td>$174,617</td>
<td>$551,113</td>
<td>$2,184,180</td>
</tr>
<tr>
<td>ImprValuei</td>
<td>Improvement value</td>
<td>$0.00</td>
<td>$124,266,068</td>
<td>$95,187</td>
<td>$349,577</td>
<td>$1,708,898</td>
</tr>
<tr>
<td>LandValuei</td>
<td>Land value</td>
<td>$0.00</td>
<td>$24,924,930</td>
<td>$56,711</td>
<td>$203,814</td>
<td>$639,431</td>
</tr>
</tbody>
</table>

**Explanatory variables common in all models**

<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>PopDens_CY</td>
<td>Population density per block</td>
<td>0.00</td>
<td>26,171</td>
<td>16</td>
<td>502</td>
<td>1,580</td>
</tr>
<tr>
<td>Renter_CY</td>
<td>Housing units occupied by renters</td>
<td>0.00</td>
<td>1,436</td>
<td>79</td>
<td>124</td>
<td>123</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>31</td>
<td>53</td>
<td>54</td>
</tr>
<tr>
<td>Unemp_CY</td>
<td>People 16/older unemployed per block</td>
<td>0.00</td>
<td>374</td>
<td>44</td>
<td>62</td>
<td>59</td>
</tr>
<tr>
<td>PCI_CY</td>
<td>Income per-capita per block</td>
<td>0.00</td>
<td>$54,598</td>
<td>$9,874</td>
<td>$11,424</td>
<td>$4,477</td>
</tr>
<tr>
<td>MP35003a_B</td>
<td>People with 3 or more air trips per yr.</td>
<td>0.00</td>
<td>509</td>
<td>38</td>
<td>70</td>
<td>54</td>
</tr>
<tr>
<td>DistInterst</td>
<td>Distance to nearest interstate (ft.)</td>
<td>28.2</td>
<td>121,166</td>
<td>46,302</td>
<td>48,249</td>
<td>24,451</td>
</tr>
<tr>
<td>DistFreeways</td>
<td>Distance to nearest freeway (ft.)</td>
<td>0.00</td>
<td>141,776</td>
<td>30,909</td>
<td>31,573</td>
<td>18,819</td>
</tr>
<tr>
<td>DistMajArter</td>
<td>Distance to nearest major artery (ft.)</td>
<td>0.00</td>
<td>60,597</td>
<td>10,944</td>
<td>15,809</td>
<td>13,715</td>
</tr>
<tr>
<td>POE_DriTime</td>
<td>Driving-time to nearest port-of-entry (minutes)</td>
<td>1.00</td>
<td>61</td>
<td>36</td>
<td>36</td>
<td>11</td>
</tr>
<tr>
<td>ShopC_DTime</td>
<td>Driving-time to nearest shopping centers (minutes)</td>
<td>1.00</td>
<td>53</td>
<td>33</td>
<td>31</td>
<td>11</td>
</tr>
</tbody>
</table>

**Land-only explanatory variables**

<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>LandAcres</td>
<td>Lot size (acres)</td>
<td>0.00</td>
<td>914</td>
<td>0.27</td>
<td>0.59</td>
<td>4.59</td>
</tr>
</tbody>
</table>

**Improvement-only explanatory variables**

<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>ImpSize</td>
<td>Improvement area (square ft.)</td>
<td>0.00</td>
<td>3,000,031</td>
<td>0</td>
<td>4,165</td>
<td>36,497</td>
</tr>
<tr>
<td>Stories</td>
<td>Number of stories</td>
<td>0.00</td>
<td>21</td>
<td>1</td>
<td>0.09</td>
<td>0.30</td>
</tr>
<tr>
<td>StoriesSqr</td>
<td>Number of stories squared</td>
<td>0.00</td>
<td>441</td>
<td>1</td>
<td>0.10</td>
<td>1.45</td>
</tr>
<tr>
<td>Baths</td>
<td>Number of bathrooms</td>
<td>0.00</td>
<td>8</td>
<td>0</td>
<td>0.00</td>
<td>0.11</td>
</tr>
<tr>
<td>BathSqr</td>
<td>Number of bathrooms squared</td>
<td>0.00</td>
<td>64</td>
<td>0</td>
<td>0.01</td>
<td>0.45</td>
</tr>
<tr>
<td>Beds</td>
<td>Number of bedrooms</td>
<td>0.00</td>
<td>7</td>
<td>0</td>
<td>0.00</td>
<td>0.07</td>
</tr>
<tr>
<td>BedSqr</td>
<td>Number of bedrooms squared</td>
<td>0.00</td>
<td>49</td>
<td>0</td>
<td>0.00</td>
<td>0.31</td>
</tr>
<tr>
<td>ImpAge</td>
<td>Age of improvement (years)</td>
<td>0.00</td>
<td>143</td>
<td>0</td>
<td>3.29</td>
<td>13.09</td>
</tr>
<tr>
<td>ImpAgeSqr</td>
<td>Age of improvement squared (years)</td>
<td>0.00</td>
<td>20,449</td>
<td>0</td>
<td>182</td>
<td>968</td>
</tr>
<tr>
<td>Depreciable</td>
<td>Depreciable life of improvement (%)</td>
<td>0.00</td>
<td>100</td>
<td>100</td>
<td>96</td>
<td>12.29</td>
</tr>
<tr>
<td>Vacant</td>
<td>Parcel without an improvement (DV)</td>
<td>0.00</td>
<td>1</td>
<td>1</td>
<td>0.91</td>
<td>0.29</td>
</tr>
<tr>
<td>Garage</td>
<td>Garage (DV)</td>
<td>0.00</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Air</td>
<td>Air conditioning (DV)</td>
<td>0.00</td>
<td>1</td>
<td>0</td>
<td>0.05</td>
<td>0.22</td>
</tr>
</tbody>
</table>

Figure 1 | Transportation Infrastructure System in El Paso County.
are also removed from the GWR equations. The GWR diagnostics include results from a baseline global model (i.e. residual squares, sigma, AdjR², AICc). 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 on property values.

**TOTAL VALUE MODELS**

The total value sample for commercial properties includes 105,611 observations (30.0% of the total population). The dependent variable is TotValue. Table 2 reports the OLS estimation results for the 15 independent variables plus the intercept term, from which 9 parameters are statistically significant according to robust 95% confidence intervals. TotValue decreases $0.84 per foot as DistInterstate increases. DistFreeways and DistMajorArteries are not statistically significant at the 5% level. POE_DrivingTime indicates that TotValue decreases $2,058 for every minute it takes to drive from a commercial property to the nearest POE. ShopC_DrivingTime indicates that for every minute it takes to drive from a commercial property to its nearest shopping center, TotValue increases $1,755. The adjusted R² indicates that the total value model explains 53.9% of the variation in TotValue. The significant Jarque-Bera statistic indicates that the residuals do not follow a normal distribution. The Koenker BP statistic is significant indicating that the residuals are nonstationary or heteroscedastic. The Joint Wald Statistic, however, indicates that the overall model is significant.

The GWR improvement value model yields 14,349 regression points with invertible matrices, equivalent to only 13.6% from the sample for commercial properties (Table 3). Wang et al. (2012) report a similar outcome where less than 10.0% of the sample yields invertible Hessians. The mean local GWR coefficients for DistInterstate and POE_DrivingTime have signs that are consistent with the OLS parameters, but with greater magnitudes. As shown by Figures 2 through 4, the impacts of transportation infrastructure in TotValue are highly sensitive to location. As DistInterstate increases, TotValue decreases $3.62 per foot according to the mean. DistInterstate ranges from a negative $394 to a positive $296 per foot, as shown in Figure 2. POE_DrivingTime indicates that for every additional driving minute to the nearest POE, the TotValue of a commercial property decreases by $22,500 on average. Coefficients from POE_DrivingTime range from a negative $588,108 to a positive $147,718 per minute, as shown in Figure 3.

For the impacts of driving time on commercial property total values in Table 3, ShopC_DrivingTime results indicate that TotValue decreases almost $9,937 per minute, on average. ShopC_DrivingTime ranges from a negative $602,337 to a positive $341,990 per minute, as shown in Figure 4. Results indicate that benefits from ShopC_DrivingTime are not capitalized by most commercial properties throughout the county, as shown in yellow in Figure 4. Some properties have negative coefficients, as shown by the parcels in blue and the darker tones in the image in Figure 4. This indicates that not all commercial parcels benefit from proximity to shopping centers, a result that is at odds with the positive sign of the OLS coefficient in Table 2.

As in other regions located near the border with Mexico, international commerce plays a prominent role in the economy of El Paso (Gibson et al., 2016). Properties with premia associated with POE_DrivingTime are
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>-564784.98</td>
<td>32277.65</td>
<td>-17.50</td>
<td>0.00*</td>
<td>132987.38</td>
<td>-4.25</td>
<td>0.00*</td>
<td>----</td>
</tr>
<tr>
<td>ImpAge</td>
<td>839.79</td>
<td>265.40</td>
<td>3.16</td>
<td>0.00*</td>
<td>1078.38</td>
<td>0.78</td>
<td>0.44</td>
<td>4.55</td>
</tr>
<tr>
<td>Air</td>
<td>35897.51</td>
<td>11207.84</td>
<td>3.20</td>
<td>0.00*</td>
<td>29758.93</td>
<td>1.21</td>
<td>0.23</td>
<td>4.46</td>
</tr>
<tr>
<td>Depreciable</td>
<td>4195.10</td>
<td>271.59</td>
<td>15.45</td>
<td>0.00*</td>
<td>600.49</td>
<td>-6.99</td>
<td>0.00*</td>
<td>4.20</td>
</tr>
<tr>
<td>LandAcres</td>
<td>-1244.54</td>
<td>363.34</td>
<td>-3.43</td>
<td>0.00*</td>
<td>29758.93</td>
<td>-0.32</td>
<td>0.75</td>
<td>1.05</td>
</tr>
<tr>
<td>ImpSize</td>
<td>15.56</td>
<td>0.05</td>
<td>314.76</td>
<td>0.00*</td>
<td>115085.77</td>
<td>1.44</td>
<td>0.15</td>
<td>12.00</td>
</tr>
<tr>
<td>Stories</td>
<td>165364.17</td>
<td>18434.53</td>
<td>8.97</td>
<td>0.00*</td>
<td>115085.77</td>
<td>1.42</td>
<td>0.15</td>
<td>16.13</td>
</tr>
<tr>
<td>Vacant</td>
<td>173080.29</td>
<td>22585.94</td>
<td>7.66</td>
<td>0.00*</td>
<td>121665.77</td>
<td>1.42</td>
<td>0.15</td>
<td>16.13</td>
</tr>
<tr>
<td>PopDens_CY</td>
<td>17.47</td>
<td>1.57</td>
<td>11.12</td>
<td>0.00*</td>
<td>6.26</td>
<td>2.79</td>
<td>0.01*</td>
<td>2.32</td>
</tr>
<tr>
<td>Unemp_CY</td>
<td>-175.99</td>
<td>420.24</td>
<td>4.18</td>
<td>0.00*</td>
<td>702.60</td>
<td>2.50</td>
<td>0.01*</td>
<td>13.98</td>
</tr>
<tr>
<td>PCI_CY</td>
<td>3.51</td>
<td>0.50</td>
<td>6.97</td>
<td>0.00*</td>
<td>1.76</td>
<td>2.00</td>
<td>0.05*</td>
<td>1.91</td>
</tr>
</tbody>
</table>

Observations: 105611  AICc: 3083612
Multiple R-Squared: 0.539  Adjusted R-Squared: 0.539

| Joint F-Statistic: 8226  Prob(>F), (21,198552) degrees of freedom: 0.00* |
| Joint Wald Statistic: 6335  Prob(>chi-squared), (21) degrees of freedom: 0.00* |
| Koenker (BP) Statistic: 10205  Prob(>chi-squared), (21) degrees of freedom: 0.00* |
| Jarque-Bera Statistic: 390970357898  Prob(>chi-squared), (2) degrees of freedom: 0.00* |

*Statistically significant probabilities have an asterisk next to them.

Located in the western, central, and eastern parts of the county. Parcels with premia are observed near the BOTA and Zaragoza POEs, but not near the downtown Paso Del Norte International Bridge. Many retail establishments in El Paso cater to Mexican shoppers by accepting pesos. Mexican shoppers and border commuters have to travel through the POEs. The further retailers are located away from the border, the less likely they are to accept pesos (Muñoz et al. 2011). In the total value model for commercial property, the a priori expectation is that parcels located closer to a POE will have a premium. Although parcels with a premium are observed near BOTA and Zaragoza, the highest premia are located distant from the POEs in Figure 3. Parcels located in downtown indicated no premia for POE_DrivingTime.

Further research is required to explore the underlying cause behind low or negative coefficients in the downtown area (e.g. exemptions, abatements, or similar agreements that reduce taxable values). A local newspaper cites the establishment of a Special Residential Revitalization District in the 1980s as the cause of a zoning issue in downtown with negative impacts on the property tax base (Mrkvicka, 2011). Property values within these special taxing districts sometimes fail to improve in the manners...
Table 3 | Total Value Model GWR Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Std. Error</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-203002</td>
<td>-4746110</td>
<td>1923541</td>
<td>987715</td>
<td>233372</td>
<td>9390194</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depreciable</td>
<td>3667</td>
<td>-7326</td>
<td>35524</td>
<td>5810</td>
<td>1454</td>
<td>84675</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ImpSize</td>
<td>14.5</td>
<td>-9.09</td>
<td>52.5</td>
<td>27.2</td>
<td>0.216</td>
<td>640</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PopDens_CY</td>
<td>33.4</td>
<td>-131</td>
<td>2676</td>
<td>1308</td>
<td>7.34</td>
<td>67255</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PCI_CY</td>
<td>8.50</td>
<td>-69.0</td>
<td>114</td>
<td>37.8</td>
<td>3.96</td>
<td>929</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DistInterstate</td>
<td>-3.62</td>
<td>-394</td>
<td>296</td>
<td>32.3</td>
<td>2.80</td>
<td>185</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POE_DrivingTime</td>
<td>-22500</td>
<td>-588108</td>
<td>147718</td>
<td>53013</td>
<td>8081</td>
<td>292829</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ShopC_DrivingTime</td>
<td>-9937</td>
<td>-602337</td>
<td>341990</td>
<td>46957</td>
<td>10272</td>
<td>290086</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Residual Squares: 1001990355825183  Sigma: 977037  R²: 0.853
Effective Number: 29.3  AICc: 32844  AdjR²: 0.849

sought by local governments (Merriman et al., 2011). Alternatively, this could reflect a change in Mexican shopper preferences from older commercial areas in downtown to newer areas. For example, the Outlet Shoppes at El Paso (in the west side) and Las Palmas Marketplace (in the east side) are not located within walking distance of any POEs in Figure 3. Similar asymmetric impacts have been documented for other metropolitan economies in recent years (Álvarez-Ayuso et al., 2016; Shibayama and Ishikawa, 2016).

The GWR global diagnostics show improvement over OLS for the AICc which declines from 3,083,612 to 32,844. Similarly, the AdjR2 improves from 0.539 in the OLS model to 0.849 in the GWR baseline model. Figure 5 indicates that spatial autocorrelation is present among the residuals in the OLS model with hot spots predominantly clustered in the western and southeastern regions of the county, as shown in red. Cold spots dominate the outer western and eastern sides of the county, as shown in blue. Spatial autocorrelation is mostly absent from the GWR residuals, shown in yellow in Figure 6. However, a few cold spots remain on the east side of the county.

**IMPROVEMENT VALUE MODELS**

The improvement value sample for commercial properties contains 105,611 observations (30.0% of the total population). The dependent variable is ImpValue.

Table 4 reports OLS estimation results for the 17 independent variables plus the intercept term, 7 of which are statistically significant according to robust 95.0% confidence intervals. In this equation, Mp35003a_B, DistInterstate, DistFreeways, and DistMajorArteries do not satisfy the 5.0% significance criterion. POE_DrivingTime indicates that ImpValue decreases $2,260 for every additional minute it takes to drive from a commercial property to the nearest POE. The impact from accessibility to a shopping center for the ImpValue is very similar to the impact estimated using the TotValue specification.

The coefficient for ShopC_DrivingTime in Table 4 indicates that for every minute it takes to drive from a commercial property to its nearest shopping center, ImpValue increases by $1,680. The impact from accessibility to a shopping center for the ImpValue is very similar to the impact estimated for TotValue. The adjusted R²
Figure 2 | Total Value GWR Model Coefficient Estimates for DistInterstate.
Figure 3 | Total Value GWR Model Coefficient Estimates for POE_DrivingTime.
Figure 4 | Total Value GWR Model Coefficient Estimates for ShopC_DrivingTime.
Figure 5 | Total Value Model Spatial Autocorrelation Test Results for OLS.
Figure 6 | Total Value Model Spatial Autocorrelation Test Results for GWR.
indicates that the improvement value model explains only 44.5% of the variation in ImpValue about its mean. The significant Jarque-Bera statistic indicates that residuals are not normal. The Koenker BP statistic is significant, indicating nonstationarity or heteroscedasticity is present in the residuals. The Joint Wald Statistic indicates that the overall model is significant.

The GWR improvement value model yields 16,232 regression points with invertible matrices, approximately 15.4% of the commercial sample data (see Table 5). The mean local coefficient for POE_DrivingTime has the same sign as that of the OLS counterpart and the magnitudes are very similar. The GWR mean estimated parameter value for ShopC_DrivingTime in Table 5 has a sign that is opposite that of the OLS estimate. Figures 7 and 8 reveal that improvements located in parcels near the downtown area have positive coefficients, in lighter shades. That pattern implies that benefits from proximity to a POE are capitalized mainly by the improvement rather than by commercial land parcels. That is contrary to what occurs for single-family in similar locations, where the land accrues higher premia than the improvements as estimated by Bujanda and Fullerton (2017).

The GWR POE_DrivingTime mean estimate in Table 5 indicates that ImpValue decreases almost $2,577 for every additional driving minute to the nearest POE. POE_DrivingTime ranges from negative $345,427 to positive $130,175 per minute depending on location, as shown in Figure 7. The parameter estimate mean for ShopC_DrivingTime indicates that ImpValue decreases by $3,177 per minute of additional drive time. The local coefficients for ShopC_DrivingTime range from negative $146,530 to positive $196,319 per minute, as shown in Table 5 and illustrated in Figure 8. Consistent with the findings in the total value model, a substantial number of improvements with high premia are located fairly distant from the POEs, on the western and eastern sides of the county. Parcels with positive ShopC_DrivingTime premia are near downtown and near the malls in the central area. The GWR global diagnostics show improvement over OLS for the AICc which drops from 3,049,392 to 217,096. AdjR² improves from 0.445 for OLS to 0.652 in the GWR baseline model. Spatial autocorrelation is practically absent from the GWR residuals.

LAND VALUE MODELS
The land value sample for commercial properties consists of 105,611 observations (30.0% of the total population). The dependent variable is LandValue. Table 6 reports OLS estimation results for 7 independent variables plus a constant term. All of the regression coefficients satisfy the 5% significance criterion. LandValue increases by $1.20 per foot as DistInterstate increases. Similarly, the DistFreeways parameter indicates an increase in LandValue of $4.84 per foot. DistMajorArteries is associated with an increase in LandValue of $5,110 per foot. POE_DrivingTime indicates that LandValue increases $1,885 for every additional minute a commercial property is located away from the nearest POE. The impact from accessibility to a POE for LandValue is contrary to the findings in TotValue and ImpValue. This reaffirms that, for commercial parcels, the benefits from accessibility to a POE are capitalized mostly by the improvement rather than the land.

In Table 6, ShopC_DrivingTime indicates that for every driving minute a commercial property is located away from its nearest shopping center, LandValue increases by $1,755. This is very similar to the findings in TotValue and ImpValue. The land value model explains 10.4% of the variation in the dependent variable about its mean. The residuals do not follow a Gaussian pattern. The Koenker BP statistic 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>-407101.72</td>
<td>25081.87</td>
<td>-16.23</td>
<td>0.00*</td>
<td>67941.03</td>
<td>-5.99</td>
<td>0.00*</td>
<td>-----</td>
</tr>
<tr>
<td>ImpAge</td>
<td>1106.54</td>
<td>228.84</td>
<td>4.84</td>
<td>0.00*</td>
<td>785.43</td>
<td>1.41</td>
<td>0.16</td>
<td>4.68</td>
</tr>
<tr>
<td>Air</td>
<td>1709.32</td>
<td>9376.45</td>
<td>0.18</td>
<td>0.86</td>
<td>27240.40</td>
<td>0.06</td>
<td>0.95</td>
<td>2.38</td>
</tr>
<tr>
<td>Depreciable</td>
<td>4316.60</td>
<td>227.22</td>
<td>19.00</td>
<td>0.00*</td>
<td>583.78</td>
<td>7.39</td>
<td>0.00*</td>
<td>4.06</td>
</tr>
<tr>
<td>LandAcres</td>
<td>-2835.19</td>
<td>308.95</td>
<td>-9.18</td>
<td>0.00*</td>
<td>2986.61</td>
<td>-0.95</td>
<td>0.34</td>
<td>1.05</td>
</tr>
<tr>
<td>ImpSize</td>
<td>11.16</td>
<td>0.04</td>
<td>265.47</td>
<td>0.00*</td>
<td>5.49</td>
<td>1.87</td>
<td>0.06</td>
<td>2.41</td>
</tr>
<tr>
<td>Stories</td>
<td>47255.32</td>
<td>9941.65</td>
<td>4.75</td>
<td>0.00*</td>
<td>98657.03</td>
<td>0.48</td>
<td>0.63</td>
<td>4.83</td>
</tr>
<tr>
<td>PopDens_CY</td>
<td>10.26</td>
<td>1.36</td>
<td>7.53</td>
<td>0.00*</td>
<td>5.49</td>
<td>1.87</td>
<td>0.06</td>
<td>2.41</td>
</tr>
<tr>
<td>Renter_CY</td>
<td>22.55</td>
<td>20.71</td>
<td>1.09</td>
<td>0.28</td>
<td>57.19</td>
<td>0.39</td>
<td>0.69</td>
<td>3.38</td>
</tr>
<tr>
<td>Vacant_CY</td>
<td>958.33</td>
<td>83.66</td>
<td>11.46</td>
<td>0.00*</td>
<td>451.95</td>
<td>2.12</td>
<td>0.03*</td>
<td>10.97</td>
</tr>
<tr>
<td>Unemp_CY</td>
<td>-201.24</td>
<td>49.87</td>
<td>-4.04</td>
<td>0.00*</td>
<td>80.48</td>
<td>-2.50</td>
<td>0.01*</td>
<td>4.64</td>
</tr>
<tr>
<td>PCI_CY</td>
<td>-1.06</td>
<td>0.46</td>
<td>-2.32</td>
<td>0.02*</td>
<td>2.25</td>
<td>-0.47</td>
<td>0.64</td>
<td>2.19</td>
</tr>
<tr>
<td>Mp35003a_B</td>
<td>-669.22</td>
<td>66.95</td>
<td>-10.00</td>
<td>0.00*</td>
<td>359.56</td>
<td>-1.86</td>
<td>0.06</td>
<td>6.85</td>
</tr>
<tr>
<td>DistInterstate</td>
<td>-0.09</td>
<td>0.18</td>
<td>-0.47</td>
<td>0.64</td>
<td>0.44</td>
<td>-0.20</td>
<td>0.84</td>
<td>10.17</td>
</tr>
<tr>
<td>DistFreeways</td>
<td>0.56</td>
<td>0.12</td>
<td>4.80</td>
<td>0.00*</td>
<td>0.40</td>
<td>1.39</td>
<td>0.17</td>
<td>2.47</td>
</tr>
<tr>
<td>DistMajorArteries</td>
<td>0.48</td>
<td>0.28</td>
<td>1.73</td>
<td>0.08</td>
<td>0.43</td>
<td>1.12</td>
<td>0.26</td>
<td>7.63</td>
</tr>
<tr>
<td>POE_DrivingTime</td>
<td>-2263.33</td>
<td>512.75</td>
<td>-4.41</td>
<td>0.00*</td>
<td>809.37</td>
<td>-2.80</td>
<td>0.01*</td>
<td>16.56</td>
</tr>
<tr>
<td>ShopC_DrivingTime</td>
<td>1676.92</td>
<td>373.74</td>
<td>4.49</td>
<td>0.00*</td>
<td>634.62</td>
<td>2.64</td>
<td>0.01*</td>
<td>9.46</td>
</tr>
</tbody>
</table>

Observations: 105611
Multiple R-Squared: 0.445
AICc: 3049392
Adjusted R-Squared: 0.445
Joint F-Statistic: 4984
Joint Wald Statistic: 3574
Koenker (BP) Statistic: 8533
Jarque-Bera Statistic: 584084025438

*Statistically significant probabilities have an asterisk next to them.

### Table 5 | Improvement Value Model GWR Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Sigma:</th>
<th>R²:</th>
<th>AdjR²:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-223067</td>
<td>-3600630</td>
<td>1604137</td>
<td>1517231</td>
<td>226186</td>
<td>12284376</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Depreciable</td>
<td>3024</td>
<td>-4858</td>
<td>31269</td>
<td>10653</td>
<td>1970</td>
<td>120744</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ImpSize</td>
<td>11.1</td>
<td>-4.07</td>
<td>44.9</td>
<td>52.7</td>
<td>0.293</td>
<td>1845</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemp_CY</td>
<td>449</td>
<td>-4884</td>
<td>7188</td>
<td>3283</td>
<td>744</td>
<td>233925</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>POE_DrivingTime</td>
<td>-2577</td>
<td>-345427</td>
<td>130175</td>
<td>72215</td>
<td>10230</td>
<td>401251</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ShopC_DrivingTime</td>
<td>-3177</td>
<td>-146530</td>
<td>196319</td>
<td>59642</td>
<td>11284</td>
<td>398829</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Residual Squares: 12085300606493702
Effective Number: 126
AICc: 217096
AdjR²: 0.652
Figure 7 | Improvement Value GWR Model Coefficient Estimates for POE_DrivingTime.
Figure 8 | Improvement Value GWR Model Coefficient Estimates for ShopC_DrivingTime.
suggesting nonstationarity or heteroscedasticity. The Joint Wald Statistic indicates, however, that the overall model is significant.

The GWR land value model yields 34,698 regression points with invertible matrices, 32.9% from the commercial sample (in Table 7). The mean values of all the local coefficients have signs that are opposite of the OLS parameters shown in Table 6. As illustrated using lighter shades of gray in Figure 9, DistInterstate is higher for the land located in the north and central parts of the county, and for a significant amount of parcels located in the eastern and southeastern parts of the county. As DistInterstate increases, LandValue decreases by $9.60 per foot according to the mean. Local coefficients for DistInterstate range from negative $182 to positive $93.60 per foot depending on location, as shown in Figure 9.

As DistFreeways increases, LandValue decreases by $2.70 per foot according to the mean. Local coefficients for DistFreeways range from negative $84.00 to positive $85.80 per foot, as shown in Figure 10. The DistMajorArteries parameter mean indicates that LandValue decreases by $20.20 per foot. Coefficients for DistMajorArteries range from negative $334 to positive $126 per foot, as shown in Figure 11. Coefficients for POE_DrivingTime in Table 7 indicate that for every additional driving minute to the nearest POE, LandValue decreases by almost $3,021 on average. Parameters from POE_DrivingTime range from negative $129,986 to positive $149,563 per minute depending on location, as shown in Figure 12.

In general, positive premia for DistFreeways are visible throughout almost all commercial land. The POE_DrivingTime regression coefficients suggest that those premia are capitalized by the improvements rather than by the land parcels in the downtown area. In contrast, parcels along the interstate exhibit positive premia for accessibility to the nearest POE. The GWR global diagnostics compare favorably to those of the OLS results with the AICc declining from 2,897,570 to 198,541. The AdjR2 increases from 0.104 in Table 6 to 0.492 for the GWR baseline model summarized in Table 7.

**CONCLUSION**

Traditional hedonic models that are global in nature can yield potentially deceptive results as a consequence of examining the impacts of transportation infrastructure proximity and accessibility using all real property values. The sample used in this effort contains 105,611 commercial property data observations for El Paso, Texas. Koenker BP test outcomes above confirm that the data are characterized by spatial nonstationarity and heteroscedasticity. Significant values for the Jarque-Bera statistics for all of the OLS models also indicate non-normally distributed residuals. Information criteria estimates and coefficients of determination, adjusted for degrees of freedom, for the GWR equations are also superior than those for the OLS outcomes. The relationships for real property values and transportation infrastructure proximity and accessibility across El Paso County are highly localized and vary significantly over space. The presence of spatial nonstationarity and heterogeneity confirm that transportation infrastructure proximity and accessibility might generate premia for real property values, but that positive premia are not always present and are even negative in some areas.

Results obtained highlight the potential importance of allowing for spatial dependence and spatial heterogeneity in econometric models. GWR is a one alternative that allows visualizing the diverse spatial relationships between transportation infrastructure and real property values. GWR estimates indicate
Table 6. Land 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>292863.10</td>
<td>3767.08</td>
<td>77.74</td>
<td>0.00*</td>
<td>10536.15</td>
<td>27.80</td>
<td>0.00*</td>
<td>-----</td>
</tr>
<tr>
<td>ImpAge2</td>
<td>8239.21</td>
<td>147.54</td>
<td>55.84</td>
<td>0.00*</td>
<td>3264.51</td>
<td>2.52</td>
<td>0.01*</td>
<td>1.01</td>
</tr>
<tr>
<td>LandAcres</td>
<td>1.34</td>
<td>0.07</td>
<td>17.92</td>
<td>0.00*</td>
<td>0.09</td>
<td>14.70</td>
<td>0.00*</td>
<td>7.31</td>
</tr>
<tr>
<td>DistInterstate</td>
<td>1.20</td>
<td>0.04</td>
<td>27.41</td>
<td>0.00*</td>
<td>0.05</td>
<td>25.99</td>
<td>0.00*</td>
<td>1.49</td>
</tr>
<tr>
<td>DistFreeways</td>
<td>4.84</td>
<td>0.11</td>
<td>43.59</td>
<td>0.00*</td>
<td>0.19</td>
<td>24.88</td>
<td>0.00*</td>
<td>5.09</td>
</tr>
<tr>
<td>DistMajorArteries</td>
<td>5110.57</td>
<td>168.00</td>
<td>30.42</td>
<td>0.00*</td>
<td>197.55</td>
<td>25.87</td>
<td>0.00*</td>
<td>7.48</td>
</tr>
<tr>
<td>POE_DrivingTime</td>
<td>1885.79</td>
<td>140.33</td>
<td>13.44</td>
<td>0.00*</td>
<td>147.90</td>
<td>12.75</td>
<td>0.00*</td>
<td>5.62</td>
</tr>
<tr>
<td>ShopC_DrivingTime</td>
<td>11.17</td>
<td>0.85</td>
<td>13.16</td>
<td>0.00*</td>
<td>1.38</td>
<td>8.10</td>
<td>0.00*</td>
<td>1.48</td>
</tr>
</tbody>
</table>

Observations: 105611  
Multiple R-Squared: 0.104  
Adjusted R-Squared: 0.104  
AICc: 2897570

| Joint F-Statistic:   | 1751      | Prob(F), (21,198552) degrees of freedom: 0.00*|
| Joint Wald Statistic:| 1717      | Prob(>chi-squared), (21) degrees of freedom: 0.00*|
| Koenker (BP) Statistic: | 1561    | Prob(>chi-squared), (21) degrees of freedom: 0.00*|
| Jarque-Bera Statistic: | 72690700138 | Prob(>chi-squared), (2) degrees of freedom: 0.00*|

*Statistically significant probabilities have an asterisk next to them.

---

Table 7 | Land Value Model GWR Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>132041</td>
<td>-1112420</td>
<td>2250256</td>
<td>1828481</td>
<td>78419</td>
<td>7641128</td>
</tr>
<tr>
<td>LandAcres</td>
<td>49707</td>
<td>-160</td>
<td>1088279</td>
<td>53121</td>
<td>614</td>
<td>220355</td>
</tr>
<tr>
<td>DistInterstate</td>
<td>-9.61</td>
<td>-182</td>
<td>93.6</td>
<td>41.3</td>
<td>2.20</td>
<td>343</td>
</tr>
<tr>
<td>DistFreeways</td>
<td>-2.70</td>
<td>-84.0</td>
<td>85.8</td>
<td>37.2</td>
<td>1.87</td>
<td>208</td>
</tr>
<tr>
<td>DistMajorArteries</td>
<td>-20.2</td>
<td>-334</td>
<td>126</td>
<td>54.3</td>
<td>3.59</td>
<td>310</td>
</tr>
<tr>
<td>POE_DrivingTime</td>
<td>-3021</td>
<td>-129986</td>
<td>149563</td>
<td>44153</td>
<td>6083</td>
<td>137962</td>
</tr>
</tbody>
</table>

Effective Number: 111  
Sigma: 546548 R^2: 0.500  
AdjR^2: 0.492
Figure 9 | Land Value GWR Model Coefficient Estimates for DistInterstate.
Figure 10 | Land Value GWR Model Coefficient Estimates for DistFreeways.
Figure 11 | Land Value GWR Model Coefficient Estimates for DistMajorArteries.
Figure 12 | Land Value GWR Model Coefficient Estimates for POE_DrivingTime.
that the different impacts from specific transportation facilities can swing from positive to negative regardless of proximity. Benefits from transportation infrastructure can be capitalized by parcels even if they are not located close to the facility. Furthermore, the local coefficients indicate, for this sample, that parcels that are adjacent to the facility do not necessarily obtain value premia.

This study employs a single cross-sectional dataset from 2013 to help quantify premia for 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 new equilibrium prices and assessed values. Future research that incorporates data over time may yield additional insights. Spatial autoregressive approaches as in Anselin (1988) and spatial panel data methods similar to Baltagi (2013) emerge as natural candidates for such efforts. Adding a time dimension would potentially allow identifying both short-term and long-term impacts of transportation infrastructure on real property values.

REFERENCES


Concas, S., 2013, “Accessibility and Housing Price Resilience,” *Transportation Research Record*, 2357, 66-76. doi: [http://dx.doi.org/10.3141/2357-08](http://dx.doi.org/10.3141/2357-08)


The University of Texas at El Paso

Announces

Borderplex Economic Outlook to 2019

UTEP is pleased to announce the 2017 edition of its primary source of border business information. Topics covered include demography, employment, personal income, retail sales, residential real estate, transportation, international commerce, and municipal water consumption. Forecasts are generated utilizing the 250-equation UTEP Border Region Econometric Model developed under the auspices of a corporate research gift from El Paso Electric Company and maintained using externally funded research support from El Paso Water and Hunt Communities.

The authors of this publication are UTEP Professor & Trade in the Americas Chair Tom Fullerton and UTEP Associate Economist Adam Walke. Dr. Fullerton holds degrees from UTEP, Iowa State University, Wharton School of Finance at the University of Pennsylvania, and University of Florida. Prior experience includes positions as Economist in the Executive Office of the Governor of Idaho, International Economist in the Latin America Service of Wharton Econometrics, and Senior Economist at the Bureau of Economic and Business Research at the University of Florida. Adam Walke holds an M.S. in Economics from UTEP and has published research on energy economics, mass transit demand, and cross-border regional growth patterns.

The border business outlook through 2019 can be purchased for $10 per copy. Please indicate to what address the report(s) should be mailed (also include telephone, fax, and email address):

__________________________
__________________________
__________________________
__________________________
__________________________

Send checks made out to University of Texas at El Paso for $10 to:

Border Region Modeling Project - CBA 236
UTEP Department of Economics & Finance
500 West University Avenue
El Paso, TX 79968-0543

Request information from 915-747-7775 or agwalke@utep.edu if payment in pesos is preferred.
The University of Texas at El Paso

Announces

Borderplex Long-Term Economic Trends to 2029

UTEP is pleased to announce the availability of an electronic version of the 2010 edition of its primary source of long-term border business outlook information. Topics covered include detailed economic projections for El Paso, Las Cruces, Ciudad Juárez, and Chihuahua City. Forecasts are generated utilizing the 225-equation UTEP Border Region Econometric Model developed under the auspices of a 12-year corporate research support program from El Paso Electric Company.

The authors of this publication are UTEP Professor & Trade in the Americas Chair Tom Fullerton and former UTEP Associate Economist Angel Molina. Dr. Fullerton holds degrees from UTEP, Iowa State University, Wharton School of Finance at the University of Pennsylvania, and University of Florida. Prior experience includes positions as Economist in the Executive Office of the Governor of Idaho, International Economist in the Latin America Service of Wharton Econometrics, and Senior Economist at the Bureau of Economic and Business Research at the University of Florida. Angel Molina holds an M.S. Economics degree from UTEP and has conducted econometric research on international bridge traffic, peso exchange rate fluctuations, and cross-border economic growth patterns.

The long-term border business outlook through 2029 can be purchased for $10 per copy. Please indicate to what address the report(s) should be mailed (also include telephone, fax, and email address):

_____________________________________
_____________________________________
_____________________________________
_____________________________________
_____________________________________

Send checks made out to University of Texas at El Paso for $10 to:

Border Region Modeling Project - CBA 236
UTEP Department of Economics & Finance
500 West University Avenue
El Paso, TX 79968-0543

Request information at 915-747-7775 or agwalke@miners.utep.edu if payment in pesos is preferred.
The University of Texas at El Paso Border Region Modeling Project is pleased to announce Basic Border Econometrics, a publication from Universidad Autónoma de Ciudad Juárez. Editors of this new collection are Martha Patricia Barraza de Anda of the Department of Economics at Universidad Autónoma de Ciudad Juárez and Tom Fullerton of the Department of Economics & Finance at the University of Texas at El Paso.

Professor Barraza is an award winning economist who has taught at several universities in Mexico and has published in academic research journals in Mexico, Europe, and the United States. Dr. Barraza currently serves as Research Provost at UACJ. Professor Fullerton has authored econometric studies published in academic research journals of North America, Europe, South America, Asia, Africa, and Australia. Dr. Fullerton has delivered economics lectures in Canada, Colombia, Ecuador, Finland, Germany, Japan, Korea, Mexico, the United Kingdom, the United States, and Venezuela.

Border economics is a field in which many contradictory claims are often voiced, but careful empirical documentation is rarely attempted. Basic Border Econometrics is a unique collection of ten separate studies that empirically assess carefully assembled data and econometric evidence for a variety of different topics. Among the latter are peso fluctuations and cross-border retail impacts, border crime and boundary enforcement, educational attainment and border income performance, pre- and post-NAFTA retail patterns, self-employed Mexican-American earnings, maquiladora employment patterns, merchandise trade flows, and Texas border business cycles.

Contributors to the book include economic researchers from the University of Texas at El Paso, New Mexico State University, University of Texas Pan American, Texas A&M International University, El Colegio de la Frontera Norte, and the Federal Reserve Bank of Dallas. Their research interests cover a wide range of fields and provide multi-faceted angles from which to examine border economic trends and issues.

A limited number of Basic Border Econometrics can be purchased for $10 per copy. Please contact Professor Servando Pineda of Universidad Autónoma de Ciudad Juárez at spineda@uacj.mx to order copies of the book. Additional information for placing orders is also available from Professor Martha Patricia Barraza de Anda at mbarraza@uacj.mx.
The University of Texas at El Paso Technical Report Series:

TX97-1: Currency Movements and International Border Crossings
TX97-2: New Directions in Latin American Macroeconometrics
TX97-3: Multimodal Approaches to Land Use Planning
TX97-4: Empirical Models for Secondary Market Debt Prices
TX97-5: Latin American Progress under Structural Reform
TX97-6: Functional Form for United States-Mexico Trade Equations
TX98-1: Border Region Commercial Electricity Demand
TX98-2: Currency Devaluation and Cross-Border Competition
TX98-3: Logistics Strategy and Performance in a Cross-Border Environment
TX99-1: Inflationary Pressure Determinants in Mexico
TX99-2: Latin American Trade Elasticities
CSWHT00-1: Tariff Elimination Staging Categories and NAFTA
TX00-1: Borderplex Business Forecasting Analysis
TX01-1: Menu Prices and the Peso
TX01-2: Education and Border Income Performance
TX02-1: Regional Econometric Assessment of Borderplex Water Consumption
TX02-2: Empirical Evidence on the El Paso Property Tax Abatement Program
TX03-1: Security Measures, Public Policy, Immigration, and Trade with Mexico
TX03-2: Recent Trends in Border Economic Analysis
TX04-1: El Paso Customs District Cross-Border Trade Flows
TX05-1: Short-Term Water Consumption Patterns in El Paso
TX05-2: Menu Price and Peso Interactions: 1997-2002
TX06-1: Water Transfer Policies in El Paso
TX06-2: Short-Term Water Consumption Patterns in Ciudad Juárez
TX07-1: El Paso Retail Forecast Accuracy
TX07-2: Borderplex Population and Migration Modeling
TX08-1: Borderplex 9/11 Economic Impacts
TX09-1: Tolls, Exchange Rates, and Borderplex Bridge Traffic
TX09-2: Menu Price and Peso Interactions: 1997-2008
TX10-1: Are Brand Name Medicine Prices Really Lower in Ciudad Juárez?
TX10-2: Border Metropolitan Water Forecast Accuracy
TX11-2: Retail Peso Exchange Rate Discounts and Premia in El Paso
TX12-1: Borderplex Panel Evidence on Restaurant Price and Exchange Rate Dynamics
TX14-1: Freight Transportation Costs and the Thickening of the U.S.-Mexico Border
TX14-2: Are Online Pharmacy Prices Really Lower in Mexico?
TX15-1: Drug Violence, the Peso, and Northern Border Retail Activity in Mexico
TX15-2: Downtown Parking Meter Demand in El Paso
TX16-1: North Borderplex Retail Gasoline Price Fluctuations: 2000-2013
TX17-1: Southern Border Recession Predictability in the United States: 1990-2015
TX18-1: Infrastructure Impacts on Commercial Property Values across El Paso in 2013
The University of Texas at El Paso
Border Business Forecast Series:

SR99-1: *Borderplex Economic Outlook: 1999-2001*
SR00-1: *Borderplex Economic Outlook: 2000-2002*
SR01-1: *Borderplex Long-Term Economic Trends to 2020*
SR01-2: *Borderplex Economic Outlook: 2001-2003*
SR02-1: *Borderplex Long-Term Economic Trends to 2021*
SR02-2: *Borderplex Economic Outlook: 2002-2004*
SR03-1: *Borderplex Long-Term Economic Trends to 2022*
SR03-2: *Borderplex Economic Outlook: 2003-2005*
SR04-1: *Borderplex Long-Term Economic Trends to 2023*
SR04-2: *Borderplex Economic Outlook: 2004-2006*
SR05-1: *Borderplex Long-Term Economic Trends to 2024*
SR05-2: *Borderplex Economic Outlook: 2005-2007*
SR06-1: *Borderplex Long-Term Economic Trends to 2025*
SR06-2: *Borderplex Economic Outlook: 2006-2008*
SR07-1: *Borderplex Long-Term Economic Trends to 2026*
SR07-2: *Borderplex Economic Outlook: 2007-2009*
SR08-1: *Borderplex Long-Term Economic Trends to 2027*
SR08-2: *Borderplex Economic Outlook: 2008-2010*
SR09-1: *Borderplex Long-Term Economic Trends to 2028*
SR09-2: *Borderplex Economic Outlook: 2009-2011*
SR10-1: *Borderplex Long-Term Economic Trends to 2029*
SR10-2: *Borderplex Economic Outlook: 2010-2012*
SR11-1: *Borderplex Economic Outlook: 2011-2013*
SR12-1: *Borderplex Economic Outlook: 2012-2014*
SR13-1: *Borderplex Economic Outlook: 2013-2015*
SR14-1: *Borderplex Economic Outlook to 2016*
SR15-1: *Borderplex Economic Outlook to 2017*
SR16-1: *Borderplex Economic Outlook to 2018*
SR17-1: *Borderplex Economic Outlook to 2019*

Technical Report TX18-1 is a publication of the Border Region Modeling Project and the Department of Economics & Finance at the University of Texas at El Paso. For additional Border Region information, please visit the academics.utep.edu/border section of the UTEP web site.