Journal of Sustainable Real Estate

ISSN: 1949-8276 (Print) 1949-8284 (Online) Journal homepage: https://www.tandfonline.com/loi/rsre20

Measuring Highway Impacts on House Prices Using Spatial Regression

Marcus T. Allen, Grant W. Austin & Mushfiq Swaleheen

To cite this article: Marcus T. Allen, Grant W. Austin & Mushfiq Swaleheen (2015) Measuring Highway Impacts on House Prices Using Spatial Regression, Journal of Sustainable Real Estate, 7:1, 83-98, DOI: 10.1080/10835547.2015.12091876

To link to this article: https://doi.org/10.1080/10835547.2015.12091876

Published online: 04 Aug 2020.

Measuring Highway Impacts on House Prices Using Spatial Regression

Authors Marcus T. Allen, Grant W. Austin, and Mushfiq Swaleheen

Abstract Generally accepted real estate valuation theory, augmented by ample empirical evidence, supports the notion of significant impacts on prices of residential properties near highways. Houses adjacent to highways are exposed to potentially increased traffic noise, although these homeowners may benefit from increased accessibility to highway systems. This study is prompted by a massive new highway construction project (25 miles at a cost of $1.5 billion over a nine-year period) that will complete a 110-mile beltway around the Orlando, Florida metropolitan area. Using observed prices of houses near existing highways, this study provides insights into the potential effects of the new highway on planned and existing houses in this market. The results indicate significant price discounts for houses adjacent to highways, houses near high-traffic highways, and houses farther from highway on-ramps, but no significant impact related to distances from houses to highways or sound barrier walls.

Real estate value theorists and practitioners widely acknowledge the importance of considering external influences when analyzing real estate values. Nearby transportation systems are a classic case of offsite factors that may affect real estate values. While highways, rail, and airports generally provide positive benefits to real estate users at the macro level by increasing accessibility, micro-level effects of planes, trains, and automobiles may be negative due to potential nuisances generated by transportation systems. For residential real estate in particular, a critical issue at the micro-level is the impact of noise from nearby transportation infrastructure on house prices. Numerous studies, some of which are discussed below, use a variety of analysis methods to detect and measure the price effects of transportation-related noise pollution generated by airports, railways, and highways in various housing markets around the world. These studies document consistently significant price discounts for noise pollution related to nearby transportation systems but, not surprisingly, the magnitudes of the reported discounts vary across markets.

Previous studies typically use one of two alternative approaches to consider the impacts of highways on house prices, including noise pollution. The first of these approaches uses noise levels measured in decibels and the second approach uses transportation infrastructure adjacency and proximity measures. As noted by Seo, Golub, and Kuby (2014, p. 54), noise levels ‘‘are quite expensive to measure for individual parcels.’’ This study relies on the second approach and uses location-based measures to assess highway impacts on house prices. The measures include a highway adjacency indicator, nearby highway traffic volume, straight-line distances from houses to highways, and the presence of sound barrier walls to examine highway impacts on house prices. Adjacency to highways, especially more heavily traveled highways, is expected to reduce house prices, but the negative impact of highway noise on house prices may be offset by sound barrier walls and increased distance from house to highway. This study also controls for potential impacts on house prices related to accessibility to the highway system. Reduced driving distance to nearby highway on-ramps may have a positive impact on house prices.

The impetus for considering highway impacts on house prices in this study is the ongoing construction of a new multi-lane, median divided, limited access, toll road near Orlando, Florida. Portions of the new highway will have sound barrier walls along the right-of-way. Plans for the Wekiva Parkway were approved in 2004 and construction began in 2013, with a projected completion date in 2021 at a cost of $1.5 billion. This 25-mile highway is the final section of a 112-mile beltway highway around the Orlando metropolitan area.[1] The Wekiva Parkway is intended to relieve congestion on U.S. Highway 441 and State Road (SR) 46, the primary surface routes through this portion of Florida. The massive scale of this highway project will undoubtedly improve mobility through the area, but the project may also negatively impact the prices of individual houses in the project’s vicinity. The purpose of this study is to document micro-level house price impacts of other existing highways in this market in an effort to provide a basis for anticipating the impact of the new highway on nearby houses, both planned and existing.

Using transaction data from this market, hedonic price analysis with spatial regression modeling suggests that the average price discount for houses adjacent to highways is approximately 4.0%, holding other value influencing factors constant.[2] The results of this analysis also document significant price discounts related to traffic volume on nearby highways. The results do not indicate that sound barrier walls or increased straight-line distances from houses to the highway impact house prices, but do indicate that houses with shorter driving distances to highway on-ramps sell at price premiums.

The following section provides a brief review of the studies that, like the present study, examine highway impacts on the value of residential real estate using the revealed preferences of market participants with either measured noise levels or location-based measures. In the remaining sections, we discuss the data, the spatial regression models used to analyze the data, and the results of the analysis, respectively. The paper closes with concluding remarks.

Studies Addressing Highway Impacts on Residential Property Values

Bateman, Day, Lake, and Lovett (2001) provide in-depth discussions of some of the key issues, methods, and results from an assortment of studies published prior to 2001 that analyze highway noise impacts on residential property values using measured noise levels. The authors review 17 studies that consider the effect of highway noise using hedonic price analysis and report an average price discount of 0.4% per decibel in those studies, with a standard deviation of 0.23%. These authors also conduct their own hedonic price study of the impact of highway noise using data from the Glasgow, Scotland area and report a house price discount of 0.2% per decibel for their sample.

Wilhelmsson (2000) provides a notable study that is not included in the literature review provided by Bateman, Day, Lake, and Lovett (2001). Using data from Stockholm, Sweden, his hedonic price estimates indicate an average highway noise discount in house prices of 0.6% per decibel. To put this finding into perspective, Wilhelmsson demonstrates that the difference in value for a house in a noisy and a quiet location in his study sample is approximately 30%.

Numerous other researchers have conducted highway noise pollution impact studies on various property types of residential real estate in markets around the world since the publication of the Bateman, Day, Lake, and Lovett (2001) literature review. Becker and Lavee (2003) report a price discount of 1.2% per decibel for apartments in urban areas in Israel. Rich and Nielson (2004) report price discounts of 0.47% per decibel for apartments and 0.54% per decibel for houses in Copenhagen, Denmark. Theebe (2004) reports an average discount of 5% from traffic noise from planes, trains, and automobiles on houses in the Netherlands. Baranzini and Ramirez (2005) report a discount in apartment rents of 0.63% per decibel in Geneva, Switzerland. Day, Bateman, and Lake (2007) report a price discount of 0.55% per decibel for residential real estate in Birmingham, England. Kim, Park, and Kweon (2007) report a price discount of 1.3% for a 1% increase in traffic noise level in decibels for single-family and row houses in Seoul, Korea. Nelson (2008) discusses prices discounts on property values associated with both aircraft (0.8% per decibel) and road traffic (0.54% per decibel). Andersson, Jonsson, and Ögren (2010) report a discount of approximately 0.7% per decibel for single-family houses in Lerum, Sweden. Blanco and Flindell (2011) report a price discount of 0.45% per decibel for apartments and flats in London, England. Brandt and Maennig (2011) report a discount of 0.23% per decibel level for condominiums in Hamburg, Germany. Li and Saphores (2012) report a negligible discount for general highway traffic (0.006% per decibel), but a more substantial discount for highway truck traffic of 0.65% per decibel for houses in Los Angeles, California.

Several additional studies examine the impact of highways on property values using location-based measures rather than noise level measurements. Hughes and Sirmans (1992, 1993) use average daily traffic counts and an indicator variable for high-traffic streets to identify significant price discounts in the Baton Rouge, Louisiana housing market. They report price discounts of 9.2% for city neighborhoods and 4.6% for suburban neighborhoods for high-traffic streets. Kawamura and Mahajan (2005) discuss the use of hedonic price models with traffic count data. Larsen (2012) reports that houses adjacent to high-traffic streets sell for discounts of 8.1%. Larsen and Blair (2014) report a price discount of 7.8% for single-family houses on high-traffic streets and a price premium of 13.8% for multi-unit rental residential properties in Kettering, Ohio. Kilpatrick, Throupe, Carruthers, and Krause (1997) show that proximity to transit corridors, not just adjacency to a corridor, is negatively related to property values and that access to the transportation infrastructure is positively related to property values in a sample of houses from Seattle, Washington. Although the intention of sound barrier walls along highways is to reduce the aural and visual nuisances of highways on nearby properties, Julien and Lanoie (2008) show that noise barrier walls between houses and highways result in price discounts of 6% in the short run and 11% in the long run in a sample from Montreal, Canada.

Our analysis follows the lead of Hughes and Sirmans (1992, 1993), Kawamura and Mahajan (2005), Larsen (2012), and Larsen and Blair (2014) in the use of location-based measures to evaluate the impact of highways on house prices. In particular, an indicator variable is used to identify houses adjacent to highways and traffic count data to identify high-volume highways. In addition, we consider the issues of straight-line distance from houses to highways and the driving distance between houses and highway on-ramps following Kilpatrick, Throupe, Carruthers, and Krause (1997) and the issue of sound barrier walls following Julien and Lanoie (2008).

Data Description

The primary source of the data is the publicly available database maintained on the official Orange County Property Appraiser website: http://www.ocpafl.org.[3] As of October 2014, the website reports 272,124 single-family, detached houses in the county. The database includes information about various attributes of each house (age, size, location, etc.), as well as transaction dates and prices. The initial sample includes 1,306 houses conveyed during the study period (January, 2012–September, 2014) and located in neighborhoods (subdivisions) bordering on one of three key highways in the metropolitan Orlando area: Florida's Turnpike, Central Florida GreeneWay (SR 417), and Daniel Webster Western Beltway (SR 429).[4] Each of these highways is a limited access, multi-lane, median divided, toll road that is similar to the proposed highway.

Visual inspections of readily available plats, maps, and photographs permit identification of highway adjacency and sound barrier walls for each house in the sample. Straight-line distances between houses and highways (in meters) and driving distances (in miles) between houses and highway on-ramps are GIS-based. After screening the initial data sample to exclude non-arm's length transactions and records with inconsistent and incomplete data, the study sample consists of 1,025 houses located in 19 suburban neighborhoods. Of the study sample, 91 houses (8.9%) are directly adjacent to a highway while 934 houses (91.1%) are not directly adjacent to a highway. Exhibit 1 provides definitions and summary statistics for the variables considered for each of the 1,025 observations. Exhibit 2 provides mean house prices by neighborhood and reports the differences in mean prices by neighborhood for adjacent and non-adjacent houses for 17 of the neighborhoods.[5] The test statistics are significant for five of the 17 neighborhoods,

Exhibit 1 | Variable Definitions and Summary Statistics

Variable	Definition	Expected Sign of Coeff.	Mean	Std. Dev.	Min.	Max.
price	Transaction price in dollars		$234,942	$85,025	$60,000	$550,000
adjacent	Highway adjacency indicator = 1 if property is adjacent to highway, 0 otherwise	Negative	0.089		0	1
sound_barrier	Sound barrier wall = 1 if sound barrier wall is present, 0 otherwise	Positive	0.024		0	1
straight_distance	Straight-line distance from house to highway, in thousands of meters	Positive	0.344	0.239	0.031	1.493
traffic_volume	Average annual daily traffic, in thousands	Negative	54.213	22.059	18.3	97
drive_distance	Driving distance from house to nearest highway on-ramp	Negative	2.871	1.515	0.5	6.4
age	Age of house in years	Negative	11.484	6.858	0	35
livarea100	Size of house in hundreds of square feet	Positive	24.477	7.441	10.160	52.020
lotacre	Size of lot in acres	Positive	0.212	0.093	0.087	0.820
pool	Swimming pool indicator = 1 if pool is present, 0 otherwise	Positive	0.351		0	1
strend	Time trend variable taking values of 1 to 33 based on month of sale during study period	Positive	17.393	9.091	1	33
strend2	Square of time trend variable to control for quadratic changes in price trends over the study period	Negative	385.097	318.761	1	1,089

Note: The number of observations is 1,025.

Exhibit 2 | Difference in Mean Prices for Adjacent and Non-Adjacent Houses by Neighborhood

Neighborhood	Observations	Mean Price ($)	# of Adjacent Houses	Mean Price of Non-Adjacent Houses ($)	Mean Price of Adjacent Houses ($)	Difference in Means *t*-statistic
1	18	125,472	2	124,094	136,500	−0.42
2	9	218,889	1	222,875	187,000	n.a.
3	102	261,058	5	258,792	305,020	−2.92
4	80	208,294	10	212,387	179,640	2.10
5	44	195,352	4	196,688	182,000	0.94
6	39	160,472	5	161,512	153,400	0.45
7	61	178,995	4	179,942	165,500	0.88
8	45	278,920	3	278,136	289,900	−0.51
9	45	427,122	4	431,476	382,500	1.27
10	38	224,455	3	227,666	187,000	2.35
11	22	333,350	3	347,405	244,333	3.06
12	11	290,773	2	294,000	276,250	0.55
13	38	201,597	22	203,800	199,996	0.30
14	47	256,949	4	262,874	193,250	2.64
15	84	301,857	6	305,780	250,867	1.47
16	18	93,617	2	94,819	84,000	0.49
17	33	108,209	3	109,130	99,000	1.49
18	92	240,961	0	240,961	n.a.	n.a.
19	199	221,968	8	222,596	206,988	0.75

with the means of non-adjacent house prices greater than the means of adjacent house prices in four of those five neighborhoods.

Spatial Regression Analysis

Hedonic price theory provides the framework for our empirical analysis. Popularized in the context of house prices by Rosen (1974) and since built upon by many others, hedonic price theory is based on the notion that the value of a house derives from its attributes and that regression analysis can be used to decompose observed house prices into the implicit price of each attribute. Modern hedonic price models recognize potential spatial effects in cross-sectional house price samples in which the relative locations of houses may affect the implicit prices of the houses' attributes in ways that cannot be adequately modeled with available location variables.

The interdependence of house prices across geographic space is difficult to deny in most markets: nearby houses tend to sell for similar prices. The presence of unmodeled spatial effects violates the assumptions of the ordinary least squares (OLS) regression estimator regarding uncorrelated and homoscedastic errors which, in turn, imply that the OLS estimator is biased and inconsistent. We address potential spatial effects in the data using spatial lag and spatial error regression models as described by Anselin (1999, 2003) and demonstrated in the context of hedonic house pricing by Kim, Phipps, and Anselin (2003) and Osland (2010).

Equation 1 shows the spatial lag regression model:

$$\ln(PRICE) = \rho \boldsymbol{W} \ln(PRICE) + \beta_j \boldsymbol{X}_j + u, \tag{1}$$

where ρ is a spatial autocorrelation parameter, $\boldsymbol{W}$ is a spatial weight matrix, $\boldsymbol{X}$ includes j property characteristics, and u is a vector of i.i.d. errors. The spatial lag model is useful when house values are affected by their own attribute, as well as the attributes of neighboring houses.

Equation 2 shows the spatial error regression model:

$$\ln(PRICE) = \beta_0 + \beta_j \boldsymbol{X}_j + \lambda \boldsymbol{W} \varepsilon + u, \tag{2}$$

where λ is the spatial autoregressive coefficient, and $\boldsymbol{W}$, $\boldsymbol{X}$, and u are as defined above. The spatial error model assumes that spatial autocorrelation results from a spatial pattern in variables such as location-specific amenities that are omitted from (cannot be controlled for in) the model and, therefore, are subsumed in the composite error term $\lambda \boldsymbol{W} \varepsilon + u$. In both models, the weight matrix identifies neighboring houses based on inverse distances, with the minimum distance of ''neighboring'' defined as the first quartile distance of the houses in the sample. Note that when ρ or λ are zero, both models collapse to the traditional hedonic price function. As demonstrated by Osland (2010), Moran's I statistic allows testing for spatial dependencies in the data while the Lagrange multiplier statistic and the robust Lagrange multiplier statistic are used to examine whether the spatial lag or spatial error model best addresses spatial dependencies in the data.

In the next section, we present the results of estimating hedonic price functions for this sample of houses and discuss the diagnostic tests for identifying whether OLS, spatial error, or spatial lag modeling is most appropriate for measuring the impacts of highways on house prices in this market based on potential spatial effects in the data.

Results

Exhibit 3 presents estimates of the implicit prices of highway impacts and other factors (control variables) on house prices using OLS and a semi-log functional

Exhibit 3 | OLS Regression Results with Neighborhood Indicators

	Model 1			Model 2		
	Coeff.	Std. Error	*t*-stat.	Coeff.	Std. Error	*t*-stat.
adjacent	−0.044	0.020	−2.143	−0.047	0.016	−2.860
sound_barrier	0.016	0.035	0.459			
straight_distance	0.045	0.023	1.955			
traffic_volume	−0.010	0.001	−8.729	−0.010	0.001	−8.502
drive_distance	−0.026	0.009	−2.805	−0.027	0.009	−2.937
age	−0.013	0.002	−8.115	−0.013	0.002	−8.006
livarea100	0.021	0.001	26.342	0.021	0.001	26.465
lotacre	0.642	0.082	7.829	0.638	0.082	7.781
pool	0.108	0.012	9.277	0.109	0.012	9.403
strend	0.021	0.002	10.479	0.021	0.002	10.519
strend2	0.000	0.000	−4.578	0.000	0.000	−4.618
neighborhood1	−0.254	0.037	−6.826	−0.268	0.037	−7.295
neighborhood2	−0.507	0.070	−7.251	−0.510	0.070	−7.295
neighborhood3	−0.424	0.047	−9.049	−0.419	0.047	−8.939
neighborhood4	0.064	0.029	2.233	0.048	0.027	1.783
neighborhood5	−0.172	0.024	−7.082	−0.172	0.024	−7.074
neighborhood6	−0.423	0.030	−14.248	−0.432	0.029	−14.675
neighborhood7	−0.269	0.028	−9.722	−0.279	0.027	−10.239
neighborhood8	0.461	0.066	6.949	0.453	0.066	6.840
neighborhood9	0.588	0.047	12.507	0.577	0.047	12.343
neighborhood10	0.407	0.054	7.493	0.378	0.052	7.246
neighborhood11	−0.019	0.040	−0.463	−0.025	0.040	−0.626
neighborhood12	−0.066	0.048	−1.369	−0.069	0.048	−1.437
neighborhood13	−0.491	0.058	−8.439	−0.486	0.058	−8.402
neighborhood14	−0.139	0.030	−4.644	−0.152	0.029	−5.235
neighborhood15	0.468	0.045	10.410	0.450	0.044	10.222
neighborhood16	−0.486	0.036	−13.441	−0.500	0.035	−14.202
neighborhood17	−0.393	0.029	−13.412	−0.410	0.028	−14.789
neighborhood18	−0.303	0.041	−7.450	−0.287	0.040	−7.190
constant	12.171	0.090	134.973	12.171	0.090	134.828

Notes: The dependent variable is ln(*price*). The number of observations is 1,025. For Model 1, the R^2 is 86.63% and the *F*-statistic is 222.26. For Model 2, the R^2 is 86.57% and the *F*-statistic is 238.05.

form for the regression equation. The semi-log specification allows intuitive interpretation of the coefficient estimates as the percentage change in price for a unit change in the independent variables. Model 1 in Exhibit 3 includes a highway adjacency indicator variable (*adjacent*), a sound barrier wall indicator variable (*sound_barrier*), a straight-line distance measure from house to highway (*straight_distance*), a traffic volume measure (*traffic_volume*), a driving distance measure from house to nearest highway on-ramp (*drive_distance*), and various control variables for house characteristics (*age*, *livarea100*, *lotacre*, and *pool*), market conditions (*strend* and *strend2*), and neighborhood characteristics (dummy variables for *neighborhood#*, where # ranges from 1 to 18).[6] Model 2 in Exhibit 3 includes the same variables as Model 1 with the exceptions of *sound_barrier* and *straight_distance*, which are not significant in results for the first model.[7]

The results for Model 2 in Exhibit 3 indicate a significant negative price effect of 4.8% [applying the Kennedy (1981) transformation] for houses adjacent to highways, a significant negative price effect of 1.0% for each unit increase in traffic volume, and a significant negative price effect of 2.6% for houses located an additional driving mile from the nearest highway on-ramp.[8] All of the control variables are significant and have the expected signs. The signs of the control variables for changing market conditions (*strend* and *strend2*) indicate that prices rise at a decreasing rate over the study period. All but three of the neighborhood dummy variable coefficients are statistically significant, indicating that most of the neighborhoods have higher or lower average prices than the comparison neighborhood (*neighborhood19*, which is the most prevalent neighborhood in the sample) holding other variables constant. The adjusted R-squares of the OLS regressions indicate that the results for Models 1 and 2 indicate approximately 87% and 86% of the variation in house prices in this market, respectively, and the F-statistics for both models are highly significant.

Due to justifiable concerns over potential spatial effects in the data that may cause the OLS estimates to be biased and inconsistent in hedonic house price regressions, Exhibit 4 presents the results of the maximum likelihood estimation (MLE) of Equation (1) for the spatial lag model. Model 3 includes all five of the primary variables of interest and Model 4 omits the *sound_barrier* and *straight_distance* variables, which are not significant in Model 3. Both models include the same control variables as those used in the OLS models. The spatial lag regression results in Model 4 indicate a significant negative price effect of 4.0% [applying the Kennedy (1981) transformation] for houses adjacent to highways, a significant negative price effect of 0.8% for each unit increase in traffic volume, and a significant negative price effect of 2.5% for houses located an additional driving mile from the nearest highway on-ramp. The coefficients on the property characteristic, market conditions, and neighborhood characteristic variables are consistent in sign and significance with the OLS results.

Exhibit 5 presents the MLE results for Equation (2), the spatial error model. Model 5 includes all five of the highway-related variables of interest and the variables *sound_barrier* and *straight_distance* variables, which are omitted from Model 6 as they are not significant in Model 5. Both models include the same control variables as those used in the OLS models. The spatial error regression results in

Exhibit 4 | Spatial Lag Regression Results

	Model 3			Model 4		
	Coeff.	Std. Error	*t*-stat.	Coeff.	Std. Error	*t*-stat.
adjacent	−0.041	0.020	−2.084	−0.039	0.016	−2.436
sound_barrier	0.023	0.034	0.672			
straight_distance	0.027	0.022	1.221			
traffic_volume	−0.008	0.001	−7.065	−0.008	0.001	−6.953
drive_distance	−0.024	0.009	−2.730	−0.025	0.009	−2.808
age	−0.011	0.002	−6.702	−0.010	0.002	−6.608
livarea100	0.020	0.001	25.955	0.020	0.001	25.985
lotacre	0.530	0.081	6.505	0.526	0.081	6.458
pool	0.102	0.011	8.998	0.102	0.011	9.062
strend	0.020	0.002	10.641	0.020	0.002	10.641
strend2	0.000	0.000	−4.561	0.000	0.000	−4.555
neighborhood1	−0.098	0.045	−2.195	−0.103	0.045	−2.307
neighborhood2	−0.449	0.068	−6.580	−0.450	0.068	−6.586
neighborhood3	−0.404	0.045	−8.888	−0.400	0.045	−8.809
neighborhood4	0.051	0.028	1.851	0.043	0.026	1.648
neighborhood5	−0.137	0.024	−5.661	−0.137	0.024	−5.633
neighborhood6	−0.328	0.033	−9.961	−0.332	0.033	−10.079
neighborhood7	−0.225	0.028	−8.079	−0.230	0.028	−8.332
neighborhood8	0.296	0.070	4.225	0.287	0.070	4.116
neighborhood9	0.398	0.056	7.140	0.387	0.055	7.030
neighborhood10	0.297	0.056	5.336	0.278	0.053	5.239
neighborhood11	−0.048	0.039	−1.212	−0.053	0.039	−1.344
neighborhood12	−0.072	0.046	−1.550	−0.075	0.046	−1.607
neighborhood13	−0.404	0.058	−6.949	−0.401	0.058	−6.955
neighborhood14	−0.159	0.029	−5.451	−0.166	0.028	−5.905
neighborhood15	0.314	0.051	6.190	0.299	0.049	6.092
neighborhood16	−0.319	0.045	−7.101	−0.323	0.045	−7.206
neighborhood17	−0.259	0.036	−7.118	−0.265	0.036	−7.385
neighborhood18	−0.244	0.041	−6.013	−0.232	0.040	−5.870
constant	7.982	0.718	11.113	7.881	0.711	11.080
rho	0.334	0.057	5.870	0.343	0.056	6.080

Notes: The dependent variable is ln(*price*). The number of observations is 1,025.

Exhibit 5 | Spatial Error Model Regression Results

	Model 5			Model 6		
	Coeff.	Std. Error	*t*-stat.	Coeff.	Std. Error	*t*-stat.
adjacent	−0.043	0.021	−2.103	−0.045	0.017	−2.684
sound_barrier	0.016	0.036	0.429			
straight_distance	0.040	0.025	1.593			
traffic_volume	−0.010	0.001	−6.683	−0.009	0.001	−6.425
drive_distance	−0.025	0.011	−2.364	−0.026	0.011	−2.419
age	−0.013	0.002	−7.513	−0.013	0.002	−7.382
livarea100	0.020	0.001	26.167	0.020	0.001	26.217
lotacre	0.561	0.086	6.540	0.556	0.086	6.469
pool	0.102	0.012	8.853	0.103	0.012	8.903
strend	0.020	0.002	10.445	0.020	0.002	10.467
strend2	0.000	0.000	−4.319	0.000	0.000	−4.339
neighborhood1	−0.257	0.057	−4.475	−0.270	0.058	−4.624
neighborhood2	−0.510	0.087	−5.862	−0.512	0.088	−5.821
neighborhood3	−0.414	0.058	−7.155	−0.408	0.058	−6.985
neighborhood4	0.041	0.039	1.064	0.027	0.038	0.704
neighborhood5	−0.176	0.034	−5.224	−0.175	0.034	−5.124
neighborhood6	−0.431	0.040	−10.673	−0.439	0.041	−10.784
neighborhood7	−0.268	0.034	−7.934	−0.276	0.034	−8.195
neighborhood8	0.467	0.077	6.060	0.459	0.078	5.919
neighborhood9	0.592	0.057	10.451	0.582	0.057	10.223
neighborhood10	0.398	0.069	5.781	0.371	0.068	5.496
neighborhood11	−0.001	0.050	−0.028	−0.006	0.050	−0.119
neighborhood12	−0.057	0.057	−0.994	−0.059	0.058	−1.017
neighborhood13	−0.478	0.072	−6.604	−0.473	0.073	−6.491
neighborhood14	−0.129	0.040	−3.229	−0.139	0.040	−3.486
neighborhood15	0.465	0.055	8.454	0.448	0.055	8.215
neighborhood16	−0.500	0.047	−10.531	−0.514	0.047	−10.883
neighborhood17	−0.409	0.039	−10.438	−0.425	0.038	−11.099
neighborhood18	−0.296	0.056	−5.300	−0.282	0.056	−5.028
constant	12.180	0.107	114.189	12.179	0.108	113.146
lambda	0.403	0.090	4.490	0.416	0.089	4.690

Notes: The dependent variable is ln(*price*). The number of observations is 1,025.

Exhibit 6 | Spatial Dependency Diagnostics

	Statistic	*p*-value
Panel A: Specification for Models 2 & 4		
Moran's I	6.610	
Spatial Lag		
Lagrange multiplier	39.107	0.000
Robust Lagrange multiplier	21.594	0.000
Spatial Error		
Lagrange multiplier	17.514	0.000
Robust Lagrange multiplier	0.001	0.975
Panel B: Specification for Models 3 & 5		
Moran's I	6.760	
Spatial Lag		
Lagrange multiplier	42.027	0.000
Robust Lagrange multiplier	22.894	0.000
Spatial Error		
Lagrange multiplier	19.144	0.000
Robust Lagrange multiplier	0.011	0.917

Note: Distance band: 0.0 < d < first quartile distance.

Model 6 indicate a significant negative price effect of 4.6% [applying the Kennedy (1981) transformation] for houses adjacent to highways, a significant negative price effect of 0.9% for each unit increase in traffic volume, and a significant negative price effect of 2.6% for houses located an additional driving mile from the nearest highway on-ramp. The coefficients on the property characteristic, market conditions, and neighborhood characteristic variables are consistent with the OLS results.

Exhibit 6 presents the results of diagnostic tests to detect spatial effects in the sample.[9] In the specification used in Models 3 and 5, the Moran's I statistic of 6.61 is significant at a confidence level greater than 99%, which strongly indicates the presence of spatial autocorrelation in the data. The Lagrange multiplier statistics for spatial error dependence and spatial lag dependence are also highly significant. The larger robust Lagrange multiplier for the spatial lag model points to that model as the appropriate choice for this sample. In the specification used in Models 2 and 4, the Moran's I statistic of 6.76 is significant at a confidence level greater than 99% and the Lagrange multiplier statistics for spatial error dependence and spatial lag dependence are also highly significant. The larger robust Lagrange multiplier for the spatial lag model again points to that model as the appropriate choice for this sample.

Conclusion

Substantial evidence in the real estate economics literature documents significant price impacts resulting from highway noise and proximity for residential properties. We use spatial regression modeling in this study to analyze the revealed preferences of market participants regarding highway impacts on house prices in the Orlando, Florida metropolitan area. The impetus for this study is a new limited access, multi-lane, median divided, 25-mile toll road under construction in this market at a cost of $1.5 billion. This study documents micro-level house price effects related to highways in this market to better understand the impact of the new highway on planned and existing nearby houses.

Using a sample of 1,025 single-family detached house transactions from 19 suburban neighborhoods located along similar existing highways in this area, the spatial lag regression results reported for Model 4 indicate a significant price discount of 4.0%, for houses adjacent to highways, a price discount of 0.8% for each unit increase in traffic volume, and a price discount of 2.5% for houses located an additional driving mile from the nearest highway on-ramp. The results do not support the contentions that house prices are impacted by the straight-line distance between houses and highways or the presence of sound barrier walls.

The magnitude of the highway adjacency effect is similar to that of Hughes and Sirmans (1992, 1993) in their study of traffic effects on suburban house prices in Baton Rouge, Louisiana, but is approximately half as large as the effects reported Hughes and Sirmans (1992, 1993) for urban houses in Baton Rouge, Louisiana and by Larsen (2012) and Larsen and Blair (2014) for urban houses in Kettering, Ohio. The results do not support Kilpatrick, Throupe, Carruthers, and Krause's (2007) finding regarding straight-line distance to transit corridors in Seattle, Washington, but do confirm that accessibility to highway systems has a positive impact on house prices. The results contradict the findings of a negative relationship between sound barrier walls and house prices in Montreal, Canada, as reported by Julien and Lanoie (2008). This analysis may prove useful to property owners, transportation system planners/engineers, eminent domain authorities, and appraisers who are concerned with the impacts of highways on house prices in this and other market areas.

Endnotes

[1] For more details about the project, see http://www.wekivaparkway.com (accessed 6/1/2015).

[2] See Palmquist (1992) for theoretical justification for the use of hedonic price modeling to value localized externalities.

[3] The exclusive use of public records as the data source for this study precludes consideration of probability of sale or time-on-market analysis as is common in studies using house price data obtained from multiple listing services (MLSs). Public records have the advantage of including all house transactions in the study area, while MLS

records only include transactions handled by broker-members of the local MLS. The authors do not have access to MLS data in this market.

[4] The initial sample consists of all houses with ownership transfers during the study period in 19 neighborhoods that have highway frontage along three major highways in the market area. The final sample does not include sales ''disqualified'' by the county tax appraiser's office as non-arm's length transactions (sales with Florida Department of Revenue sales codes other than 01 and 02), nor does the sample include foreclosure transfers.

[5] Differences in means for adjacent and non-adjacent cannot be tested for two of the 19 neighborhoods due to data limitations: *neighborhood2* has only one adjacent house and *neighborhood18* has no adjacent houses.

[6] Sirmans, MacPherson, and Zietz (2005) provide a comprehensive discussion of the variety of house attributes used in hedonic price studies.

[7] This study adopts a 95% confidence level to evaluate statistical significance in all instances.

[8] Kennedy (1981) demonstrates that the percentage change in the dependent variable is equal to $e^{(\beta - 1/2 Var(\beta))} - 1$, where β is the OLS coefficient on an indicator (binary dummy) variable in a semi-log regression.

[9] For a discussion of these test statistics and their interpretations, see Osland (2010).

References

Andersson, H., L. Jonsson, and M. Ögren. Property Prices and Exposure to Multiple Noise Sources: Hedonic Regression with Road and Railway Noise. *Environmental Resource Economics*, 2010, 45, 73–89.

Anselin, L. Spatial Econometrics. School of Social Sciences, University of Texas at Dallas, 1999.

——. Spatial Externalities, Spatial Multipliers, and Spatial Econometrics. *International Regional Science Review*, 2003, 26:2, 153–66.

Baranzini, A. and J.V. Ramirez. Paying for Quietness: The Impact of Noise on Geneva Rents. *Urban Studies*, 2005, 42:4, 633–46.

Bateman, I.J., B. Day, I. Lake, and A.A. Lovett. The Effect of Road Traffic on Residential Property Values: A Literature Review and Hedonic Pricing Study. Report to the Scottish Office, Development Department, Edinburgh, 2001.

Becker, N and D. Lavee. The Benefits and Costs of Noise Reduction. *Journal of Environmental Planning and Management*, 2003, 46:1, 97–111.

Blanco, J.C. and I. Flindell. Property Prices in Urban Areas Affected by Road Traffic Noise. *Applied Acoustics*, 2011, 72, 133–41.

Brandt, S. and W. Maennig. Road Noise Exposure and Residential Property Prices: Evidence from Hamburg. *Transportation Research Part D*, 2011, 16, 23–30.

Day, B., I. Bateman, and I. Lake. Beyond Implicit Prices: Recovering Theoretically Consistent and Transferable Values for Noise Avoidance from a Hedonic Property Price Model. *Environmental and Resource Economics*, 2007, 37, 211–32.

Hughes, W.T. and C.F. Sirmans. Traffic Externalities and Single-Family House Prices. *Journal of Regional Science*, 1992, 32:4, 487–500.

——. Adjusting House Prices for Intra-Neighborhood Traffic Differences. *The Appraisal Journal*, 1993, 61:4, 533–38.

Julien, B. and P. Lanoie. The Effect of Noise Barriers on the Market Value of Adjacent Residential Properties. *International Real Estate Review*, 2007, 10:2, 113–30.

Kawamura, K. and S. Mahajan. Hedonic Analysis of Impacts of Traffic Volumes on Property Values. Transportation Research Record: Journal of the Transportation Research Board, No. 1924, Transportation Research Board of the National Academies, Washington, D.C., 2005, 69–75.

Kennedy, P.E. Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations. *American Economic Review*, 1981, 7, 801.

Kilpatrick, J.A., R.L. Throupe, J.I. Carruthers, and A. Krause. The Impact of Transit Corridors on Residential Property Values. *Journal of Real Estate Research*, 2007, 29:3, 303–20.

Kim, C.W., T.T. Phipps, and L. Anselin. Measuring the Benefits of Air Quality Improvement: A Spatial Hedonic Approach. *Journal of Environmental Economics and Management*, 2003, 45, 24–39.

Kim, K., S. Park, and Y. Kweon. Highway Traffic Noise Effects on Land Price in an Urban Area. *Transportation Research Part D*, 2007, 12, 275–80.

Larsen, J.E. Surface Street Traffic Volume and Single-Family House Price. *Transportation Research Part D*, 2012, 17, 317–20.

Larsen, J.E. and J.P. Blair. Price Effects of Surface Street Traffic on Residential Property. *International Journal of Housing Markets and Analysis*, 2014, 7:2, 189–203.

Li, W. and J.D. Saphores. Assessing the Impacts of Freeway Truck Traffic on Residential Property Values: A Southern California Case Study. *Transportation Research Record*, 2012, 2288, 48–56.

Nelson, J.P. Hedonic Property Value Studies of Transportation Noise. In *Hedonic Methods in Housing Market Economics*. A. Baranzini, et al. (eds.). New York: Springer, 2008, 57–82.

Osland, L. An Application of Spatial Econometrics in Relation to House Price Modeling. *Journal of Real Estate Research*, 2010, 32:3, 289–320.

Palmquist, R.B. Valuing Localized Externalities. *Journal of Urban Economics*, 1992, 31:1, 59–68.

Rich, J.H. and O.A. Nielsen. Assessment of Traffic Noise Impacts. *International Journal of Environmental Studies*, 2004, 61, 19–29.

Rosen, S. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *The Journal of Political Economy*, 1974, 82:1, 34–55.

Seo, K., A. Golub, and M. Kuby. Combined Impacts of Highways and Light Rail Transit on Residential Property Values: A Spatial Hedonic Price Model for Phoenix, Arizona. *Journal of Transport Geography*, 2014, 41, 53–62.

Sirmans, G.S., D.A. MacPherson, and E.N Zietz. The Composition of Hedonic Pricing Models. *Journal of Real Estate Literature*, 2005, 13:1, 3–46.

Theebe, M.A.J. Planes, Trains, and Automobiles: The Impact of Traffic Noise on House Prices. *Journal of Real Estate Finance and Economics*, 2004, 28:2/3, 209–34.

Wilhelmsson, M. The Impact of Traffic Noise on the Values of Single-Family Houses. *Journal of Environmental Planning and Management*, 2000, 43:6, 799–815.

Marcus T. Allen, Florida Gulf Coast University, Fort Myers, FL 33965 or timallen@fgcu.edu.

Grant W. Austin, American Valuation, Inc., Orlando, FL 32832 or amervalu@bellsouth.net.

Mushfiq Swaleheen, Florida Gulf Coast University, Fort Myers, FL 33965 or mswalehe@fgcu.edu.