Impacts of Transportation Investment on Real Property Values:

An Analysis with Spatial Hedonic Price Models

by

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ABSTRACT

Transportation infrastructure in urban areas has significant impacts on socio-economic activities, land use, and real property values. This dissertation proposes a more comprehensive theory of the positive and negative relationships between property values and transportation investments that distinguishes different effects by mode (rail vs. road), by network component (nodes vs. links), and by distance from them. It hypothesizes that transportation investment generates improvement in accessibility that accrue only to the nodes such as highway exits and light rail stations. Simultaneously, it tests the hypothesis that both transport nodes and links emanate short-distance negative nuisance effects due to disamenities such as traffic and noise. It also tests the hypothesis that nodes of both modes generate a net effect combining accessibility and disamenities. For highways, the configuration at grade or above/below ground is also tested. In addition, this dissertation hypothesizes that the condition of road pavement may have an impact on residential property values adjacent to the road segments. As pavement condition improves, value of properties adjacent to a road are hypothesized to increase as well. A multiple-distance-bands approach is used to capture distance decay of amenities and disamenities from nodes and links; and pavement condition index (PCI) is used to test the relationship between road condition and residential property values. The hypotheses are tested using spatial hedonic models that are specific to each of residential and commercial property market. Results confirm that proximity to transport nodes are associated positively with both residential and commercial property values. As a function of distance from highway exits and light rail transit (LRT) stations, the distance-band coefficients form a conventional distance decay curve. However, contrary to our hypotheses, no net effect is

evident. The accessibility effect for highway exits extends farther than for LRT stations in residential model as expected. The highway configuration effect on residential home values confirms that below-grade highways have relatively positive impacts on nearby houses compared to those at ground level or above. Lastly, results for the relationship between pavement condition and residential home values show that there is no significant effect between them.

Some differences in the effect of infrastructure on property values emerge between residential and commercial markets. In the commercial models, the accessibility effect for highway exits extends less than for LRT stations. Though coefficients for short distances (within 300m) from highways and LRT links were expected to be negative in both residential and commercial models, only commercial models show a significant negative relationship. Different effects by mode, network component, and distance on commercial submarkets (i.e., industrial, office, retail and service properties) are tested as well and the results vary based on types of submarket.

Consequently, findings of three individual paper confirm that transportation investments mostly have significant impacts on real-estate properties either in a positive or negative direction in accordance with the transport mode, network component, and distance, though effects for some conditions (e.g., proximity to links of highway and light rail, and pavement quality) do not significantly change home values. Results can be used for city authorities and planners for funding mechanisms of transport infrastructure or validity of investments as well as private developers for maximizing development profits or for locating developments.

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CHAPTER 1

INTRODUCTION

Overview

Transportation infrastructure in urban areas has significant impacts on socio-economic activities, land use, and real property values. Real property values are sensitive to investment of transportation infrastructure such as highway and light rail transit because transportation investment improves accessibility of nearby properties, which is capitalized in real property values according to classical economic geography theories (Von Thünen 1826; Weber 1929; Alonso 1964; Adams 1970). Transportation infrastructure, however, does not always generate positive effects; it also generates nuisance effects such as traffic noise and air pollution. Nuisance effects have been found to have a negative influence on property values. Moreover, quality or condition of transportation infrastructure may also have an influence on property values along the transportation network, such as by reducing noise or improving aesthetic conditions of the neighborhood.

Numerous empirical studies have been performed to test impacts of transportation investment on real-estate values (Vessali 1996). Hedonic price models using multiple regression are a widely used and powerful measurement method for land-use impacts (Hanson and Giuliano 2004). The focus of previous studies has varied by the dependent variables used (e.g., residential or commercial property values), the mode of transportation (e.g., airport, highway, or rail), and proximity to network nodes and/or links. For instance, some studies measured only nuisance effects (e.g., noise and air pollution) of highway and/or rail transit, while others analyzed positive effects (i.e., accessibility) of highway and/or rail. Some studies measured both accessibility and nuisance effects of highway and/or rail. Many studies used Euclidean distance to measure accessibility or nuisance effects, Moreover, some studies used a single buffer around transportation infrastructure to estimate where the effects may be felt, while others used multiple distance bands to estimate the decay of effects. A few studies took an alignment, configuration, or noise barrier of the transportation corridor into account, though most highways within urban areas have overpasses, underpasses, and noise barriers. To the best of my knowledge, no study has been published in the peer-reviewed literature that has estimated the relationship between road pavement condition and property values. Moreover, though spatial dependences in the hedonic price models are commonplace and may result in biased and inconsistent estimates if ignored (Anselin, 1988), only some recent studies took this into account.

To unpack the positive and negative impacts of transportation facilities on real property values over space, one should combine all of the key factors into a single model for identifying the variables of most interest. For instance, one should take both transportation modes into account in order to prevent omitted variable bias (Debrezion et al., 2007). The same principle should be applied for both accessibility and nuisance effects of transportation facilities in order to derive unbiased estimates (Nelson 1982).

In addition, accessibility or nuisance effects on residential and commercial property markets may differ in terms of geographical extent and rate of distance decay. Explanatory variables, which explain property values of each market, may differ as well. Therefore, a market-specific and spatially disaggregated approach should be employed. Lastly, it is also worth investigating how road pavement condition, which is surveyed and estimated for arterial and connection roads for management purpose, affects property values along the corridor.

In this regard, the City of Phoenix is a suitable case study area to test the models for combined impacts of highways and light rail transit on residential and commercial property value because multiple modes of transportation infrastructure (i.e., highways and light rail transit) exist. For the impacts of pavement condition on residential property values, Solano County, California was selected because Solano Transportation Authority (STA) requested a consulting project to analyze impacts of road pavement condition on residential property values to get policy implications and this falls in the research scope of this dissertation. This fact confirms the broader impact of this type of modeling and its real-world utility.

Problem Statement: Research Questions and Hypotheses

Positive and negative effects of transportation investment create relative advantages and disadvantages for different kinds of real estate at different distances from the nodes and links of different types of transportation networks. All other things being equal, based on these relative advantages and disadvantages, the locations of socio-economic activities may shift, changes of land use and urban structure may follow, and values of the property may change accordingly. Thus, the overarching research question for this dissertation is "how does transportation investment affect real property values?" The detailed research questions are as follows:

- How do real property markets (i.e., single-family housing and commercial property) value the positive effects of accessibility provided by highway and light rail nodes and links?

- How do real property markets value disamenities of proximity to the highway and light rail nodes and links?
- How do these positive and negative effects decay with distance from highway and light rail transit infrastructure?
- Do the commercial submarkets (i.e., industrial, office, service and retail properties) have dissimilar effects on the sale prices?
- Do the specific types of highway configurations—elevated or below-grade alignments—influence residential property values differently.
- How does the residential property market value the condition of road pavement?

On the basis of urban economic theories and empirical studies, this dissertation hypothesizes that transportation investment generates improvements in accessibility that accrue only to the nodes such as highway exits and light rail stations because vehicles cannot access highways between exits and rail passengers cannot access trains between stations. Simultaneously, both transport nodes and links may emanate negative effects such as noise and air pollution but possibly transport nodes may emanate more negative effects than links because of heavy traffic and/or crimes. Both positive and negative effects should decay with increasing distance, but the property value gradient should be steeper and less extended for light rail than for highway because of non-motorized travel to light rail stations. In addition, this study also hypothesizes that transportation investment (i.e., repair, rehabilitation, or re-pavement) for pavement condition could increase positive effects on values of residential properties adjacent to improved arterial, neighborhood connector, and residential roads due to the reduction of noise level and improved aesthetic condition in neighborhood. Positive impacts on residential property values where pavement condition is improved by repair or rehabilitation may appreciate more than property values with a bad pavement condition.

Significance

This dissertation supports classical urban economic theory, such as bid-rent curves for urban residents and commercial firms, which differ in gradient and extent due to the location of utility maximization for each market (Alonso 1964). It also empirically tests this urban economic theory on real-world transportation infrastructure, which changes the relative location of utility maximization by improving accessibility.

In addition, while most hedonic price studies took only selected factors (e.g., positive and negative effects of single transportation mode, positive or negative effects of multiple transportation modes) into consideration, this dissertation takes all these key factors into account for estimating combined impacts of transportation infrastructure. Theoretically, it unifies a number of disparate previous findings in the hedonic price literature into a single, general, idealized schematic model incorporating road and rail, nodes and links, amenities and disamenities, and distance decay of all of these effects. An additional methodological contribution is how to design a hedonic regression model to measure and test these effects statistically and spatially in a single model.

The results may be useful to private and public sectors in terms of buying and constructing real property and transportation planning. For instance, property buyers may be able to identify the location where net benefit of accessibility is maximized. Property construction companies also may be able to decide where to build real property for maximizing profit and sales. Transportation planning authorities, on the other hand, may be able to secure and distribute tax revenue based on the accessibility benefit and/or nuisance effects captured by this study. This study can inform policy makers on designing tax-increment financing (value capture) mechanisms for funding new public-sector transportation investments (Anderson 1990; Medda 2012).

Dissertation Structure

This dissertation is composed of three individual articles with an overarching introduction and conclusions. Chapter 1 has introduced the dissertation. Chapter 2 and 3 investigate impacts of highway and light rail transit on residential and commercial property values in Phoenix, Arizona, respectively. Chapter 4 examines impacts of road pavement condition on residential property values along the arterial and connection roads in Solano County, California. Chapter 5 offers overarching conclusions for the dissertation.

CHAPTER 2

IMPACTS OF HIGHWAYS AND LIGHT RAIL TRANSIT ON RESIDENTIAL PROPERTY VALUES

Abstract

This study analyzes the positive and negative relationships between housing prices and proximity to light rail and highways in Phoenix, Arizona. We hypothesize that the accessibility benefits of light rail transit (LRT) and highways accrue at nodes (stations and highway exits specifically), while disamenities emanate from rail and highway links as well as from nodes. Distance decay of amenities is captured using multiple distance bands, and the hypotheses are tested using a spatial hedonic model using generalized spatial two-stage least squares estimation. Results show that proximity to transport nodes was significantly and positively associated with single-family detached home values. As a function of distance from highway exits and LRT stations, the distance-band coefficients form a classic distance decay curve, but we do not find the hypothesized net effect in which the positive effect of accessibility close to the node is reduced by a disamenity effect of traffic and noise. The positive accessibility effect for highway exits extends farther than for LRT stations as expected. Coefficients for the distance from highway and LRT links, however, are not significant. We also test the effect of highway design on home values and find that below-grade highways have relatively positive impacts on nearby houses compared to those at ground level or above.

Keywords: highway, light rail, spatial hedonic regression, node, link, home value

Introduction

Highway systems and light rail transit (LRT) in and around cities have significant impacts on human activity and quality of life that bring both positive (i.e., accessibility of a highway exit or a light rail station) and negative (i.e., noise and air pollution) effects that are reflected to some degree in the market prices of nearby real estate (Bowes and Ihlanfeldt, 2001; Poulos and Smith, 2002; Ryan, 2005; Armstrong and Rodriguez, 2006; Hess and Almeida, 2007; Kilpatrick et al., 2007; Giuliano et al., 2010; Golub et al., 2012). It is difficult, however, to estimate how real-estate markets value accessibility (in distance or minutes), traffic noise (in decibels), or air pollution (in ppm) because market responses may vary in different ways with increasing spatial distance from the effects in question (Nelson, 1982). In addition, the amenities and disamenities may not accrue or decay equally with increasing distance from transport nodes such as rail stations or highway exits as they do from the arcs or links of the networks. It is thus important to investigate how the costs and benefits are distributed geographically in relation to highway and rail networks and nodes.

In this paper, we propose a theoretical model for how amenity and disamenity should decay differently from links and nodes of rail and road networks. We then use hedonic regression models to measure the net impacts on single-family home values with respect to their distance from highways and exits, and light-rail stations and lines, in Phoenix, Arizona. Our core research questions include: How does the single-family housing market value the positive effects of accessibility provided by highway exits and light rail stations, respectively? How does the market value the disamenities of proximity to the freeway and rail links? Finally, how do these effects decay with distance? We also test whether specific types of highway configurations, such as elevated and below-grade alignments, influence property values differently.

Literature Review

The prior research on hedonic housing price models of transportation impacts is quite extensive: see for instance review papers such as Vessali (1996) and Diaz (1999) for rapid transit and Bateman et al. (2001) for roads. To help situate our paper within that literature, Table 1 summarizes previous studies in terms of the transportation-related factors they considered:

- amenity (accessibility) and disamenity (noise, air pollution, crime) or both
- distance decay of amenity or disamenity;
- mode(s) of transport studied;
- whether distance effects are measured from the nodes or links of the network.

Table 1
Summary of Selected Literature on Road and Rail Impacts in Hedonic Price Models.

Authors	Study Focus	Measurement Method		Transport Mode		Network Element	
		Decibel/Traffic Volume	Distance Measure	Highway or Road	Rail or LRT	Links	Nodes
Gamble et al., 1974	Disamenity	O		O		O	
Langley 1976	Disamenity		Single-band	O		O	
Nelson 1978	Disamenity	O		O		O	
Bowes and Ihlanfeldt, 2001	Accessibility & disamenity		Multi-band	O	O		O
Ryan 2005	Accessibility		Actual distance	O	O		O
Clark 2006	Disamenity		Single-band (link) Multi-band (rail crossing)		O	O	
Armstrong and Rodriguez 2006	Accessibility		Travel time/Single-band	O	O		O
Hess and Almeida 2007	Accessibility		Actual distance		O		O
Kilpatrick et al., 2007	Accessibility & disamenity		Actual distance	O		O	O
Kim et al., 2007	Disamenity		Actual distance	O		O	
Andersson et al., 2010	Disamenity	O (link)	Actural distance (node)	O	O	O	O
Golub et al. 2012	Accessibility & disamenity		Actual distance		O	O	O
Li and Saphores 2012	Disamenity	O	Multi-band	O		O	
This paper	Accessibility & disamenity		Multi-band	O	O	O	O

The earliest work on transportation impacts in hedonic models focused more on disamenities than amenities (Gamble et al., 1974; Langley, 1976; Nelson, 1978). Traffic noise was the most studied disamenity in the hedonic literature with respect to transportation facilities such as roads and railways (Gamble et al., 1974; Langley, 1976; Nelson, 1978; Clark, 2006; Kim et al., 2007; Andersson et al., 2010; Li and Saphores, 2012). Early hedonic price models in the 1970s used noise measurements based on a fixed distance (usually 1,000 feet or less) from highways. Models using cross-sectional or time-series data generally concurred that residential property values are negatively affected by the level of noise (Nelson, 1982).

Actual noise levels, however, are quite expensive to measure at the parcel level, which led to the use of distance as a fairly good proxy for field measurement of actual noise levels (Bailey, 1977). While many studies considered a single fixed distance area (e.g., within 1000 ft. or a quarter mile) considered to be an impact zone of noise pollution (Langley 1976; Kim et al., 2007), some studies used dummy variables for multiple distance bands (Bowes and Ihlanfeldt, 2001; Clark, 2006; Li and Saphores, 2012). Multiple distance bands allow hedonic models to capture non-linear relationships between price impacts and distance from a transportation facility that may result from distance decay and/or the net effects of accessibility and disamenities (De Vany, 1976). For instance, Golub et al. (2012) showed that while proximity to LRT stations generally has a positive effect on property values that decays with distance from the station, extremely close proximity (i.e., within 200 ft.) is penalized by the market for single-family home values (Golub et al., 2012). This type of "donut" effect for residential property values is something we investigate further in the present paper.

More recently, thanks to the growing use of geospatial data, geographic information systems (GIS) and spatial analysis techniques, researchers have been able to calculate actual distance to highways from each parcel to use as an explanatory variable (Geoghegan et al., 1997; Hess and Almeida, 2007). Researchers have tested which of several distance metrics has the closest statistical relationship with property values (Thériault et al., 1999). Hess and Almeida (2007) found that a network distance model returned more significant parameter estimates, while a Euclidean distance model returned higher but more uncertain parameter estimates. Both of their models concluded that accessibility has a positive effect on residential property values in general, and the value of property located in the study area decreases by $2.31 per foot of Euclidian distance from a light rail station, compared with $0.99 per foot of network distance.

Since noise is a function of both distance and traffic volume, Li and Saphores (2012) used distance buffers interacting with different traffic count metrics. Their study of residential property values in Southern California not only confirmed that the negative impact on sales prices was larger for the 100-200m band than the 200-400m band, but also that sale prices were more sensitive to truck flow volume specifically than to overall traffic volume (Li and Saphores, 2012).

Accessibility effects on residential property values for highway exits and railway stations have also been studied. Many researchers, however, used actual distance or travel time measurements from the highway exits and railway stations to investigate the price effect by each measurement unit (Ryan, 2005; Armstrong and Rodriguez 2006; Hess and Almeida, 2007), which can restrict the relationships between price impacts and distance from highway exits or railway stations. In addition, studies mentioned above did not take into account traffic noise, air pollution, or crime rate as disamenity factors that might negatively influence property values near highway exits and/or railway stations.

While many researchers have modeled the price effects of a single type of transportation infrastructure on either proximity or disamenity, relatively few have considered the effects of multiple transportation modes such as rail and road simultaneously. Ryan (2005) found that accessibility to highways plays a more important role than accessibility to LRT for non-residential property values. Andersson et al. (2010) found that road noise impacts on property values are larger than railway noise impacts. These two studies partially support our theoretical framework in the next section, in that both accessibility and noise impacts are larger for road than for railway, though Ryan (2005) studied non-residential property and neither study used distance bands to test the non-linearity of the relationships.

A factor that has not received enough attention to date is whether the effects of proximity vary depending on whether distance is measured from the nodes (i.e., exits or stations) or the links of the network. Many studies have investigated one or the other, but few have tried to disentangle the price effects of nodes vs. links. Of the papers reviewed, only Golub et al. (2012) distinguished between distance from the nodes and the links for rail, while Kilpatrick et al. (2007) did so for highways. Anderssson et al. (2010) conducted perhaps the most comprehensive analysis: they used actual distance from the nodes for rail and highway but decibels for noise measure of the links for rail and highway.

Although not shown in Table 1, some studies have investigated whether the noise discount may be affected by highway configurations such as tunnels, noise barriers, over- or underpasses, and sound berms. A study in Montreal, Canada showed that construction of noise barriers generated a small negative effect in the short run (6% decrease in sale prices) but generated a relatively large negative effect in the long run (11% decrease) (Julien and Lanoie, 2008). Another study in South Korea showed that residential property values are negatively associated with highway overpasses (Kim et al., 2007).

The final paper reviewed here is excluded from Table 1 because it dealt with airports rather than rail or highway. Nevertheless, De Vany (1976) provides an important theoretical foundation for our work because it hypothesized an idealized relationship of price with distance that separates out a positive accessibility premium and a negative noise discount, each of which decays at a different rate with increasing distance from the airport. The two curves are added to form a hypothetical net effects, inverted U-shaped, curve. De Vany (1976) then developed an empirical model with multiple distance bands around Love Field airport in Dallas, Texas and plotted their coefficients against distance, which proved consistent with his proposed theoretical framework. Specifically, he found that the negative noise externalities were larger than the accessibility effect within one mile, while the net effect was positive for the 2-3 mile band.

In this study, we build on De Vany's (1976) theoretical and empirical approach to studying airports, and adapt it to modeling the net accessibility and disamenity effects of rail and highway. As Table 1 shows, our study will differ from previous work on highway and rail by combining the effects of links and nodes for both highways and LRT using multiple distance bands. Our approach also controls for whether the highways are above, at, or below grade, in addition to other more commonly used structural and neighborhood control variables as well as proximity to several categories of open space amenities.

Theoretical Model

In this section, we expand De Vany's theoretical net effects model for airports into a 2x2 schematic diagram for the effects of the nodes and links of rail and highway networks. In doing so, one must consider the difference between accessibility and disamenities such as noise and air pollution, the difference in how their effects decay with distance from nodes and links, and the difference between highway and rail. The following observations guided the development of the theoretical model.

First, accessibility accrues only to the nodes because travelers cannot access limited-access freeways and light-rail trains except at exits and stations respectively. Thus, if the effects of nodes and links are treated separately, the positive externalities of accessibility should be maximized at the nodes themselves and decay from there.

Second, disamenity, primarily noise, should emanate from both nodes and links and decay with increasing distance (Nelson, 1982). Other particular disamenities can depress housing values to varying extents, such as crime or traffic around rail stations (Bowes and Ihlanfeldt, 2001), or air pollution around highways (Bae et al., 2007).

Third, nodes should generate net benefits resulting from the sum of the positive and negative impacts at each distance from the exit or station. Links, on the other hand, logically should generate only negative disamenities.

Fourth, the negative disamenities diffusing from the nodes and links should theoretically decay more steeply with distance than the positive benefits of accessibility. We hypothesize this first because noise falls off rapidly and the health effects of air pollution are not well understood by the general public and the perception of it can be subjective and inconsistent (Nelson, 1982). Second, accessibility benefits extend farther geographically due to extended access provided by motor vehicles.

Fifth, rail stations should generate a steeper decay of accessibility and earlier leveling off to negligible levels because access modes include slower forms of transportation such as walking, bicycling, or bus. Highway exits should generate a more gradual decay and extended range because access is almost exclusively by private automobile.

Sixth, highway links and nodes should generate higher levels of disamenity because the traffic noise and pollution is constant, and the spatial extent of that disamenity should reach to farther distance bands. Rail links and nodes may generate lower levels of disamenity because the traffic and noise are intermittent, although perceptions of crime and/or loud voices and train horns from the station area could alter this hypothesis.

These explanations are combined in the 2x2 diagram in Fig. 1. Network links should experience only the disamenity, with a medium negative effect decaying towards zero more quickly for rail than for highway. For nodes, the net benefit from adding the steep negative disamenity curve to the higher and more gradual positive accessibility decay curve should theoretically yield a reverse-U shaped curve (i.e., a donut effect) that could be positive at all distances and skewed to the right, more so for highway than for rail. Next we introduce the hedonic regression method we used to test this hypothesis.

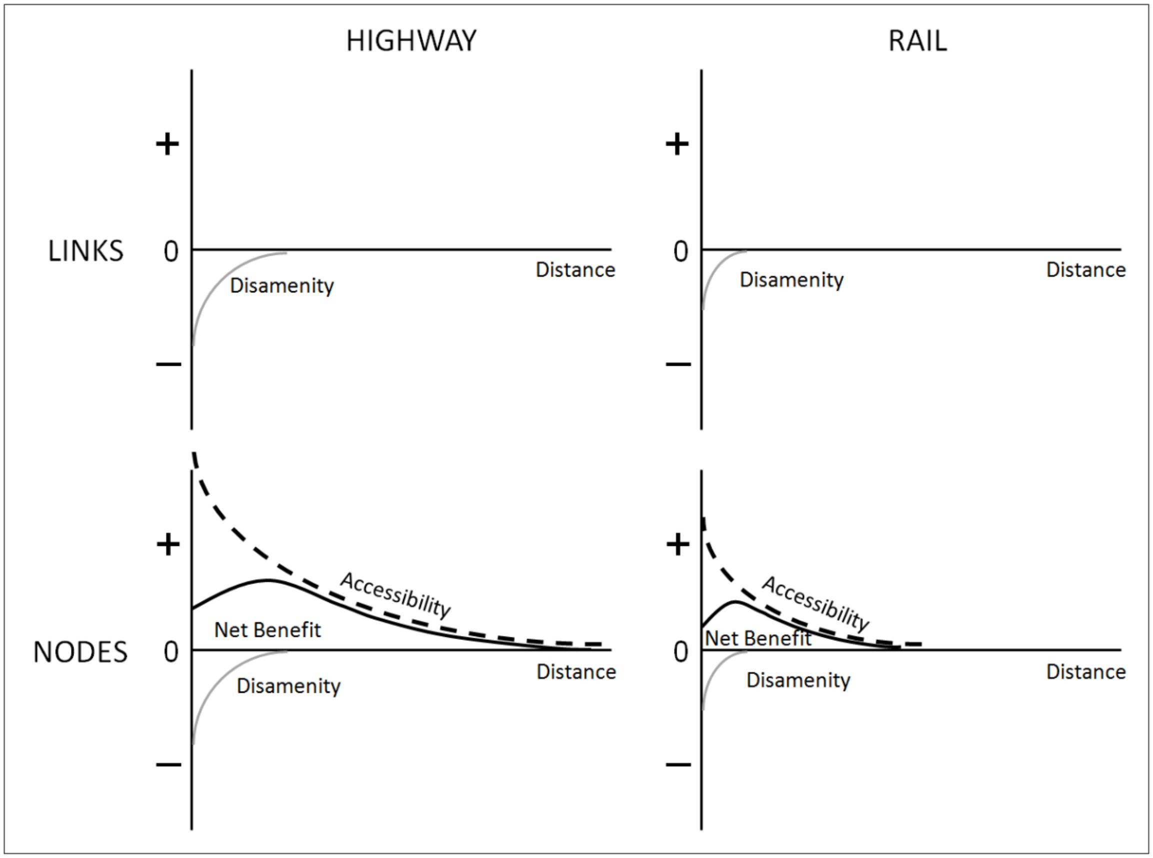

Fig. 1. Conceptual Framework for Net Benefit of Combined Impacts of Accessibility and Disamenity

Methods

The term "hedonic modeling" was coined by Court in 1939 and popularized by researchers such as Griliches (1961) and Rosen (1974)—see Goodman (1998). Hedonic modeling is designed to estimate the implicit value of differences in property characteristics, which includes amenities and disamenities. Thus, hedonic modeling is well suited to estimating the market value of externalized costs such as noise or pollution, or externalized benefits such as access to freeways or light rail. Empirical hedonic models using house sales prices as the dependent variable are widely accepted because housing is a commonly traded and commonly understood good that has a specific set of characteristics (Champ et al., 2003; Morancho, 2003). Housing prices can be determined by internal and external characteristics such as structural characteristics (e.g., lot size, interior square footage, number of rooms, number of stories, age, presence of a garage or pool), neighborhood characteristics (e.g., proximity to central business district, highways, and bodies of water), and environmental characteristics (e.g., urban open spaces and amount of greenness nearby).

Nonlinear relationships are common in hedonic pricing models. Housing prices are known to increase at a decreasing rate with lot size and interior square footage, for instance (Champ et al 2003). Neighborhood characteristics may also be non-linear because of distance decay (Andersson et al 2010). In this paper, we tested linear, semi-log, and translog (ln-ln) functional forms (Malpezzi, 2003). The translog model was selected based on comparing the linearity of scatterplots for the transformed variables and the results of adjusted R-squared, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). In addition, heteroskedasticity was evaluated using the Koenker-Bassett test (Kim et al., 2003; Drukker et al., 2013).

Spatial effects, in the form of spatial dependence, spatial heterogeneity, or both, are another common issue with hedonic real estate models. Spatial dependence or spatial autocorrelation implies spatial correlation among observations in cross-sectional data that are assumed to be independent, while spatial heterogeneity implies spatial correlation of the error terms (Anselin, 1988). To obtain unbiased, consistent, and efficient estimates, spatial dependences and heteroskedasticity should be tested and addressed with proper methods if either one or both spatial effects exist (Anselin, 1988; Kim et al., 2003). Moran's I statistics and Lagrange multiplier tests were used to test for presence of spatial effects (Champ et al., 2003).

A number of approaches have been developed to deal with spatial effects. One widely used approach is to add spatial fixed-effects dummy variables (e.g., zip code zones, school districts, or census block groups) in a hedonic regression model to represent neighborhood effects or housing submarkets (Kuminoff et al, 2010). A more recently developed alternative, which we take in this paper, is the spatial econometric approach (Anselin, 1988; Anselin and Florax, 1995; Anselin and Bera, 1998). The spatial econometric approach directly incorporates data about the contiguity of observations and does not require any preconceived assumptions about which fixed-effects zonation system best matches housing submarkets (Anselin and Arribas-Bel, 2013, p. 7).

Given that test results confirm the presence of both spatial dependences and heteroskedasticity in our dataset (see Results, below), we, thus, applied combined spatial lag and spatial error model using the generalized spatial two-stage least squares (GS2SLS) estimator with the heteroskedasticity option using GeoDaSpace software (Arraiz et al., 2010; Drukker et al., 2013). Queen contiguity was used to generate the spatial weights matrix. Equation (1) and (2) provide the general form of combined spatial lag and error model used in this paper:

$$P = \alpha + \rho \mathrm{W} P + \beta X + \varepsilon \tag{1}$$

$$\varepsilon = \lambda \mathrm{W} \varepsilon + \mu \tag{2}$$

where P is a vector of house sales prices; α is the constant term; ρ is the coefficient of the spatial autocorrelation; W is the standardized spatial weights m×m matrix with zero diagonal terms that assigns the potential spatial correlation; the product $\mathrm{W}P$ is the spatially lagged dependent variable; X is the $m \times n$ matrix of explanatory variables; β is the $n \times 1$ vector of the coefficients of the explanatory variables; ε is the $n \times 1$ vector of spatial autoregressive error term; λ is the coefficient of the spatially correlated error term; $W\varepsilon$ is the spatially lagged error terms; and μ is independent but heteroskedastically distributed error. Thus, if there are no spatial effects in the dependent variable, the coefficients of the spatially correlated lag and error (i.e., ρ and λ**)** become zero, and then both equations (1) and (2) reduce to a standard OLS model.

In this paper, we estimate and report results for the combined spatial lag and error model using the GS2SLS estimator with positive and significant ρ and λ. We also distinguish between direct and indirect effects in interpreting the coefficients, as recommended for models that use a spatial lag term (Kim et al., 2003; Fischer and Wang, 2011).

Study Area and Data

The study area is the City of Phoenix, Arizona, located in the Sonoran Desert in the southwestern US and incorporated as a city in 1881. It is the capital and largest city (517 square miles) in the State of Arizona. It is the sixth most populous city (1.4 million), situated in the 14^{th} largest Metropolitan Statistical Area (4.2 million) in the US. Because much of its growth occurred in the mid to late 20^{th} century, it features a moderately dense urban land-use structure well connected by arterials and freeways, which lowers the public transportation mode share compared to other US cities of a similar size. Transportation mode shares to work for the Phoenix MSA are 89.1% by motor vehicles (solo driver and carpool), 0.7% by bicycle, 2.3% by public transit (half of the rate for the US overall), 6.3% by non-motorized modes, and 1.6% by other (Kuby and Golub, 2009, p. 37). Phoenix is a prototypical example of cities largely built up in automobile era; if this research shows significant price effects of proximity to light rail, a stronger case can be made for investing in public transit in similar cities.

Data for this study were gathered from various sources (Fig. 2). The dependent variable is the sales price of single-family detached homes in 2009 obtained from the Maricopa County Assessor's Office (MCAO). The Assessor’s dataset included various attributes of each house that were incorporated as structural explanatory variables, such as lot size, interior living space, number of bathroom fixtures (bathtubs, toilets, etc.), presence of a swimming pool, and construction year. Other attributes in the Assessor’s dataset such as number of rooms, number of stories, size of patio, size of garage, and date of sale were not included in the model because of missing information and multicollinearity.

For the spatial regression models, we created a spatial weights matrix using Thiessen polygons based on the centroids of all parcels sold in 2009. We also added a monthly home price index variable to control for the volatile housing market of 2009. Despite the volatility, we focus on 2009 because it is the first full year of light rail operation, which opened in December 2008.

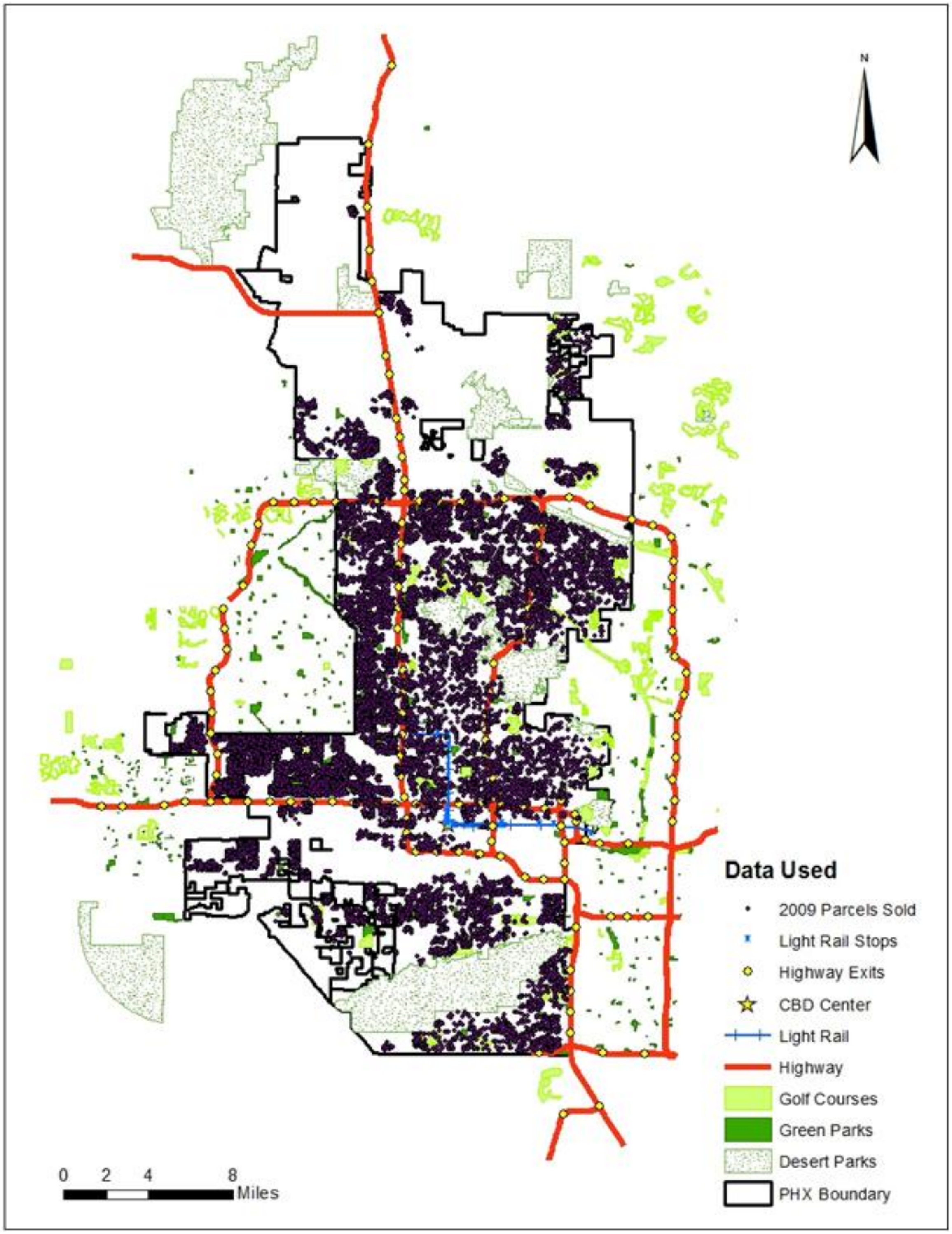

Fig. 2. Key Dataset Used for Extracting Explanatory Variables for Hedonic Regression

For neighborhood characteristics of a home, tract-level median household income and population density were collected from the 2010 U.S. Census. Neighborhood amenities such as green urban parks, desert parks, and golf courses were collected from available GIS data sources and used to create a proximity measure to each. We measured the distance between downtown Phoenix and each residential property from the intersection of Central Avenue and Washington Street, representing the central point of the Central Business District (CBD). Distance from highways was measured in three bands up to 350m (about .21 miles). Distances from highway exits to parcels were measured in 400m bands, up to 3200m (about 1.92 miles). Distances from the LRT stations to individual parcels were measured in 300m bands out to 3000m (about 1.8 miles), and distances from the LRT track were measured in 100m bands, out to 300m (.18 miles). All distances were measured in Euclidean terms.

For the environmental characteristics, we used land-cover classification data produced by the Central Arizona-Phoenix Long-Term Ecological Research (CAP-LTER) project based on 2005 and 2009 high-resolution QuickBird imageries (Fig. 3). The percentage of land area covered by trees or grass within a 200m buffer around each individual property sold were extracted to estimate neighborhood greenery. In addition, the highway configurations (below grade, elevated, or at grade) were manually analyzed using the Google Earth street view and assigned as dummy variables to each home according to the characteristic of the nearest highway link.

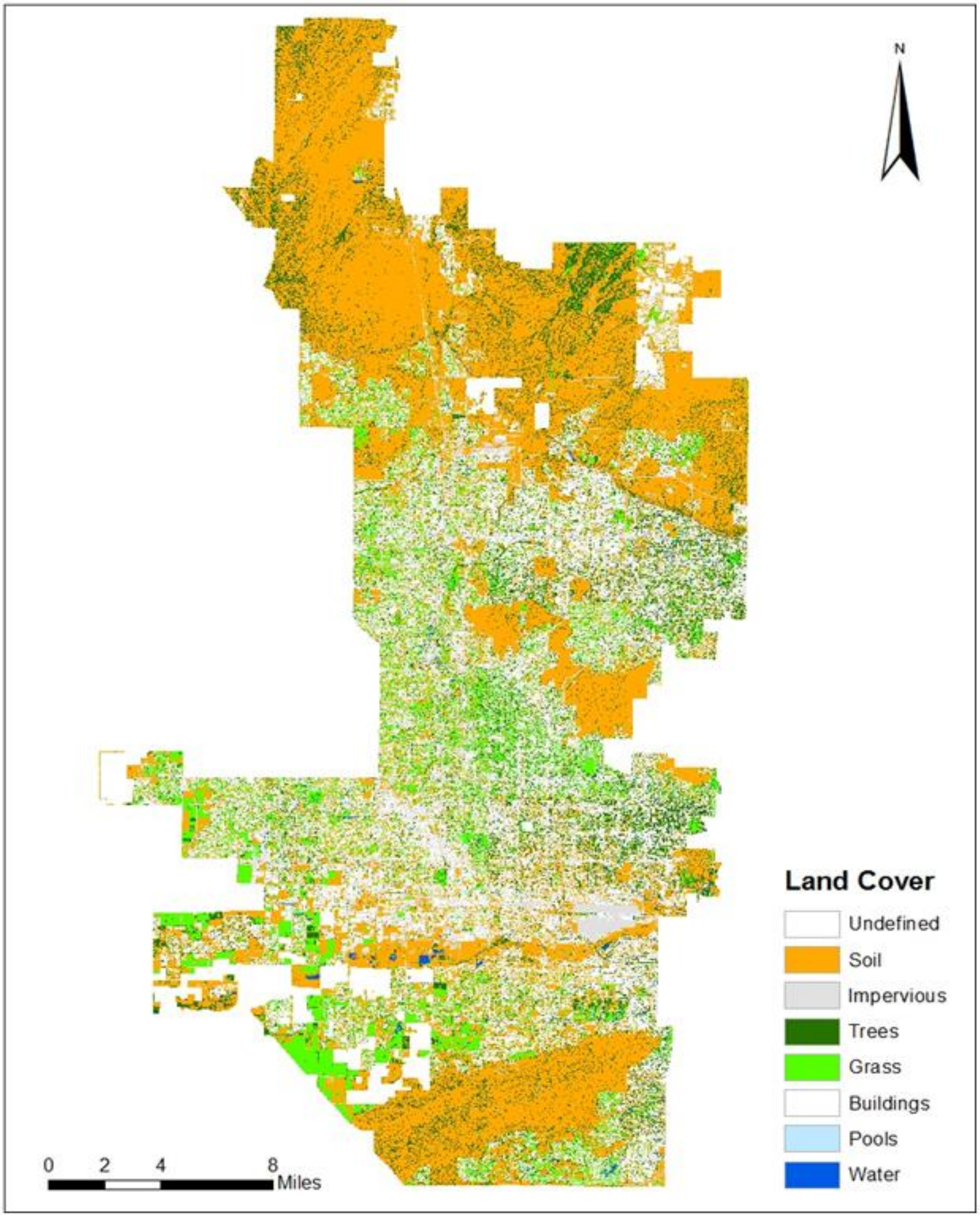

Fig. 3. Phoenix Land Cover Classification Map Using Quickbird Imageries (*Source:* Central Arizona-Phoenix Long-Term Ecological Research (CAP LTER), National Science Foundation Grant No. BCS-1026865).

There were 24,155 single-family home sales in 2009 in the County Assessor's database. Of these, 4,006 observations were dropped due to missing data, improper attribute values, and outliers such as lot sizes much larger than usual (e.g., lot size over 50,000 sq ft or sale price over $2 million), leaving 20,149 observations. APPENDIX A describes the summary statistics of the variables.

Results

Multiple regression analysis was initially conducted using SPSS Statistics 20 for Windows. A best fit was found using a translog form, likely due to the non-linear relationships between many of the independent variables and sales prices. The resulting model fit is quite strong with an adjusted R^2 of 0.766. As noted in the Methods section, however, presence of spatial dependence and spatial heterogeneity was confirmed by the robust Lagrange multiplier test value of 272.27 (p=.000) for lag, 1498.32 (p=.000) for error, and a Koenker-Bassett test value of 1,607.97 (p=.000) for heteroskedasticity. To take spatial effects into consideration, we applied a combined spatial lag and spatial error model using GeoDaSpace to estimate the coefficients of the explanatory variables.

Table 2
Estimation Results.

Variable	Coef	Std. Err.	z-stat	Sig.
(Constant)	1.4248	0.204	6.99	0.000
Structural Variables (S_i)				
Sqm (ln)	0.6276	0.0163	38.56	0.000
Area_sqm (ln)	0.1726	0.0099	17.44	0.000
Bathfix	0.0381	0.0023	16.41	0.000
Age	-0.0060	0.0003	-21.96	0.000
Pool	0.0815	0.0063	12.87	0.000
Neighborhood Variables (N_i)				
N_GPark (ln)	0.0012	0.0039	0.31	0.759
N_DPark (ln)	-0.1491	0.0039	-38.36	0.000
N_Golf (ln)	-0.0342	0.0033	-10.37	0.000
N_CBD (ln)	0.0794	0.0114	6.98	0.000
Hway_150m	-0.0271	0.0265	-1.02	0.306
Hway_250m	0.0013	0.0242	0.05	0.959
Hway_350m	-0.0204	0.0228	-0.90	0.369
LT_100m	-0.0246	0.1480	-0.17	0.868
LT_200m	-0.0155	0.1080	-0.14	0.886
LT_300m	-0.1202	0.0850	-1.41	0.157
Exit_400m	0.1455	0.0300	4.85	0.000
Exit_800m	0.0980	0.0132	7.45	0.000
Exit_1200m	0.1161	0.0106	10.95	0.000
Exit_1600m	0.1097	0.0114	9.66	0.000
Exit_2000m	0.1064	0.0121	8.79	0.000
Exit_2400m	0.0528	0.0118	4.48	0.000
Exit_2800m	0.0859	0.0122	7.05	0.000
Exit_3200m	0.0705	0.0125	5.64	0.000
S_300m	0.8835	0.1225	7.21	0.000
S_600m	0.6597	0.0693	9.52	0.000
S_900m	0.5477	0.0506	10.82	0.000
S_1200m	0.4296	0.0446	9.63	0.000
S_1500m	0.4089	0.0440	9.30	0.000
S_1800m	0.2398	0.0497	4.82	0.000
S_2100m	0.2435	0.0326	7.46	0.000
S_2400m	0.1885	0.0323	5.83	0.000
S_2700m	0.1647	0.0301	5.47	0.000
S_3000m	0.1010	0.0250	4.04	0.000
M_income (ln)	0.4102	0.0159	25.88	0.000
Pop_dens (ln)	-0.0275	0.0061	-4.53	0.000
Environmental Variables (G_i)				
P_trees	2.3515	0.0607	38.75	0.000
P_grass	0.4088	0.0432	9.47	0.000
Above	0.0010	0.0541	0.02	0.986
Below	0.1695	0.0332	5.11	0.000
H_Index	-0.0006	0.0003	-1.97	0.049
Rho (ρ)	0.1297	0.0089	14.65	0.000
Lambda (λ)	0.3915	0.0115	33.94	0.000
Pseudo R^2	0.782			
Spatial Pseudo R^2	0.769			

Table 2 shows the coefficients, significance levels, and Pseudo R^2 for the spatial lag and error model. While the Pseudo R^2 (.782) cannot be interpreted exactly as one would interpret an OLS R^2, a higher Pseudo R^2 still can be interpreted as better model fit than a lower one (Anselin, 1988). The spatial hedonic regression results partially validate our theoretical model of the accessibility and amenity impacts of highway and LRT *nodes* on the residential property values, but are not validated for the highway and LRT *links*.

Overall, most of the independent "control" variables are highly significant at the 0.001 level except distance to nearest green parks, and highways above grade. All of the coefficients for the structural variables have the expected signs. Measures of living area, lot size, number of bathroom fixtures, and presence of a pool are positively related to housing prices, while the age of the house is negatively related. For instance, marginal willingness to pay (MWTP) for one m^2 increment of living area is \$596, which includes indirect effect of \$77 captured through a spatial multiplier (i.e., $[\mathbf{I} - \rho\mathbf{W}]^{-1}$), while MWTP for a year increment of house age is -\$857, which also includes indirect effect of -\$111. The signs of the socioeconomic and neighborhood coefficients are as expected, with a few exceptions. The coefficient of median household income is positive as expected, and that for population density is negative as expected, and both are significant at the 0.001 level. The effect of proximity to green parks is not significant. This is somewhat corroborated by the literature, which has shown mixed results, both positive and negative, for the price effects of proximity to green parks (e.g., Tyrväinen, 1997; Shultz and King, 2001). Neighborhood characteristics such as proximity to nearest large desert preserve and golf courses have a positive effect on the property values, while distance from the CBD has a negative effect. The amount of green space with trees and grass in the neighborhood positively affect property values as expected. The land fraction covered with trees is more valuable than for grass, which makes sense considering the shade and cooling benefits of trees compared with grass. Thus, MWTP for one percent increment of tree coverage is $3,364, which includes indirect effects of $436 because of the spatially weighted average of housing prices in a neighborhood, while MWTP for one percent increment of grass coverage is $585 including indirect effects of $76.

Finally we turn to the transportation infrastructure variables of greatest interest in this study. Our hypotheses concerning the disamenity of proximity to highway and light rail links are not validated in this study. The results indicate that while five of the six coefficients on the dummy variables for the distance bands from highways (up to 350m) and light-rail (up to 300m) have negative signs as hypothesized, none are even close to being significant, even at the 0.1 level. Thus, disamenities such as noise, represented by distance from both highway and light rail track, appear to have no significant effect on residential property values.

Accessibility effects, on the other hand, are very significant at the 0.001 level for all distance bands. As shown in Figs. 4 and 5, both accessibility relationships exhibit a distance decay functional form consistent with Fig. 1—but without the hypothesized "donut" effect. Both curves begin at the highest benefit level for the closest distance around exits and stations and decay towards zero at longer distances. For highway exits, benefits are highest for residences within 400m (1/4 mile) from a highway exit, and decrease very gradually from there (Fig. 4). For LRT stations, the coefficients are again positive and highest for homes within 300m away (0.19 mile), and gradually decrease from there (Fig. 5). Contrary to our hypotheses, the “donut” effects based on nuisance effects at short distances around the highway exits and rail stations are not evident in either graph. Thus, MWTP for a median priced home in the 400m band of highway exit is $22,405, which includes indirect effects of $2,906 because of the spatially weighted average of housing prices in a neighborhood, while MWTP for one in the 300m band of LRT station is $203,055 including indirect effects of $26,336.

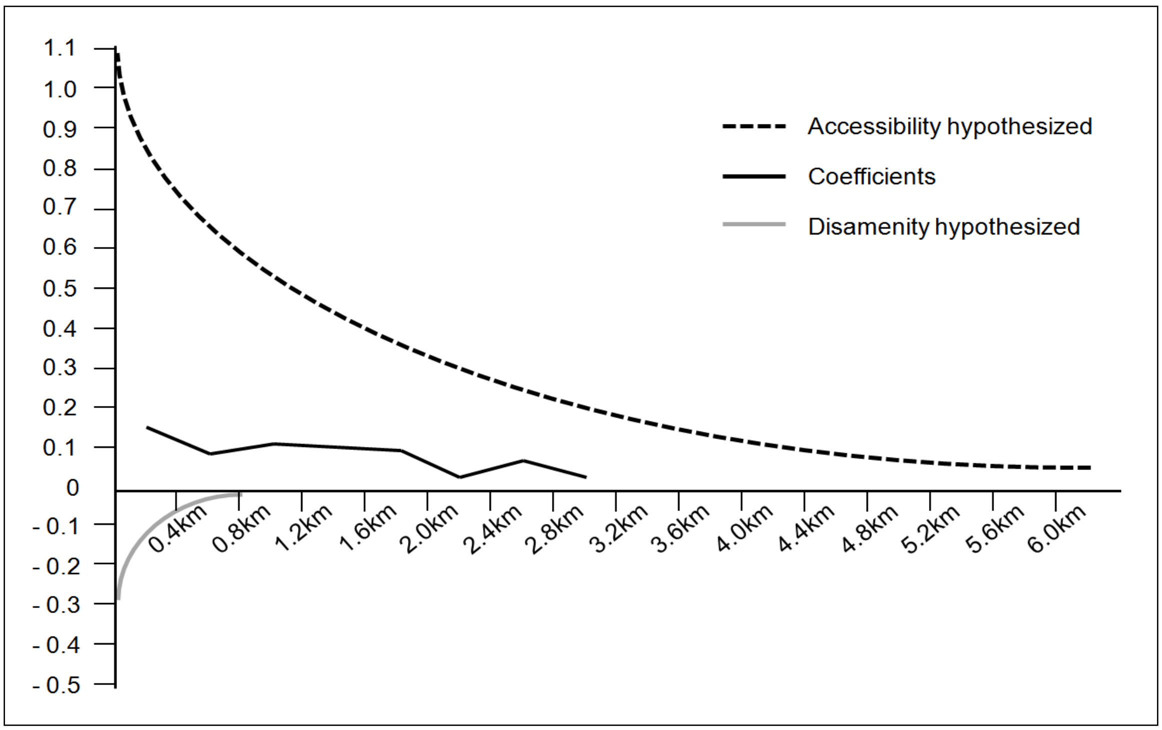

Fig. 4. Coefficients of Distance from the Highway Exit

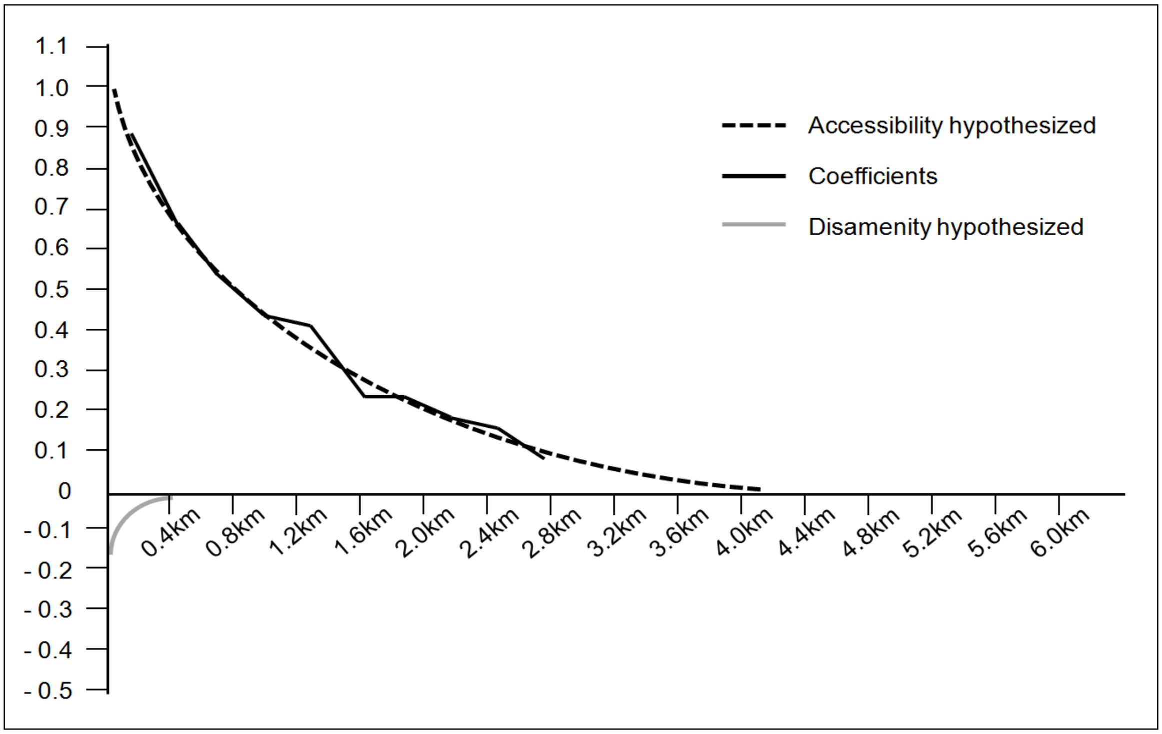

Fig. 5. Coefficients of Distance from the Light Rail Station

The results partially validate our hypotheses that higher-speed vehicles (cars) travel longer distance in a short period of time and thus dramatically extend the range of accessibility benefits. However, in addition to the greater extent of the highway accessibility effect, the absolute size of the coefficients for highway is lower than for rail across the impact range. We speculate that this may be due to Phoenix's extensive highway network that shares the impacts across the city, whereas only a small portion of the city shares the light rail benefit. On the other hand, it makes intuitive sense and validates our hypothesis that the benefit of LRT stations decline steeper than that of highway because residents access LRT stations via numerous modes, including slower ones such as walking, biking, or bus. However, it is surprising that the geographical range of impacts of LRT station reaches up to 3000m.

Although we do not have clear evidence why there are no disamenity impacts for both highway and light rail links, there are a couple of possible explanations. First, properties adjacent to highway links are protected by sound walls, which reduces noise disamenity, and possibly reduces some air-pollution as well. Second, the data used for measuring distance from highway links is a road centerline feature, which creates inaccurate distance bands because highway link has non-negligible width. Third, noise nuisance of light rail may not exceed noise generated by traffic on the same road because light rail tracks are built mostly in the middle of road way and light rail operates less frequently than cars do. Fourth, light rail is operated by electricity, so it does not emit polluted air.

The lack of evidence for a donut effect around nodes may be explained in similar ways. Noise and air-pollution may be reduced by sound barriers near highway exits and point feature class used for measuring distance bands for the exits does not create accurate distance variables. Moreover, noise nuisance and air pollution near light rail stations may be too small to capture for the same reasons with the light rail link.

Lastly, the regression result of the variable representing the highways situated below grade is statistically significant at the level of 0.001 with a positive coefficient as expected, presumably due to their reduced noise levels and visibility. The estimated coefficient of the elevated highways, however, is not significant.

Conclusions

The purpose of this study was to measure the net effects of the nodes and links of road and rail infrastructure on single-family home values using spatial hedonic regression techniques with distance bands. Previous studies have developed separate models of some subset of these relationships, such as between housing prices and highway noise (Gamble et al., 1974; Langley, 1976), noise of both road and rail (Andersson, 2010), rail accessibility (Cervero, 1996; Hess and Almeida, 2007; Golub et al., 2012), or accessibility of both highway and light rail (Ryan, 2005). To our knowledge, however, no hedonic pricing study of the effect of highway and LRT on house prices has attempted to disentangle the positive and negative distance-decay effects of proximity to the infrastructure of light rail and highway nodes and links simultaneously. We hypothesized that the accessibility benefits of light rail and highway accrue to the LRT stations and highway exits (i.e., the network nodes) specifically, while the disamenities of noise and pollution should emanate from the rail and highway links as well as the nodes. Using distance buffers, we have tested the significance of the distance from the nodes and links and plotted the coefficients as a function of the distance from the infrastructure to estimate the distance decay of net amenities and disamenities. Numerous other independent variables were included to control for structural characteristics of the house and of the neighborhoods, including several measures of green space and distance from different kinds of parks. In addition, a monthly home sales price index was added to control for the volatility of the housing market over the course of 2009 immediately following the opening of the Valley Metro LRT, and a spatial regression model was used to test and control for spatial effects.

The main results of the study show that distances from both kinds of transport nodes (LRT stations and highway exits) show a typical exponential decay curve consistent with the theorized model for benefit. Unexpectedly, however, they are not consistent with our hypothesis of a negative disamenity effect in the immediate vicinity of stations and exits. The greater range of highway accessibility benefits is also consistent with our hypothesis based on the faster speed of travel to and from highway exits using motor vehicles compared with the slower speed of some of the modes of transport used to access LRT stations. However, magnitude of accessibility benefit of LRT stations is much larger than that of highway exits, contrary to our hypothesis. The effects of proximity to the road and rail links were not significant. Below-grade highways had a relatively positive impact on nearby houses compared with highways at ground level or above.

Further research is required to investigate why proximity to the nodes and links—which theoretically should have a primarily negative disamenity from noise and air pollution—was not statistically significant for both highway and rail. One possible explanation is that local highway authorities have properly installed sound walls or sound berms along the highway adjoining residential areas and applied noise dampening pavements to reduce noise impact, and the relevant laws such as the US Noise Control Act work well in Phoenix, Arizona[1]. Another possible explanation is that the number of properties located very close to exits or rail stations is very small and this may bias the statistical relationship between distance bands one way or the other.

Results for the highway links might be improved with more accurate data. For instance, highways have non-negligible width, and some have more lanes than others. Using the centerlines of highways is not an exact measure of the distance from houses to the edge of the highway. Representing highways as polygons rather than lines might

[1] Almost all residential houses adjacent to the highway in Phoenix are protected by noise barriers or sound berms.

produce more accurate and significant results. We leave the further investigation of these and other explanations to future research.

Finally, this paper focused on single-family detached housing values. It would be useful to apply the multi-band, node-link approach developed here to multi-family housing and commercial real estate, as this would provide useful information to developers, planners, and policy-makers concerned with infill and transit-oriented development.

CHAPTER 3

IMPACTS OF HIGHWAYS AND LIGHT RAIL TRANSIT ON COMMERCIAL PROPERTY VALUES

Abstract

This study investigates the impacts of positive and negative externalities of highways and light rail on commercial property values in Phoenix, Arizona. We hypothesize that the positive externality (i.e., accessibility) of highway and light rail accrues at exits and stations, whereas nodes and links of highways and light rail emanate negative effects. Positive and negative effects decay with increasing distance and are captured by multiple distance bands. Hypotheses are tested using a spatial error regression model. Results show that accessibility benefits of transport nodes are positively and significantly associated with all commercial property values. The distance-band coefficients form a typical distance decay curve for both modes with no detectable donut effect immediately around the nodes. Unexpectedly, impacts of light rail stations extend farther than those of highway exits. As hypothesized, the links of highway and light rail are negatively associated with property values. When the sample is subdivided by type of commercial property, the magnitude and extent of impacts of distance are surprisingly consistent, with light rail stations having more positive impact than highway exits on all three classes of commercial property: industrial, office, and retail and service. Rail links have a significant negative impact on price for all three types of commercial property, but highways have a significant negative impact only on industrial and retail/service properties.

Keywords: highway, light rail, spatial error model, node, link, commercial property value

Introduction

Numerous studies have focused on transportation facilities as an important determinant of property values because they provide accessibility as well as nuisance effects that may alter property values (Vessali 1996; Bateman et al, 2001). While a considerable body of hedonic literature has investigated residential property values, fewer studies have addressed non-residential or commercial property values (Weinberger 2001; Ryan 2005). Of these, even fewer have considered the impacts of multiple modes of transportation, such as rail and highway, and fewer still have attempted to disentangle the separate effects of transportation nodes and links in their models so that they can capture the distance decay of positive and negative impacts. Seo et al. (2014) built a hedonic price model with this comprehensive set of factors (i.e., distance decay around the nodes and links of highways and light rail transit) for residential property values in Phoenix, Arizona. This study extends that work to an analysis of commercial property.

The purpose of this study is to use the theoretical framework of Seo et al. (2014) to estimate the net impacts of network nodes and links of rail and road facilities on commercial property values in Phoenix, AZ. This study may help locating commercial property to maximize accessibility and profit based on the distance from transport nodes. This study may also inform policy makers on designing tax-increment financing[2] mechanisms for funding new public transportation investments (Anderson 1990; Medda 2012). We utilize hedonic regression models to estimate the impacts at various distances of nodes and links of highways and light rail networks on commercial property values. We also subdivide commercial properties into office, industrial, and retail and service

[2] Tax increment financing (TIF) is a special funding tool used as a subsidy for infrastructure and community-improvement projects such as redevelopment in urban core and new road construction.

categories to test whether transportation facilities have dissimilar effects on the sale prices of different types of commercial property. Hence, the specific research questions are:

- How do commercial property markets (i.e., as a whole and by type) value the positive and negative effects of proximity to highway compared with light rail facilities?
- How do commercial property markets value amenities and disamenities of proximity to transport nodes compared with transport links?
- How do these positive and negative effects decay (or increase) with distance to transportation infrastructure?
- How do such effects vary by type of commercial property?
- We compare the results of our model with Seo et al.'s results for residential property values in the same city and time period.

Literature Review

As noted earlier, the literature on hedonic studies of transportation infrastructure impacts on residential property values is quite extensive. In contrast, a relatively smaller body of literature exists on the determinants of commercial property values, and only a handful of studies focused on the transportation-related factors (Weinberger 2001; Ryan 2005; Billings 2011; Golub et al., 2012). Many studies focused mainly on the impacts of access to the central business district (CBD), but some of these studies also included transportation-related factors as explanatory variables (Clapp 1980; Brennan et al., 1984; Sivitanidou 1995; Sivitanidou 1996; Dunse and Jones 1998). APPENDIX B summarizes selected hedonic studies of commercial property values with regard to the transportation-related factors they considered:

- dependent variables (type of commercial property)
- amenity (accessibility) and disamenity (noise, traffic, air pollution, crime) or both
- distance decay of these effects;
- mode(s) of transport studied;
- whether distance effects are measured from the nodes or links of the network.
- time frame (single- or multi-year)

Dependent variables used for the studies on commercial property vary based on availability (i.e., sales transaction data, actual transacted rents or effective rents, asking rents, and assessed property or land values). Although actual transacted sales prices are preferred (Ihlanfeldt and Martinez-Vazquez 1986) because they capture the real property market behaviors, commercial property sales prices or effective rents are hard to obtain because these data are often not open to public use (Mills 1992; Wheaton and Torto 1994; Landis and Loutzenheiser 1995; Bollinger et al., 1998).The majority of studies utilized asking rents as the dependent variable, which were usually provided by large commercial real-estate consulting or brokerage firms such as CoreLogic, Coldwell Banker, and TRI Commercial Real Estate Services for academic research (Mills 1992; Landis and Loutzenheiser 1995; Bollinger et al., 1998; Ryan 2005). The use of asking rents is supported by Glascock et al. (1990), who found an extremely close relationship between effective rents and asking rents. However, both actual transacted rents and asking rents from the databases of commercial real estate service firms may yield biased samples. For instance, some databases of commercial real estate firms are limited to a specific size of office spaces (Landis and Loutzenheiser 1995). Moreover, sometimes the number of cases was too small for estimating a model (Dunes and Jones 1998; Nelson 1982). Brennan et al. (1984) used actual transacted office rents as a dependent variable with only 29 cases. As an alternative, Sivitanidou (1996) and Cervero and Duncan (2002) used assessed property values as the dependent variable.

The use of assessed or estimated property values has an advantage over the use of actual sales prices, effective rents, and asking rents. The assessed property values are not a sample but rather the whole population, meaning that sampling error is greatly reduced (Champ et al., 2003). Sivitanidou (1996) found a correlation between sales prices and assessed values on office-commercial firms of 0.98 for office-commercial firms, which led her to use assessed values in order to cope with spatial collinearity issues with a larger number of cases. Transit-related hedonic research by Cervero and Duncan (2002) used estimated land values, which were apportioned from total taxable property values including improvements by the county assessor's office. They argued that there is no evidence that estimated land values are biased in a certain direction. However, despite these advantages, the use of assessed property value as the dependent variable is still problematic, because the way some assessor offices estimate property values can be similar to hedonic regression (Arizona Department of Revenue 2009), making circular reasoning a concern.

In addition, most studies have considered only one type of commercial property, such as office property (Landis and Loutzenheiser 1995; Dunse and Jones 1998), industrial property (Sivitanidou and Sivitanides 1995), or retail property (Damm et al, 1980). In contrast, Ryan (2005) studied two types of commercial properties (i.e., office and industrial properties), while others have analyzed commercial property as a whole (Cervero and Duncan 2002; Golub et al, 2012). Effects may differ across commercial property categories: in Ryan's 2005 study, while highway accessibility had a positive influence on office property values, neither highway nor light rail transit had a significant relationship with industrial property values. Thus, one should consider estimating impacts of both commercial property as a whole and each type of commercial property.

Most of the previous studies of the relationship between transportation infrastructure and commercial property value focused on testing hypotheses related to the positive effects of accessibility (Damm et al., 1980; Landis and Loutzenheiser 1995; Sivitanidou 1995; Bollinger et al., 1998; Ryan 2005). Only one study took nuisance effects into consideration for commercial property (Golub et al., 2012). If a study does not consider nuisance effects but considers only positive effects with respect to the transportation infrastructure located in the study area, it may cause omitted variable bias (Nelson 1982; Champ et al., 2003; Debrezion et al., 2007). While some may argue that nuisance effects have no influence on the commercial property values, factors including nuisance effects that may have impact on property values should be tested (Damm et al. 1980).

Accessibility of commercial properties to transportation nodes and/or links has been measured in several different ways in previous studies:

- Euclidean distance (Sivitanidou 1996; Ryan 2005; Golub et al., 2012)
- a single Euclidean distance band as the impact zone (Bollinger et al. 1998; Cervero and Duncan 2002)

- multi-band distance (Landis and Loutzenheiser 1995; Weinberger 2001)
- mixed measurement methods such as Euclidean distance for highway exits and a single-band distance for the rail stations (Damm et al. 1980), a multi-band distance for light rail transit stations and a single-band distance for highway exits (Sivitanidou 1995)
- number of passing highways within the study area (Weinberger 2001)

How a researcher operationalizes distance as a proxy for transportation accessibility in a regression model is a critical decision. Ideally, the method should capture the impacts of accessibility on property values in terms of geographical extent with non-linearity. The method should also capture the net effects of accessibility and disamenities (De Vany 1976). The multi-band approach is a way of capturing a non-linear relationship between price impacts and distance from a transportation network. In a study of residential values, Seo et al. (2014) captured the benefits of nodes of highways and light rail transit using 400-meter and 300-meter multiple distance bands up to 3200 meters and 3000 meters, respectively. The benefit peaks at 400-meter band from the highway exits and 300-meter band from the light rail stations, which are the closest distance bands for both nodes. In an another study of residential values, Salon et al. (2014) also captured the benefits of nodes of the bus rapid transit (BRT) and the Metro rail using multiple distance bands in Guangzhou, China. They found that no disamenity effect for the Metro, but substantial disamenity value for the BRT. In contrast, Cervero and Duncan (2002) showed that commercial land values within 1/2 mile of highway interchange are unexpectedly penalized by being close to the highway access points. These results confirm the usefulness of a multiple bands approach for determining the potential non-linear decay of the net effects of transportation infrastructure on commercial property values.

As shown in APPENDIX B, only Golub et al.(2012) included proximity to network links as a disamenity variable in a hedonic model for commercial properties. To the best of our knowledge, there have been no studies that analyzed both nodes and links of both highways and rail transit for all types of commercial property values (i.e., office, industrial, retail and service properties), though some studies dealt simultaneously with nodes of both modes (Bollinger et al. 1998; Weinberger 2001; Billings 2001; Ryan 2005).

Property values, including for commercial property, are known to be influenced by the value of surrounding properties. This kind of an external neighborhood effect is called spatial dependence or autocorrelation and the spatial autocorrelation can be present in both the dependent variable and the error term of a regression model. To incorporate external neighborhood effects, researchers are more frequently testing and adjusting for spatial dependence using alternative hedonic models (e.g., spatial lag and/or error model) for residential hedonic models (Partridge et al., 2012). Spatial approaches, however, do not seem to be common yet in commercial hedonic models. Bollinger et al. (1998) is the only commercial study we found that tested for spatial dependence, but they found no evidence of spatial effects using the Cliff-Ord test. Nevertheless, testing for spatial dependence is important, because hedonic modeling with spatial dependence in the dependent variable produces inconsistent estimates, while spatial dependence in the error term causes inefficient parameter estimates (LeSage and Pace 2009; Anselin 1988).

Based on this review of the hedonic literature, we reach a number of conclusions about how to analyze the amenity and disamenity effects of transportation infrastructure on commercial property values. First, the ideal dependent variable is the actual transacted sale prices of commercial property. Second, in addition to analyzing commercial property as a whole, it is valuable to subdivide the sample into types of commercial property if the sample size in each category is large enough. Third, the study method should allow for the possibility of both accessibility and nuisance effects of transportation infrastructure. Fourth, the multiple bands approach is well suited to determine the geographical extent of impacts of transportation investments and network nodes. Fifth, both highways and rail transit should be included simultaneously if both modes exist in the study area. Sixth, multi-year (from 2009 to 2014) data can be used to secure enough observations. Seventh, the presence of spatial dependence should be tested explicitly.

Theoretical Framework

As a theoretical framework, this study incorporates the seven factors identified above by adopting the net effects model of Seo et al. (2014) for highways and light rail transit, which was expanded from De Vany's (1976) theoretical net effects model for airports. The theoretical model shown in Fig. 6 is based on the following underlying hypotheses (Seo et al. 2014). First, accessibility should accrue only to the nodes of a rail or freeway network and decay from there, because travelers can only access the network at the stations and highway entrances. Second, negative disamenities such as noise, crime, pollution, or traffic should have a more limited spatial impact that decays more steeply with distance from the network nodes and links than the positive benefits of accessibility. Third, network nodes should therefore exhibit net effects resulting from the sum of the positive and negative impacts. Lastly, highway exits should generate a more gradual decay and extended range than rail stations do because of the different travel speeds of their dominant modes of access (motorized vs. non-motorized).

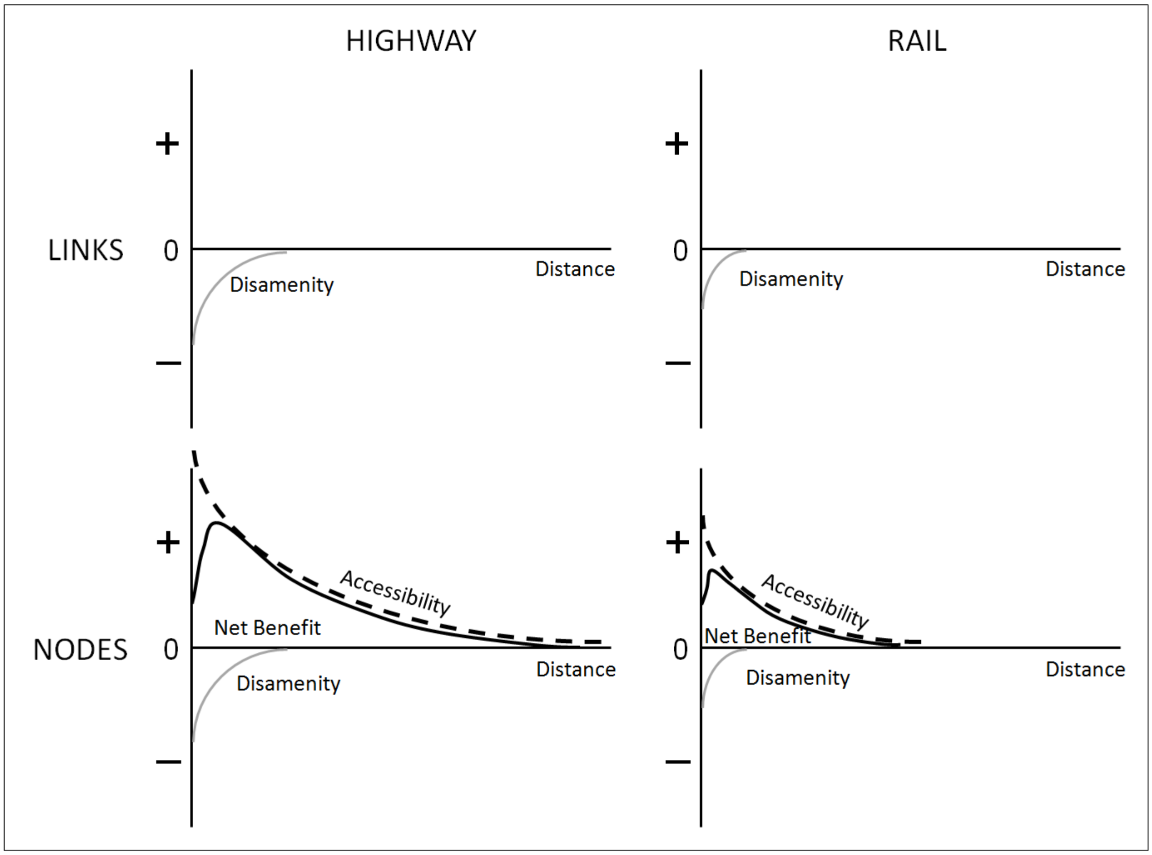

Fig. 6.Conceptual Framework for Net Benefit of Combined Impacts of Accessibility and Disamenities (Source: Seo et al., 2014 - Modified for Commercial Property)

In Seo et al. (2014), this theory was tested on residential property values in Phoenix, Arizona. For highway exits, benefits peaked at the closest distance (400m) from a highway exit, and decreased steadily from there, but the magnitude of impacts was small in general. For LRT stations, the coefficients were again positive for homes close to a station, peaked within 300m, and gradually decreased from there. Unexpectedly, the hypothesized “donut” effects around nodes were not evident in results for either mode for residential property. The proximity to nodes of highways and light rail were highly significant at the level of 0.001, while the proximity to links of highways and light rail were not significant even at the level of 0.1. This companion paper tests this model on commercial property.

Theoretically, we might expect some differences between the effects on residential and commercial property. First, nuisance effects on commercial property are hypothesized to be less negative compared with residential property because activities on commercial property may themselves cause a considerable amount of noise nuisance (e.g., mechanical noise in industrial property, customer-caused traffic and noise in retail and service properties) and commercial activities take place in the daytime when nuisances are more acceptable. In addition, crowds near transportation nodes that may generate nuisances can be favorable to commercial property but not to residential property markets. Thus, peaks of the net benefit curves in the Fig. 6 should be skewed more to the left or there may be no donut effects.

Commercial property can be subdivided into office, industrial, and retail/service categories, and the impacts of transportation infrastructure are likely to vary by type (Ryan 1995). According to industrial location theory, transportation cost of inputs and outputs is one of the most important factors with labor cost and agglomeration economies (Weber 1929). Thus, for industrial property, it may be more important to locate for minimizing transportation cost of shipping products and materials rather than to be near light rail stations[3]. On the other hand, office property generally does not ship much in the way of materials and/or products, but employees benefit from light-rail access for daily

[3] However, if a freight rail network exists in the study area, industrial property may be found near freight rail stations to reduce transport cost of inputs and outputs based on the traits of industry.

commuting and customers benefit from occasional access as well. Hence, we hypothesize that office property will put a higher premium on locating near light-rail stations and highway exits to minimize transportation costs of both customers and employees. Lastly, retail and service properties need easy access for their employees and customers to minimize labor cost and maximize profits. Thus, retail and service properties may be willing to pay more to be located near highway exits and light rail transit stations. In addition, retail and service properties may prefer to locate in or near a shopping mall for multi-purpose shopping agglomeration economies.

Methods

This paper extends the methodology developed by Seo et al. (2014) for residential property to commercial property. This methodology utilizes hedonic regression analysis to capture the relationships between proximity of transportation infrastructure and commercial property values while controlling for other determinants of value. To select a suitable functional form, scatter plots for the variables and log-transformed variables were analyzed for linearity, and the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were examined to compare relative quality of models. To avoid multicollinearity, the variance inflation factor (VIF) was also examined. For the goodness of fit, adjusted R^2 values were compared. Consequently, we selected the double-log functional form, which has an advantage in estimating price elasticities. It is expressed as:

$$\ln P_i = \alpha + \beta_1 \ln S_i + \beta_2 \ln N_i + \beta_3 \ln L_i + \beta_4 D_i + \varepsilon_i \qquad (1)$$

where P_i is the price of commercial property i; α is a constant; S_i are structural characteristics for property i;N_i are neighborhood characteristics for property i; L_i are locational characteristics for property i; and D_i are distance band dummies for property i; and β_1, β_2, β_3, β_4 represent the coefficients of S_i, N_i, L_i, and D_i respectively; and ε_i is random error for property i. The dependent variable is the sale price of commercial property adjusted by the monthly home price index (HPI; S&P Dow Jones Indices) to enable use of a multi-year dataset from 2009 to 2014.

Spatial effects were tested with the Lagrange Multiplier (LM) statistic using spatial weight matrices (Anselin and Rey 2014). To identify and select a suitable spatial regression model, we tested two different spatial weighting schemes such as contiguity (i.e., rook and queen contiguity using Thiessen polygons) and distance-based approaches (i.e., k-nearest neighbor or the Euclidean distance using property points data). These were compared using pseudo R^2 and Lagrange Multiplier test results and the model with the spatial weight matrix using the Euclidean distance approach was selected. The LM error test value of 15.117 (p = .000) confirmed the presence of spatial dependence in the error term, while the LM lag test value of 0.328 (p = .57) rejected the presence of spatial dependence in dependent variable. The Koenker-Bassett test value of 52.815 (p = .000) confirmed the heteroscedasticity in the dataset. Thus the spatial error model with heteroscedasticity option was selected for this study. Equation (2) and (3) provide the general forms of spatial error model:

$$P = \alpha + \beta X + \varepsilon \tag{2}$$

$$\varepsilon = \lambda W\varepsilon + \mu \tag{3}$$

where P is a vector of property sales prices; α is the constant term; β is the n×1 vector of the coefficients of the explanatory variables; ε is the n×1 vector of spatially autoregressive errors; λ is the coefficient on the spatially lagged error; $W\varepsilon$ is the spatially lagged portion of the error; and μ is an independent but heteroscedastically distributed error. Regression analyses were carried out separately for commercial property as a whole, office property, industrial property, and retail and service properties because impacts of the proximity of highways and LRT may differ by type of commercial market.

Study Area and Data

Study Area

The City of Phoenix, Arizona was selected as the study area because one of the study purposes is to compare the results for commercial property to Seo et al. (2014)'s residential property model. The City of Phoenix is the center of commercial property markets in the Greater Phoenix Area, where most of the high-rise office buildings are located (Fig. 7). Phoenix is also the most active industrial property market in the Greater Phoenix Area (Colliers International 2015). As of 2014 there were 47,882 commercial property parcels within the city limits, excluding some properties categorized as commercial but used for residential purposes (e.g., apartment, condos, and multifamily homes).

Phoenix is an automobile-centered city that is well connected by highways and grid-style arterials. Though there are multiple strong commercial centers across the city, downtown Phoenix is the original core of the city and some cultural, commercial, and governmental activities are still concentrated there. Light rail transit (LRT) opened in 2008 and runs east and north of the central business district (CBD) through job-rich corridors. Freeways encircle the CBD and extend east, west, and north from downtown. Phoenix Sky Harbor Airport is one of the most centrally located major airports in the

United States, just a few miles east of the CBD and connected to the light rail by an elevated, automated rubber-tired people mover. Thus, many commercial properties are located along these arterials, highways, and LRT networks, but relatively more commercial properties are located near the CBD and airport. In terms of noise disamenity, commercial properties along the highways are not protected by sound walls, while all the residential properties are protected by sound walls or earth berms.

Data

Commercial property sales data were obtained from the Maricopa County Assessor’s Office for use as the dependent variable for this study. This dataset contains sale prices and dates for commercial properties that were sold between 2009 and 2014, and also includes structural characteristics such as parcel size, total interior area, a number of stories, building condition, and construction year. Initially, 8,159 commercial properties were extracted from the Assessor’s 2015 data. We first removed from the dataset 3,280 properties used for residential purposes. We also removed some commercial properties that sold for less than $50,000, which we considered outliers. We also removed properties with insufficient information. Lastly, we found many cases of duplicated prices for groups of neighboring properties were sold as a bundle with a single combined sale price. Rather than delete them from the study, we assigned a proportional sale price to each parcel prorated by limited property value (LPV) for each member parcel provided by Assessor's office.

The remaining 3,642 observations were further divided into 1,214 office properties, 360 industrial properties, and 2,068 retail and service properties. For the dependent variable, inflation-adjusted sale prices were calculated by using the home price index (HPI) for the city of Phoenix (S&P Dow Jones Indices). The 2010 tract-level median household income and population density were obtained from the U.S. Census Bureau to represent neighborhood characteristics. Locational characteristics such as Euclidean distance to downtown Phoenix, Sky Harbor Airport, shopping malls, and major arterials were measured using ArcGIS 10.2.2 software and readily available GIS datasets (see Table 3 for summary of variables).

To develop the best model for testing the transportation amenity/disamenity hypotheses, many different distance measurements in terms of distance bands and distance extended ranges were tested (Table 4 and Fig.8 for multiple distance band approach). Euclidean rings were used to measure all distances. Distances from highway links were measured in three bands, out to 350m as the noise disamenity zone (Nelson 1982).[4] The distance from a highway exit to each commercial property was measured in sixteen 300m bands, out to 4800m (about 3 miles). The distance from LRT stations to individual commercial properties was measured in five 300m bands, out to 1500m (about 0.94 miles), and distances from the LRT track were measured in 100m bands, out to 300m (0.18 miles).

[4] In Nelson (1982)'s review paper, 300m or 1000feet is considered as a noise zone. However, we used 350m as the impact zone because highway centerline was used to measure distance. Thus three multiple bands are 0-150m, 150-250m, and 250-350m.

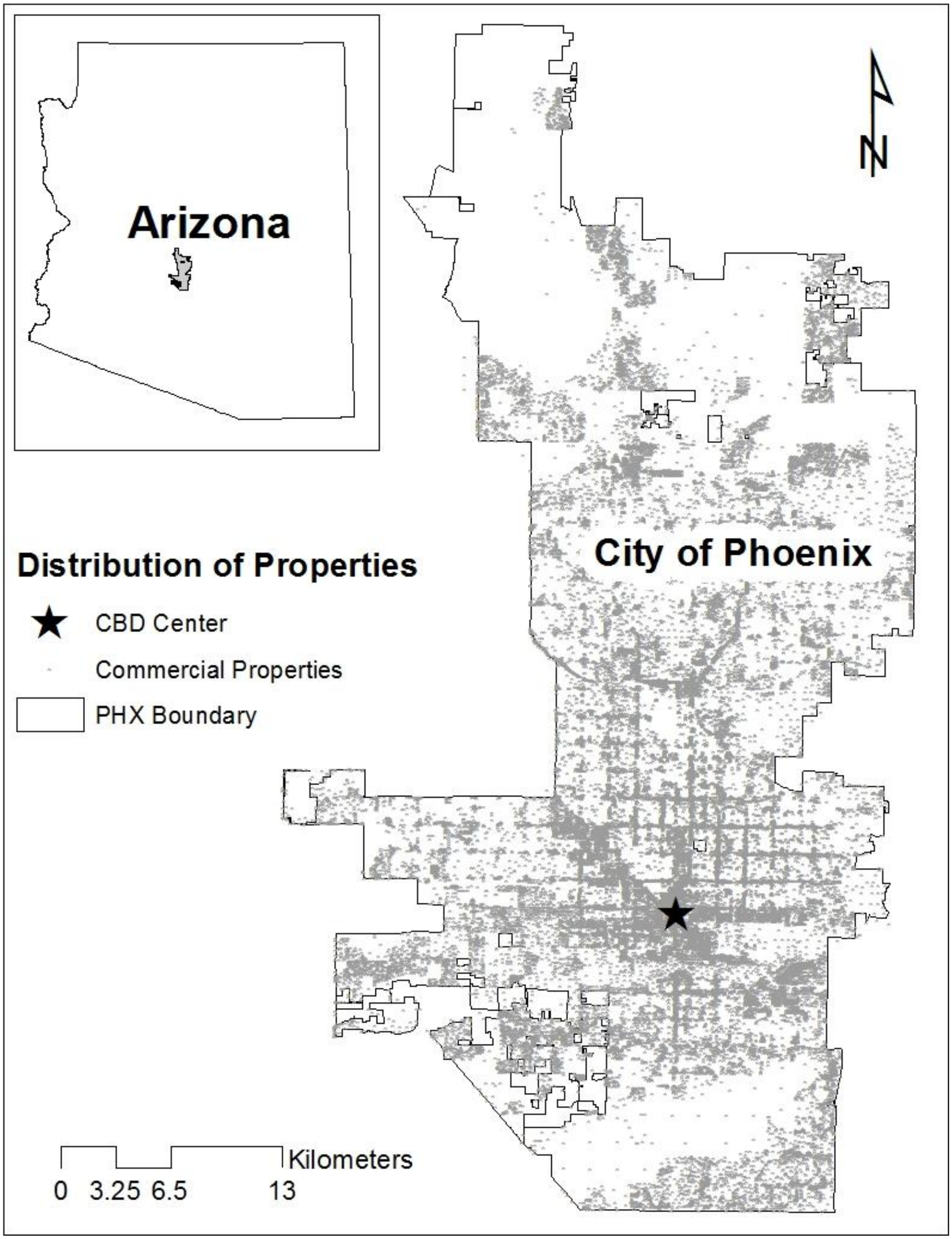

Fig. 7. Study Area and Distribution of All Commercial Properties.

Table 3
Summary of Main Variables (Observations = 3,642).

Variable	Description	Mean	Std. Dev.	Min	Max
Dependent variable					
Adj_Price	Sale price ($) adjusted by HPI	2,615,819	8342126	142	151,000,000
Structural variables					
Lot	Parcel size (sqft)	75,698	255913	51	6,973,608
T_Interior	Total interior area (sqft)	32,782	80942	2	1,267,498
Stories	Number of stories	1	1	1	22
Age	Age of property (years)	27	20	0	123
Neighborhood variables					
Median_HH	Median household income ($)	45,288	21585	9,668	151,603
Pop_Dens	Population density (per km²)	1,592	1097	74	9,052
Locational variables					
Dist_CBD	Nearest distance from city center (m)	13,555	9724	200	48,875
Dist_Air	Nearest distance from airport (m)	12,301	6496	952	36,314
Dist_Mall	Nearest distance from shopping mall (m)	2,406	1494	6	8,436
Dist_Arterial	Nearest distance from arterial road (m)	178	173	19	1,327
Dist_Exit	Nearest distance from freeway exit (m)	1,746	1,612	73	13,938
Dist_Station	Nearest distance from light rail station (m)	9,101	7,901	49	40,688

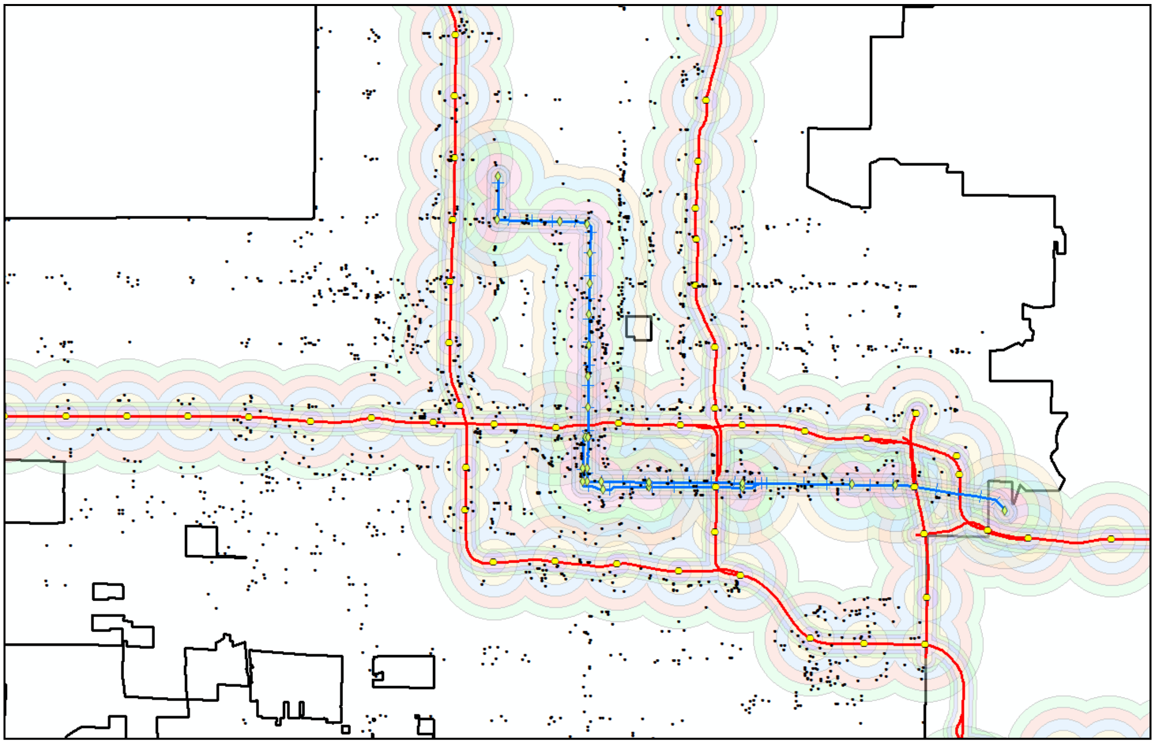

Fig. 8. Map of Multiple Distance Band Approach. Black Dots Represent Sold Commercial Properties.

Table 4
Percentage of Observations in Distance Dummy Variables.

Dummy variable	Description	%
Exit_300m	Less than 300m from highway exit	5
Exit_600m	300-600m from highway exit	17
Exit_900m	600-900m from highway exit	17
S_300m	Less than 300m from light rail station	1.2
S_600m	300-600m from light rail station	1.4
S_900m	600-900m from light rail station	5
S_1200m	900-1200m from light rail station	17
S_1500m	1200-1500m from light rail station	17
S_1800m	1500-1800m from light rail station	2.4
S_2100m	1800-2100m from light rail station	4.4
Hwy_150m	Less than 150m from highway link	3.2
Hwy_250m	150-250m from highway link	3.1
Hwy_350m	250-350m from highway link	1.5
LT_100m	Less than 100m from light rail track	2.3
LT_200m	100-200m from light rail track	2.4
LT_300m	200-300m from light rail track	5.9

Results

All Commercial Property

Table 5 shows the coefficients, significance levels, Pseudo R^2, and Lambda (λ) for the spatial error models for all commercial properties and for three commercial property submarkets (see APPENDIX C to F for details)[5]. The Pseudo R^2 (.792) of spatial error model and the R^2 (.791) of standard OLS model are similar and exceed the range of published results (i.e., R^2 of 0.33 – 0.73) of other hedonic studies of commercial property (Clapp 1980; Ryan 1995; Dunse and Jones 1998; Golub et al., 2012). Overall, most of the control variables are highly significant at the 0.001 level and the signs are as expected except for population density.

[5] Hedonic models were estimated with and without the 2009 data because of the sharp fluctuations of the real estate market caused by financial crisis. Results, however, did not differ substantially, and therefore the final results included all years of data.

Table 5
Estimation Results of Commercial Markets.

	All commercial (N=3,642)	Industrial (N=360)	Office (N=1,214)	Retail & Service (N=2,068)
Variable	Coef	Coef	Coef	Coef
(Constant)	6.313	5.191	7.48	6.258
Structural Variables (S_i)				
Lot (ln)	0.646***	0.530***	0.570***	0.649***
T_Interior (ln)	0.254***	0.485***	0.321***	0.234***
Stories	0.089***	-2.143***	0.060***	0.187***
Age	-0.014***	-0.012***	-0.013***	-0.012***
Neighborhood Variables (L_i)				
Median_HH (ln)	0.227***	0.149	0.171***	0.214***
Pop_Dens (ln)	-0.011	0.031	0.025	-0.012
LocationalVariables (N_i)				
Dist_CBD (ln)	-0.073**	0.085	-0.068	-0.105**
Dist_Air (ln)	-0.135***	-0.193***	-0.225***	-0.078*
Dist_Mall (ln)	-0.178***	-0.009	-0.215***	-0.136***
Dist_Arterial (ln)	-0.092***	0.006	-0.018	-0.163***
Exit_300m	0.448***	0.273**	0.485***	0.141
Exit_600m	0.129***	0.296***	0.103	0.083
Exit_900m	-0.018	0.083	-0.006	-0.014
S_300m	1.138***	n/a	0.761***	1.081***
S_600m	0.614***	1.701***	0.543***	0.411***
S_900m	0.382***	0.515**	0.291***	0.339***
S_1200m	0.288***	0.271	0.437***	0.147
S_1500m	0.225**	n/a	0.197	n/a
S_1800m	0.161*	n/a	n/a	n/a
S_2100m	0.060	n/a	n/a	n/a
Hwy_150m	-0.372***	-0.499***	-0.139	-0.353***
Hwy_250m	-0.411***	-0.626***	0.070	-0.332***
Hwy_350m	-0.159***	-0.321***	0.043	-0.226***
LT_100m	-0.474***	-0.112	-0.483***	-0.425*
LT_200m	-0.610***	-1.252***	-0.137	-0.611***
LT_300m	-0.611***	-1.928***	-0.438***	-0.444**
Lambda (λ)	0.1***	0.211***	0.22***	0.547
Pseudo R^2	0.792	0.871	0.83	0.782

*** Significant at 0.01 level; ** Significant at 0.025 level; * Significant at 0.05 level

Not surprisingly, all structural variables are significant at the 0.001 level. For the neighborhood variables, median household income is highly significant at the 0.001 level, while population density is not statistically significant. For the locational variables, proximities to CBD, airport, shopping malls, and arterial streets are positively associated with the price and all are significant at the 0.01 level.

Proximities to highway exits and LRT stations, which are the variables of greatest interest, are highly significant mostly at the 0.001 level and positively associated with the price except in the 900m band away from highway exits and in the 2,100m band away from a LRT station. In addition, distance bands from both highway and LRT links are all significant and negatively associated with the commercial property values as hypothesized. Thus, although the price impact of light rail station itself is positive, the sales price of commercial properties located distance bands of a light rail station can vary based on the sections intersected with distance bands of light rail link because negative coefficients of distance bands of light rail link should be summed up (see Fig 9 for details). For instance, the sales price of properties located in a section that is intersected with 300m band of light rail station and 100m band of light rail link increased around 185%, while the sales price of properties located in a section that is intersected with 600m band of light rail station and 100m band of light rail link increased around 51%. However, contrary to our hypothesis, the geographical range of the impact of highway exits is less extended than that of light rail station. Surprisingly, the accessibility benefits of being close to a light rail station are much larger than those of being close to a highway exit.

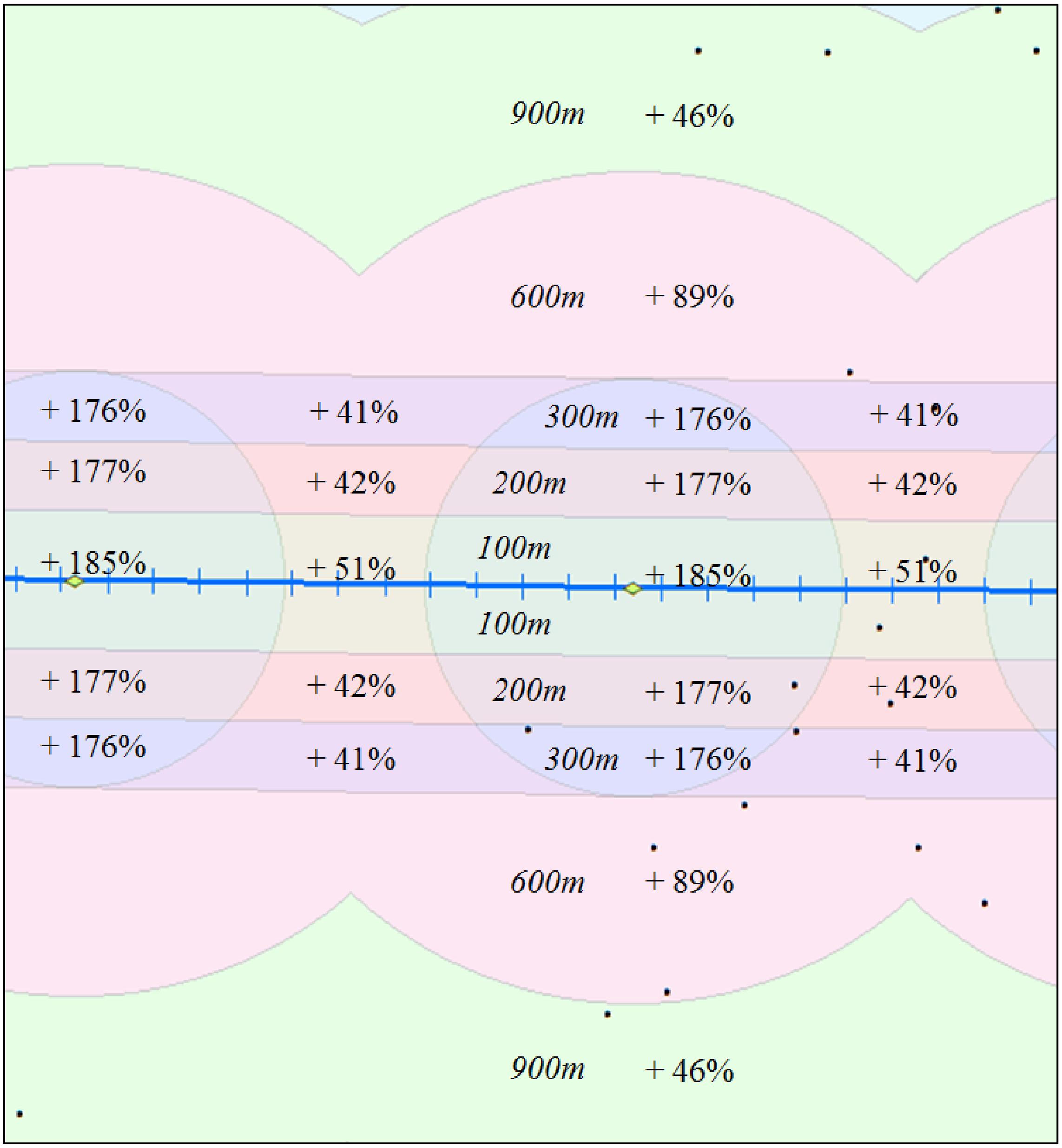

Fig. 9. Summed Up Price Impacts Near Light Rail Station Area. Black Dots Represent Sold Properties.

One possible explanation for this could be that high speed of motorized vehicles used for highway access overcomes the physical distance barrier over quite a long range (e.g., 2-3miles and this covers 88-96% of observations) and this makes accessibility benefit of most area fairly similar, which in turn lessens the impact except for areas very close to highway exit (i.e., within 600m). In contrast, access to light rail station is mostly made by non-motorized modes (walk and bike), meaning that distance really matters for those who live near light rail station for commuting, shopping, and other activities. Thus the price premium of being close to light rail station accrues right at the station and declines steeply from there. Surprisingly, the geographical extent of the effect of LRT stations reaches much farther (i.e., 1800m or 1.12mile) and the magnitude of impacts are much larger than we expected.

Compared with the results of Seo et al.'s (2014) residential model, the coefficients of accessibility of commercial property to highway exits are much less extended geographically and there is no "donut" effect for both results. Impacts of accessibility to LRT stations are also less extended for commercial than for residential property (see Fig. 10 and Fig. 11).

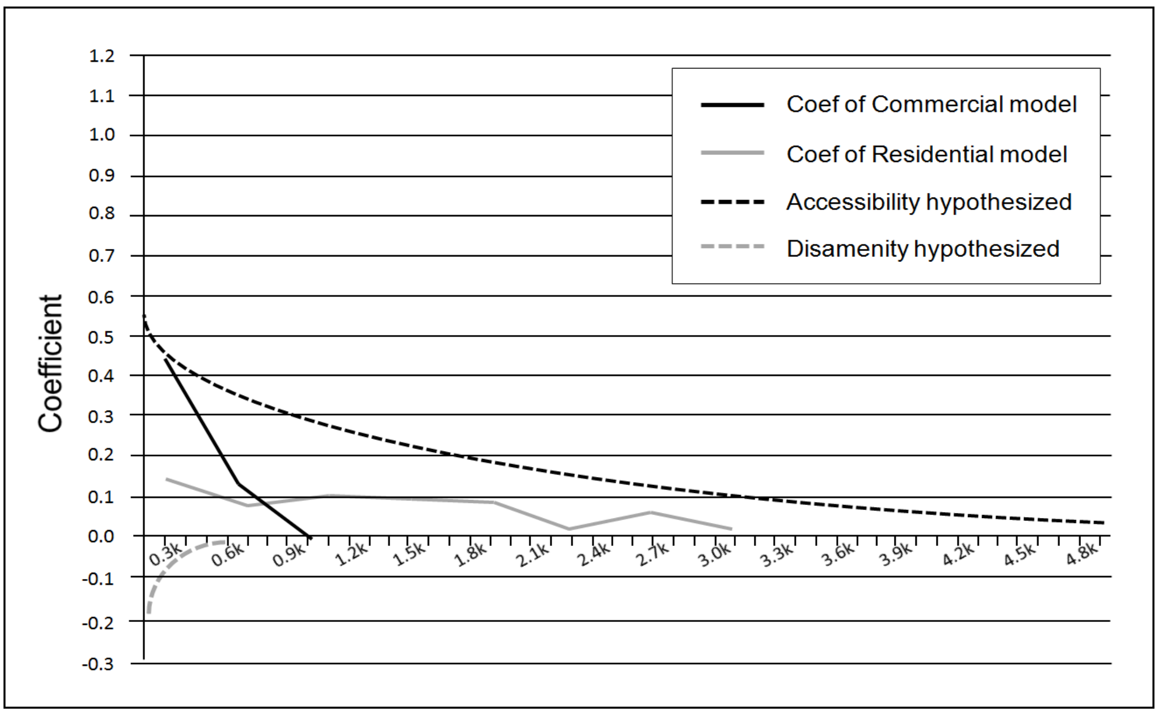

Fig. 10. Coefficients of Distance to Highway Exits.

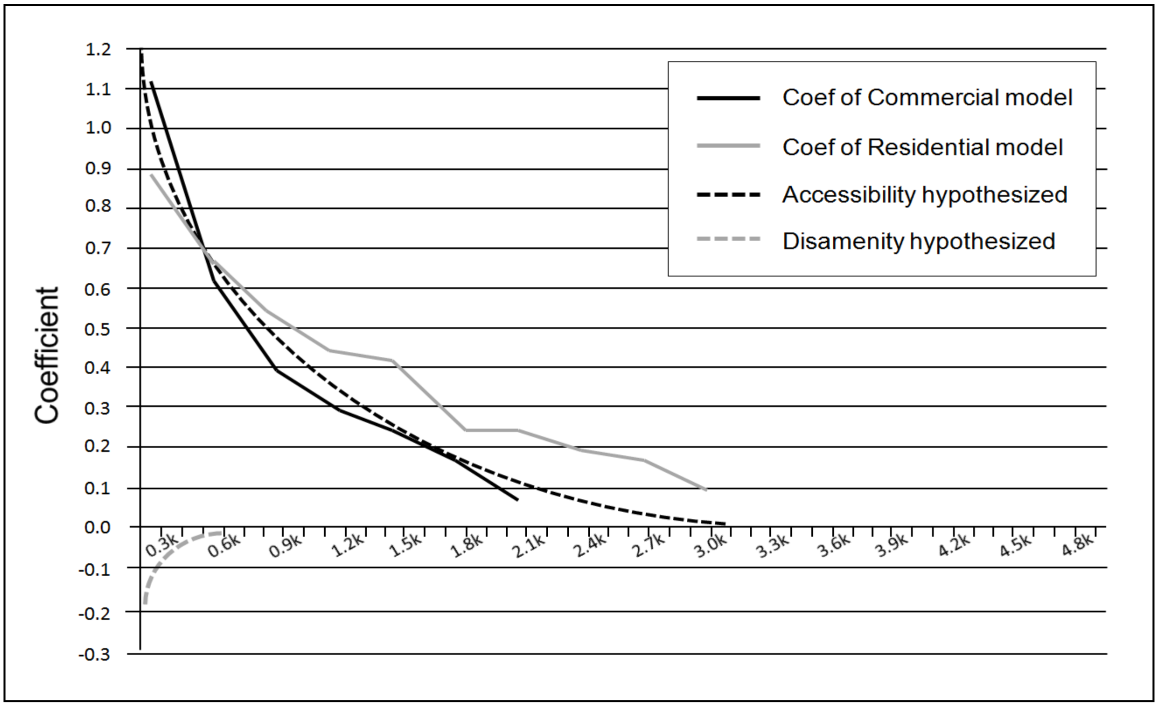

Fig. 11. Coefficients of Distance to Light Rail Stations.

The disamenity impacts of highway and light rail links are highly significant and negatively associated with the sale price as hypothesized (Fig. 12). Contrary to the residential model, commercial properties near highway links are exposed directly to traffic noise and air-pollution because noise barriers are not built to project them. In addition, even though light rail emits no air pollution and only a small amount of noise, light rail track significantly hinders employees, shoppers and service beneficiaries to access their destination by car driving because the rail track lies in the middle of arterial road.

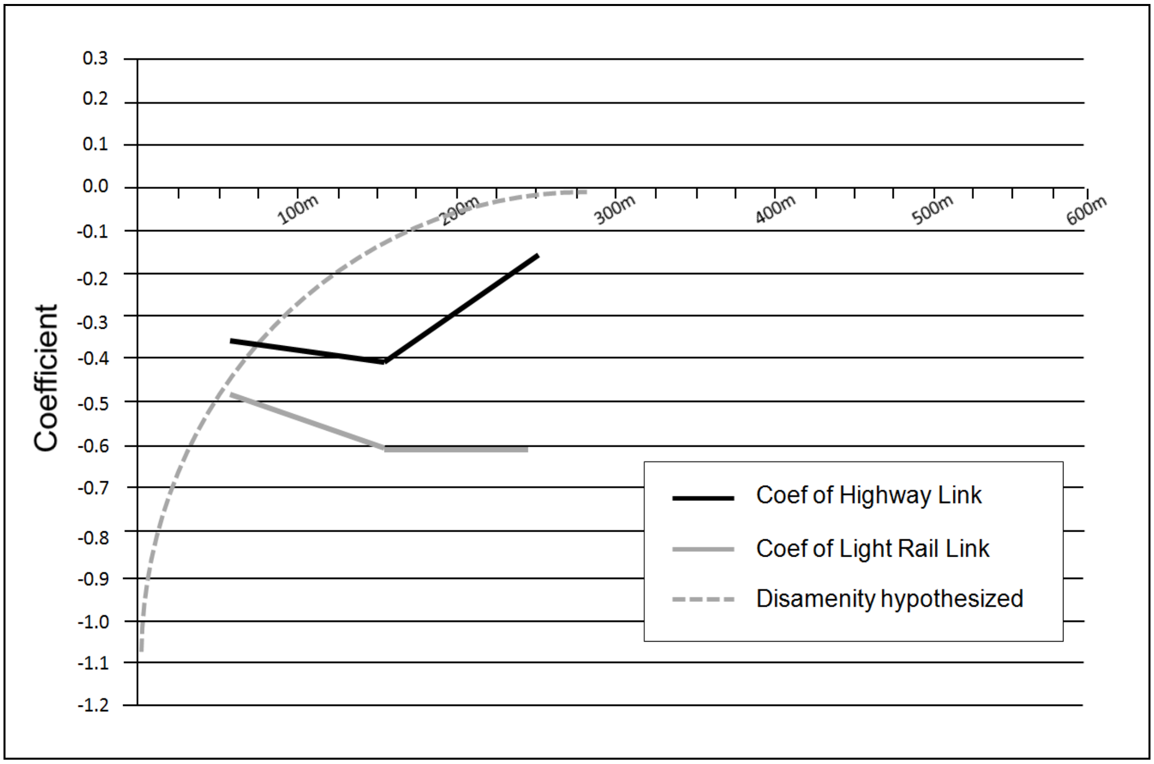

Fig. 12. Coefficients of Distance to Highway and Light Rail Links (Residential Results are not Shown because Coefficients were not Significantly Different from Zero).

Industrial Property

For industrial property, the resulting model fit is quite strong with the adjusted R^2 of 0.86 for standard OLS and pseudo R^2 of 0.87 for spatial error models. As with the model for all commercial property, structural variables such as lot square footage, interior square footage, number of stories, and age of property are all significant at the 0.001 level and unexpectedly the number of stories is negatively associated with the price (see Table 5). All neighborhood variables factored insignificantly in the price. For the locational variables, only some distance bands are statistically significant. For instance, 300m – 600m distance bands from highway exits and 600m – 900m distance bands from light rail stations are significant and positively associated with the price, though size of impact of light rail stations are larger than that of highway exits, partially validating our hypothesis.

Disamenity impacts of highways and light rail links are negative and statistically significant except for the rail_100 dummy variable. In terms of dollar value change, industrial properties, for instance, located between 300m and 600m from highway exit that is not intersected with distance bands of highway link increased 34% in property value, which is equivalent to a $203,295, increase for a property with the median value of $590,807. Impact ranges of highway exits are similar with other commercial submarkets, while light rail stations are relatively shorter in extent than other commercial submarkets.

Office Property

The resulting model fit for office property is quite strong with the adjusted R^2 and pseudo R^2 of 0.83 for both standard OLS and spatial error models. Coefficients of all structural variables such as lot square footage, interior square footage, number of stories, and age of property are all highly significant at 0.001 level and the signs are as expected. For the neighborhood variables, median income is positive and statistically significant at 0.001 level as expected but population density is statistically insignificant. For the locational variables, proximity to both the airport and to shopping malls are highly significant and positive in determining price, while proximity to the CBD and arterial roads are not significant. For the transportation variables, proximity to highway exit is positive and significant only at the 300m band but being closer to light rail stations is positively associated with the price up to 1200m. Proximity to light rail links is negative and significant at 100m and 300m bands, while proximity to highway links is insignificant, partially validating our hypothesis. In this model, office properties located within 300m from a highway exit, where the most benefits are accrued, increased 62% in sale price, all else being equal.

Retail and Service Properties

The resulting model fit for retail and service properties is also quite a strong with an adjusted R^2 of 0.78 for both standard OLS and spatial error models. Structural variables such as lot square footage, interior square footage, and age of property are again significant at 0.001 level and signs are as expected. Median household income is significant and positively associated with the price but population density is not significant as neighborhood characteristics.

For the locational variables, proximity to the CBD, airport, shopping malls, and arterial roads are all significant and positive in determining price. Surprisingly, however, proximity to highway exits is not significant for any distance band, invalidating our hypothesis. One possible explanation for this may be that the primary travelers are different from other commercial submarkets. For instance, the main travelers for industrial and office properties are likely the employees, while for many retail and service properties the customers may outnumber the employees. Thus, accessibility benefits for commuting may be an important factor for employees as well as employers to reduce transportation costs. On the other hand, in an automobile-centered city like Phoenix, shoppers and service beneficiaries may care less whether the destination property is located near a highway exit, because high speed of car driving and grid-like arterial networks overcome physical distance of 1 or 2miles quite easily, though accessibility is still important to all travelers. Contrary to highway exits, proximity to light rail stations are positive and highly significant at distance bands up to 900m, validating our hypothesis.

In this model, commercial properties located within 300m from a light rail station increased around 195% in sale price, while locating within 100m from the light rail link lowered the price by 35%. The net effect is +160%, which is equivalent to an increase of $1,091,972 for a property with the value of $681,916. Highway and light rail links are all significant and negative in determining price as hypothesized.

Conclusions

The purpose of this paper was to identify the net effects of the nodes and links of highway and light rail transit on commercial property values. To do this, hedonic price models were built upon the foundation of De Vany's (1976) work and extended from Seo et al’s (2014) work. The models were devised to unify a number of disparate previous findings in the hedonic literature into a single model for the commercial property market incorporating highway and light rail, nodes and links, amenities and disamenities, and distance decay for all these effects. In addition, we tested how the nodes and links of the networks differentially impact distinct commercial submarkets, and compared the results between residential and commercial hedonic models.

We hypothesized that positive impacts of accessibility accrue to the highway exits and light rail stations, while the nuisance effects of noise and air pollution should emanate from the highways and light rail nodes and links. We further hypothesized that the nuisance effects would be smaller for commercial property than for residential property. Using the multiple distance bands approach, the estimated results of the spatial error regression model confirmed that distance from the nodes and links was a significant determinant of commercial property values and plotted coefficients showed distance decay of amenities, which has a typical exponential decay curve for highway and light rail nodes and almost same shape as hypothesized curve for light rail stations. Unexpectedly the light rail stations have larger impacts with greater geographic reach than highway exits. The results for industrial property confirmed that both highway exits and light rail stations have significantly positive impacts on the price in closer distance bands. For office property values, proximity to the highway exits and light rail stations have positive impacts but the impact of light rail stations extend further. Proximity to the light rail links has negative impacts, while proximity to the highway links has no effect, contrary to expectations. For the retail and service properties, proximity to the light rail stations has positive impacts, while unexpectedly proximity to the highway exits has no effect. Finally, the magnitude and extent of effects of distance vary based on the types of infrastructure and the types of commercial property. For instance, price bonuses from distance (e.g., 300-600m from highway exit that does not intersect with distance bands of highway link) for industrial property is 34% while that of the office property is 11%. Thus, the impacts of highway accessibility are larger for industrial properties than for office properties in that specific area.

Comparing these commercial results with Seo et al.'s (2014) residential hedonic model, our hypothesis was confirmed that the accessibility benefits reach farther for residential property than for commercial property. Theoretically, the results of the spatial hedonic model support a bid rent theory for commercial firms that would differ in gradient and extent from the results of residential model due to location of utility maximization for each market (Alonso 1964). Empirically, our model has tested the bid rent theory for commercial property markets' responses to real world transportation facilities, which changes the relative location of utility maximization by improving accessibility. Together with Seo et al's (2014) residential model, this study may contribute to unify a number of disparate previous findings in the hedonic price literature into a single, general idealized schematic model incorporating road and rail, nodes and links, amenities and disamenities, and the distance decay functions for all of these effects.

Lastly, the results of this study may be useful to commercial property buyers to identify the location where net benefit of accessibility is maximized. Commercial property construction companies may be able to decide where to build developments for maximizing profit and sales by predicting where markets will reward location the most. On the other hand, transportation planners may be able to secure and distribute tax revenue based on the positive and negative effects captured by the study. City authorities may possibly use these results as a basis for value capture and tax increment financing of transportation projects, which depend on knowing the size and extent of benefits to nearby property.

CHAPTER 4

PAVEMENT CONDITION AND PROPERTY VALUES

Abstract

This paper estimates the relationship between pavement condition and residential property value in Solano County. We hypothesize that pavement condition impacts property values: directly as an indicator of neighborhood blight, and indirectly through its effect on traffic conditions and noise. Both effects are expected to be in the same direction; as pavement condition declines, property values are expected to decline as well. Hedonic regression models are used to estimate the contribution of road pavement condition to home sales value. We developed regression models for the County as a whole and each city, because Solano County as a whole and each city have different locational and neighborhood characteristics, which should be addressed for developing best model specification and figured out whether individual city has a different relationship between pavement condition and residential home prices. Results for Solano County models with a full dataset and a surveyed PCI dataset confirm that there is no significant relationship between pavement condition and residential sales price. However, separate estimates for the each city are mixed with positive, negative, and zero effects. Because the contribution of road pavement condition to the value of a home is inconsistent by models, results cannot be conclusively estimated.

Keywords: PCI, residential home value, hedonic model, pavement condition

Introduction

Road pavement condition is directly related to generation of nuisances such as traffic noise and air pollution, which cause an unpleasant environment and heath issues of neighborhood adjacent to a road. Pavement management agency spends significant amount of public expenditure every year to maintain and to reduce the impacts of nuisances caused by pavement deterioration (Pellecuer et al., 2014). Thus, it may be worth investigating how pavement condition can influence on the neighborhood welfare in monetary terms.

Many studies aim to estimate the impacts of environmental or nonmarket goods on human welfare. A number of economic valuation methods have been developed and used to estimate these impacts, including contingent valuation models, travel cost models, and hedonic price models (Champ et al., 2003). In this study, we used the hedonic approach to estimate the influence of pavement condition on residential property value using Pavement Condition Index (PCI). PCI represents the structural and material integrity of a pavement in a numerical value (Gharaibeh et al., 2010). The PCI is expressed on a scale between 0 and 100, where a value of 100 represents the best possible condition (Shahin et al., 1978). We develop a hedonic model of property value as a function of various characteristics of the property, including the PCI on the street. There are two ways that pavement condition might impact property values: directly as an indicator of neighborhood blight, and indirectly through its effect on traffic conditions and noise, which in turn impacts property values. Both effects are expected to be in the same direction; as pavement condition declines, property values are expected to decline as well.

In the following sections we present the data used and more details about the model, and its results. First, we reflect on existing work in this area as it informs this study. Then, after we describe study area, data processing, and examination of PCI data, we formulate our general regression model and present specific results for the selected models that can represent relationships between residential property values and PCI. We finish with a discussion and conclusions.

Literature Review

In this section, we first review the hedonic price model and then review on existing work in relation to this study. Although we reviewed a research report that is directly related to this study, we mostly reflected on works that are closely related to this area such as relationship between pavement condition and traffic noise, impacts of traffic noise on residential property values, and impacts of traffic speed and noise on health because there is no peer-reviewed paper in literature.

Hedonic Price Model

The hedonic price model is the most widely used approach. These models estimate the economic value of nonmarket goods by separating the total value of the good (for example, real estate) – for which a market price is known – into the value of each of its characteristics, including “nonmarket” characteristics. Real estate has both differentiated characteristics (e.g., lot size, living area, number of stories, and number of rooms) and a location. Variation in the location of real property relative to environmental amenities (“benefits” i.e. local parks, schools, or transportation accessibility) or disamenities (“negative impacts” i.e. noise, crime, pollution, or neighborhood blight) provides the information needed to estimate the impact of those amenities and disamenities on the property's value. The existing literature generally supports the hypothesis that neighborhood amenities – including high quality transportation infrastructure – have a positive influence on property values (e.g., Shultz and King, 2001; Boyle and Kiel, 2001; Bateman et al., 2001; Salon et al., 2014; Seo et al., 2014), and that disamenities have a negative impact (e.g., Hite et al., 2001; Nelson, 1982; Li and Saphores, 2012).

Relationship between Pavement Condition and Property Value

To the best of our knowledge, there is no peer-reviewed study that has directly estimated the relationship between pavement condition and property values. In one unpublished study, Rasmussen and Yang (2012) used a hedonic model with regression analysis to determine the relationship between pavement condition and residential property values. They investigated whether 1) street improvements resulted in an increase in property value and 2) the benefits to homeowners outweighed the cost of pavement/street improvements.

Initially they found that property values decreased with increasing street/pavement condition and it was significant at the 0.1 level. Then they created home price indicator variables (i.e., above and below sample mean: $178,384) and interacted these indicator variables with Street Condition Index (SCI) variable. This interaction model resulted that property values increased with increasing street/pavement condition when the home sale prices are above the sample mean (e.g., 1 point increase in SCI causes to 0.07% increase in home price). However, using the home price indicator dummy variables in their hedonic models is not valid. The problem is that this introduces a dummy variable for being in the top half (or bottom half) of the sample, which of course is positively correlated with higher home values. Thus, interacting with these top or bottom half dummy variables with SCI naturally produces a positive or negative effect based on the home price indicator variables. Instead of using home price indicator dummy variables, they should ran an interaction model with a dependent variable of top half or bottom half to avoid this issue.

Relationship between Pavement Condition and Traffic Noise

Many studies have investigated the impact of traffic noise on property values (e.g., Nelson 1978; Nelson 1982; Bateman et al., 2001). Traffic noise is closely related to the pavement condition because one of the two main components[6] of traffic noise is the friction between vehicle tires and the paved road surface (Mun et al., 2007).

There is substantial evidence that traffic noise increases with declining pavement condition, which happens as pavements age (Bendtsen et al., 2010a; ADOT, 2012; TRB, 2013). The PCI provides information about pavement aging by including measures of distress, levels of severity, and distress density. That said, it is important to note that pavement-related traffic noise is also influenced by factors such as pavement materials (e.g., asphalt concrete, Portland cement concrete or rubberized asphalt concrete), pavement texture types (e.g., longitudinal or transverse tine), traffic volume, vehicle types (e.g., truck or passenger car), and vehicle speed (Mun et al., 2007). In areas where these additional factors do not vary substantially but pavement quality does, the PCI may be a good proxy for measures of traffic noise.

[6]The other component is the vehicle power-train operation. In recent years, power-train noise has been substantially reduced due to consumer demand for quieter vehicles (Sandberg 2001).

Impact of Road Noise on Residential Property Value

The hedonic modeling literature includes many studies of the traffic noise impacts on property values (e.g., Vessali 1996; Bateman et al., 2001). In fact, traffic noise near the highway network was the main focus of many of the first transportation related hedonic studies. Nelson (1982) reviewed and summarized nine empirical hedonic studies focusing on the nuisance of traffic noise, with the result that highway traffic noise is estimated to have a negative impact on residential property values. Studies that included the traffic noise from arterial roads came to the same conclusion (Kawamura and Mahajan 2005; Sebastian and Wolfgang 2011).

Hedonic studies typically use property sales prices as the dependent variable as well as explanatory variables representing characteristics of the properties (e.g., lot size, living area size, number of rooms, number of stories, age of building), the neighborhoods where they are located (e.g., median household income, population density, proximity of neighborhood park or open space), and the location of that neighborhood within a larger region (e.g., school district, distance to the central business district, proximity of transportation infrastructure) (Bateman et al., 2001). However, since there are no predetermined characteristics that are suitable for all hedonic models, knowledge of the local property markets and prior empirical studies are essential to define potentially important factors (Champ et al., 2003). Especially important factor is how variables of interest (i.e., pavement condition index in this study) are measured and how that may affect models using those data.

To measure traffic noise, some researchers used field measurement data in decibels (dB) or traffic volumes (Gamble, 1974; Sebastian and Wolfgang 2011; Li and

Saphores, 2012), while others used a certain distance from the roads (i.e., 1000ft or 300m) as a noise impact zone (Langley 1976; Kim et al., 2007; Seo et al., 2014). Noise levels measured in decibels are clearly more accurate than other approaches such as traffic counts or impact zones. However, measuring actual decibels of noise at the parcel level is expensive. This issue led to the use of alternative approaches such as distance measures as a proxy for field measurement of the noise nuisance (Bailey, 1977); the traffic noise effect decays with distance according to a logarithmic scale and fades away within 1000ft of the noise source (Nelson, 1982). Traffic noise emanates not only from link of network but node (e.g., highway exits and rail stations) as well, though negative noise effects of node are usually offset by benefit of accessibility (Seo et al 2014). These two sources of noise nuisance should be considered simultaneously when impacts analyses including these factors are done.

Although previous studies revealed 1000ft or 300m as an impact zone along road links, the actual extent of the impact zone depends on the road configuration (i.e., overpass or underpass), the presence of a sound wall or earth berm, the traffic volume, the types of vehicles passing by, and the pavement condition. Seo et al. (2014) included both the highway configuration and the distance from the road in their hedonic model to determine whether residential property values respond differently to elevated, below-grade, or at-grade highways. Their results showed that below-grade highways have less impact than at-grade highways, though the impact from elevated highways was not statistically significant (Seo et al., 2014). Li and Saphores (2012) examined impacts of truck traffic along highway links in Los Angeles, CA using a multiple distance band approach (i.e. within100m, 100-200m, and 200-400m) to identify impact zones. Their results show that the residential properties located within the 100-200m band experience more negative impact than those located within the 200-400m band, though the effect on properties closest to the highway (within 100m) was not statistically significant (Li and Saphores, 2012).

Impact of Traffic Speed and Traffic Noise on Health

One mechanism for connecting pavement condition to community impacts and conditions is through health impacts. Degraded pavement condition may lead to reduced speeds, and/or increased incidence of deceleration and acceleration. Either of these occurrences could lead to increased vehicle emissions (Zhang et al., 2011). Vehicle emissions are a primary source of air pollutants in urban and suburban areas (TRB, 2002) and these emissions can contribute to a wide range of health impacts, from cardiovascular problems to adverse birth outcomes and diminished male fertility (WHO, 2005). Indoor, residential air quality is related to distance from roads (Lawson et al., 2011), which means that health impacts from degraded air quality will be greatest near roads with heavy or congested traffic. It is likely that improved pavement condition and other factors affecting free circulation of traffic could reduce these emissions and incidence of related health impacts.

Based on the literature review, we found that there is no peer-reviewed study on relationship between pavement condition and home sales price. Pavement condition, however, is related to other factors such as noise nuisance that has been studied. In addition, PCI differs from most transportation infrastructure that has been studied in hedonic literature, such as rail or highway, because PCI is estimated on every street.

Thus, it is not a question of how far away is the transport network, but what is its condition.

Study Area and Data

Study Area

Solano County, CA is located in the northeastern part of San Francisco Bay Area and contains 7 incorporated cities: Vallejo, Vacaville, Fairfield, Suisun City, Benicia, Dixon, and Rio Vista (see Fig. 13). Solano County had a population of 413,344 according to the 2010 U.S. Census Bureau and has 105,249 single family residential parcels in 2015 based on the County Assessor's data. Interstate highway 80 and an Amtrak rail line cut through the County. The pavement condition of road segments is surveyed at regular intervals. Estimated values are also available for the months between surveys, and are based on a pavement deterioration model.

Data Processing

Data come from multiple sources including Solano County assessor's office, Solano Transportation Authority (STA), and ESRI web maps. Full details provided in Table 6.

To conduct this analysis, it is necessary to obtain sales price, assessor-based single family parcel and home characteristics, and nearby road PCI for all included properties. The STA provided GIS data necessary to discover relationships between single family home sales prices and PCI. With these GIS data sets variables were created for hedonic regression analysis. Additional data sets were created using satellite imagery for explanatory variables such as highway exits, central business district (CBD), and water feature classes.

For the dependent variable of home price, we used the property sales records provided by STA. The original dataset contained 34,000 property sales records that included addresses, sale prices, and sale dates, but were not connected by parcel number to the assessor dataset that contains detailed information about each property. Through a text-based address-matching routine, 31,038 of these records were successfully merged with the assessor data. Records of non-single family homes were removed.

Table 6
List of Data Provided

Data	File type	Feature type	Core attributes	Source
34,000 home sales price	.shp	Point	· Property address · Sold date · Sold price	STA
Parcel_2015	.shp	Polygon	· APN · X, Y coordinates · Structural characteristics · Property address	Assessor's Office
Road PCIs	.shp	Line	· PCI date · PCI · Estimated PCI (2009-2015)	STA
County boundary	.shp	Polygon		STA
City boundary	.shp	Polygon		STA
Park	.shp	Point /Polygon		STA
TransitHub	.shp	Point		STA
Airports	.shp	Point		STA
Landfills	.shp	Point		STA
School	.shp	Point		STA
Capitol station	.shp	Point		STA
Highway	.shp	Line		STA
Amtrak Corridor	.shp	Line		STA
Express bus route	.shp	Line		STA
Contour	.shp	Line		STA

Additional challenges required us to discard approximately one-third of the remaining sales observations. These included missing structural information about the property, lack of PCI values for the road segments adjacent to the property, and properties that were sold multiple times in the study period were removed. The reason that multiple sales of the same property cannot be used in this analysis is that our work uses spatial econometrics to control for spatial error dependence. Using these methods, spatially identical observations would have complicated the analysis. After cleaning, 19,608 observations remained in the data set (see Fig.13 for study area).

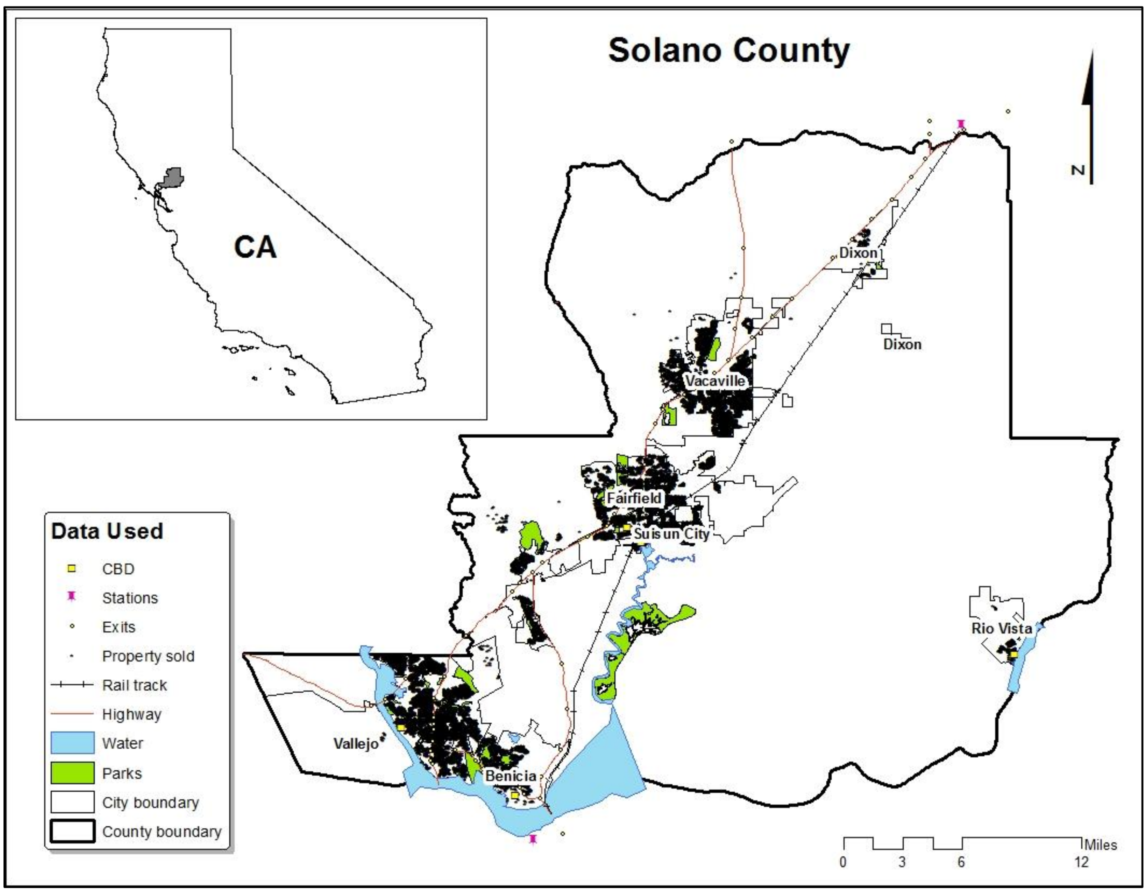

Fig. 13. Study Area and Data Used

In addition to these characteristics, tract-level population density and median household income from the U.S. Census Bureau were included as control neighborhood characteristics in the analysis. For the locational characteristics, the “near” function in ArcGIS was used to calculate the Euclidean distance between each property and the closest Central Business District (CBD), highway exit, highway link, rail station, rail track, airport, water, park, and landfill. PCI, the variable of most interest in this study, was assigned to adjacent properties by first creating a buffer around each road, and then performing a spatial join with the property sale point data. Year and city dummy variables were created using attributes from the property sales data and city boundary polygon feature class, respectively. It is important to note that the dependent variable was adjusted by the home price index (HPI) for San Francisco and San Jose area to control for the volatility of the real estate market from 2009 to 2015. Table 7 provides descriptive statistics for the main variables used in this analysis and Table 8 provides a percentage of observations for each city and year.

Table 7

Descriptive Statistics of Main Variables (N = 19,608)

Variable	Description	Mean	Std. Dev.	Min	Max
HPI_adj_Price	Dependent variable	338895.74	153793.99	39584.25	1562303.16
Structural Variable					
LOT_Sqft	Square footage of parcel	6901.98	3365.71	650	194277
Living_Sqf	Square footage of interior area	1659.43	628.93	424	6051
Age	Age of house	34.43	21.52	0	149
FirePlc_du	Fire place (dummy)	0.83	0.38	0	1
N_Rooms	Number of rooms	5.57	1.29	2	13
N_Story	Second story = 1 (dummy)	0.39	0.49	0	1
Pooldum	Presence of Pool	0.0679	0.2515	0	1
GARAGE	Square footage of garage	440.53	149.93	0	4320
Neighborhood Variable					
M_HH_Income	Median household income	73887.39	23698.85	14965	145625
POP_dens	Population density/sqml	4418.97	2973.97	36.39	12228.51
PCI_Year_Same	Estimated PCI same year home sold	61.37	27.01	0	98.40
Locational Variable					
CBD	Distance to nearest CBD	3894.47	2119.89	92.22	12236.66
Station	Distance to Amtrak Station	10622.20	5366.96	246.62	32344.42
All_Arterial	Arterial road dummy	0.0214	0.145	0	1
Hwy_exit	Distance to highway exit	2356.92	3631.32	89.93	33623.88
Park	Distance to regional park	551.28	534.27	0.06	5340.33
Rail_300	300m within rail track	0.02	0.14	0	1
Hwy320	320m within highway center line	0.10	0.30	0	1

Table 8
Percent of Observations for Each City and Year

City	% of observations	Year	% of observations
Vacaville	26	2009	11
Rio Vista	1	2010	19
Dixon	1	2011	19
Vallejo	31	2012	19
Suisun City	8	2013	13
Benicia	5	2014	11
Fairfield	25	2015	9
Solano County	1		

PCI Examination

Substantial effort was put into thoroughly examining the PCI data to understand the relationship between PCI and the other variables used in the hedonic models, and to diagnose inconsistent PCI coefficients (i.e., sign changes in different models) in the results of the selected regression models. The data included an estimated PCI value for each road segment for each year from 2009 to 2015. As explained above, these estimates are based on periodic field surveys of pavement condition. A pavement condition deterioration model is used to estimate PCI for any years between field surveys. The data also included the date and surveyed pavement condition value for the most recent PCI survey. In the remainder of this section, we highlight some data quality issues that we encountered when using these PCI data.

First, surveyed PCI values may have measurement errors that could affect the results of hedonic regressions (Champ et al., 2003). An expert in grading the pavement condition of each road segment provides the PCI values in years when a road condition survey was done. The problem is that the same expert does not survey all of the roads in the County, leading to the possibility of inconsistency in surveyed PCI values. There has recently been a training program for pavement condition surveyors that aims to address this issue. However, the data we are using spans the period both before and after the training program.

Second, we found large changes in PCI values between estimated values in one year and surveyed values in the next. In the case of large PCI increases, it would make sense that road maintenance and/or capital improvement operations substantially improved the pavement condition, and then a new pavement survey confirmed it (e.g., an estimated PCI of 37 in 2013 and a surveyed PCI of 100 in 2014). However, changes in the opposite direction (e.g., an estimated PCI of 65 in 2010 and a surveyed PCI of 27 in 2011) are problematic because there is no reasonable explanation for them, and one or both of those PCI values are likely to be far from correct. If the estimated PCI is incorrect in these cases, it casts doubt on all estimated PCI values in the dataset. There are 891cases in our data where PCI values "jump" downward by more than 20 points from one year to the next, not including those cases where we know that the reason is a new PCI survey.

Because of these doubtful estimated PCI values, we ran two regression models—one with the full dataset including estimated PCI (i.e., 19,608 cases) and another that is restricted in surveyed PCI dataset (i.e., 2,960 cases). We have identified cases where year-to-year increases occurred, and marked them as likely additional survey years. We have also marked year-to-year drops of more than 7 PCI points as likely additional survey years. This increases our sample size of homes sold in years with surveyed PCI to more than 5000.

Methods

Specifying the Hedonic Model

To select the best functional form for a regression model, scatter plots between the dependent and explanatory variables were examined. Scatter plots of log-transformed variables were also compared. The variance inflation factor (VIF) was also examined because of the high likelihood of multi-collinearity among some proximity variables such as highway exits, transit hub, and Amtrak station. Multi-collinearity was found, and as a result, proximity to airports, landfill, and transit hubs were removed from the model. The double-log functional form was selected for this study and is expressed as

$$\ln P_i = \alpha + \beta_1 \ln S_i + \beta_2 \ln N_i + \beta_3 \ln L_i + \beta_4 D_i + \varepsilon_i \quad (1)$$

Where:

P_i is the price of property *i*
α is a constant
S_i are structural characteristics for property *i*
N_i are neighborhood characteristics for property *i*
L_i are locational characteristics for property *i*
D_i are proximity band dummies for property *i*
β_1, β_2, β_3, β_4 represent the coefficients of S_i, N_i, L_i, and D_i respectively, and
ε_i is random error for property *i*.

In addition to general hedonic model for this study represented above, a hedonic model for individual city was developed because each city has different characteristics for the location and/or neighborhood variables as well as different pavement expenditure and PCI trends. For instance, because Vallejo and Benicia are adjacent to the coastline, which usually has a positive impact on property value near coastline, this characteristic are included in the hedonic model for these cities.

Spatial Autocorrelation

Recently, it is becoming more common to recognize inherent spatial effects (e.g., spatial autocorrelation) among parcels in hedonic models (Patridge et al., 2012). When home prices exhibit spatial autocorrelation, a hedonic model will generate inconsistent estimates. The presence of spatial autocorrelation in the error term produces inefficient parameter estimates (LeSage and Pace, 2009).

Spatial dependence was tested with the current data set. Thiessen polygon and binary distance using point data for houses sold were used to create spatial weight matrices for the spatial dependence test. Lagrange Multiplier (LM) test statistics, which allow us to identify presence of either spatial autocorrelation in the dependent variable or spatial autocorrelation in the error term or both (Anselin and Rey 2014), were used as the testing method. In the current data set, LM test statistics specified presence of spatial autocorrelation in the error term only, and this was confirmed through mapping of regression residuals. Thus, the spatial error model, which can control for spatial autocorrelation in the error term, was used for the final regression analysis. The general form of the spatial error model is shown in Equations (2) and (3)

$$P = \alpha + \beta X + \varepsilon \tag{2}$$

$$\varepsilon = \lambda W\varepsilon + \mu \tag{3}$$

where:

P is a vector of property prices
α is the constant term;
β is the n×1 vector of the coefficients of the explanatory variables
X is the m×n matrix of explanatory variables
ε is the n×1 vector of spatial autoregressive error term
λ is the coefficient of the spatially correlated error term
W is the standardized spatial weights m×m matrix with zero diagonal terms that assigns the potential spatial correlation

Wε is the spatially lagged error terms, and
μ is independent but heteroskedastically distributed error

Results

All Properties

Initial regression analysis was performed using StataSE 12 for Windows to determine the best model. The Lagrange Multiplier (LM) test value of 0.056 ($p = 0.81$) for lag and 56.21 ($p = 0.000$) for error confirmed spatial dependence in error term. A Koenker-Bassett test value of 2203.51 ($p = 0.000$) confirmed spatial heterogeneity in the data. Thus, we applied a spatial error model with heterogeneity option using GeoDaSpace to estimate the coefficients of the independent variables. Table 9 shows the coefficients, standard error, z-Stat, and significance for the spatial error model. The resulting model fit is fairly strong with a Pseudo R^2 of 0.79[7] and an OLS adjusted R^2 of 0.79.

Structural variables are all statistically significant at the 0.001 level and all signs of coefficients are as expected. For instance, number of stories and age of house are negative and significant, while other structural variables such as home square footage, lot size, number of rooms, number of fireplaces, presence of pool, and square footage of garage are all positive and significant as expected.

For neighborhood variables, median household income is positively associated with property value and highly significant at the 0.001 level, while population density is negatively associated with property value and highly significant at the 0.001 level. Signs of the coefficients are as expected.

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[7] Pseudo R^2 cannot be interpreted as one would interpret an OLS R^2, however, a higher Pseudo R^2 still can be interpreted as better model fit than a lower one (Anselin 1988).

Overall, most of the locational variables are highly significant at the 0.001 level except distance from highway exit and some of the city dummy variables. For instance, proximity to the central business district (CBD) and arterial roads, which represent the accessibility of jobs and transportation, are positively associated with the property values.

Finally, the coefficient of PCI, the variable of the greatest interest, is not statistically significant. This means that with our data, we cannot detect a relationship between residential property values and pavement condition adjacent to the home. As noted earlier, however, the PCI data may contain errors. We also analyze subsamples of the data set.

Table 9
Estimation Results of All Properties (N = 19,608)

Variable	Coef.	Std.err	z-Stat	Sig.
(CONSTANT)	5.982954	0.114775	52.128	0.000
Structural variables				
ln_LivinSq	0.607351	0.011209	54.184	0.000
ln_LotSqft	0.100787	0.005948	16.945	0.000
N_Rooms	0.014791	0.002364	6.256	0.000
N_Story	-0.022165	0.004415	-5.020	0.000
Age	-0.003681	0.000175	-21.023	0.000
FIREPLC	0.061121	0.005251	11.639	0.000
pooldum	0.061718	0.005626	10.970	0.000
ln_Garage	0.011299	0.001813	6.231	0.000
Neighborhood variables				
ln_M_incom	0.151992	0.008438	18.013	0.000
ln_PopDens	-0.035832	0.001538	-23.296	0.000
PCI_Year_Same	-0.000085	0.000080	-1.056	0.291
Locational variables				
ln_CBD	-0.018795	0.003904	-4.815	0.000
ln_Exit	-0.008250	0.003262	-2.530	0.011
All_Arterial	-0.058370	0.011953	-4.883	0.000
ln_Park	0.012945	0.001522	8.506	0.000
Hwy320	-0.050669	0.006406	-7.910	0.000
Benicia	0.429382	0.030476	14.089	0.000
Dixon	0.049858	0.030987	1.609	0.108
Fairfield	-0.004017	0.029677	-0.135	0.892
Rio Vista	-0.254982	0.036022	-7.078	0.000
Suisun City	-0.086364	0.030381	-2.843	0.004
Vacaville	0.099618	0.029713	3.353	0.001
Vallejo	-0.000263	0.029755	-0.009	0.993
Y_09	-0.032701	0.007157	-4.569	0.000
Y_10	-0.061449	0.005679	-10.821	0.000
Y_11	-0.122764	0.005694	-21.560	0.000
Y_12	-0.119231	0.005538	-21.530	0.000
Y_13	-0.064783	0.006109	-10.604	0.000
Y_14	0.026119	0.005962	4.381	0.000
Lambda	0.079738	0.011013	7.240	0.000
Pseduo R^2	0.79			
OLS Adjusted R^2	0.79			

Properties with Surveyed PCI

Because the estimated PCI may include errors due to the road deterioration prediction model over or underestimating the true pavement condition, we estimate our model on the subset of home sales that occurred in a year when PCI was surveyed. This subsample includes both home sales that occurred in the year when the PCI was most recently surveyed – as listed in the dataset – as well as home sales that occurred in a year for which we presume that the PCI must have been surveyed – based on the year-to-year patterns of estimated PCI values. Like the full sample, spatial autocorrelation for the error term was detected in this subsample, confirmed by the LM test value of 0.639 ($p = 0.4$) for lag and 80.5 ($p = 0.000$) for error. A Koenker-Bassett test value of 671.99 ($p = 0.000$) also confirmed the presence of heterogeneity in the subsample. Thus, we again applied a spatial error model with heterogeneity option using GeoDaSpace. Table 10 shows the results of analysis. The resulting model fit is fairly strong with a Pseudo R^2 of 0.8 and an OLS adjusted R^2 of 0.8.

Overall, the results are not different from the All Property model. For instance, structural variables are all statistically significant at the 0.01 level except N_Story which is still statistically significant at the 0.05 level and all coefficients signs are as expected. For the neighborhood variables, median household income is positively associated with property value and highly significant at the 0.001 level, while population density is negatively associated with property value and highly significant at the 0.001 level. Signs of both coefficients are as expected. For the locational variables, however, some variables are less significant than the same variables are in the All property model. For instance, distance to Hwy320 dummy variable is significant at the 0.05 level and distance to

All_Arterial is not significant even at the 0.05 level. However, all signs are consistent with the All property model. The coefficient of PCI is not significant even at the 0.1 level, thus there is no detectable relationship between residential property values and pavement condition.

Table 10

Estimation Results of the Properties with Surveyed PCI (N = 5,121)

Variable	Coef.	Std.err	z-Stat	Sig.
(CONSTANT)	6.604103	0.236379	27.939	0.000
Structural variables				
ln_LivinSq	0.629901	0.022041	28.579	0.000
ln_LotSqft	0.097577	0.011482	8.498	0.000
N_Rooms	0.017324	0.004777	3.626	0.000
N_Story	-0.017726	0.008291	-2.138	0.033
Age	-0.004154	0.000338	-12.306	0.000
FIREPLC	0.052614	0.009586	5.488	0.000
pooldum	0.059255	0.011109	5.334	0.000
ln_Garage	0.009597	0.003700	2.594	0.009
Neighborhood variables				
ln_M_incom	0.100088	0.017196	5.820	0.000
ln_PopDens	-0.040270	0.003077	-13.088	0.000
PCI_Year_Same	0.000093	0.000168	0.552	0.581
Locational variables				
ln_CBD	-0.022683	0.007942	-2.856	0.004
ln_Exit	0.003356	0.006611	0.508	0.612
All_Arterial	-0.026363	0.021123	-1.248	0.212
ln_Park	0.010028	0.003005	3.337	0.001
Hwy320	-0.026573	0.012152	-2.187	0.029
Benicia	0.535993	0.046990	11.407	0.000
Dixon	0.078867	0.046617	1.692	0.091
Fairfield	0.104530	0.044737	2.337	0.019
Rio Vista	-0.284656	0.062014	-4.590	0.000
Suisun City	-0.050384	0.046704	-1.079	0.281
Vacaville	0.143726	0.044860	3.204	0.001
Vallejo	0.057584	0.044455	1.295	0.195
Y_09	-0.243667	0.077953	-3.126	0.002
Y_10	-0.364392	0.076756	-4.747	0.000
Y_11	-0.323492	0.077158	-4.193	0.000
Y_12	-0.364124	0.077115	-4.722	0.000
Y_13	-0.292879	0.076594	-3.824	0.000
Y_14	-0.266451	0.076820	-3.468	0.001
Lambda	0.140602	0.017833	7.884	0.000
Pseduo R^2	0.8			
OLS Adjusted R^2	0.8			

Properties of Each City

As noted previous section, both neighborhood and locational characteristics as well as pavement related expenditure are different in each city. Thus, some control variables in specific cities should be removed or added. For example, Rio Vista is a very small city and around 98% of sold homes are located within 2 miles of one another. This means that certain neighborhood (e.g., population density) or locational (e.g., distance to water front) characteristics in Rio Vista are essentially the same for all properties. Thus, these control variables should be excluded in the regression model.

Table 11 shows a summary of the results for all cities. Some cities such as Vallejo, Vacaville, Fairfield, Suisun City, and Rio Vista required the spatial error model with heterogeneity option, while other cities did not. The resulting model fits are generally strong, with R-squared statistics ranging from 0.64 to 0.86. The relationship between PCI and property value seemed to differ by city. Like the County-level models presented earlier, some city models yielded statistically insignificant results such as Vallejo, Vacaville, and Solano County. PCI results for Dixon and Rio Vista are negative and significant at the 0.01 and 0.05 level respectively, while Fairfield’s is positive and highly significant at the 0.001 level. In Suisun City, the relationship between PCI and home values are positive and somewhat significant at the 0.1 level, while in Benicia the relationship between PCI and home values are negative and somewhat significant at the 0.1 level (see APPENDIX G to N for full city-specific results tables).

Table 11
Estimation Results of Cities

City	N = 19608	Model	Adj- R^2 /Pseudo R^2	PCI			
				Coef.	Std.err	z-Stat	Sig.
Vallejo	6127	Spatial error/Het	0.70	-0.000199	0.000127	-1.568	0.117
Vacaville	5165	Spatial error/Het	0.77	-0.000135	0.000173	-0.781	0.435
Fairfield	4962	Spatial error/Het	0.86	0.000692	0.000184	3.766	0.000
Suisun City	1645	Spatial error/Het	0.69	0.000292	0.000159	1.837	0.066
Benicia	971	OLS (no spatial autocorrelation)	0.75	-0.000409	0.000242	-1.689	0.091
Dixon	279	OLS (no spatial autocorrelation)	0.81	-0.003663	0.000678	-5.404	0.000
Rio Vista	243	Spatial error/Het	0.64	-0.000931	0.000405	-2.298	0.022
Solano County	216	OLS (no spatial autocorrelation)	0.85	0.001273	0.000881	1.444	0.150

Discussion and Conclusions

The purpose of this study was to identify the relationship between residential property values and pavement condition. We hypothesized that higher PCI is positively associated with property values. Although there is no peer reviewed literature directly related to this study, many previous studies have developed hedonic models of neighborhood blight (Anderson, 1990; Man and Rosentraub, 1998; Dye and Merriman, 2000). We developed hedonic regression models for all properties, properties assigned surveyed PCI, and for each city. In general, structural, neighborhood, and locational variables for all models are not significantly different in sign except for in some of the city-specific models.

However, in terms of PCI, results vary across all models (i.e., positive in 2 cities, negative in 3 cities, and zeros in 2 cities). We have tried many different combinations such as time periods (2009 - 2011/2012 - 2015), focusing on certain ranges of property values (high / low), and adding other neighborhood characteristics, but the results remained basically unchanged. According to this model, pavement condition as represented by PCI does not appear to have a strong and consistent relationship with home values in Solano County. Further, the negative signed results are troubling because there is no reasonable explanation for them – a better road should never diminish the value of a house. The fact that we obtain these counterintuitive results suggests one or both of the following: (1) there may be a problem in the data or (2) road pavement condition is closely related to characteristics of the home or neighborhood that do diminish the value of a house.

CHAPTER 5

CONCLUSIONS

Overview

This dissertation examined the relationship between transportation infrastructure and property values using spatial hedonic regression models. This dissertation proposed a generalized and more comprehensive theory of the positive and negative relationships between transportation infrastructure and real property values, which disentangles different effects by road and rail, by nodes and links, and by distance from them. A distance band approach was used to capture effects of non-linear distance function and distance ranges. None of previous studies have conducted a unified approach as developed here to differentiate all these effects.

The strongest conclusion drawn from the results of the Chapter 2 and 3 is that proximity to transport nodes was associated positively with both residential and commercial property values. As a function of distance from highway exits and LRT stations, the distance-band coefficients formed a typical positive longer-range distance–decay pattern of accessibility effect but there is no shorter range distance–decay of disamenity effect. As hypothesized, the accessibility effect for highway exits extended farther than for LRT stations in residential property model, but for commercial property models the distance range of the two modes was reversed and effect of LRT stations extended farther than that of highway exits. For both types of property, the magnitude of accessibility effect for highway exits is smaller than for LRT stations. Unexpectedly, the hypothesized negative effect on property values immediately surrounding rail stations and highway exits was not evident for either mode or either property type. As speculated in the relevant chapters, these results may be explained by the inherent characteristics of property type (tolerance of noise: resident vs. commercial), features not controlled for (noise barrier), and inaccurately estimated data (point for nodes and centerline for links). These explanations need to be further investigated.

Coefficients for the distance from highway and LRT links were generally negative but not significant in the residential model. However, in the all-commercial model, the coefficients for the distance from highway and LRT links were significant and negative, as expected. However, coefficients for the distance from highway and LRT links vary based on the submarket of commercial property. Another results of Chapter 2 for the effect of highway configuration on home values showed that below-grade highways have relatively positive impacts on nearby houses compared to those at ground level or above in Phoenix, Arizona. Lastly, the main conclusion that can be drawn from the results of the analyses presented in Chapter 4 is that pavement condition had no relationship with the residential property values in Solano County, California.

Implications

This dissertation contributes to the hedonic literature in that Chapter 2 and 3 have unified a number of disparate previous findings in the hedonic literature into a single model for residential and commercial property markets (Golub et al, 2012), incorporating highway and light rail (Bowes and Ihlanfeldt 2001; Ryan 2005; Andersson et al, 2010), nodes and links (Kilpatrick et al, 2007; Andersson et al, 2010), and distance decay of all these effects. Theoretically, the results of Chapter 2 and 3 support Alonso's bid rent theory for residential and commercial property markets, and also support a bid rent theory for commercial properties that differs somewhat in gradient and extent from the results of residential property model due to location of utility maximization for each market (Alonso 1964). The results of Chapter 2 and 3 may be useful to property buyers to identify the location where net benefit of accessibility is maximized. Real-estate developers may be able to decide where best to build real estate for maximizing benefit by predicting where markets will reward location the most. Transportation planners, on the other hand, may be able to secure and distribute tax revenue based on the positive and negative effects captured by this dissertation. City authorities could use these results as a basis for value capture and tax increment financing of transportation projects, which depend on knowing the size and extent of benefits to nearby property.

Chapter 4 contributes to the hedonic literature by analyzing the relationship between home values and road pavement condition, which has not been published in the peer-reviewed literature yet. A small but positive effect of pavement condition on home values was hypothesized. Despite testing several different model formulations, no significant positive relationship was found. These non-significant results need to be confirmed by other studies, which would be important for public policy in terms of whether housing values are a valid justification for street maintenance.

Future Research

The three individual articles presented in this dissertation untangled relationships between property values and transportation infrastructure that is invested for accessibility, mobility, and economic development. However, not all results are as hypothesized and there may be reasons why some results are not correspond with hypotheses. Specifically, donut effect from highway exits and LRT stations has not been found in both residential and commercial property models. Besides, negative effect from highways and LRT links was not captured in residential property model, while it was captured in commercial property model. One possible reason is the data used for highway links and exits, which have non-negligible width (e.g., width of highway links is about 35-90m and width of some highway interchanges is about 160m), and the traffic noise effect decays with distance based on a logarithmic scale and fades away within 300m of the noise source (Nelson, 1982). Using the centerlines of highway and the points of exit cannot measure the exact distance from the properties to the edge of the highway nodes and links. Thus, further research may be required to investigate with more accurate data why proximity to the links—which theoretically should have a primarily negative disamenity from noise and air pollution and no positive accessibility effect— and proximity to the exits—which theoretically should have a net effect of accessibility and disamenity— was not captured for highway and rail in Chapter 2.

Since light rail transit is a new type of transport investment in Phoenix, it may be interesting to study how this investment influences land use, population, employment, walkability, and property values in geographical extent. By comparing those factors in terms of pre-LRT and post-LRT periods, impacts and service area of stations might be identified and validity of LRT investment might be supported. Furthermore, it may be valuable to investigate whether sidewalk or bike infrastructure positively impacts on property markets including single- and multi-family home and commercial property, because walkability has been proved to increase home values in some cities in the U.S. and Canada where walkability is increased (Cortright 2009; Chad 2012; Li et al, 2015).

In relation to road pavement, the City of Phoenix has applied new pavement material (e.g., rubberized asphalt) to roads to reduce traffic noise. This can be an interesting subject of future study. Because quiet pavement can reduce traffic noise about 5.1 dB, reduction of noise level may positively affect residential property values. Quiet pavement projects are still being evaluated whether they can be used as an alternative or supplement to noise barriers (Donavan et al., 2013). No study has examined the impact of quiet pavement on property values.

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APPENDIX A

SUMMARY OF MAIN VARIABLES

(Observations = 20,149)

Variable	Description	Mean	Std. Dev.	Min	Max
Structural variables					
Price	Sale price ($) - *dependent variable*	124,499	122,915	10,000	1,950,000
Sqm	Living area (m²)	150.639	56.757	33.445	662.956
Area_sqm	Lot size (m²)	7,210	3,556	1,542	46,282
Bathfix	Number of bathroom fixtures	6.567	2.335	2	25
Age	Age of house (years)	31.4	19.3	1	101
Pool	Presence of pool (dummy)	0.254	0.4353	0	1
Neighborhood variables					
N_GPark	Nearest green park (m)	1,092	957.7	11.17	7522.98
N_DPark	Nearest t desert park (m)	6,735	5,675	11.88	21,649
N_Golf	Nearest golf course (m)	2,594	1,859	6.59	17,519
N_DCenter	Nearest distance from city center (m)	15,129	7,521	961	47,505
Hway_150m	< 150m from highway (dummy)	0.01816	0.13355	0	1
Hway_250m	150-250m from highway (dummy)	0.02308	0.15016	0	1
Hway_350m	250-350m from highway (dummy)	0.02209	0.14697	0	1
Exit_400m	< 400m from highway exit (dummy)	0.01906	0.13673	0	1
Exit_800m	400-800m from highway exit (dummy)	0.10194	0.30258	0	1
Exit_1200m	800-1200m from highway exit (dummy)	0.13872	0.34566	0	1
Exit_1600m	1200-1600m from highway exit (dummy)	0.11385	0.31764	0	1
Exit_2000m	1600-2000m from highway exit (dummy)	0.09291	0.29031	0	1
Exit_2400m	2000-2400m from highway exit (dummy)	0.09345	0.29107	0	1
Exit_2800m	2400-2800m from highway exit (dummy)	0.08308	0.27601	0	1
Exit_3200m	2800-3200m from highway exit (dummy)	0.06765	0.25114	0	1
S_300m	< 300m from light rail station (dummy)	0.00104	0.03227	0	1
S_600m	300-600m from light rail station (dummy)	0.00382	0.06170	0	1
S_900m	600-900m from light rail station (dummy)	0.00819	0.09012	0	1
S_1200m	900-1200m from light rail station (dummy)	0.01003	0.09963	0	1
S_1500m	1200-1500m from light rail station (dummy)	0.00928	0.09589	0	1
S_1800m	1500-1800m from light rail station	0.00744	0.08596	0	1

	(dummy)				
S_2100m	1800-2100m from light rail station (dummy)	0.01658	0.12768	0	1
S_2400m	2100-2400m from light rail station (dummy)	0.01544	0.12328	0	1
S_2700m	2400-2700m from light rail station (dummy)	0.01653	0.12749	0	1
S_3000m	2700-3000m from light rail station (dummy)	0.01806	0.13318	0	1
LT_100m	< 100m from light rail track (dummy)	0.00025	0.01575	0	1
LT_200m	100-200m from light rail track (dummy)	0.00099	0.03149	0	1
LT_300m	200-300m from light rail track (dummy)	0.00194	0.04395	0	1
M_income	Median household income ($)	53,387	21,650	9,668	231,500
Pop_dens	Population density (per km^2)	2,233	1,070	4	6,377
Environmental variables					
P_Trees	Portion of 200m buffer covered by trees	0.10047	0.0663	0.0008	0.5491
P_Grass	Portion of 200m buffer covered by grass	0.12513	0.0789	0	0.5714
Above	Highway lies above ground level (dummy)	0.00913	0.0951	0	1
Below	Highway lies below ground level (dummy)	0.01295	0.1131	0	1
H_Index	Monthly home sales Index	173.292	7.9949	163.4	194.7

APPENDIX B

SUMMARY OF SELECTED LITERATURE ON ROAD AND RAIL IMPACTS IN HEDONIC PRICE MODELS FOR COMMERCIAL PROPERTIES

Authors	Dependent Variable	Study Focus	Distance Measure	Transport Mode		Network Element		Time frame
				Highway or Road	Rail or LRT	Links	Nodes	
Damm et al., 1980	Assessed landvalues (Retail)	Accessibility	Actual distance/0. 1 mile dummy		O		O	Multi-year (1969-1976)
Landis and Loutzenheiser 1995	Asking rents (Office)	Accessibility	Multi-band (200m bands up to 1/2 mile)		O		O	Single-year (1993)
Sivitanidou 1995	Effective rents (Office)	Accessibility	# of passing highway/Actual distance from Airport	O	Airport		O	Single-year (1990)
Sivitanidou 1996	Assessed property values (Office)	Accessibility	Actual distance	O		O		Single-year (1992)
Bollinger et al., 1998	Asking rents (Office)	Accessibility	Single-band (1/4 mile for rail transit, 1 mile for Hwy)	O	O		O	Multi-year (1990, 1994, 1996)
Weinberger 2001	Effective rents (Commercial whole)	Accessibility	Multi-band (1/4 mile bands for LRT & 1 mile bands for Hwy)	O	O		O	Multi-Year (1984-2000)
Cervero and Duncan 2002	Assessed land values (Commercial whole)	Accessibility	Single-band (1/4 mile for rail & 1/2 mile for Hwy)		O		O	Two-year (1998-1999)

Ryan 2005	Asking rents (Office/ Industrial)	Accessibility	Actual distance	O	O		O	Multi-year (1986-1995)
Billings 2001	Sale Prices (Commercial whole)	Accessibility	Single band (1 mile for rail)/Actual distance (Hwy)	O	O		O	Multi-year (1994-2008)
Golub et al., 2012	Sale Prices (Commercial whole)	Accessibility &disamenity	Actual distance		O	O	O	Multi-year (1988-2010)
This study	Sale Prices (Commercial Whole/Office /Industrial /Retail)	Accessibility &disamenity	Multi-band	O	O	O	O	Multi-year (2000-2014)

APPENDIX C

ESTIMATION RESULTS FOR THE WHOLE COMMERCIAL PROPERTIES

(N = 3,642)

Variable	Coef	Std. Err.	z-stat	Sig.
(Constant)	6.3127	0.5180	12.19	0.000
Structural Variables (S_i)				
Lot(ln)	0.6457	0.0091	70.80	0.000
T_Interior (ln)	0.2540	0.0139	18.31	0.000
Stories	0.0886	0.0163	5.43	0.000
Age	-0.0140	0.0011	-13.15	0.000
Neighborhood Variables (L_i)				
Median_HH (ln)	0.2265	0.0354	6.40	0.000
Pop_Dens (ln)	-0.0109	0.0137	-0.80	0.426
LocationalVariables (N_i)				
Dist_CBD (ln)	-0.0732	0.0317	-2.31	0.021
Dist_Air (ln)	-0.1350	0.0229	-5.89	0.000
Dist_Mall (ln)	-0.1782	0.0165	-10.79	0.000
Dist_Arterial (ln)	-0.0919	0.0179	-5.13	0.000
Exit_300m	0.4481	0.0769	5.83	0.000
Exit_600m	0.1287	0.0403	3.19	0.001
Exit_900m	-0.0176	0.0341	-0.52	0.605
S_300m	-0.6099	0.1197	-5.09	0.000
S_600m	-0.6107	0.1280	-4.77	0.000
S_900m	-0.0732	0.0317	-2.31	0.021
S_1200m	-0.1350	0.0229	-5.89	0.000
S_1500m	-0.1782	0.0165	-10.79	0.000
S_1800m	-0.0919	0.0179	-5.13	0.000
S_2100m	0.4481	0.0769	5.83	0.000
Hwy_150m	0.1287	0.0403	3.19	0.001
Hwy_250m	-0.0176	0.0341	-0.52	0.605
Hwy_350m	1.1380	0.1367	8.32	0.000
LT_100m	0.6137	0.0765	8.02	0.000
LT_200m	0.3819	0.0749	5.10	0.000
LT_300m	0.2878	0.0797	3.61	0.000
Lambda (λ)	0.1004	0.0271	3.70	0.000
Pseudo R^2	0.792			

APPENDIX D

ESTIMATION RESULTS FOR THE INDUSTRIAL PROPERTIES

(N = 360)

Variable	Coef	Std. Err.	z-stat	Sig.
(Constant)	5.1911	1.4664	3.54	0.000
Structural Variables (S_i)				
Lot(ln)	0.5300	0.0252	21.05	0.000
T_Interior (ln)	0.4849	0.0417	11.64	0.000
Stories	-2.1428	0.4318	-4.96	0.000
Age	-0.0123	0.0028	-4.33	0.000
NeighborhoodVariables (L_i)				
Median_HH (ln)	0.1494	0.1019	1.47	0.142
Pop_Dens (ln)	0.0312	0.0317	0.99	0.324
Locational Variables (N_i)				
Dist_CBD (ln)	0.0848	0.0739	1.15	0.251
Dist_Air (ln)	-0.1928	0.0679	-2.84	0.004
Dist_Mall (ln)	-0.0094	0.0494	-0.19	0.850
Dist_Arterial (ln)	0.0061	0.0359	0.17	0.865
Exit_300m	0.2735	0.1217	2.25	0.025
Exit_600m	0.2957	0.0870	3.40	0.001
Exit_900m	0.0831	0.0817	1.02	0.309
S_600m	1.7012	0.4288	3.97	0.000
S_900m	0.5148	0.2349	2.19	0.028
S_1200m	0.2707	0.3929	0.69	0.491
Hwy_150m	-0.4986	0.1108	-4.50	0.000
Hwy_250m	-0.6264	0.1096	-5.72	0.000
Hwy_350m	-0.3208	0.1291	-2.48	0.013
LT_100m	-0.1123	0.4200	-0.27	0.789
LT_200m	-1.2516	0.2502	-5.00	0.000
LT_300m	-1.9279	0.7329	-2.63	0.009
Lambda (λ)	0.2111	0.0512	4.12	0.000
Pseudo R^2	0.871			

APPENDIX E

ESTIMATION RESULTS FOR THE OFFICE PROPERTIES

(N = 1,214)

Variable	Coef	Std. Err.	z-stat	Sig.
(Constant)	7.4797	0.8121	9.21	0.000
Structural Variables (S_i)				
Lot (ln)	0.5704	0.0155	36.79	0.000
T_Interior (ln)	0.3212	0.0254	12.66	0.000
Stories	0.0600	0.0178	3.36	0.001
Age	-0.0131	0.0015	-8.50	0.000
Neighborhood Variables (L_i)				
Median_HH (ln)	0.1715	0.0536	3.20	0.001
Pop_Dens (ln)	0.0248	0.0217	1.14	0.253
Locational Variables (N_i)				
Dist_CBD (ln)	-0.0678	0.0433	-1.57	0.117
Dist_Air (ln)	-0.2253	0.0357	-6.32	0.000
Dist_Mall (ln)	-0.2150	0.0280	-7.69	0.000
Dist_Arterial (ln)	-0.0180	0.0226	-0.80	0.426
Exit_300m	0.4852	0.1272	3.82	0.000
Exit_600m	0.1026	0.0595	1.72	0.085
Exit_900m	-0.0064	0.0482	-0.13	0.895
S_300m	0.7605	0.1704	4.46	0.000
S_600m	0.5427	0.0929	5.84	0.000
S_900m	0.2913	0.1121	2.60	0.009
S_1200m	0.4369	0.1222	3.58	0.000
S_1500m	0.1974	0.1559	1.27	0.205
Hwy_150m	-0.1386	0.1290	-1.07	0.283
Hwy_250m	0.0703	0.1121	0.63	0.530
Hwy_350m	0.0425	0.0879	0.48	0.628
LT_100m	-0.4832	0.1469	-3.29	0.001
LT_200m	-0.1370	0.1829	-0.75	0.454
LT_300m	-0.4380	0.1452	-3.02	0.003
Lambda (λ)	0.2197	0.0388	5.66	0.000
Pseudo R^2	0.83			

APPENDIX F

ESTIMATION RESULTS FOR RETAIL AND SERVICE PROPERTIES

(N = 2,068)

Variable	Coef	Std. Err.	z-stat	Sig.
(Constant)	6.2584	0.8042	7.78	0.000
Structural Variables (S_i)				
Lot (ln)	0.6492	0.0180	36.00	0.000
T_Interior (ln)	0.2341	0.0197	11.88	0.000
Stories	0.1872	0.0502	3.73	0.000
Age	-0.0122	0.0012	-10.35	0.000
Neighborhood Variables (L_i)				
Median_HH (ln)	0.2137	0.0621	3.44	0.001
Pop_Dens (ln)	-0.0116	0.0251	-0.46	0.644
Locational Variables (N_i)				
Dist_CBD (ln)	-0.1048	0.0457	-2.29	0.022
Dist_Air (ln)	-0.0781	0.0406	-1.92	0.054
Dist_Mall (ln)	-0.1364	0.0268	-5.08	0.000
Dist_Arterial (ln)	-0.1626	0.0280	-5.80	0.000
Exit_300m	0.1408	0.1216	1.16	0.247
Exit_600m	0.0830	0.0641	1.29	0.195
Exit_900m	-0.0144	0.0580	-0.25	0.804
S_300m	1.0809	0.2232	4.84	0.000
S_600m	0.4114	0.1257	3.27	0.001
S_900m	0.3393	0.1273	2.67	0.008
S_1200m	0.1473	0.1138	1.29	0.196
Hwy_150m	-0.3532	0.1066	-3.31	0.001
Hwy_250m	-0.3318	0.1015	-3.27	0.001
Hwy_350m	-0.2262	0.0810	-2.79	0.005
LT_100m	-0.4247	0.1905	-2.23	0.026
LT_200m	-0.6110	0.1987	-3.08	0.002
LT_300m	-0.4440	0.1861	-2.38	0.017
Lambda (λ)	0.5474	0.0335	16.32	0.000
Pseudo R^2	0.782			

APPENDIX G

DETAILED RESULTS FOR VALLEJO

(N = 6,127)

Variable	Coef.	Std.err	z-Stat	Sig.
(CONSTANT)	6.017576	0.264061	22.789	0.000
Structural variables				
ln_LivinSq	0.427330	0.023678	18.048	0.000
ln_LotSqft	0.073282	0.011486	6.380	0.000
N_Rooms	0.038432	0.004267	9.007	0.000
N_Story	0.043093	0.011087	3.887	0.000
Age	-0.004024	0.000331	-12.174	0.000
FIREPLC	0.088164	0.009613	9.171	0.000
pooldum	0.082147	0.022325	3.680	0.000
ln_Garage	0.015765	0.002424	6.503	0.000
Neighborhood variables				
ln_M_incom	0.272882	0.018122	15.058	0.000
ln_PopDens	0.002007	0.005805	0.346	0.729
PCI_Year_Same	-0.000199	0.000127	-1.568	0.117
Locational variables				
ln_CBD	-0.165956	0.014277	-11.624	0.000
ln_Exit	0.065236	0.007834	8.328	0.000
All_Arterial	-0.064767	0.019322	-3.352	0.001
ln_Park	0.044381	0.004495	9.873	0.000
Hwy320	-0.010824	0.012022	-0.900	0.368
In_Water	0.041894	0.004868	8.607	0.000
Y_09	-0.160042	0.015318	-10.448	0.000
Y_10	-0.199754	0.012974	-15.396	0.000
Y_11	-0.277327	0.013000	-21.333	0.000
Y_12	-0.262691	0.012442	-21.113	0.000
Y_13	-0.181814	0.013709	-13.262	0.000
Y_14	-0.032750	0.013965	-2.345	0.019
Lambda	0.197763	0.014103	14.022	0.000
Pseduo R^2	0.6975			
OLS Adjusted R^2	0.6968			

APPENDIX H

DETAILED RESULTS FOR VACAVILLE

(N = 5,165)

Variable	Coef.	Std.err	z-Stat	Sig.
(CONSTANT)	7.323418	0.192834	37.978	0.000
Structural variables				
ln_LivinSq	0.592843	0.019064	31.097	0.000
ln_LotSqft	0.139476	0.010687	13.051	0.000
N_Rooms	0.002322	0.003805	0.610	0.542
N_Story	-0.031342	0.006297	-4.977	0.000
Age	-0.006558	0.000351	-18.679	0.000
FIREPLC	0.028646	0.007788	3.678	0.000
pooldum	0.070016	0.006079	11.517	0.000
ln_Garage	0.004628	0.003618	1.279	0.201
Neighborhood variables				
ln_M_incom	0.053484	0.015073	3.548	0.000
ln_PopDens	-0.032788	0.003319	-9.880	0.000
PCI_Year_Same	-0.000135	0.000173	-0.781	0.435
Locational variables				
ln_CBD	-0.069189	0.008111	-8.530	0.000
ln_Exit	0.027390	0.006860	3.993	0.000
All_Arterial	-0.021555	0.017183	-1.254	0.210
ln_Park	-0.001989	0.002515	-0.791	0.429
Hwy320	-0.081328	0.023540	-3.455	0.001
Y_09	0.068406	0.009486	7.211	0.000
Y_10	0.003586	0.007541	0.476	0.634
Y_11	-0.044223	0.008097	-5.461	0.000
Y_12	-0.051043	0.007302	-6.990	0.000
Y_13	-0.010513	0.008366	-1.257	0.209
Y_14	0.040298	0.007075	5.696	0.000
Lambda	0.213770	0.015327	13.947	0.000
Pseduo R^2	0.7742			
OLS Adjusted R^2	0.7734			

APPENDIX I

DETAILED RESULTS FOR FAIRFIELD

(N = 4,962)

Variable	Coef.	Std.err	z-Stat	Sig.
(CONSTANT)	5.970766	0.206266	28.947	0.000
Structural variables				
ln_LivinSq	0.614502	0.020017	30.699	0.000
ln_LotSqft	0.137969	0.010184	13.548	0.000
N_Rooms	0.017865	0.003817	4.681	0.000
N_Story	-0.055483	0.006912	-8.027	0.000
Age	-0.006447	0.000455	-14.161	0.000
FIREPLC	0.005869	0.008483	0.692	0.489
pooldum	0.050344	0.009756	5.160	0.000
ln_Garage	0.004081	0.003764	1.084	0.278
Neighborhood variables				
ln_M_incom	0.136661	0.015741	8.682	0.000
ln_PopDens	-0.035981	0.003214	-11.194	0.000
PCI_Year_Same	0.000692	0.000184	3.766	0.000
Locational variables				
ln_CBD	0.000764	0.007800	0.098	0.922
ln_Exit	-0.032463	0.004951	-6.557	0.000
All_Arterial	-0.027879	0.021930	-1.271	0.204
ln_Park	-0.000687	0.002571	-0.267	0.789
Hwy320	-0.036053	0.007892	-4.568	0.000
Rail_300	-0.047694	0.019161	-2.489	0.013
Y_09	-0.079683	0.011119	-7.167	0.000
Y_10	-0.053059	0.009912	-5.353	0.000
Y_11	-0.092784	0.008800	-10.544	0.000
Y_12	-0.097514	0.009059	-10.764	0.000
Y_13	-0.058329	0.010119	-5.764	0.000
Y_14	0.036923	0.011120	3.320	0.001
Lambda	0.302072	0.018920	15.966	0.000
Pseduo R^2	0.8595			
OLS Adjusted R^2	0.8591			

APPENDIX J

DETAILED RESULTS FOR SUISUN CITY

(N = 1,645)

Variable	Coef.	Std.err	z-Stat	Sig.
(CONSTANT)	6.646483	0.445893	14.906	0.000
Structural variables				
ln_LivinSq	0.541919	0.032842	16.501	0.000
ln_LotSqft	0.076824	0.019962	3.849	0.000
N_Rooms	0.005695	0.006883	0.827	0.408
N_Story	0.004021	0.011902	0.338	0.736
Age	-0.004813	0.000673	-7.155	0.000
FIREPLC	0.030999	0.021440	1.446	0.148
pooldum	-0.030921	0.025837	-1.197	0.231
ln_Garage	-0.019370	0.009480	-2.043	0.041
Neighborhood variables				
ln_M_incom	0.158558	0.045066	3.518	0.000
ln_PopDens	-0.022626	0.003959	-5.715	0.000
PCI_Year_Same	0.000292	0.000159	1.837	0.066
Locational variables				
ln_CBD	0.063991	0.025976	2.463	0.014
ln_Exit	-0.079662	0.075862	-1.050	0.294
All_Arterial	0.006775	0.026849	0.252	0.801
ln_Park	0.008232	0.007400	1.112	0.266
Rail_300	0.048228	0.019632	2.457	0.014
Y_09	-0.012626	0.016503	-0.765	0.444
Y_10	-0.042801	0.012676	-3.377	0.001
Y_11	-0.132169	0.012437	-10.627	0.000
Y_12	-0.128496	0.012322	-10.428	0.000
Y_13	-0.089400	0.015582	-5.737	0.000
Y_14	0.014054	0.014192	0.990	0.322
Lambda	0.187196	0.052399	3.573	0.000
Pseduo R^2	0.6884			
OLS Adjusted R^2	0.6845			

APPENDIX K

DETAILED RESULTS FOR BENICIA

(N = 971)

Variable	Coef.	Std.err	z-Stat	Sig.
(CONSTANT)	9.677788	0.394037	24.561	0.000
Structural variables				
ln_LivinSq	0.370596	0.032714	11.328	0.000
ln_LotSqft	0.130883	0.019022	6.881	0.000
N_Rooms	0.031007	0.006182	5.016	0.000
N_Story	-0.033080	0.012277	-2.695	0.007
Age	-0.002529	0.000778	-3.251	0.001
FIREPLC	0.030715	0.017734	1.732	0.084
pooldum	0.036694	0.021116	1.738	0.083
ln_Garage	0.012369	0.005299	2.334	0.020
Neighborhood variables				
ln_M_incom	-0.017523	0.034474	-0.508	0.611
ln_PopDens	0.027344	0.006047	4.522	0.000
PCI_Year_Same	-0.000409	0.000242	-1.689	0.091
Locational variables				
ln_CBD	-0.073841	0.017193	-4.295	0.000
ln_Exit	0.048054	0.016273	2.953	0.003
All_Arterial	0.569833	0.155511	3.664	0.000
ln_Park	0.005921	0.005772	1.026	0.305
Hwy320	-0.067580	0.021376	-3.162	0.002
ln_Water	-0.052992	0.008896	-5.957	0.000
Y_09	0.152637	0.022313	6.841	0.000
Y_10	0.059731	0.018831	3.172	0.002
Y_11	0.012265	0.017994	0.682	0.496
Y_12	0.007036	0.017623	0.399	0.690
Y_13	0.003733	0.018209	0.205	0.838
Y_14	0.012183	0.020224	0.602	0.547
OLS Adjusted R^2	0.7453			

APPENDIX L

DETAILED RESULTS FOR DIXON

(N = 279)

Variable	Coef.	Std.err	z-Stat	Sig.
(CONSTANT)	8.420707	1.192911	7.059	0.000
Structural variables				
ln_LivinSq	0.452588	0.049480	9.147	0.000
ln_LotSqft	0.112033	0.029315	3.822	0.000
N_Rooms	-0.002657	0.009707	-0.274	0.785
N_Story	-0.000344	0.017246	-0.020	0.984
Age	0.000324	0.000888	0.365	0.715
FIREPLC	0.158933	0.029164	5.450	0.000
pooldum	0.033420	0.020374	1.640	0.102
ln_Garage	0.007918	0.014536	0.545	0.586
Neighborhood variables				
ln_M_incom	-0.234321	0.089847	-2.608	0.010
ln_PopDens	-0.059096	0.019751	-2.992	0.003
PCI_Year_Same	-0.003663	0.000678	-5.404	0.000
Locational variables				
ln_CBD	0.348714	0.048736	7.155	0.000
ln_Exit	0.076687	0.028198	2.720	0.007
ln_Park	0.003750	0.009479	0.396	0.693
Hwy320	0.010192	0.019681	0.518	0.605
Y_09	0.144242	0.028864	4.997	0.000
Y_10	0.083654	0.026488	3.158	0.002
Y_11	0.018345	0.025816	0.711	0.478
Y_12	0.025416	0.026028	0.976	0.330
Y_13	0.031182	0.027046	1.153	0.250
Y_14	0.065733	0.026933	2.441	0.015
OLS Adjusted R^2	0.8149			

APPENDIX M

DETAILED RESULTS FOR RIO VISTA

(N = 243)

Variable	Coef.	Std.err	z-Stat	Sig.
(CONSTANT)	6.346067	0.638800	9.934	0.000
Structural variables				
ln_LivinSq	0.705706	0.091025	7.753	0.000
ln_LotSqft	0.129136	0.070403	1.834	0.067
N_Rooms	0.034533	0.017685	1.953	0.051
N_Story	-0.139873	0.039638	-3.529	0.000
Age	-0.003281	0.000791	-4.146	0.000
FIREPLC	-0.029101	0.031292	-0.930	0.352
pooldum	0.086338	0.086198	1.002	0.317
ln_Garage	-0.008615	0.007140	-1.207	0.228
Neighborhood variables				
PCI_Year_Same	-0.000931	0.000405	-2.298	0.022
Y_09	-0.138584	0.048934	-2.832	0.005
Y_10	-0.151194	0.036412	-4.152	0.000
Y_11	-0.207345	0.036211	-5.726	0.000
Y_12	-0.188465	0.036254	-5.198	0.000
Y_13	-0.103171	0.033410	-3.088	0.002
Y_14	0.048593	0.046521	1.045	0.296
Lambda	-0.610613	0.191054	-3.196	0.001
Pseduo R^2	0.6398			
OLS Adjusted R^2	0.6180			

APPENDIX N

DETAILED RESULTS FOR SOLANO COUNTY

(N = 216)

Variable	Coef.	Std.err	z-Stat	Sig.
(CONSTANT)	4.280763	2.052283	2.086	0.038
Structural variables				
ln_LivinSq	0.443149	0.100598	4.405	0.000
ln_LotSqft	0.089109	0.039804	2.239	0.026
N_Rooms	0.058248	0.024582	2.370	0.019
N_Story	-0.032097	0.073511	-0.437	0.663
Age	-0.001703	0.001392	-1.224	0.222
FIREPLC	0.105739	0.048151	2.196	0.029
pooldum	0.163395	0.097167	1.682	0.094
ln_Garage	0.012484	0.008900	1.403	0.162
Neighborhood variables				
ln_M_incom	0.435086	0.160509	2.711	0.007
ln_PopDens	-0.121374	0.035711	-3.399	0.001
PCI_Year_Same	0.001273	0.000881	1.444	0.150
Locational variables				
All_Arterial	-0.099721	0.096433	-1.034	0.302
Y_09	-0.220836	0.107073	-2.062	0.040
Y_10	-0.260180	0.089342	-2.912	0.004
Y_11	-0.228775	0.090660	-2.523	0.012
Y_12	-0.126993	0.097208	-1.306	0.193
Y_13	-0.156346	0.090474	-1.728	0.086
Y_14	-0.111331	0.093819	-1.187	0.237
OLS Adjusted R^2	0.8455			

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