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Transportation Noise Impacts on Residential Property Values in Los Angeles County:

A Spatial Hedonic Analysis

DISSERTATION

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DOCTOR OF PHILOSOPHY

in Transportation Science

by

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DEDICATION

To my parents, in loving memory

Hiroshi Matsubara (1924-2015)
Shizue Suzie Matsubara (1943-1997)

As you each were never afforded this opportunity, this achievement is for you. Enjoy.

To every single one of my family and friends who supported and inspired me on this long and precarious journey.

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VITA

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FIELD OF STUDY

Spatial econometric analyses of transportation corridor impacts on urban communities

ABSTRACT

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by

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Doctor of Philosophy in Transportation Science

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Professor Michael G. McNally, Chair

As population densities in urban areas increase, the associated demand on transportation infrastructure continues to exacerbate impacts on surrounding communities. These demands create a number of socioeconomic burdens including housing price impacts when communities are regularly exposed to excessive noise levels. Although noise impacts are not as commonly recognized or assessed in comparison to other environmental issues such as air, ground, or water pollution, it has been well documented in the literature that a wide range of health issues exist when communities are exposed to noise from transportation infrastructure. From a research perspective, the correlation of these health issues to the presence of impactful noise is difficult to quantify, as noise is subjective and requires translation into varying degrees of annoyance to deem it as detrimental from both health and economic perspectives. This dissertation utilizes spatial hedonic price (HP) models to estimate individuals' marginal willingness-to-pay (MWTP) to reside in noise-impacted areas. These MWTP values can then be used to both valuate economic impacts and as a noise annoyance level proxy to identify zones that are at-risk due to excessive transportation noise exposure.

The first analysis in this dissertation reviews salient transportation noise-related papers that have been published since Navrud’s comprehensive 2002 transportation noise literature review. In a review of recent literature, this dissertation found that transportation noise research has evolved to include advanced Geographic Information System data, and leverages increasingly powerful processors and statistical analysis programs. In addition, although significant transportation noise research has been conducted in Europe following EU Environmental Noise Directive 2002/49/EC, a relatively minimal number of studies have been conducted in the United States -- especially in Southern California, revealing a research gap that this dissertation helps to address.

The second analysis investigates the impacts of aircraft operations around Los Angeles International Airport. Using a subset of 2010-2014 single-family home sales data from the Los Angeles County Office of the Assessor (LACOA), HP spatial autoregressive models with autoregressive disturbances (SARAR) were estimated. The study hypothesizes and confirms that a negative impact value would be observed for homes being located within noise-mapped zones around the airport, along with an improvement in estimation values compared to previous fixed spatial effects ordinary least squares techniques.

The third analysis in this dissertation investigates two important topics. First, it hypothesizes negative home value impacts from nearby freight rail operations in the densely populated South Bay region of Los Angeles County. Noise from freight rail lines is analyzed using an HP SARAR model and confirm negative valuation impacts to homes located near these rail lines. Second, it hypothesizes that by using a subset of the master LACOA dataset above, varying levels of spatial homogeneity can be comparatively analyzed between two samples that use similar data and modeling techniques. Results indicate that when neighboring zones have distinct differences in jurisdiction, fixed spatial effect delineations remain statistically significant.

However, when neighboring zones have similar jurisdictional or demographic characteristics, spatial model parameters are able to account for fixed delineations.

CHAPTER 1

Introduction

"Everything is related to everything else. But near things are more related than distant things."

-Waldo R. Tobler (1970)

Overview

This dissertation will present a spatial econometric analysis of transportation-related noise impacts in Los Angeles County, California. To date, there has been minimal research focus on the economic and health impacts from transportation noise in Southern California. In comparison, substantial research has been conducted on transportation-related airborne pollution and its effects in the area (Su *et al.*, 2009; Houston *et al.*, 2014; Laurent *et al.*, 2014; Gabbe, 2018; Muthukumar *et al.*, 2021). Considering the overall volume of transportation activity in the region, this gap in research is surprising. When compared to densely populated areas in other similarly developed countries, the lack of attention given to this topic in the United States (U.S.) becomes evident. Extensive research has been conducted in Europe, for example, which has highlighted both the economic and health costs of regular exposure to excessive noise (Babisch, 2005; Stansfeld *et al*., 2005; Van Kempen *et al*., 2010; Dratva *et al*., 2011; Eriksson *et al*., 2012). Much of this research has been driven by European Union (EU) Environmental Noise Directive (END) 2002/49/EC (European Parliament, 2002) which mandates the monitoring and regulation of environmental noise in urban areas. As demonstrated by the volume of research conducted in Europe, this topic presents a wealth of research opportunity in the U.S. that has yet to be fully investigated.

Model specification in the transportation noise impact literature has also evolved to include more advanced econometric techniques. While many previous studies have relied on fixed effects models which did not consider spatial impacts in their data, recent trends in the published literature have favored models that better address spatial heterogeneity in their specifications (Seo *et al.*, 2014; Beimer and Maennig, 2017; Chica-Olmo *et al.*, 2019). This dissertation will contribute to the published research by utilizing spatial HP modeling to estimate transportation noise impacts on the single-family home real estate market in Los Angeles County.

Figure 1-1: Los Angeles County Map

Covering an area of 4,083 square miles, Los Angeles County is currently the most populous county in the U.S. with a 2020 population of 10,014,009 (United States Census Bureau, 2020). Projections indicate continued growth of approximately 9.2% over the next ten years, with a 2030 population estimate of 10,930,986 (California Department of Finance, 2022). To support this population, the county maintains an extensive transportation infrastructure which includes a freeway network of 515 miles (California Department of Transportation, 2020), a passenger rail network of approximately 640 miles (Metrolink, 2021; Los Angeles County Metropolitan Transportation Authority, 2021), and the second busiest commercial airport in the U.S. (Los Angeles World Airports, 2020). In addition, Los Angeles County hosts the largest seaport complex in the country which is served by two Class I railroads (United States Department of Transportation Federal Railroad Administration, 2021a).

Recent Los Angeles County data indicate a leveling in growth of annual Vehicle Miles Traveled (VMT), with passenger rail and air transportation maintaining their current growth trajectories (Los Angeles World Airports, 2020; Metrolink, 2021; Los Angeles County Metropolitan Transportation Authority, 2021). Freight traffic though the Ports of Los Angeles and Long Beach is projected to continue current growth trends through 2030 (The Port of Los Angeles, 2022). Overall, the aggregated transportation demand in the region will continue to present potential economic and health impacts in noise-affected areas.

Transportation Noise Research Overview

In the published literature, noise from various modes of transportation has been found to have quantifiable impacts from both economic and health perspectives (Giles-Corti *et al.*, 2016; Lan *et al.*, 2020; Schwela, 2021). These noise impact studies generally fall into two categories: Revealed Preference (RP) and Stated Preference (SP). RP studies typically estimate marginal willingness-to-pay (MWTP) values by investigating choices that observed individuals have made; this choice is often their residential location along with that particular location's amenities or disamenities (Scotchmer, 1985). A noise impact study, for example, would focus on the disamenity of a particular type or source of noise. These econometric noise impact studies often utilize RP HP models to estimate consumer preferences in the residential real estate marketplace. Observed behaviors can then be used as a proxy to understand the presence of perceived noise annoyance (Scotchmer, 1985), which in turn, can then be correlated to various types of noise related health impacts (Baranzini *et al.*, 2010). MWTP values have also been estimated with SP noise impact studies, which generate results through the use of surveys that present hypothetical situations (Bristow *et al.*, 2015). SP studies, however, are more commonly used to estimate annoyance levels that result from nearby noise sources, which can then be used to understand potential health impacts. In some instances, researchers have combined RP and SP models in efforts to better focus on specific preferences or behaviors (Van Praag and Baarsma, 2005; Bellinger, 2006).

Economic impact studies that investigate transportation noise most often utilize RP HP models (Bristow *et al.*, 2015). These studies typically use one of three methods to quantify noise exposure by location: published noise maps to represent noise exposure by captured geographic location, actual measured noise at various study locations, or distance from a noise source as a noise level proxy. MWTP can then be estimated according to residents' preferences for increased or decreased levels of noise. Some studies utilize a Noise Depreciation Index (NDI) which valuates MWTP per decibel of noise (Walters, 1975; Nelson, 1982). While this statistic does not consider the fact that noise sensitivity by volume level is not linear in response, these data can still be useful for comparison purposes between studies or for policy decisions (Theebe, 2004).

Published studies on the health impacts of transportation noise reveal both physical and mental health impacts (Peris and Fenech, 2020). According to the World Health Organization (WHO), "Health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity." (World Health Organization, 2006). In Europe in particular, several studies have shown that traffic noise alone affects the health of nearly one-third of the population (World Health Organization, 2009). Transportation noise has been linked to annoyance, sleep disturbance, and stress (Ouis, 2002; Maschke and Hecht, 2004). Additionally, a number of detrimental health effects has been correlated to unwanted noise exposure such as: hypertension, heart attack and stroke, ischemic heart disease, immune system suppression, infertility, birth defects, and acceleration of the aging process (Babisch, 2005; Passchier-Vermeer and Passchier, 2000; WHO, 2005; Dratva *et al.*, 2011; Eriksson *et al.*, 2012). Research has also related reduced cognitive performance and loss of productivity to sleep loss due to disturbance from noise (Elmenhorst *et al.*, 2010). The large number of people exposed to transportation noise combined with the wide range of potential health impacts suggests that the health burden of transportation noise could be substantial in noise-affected communities (Eriksson *et al.*, 2012).

Research Significance

While extensive transportation noise research has been conducted in Europe, this topic has received considerably less attention in the U.S. (Nelson, 2004). Furthermore, few studies have focused specifically on the Southern California area (Rahmatian and Cockerill, 2004). This dissertation seeks to help address this research gap by investigating impacts on the real estate market from operations at Los Angeles International Airport and from freight rail operations in the South Bay community of Los Angeles County. In addition, an extensive review of transportation noise-related literature is conducted to evaluate the current state of research on the topic.

Research methodology is also a topic of interest with this dissertation. Previously, most studies have relied on fixed effects models to evaluate transportation noise impacts (Rahmatian and Cockerill, 2004; Bellinger, 2006; Clark, 2006). However, because of variation in characteristics by geographic location, aggregate modeling may not provide an accurate representation of a study area's clustering patterns or spillover effects (Tobler, 1970). This has been shown to result in modeling errors due to spatial autocorrelation (Cliff and Ord, 1969). As recent studies have turned to spatial modeling techniques to address this issue, this dissertation will also explore the robustness of these spatial models by analyzing two dissimilarly impacted study areas within the same dataset. This dissertation will attempt to address the following research questions:

- Are real property markets impacted by large scale aircraft operations in a densely populated urban setting with multiple modes of transportation infrastructure?
- Do aircraft noise maps that designate average annual noise levels have statistically significant negative impacts on affected residential areas?

- How do real property markets value the disamenity of freight rail line proximity in residential areas?
- How do freight rail operations differ in impact when compared to transit or light rail operations?
- Do spatial modeling techniques improve upon results from past studies that utilized fixed effects models?
- Do spatial models differ in their estimations in dissimilarly delineated geographical study areas?

Estimating dollar cost impacts allows for a better understanding from an economic or cost-benefit perspective. Potential health impacts can be considered as well, as RP MWTP values can reveal the presence of noise annoyance or avoidance in residential neighborhoods (Baranzini *et al.*, 2010). Results from this dissertation can be used to assist policy makers in decisions that involve impacts from transportation noise sources.

Dissertation Structure

This dissertation is composed of three research articles which are preceded by an introduction and overarching conclusions. Chapter 1 introduces this dissertation and presents important research questions to be answered. Chapter 2 conducts an extensive review of transportation noise impact research from both economic and health perspectives. Chapter 3 presents the spatial HP price method as it applies to transportation noise impacts in an urban environment. Chapter 4 details the dataset to be used in Chapters 5 and 6. Chapter 5 investigates aircraft noise impacts from operations at Los Angeles International Airport on residential property values in surrounding communities in Los Angeles County, California. Chapter 6 examines the impacts of Class I freight rail activity on nearby residential property values in densely populated areas in the South Bay region of Los Angeles County. Finally, Chapter 7 presents conclusions to the research conducted in this dissertation.

CHAPTER 2

The Economic and Health Impacts of Transportation Noise: A Literature Review

Introduction

This chapter presents a review of published literature on transportation noise impacts in urban areas, with the objective of identifying gaps for similar research in the Southern California area. Literature was drawn from studies conducted in Europe, Asia, Africa, and North and South America in an effort to understand transportation noise impacts as they relate to different urban settings, cultures, and various levels of socioeconomic status. Salient papers published after Navrud's extensive transportation noise study in 2002 (Navrud, 2002) were reviewed and categorized by transportation mode type (aircraft, road, rail, and combined modes) and study type (revealed preference, stated preference, and hybrid methods). The chapter then reviews select studies that illustrate some of the adverse health effects caused by exposure to both transportation noise and excessive noise levels in general.

Two types of studies are most commonly used to analyze the effects of transportation noise: revealed preference (RP) and stated preference (SP). RP studies most often rely on real estate sales data and hedonic price (HP) models (Rosen, 1974) to determine the impacts of noise. Using historical real estate transaction data in specific study areas, HP models can estimate consumers' economic value of amenities and other environmental characteristics, including noise avoidance, in the residential housing market (Nelson, 2008). Results of these HP studies are often represented in the form of a Noise Depreciation Index (NDI), which indicates the effect of housing price change in percent, per A-Weighted 1 dB (dBA) increase in noise level (Walters, 1975).

SP studies rely on data gathered through conducted surveys or interviews to determine willingness-to-pay (WTP) behavior. Transportation noise SP studies generally consist of choice experiment (CE), conjoint analysis (CA), or contingent valuation (CV) techniques, which explore WTP through hypothetical situations or changes in noise levels. While not commonly utilized in earlier transportation noise studies (Navrud, 2002), contingent valuation analysis has become the most frequently used in recent years (Carson and Hanemann, 2005). Another type of study, avoidance cost, has seen limited use, mostly by German governmental agencies.

A review of some of the first published transportation noise literature revealed that early models often relied on limited numbers of explanatory variables, simple linear regression models, and frequently used linear distance to the noise source instead of actual noise measurement or noise level modeling (Holsman and Paparoulas, 1982). Later studies have evolved to incorporate more advanced econometric techniques, and have benefitted from the availability of richer datasets and geographic information systems advancements.

Following EU European Noise Directive (END) 2002/49/EC on noise assessment (European Parliament, 2002), transportation noise data has been regularly collected throughout Europe for research and noise map generation. Consequently, when compared to the rest of the world, European countries have received the greatest attention in the area of transportation noise research. Additionally, among the three major sources of transportation noise (aircraft, road, and rail), aircraft noise often receives the most attention for study and research due to its extensive policy and environmental implications.

This literature review will begin by focusing on aircraft noise studies. Road and then rail noise impact studies are reviewed next, followed by literature that analyzes multiple mode noise impacts. Finally, papers that focus on health impacts are reviewed to gain a better understanding of the actual mental and physiological impacts caused by transportation noise.

Aircraft Noise Studies

Traditionally, aircraft noise valuation studies have relied upon RP techniques, utilizing HP models in most cases (Nelson, 2004). Analysis of aircraft noise has gained popularity in recent years, especially in developing countries (Akpan *et al.*, 2012; Chalermpong, 2010; Elmehdi, 2012). Policymakers in these areas have become more concerned about the detrimental health and economic impacts of noise, and have made efforts to better understand the level and frequency of noise annoyance on residents.

SP approaches had previously seen little use in the area of aircraft noise valuation but have become more popular in recent years; when properly paired with RP models, they have proven effective in estimating MWTP (Van Praag and Baarsma, 2005).

Revealed Preference Studies

In an HP study around Raleigh-Durham International Airport in North Carolina, Pope (2008) observed that a 1997 official disclosure of noise level to potential home buyers and sellers had a significant negative impact on housing prices. While this noise information was already publicly available, the mandatory disclosure served to reinforce buyers' awareness of noise levels, resulting in an additional 2.9 percent decrease in property prices beyond the 7.9 percent noise discount already in effect. This 37 percent change implies that buyers were probably not fully informed about airport noise in the area, but more importantly, it suggests that implicit price estimates may often only be a lower bound for noise disamenities.

Cohen and Coughlin (2009) studied 1995 to 2002 single-family home sales near the Hartsfield-Jackson Atlanta International Airport using noise contour maps from 1995 and 2003 supplied by the City of Atlanta Department of Aviation. Those data were used in conjunction with

GIS software to map 2,370 single-family homes in 65 dBA and 70 dBA noise areas adjacent to the airport. Their HP models indicated an overall increase in property values over time as noise decreased between 1995 and 2003, which they attributed to increasingly stringent noise regulations. Property values were positively correlated with distance to the airport, and depending on model specification, indicated discounts between 7.5 percent and 10.6 percent in the 65 dBA noise areas, with 12.3 percent to 17.7 percent discounts in the 70 dBA areas. Larger discounts were observed during the 2000-2002 period, warranting further investigation and research.

The first known aircraft noise study in Thailand, an HP study by Chalermpong (2010) near Suvarnabhumi International Airport near Bangkok analyzed 384 real estate sales of new homes that occurred between 2002 and 2008. Key investigation surrounded the possibility of anticipatory reaction to aircraft noise effects from the initiation of airport operations, which began in September of 2006. OLS with spatial weighting was utilized to correct for spatial autoregression in the data, with a resulting NDI of -2.12 percent. While prices of properties sold after 2006 decreased between 8.55 percent and 19.15 percent, no anticipatory effects were observed prior to 2006. Conclusions indicate that residents were not aware of potential noise impacts, but were substantially affected by noise once airport operations commenced.

Boes and Nuesch (2011) argued that cross-sectional HP studies suffer from omitted variable bias due to unobserved neighborhood characteristics. In a quasi-experiment repeat-rent apartment study, they took advantage of an October 2003 change in flight regulations at Zurich Airport that created an exogenous variation in aircraft noise levels. They included fixed effects and time-varying controls in their difference-in-difference model to analyze a panel of 687 apartment rentals between 2001 and 2006, with noise values estimated from a model specified by the Swiss Federal Laboratories for Materials Science and Technology (EMPA). It was estimated that apartment rents experienced an NDI of -0.5 percent. Their results suggest that cross-sectional noise studies generally overestimate noise impacts due to the negative correlation between aircraft noise and omitted amenities, and that noise effects are unlikely to be constant over the entire noise range.

Stated Preference Studies

Carlsson *et al.* (2004) studied the area adjacent to Broma Airport in Stockholm, Sweden, to investigate residents' WTP to avoid aircraft noise. They sent 1,558 questionnaires in 2003 and obtained a 46% response rate. Demographic information was polled along with hypothetical monetarily compensated choice sets that proposed increases or decreases in the number of airport landings beyond actual volumes. Increases in the number of landings offered payment to the respondent, with decreases requiring payment from the respondent. Time of day and weekday/weekend variables were also incorporated into the survey. Mixed logit models were used to estimate WTP for the various scenarios considered, with higher marginal valuations observed for mornings and evenings. The authors noted an interesting asymmetry in responses depending on the scenario considered: in the group polled for increases in the number of landings, 45 percent preferred no change, but this percentage increased to 75 percent in the group that was polled for a proposed decrease.

Thanos *et al.* (2011) capitalized on the relocation of Athens' airport in 2000 by conducting a door-to-door stated choice survey of 700 area residents in 2005. They recorded opinions on actual temporal changes in airport noise, with relevant monetary valuations measured through hypothetical variations in local tax payments. Noise data was modeled by EUROCONTROL and was estimated for each respondent's residential location. Using multinomial logit models, WTP values from noise at the old and new airport locations were found to be very similar, with the most notable differences arising from respondents' education and income levels.

In South Nigeria, Akpan *et al.* (2012) conducted an SP study around Port Harcourt International Airport. A survey questionnaire was randomly distributed to 1,800 residents within 45km of the airport which resulted in an 86 percent response rate. Those data were used for initial estimates of demographic concern with noise, which indicated that middle and higher income individuals of working age were most concerned with noise. Effects of noise above 65 dBA at night were relatively low, indicating the possibility of adaptation to higher average noise levels. Overall, annoyance increased with higher noise levels. Results also indicate that annoyance from aircraft noise increased with income level, which parallels findings in urban areas in developed countries.

Elmehdi (2012) conducted a first-ever survey at Dubai International Airport, to measure annoyance by area residents from aircraft noise. Primary noise data was gathered from nine locations near the airport, and face-to-face interviews were conducted with 207 respondents, each of whom lived within 150 meters of one of the nine measurement locations. Forty one percent of the respondents indicated high annoyance with aircraft noise, with 13 percent indicating no annoyance. Background noise was indicated to be higher than average in this study, however. Annoyance was also found to be higher than that for similar studies conducted in other parts of the world. Additional noise location measurements are planned for future research to continue investigation at this site.

Hybrid Revealed/Stated Preference Studies

Van Praag and Baarsma (2005) performed a hybrid HP/SP study in the vicinity of the Schiphol Airport in Amsterdam. Their study was intended to estimate the compensation cost for noise that residents are subjected to in neighborhoods near the airport. A 1998 questionnaire was mailed to residents within 50 kilometers of the airport, with a 17 percent response rate. Fourteen hundred respondents answered the 51-question SP survey, which included nine sources of noise to mask the main purpose of this study, and an ordered probit model was estimated to quantify residual shadow cost of aircraft noise. Noise perception was found to be dependent on a number of demographic variables, including income, family size, monthly expenses, and residential features. As predicted, the presence of noise had a negative effect on respondents' sense of well-being. Representative monetary compensation amounts varied, but were mostly dependent upon level of residence insulation from noise, with a decreasing percentage of compensation required as overall noise levels increased.

Road Noise Studies

Although aircraft noise has historically received the most attention, researchers have recently started to focus their attention on road noise partly because of increasing concerns about the health impacts of environmental noise in urban areas. With road noise being found to be one of the most prevalent sources of noise annoyance (Piccolo *et al.* 2005; Ndrepepa and Twardella, 2011), salient papers dealing with urban road noise are reviewed below.

Revealed Preference Studies

Kim *et al.* (2007) conducted an HP study of single-family and row houses in areas adjacent to the Inner Circular highway, in central Seoul, Korea. Real estate, demographic, property, and traffic data were gathered from 2002 to 2004. They focused on a 500-meter buffer zone around the highway that was composed mostly of mixed commercial and residential areas. Distance to the highway was used as a proxy for noise levels, with dummy variables used to identify areas with tunnels, overpasses, or noise barriers. Using OLS, they found an NDI of -1.3%, which is on the higher side of typically observed estimates.

Blanco and Flindell (2011) conducted a comparative HP study of real estate listings for apartments and flats from 2005 from three U.K. municipalities; 407 listings from London, 226 listings from Birmingham, and 86 listings from Sutton Coldfield. Using a standard HP model estimated with OLS, they found significant NDI values of -0.45% and +0.58% in London and Sutton Coldfield, respectively. Although results for London were comparable with previous studies, the positive NDI value for Sutton Coldfield was not. The researchers theorize that the Sutton Coldfield value of +0.58% was attributed to a case of higher property prices in higher sound level areas, with the positive value of proximity to the central business district offsetting negative effects from noise.

Brandt and Maennig (2011) estimated a quadratic HP model to assess the impacts of road noise on condominium sale prices in Hamburg, Germany. Based on 4,832 transactions from April 2002 through March 2008, the study included block-level government-provided noise data and demographic variables. A spatial lag term was used to control for spatial autocorrelation, with variables included to account for aircraft and rail noise. Accessibility benefits based on road width were also accounted for in the model. Non-linear values for road noise effects were observed, with an average NDI of -0.23% at approximately 55 dBA. Lower impacts from road noise were observed at lower noise levels, with higher effects occurring at higher noise levels, demonstrating a response similar to CV survey studies.

Stated Preference Studies

Wardman and Bristow (2004) compared SP and CV models in a study of consumer behavior dealing with air quality and traffic noise in Edinburg, Scotland. Surveys were completed between September and November 1996 by 398 respondents residing in single-family homes. Along with perceived environmental quality ratings, hypothetical CV situations of 50 percent improvements in air quality and noise situations were presented in the survey. Variations in WTP for these two environmental attributes were found not only to be influenced by income level and household size, but also by the number of adults in a household. Additionally, they observed that CV WTP values were consistently lower than SP values for the same attributes, which concurred with other studies as well (e.g., see Arsenio *et al.*, 2002). This is consistent with observations by

Hanley *et al.* (2001) that intended CV payments are generally less than payments observed during actual behavior.

Arsenio *et al.* (2006) conducted an SP traffic noise experiment, where respondents were asked to rate environmental variables on a 0-100 scale in different apartment units within the same building. Along with noise as one of the variables, variables characterizing view and sunlight were incorporated in their survey to mask the purpose of their study, with housing service charge used as a representative cost variable. Mean noise measurements were recorded in each study apartment for use in comparison to perceived noise results. Binary and mixed logit choice models were then estimated to estimate their respondents' marginal value of perceived noise. Results indicated that changes in noise levels were non-linear and were perceived to be noisier at higher levels.

Using extensive primary noise measurement maps in Valladolid, Spain, Martin *et al.* (2006) conducted an SP survey to assess road noise annoyance and associated WTP. In 2002, 490 primary noise measurement locations were taken throughout the city. Locations were separated by a 250-meter grid pattern, with four day and four night measurements recorded during varying times of the year. 296 locations were selected based on their proximity to dwellings, with a single survey conducted at each location. Surveys consisted of demographic, noise annoyance, and valuation of hypothetical situation questions. Results indicate that areas where individuals are highly annoyed by noise coincide closely with areas that experience noise levels above 65 dB A. Approximately 29 percent of these respondents had already performed some type of noise insulation at their residences. Fifty four percent of those polled indicated that they would prefer to live in a noise-free environment, even at the expense of living in a property of lower value than their current residence. In addition, 50 percent of people surveyed were willing to pay between 3 and 96 euros per year to reduce noise to some degree.

Li *et al.* (2009) surveyed 667 random Hong Kong residents between July 2007 and June 2008. They presented discrete choice apartment scenarios to respondents, along with noise annoyance ratings based on a ten-point scale. Noise measurements were also taken to compare measured noise versus polled annoyance levels. A conditional logit model showed that observed MWTP was higher for higher income individuals (HK$5.0 vs. HK$3.4 at 55 dBA; HK$8.7 vs. HK$5.9 at 75 dBA). Higher MWTP was also observed at higher noise levels, demonstrating the non-linear impact of noise.

Lera-Lopez *et al.* (2012) conducted a CV study in Navarre, Spain to investigate road noise MWTP in a smaller village-type area. Nine hundred people were polled in face-to-face interviews and asked to consider various scenarios of noise and pollution, with monetary valuation represented by a hypothetical tax payment. Demographic information, respondents' environmental concern levels, and neighborhood characteristic data were also gathered. In addition, the number of transportation trucks registered in the area was estimated, as trucks contribute significantly to noise and air pollution. ARESSE Engineering (ARESSE) noise and pollution model estimates were used to designate zones by pollution and noise level categories in a GIS model of the study area. Probit model results indicate that younger individuals with higher educational levels have a higher MWTP, especially if they live in areas with higher truck traffic. People with higher environmental awareness, as well as people already exposed to higher levels of noise and pollution also demonstrated a higher MWTP.

Banerjee (2013) drew samples from an ongoing major public health survey conducted in Asansol, India to assess noise annoyance among local adults. Surveys were completed by 221 residents living in the area for ten or more years and whose residence was located within 50m of a highway, arterial, or secondary road. Primary noise data were collected at various locations and times of day to measure actual noise levels, which could then be correlated with stated annoyance levels. Results revealed slightly more annoyance by males, and increasing annoyance with higher noise levels. As in other SP studies, this study found middle-aged individuals to be most annoyed by transportation noise.

Mirsanjari (2013) conducted a noise annoyance study in downtown Tehran, Iran, near the Kordestan Highway. Surveys were completed by 140 respondents, gathering both demographic and categorical levels of noise annoyance. Primary noise data were recorded at 14 locations near the survey zone over a two-week period, both during the day and at night. Measured data revealed noise levels between 62.6 dBA and 77 dBA, which were well above the specified acceptable limit of 60 dBA. Survey results indicated that 37.9 percent of respondents were annoyed or highly annoyed by noise, especially between 6pm and 10pm for 43 percent of respondents; moreover, 46.2% of respondents revealed that traffic noise disturbed their sleeping patterns, and that traffic noise was more annoying than street or construction noise in the area.

Rail Noise Studies

A number of RP and SP studies have been conducted on the analysis of railway impacts. However, most of these studies focus on factors related to passenger rail accessibility benefits. As noted by Navrud (2002), there has previously been very limited study solely in the area of rail noise valuation. Prior to his 2002 transportation noise review, only two RP studies had been conducted that specifically focused on the valuation of rail noise.

Revealed Preference Studies

Using 1996 and 1999 housing sale data, Simons and El Jaouhari (2004) studied the effects of a 1997 announcement of freight train routing changes in Cuyahoga County, Ohio. Based on sales data of 32,700 single-family homes in the area, their HP OLS model showed no significant pricing impacts based on rail distance or number of nearby freight train trips for the 1996 dataset. For the 1999 dataset, however, statistically significant negative effects were observed in each of the survey buffer zones, which were 250, 500, and 750 feet from the rail line. Pricing effects among the various housing price categories of between -$84.92 to -$262.01 per nearby freight train trip correlated to overall price changes of -0.104% to -2.677%, respectively.

Cushing-Daniels and Murray (2005) conducted a study in the state of Wisconsin to investigate the welfare effects of warning whistles on trains. Data from 1999 to 2004 from the US Census Bureau, US Federal Railroad Administration, and the Wisconsin Department of Transportation was used for the study. While the purpose of their research was to focus on the societal cost of accidents and deaths in relation to train whistle bans, the HP portion of the study provided a valuation of the presence of whistle bans on housing prices. A two-stage least squares model was used to estimate the housing price effects of various demographic and property characteristics, one of which was the implementation of a ban on train whistles. Using OLS semi log model, a coefficient value of 0.139 representing the percent of area crossings with a whistle ban in place was observed. In the absence of a train whistle ban, this coefficient would also represent the negative cost of train whistle use.

Chang and Kim (2013), in response to recommendations on construction and maintenance of noise-reduction walls by the Korea Rail Network Authority in Seoul, Korea, conducted HP estimates of rail noise using 1,088 observations of housing sale transactions from the local area. Property, accessibility, demographic, and neighborhood characteristics were used as variables to estimate the model. A proprietary formula for property noise level from the Korea Development Institute (2008) was used to estimate noise levels at each property. Of the 1,088 observations, 925 (or 85%) were randomly selected and used for model estimation, with the remaining 163 (or 15%) of the sample used for model validation. An NDI value of -0.53% was observed with the model, which was well within predicted values for the study.

Freight rail influences on 270 single-family home values were analyzed in Santa Marta, Columbia by Chica-Olmo et al. (2019) using spatial autoregression, spatial error, and regression kriging models. An item of interest in their analysis was using Moran's *I* and Akaike Information Criterion statistics to optimize spatial weight bandwidth values. They found that outputs from the three models was similar in result, with negative impacts significant up to 320 meters from the rail line. Negative impacts were between 14% and 23.7%, which align with results from previous HP studies.

Stated Preference Studies

Ali (2005) conducted a noise annoyance field study in Assiut, Egypt. Primary day and night noise measurements were taken in five different areas around the city, at six distances ranging from 25m to 800m from the railway track. 714 respondents were polled for the survey portion of the study, which included annoyance questions, psychological and physiological effect questions, and choices of solutions for rail noise mitigation. 51.3 percent of respondents noted that railway noise was audible, with 48.5 percent of that group stating that they were annoyed or highly annoyed. These responses were from areas that experienced 80 dBA or higher noise levels from railway traffic. Some areas experienced noise levels of over 90 dBA, which is well above the threshold to cause hearing damage.

Hybrid Revealed/Stated Preference Studies

Bellinger (2006) conducted a study on the effects of train horn noise in Wormleysburg, Pennsylvania. Observations for 192 housing sale transactions from 1980 to 2004 were used for the HP portion of the study, with housing prices adjusted for inflation using a Harrisburg, Pennsylvania housing price index. Only property variables were used for the OLS regression, along with a modeled noise value based on distance from the railway track. Results indicated an NDI of -0.41% based on a noise threshold of 50 dBA. A survey of 126 area respondents was also conducted in the summer of 2005. Noise and annoyance ratings between 1 and 5 were polled, along with the choice of any hypothetical monetary value to eliminate all train horn noise in the area. As expected, survey results indicated higher annoyance in the higher horn noise areas, with the MWTP portion of the survey indicating values between $13.06 and $30.18 per month. RP and SP results were not combined and were analyzed separately in this study.

Combined Transportation Mode Noise Studies

It has been observed that aircraft noise ranks as the most annoying type of transportation noise, followed by road noise and then rail noise (Elmenhorst *et al.*, 2014; Brink *et al.*, 2019). Aircraft noise is considered to cause the highest negative impact, due to its high noise levels when present and its infrequency. While rail also generates infrequent disturbances, it has much less impact than aircraft due to the ability to hear trains coming well in advance. Sound insulation in residences is also effective in reducing rail noise but is much less effective with noise from aircraft. Road noise is characterized by constant levels of noise, which results in less disturbance even with higher overall noise levels. Many combined noise studies are conducted to understand the differing impacts of various noise sources when directly compared to each other, and are often used to validate results from single-source studies.

Revealed Preference Studies

Theebe (2004) conducted a piecewise HP transportation noise study in the western Netherlands in the provinces of North-Holland, South-Holland, and Utrecht. Based on real estate sales data from 1997 to 1999, over 160,000 transactions of single- and multi-family homes were analyzed, along with government-supplied noise and demographic data. Noise levels were determined by using average noise data within 100-meter by 100-meter grid zones. Distance to highway onramps and rail stations was also incorporated into the analysis to determine accessibility effects due to transportation corridor proximity. By using dummy variable categories for varying noise levels (in 5 dBA increments), a non-linear response to noise was observed with NDIs ranging from no impact below 65 dBA to -0.5 percent at 70 dBA. Additionally, higher income areas were more sensitive to noise, as were residents in multifamily homes when compared to those living in single-family homes.

Baranzini and Ramirez (2005) studied aircraft and road noise in Geneva, Switzerland, using government-supplied data on 13,034 apartment rental locations from 2003. Approximately 80 percent of the apartment units in the study were rented by private owners, with the remaining 20 percent being government owned and rented. Noise data was furnished by the Geneva Cantonal Office, which specified average noise levels by property and building facade. Except for 1,847 apartments that were deemed to be in aircraft noise-only zones, aircraft and road noise were assumed to be a combined externality. It was observed that public sector rentals experienced higher sensitivity to noise effects in both study areas, with combined source NDIs of -0.175 percent and -0.645 percent for private and public sector apartments, respectively. Aircraft noise study areas also observed higher sensitivity with public sector housing, with NDIs of -0.657 percent and -0.789 percent.

Day *et al.* (2007) utilized a two-stage HP model to estimate MWTP values based on levels of aircraft, road, and rail noise in Birmingham, U.K. Real estate sales data for 10,640 single-family home transactions from 1997 was used for the study, along with 1991 demographic data sourced from the U.K. census bureau. Noise levels for each type of noise source for each property were estimated using governmental Defra noise maps (Department for Environment, Food and Rural Affairs). Transaction data was segregated into eight separate market segments based on location, price, property, and demographic parameters. The first stage of the study specifies a partially linear regression model with spatial smoothing to estimate separate coefficient values for aircraft, road, and rail noise. Due to the relatively small number of areas affected by aircraft noise, the second stage of the study focused only on road and rail noise. In the second stage, implicit noise price values are used with an Amemiya Generalised Least Squares (AGLS) (Amemiya, 1979) to estimate demand function MWTP values. Based on 1997 pricing levels, road noise estimates ranged between £31.49 at 56 dBA and £91.15 at 81 dBA, with rail noise estimates of between £83.61 at 56 dBA and £139.65 at 81 dBA. The authors theorize that the observation of higher prices for rail noise versus road noise, which is not typical, could possibly be a result of inconsistent and extreme noise peaks from rail sources, as opposed to the relatively constant noise levels that are observed with road traffic.

Andersson *et al.* (2010) studied road and railway noise on property prices using 1996 to 2006 single-family home sales transactions from the Lerum, Sweden area. Governmental records were used to compile the sales data, which also included property and neighborhood characteristics. (The number of transactions was not specified). Noise calculations for each property were used from a previous study by Ohrstrom *et al.* (2005), with separate calculations performed for road and rail noise levels. Distance to rail stations was included to account for accessibility effects, with a spatial lag model specified to account for spatial dependence effects. Using only properties with noise levels above 50 dBA, semi-log results indicated NDI values of approximately -1.15 to -1.69 percent for road noise, and -0.36 to -0.72 percent for rail noise.

Stated Preference Studies

Lam *et al.* (2009) compared annoyance from road and rail noise in a survey-based study in Hong Kong. Questionnaires were verbally administered to 597 apartment residents that scored perceived noisiness and annoyance levels from road and rail noise. Fifteen-minute noise measurements were also taken at each interview residence. Noise levels for specific sources were modeled based on traffic or train volumes and distance to the noise source. Regression results showed that annoyance levels are more closely correlated to perceived annoyance, rather than to actual noise levels. This indicates that intermittent disturbances, such as train noise for example, have a higher effect on annoyance when compared to average overall noise levels. Further observations noted that in road noise-dominant situations, rail noise is the main determinant of annoyance, most likely due to individuals becoming more accustomed to road noise and more sensitive to rail noise. In rail noise-dominant situations, rail again is observed to be the main determinant of annoyance, due to the lack of high background road noise.

Nguyen *et al.* (2011) studied aircraft and road noise annoyance among residents in areas near the airports in Ho Chi Minh City and Hanoi, Vietnam. Surveys were completed by 1,562 residents in August and September of 2008 in Ho Chi Minh City, with 1,397 residents polled in August and September of 2009 in Hanoi. Approximately 55 percent of those polled in each area were asked only about aircraft noise annoyance, with the remainder being polled on combined aircraft and road noise. In addition to the survey, primary noise measurements were taken for 24-hour periods at nineteen sites near the two airport areas. Initial results indicated that three to five percent more residents in Vietnam were highly annoyed at aircraft noise when compared to EU residents who experienced the same noise levels. As expected, highest annoyance levels were experienced by those living under aircraft landing paths, with observed noise levels of 71 dBA and 61 dBA in each of these areas, respectively. Highest annoyance responses were observed in Hanoi, which the researchers attribute to the lower volume of aircraft and road traffic, and subsequently lower noise levels. Traffic noise levels observed were also higher than averages recorded in the EU, most likely due to the high number of motorbikes vs. cars and trucks.

Health Impact Studies

In an early transportation-specific study, Wilkinson (1984) observed that traffic noise was specifically linked to a decrease in the quality of sleep. For the study, twelve subjects consisting of six pairs of people who lived in the same residence were observed for two weeks, using the subjects' regular sleep areas for the study. The first week consisted of keeping the residence in its original configuration, with double glazed windows installed for the second week of study. The reduced noise configuration lowered traffic noise by an average of 5.8 dBA. EEG and survey data were used to determine effects from the noisier environment. Stage 4 sleep and low frequency, high amplitude EEG delta waves were observed to be higher in the low noise configuration, indicating increased deep sleep behavior. Reaction time tests showed improvement, and subjects indicated sleeping better.

In a review by Job (1988), it was observed that noise exposure and its subsequent reaction is remarkably similar among different nationalities and cultures, especially transportation noise. Reviews of studies in ten countries and among nine noise sources showed similar noise/reaction correlations in the areas of aircraft, road, and rail noise. Impulsive noise sources such as quarry blasting, artillery, rifle shooting, and drop forging showed less correlation when compared to transportation noise sources, indicating consistent reaction to transportation noise, regardless of country or region. This evidence demonstrates that regardless of socioeconomic status, individuals in all regions, including developing and developed countries, are equally susceptible to the adverse effects of transportation noise exposure.

Babisch (2000) conducted a meta-analysis to investigate the relationship between transportation noise and cardiovascular diseases, including hypertension and myocardial infarction. A risk curve odds ratio of 1.1 to 1.5 was observed for the incidence of myocardial infarction when exposed to road noise levels above 60 dBA. In Germany, this represents approximately 4,000 myocardial infarction cases per year for the year 1999. For all ischemic heart diseases, road noise exposure correlates to an estimated 27,000 cases per year.

Eriksson *et al.* (2012) also correlated transportation noise to cardiovascular health in a 2007 Swedish study. Using 25,851 subjects, data from a National Environmental Health Survey was used to analyze the relationship between health and annoyance with road and rail noise. Logistic regression models estimated prevalence odds ratios between nearby traffic volume relationships and self-reported hypertension and cardiovascular disease. Results showed an increased risk of cardiovascular disease among subjects exposed to rail noise greater than 50 dBA.

In Switzerland, Dratva *et al.* (2011) investigated the correlation between traffic noise and ischemic heart disease. Eight municipalities were used for the study: Basel, Wald, Davos, Lugano, Montana, Paverne, Aarau, and Geneva. A total of 6,450 subjects were measured in 1991 for blood pressure level, and were polled on their demographic and health status. Repeat measurements were taken in 2002 and 2003 to assess any changes in cardiovascular and other health measures. Governmental noise models were used to estimate noise exposure levels in 10-meter by 10-meter grids, with a dispersion model used to estimate PM_{10} levels, and a hybrid model used to estimate NO_2 levels. While no significant effects were observed on blood pressure from road noise, linear regression models indicated positive effects on blood pressure level for rail noise exposure. Night time noise effects were estimated to be higher than night time, and those who reported physician-diagnosed hypertension or diabetes were affected even more.

Van Kempen *et al.* (2010) studied the effects of aircraft and road noise on the cognitive effects on schoolchildren in the area surrounding Schiphol Amsterdam Airport in The Netherlands. Data for 553 primary school children aged 9 to 11 years were drawn from a previous international study that was conducted from April to October 2002 (Stansfeld *et al.* 2005). Government noise models were used to estimate average noise exposure level by location, with resolution grids of 250-meters by 250-meters for aircraft noise and 25-meters by 25-meters for road noise. Noise exposure was estimated for both school and home locations for each of the children, which ranged from 36 dBA to 63 dBA at school, and 34 dBA to 63 dBA at home. A range of tests were administered, ranging from basic reaction time and hand-eye coordination tests, to cognitive pencil and paper tests. Results did not show effects on performance from noise levels at home. While simple tasks were not affected by noise levels at home or at school, children at schools with high noise exposure, however, were negatively affected with more difficult cognitive tasks.

These transportation noise health effects and their resulting economic impacts clearly demonstrate the need for continued monitoring and management of transportation noise exposure levels for all modes, particularly in densely populated urban areas.

Conclusions

Interestingly, many noise-related studies still do not focus on measured noise as a variable, but use distance to the noise source as a linear proxy to represent noise levels. Some studies, however, utilize distance solely as an input for noise level models formulated from previously gathered study data. Regardless, while various noise sources from aircraft, road, and rail can have similar dBA levels when measured, each can result in very different perceptions of loudness, vibration, and annoyance, making relevant comparisons between the modes difficult. Studies that effectively combine RP and SP techniques can reduce this disparity by assigning weights to noise levels based on perceived levels of annoyance. In addition, reviewed literature indicates that response to transportation noise is not linear, but rather is dependent upon marginal noise level increases and existing noise thresholds.

The incorporation of GIS technology in more recent studies has resulted in the increased utilization of spatially weighted models. These models provide improved estimates of the relationship between transportation noise and the surrounding environment, and have greatly improved model specifications that address spatial heterogeneity.

Aside from higher income individuals being more sensitive to transportation noise in some study situations, SP response to transportation noise is surprisingly consistent for many aspects of annoyance, regardless of nationality, culture, or demographic. Observed differences are mostly determined by age, with working-aged adults being most affected. This is often accompanied by increased sensitivity at higher noise levels. Individuals of all age groups, however, suffer a wide range of adverse health effects as a result of noise exposure, even at lower levels or for short periods.

Based on this literature review, it is also observed that transportation noise effects have received limited research attention in Southern California. Given the wide range of transportation modes and the extensive transportation infrastructure in the region, this is surprising. This dissertation aims to fill some of these gaps by conducting analyses on the noise impacts from transportation infrastructure on the residential real estate market in Los Angeles County. It will also contribute to the literature by utilizing state-of-the-art spatial modeling techniques to better understand overall economic impacts from environmental noise in densely populated urban areas.

Table 2-1: Summary of Aircraft Noise Studies

Author(s)	Method(s) Used	Data Info	Key Variables	Key Findings
Revealed Preference Studies				
Pope (2008)	HP; OLS	Raleigh-Durham, North Carolina; 16,856 single-family home sales from 1992 to 2000; Government shapefile for 55 dB+ zones	Property characteristics; Noise map location categorization	7.9% noise discount, with additional 2.9% discount due to noise disclosure
Cohen & Coughlin (2009)	HP; OLS	Atlanta, Georgia; 2,370 single-family home sales from 1995-2002; Government noise contour maps from 1995 & 2003	Property, demographic characteristics; Noise map location categorization	65 dB areas discounted 7.8% to 11.7% 70 dB areas discounted 0.7% to 6.0%
Chalermpong (2010)	HP; OLS with Spatial weighting	Bangkok, Thailand; 384 new home transactions from 2002-2008 (Single-family, duplex, townhomes); Airport opened 2006	Property characteristics; Distance to noise source	NDI of -2.12% Discounts attributed to initiation of airport operations
Boes & Nuesch (2011)	HP; Difference-in-Difference OLS	Zurich, Switzerland; 687 apartment rent panel observations from 2001-2006; EMPA noise model; Oct. 2003 flight regulation change	Property, location characteristics; EMPA model-generated noise data	NDI of -0.5%

Table 2-1 (cont.)

Author(s)	Method(s) Used	Data Info	Key Variables	Key Findings
<u>Stated Preference Studies</u>				
Carlsson *et al.* (2004)	CV; Mixed logit	Stockholm, Sweden; Questionnaire from 2003 with 717 respondents; Respondents polled on either increases or decreases in landings	Airport usage frequency; Monetary valuation of increases or decreases in flight frequencies	MWTP varies with time of day, higher in morning and evening; Some prefer no change in noise level
Thanos *et al.* (2011)	CV; Mutinomial logit	Athens, Greece; Questionnaire from 2005 with 700 respondents; Respondents polled on actual noise-change scenarios & tax values; EUROCONTROL noise model; Airport moved location in 2000	Demographic characteristics; Stated choice noise level data; Monetary valuation through tax values; EUROCONTROL noise model data	Monthly household MWTP for terminating aircraft noise exposure is 13.12€; Avoiding the onset of aircraft noise is 9.53€
Akpan *et al.* (2012)	Survey	Port Harcourt, South Nigeria; Questionnaire with 1,552 respondents	Demographic characteristics; Day/night noise levels	Higher noise sensitivity with middle age and higher income individuals; Income and noise positively correlated; Increasing annoyance with increasing noise levels
Elmehdi (2012)	Survey	Dubai, UAE; 207 interviewees surveyed with 0 to 10 scale noise annoyance questions (2008); Nine primary noise measurement locations (2007)	Demographic, health characteristics; Primary noise data; Day/night and averaged noise levels	41% highly annoyed 13% not annoyed
<u>Hybrid Revealed/Stated Preference Studies</u>				
Van Praag & Baarsma (2005)	HP & Ordered probit	Amsterdam, Netherlands; Questionnaire from 1998 with 1,400 respondents; Well-being & noise nuisance questions w/ 1-10 and monetary responses; Government noise data	Environmental, demographic, noise characteristics; Survey data	Noise perception depending on income, family size, expenses, property characteristics; Negative effect from noise on sense of well-being; Representative monetary compensation for noise decreased as overall noise levels increased

Table 2-2: Summary of Road Noise Studies

Author(s)	Method(s) Used	Data Info	Key Variables	Key Findings
<u>Revealed Preference Studies</u>				
Kim *et al.* (2007)	HP; OLS	Seoul, Korea; Single-family and row housing; Data from 2002-2004; 500m buffer to highway; Distance used for noise proxy	Property, neighborhood, traffic characteristics; Traffic volume; Distance to roadway	NDI of -1.3%
Blanco & Flindell (2011)	HP; OLS	London/Birmingham/Sutton Coldfield, U.K.; 407/226/86 apartment & flat sales data from 2005; 2001 census demographic data	Property, demographic characteristics	London NDI of -0.45%; Sutton Coldfield NDI of +0.58%; Accessibility benefits in smaller areas can outweigh typical results
Brandt & Maennig (2011)	HP; OLS & Spatial Lag	Hamburg, Germany; 4,832 condominium sales from 2002-2008; GIS distance data to public & environmental infrastructure	Property, accessibility, neighborhood characteristics; Government noise model data;	Block-level analysis resulted in average NDI of -0.23%; Non-linear NDI response at different noise levels
<u>Stated Preference Studies</u>				
Wardman & Bristow (2004)	CV; Binary logit	Edinburg, Scotland; Traffic noise & air quality study; Sept-Nov 1996 survey, 398 respondents; A or B property choice sets with varying environmental attributes	Property, neighborhood, environmental, demographic characteristics; Perceived environmental effects; A or B property choice sets	MWTP influenced by income level, household size, number of adults; CV MWTP values consistently lower than SP values
Arsenio *et al.* (2006)	CV; OLS, Binary & Mixed logit	Lisbon, Portugal; 412 apartment residents from June-November 1999; Various combination apartments offered as choices; Primary noise measurements for each apartment	Property, demographic characteristics; Measured noise data; Perceived noise levels	Non-linear effect from noise levels; MWTP increased with noise level; MWTP higher for noise increases vs. reductions

Table 2-2 (cont.)

Author(s)	Method(s) Used	Data Info	Key Variables	Key Findings
<u>Stated Preference Studies (cont.)</u>				
Martin *et al.* (2006)	CV; Categorical analysis	Valladolid, Spain; 296 dwelling questionnaires at primary noise measurement locations; Categorical annoyance levels; Hypothetical valuations	Property, demographic, neighborhood characteristics; Measured noise data; Perceived annoyance survey data	Highly annoyed areas coincide with 65 dBA or greater noise areas; 54% would downgrade housing for silent environment; 50% would pay 3 to 96 euros/yr to reduce noise
Li *et al.* (2009)	CV; Conditional logit	Hong Kong; 667 respondents from 2007-2008; Choice survey; Primary noise measurement; 0-10 annoyance level	Property, demographic, neighborhood characteristics; Measured noise data; Perceived annoyance survey data	Non-linear effects from noise levels; Higher income levels produced higher MWTP; Higher initial noise levels produced higher MWTP
Lera-Lopez *et al.* (2012)	CV; Probit	Navarre, Spain; 900 face-to-face interviews; Categorical annoyance levels; Noise & pollution model estimates; Valuation via hypothetical tax	Property, demographic characteristics; Noise model data; Perceived annoyance survey data	Higher MWTP observed with younger individuals, higher education levels, higher truck traffic areas, higher noise areas
Banerjee (2013)	Logistic regression; Odds ratios	Asansol, India; 221 samples taken from ongoing public health survey; Categorical annoyance levels; Primary noise measurements	Demographic characteristics; Measured noise data; Perceived annoyance survey data	Annoyance increases with noise level; Ages 34-40 are most annoyed, followed by ages 50-60
Mirsanjari (2013)	Categorical analysis	Tehran, Iran; 140 questionnaire respondents Primary noise measurements at 14 locations	Demographic characteristics; Measured noise data; Perceived annoyance survey data	37.9% annoyed or highly annoyed; 6pm-10pm peak annoyance period; Traffic noise most annoying

Table 2-3: Summary of Rail Noise Studies

Author(s)	Method(s) Used	Data Info	Key Variables	Key Findings
Revealed Preference Studies				
Simons & El Jaouhari (2004)	HP; OLS	Cuyahoga County, Ohio; 1996 & 1999 single-family housing sale data (14,900 & 17,800 observations); 250'/500'/750' distance buffer to track as noise proxy	Property characteristics; Distance to noise source	-0.104% to -2.667% change in housing price per nearby freight train trip
Cushing-Daniels & Murray (2005)	HP; OLS	Wisconsin; 1999-2004 governmental housing, demographic, rail line data; Census block or ZIP code noise area categorization	Property, neighborhood characteristics; Noise presence categorized by block or ZIP code	Log of price effect of -0.139 per percent of area crossings without whistle ban
Chang & Kim (2013)	HP; OLS	Seoul, Korea; 925 home sale transactions; Government real estate data; Noise, air, environmental data; Proprietary noise level formula	Property, demographic, accessibility, environmental characteristics; Noise level	NDI of -0.53%
Chica-Olmo *et al.* (2019)	HP; SAR, SEM, RK	Santa Marta, Columbia; 270 single-family home transactions	Moran's *I* and AIC statitstics used to optimize spatial weights	-14% to -23.7% impact on values
Stated Preference Studies				
Ali (2005)	Survey	Assiut, Egypt; Primary noise measurement data; 714 survey respondents, 1-5 annoyance, mitigation suggestion survey	Property, demographic, neighborhood characteristics; Primary noise data; 1-5 annoyance scale survey data;	51.3% of residents heard noise, with 48.5% of those being highly annoyed; 32% suggested limiting rail traffic at night as a solution
Combined Revealed/Stated Preference Studies				
Bellinger (2006)	HP; OLS CV; Preference survey	Wormleysburg, Pennsylvania; 192 housing sales from 1980-2004; Generic noise map; Questionnaire from 2005 with 126 survey respondents; 1-5 annoyance level and hypothetical MWTP value	Property characteristics; Distance to noise source; Survey ratings & MWTP values	NDI of -0.41% MWTP of $13.06 to $30.18

Table 2-4: Summary of Combined Transportation Mode Noise Studies

Author(s)	Method(s) Used	Data Info	Key Variables	Key Findings
<u>**Revealed Preference Studies**</u>				
Theebe (2004)	HP; OLS with Spatial weighting	Aircraft/Road/Rail; Western Netherlands; 160,000+ single- and multi-family home transactions from 1997-1999; Government noise and demographic data from 1999	Property, demographic characteristics; 100m x100m grid noise map data; Dummy variable noise categories	NDI of 0.0% @ 65 dB NDI of -0.5% @ 75 dB Non-linear NDI based on noise levels; Higher income areas and multifamily homes more sensitive to noise
Baranzini & Ramirez (2005)	HP; OLS	Aircraft/Road; Geneva, Switzerland; 13,034 apartment rental transactions from 2003; Governmental noise and property data	Property, neighborhood characteristics; Noise map data	Combined noise source NDIs: Private -0.175% Public -0.645% Aircraft noise NDIs: Private -0.657% Public -0.789%
Day *et al.* (2007)	HP; Partially linear model with spatial smoothing; AGLS	Aircraft/Road/Rail; Birmingham, U.K.; 10,640 single-family home transactions from 1997; Demographic data from 1991; Defra noise model data	Property, location, demographic characteristics; Model-generated noise data	MWTP per dBA of: £31.49 @ 56 dBA & £91.15 @ 81 dBA (Road) £83.61 @ 56 dBA & £139.65 @ 81 dBA (Rail)
Andersson *et al.* (2010)	HP; OLS with Spatial lag	Road/Rail; Lerum, Sweden; Single-family home sales from 1996-2006; Noise modeled by location	Property, location, demographic characteristics; Model-generated noise data	NDI of -1.15% to -1.69% (Road) NDI of -0.36% to -0.72% (Rail)

Table 2-4 (cont.)

Author(s)	Method(s) Used	Data Info	Key Variables	Key Findings
<u>Stated Preference Studies</u>				
Lam *et al.* (2009)	OLS	Road/Rail; Hong Kong; 597 apartment residents polled on perceived annoyance levels; Primary noise measurements at each surveyed apartment; Modeled noise data for road and rail	Demographic, property characteristics; Rating scale noise survey data; Modeled and primary noise data	Annoyance more closely related to perceived annoyance levels vs. actual noise levels; Rail noise main determinant of annoyance in both road and rail noise -dominant environments
Nguyen *et al.* (2011)	OLS	Aircraft/Road; Ho Chi Minh City & Hanoi, Vietnam; 2008 HCM questionnaire w/ 1,562 respondents; 2009 Hanoi questionnaire w/ 1,397 respondents; 1-5 and 1-10 annoyance level choices	Demographic characteristics; Rating scale noise level data; Primary noise data	Respondents more sensitive to noise compared to EU studies by 2-3 dB; Lower noise threshold in Hanoi but more highly annoyed residents (vs. HCM)

CHAPTER 3

Spatial Hedonic Noise Impact Modeling

Hedonic Price Method

To quantify the impacts of noise, this dissertation will rely on the hedonic price (HP) method applied to the Southern California single-family housing market. In the classical HP framework, Rosen (1974) analyzes that a good's value is not independent of its characteristics, with an analysis of the environmental characteristic of noise impacts written as:

$$P = \mathrm{f}(S, N, E, \varepsilon), \tag{1}$$

where:

- $\boldsymbol{P}$ is a vector of housing prices;
- $\boldsymbol{S}$, $\boldsymbol{N}$, and $\boldsymbol{E}$ are matrices of structural, neighborhood, and environmental variables (including noise levels in this instance); and
- $\boldsymbol{\varepsilon}$ is a vector of error terms

The partial derivative of f with respect to explanatory variable *j* is an implicit price that represents the marginal willingness-to-pay (MWTP) for the represented characteristic.

The classical HP framework analyzed by Rosen (1974) requires strong conditions to hold, including market equilibrium with perfect competition, perfect information, and a continuum of products. However, Benkard and Bajari (2005) proved that the HP method is still valid when competition is imperfect, when there is no continuity of products, and when not all product characteristics are observable, which is often the case in housing markets. Moreover, Benkard and Bajari (2005) showed that if demand is given by the HP model, there exists an HP function.

Fixed Effects Models

Early HP studies utilized fixed effects models that relied on distance to specific points, links, or zones from observed variables of interest. These variables were spatially aggregated and did not consider heterogeneity across geographical space, nor did they consider the potential for spatial dependence between observations. Linear regression models that utilized ordinary least squares (OLS) were often used for estimation. With these models, omitted variable bias in the form of parameter overestimation typically occurs; spatial effects may not be included in the parameter values and assumptions are made about the independence of residuals (Anselin, 1988). In this case, the fixed effects model assumes the form:

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

where:

- n designates the sample size and q the number of explanatory variables including a constant term;
- $\boldsymbol{P}$ is an $n \times 1$ vector of single-family residential property prices;
- $\boldsymbol{X}$ is an $n \times q$ matrix of exogenous explanatory variables;
- $\boldsymbol{\beta}$ is a $q \times 1$ vector of unknown coefficients; and
- $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of independently distributed errors with zero mean.

Spatial Autocorrelation

Spatial autocorrelation (SAC) refers to the presence of a systematic clustering or dispersion of observations in space (Cliff and Ord, 1973). Based on structure or dependence, the degree of this relation decreases with distance (Tobler, 1970). Similar to time series data where autocorrelation occurs as a serial dependence of an observed variable on itself, SAC adds dependence between an observation in space and observations that are located nearby. However, unlike the traditional time series lag, this spillover influence is two-way between an observation in space and nearby observations. If not addressed in the model specification, the presence of spatially correlated omitted variables will generally appear in the error term. As with fixed effects model errors, this will then violate the assumption of independently and identically distributed (i.i.d.) residuals (Anselin, 1988).

To detect SAC in a variable, two tests are commonly used: Geary's c (Geary, 1954) and Moran's *I* (Moran, 1950). Geary's c is a statistical measure of SAC appropriate for evaluation of binary nearness, which can be based on geometric features such as shared edges or corners. In contrast, Moran's *I* analyzes the presence of SAC based on distance. Variables distributed across space are evaluated with a statistic that ranges from -1 to 1; an index value near -1 indicates strong negative SAC, a value near 1 indicates heavy clustering due to strong positive SAC, and a value near 0 suggests random spatial distribution with no SAC. Because the data used in this dissertation is based on distribution across space, Moran's *I* is used to test for SAC. Moran's *I* is defined as:

$$I = \frac{N}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{3}$$

where:

- N is the sample size;
- X is the variable of interest;

- $\bar{X}$ is the mean of X; and
- w_{ij} is the spatial weights matrix

As autocorrelation can exist within the dependent variable or within the error term, Lagrange Multiplier (LM) tests for spatial autoregressive lag versus spatial autoregressive error can be initially used (Anselin *et al.*, 1996) to detect the type of SAC that is present. However, simple LM tests assume the absence of either spatial lag or spatial error but do not consider that they exist concurrently. Secondary robust LM tests (Anselin *et al.*, 1996) address this assumptive shortcoming, and provide independently robust diagnostic results for the presence of both spatial lag and spatial error autoregression.

Spatial Weights Matrix

By definition, spatial models and spatial test statistics rely on data that delineate the geographical relationship between observations in space. To represent this relationship between observation i and neighbors j within a vector of size n, a spatial matrix $\boldsymbol{W}$ of size n x n is used. Initial matrix values are be obtained by calculating off-diagonal terms from $w_{ij} = (d_{ij})^{-2}$ for $d_{ij} \leq d$ and 0 otherwise, where d_{ij} is the straight-line distance between properties i and j; and d is typically the bandwidth parameter that corresponds to the peak value from Moran's I correlogram for, in this instance, residential property sale prices. Since weight matrix $\boldsymbol{W}$ captures spatial interactions with nearby properties and a property does not spatially interact with its own selling price, the diagonal terms of $\boldsymbol{W}$ are 0. The rows of $\boldsymbol{W}$ are normalized to sum to 1 to facilitate the interpretation of results.

Spatial Models

Expanding on the fixed effects model in Equation (2), the presence of spatial autoregressive lag (SAR) specifies the use of a model that takes the following form when *n* designates the sample size and *q* the number of explanatory variables including a constant term:

$$\boldsymbol{P} = \lambda \boldsymbol{W}\boldsymbol{P} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{4}$$

where:

- *n* designates the sample size and q the number of explanatory variables including a constant term;
- $\boldsymbol{P}$ is an $n \times 1$ vector of residential property prices;
- λ ($|\lambda|<1$) is an unknown spatial lag parameter;
- $\boldsymbol{W}$ is an $n \times n$ spatial weight matrix, which reflects spatial interactions;
- $\boldsymbol{X}$ is an $n \times q$ matrix of exogenous explanatory variables;
- $\boldsymbol{\beta}$ is a $q \times 1$ vector of unknown coefficients;
- $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of independently distributed errors with zero mean.

In Equation (4), the term $\lambda \boldsymbol{W}\boldsymbol{P}$ reflects the effect of neighboring property prices and accounts for locally constant omitted variables.

Conversely, modeling in the presence of spatial autoregression in the error term (SEM) follows the form:

$$\begin{cases} \boldsymbol{P} = \boldsymbol{X\beta} + \boldsymbol{u}, \\ \boldsymbol{u} = \rho \boldsymbol{W u} + \boldsymbol{\varepsilon}, \end{cases} \tag{5}$$

where:

- n designates the sample size and q the number of explanatory variables including a constant term;
- $\boldsymbol{P}$ is an $n \times 1$ vector of residential property prices;
- ρ ($|\rho|<1$) is an unknown spatial error parameter;
- $\boldsymbol{W}$ is an $n \times n$ spatial weight matrix, which reflects spatial interactions;
- $\boldsymbol{X}$ is an $n \times q$ matrix of exogenous explanatory variables;
- $\boldsymbol{\beta}$ is a $q \times 1$ vector of unknown coefficients;
- $\boldsymbol{u}$ is an $n \times 1$ vector of correlated residuals; and
- $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of independently distributed errors with zero mean.

In Equation (5), the term $\rho\boldsymbol{Wu}$ reflects the specification for residual spatial autocorrelation. Finally, in the presence of both spatial autoregression and spatial autoregressive error (SARAR), the appropriate model would follow the form:

$$\begin{cases} \boldsymbol{P} = \lambda \boldsymbol{WP} + \boldsymbol{X\beta} + \boldsymbol{u}, \\ \boldsymbol{u} = \rho \boldsymbol{W u} + \boldsymbol{\varepsilon}, \end{cases} \tag{6}$$

where:

- n designates the sample size and q the number of explanatory variables including a constant term;
- $\boldsymbol{P}$ is an $n \times 1$ vector of single-family residential property prices;
- λ ($|\lambda|<1$) is an unknown spatial lag parameter;
- ρ ($|\rho|<1$) is an unknown spatial error parameter;

- $\boldsymbol{W}$ is an $n \times n$ spatial weight matrix, which reflects spatial interactions;
- $\boldsymbol{X}$ is an $n \times q$ matrix of exogenous explanatory variables;
- $\boldsymbol{\beta}$ is a $q \times 1$ vector of unknown coefficients;
- $\boldsymbol{u}$ is an $n \times 1$ vector of correlated residuals; and
- $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of independently distributed errors with zero mean.

In relation to previous models, Equation (6) reduces to a SEM model (Equation (5)) when λ=0, and reduces to a SAR model (Equation (4)) when ρ=0. When ρ=0 and λ=0 simultaneously, a fixed effects model (Equation (2)) is obtained.

SARAR models can be estimated via Maximum Likelihood (ML) or generalized spatial two-stage least squares (GS2SLS). Both ML and GS2SLS will be utilized, as ML estimation can lead to inconsistent estimators when errors are heteroskedastic (Arraiz *et al.*, 2010). In contrast, the GS2SLS estimator proposed by Arraiz *et al.* (2010), which uses generalized-method-of-moments and instrumental variables, yields consistent parameter estimates (λ, $\boldsymbol{\beta}$, and ρ in Equation (6)) even in the presence of heteroskedastic error.

CHAPTER 4

Los Angeles County Dataset

Los Angeles County Office of the Assessor Transaction Records

Data to be used in this dissertation was derived from Los Angeles County Assessor Office (LACOA) fiscal year residential real estate transaction records that occurred between July 2010 and June 2014. This dataset consisted of 746,211 transactions, of which 182,554 were for single-family home sales.

Filtering for single-family home transactions only, dataset cleaning was performed with Stata scripts and Microsoft Excel. Wherever possible, missing or erroneous fields were corrected using cross-referenced information from the LACOA, Google Maps, and other official public records. Observations for which required fields could not be fully rectified were removed. Recorded sales priced below $90,000 and above $2,000,000 were judged to be atypical value ranges for the market in this particular area of Los Angeles County and were also removed. To avoid potential issues with distressed properties, observations that were found to be listed as foreclosures on PropertyShark.com were assigned a binary variable. Records for properties listed more than once in the dataset (indicating potential distressed status) were assigned a binary resold variable. This resulted in a final dataset containing 171,475 observations. Structure variables derived from the dataset are listed in Table 4-1.

Table 4-1: Los Angeles County Office of the Assessor Dataset Variables

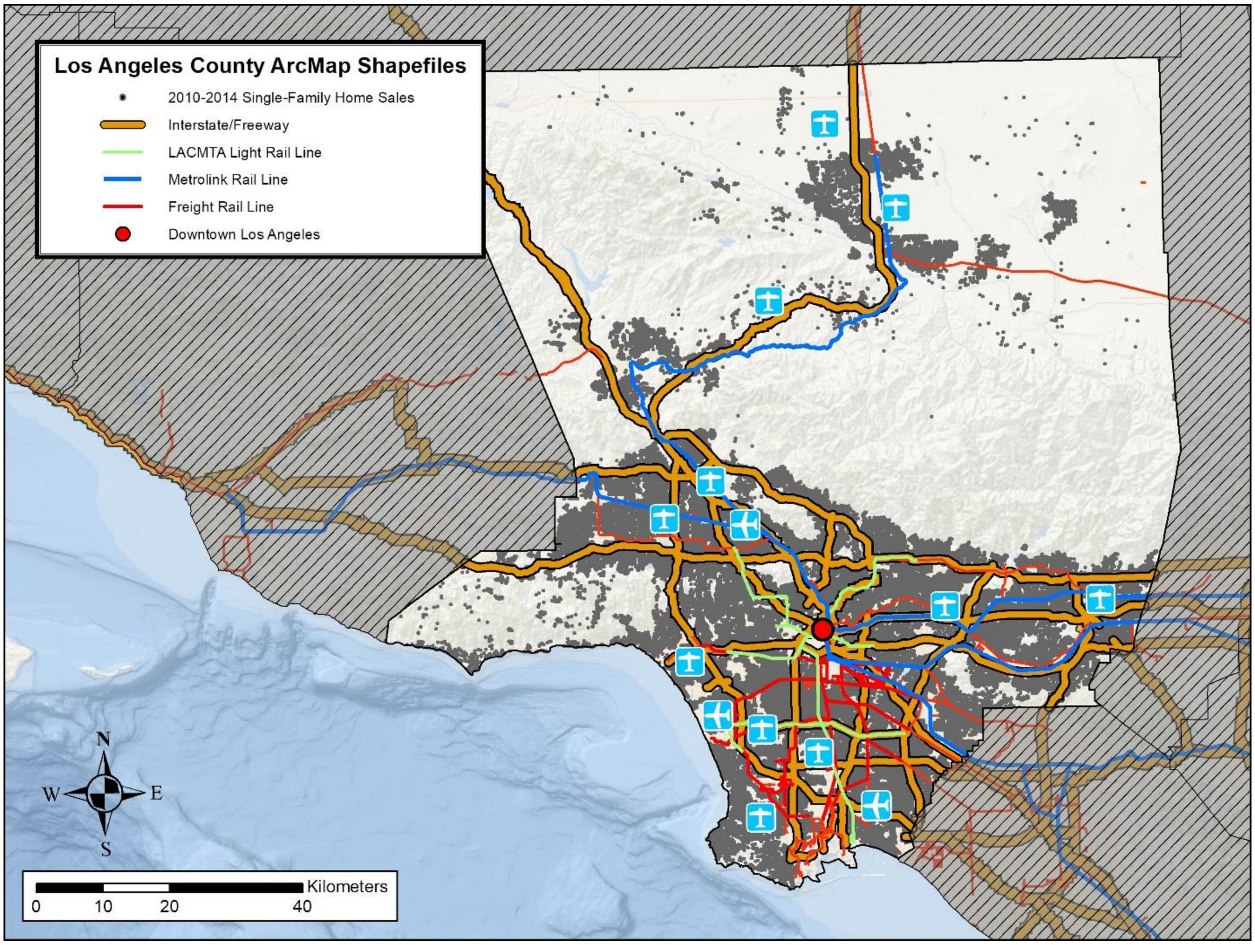
Variable	Description	Comments
Sale Price	Property selling price in dollars	Unadjusted price from year sold
Sale Date	Transaction date	Year, month, and day sold
Year Built	First year sold after initial construction	Used to calculate age of structure
Building Square Footage	Interior area of structure in square feet	
Lot Square Footage	Area of property lot in square feet	
Bedrooms	Number of bedrooms	
Bathrooms	Number of bathrooms	
Pool	Presence of pool on property	

ArcMap GIS Geocoding

Using address and property location fields in the dataset, observed transactions were geocoded onto a corresponding map of Los Angeles County using ESRI ArcMap 10.3. Observations were located at parcel centroid locations based on parcel maps obtained from the LACOA. XY coordinates by meter were then appended to each observation for use as coordinate variables in weight matrix operations.

City and neighborhood boundaries obtained from the LACOA and the Los Angeles Times datadesk were added to delineate jurisdictional binary variables (Los Angeles Times, 2017). Central business district, airport, school, and recreational beach areas were also mapped along with 2012 TIGER freeway, transit rail, and freight rail layers (United States Census Bureau, 2020; Los Angeles County Metropolitan Transit Authority, 2020; California Department of Transportation, 2020). Finally, distances to these features from each geocoded location were calculated where applicable. Euclidean or network distances to each feature category were used based on proximity or network access relevance. Additional variables were generated specific to analyses in Chapters 5 and 6, which are outlined in those Chapters.

Figure 4-1: Los Angeles County ArcMap Shapefiles



CHAPTER 5

An Econometric Spatial Hedonic Analysis of Aircraft Noise Impacts at Los Angeles International Airport

Introduction

This chapter presents a spatial hedonic price (HP) analysis of aircraft noise impacts generated by Los Angeles International Airport (LAX) on the single-family residential housing market. In the published literature, considerable research has been conducted on aircraft-related noise impacts in Europe (Hajnal, 2017; Winke, 2017; Clark and Paunovic, 2018), following European Union (EU) Environmental Noise Directive (END) 2002/49/EC (European Parliament, 2002). Comparatively, however, aircraft noise research in the United States has been comparatively limited -- especially in Southern California. A review of recently published aircraft noise HP literature revealed only one study that focused on Southern California airports, which compared large versus small airport impacts (Rahmatian and Cockerill, 2004). Similar to their 2004 study, this chapter hypothesizes that the sale price of single-family homes will be negatively impacted due to being located in areas exposed to excessive aircraft noise. However, in contrast to Rahmatian and Cockerill (2004) who relied on fixed effects models for their analysis, this study will utilize spatially weighted HP modeling techniques to analyze the impacts of aircraft operations at LAX on surrounding communities. Resulting estimates will contribute to the published literature by providing a better understanding of consumers' marginal willingness-to-pay (MWTP) for choosing to reside within aircraft noise impacted zones near LAX.

Background

Los Angeles International Airport

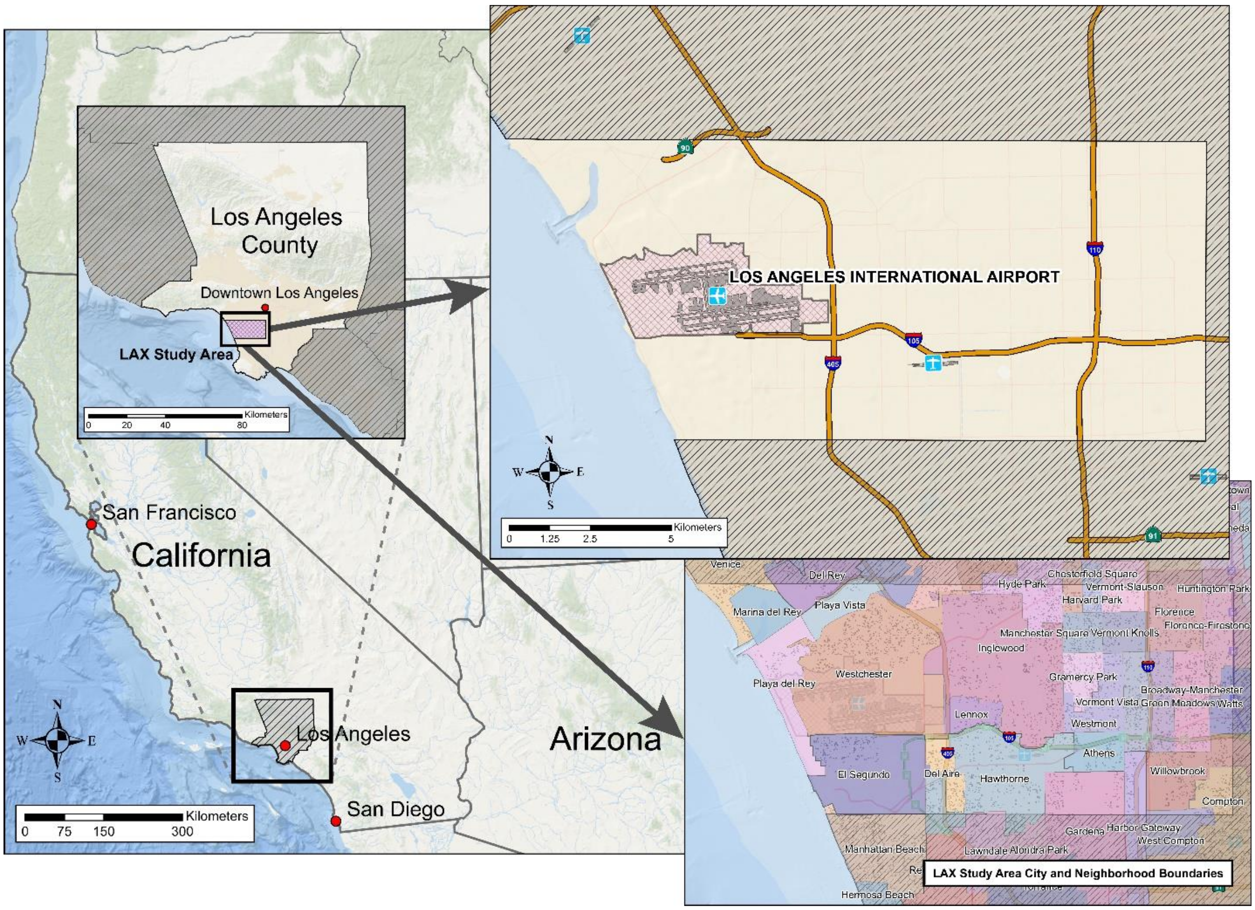
Owned and operated by the LAWA department of the city of Los Angeles, LAX is the largest airport in the state of California and the second busiest airport in the United States for passenger boardings after Hartsfield-Jackson Atlanta Airport in Georgia (Federal Aviation Administration, 2020). The airport also ranks as the fifth busiest airport in the world, with 707,833 aircraft movements in 2018. Passenger volumes have increased 5.4 percent from 2013 to 2018, higher than the overall U.S. commercial airport growth rate of 4.18 percent (Los Angeles World Airports, 2020). In addition, LAX serves as a primary North American logistics hub for the import and export of international air cargo.

LAX is located within the Westchester neighborhood of the city of Los Angeles and is approximately 15 miles southwest of Downtown Los Angeles. The western perimeter of the airport property is bordered by the Pacific coastline, with the remainder of the airport surrounded by densely populated neighborhoods. Established in 1929, the approximately 3,500-acre airport property currently retains four full length runways, the longest of which is 12,090 feet (Los Angeles World Airports, 2020). Communities primarily affected by aircraft operations are located within the cities of Los Angeles and Inglewood, along with a small portion of northern El Segundo.

Daytime aircraft traffic at LAX normally approaches directly from the east for landing on one of two parallel east-west runways, and takes off heading west over the Pacific Ocean. Flights approaching from the west/northwest or the south arrive at higher altitudes prior to vectoring for descent along the east-west landing pattern, and do not typically contribute to logged noise incidents within the designated study area. These take-off and landing patterns are reversed to west-east only during unusual wind or weather conditions (Los Angeles World Airports, 2020).

Residential properties directly east of the airport are located beneath the vectoring path of landing or departing aircraft. From 12:00 am to 6:30 am, aircraft arrive and depart over the ocean to the west to minimize nighttime community disturbances. In this configuration, the north runway is primarily utilized for arrivals, and the south runway for departures.

Figure 5-1: Los Angeles International Airport Study Area



Aircraft Noise Measurement Standards

Noise is described as unwanted sound energy transferred through the air. Measurement of sound is accomplished through a logarithmic energy scale in units referred to as decibels (dB). While various weighting scales are used to emphasize various high or low frequency sound energy, the A-weighted scale (dBA) is typically used for environmental noise measurements. This scale most closely approximates human hearing by emphasizing higher frequency sensitivity (Fletcher and Munson, 1933).

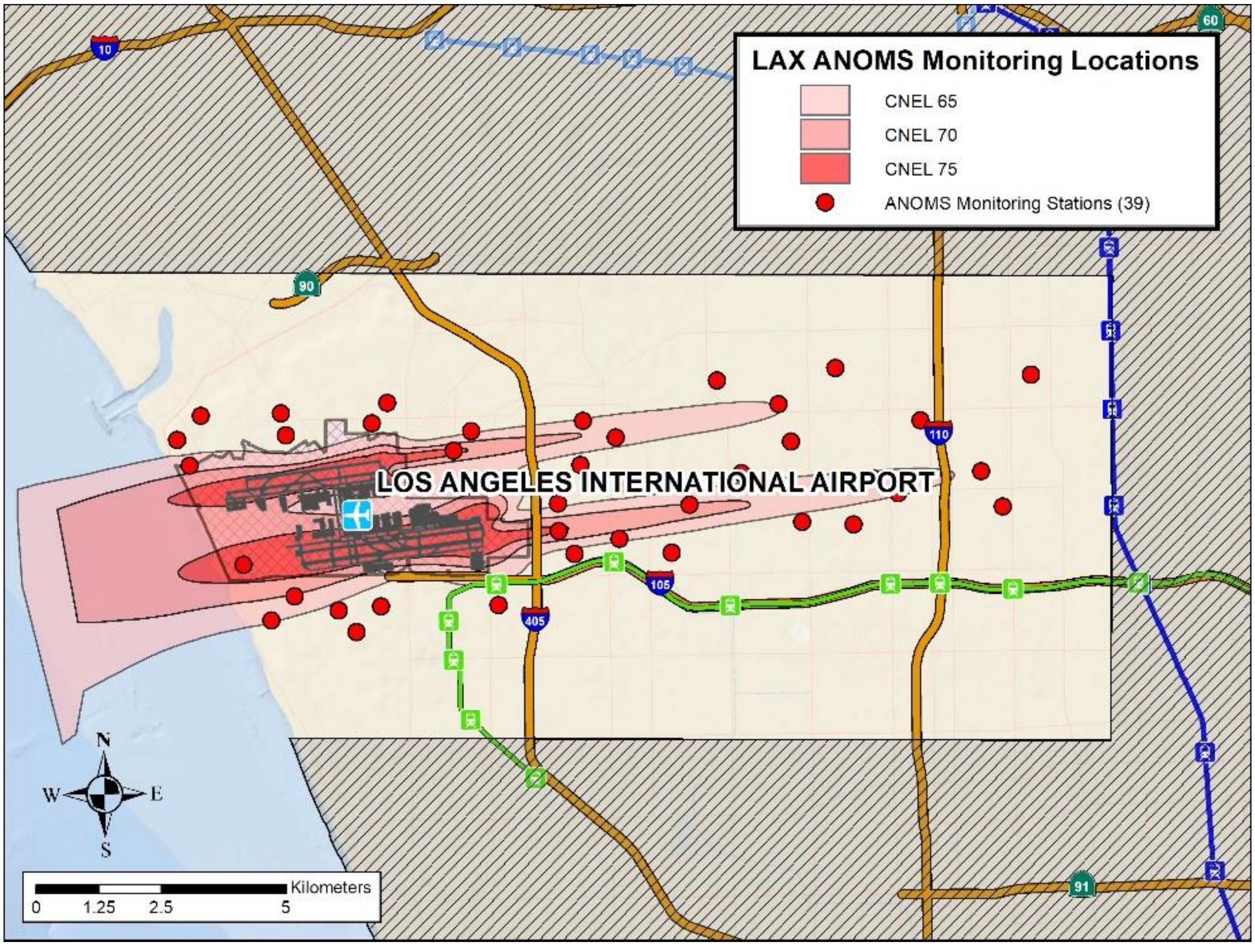
Federal Aviation Administration (FAA) standards utilize a dBA-based Day-Night Average Sound Level (DNL) metric to describe environmental noise exposure from aircraft operations (Federal Aviation Administration, 2021). This metric represents an average cumulative exposure to noise for one 24-hour period and includes a number of factors that include aircraft type, weight, and flight path, along with accompanying measured single-event noise level and duration. DNL values can also be averaged for longer periods of time which may include quarterly or annual averages. To compensate for nighttime impacts, DNL calculations include a +10 dBA penalty for events that occur between 10:00 pm and 7:00 am. Beyond federal DNL metric standards, the state of California has adopted a more stringent Community Noise Equivalent Level (CNEL) metric which adds an additional +5 dBA penalty for evening events that occur between 7:00 pm and 10:00 pm (Federal Aviation Administration, 1984). CNEL data and statistics are accepted by the FAA to be used in place of DNL measurements and analysis. As per the 1976 Aviation Noise Abatement Policy (ANAP), the FAA and California have adopted DNL or CNEL 65 dBA to be the threshold for significant noise exposure from airport operations (California Department of Transportation, 2020).

Stemming from ANAP and the Aviation Safety and Noise Abatement Act of 1979, airport noise contour map procedures were formalized in 1985 by the FAA with Federal Aviation Regulations (FAR) Part 150 (Federal Aviation Administration, 1984). This regulation stipulated the process and methodology for standardizing aircraft noise exposure map (NEM) reporting in the United States (U.S.). To assist with land use compatibility standards, FAR Part 150 specifies mapping of DNL 65, 70, and 75 dBA zones with a suggested minimum frequency of five-year increments for map generation and report documentation. While FAR Part 150 relegates land use compatibility thresholds to local municipalities, areas exposed to levels below DNL 65 dBA are considered compatible for all uses, while zones exposed to levels DNL 75 dBA and higher are generally considered incompatible for residential use, as well as for school, hospital, nursing home, and church uses (Federal Aviation Administration, 2021b).

LAX Noise Contour Maps

CNEL noise data from LAX aircraft operations are logged by 39 Aircraft Noise Operation Monitoring System (ANOMS) recording stations located in the surrounding neighborhoods (Figure 5-2). This data is then used by Los Angeles World Airports (LAWA) along with collected aircraft data to generate quarterly mappable aircraft noise impact contours (Los Angeles World Airports, 2020). Despite continual increases in overall operation volumes, LAX CNEL contour sizes have gradually decreased over time due to ongoing improvements in quieter aircraft technology (Los Angeles World Airports, 2020). It should be noted, however, that an estimated 4.5 percent increase in contour sizes was projected for the 2015 to 2020 time period which has been attributed to continuing increases in overall traffic volumes (Los Angeles World Airports, 2020).

Figure 5-2: LAX ANOMS Monitoring Station Locations



LAX Noise Impacts

LAX noise impacts in neighboring communities began to surface in 1959 with the introduction of jet aircraft operations (Los Angeles City Planning, 1998). In response to community complaints, a Sound Abatement Coordinating Committee was formed in July 1959 which consisted of members from the airport and airline industry. Rerouting of takeoff and landing patterns were recommended by the committee and adopted by the Los Angeles Department of Airports (DOA) (later renamed LAWA) (Los Angeles City Planning, 1998). This, however, achieved minimal resolution in regards to community complaints. In 1965, legal action determined which properties were exposed to excessive noise levels and required mandatory mitigation. Some of these properties, however, were not able to be sound insulated at a reasonable cost and were subsequently deemed incompatible for residential use. This resulted in LAWA and the FAA being forced to acquire over 2,800 homes and relocate nearly 7,000 residents in noise impacted areas (Los Angeles World Airports, 2020).

LAX Residential Sound Insulation Program

In 1997, in partnership with the FAA, LAWA initiated its Residential Sound Insulation Program (RSIP). This noise mitigation program addressed noise level issues in residential housing units that were determined to be within CNEL 65+ dBA noise contour zones around LAX during the fourth quarter operations of 1992. RSIP mitigated over 17,000 homes through 2013. Allocated costs per residential unit ranged from $27,000 to $32,000, and included modifications such as replacement of windows and/or doors with sound-insulated units, adding insulation in attics, installing noise baffles in vents and chimneys, and in some cases, the installation of an HVAC system. Program guidelines stipulated either a maximum interior noise level of 45 dBA or a -5 dBA reduction in interior noise after completion of the insulation work (Los Angeles World Airports, 2021). The ongoing FAA-funded RSIP currently continues to review and retrofit residences in communities that are deemed to be impacted by airport operations.

Literature Review

To date, the largest share of published research related to noise caused by aircraft operations at LAX has been on public health impacts (Westerdahl *et al.*, 2008; Shirmohammadi *et al.*, 2017; Riley *et al.*, 2021). Rahmatian and Cockerill, (2004) conducted the only published HP study on LAX, in which they found that distances of up to 4,500 meters from the airport property had an impact of -4 to -10% on housing prices. These impacts were nearly double when homes were located within 10,000 meters from the airport but beneath the actual flight path. Other recent studies in the U.S. found similar results with impacts between -0.7 to -11.7% when located within 65 to 70 dBA noise impacted zones (Pope, 2008; Cohen and Coughlin, 2009).

As the second largest commercial airport in North America located in the most populated county in the U.S., it is important to fully understand the economic impacts from aircraft noise at LAX. This study proposes to contribute to the existing literature by utilizing state-of-the-art spatial econometric HP modeling techniques to estimate the impacts of aircraft operations on the single-family home real estate market. This will also provide stakeholders and policy makers a better understanding of residents' MWTP for residing in these noise-affected areas.

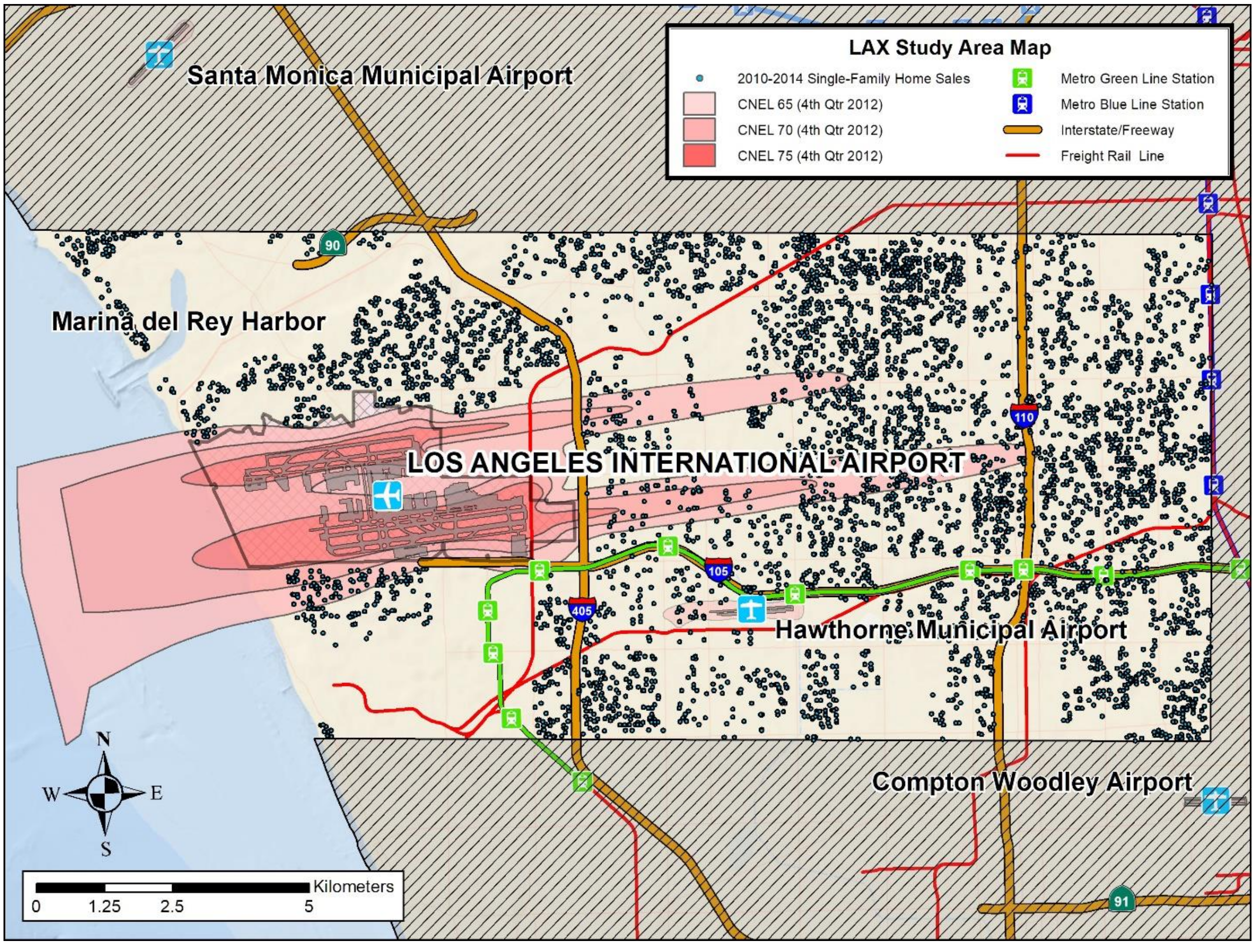
Study Area and Data

Study Area

The study area for this chapter consists of a 10 km by 20 km area around LAX and contains CNEL 65, 70, and 75 dBA airport noise contours from the fourth quarter of 2012 (Figure 5-3). This study area was chosen as it consists mostly of delineated neighborhoods within the city of Los Angeles. It is hypothesized that there will be some degree of spatial homogeneity across a single municipality despite the presence of distinctly defined neighborhoods. Also captured in the study area are nine Los Angeles County designated places (CDPs); the city of Inglewood; and portions of the cities of Compton, Culver City, El Segundo, Gardena, Hawthorne, and Manhattan Beach.

Three major freeways travel through the study area (Interstates 105, 110, and 405) as well as State Route 90. Los Angeles County Metro Transportation Authority (LAMCTA) light rail lines are present (Blue and Green Lines) as well as three freight rail lines that provide local business service. Hawthorne Municipal Airport is located near the southern edge of the study area, but noise from operations above CNEL 65 are generally contained within the airport property perimeter. Finally, Marina del Rey Harbor, a recreational and residential harbor area, is located at the northwest corner of the study area.

Figure 5-3: LAX Study Area Map



Los Angeles County Office of the Assessor Real Estate Dataset

Data analyzed in this study was derived from the LACOA-derived dataset described in Chapter 4. Within the 10 km by 20 km study area, 9,386 observations were captured from the original dataset's 171,475 observations. As described in Chapter 4, the LACOA dataset was cleaned and appended with relevant geographical data using ArcMap. The majority of the study area observations fall within city of Los Angeles jurisdiction at 4,952, with the city of Inglewood having the second highest number of observations at 1,086 (Table 5-1). It should be noted that the portions of the city of Los Angeles captured within the study area comprise 18 neighborhoods. This includes the city of Los Angeles neighborhood of Westchester in which LAX is located.

Table 5-1: LAX Noise Impacted Properties

City/Neighborhood	Observations	CNEL 65	CNEL 70	% CNEL 65+	Area (Sq mi)
Incorporated Cities					
Compton	260				10.26
Culver City	3				5.19
El Segundo	268	87	36	45.9%	5.46
Gardena	224				5.84
Hawthorne	617				6.23
Inglewood	1,086	171	28	18.3%	9.12
Los Angeles (Sum of neighborhoods below)	4,952	140		2.8%	61.82
Manhattan Beach	19				3.97
Unincorporated LA County CDPs					
Del Aire	260				0.99
Florence	383				2.8
Florence-Firestone	331				3.58
Ladera Heights	75				2.94
*Lennox	90	22	33	61.1%	1.06
View Park-Windsor Hills	9				1.84
West Compton	28				1.65
Westmont	375	60		16.0%	1.84
Willowbrook	406				3.77
City of Los Angeles Neighborhoods					
Athens	147				1.33
Broadway-Manchester	341	2		0.6%	1.56
Chesterfield Square	142				0.63
Del Rey	29				2.45
Gramercy Park	333	72		21.6%	1.13
Green Meadows	663				2.22
Harbor Gateway	104				5.14
Harvard Park	170				0.64
Hyde Park	374				2.88
Manchester Square	314	6		1.9%	1.01
Playa del Rey	138	14		10.1%	2.75
Playa Vista	25				1.3
Venice	153				3.17
Vermont Knolls	217				1.14
Vermont Vista	418	42		10.0%	1.65
Vermont-Slauson	179				1.44
Watts	167				2.12
Westchester	1,038	4		0.4%	10.81

n=9,386
*Two additional Lennox observations are located within the CNEL 75 zone

Following the classical HP framework (Rosen, 1974), price sold was used as the dependent variable for this analysis. Median value in the study area dataset within the $90,000 and $2,000,000 upper and lower bounds was $259,002. To estimate elasticity of demand and to accommodate percent change comparisons to other published study results, a log transformation was performed on the price sold variable vector.

Structural Characteristics

Structural variables derived from LACOA data include year built, lot square footage, structure square footage, number of bedrooms and bathrooms, and presence of a pool on the property. Binary variables were created for properties that were noise mitigated through LAWA's RSIP (Los Angeles World Airports, 2021). Due to incomplete recordkeeping, two separate binary variables for noise mitigated properties were created: one for properties with an unknown mitigation date, and a second for properties mitigated prior to their sale date. Additional binary variables for foreclosed properties and previously sold properties were also appended to the LACOA data. To account for temporal variances in the dataset, binary variables were generated for the sale date based on calendar quarter, with the second quarter of 2014 omitted as the reference category to avoid collinearity issues.

Neighborhood Characteristics

Binary variables for neighborhoods, which capture fixed spatial effect unobserved variables (such as school quality and crime, for example), were generated within ArcMap based on city and neighborhood boundaries (Los Angeles Times, 2017). To avoid categorical collinearity, the Willowbrook neighborhood was omitted and used as the reference category. As is typical throughout the polycentric Southern California region, multiple central business districts (CBDs) exist near or within the study area. Because of this polycentricity, accessibility to freeway and light rail transportation corridors was used as a proxy for capturing CBD access value, as opposed to CBD proximity by distance (Richardson, 1990; Giuliano and Small, 1991). This accessibility was represented by two 400-meter network distance buffers for light rail stations (Debrezion *et al.*, 2007; Hess and Almeida, 2007; Diao *et al.*, 2016; Ransom, 2018), and three 1,000-meter network distance buffers for freeway onramps (Seo *et al.*, 2014). Binary variables were generated for buffer distances to the nearest school (0 to 250 meters and 251 to 500 meters) (Sah *et al.*, 2016). Distances of 0 to 150 meters and 151 to 300 meters were used for beachfront and local marina proximity buffers, as this was found to be the range of statistically significant influence on beach area property prices (Landry and Hindsley, 2011; Catma, 2020).

Environmental Characteristics

Noise impacts from LAX operations are represented by binary variables that indicate the various levels of noise exposure in the areas surrounding the airport property. To determine which homes fall within aircraft noise impacted areas, CNEL noise contour shapefiles were sourced from LAWA. Contours from fourth quarter 2012 operations were chosen as a median time period to align with the 2010 to 2014 dataset range. These contours were projected onto the study area using ArcMap and were used to assign binary variables for exposure levels of CNEL 65, 70, and 75 dBA. Based on Rahmatian and Cockerill’s (2004) observation that average property prices close to airports were negatively affected by distances less than 2,000 meters, binary distance variables for the LAX airport property were generated in ArcMap for distances of 0 to 1,000 and 1,001 to 2,000 meters.

Previous HP studies have found significant impacts when located near transportation corridors. Following these findings, additional environmental variables were generated for areas located near freeways, light rail lines, and freight rail lines. To capture impacts from these transportation corridors, binary variables were generated for freeway proximity (0 to 150 and 151 to 300 meters) (Bowes and Ihlanfeldt, 2001; Li and Saphores, 2012; Seo *et al.*, 2014), light rail line proximity (0 to 150 and 151 to 300 meters) (Bowes and Ihlanfeldt, 2001; Hess and Almeida, 2007; Diao *et al.*, 2016), and freight rail line proximity (0 to 150 and 151 to 300 meters) (Simons and El Jaouhari, 2004; Clark, 2006; Chica-Olmo *et al.*, 2019).

Table 5-2: Structural Variable Summary Statistics

Variable	Mean	Std Dev	Min	Max
Sale price (259,002 median value)	358,262.8	277,426.6	90,000	1,999,019
Lot size (sq ft)	5,738.9	1,896.1	904	86,301
Building size (sq ft)	1,370.3	561.0	432	6,329
Bedrooms	2.8	0.8	1	8
Bathrooms	1.7	0.8	1	6
Pool on property	0.0349	0.1837	0	1
Age when sold (years)	70.2	19.2	1	121
Noise mitigated prior to sale	0.0115	0.1067	0	1
Noise mitigated (unknown date)	0.0506	0.2192	0	1
Foreclosure sale	0.0098	0.0985	0	1
Resold within previous year	0.0612	0.2396	0	1
Sold during 2010 Quarter 3	0.0646	0.2458	0	1
Sold during 2010 Quarter 4	0.0613	0.2398	0	1
Sold during 2011 Quarter 1	0.0621	0.2414	0	1
Sold during 2011 Quarter 2	0.0712	0.2571	0	1
Sold during 2011 Quarter 3	0.0746	0.2627	0	1
Sold during 2011 Quarter 4	0.0771	0.2668	0	1
Sold during 2012 Quarter 1	0.0737	0.2613	0	1
Sold during 2012 Quarter 2	0.0678	0.2513	0	1
Sold during 2012 Quarter 3	0.0518	0.2216	0	1
Sold during 2012 Quarter 4	0.0556	0.2292	0	1
Sold during 2013 Quarter 1	0.0484	0.2146	0	1
Sold during 2013 Quarter 2	0.0632	0.2433	0	1
Sold during 2013 Quarter 3	0.0658	0.2480	0	1
Sold during 2013 Quarter 4	0.0637	0.2443	0	1
Sold during 2014 Quarter 1	0.0597	0.2369	0	1
Sold during 2014 Quarter 2	0.0395	0.1949	0	1

n=9,386

Table 5-3: Neighborhood Amenity Variable Summary Statistics

Variable	Mean	Std Dev	Min	Max
Nearest school property (up to 250m)	0.2944	0.4558	0	1
Nearest school property (251-500m)	0.4152	0.4928	0	1
Nearest beach recreation area (up to 150m)	0.0040	0.0635	0	1
Nearest beach recreation area (151-300m)	0.0084	0.0914	0	1
Proximity to Marina del Rey Harbor (up to 150m)	0.0005	0.0231	0	1
Proximity to Marina del Rey Harbor (151-300m)	0.0069	0.0829	0	1
Nearest freeway onramp network distance (up to 1,000m)	0.1826	0.3864	0	1
Nearest freeway onramp network distance (1,001-2,000m)	0.2832	0.4506	0	1
Nearest freeway onramp network distance (2,001-3,000m)	0.2657	0.4417	0	1
Nearest light rail station network distance (up to 400m)	0.0034	0.0583	0	1
Nearest light rail station network distance (401-800m)	0.0271	0.1623	0	1

n=9,386

Table 5-4: City/Neighborhood Variable Summary Statistics

Variable	Mean	Std Dev	Min	Max
City of Los Angeles Neighborhoods				
Athens	0.0157	0.1242	0	1
Broadway-Manchester	0.0363	0.1871	0	1
Chesterfield Square	0.0151	0.1221	0	1
Del Rey	0.0031	0.0555	0	1
Gramercy Park	0.0355	0.1850	0	1
Green Meadows	0.0706	0.2562	0	1
Harbor Gateway	0.0111	0.1047	0	1
Harvard Park	0.0181	0.1334	0	1
Hyde Park	0.0398	0.1956	0	1
Manchester Square	0.0335	0.1798	0	1
Playa del Rey	0.0147	0.1204	0	1
Playa Vista	0.0027	0.0515	0	1
Venice	0.0163	0.1266	0	1
Vermont Knolls	0.0231	0.1503	0	1
Vermont Vista	0.0445	0.2063	0	1
Vermont-Slauson	0.0191	0.1368	0	1
Watts	0.0178	0.1322	0	1
Westchester	0.1106	0.3136	0	1
Incorporated Cities				
Compton	0.0277	0.1641	0	1
Culver City	0.0003	0.0179	0	1
El Segundo	0.0286	0.1666	0	1
Gardena	0.0239	0.1526	0	1
Hawthorne	0.0657	0.2478	0	1
Inglewood	0.1157	0.3199	0	1
Manhattan Beach	0.0020	0.0449	0	1
Unincorporated Los Angeles County CDPs				
Del Aire	0.0277	0.1641	0	1
Florence	0.0408	0.1978	0	1
Florence-Firestone	0.0353	0.1845	0	1
Ladera Heights	0.0080	0.0890	0	1
Lennox	0.0096	0.0975	0	1
View Park-Windsor Hills	0.0010	0.0310	0	1
West Compton	0.0030	0.0545	0	1
Westmont	0.0400	0.1959	0	1
Willowbrook	0.0433	0.2034	0	1

n=9,386

Table 5-5: Environmental Variable Summary Statistics

Variable	Mean	Std Dev	Min	Max
Within LAX CNEL 65 dBA noise contour	0.0511	0.2203	0	1
Within LAX CNEL 70 dBA noise contour	0.0103	0.1011	0	1
LAX distance (Up to 1,000m)	0.0967	0.2956	0	1
LAX distance (1,001-2,000m)	0.0811	0.2730	0	1
Nearest freeway distance (up to 200m)	0.0657	0.2478	0	1
Nearest freeway distance (201-400m)	0.0854	0.2796	0	1
Nearest light rail line distance (up to 150m)	0.0189	0.1360	0	1
Nearest light rail line distance (151-300m)	0.0308	0.1728	0	1
Nearest freight rail line distance (up to 150m)	0.0307	0.1725	0	1
Nearest freight rail line distance (151-300m)	0.0445	0.2063	0	1

n=9,386

Dataset Diagnostics

Variance Inflation Factor diagnostics were performed on the independent dataset variables, to determine any potential for multicollinearity in the model specification. Results of this diagnostic were values between 1.01 and 5.19 for the variables, with a mean value of 1.99 (Table 5-6). These results indicate validity for inclusion of the complete variable set in the analysis with low potential for multicollinearity issues.

TABLE 5-6: Variance Inflation Factor Multicollinearity Diagnostics

Variable	VIF	R-Squared	Variable	VIF	R-Squared
LnLotSqft	1.61	0.3796	Fwy1	1.74	0.4250
LnBldgSqft	3.77	0.7350	Fwy2	1.45	0.3084
Bed	1.96	0.4885	LtRail1	1.59	0.3706
Bath	3.00	0.6668	LtRail2	1.55	0.3546
Pool	1.08	0.0746	Freight1	1.18	0.1524
AgeSold	1.87	0.4666	Freight2	1.19	0.1620
MitigatedSold	1.38	0.2779	Neigh1	1.43	0.3023
MitigatedUnk	1.77	0.4348	Neigh2	2.06	0.5152
Foreclosure	1.01	0.0116	Neigh3	1.47	0.3206
Resold	1.12	0.1035	Neigh4	1.70	0.4123
Q1	2.49	0.5983	Neigh5	1.02	0.0162
Q2	2.42	0.5870	Neigh6	2.04	0.5109
Q3	2.44	0.5904	Neigh7	1.10	0.0945
Q4	2.63	0.6201	Neigh8	2.80	0.6434
Q5	2.70	0.6301	Neigh9	2.12	0.5288
Q6	2.77	0.6389	Neigh10	1.95	0.4869
Q7	2.73	0.6332	Neigh11	1.57	0.3624
Q8	2.61	0.6161	Neigh12	1.96	0.4901
Q9	2.21	0.5475	Neigh13	2.64	0.6217
Q10	2.29	0.5636	Neigh14	1.42	0.2953
Q11	2.13	0.5305	Neigh15	1.55	0.3535
Q12	2.45	0.5913	Neigh16	2.50	0.5999
Q13	2.51	0.6017	Neigh17	2.21	0.5485
Q14	2.46	0.5936	Neigh18	3.60	0.7220
Q15	2.37	0.5789	Neigh19	1.30	0.2283
School1	1.73	0.4204	Neigh20	1.57	0.3624
School2	1.65	0.3938	Neigh21	1.91	0.4777
Beach1	1.66	0.3983	Neigh22	1.66	0.3979
Beach2	1.93	0.4818	Neigh23	2.11	0.5263
MDRHarbor1	1.10	0.0909	Neigh24	1.10	0.0892
MDRHarbor2	2.10	0.5228	Neigh25	2.62	0.6178
FwyRamp1	3.24	0.6910	Neigh26	1.65	0.3929
FwyRamp2	2.94	0.6604	Neigh27	2.30	0.5644
Ramp3	2.14	0.5327	Neigh28	1.60	0.3736
LtRailStation1	1.14	0.1236	Neigh29	1.03	0.0336
LtRailStation2	1.33	0.2465	Neigh30	1.51	0.3384
LAX65CNEL	1.50	0.3320	Neigh31	1.08	0.0714
LAX70CNEL	1.34	0.2538	Neigh32	5.19	0.8074
LAXDist1	3.39	0.7053	Neigh33	1.92	0.4779
LAXDist2	1.92	0.4778	*MEAN*	*1.99*	

To validate the presence of spatial autocorrelation (SAC) in the dataset, a baseline OLS model was estimated to generate residuals for spatial dependence diagnostics (Anselin *et al.*, 1996). Next, this vector of disturbance values was evaluated using Moran's *I*, Lagrange Multiplier (LM), and Robust Lagrange Multiplier (LMR) tests. Moran's *I* confirmed the presence of SAC in the error term with a statistically significant result of 0.2394. Next, LM lag and LM error tests were performed, which indicated SAC within both the dependent variable, and the error term, respectively. LM lag and error tests, however, assume that SAC is mutually exclusive in the dependent variable and the error term. With the presence of SAC in both terms, secondary LMR tests were performed which also confirmed SAC in both the dependent variable and the error term (Anselin *et al.*, 1996).

Table 5-7: Spatial Autocorrelation Diagnostics

Test	Statistic	p-value
Moran's *I*	0.2394	0.000
Lagrange Multiplier (Spatial lag)	24.55	0.000
Robust Lagrange Multiplier (Spatial lag)	16.45	0.001
Lagrange Multiplier (Spatial error)	864.21	0.000
Robust Lagrange Multiplier (Spatial error)	856.11	0.000

Methodology

Hedonic Price Models

This study applies the hedonic price (HP) method as discussed in the opening chapter to the real property market in the area surrounding LAX. Again, the HP model applied to this market to analyze the impacts of noise can typically be written:

$$\boldsymbol{P} = f(\boldsymbol{S}, \boldsymbol{N}, \boldsymbol{E}, \boldsymbol{\varepsilon}) \tag{7}$$

where:

- $\boldsymbol{P}$ is a vector of housing prices;
- $\boldsymbol{S}$, $\boldsymbol{N}$, and $\boldsymbol{E}$ are matrices of structural, neighborhood, and environmental variables; and
- $\boldsymbol{\varepsilon}$ is a vector of error terms

Again, from Chapter 3, the partial derivative of f with respect to explanatory variable *j* is an implicit price that represents the MWTP for the represented characteristic.

Spatial Autocorrelation

As per diagnostic results indicating the presence of spatial autocorrelation within both the dependent variable and the error term (Table 5-7), it was determined that a Kelejian-Prucha spatial autoregressive model with autoregressive disturbances (SARAR) estimation was appropriate for this particular dataset (Elhorst, 2010), which from Chapter 3 follows the form:

$$\begin{cases} \boldsymbol{P} = \rho \boldsymbol{W} \boldsymbol{P} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{u}, \\ \boldsymbol{u} = \lambda \boldsymbol{W} \boldsymbol{u} + \boldsymbol{\varepsilon}, \end{cases} \tag{8}$$

where:

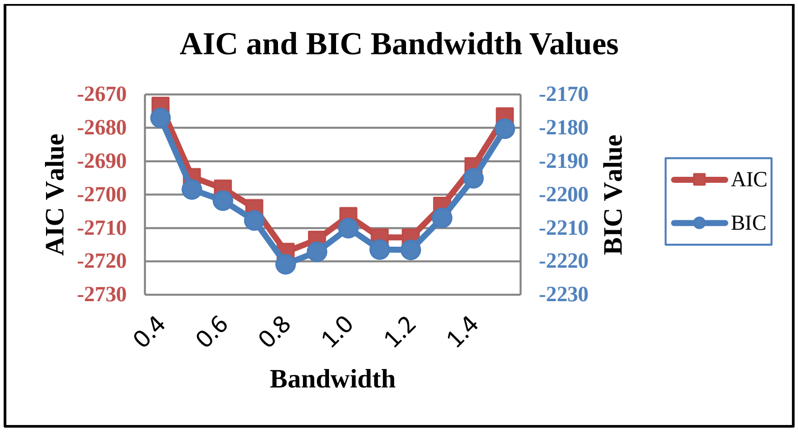
- *n* designates the sample size and q the number of explanatory variables including a constant term;
- $\boldsymbol{P}$ is an $n \times 1$ vector of single-family residential property prices;

- ρ ($|\rho|<1$) is an unknown spatial lag parameter;
- λ ($|\lambda|<1$) is an unknown spatial error parameter;
- $\boldsymbol{W}$ is an $n \times n$ spatial weight matrix, which reflects spatial interactions;
- $\boldsymbol{X}$ is an $n \times q$ matrix of exogenous explanatory variables;
- $\boldsymbol{\beta}$ is a $q \times 1$ vector of unknown coefficients;
- $\boldsymbol{u}$ is an $n \times 1$ vector of correlated residuals; and
- $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of independently distributed errors with zero mean.

Spatial Weight Matrix

Optimal weight matrix bandwidth distance specifications are not well defined in the literature, but can be validated by a number of tests, including Moran's *I*, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) analysis (Elhorst, 2010, Chica-Olmo *et al.*, 2019). For this analysis, AIC and BIC values from preliminary iterative ML model estimations were plotted using various weight matrix distances. Distance values from 0.4 to 1.6 kilometers were evaluated, with minimal AIC and BIC values occurring at a 0.8 kilometer bandwidth distance (Figure 5-4). This distance was then utilized as the weight matrix distance value for the actual estimations in this study (Chica-Olmo *et al.*, 2019).

Figure 5-4: AIC and BIC Weight Matrix Bandwidth Values



Interpreting SARAR Results

Spatial model interpretation differs from fixed effects models due to the possibility of the presence of spatial spillover effects from neighboring observations. Using a log transformation of the dependent price sold variable, and as discussed in Chapter 3, the spatial lag term $\lambda \boldsymbol{W}\, log(\boldsymbol{P})$ SARAR model results require additional interpretation when compared to simple linear regression results (Kelejian and Prucha, 1998). To better understand this term,

$\boldsymbol{V} \equiv (\boldsymbol{I} - \lambda \boldsymbol{W})^{-1}$ is expanded and the log of (**P**) is isolated on the left side of Equation (8) as follows:

$$\boldsymbol{V} \equiv (\boldsymbol{I} - \lambda \boldsymbol{W})^{-1} = \boldsymbol{I} + \lambda \boldsymbol{W} + \lambda^2 \boldsymbol{W}^2 + \ldots \quad (9)$$

When |λ|<1 this expression is well defined because **W** is row-normalized and the product of row-normalized matrices is row-normalized. Hence, Equation (8) becomes:

$$\begin{cases} log(\boldsymbol{P}) = \boldsymbol{X\beta} + \lambda \boldsymbol{WX\beta} + \lambda^2 \boldsymbol{W}^2 \boldsymbol{X\beta} + \lambda^3 \boldsymbol{W}^3 \boldsymbol{X\beta} + \ldots + \boldsymbol{\omega} \\ \boldsymbol{\omega} \equiv (\boldsymbol{I} - \lambda \boldsymbol{W})^{-1} (\boldsymbol{I} - \rho \boldsymbol{W})^{-1} \boldsymbol{\varepsilon} \end{cases} \quad (10)$$

Since E(ω)=0, the first equation of Equation (10) shows that the expected value of log(P) equals a mean value **Xβ** plus a linear combination of mean values taken by neighboring properties (the terms $[\lambda \boldsymbol{W} + \lambda^2 \boldsymbol{W}^2 + \lambda^3 \boldsymbol{W}^3 + \ldots] \boldsymbol{X\beta}$). To better understand these impacts,

$log(\boldsymbol{P}) = \boldsymbol{V}(\boldsymbol{X\beta} + \boldsymbol{u}) = \boldsymbol{VX\beta} + \boldsymbol{\omega}$ can be expanded (LeSage and Pace, 2009):

$$\begin{pmatrix} log(P_1) \\ log(P_2) \\ \vdots \\ log(P_N) \end{pmatrix} = \boldsymbol{V}\begin{pmatrix} \beta_0 \\ \beta_0 \\ \vdots \\ \beta_0 \end{pmatrix} + \sum_{q=1}^{Q-1} \beta_q \begin{pmatrix} \boldsymbol{V}_{11} & \boldsymbol{V}_{12} & \dots & \boldsymbol{V}_{1N} \\ \boldsymbol{V}_{21} & \boldsymbol{V}_{22} & \dots & \boldsymbol{V}_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \boldsymbol{V}_{N1} & \boldsymbol{V}_{N2} & \dots & \boldsymbol{V}_{NN} \end{pmatrix} \begin{pmatrix} \boldsymbol{X}_{1q} \\ \boldsymbol{X}_{2q} \\ \vdots \\ \boldsymbol{X}_{Nq} \end{pmatrix} + \boldsymbol{\omega} \tag{11}$$

where:

- for $(i,j) \in \{1,\dots,N\}^2$ and for $q \in \{1,\dots,Q\text{-}1\}$, $\log(P_j)$ is the logarithm of the price of the j^{th} property;
- $\mathbf{V}_{ij}$ is the i^{th} line and j^{th} column element of $\boldsymbol{V} \equiv (\boldsymbol{I} - \lambda \boldsymbol{W})^{-1}$;
- $\mathbf{X}_{jq}$ is the j^{th} line and q^{th} column element of $\mathbf{X}$**;** and
- $\boldsymbol{\omega} \equiv (\boldsymbol{I} - \lambda \boldsymbol{W})^{-1}(\boldsymbol{I} - \rho \boldsymbol{W})^{-1}\boldsymbol{\varepsilon}$.

If $\boldsymbol{X}_{jq}$ is a continuous variable, taking the derivative of $log(P_i)$ with respect to $\boldsymbol{X}_{jq}$ using Equation (11) gives:

$$\frac{\partial\, log(P_i)}{\partial \boldsymbol{X}_{jq}} = \beta_q \boldsymbol{V}_{ij} \tag{12}$$

which represents the semi elasticity of price for property *i* with respect to a change in characteristic *q* ($\mathbf{X}_{jq}$) of property *j*, and the elasticity of price for property *i* with respect to a change in characteristic x_{jq} of property *j* if $\mathbf{X}_{jq}$ is the logarithm of x_{jq}. It differs from 0 when $\lambda \neq 0$ if observations *i* and *j* are spatial "neighbors" and if $\beta_q \neq 0$. Compared to a linear regression model where $\mathbf{V}_{ii}=1$ and $\mathbf{V}_{ij}=0$ for $i \neq j$, $\mathbf{V}_{ij}$ thus plays the role of a spatial correction factor. Equation 12 also shows that the β_q coefficients do not have the same meaning as in a linear regression model.

Since a large number of such partial derivatives could be non-zero, this follows LeSage and Pace (2009) and calculates for each explanatory variable $q \in \{1,..,Q\text{-}1\}$ the following scalar summary measures:

- Average Direct Impact (ADI_q) is obtained by averaging the main diagonal terms of $\beta_q\boldsymbol{V}$:

$$ADI_q = \beta_q N^{-1} \sum_{i=1}^{N} \boldsymbol{V}_{ii} \tag{13}$$

This captures feedback passing through neighbors and back to each observation. Inserting Equation (12) into Equation (13) for a non-log transformed continuous variable $\mathbf{X}_{jq}$ shows that ADI_q is the average semi-elasticity of price with respect to variable q across all properties in the sample.

- Average Indirect Impact (AII_q) is calculated by averaging only the off-diagonal terms of $\beta_q\boldsymbol{V}$:

$$AII_q = \beta_q N^{-1} \sum_{(i,j)\in\{1,\dots,N\}^2}^{i\neq j} \boldsymbol{V}_{ij} = N^{-1} \sum_{j=1}^{N} \left(\sum_{i\in\{1,\dots,N\}}^{i\neq j} \beta_q \boldsymbol{V}_{ij} \right) \tag{14}$$

This represents spatial spillovers (i.e., impacts to/from other observations only). Keeping in mind Equation (12), the last term in Equation (14) shows that AII_q is the average impact of a marginal change in $\boldsymbol{X}_{jq}$ on the price of all properties except for property j.

- Average Total Impact (ATI_q), obtained by averaging all row sums of the $\beta_q\boldsymbol{V}$ matrix; it is the sum of direct and indirect impacts. Simplifying the sum of ADI_q and AII_q gives

$$ATI_q = \frac{\beta_q}{1-\lambda}. \tag{15}$$

If $\mathbf{X}_{jq}$ is a binary or a count variable, changing its value by one unit affects the log value of the price of property i as follows:

$$\Delta\, log(P_i) = \beta_q \boldsymbol{V}_{ij} \tag{16}$$

Statistical significance of ADI_q, AII_q, and ATI_q is assessed by again following LeSage and Pace (2009) after assuming $\boldsymbol{\beta}$, λ, ρ and σ^2 are normally distributed with mean values and a covariance matrix obtained from estimating Equation (8). Using Stata, 10,000 draws were utilized to estimate statistical significance based on the resulting empirical distributions.

Finally, the average expected percentage change in the price of property *i* from a one unit change in the binary/count variable $\mathbf{X}_{iq}$ is given by using the expression of the expected value of a lognormal distribution:

$$\left(\frac{\Delta P}{P}\right)_q = N^{-1} \sum_{i=1}^{N} \left[exp(\beta_q \boldsymbol{V}_{ii} + 0.5 \boldsymbol{V}_{ii}^2 \sigma_q^2) - 1 \right] \quad (17)$$

where σ_q^2 is the variance of the distribution of log(β_q).

Results and Conclusions

Fixed and Spatial Effects Model Results

Stata 13 was used to estimate three models using the log transformed value of Price Sold as the dependent variable. An OLS fixed effects model was estimated for a baseline reference (Elhorst, 2010). To address SAC detected in the dataset, two SARAR models were then run to estimate parameters for these same independent variables using ML and GS2SLS methods. Results from all three models are shown in Tables 5-8 through 5-11.

Overall, OLS R^2 and Adjusted R^2 values were 0.869 and 0.868, respectively, indicating a good fit for that model – which is often the case, even when spatial autocorrelation is present but may not have been accounted for (Elhorst, 2010). Significant spatial lag parameters of 0.5887 and 0.7103 for ML and GS2SLS estimations, along with values of 0.4618 and 0.2406 for the spatial error parameters, indicate considerable influence from the spatial weight influences in the SARAR models.

Again, aside from statistical significance, it is important to note that interpretation of GS2SLS SARAR parameters is not directly comparable to marginal or elasticity value interpretations of OLS parameter estimates. Instead, ADI, AII, and ATI are calculated and averaged for each independent variable (Tables 5-12 through 5-15) (LeSage and Pace, 2009).

Structural Variables

Parameter estimates in all three models for primary structural variables (log of structure and lot square footage, number of bedrooms and bathrooms, pool presence, and age when sold), were statistically significant, with expected positive or negative values. The two noise mitigation coefficient parameters were not significant across model results. Both binary foreclosure and recently resold variables indicated significance across all three models, with negative parameter values.

Temporal quarterly sale date variables showed significance in all quarters with all three models. Parameter values were similar across all three model estimates and indicated generally steady increases in value over time, as would be expected in the region's appreciating housing market.

Neighborhood Variables

Neighborhood distance buffers for school proximity were significant only within 250 meters with the OLS model with a negative impact of -0.0121. Beach recreation area distance was significant and positive within 150 meters with the OLS model, and across all three models for distances of 251 to 500 meters. Proximity to Marina del Rey Harbor showed significance only in the 151- to 300-meter distance with a negative parameter value. This may indicate the nearness as a disamenity due to the heavy traffic, congestion, and parking issues that are present in the immediate area along with the lack of any simple recreational amenity offered by the harbor. Light rail station showed no significance up to the 800-meter network distance that was analyzed indicating that while people who live in single-family homes in the sample area may use public transit regularly, it is not necessarily an influential amenity for housing location choice. Freeway onramps did show positive and significant impacts up to 3,000 network meters across all three models, however, indicating that vehicle travel and freeway accessibility could be important for residents in the sample area.

Fixed spatial effects variables for geographic delineation showed significance in all but the Los Angeles County CDP of West Compton in the OLS model. ML and GS2SLS models showed significance in 20 of the 33 zones, indicating heavy dependence of the OLS model to account for spatial heterogeneity across the geographic sample space. Within the two spatial model results, when compared to the City of Los Angeles neighborhoods and the Los Angeles County CDPs, incorporated cities showed the highest ratio of significant zones, with five of seven and six of seven cities showing significance in the ML and GS2SLS models, respectively.

Environmental Variables

Light rail and freight rail line proximity showed parameter significance only in the OLS model and for distances of less than 150 meters to a light rail line at -0.0510. Properties located within 200 meters of a freeway showed significance across all three models, with an expected negative sign, with distances of 201 to 400 meters significant and negative only in the OLS model output. Finally, proximity to the LAX property indicate a positive influence on housing prices, with significant and positive parameters across all three models for all distances up to 2,000 meters. This may not indicate proximity as actually being a positive amenity, but could be influenced by the 268 observations in the El Segundo neighborhood just south of the airport property, which have a mean value of $858,672 versus the sample mean of $259,002. Further investigation would be required to confirm if this is the case.

Focusing on the LAX CNEL parameters of interest, OLS and ML estimations indicated significant negative parameters for both CNEL 65 and CNEL 70 noise contour zones. Both zones were not significant in the GS2SLS model. OLS parameter estimates of -0.0510 and -0.1194 versus ML estimates of -0.0240 and -0.0516 indicated values of roughly half when comparing fixed versus spatial effects models. These findings are very similar to Rahmatian and Cockerill (2004) who utilized OLS models to estimate impacts to be between 4% and 10%. Again, overestimation is often an indication of omitted variable bias in OLS when estimating spatially autocorrelated data. While not significant, GS2SLS estimates were in line with ML values at -0.0130 and -0.0373, which would result in ADI values of -0.0126 and -0.0388 and ATI values of -0.0427 and -0.1314. Finally, these results indicate an overall impact of -2.4% and -5.16% with ML estimation for CNEL 65 and CNEL 70 exposure, respectively, with actual dollar value impacts of $6,216 and $13,365 based on a sample median price of $259,002. Calculated NDIs of 0.48% and 1.03% for CNEL 65 and CNEL 70 zones are comparable to findings in previous studies (Nelson, 2004; Cohen & Coughlin, 2009; Chalermpong, 2010; Boes and Nuesch, 2011)

Table 5-8: Model Results - Structural Variables

Variable	OLS	ML	GS2SLS
LnLotSqft	0.1292***	0.1248***	0.1189***
LnBldgSqft	0.3718***	0.3312***	0.3251***
Bedrooms	0.0141***	0.0167***	0.0170***
Bathrooms	0.0294***	0.0252***	0.0253***
Pool on property	0.0503***	0.0280**	0.0237**
Age when sold (years)	-0.0013***	-0.0007***	-0.0006***
Noise mitigated prior to sale	-0.0245	-0.0300	-0.0320
Noise mitigated (unknown date)	-0.0020	0.0027	0.0020
Foreclosure sale	-0.0856***	-0.0777***	-0.0783***
Resold within previous year	-0.2406***	-0.2387***	-0.2382***
Sold during 2010 Quarter 3	-0.2114***	-0.2097***	-0.2081***
Sold during 2010 Quarter 4	-0.2167***	-0.2182***	-0.2174***
Sold during 2011 Quarter 1	-0.2462***	-0.2397***	-0.2382***
Sold during 2011 Quarter 2	-0.2374***	-0.2367***	-0.2351***
Sold during 2011 Quarter 3	-0.2415***	-0.2389***	-0.2378***
Sold during 2011 Quarter 4	-0.2562***	-0.2532***	-0.2522***
Sold during 2012 Quarter 1	-0.2925***	-0.2878***	-0.2867***
Sold during 2012 Quarter 2	-0.2458***	-0.2489***	-0.2480***
Sold during 2012 Quarter 3	-0.2237***	-0.2262***	-0.2249***
Sold during 2012 Quarter 4	-0.2145***	-0.2089***	-0.2087***
Sold during 2013 Quarter 1	-0.1570***	-0.1560***	-0.1551***
Sold during 2013 Quarter 2	-0.0831***	-0.0883***	-0.0875***
Sold during 2013 Quarter 3	-0.0425***	-0.0463***	-0.0454***
Sold during 2013 Quarter 4	-0.0450***	-0.0468***	-0.0471***
Sold during 2014 Quarter 1	-0.0292**	-0.0313**	-0.0302**
Additional Parameters and Statistics			
Constant	8.6734	1.7641***	0.3555
Spatial Lag Coefficient (λ)		0.5887***	0.7103***
Spatial Error Coefficient (ρ)		0.4618***	0.2406***
R^2	0.869		
Adjusted R^2	0.868		

*p<0.10, **p<0.05, ***p<0.01

Table 5-9: Model Results – Neighborhood Amenity Variables

Variable	OLS	ML	GS2SLS
Nearest school property (up to 250m)	-0.0121*	-0.0089	-0.0058
Nearest school property (251-500m)	-0.0086	-0.0025	-0.0005
Nearest beach recreation area (up to 150m)	0.1338***	0.0404	0.0322
Nearest beach recreation area (151-300m)	0.2066***	0.1019***	0.0889**
Proximity to Marina del Rey Harbor (up to 150m)	-0.1491	-0.0637	-0.0977
Proximity to Marina del Rey Harbor (151-300m)	-0.2748***	-0.2074***	-0.2501***
Nearest freeway onramp network distance (up to 1,000m)	0.0369***	0.0377***	0.0430***
Nearest freeway onramp network distance (1,001-2,000m)	0.0022	0.0135	0.0174**
Nearest freeway onramp network distance (2,001-3,000m)	0.0129*	0.0241***	0.0304***
Nearest light rail station network distance (up to 400m)	0.0614	0.0329	0.0243
Nearest light rail station network distance (401-800m)	-0.0010	-0.0105	-0.0178

*p<0.10, **p<0.05, ***p<0.01

Table 5-10: Model Results – City/Neighborhood Variables

Variable	OLS	ML	GS2SLS
City of Los Angeles Neighborhoods			
Athens	0.1334***	0.0182	-0.0180
Broadway-Manchester	-0.0530***	-0.0008	0.0135
Chesterfield Square	0.1387***	0.0729**	0.0621***
Del Rey	1.0994***	0.3534***	0.2003***
Gramercy Park	0.2030***	0.0674***	0.0379**
Green Meadows	-0.0490***	-0.0095	0.0098
Harbor Gateway	0.2230***	0.0548	0.0215
Harvard Park	0.0765***	0.0402	0.0389*
Hyde Park	0.2593***	0.1214***	0.0958***
Manchester Square	0.1805***	0.0452*	0.0175
Playa del Rey	1.1774***	0.3051***	0.1516***
Playa Vista	1.0118***	0.3094***	0.1784***
Venice	1.6635***	0.6273***	0.4410***
Vermont Knolls	0.0749***	0.0111	0.0065
Vermont Vista	0.0306*	0.0426*	0.0371**
Vermont-Slauson	0.0666***	0.0451	0.0507**
Watts	-0.1553***	-0.0542**	-0.0431*
Westchester	1.0040***	0.3064***	0.1650***
Incorporated Cities			
Compton	0.0567***	0.0247	0.0179
Culver City	0.7435***	0.0898	-0.0832**
El Segundo	1.1678***	0.3453***	0.1775***
Gardena	0.3370***	0.1111***	0.0565***
Hawthorne	0.4836***	0.1771***	0.1147***
Inglewood	0.2921***	0.0891***	0.0471***
Manhattan Beach	1.5299***	0.7012***	0.5152***
Unincorporated Los Angeles County CDPs			
Del Aire	0.6389***	0.1817***	0.1148***
Florence	0.0059	0.0241	0.0236
Florence-Firestone	-0.0282*	-0.0047	0.0065
Ladera Heights	0.7171***	0.1334***	-0.0033
Lennox	0.1902***	0.0616*	0.0352
View Park-Windsor Hills	0.5449***	0.1805**	0.1357***
West Compton	0.0175	0.0066	-0.0001
Westmont	0.0735***	-0.0077	-0.0218

*p<0.10, **p<0.05, ***p<0.01

Table 5-11: Model Results – Environmental Variables

Variable	OLS	ML	GS2SLS
Within LAX CNEL 65 dBA noise contour	-0.0510***	-0.0240*	-0.0130
Within LAX CNEL 70 dBA noise contour	-0.1194***	-0.0516**	-0.0373
LAX distance (Up to 1,000m)	0.0565***	0.0373**	0.0335**
LAX distance (1,001-2,000m)	0.0345***	0.0257*	0.0209*
Nearest freeway distance (up to 200m)	-0.0706***	-0.0497***	-0.0493***
Nearest freeway distance (201-400m)	-0.0309***	-0.0081	-0.0084
Nearest light rail line distance (up to 150m)	-0.0510**	-0.0130	-0.0126
Nearest light rail line distance (151-300m)	0.0238	0.0222	0.0220
Nearest freight rail line distance (up to 150m)	0.0135	0.0153	0.0155
Nearest freight rail line distance (151-300m)	0.0145	0.0110	0.0124

*p<0.10, **p<0.05, ***p<0.01

Conclusions

This chapter analyzes the impacts of aircraft noise on the community around LAX by using a spatial HP method on single-family home sales from 2010 to 2014. The presence of spatial dependence in the dataset required a spatially weighted regression model to properly estimate these impacts. Using a Spatial Autoregressive Model with Autoregressive Disturbances (SARAR) model estimated with a Generalized Spatial Two Stage Least Squares (GS2SLS) procedure, results were compared to fixed effects Ordinary Least Squares (OLS) and spatially weighted Maximum Likelihood (ML) estimates. Results indicate that aircraft noise impacts are significant on single-family residences within both the CNEL 65 and CNEL 70 noise impacted zones around Los Angeles International Airport. Average SARAR modeled values of -2.4% and -5.16% resulted in -$6,216 and -$13,365 impacts on individual property prices for the two noise affected zones. Compared to fixed effects OLS model estimates of -5.1% and -11.94% property price impacts, these results suggest an overestimation by OLS results due to unobserved spatial autocorrelation within the dataset. Strong statistical significance among fixed effect neighborhood delineations was not present in some City of Los Angeles and County of Los Angeles CDPs, indicating the possibility of the presence of spatial homogeneity in neighboring zones that are similar in jurisdiction or demographics.

Proper geographic delineation and validation of airport noise levels within the community is important, as it has been established that environmental noise can have significant impacts on public health. Accurate assessment of these noise affected zones and their relative impacts are beneficial not only for economic and policy reasons, but for public health implications as well. The results from this study indicate that while consumers are willing to pay discounted prices to be located in noise affected zones near LAX, they may be subjecting themselves to health risks that can stem from unwanted noise from aircraft operations.

Future Research

Future research should include noise measurements at impacted properties to provide actual noise exposure data during day-to-day real-time situations. Both inside and outside measurements could also provide a clearer understanding of structural influences on noise level differentials as they pertain to individual residences. In addition, surveys could be used to assess perceived noise impacts on residents, which would allow better estimation of annoyance levels and the direct health issues that are caused by aircraft operations and other environmental noise sources.

Table 5-12: SARAR GS2SLS Average Direct and Indirect Impacts – Structural Variables

Variable	GS2SLS Parameter	ADI +	AII =	ATI
LnLotSqft	0.1189***	0.1215***	0.2921***	0.4136***
LnBldgSqft	0.3251***	0.3259***	0.7862***	1.1121***
Bedrooms	0.0170***	0.0176***	0.0424***	0.0600***
Bathrooms	0.0253***	0.0256***	0.0619***	0.0875***
Pool on property	0.0237**	0.0240**	0.0581**	0.0820**
Age when sold (years)	-0.0006***	-0.0006***	-0.0015***	-0.0022***
Noise mitigated prior to sale	-0.0320	-0.0329	-0.0792	-0.1120
Noise mitigated (unknown date)	0.0020	0.0013	0.0034	0.0047
Foreclosure sale	-0.0783***	-0.0773***	-0.1863***	-0.2636***
Resold within previous year	-0.2382***	-0.2397***	-0.5782***	-0.8179***
Sold during 2010 Quarter 3	-0.2081***	-0.2098***	-0.5057***	-0.7155***
Sold during 2010 Quarter 4	-0.2174***	-0.2196***	-0.5295***	-0.7491***
Sold during 2011 Quarter 1	-0.2382***	-0.2413***	-0.5816***	-0.8228***
Sold during 2011 Quarter 2	-0.2351***	-0.2379***	-0.5734***	-0.8113***
Sold during 2011 Quarter 3	-0.2378***	-0.2405***	-0.5795***	-0.8200***
Sold during 2011 Quarter 4	-0.2522***	-0.2562***	-0.6181***	-0.8743***
Sold during 2012 Quarter 1	-0.2867***	-0.2894***	-0.6978***	-0.9872***
Sold during 2012 Quarter 2	-0.2480***	-0.2506***	-0.6040***	-0.8546***
Sold during 2012 Quarter 3	-0.2249***	-0.2258***	-0.5439***	-0.7697***
Sold during 2012 Quarter 4	-0.2087***	-0.2111***	-0.5091***	-0.7203***
Sold during 2013 Quarter 1	-0.1551***	-0.1578***	-0.3801***	-0.5380***
Sold during 2013 Quarter 2	-0.0875***	-0.0890***	-0.2148***	-0.3037***
Sold during 2013 Quarter 3	-0.0454***	-0.0469***	-0.1127***	-0.1597***
Sold during 2013 Quarter 4	-0.0471***	-0.0487***	-0.1168***	-0.1656***
Sold during 2014 Quarter 1	-0.0302**	-0.0315**	-0.0755**	-0.1069**

*p<0.10, **p<0.05, ***p<0.01

Table 5-13: SARAR GS2SLS Average Direct and Indirect Impacts – Neighborhood Amenity Variables

Variable	GS2SLS Parameter	ADI +	AII =	ATI
Nearest school property (up to 250m)	-0.0058	-0.0061	-0.0144	-0.0205
Nearest school property (251-500m)	-0.0005	-0.0009	-0.0021	-0.0030
Nearest beach recreation area (up to 150m)	0.0322	0.0362	0.0897	0.1259
Nearest beach recreation area (151-300m)	0.0889**	0.0907**	0.2194**	0.3102**
Proximity to Marina del Rey Harbor (up to 150m)	-0.0977	-0.0982	-0.2410	-0.3392
Proximity to Marina del Rey Harbor (151-300m)	-0.2501***	-0.2526***	-0.6106***	-0.8633***
Nearest freeway onramp network distance (up to 1,000m)	0.0430***	0.0419***	0.1006***	0.1425***
Nearest freeway onramp network distance (1,001-2,000m)	0.0174**	0.0169**	0.0407**	0.0576**
Nearest freeway onramp network distance (2,001-3,000m)	0.0304***	0.0306***	0.0736***	0.1042***
Nearest light rail station network distance (up to 400m)	0.0243	0.0227	0.0533	0.0760
Nearest light rail station network distance (401-800m)	-0.0178	-0.0165	-0.0406	-0.0571

*p<0.10, **p<0.05, ***p<0.01

Table 5-14: SARAR GS2SLS Average Direct and Indirect Impacts – City/Neighborhood Variables

Variable	GS2SLS Parameter	ADI +	AII =	ATI
City of Los Angeles Neighborhoods				
Athens	-0.0180	-0.0177	-0.0443	-0.0619
Broadway-Manchester	0.0135	0.0123	0.0306	0.0428
Chesterfield Square	0.0621***	0.0625**	0.1502**	0.2127**
Del Rey	0.2003***	0.2049***	0.4878***	0.6926***
Gramercy Park	0.0379**	0.0403***	0.0958***	0.1361***
Green Meadows	0.0098	0.0115	0.0290	0.0405
Harbor Gateway	0.0215	0.0222	0.0522	0.0744
Harvard Park	0.0389*	0.0408*	0.0982*	0.1390*
Hyde Park	0.0958***	0.0973***	0.2327***	0.3299***
Manchester Square	0.0175	0.0174	0.0407	0.0581
Playa del Rey	0.1516***	0.1544***	0.3637***	0.5181***
Playa Vista	0.1784***	0.1858***	0.4424***	0.6282***
Venice	0.4410***	0.4496***	1.0729***	1.5226***
Vermont Knolls	0.0065	0.0105	0.0244	0.0350
Vermont Vista	0.0371**	0.0383***	0.0925***	0.1308***
Vermont-Slauson	0.0507**	0.0549***	0.1321***	0.1870***
Watts	-0.0431*	-0.0433	-0.1034	-0.1467
Westchester	0.1650***	0.1694***	0.4018***	0.5712***
Incorporated Cities				
Compton	0.0179	0.0155	0.0379	0.0534
Culver City	-0.0832**	-0.0803**	-0.2008**	-0.2812**
El Segundo	0.1775***	0.1826***	0.4310***	0.6136***
Gardena	0.0565***	0.0554***	0.1310***	0.1863***
Hawthorne	0.1147***	0.1204***	0.2874***	0.4078***
Inglewood	0.0471***	0.0475***	0.1129***	0.1604***
Manhattan Beach	0.5152***	0.5121***	1.2236***	1.7358***
Unincorporated Los Angeles County CDPs				
Del Aire	0.1148***	0.1214***	0.2890***	0.4103***
Florence	0.0236	0.0246	0.0593	0.0838
Florence-Firestone	0.0065	0.0065	0.0168	0.0233
Ladera Heights	-0.0033	0.0006	-0.0053	-0.0047
Lennox	0.0352	0.0346	0.0820	0.1166
View Park-Windsor Hills	0.1357***	0.1359***	0.3270***	0.4629***
West Compton	-0.0001	-0.0002	0.0002	0.0000
Westmont	-0.0218	-0.0201	-0.0498	-0.0699

*p<0.10, **p<0.05, ***p<0.01

Table 5-15: SARAR GS2SLS Average Direct and Indirect Impacts – Environmental Variables

Variable	GS2SLS Parameter	ADI +	AII =	ATI
Within LAX CNEL 65 dBA noise contour	-0.0130	-0.0126	-0.0301	-0.0427
Within LAX CNEL 70 dBA noise contour	-0.0373	-0.0388	-0.0926	-0.1314
LAX distance (Up to 1,000m)	0.0335**	0.0335**	0.0807**	0.1141**
LAX distance (1,001-2,000m)	0.0209*	0.0214*	0.0516*	0.0730*
Nearest freeway distance (up to 200m)	-0.0493***	-0.0491***	-0.1182***	-0.1673***
Nearest freeway distance (201-400m)	-0.0084	-0.0086	-0.0202	-0.0288
Nearest light rail line distance (up to 150m)	-0.0126	-0.0141	-0.0338	-0.0479
Nearest light rail line distance (151-300m)	0.0220	0.0204	0.0492	0.0696
Nearest freight rail line distance (up to 150m)	0.0155	0.0160	0.0391	0.0550
Nearest freight rail line distance (151-300m)	0.0124	0.0128	0.0311	0.0439

*p<0.10, **p<0.05, ***p<0.01

Table 5-16: SARAR GS2SLS Environmental Variable Average Impact Valuations

Variable	ATI Value	†Impact
Within LAX CNEL 65 dBA noise contour	-0.0427	$ -11,057
Within LAX CNEL 70 dBA noise contour	-0.1314	$ -34,039
LAX distance (Up to 1,000m)	0.1141**	$ 29,563
LAX distance (1,001-2,000m)	0.0730*	$ 18,916
Nearest freeway distance (up to 200m)	-0.1673***	$ -43,332
Nearest freeway distance (201-400m)	-0.0288	$ -7,464
Nearest light rail line distance (up to 150m)	-0.0479	$ -12,396
Nearest light rail line distance (151-300m)	0.0696	$ 18,023
Nearest freight rail line distance (up to 150m)	0.0550	$ 14,255
Nearest freight rail line distance (151-300m)	0.0439	$ 11,372

*p<0.10, **p<0.05, ***p<0.01

†Based on median sale price of $259,002

CHAPTER 6

Single-family Home Real Estate Value Impacts from Freight Rail Noise in the South Bay Region of Los Angeles County, California: A Spatial Hedonic Analysis

Introduction

The analysis in this chapter focuses on the noise impacts of freight rail operations on the single-family residential marketplace in the South Bay area of Los Angeles County, California from a spatial hedonic price (HP) perspective. Following the Chapter 2 literature review of this dissertation, it is reiterated that aircraft noise is often found to have the highest impact on transportation noise-affected communities, with road and rail noise impacts garnering the most attention from researchers overall. The majority of published rail noise studies, however, have focused on transit or light rail modes (Navrud, 2002) with minimal research conducted on freight rail noise impacts. Even within the breadth of freight rail studies as a whole, research has predominantly focused on technical topics, innovation, and network efficiencies (Connolly *et al.*, 2014; Soleimani *et al.*, 2019; Besinovic, 2020; Izadi *et al.*, 2020). This gap in research is important to address, especially in the Southern California region, due to the increasing burdens placed on urban transportation infrastructures due to ongoing population growth.

Previous freight rail noise studies in the United States (U.S.) utilized fixed effects HP models to estimate impacts on neighboring communities (Simons and El Jaouhari, 2004; Cushing Daniels, 2005; Bellinger, 2006; Clark, 2006). As referenced in Chapter 3, fixed effects models do not account for spatial heterogeneity in the dataset, which results in biased parameter estimations.

Aligning with a recent study in Santa Marta, Columbia (Chica-Olmo *et al.*, 2019) which used spatial HP models to estimate freight rail impacts on single-family home sales, this chapter proposes to investigate freight rail impacts on a densely populated residential area in Los Angeles County. The hypothesis in this study is that freight train noise and vibration, audible train warning equipment at crossings, and train horns have a negative impact on nearby residential property values. This HP study will provide Revealed Preference (RP) estimates of residents' marginal willingness-to-pay (MWTP) for residing near freight rail lines and their associated crossings; this includes a diminishing noise impact as distance to the rail line or rail crossing increases.

Background

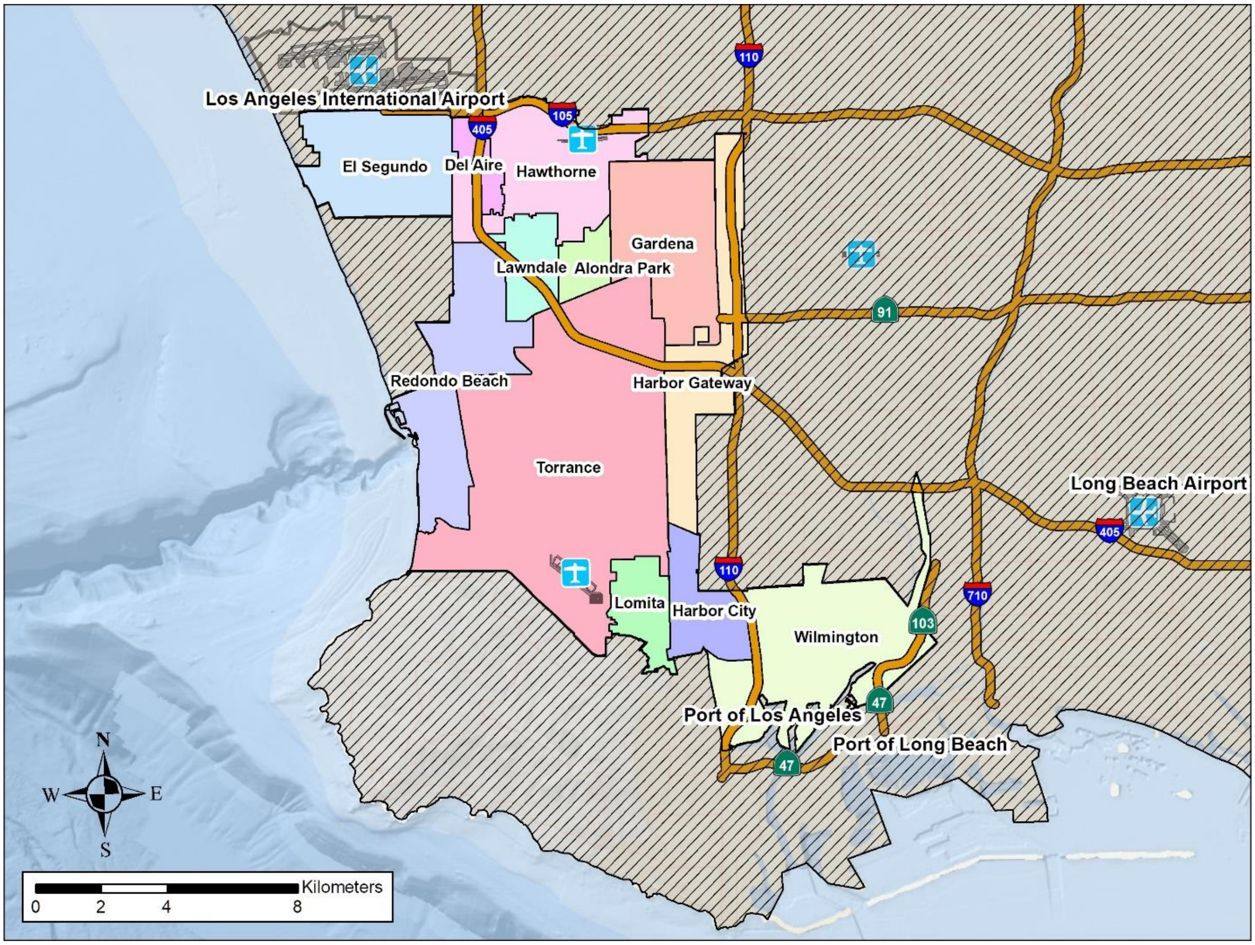
South Bay Study Area

The geographical area chosen for this study is located within a densely populated region of Los Angeles County, California, referred to as the South Bay. This region at the southern tip of Los Angeles County is located approximately ten miles south-southwest of downtown Los Angeles, and is adjacent to the Santa Monica Bay to the west and the San Pedro Bay to the south. The South Bay spans approximately 105 square miles and comprises fifteen incorporated cities, four designated neighborhoods within the city of Los Angeles, and three unincorporated Los Angeles County census designated places (CDPs). Population in the region is approximately 750,000 with a highly diverse ethnic and income demographic which varies by city and by neighborhood (United States Census Bureau, 2020). Additionally, because of its proximity to the Port of Los Angeles (POLA) and the Port of Long Beach (POLB), collectively referred to as the San Pedro Bay Ports (SPBP), the South Bay has become a major industrial and corporate hub for many large corporations (South Bay Cities Council of Governments, 2022). This robust economic presence has been the driver behind the region's dense population and continuing growth, as well as the catalyst behind the development of its extensive transportation infrastructure.

The SPBP, which collectively rank as the fifth-busiest port in the world (The Port of Los Angeles, 2022), has fostered extensive corporate and industrial development in the neighboring South Bay. Notably, automakers Toyota (until moving to Texas in 2017) and Honda established their original North American headquarter campuses in Torrance (Toyota Motor Sales, 2017; Honda Motor Company, 2022), with Nissan having their corporate headquarters in Gardena until moving to Tennessee in 2007 (Nissan, 2022). The South Bay has also served as a cornerstone location to the aerospace industry, with the latest addition being SpaceX headquarters in

Hawthorne. Additionally, although no longer a major oil drilling region due to mostly depleted oil fields, the petroleum refining industry continues to operate six major transportation fuel refineries in the area. Two of these refineries are ranked as the first and second largest fuel producers in the Western United States by volume, and are located in Carson (Tesoro) and El Segundo (Chevron), respectively. Each processes over 250,000 barrels of oil per day, with the two facilities collectively producing nearly four billion gallons of transportation fuel annually (California Energy Commission, 2022). This accounts for approximately 40 percent of motor vehicle and 80 percent of jet fuel consumed in Southern California (Chevron Corporation, 2022). In terms of cargo movement for the U.S. as a whole, approximately 40 percent of all containers imported and 24 percent of containers exported travel through the SPBP (The Port of Los Angeles, 2022). These large-scale industry and import/export operations continue to capitalize on the region's extensive freight rail infrastructure and its inherent economies of scale.

Figure 6-1: South Bay Freight Rail Study Area



Transportation Corridors

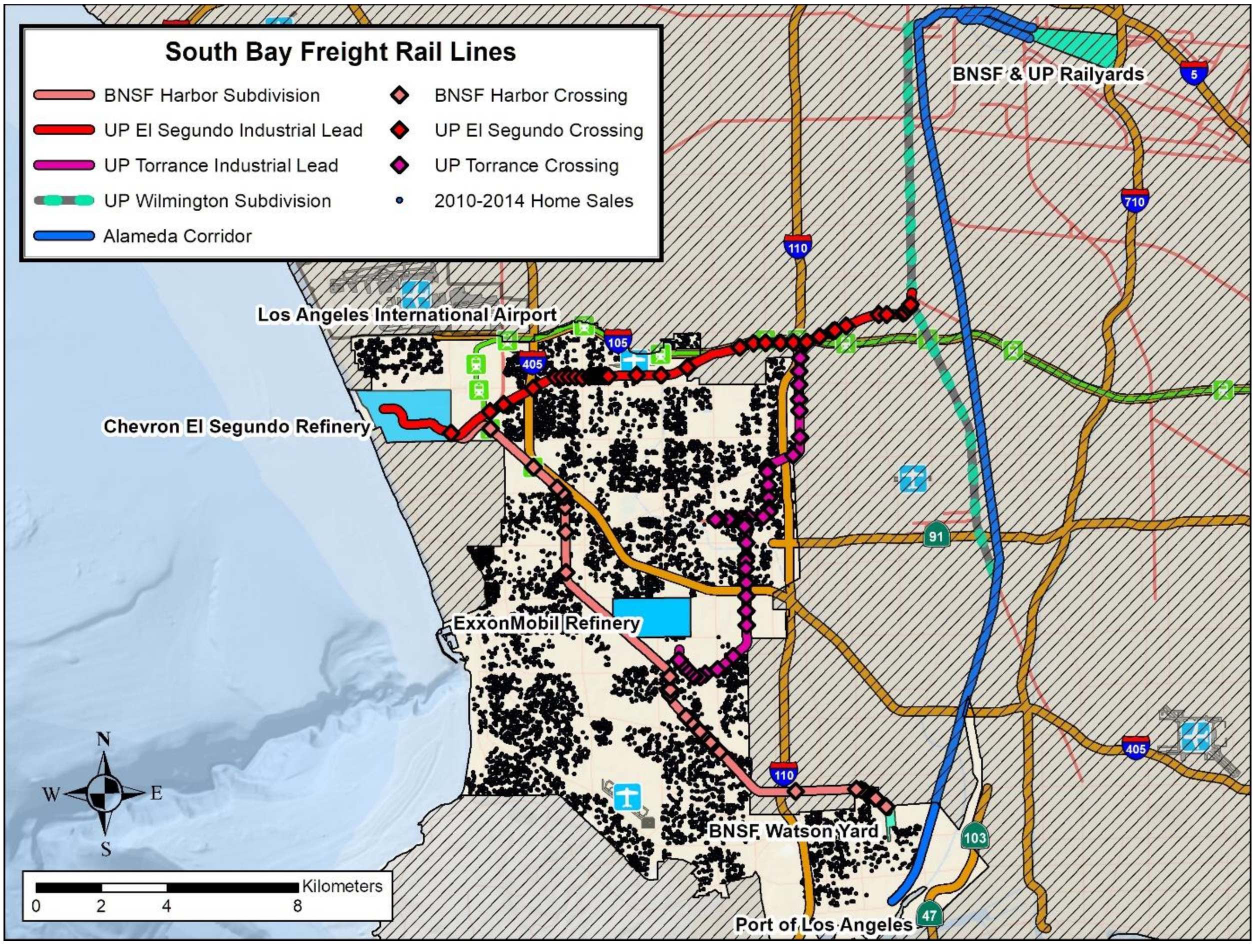
High volume motor vehicle traffic within the South Bay takes place on a network of arterial roadways and on five freeways: U.S. Interstates I-105, I-110, and I-405; and California State Routes SR47 and SR91. In the study area, the highest freeway AADT of over 250,000 vehicles occurs along I-405, the consistently busiest freeway in the United States. Primary truck traffic out of the SPBP occurs on I-710, which travels just outside of the South Bay's eastern perimeter (California Department of Transportation, 2022).

The majority of air traffic in the area centers around Los Angeles International Airport (LAX), which ranks as the fifth busiest airport in the world. The airport is located at the northernmost border of the South Bay and at the western terminus of I-105. Air traffic from LAX generally travels east-west with minimal overflight traffic south of the airport (Los Angeles World Airports, 2022). In addition to LAX, three municipal airports operate within the region: Hawthorne Municipal Airport (Jack Northrop Field), Compton/Woodley Airport, and Torrance Municipal Airport (Zamperini Field). Noise from operations associated with these municipal airports is generally contained within airport property perimeters, and does not exceed 60 dBA CNEL in the adjacent communities (California Department of Transportation, 2020). In addition, measured air traffic noise from Long Beach Airport, which is approximately 10 miles to the east, does not exceed 60 dBA CNEL in the study area and imparts no noise impacts to this study (City of Long Beach, 2022).

A single transit rail line operates within the South Bay: the 19.5-mile Los Angeles County Metropolitan Transportation Authority (LACMTA) Green Line. The westbound Green Line originates in the city of Norwalk approximately 12.5 miles east of the South Bay, and is a spur route to the LACMTA Los Angeles-to-Long Beach Blue Line. The Green Line begins its travel due west from Norwalk along the center of I-105 and crosses into the South Bay via Hawthorne's eastern perimeter. It then travels 6.9 miles through Hawthorne and El Segundo, terminating in Redondo Beach (United States Department of Transportation Federal Railroad Administration, 2022a).

Freight rail traffic between the SPBP and the regional Burlington Northern Santa Fe (BNSF)/Union Pacific (UP) Los Angeles rail hub in Vernon was previously handled by three local rail line routes. Upon completion of the $2.4 billion Alameda Corridor in 2002, rail traffic for these routes was consolidated onto the direct and mostly below-grade 20-mile Alameda line (Alameda Corridor Transportation Authority, 2022). After consolidation, the BNSF Harbor Subdivision, one of the three original SPBP-to-Vernon lines, retained 12.4 miles of its 27.6 miles of track and currently serves as a local South Bay spur route with service stops between the POLA-adjacent BNSF Watson Yard and El Segundo. The 9.6-mile Union Pacific (UP) El Segundo Industrial Lead also currently serves as a South Bay spur route along with its sister route, the 8.4-mile UP Torrance Industrial Lead. These UP lines diverge from the 11.7-mile southbound UP Wilmington Subdivision at Watts Junction, 5.6 miles from the Vernon regional railyard. Another of the four original SPBP-to-Vernon routes, the Wilmington Subdivision originates at Control Point West Redondo near Vernon, travels adjacent to the LACMTA Blue Line, and terminates in Rancho Dominguez at Control Point Alameda where it merges back to the main Alameda rail network (United States Department of Transportation Federal Railroad Administration, 2022a). The Harbor Subdivision, El Segundo Industrial Lead, and Torrance Industrial Lead are the focus of this freight rail study.

Figure 6-2: South Bay Freight Rail Lines



Trackage for the three freight rail lines in this study are not shared with passenger rail traffic and are mostly at-grade where they pass through residential areas. In these areas, the railway right of ways often run immediately adjacent to residential lots or properties. Designated maximum railcar speeds within the study area vary from 10 to 40 miles per hour, but typical speeds are in the 5 to 10 mile-per-hour range due to traffic and safety concerns (United States Department of Transportation Federal Railroad Administration, 2022a). No U.S. Department of Transportation Federal Railroad Administration (FRA) quiet zones exist along these lines (United States Department of Transportation Federal Railroad Administration, 2022b), and Code of Federal

Regulations (CFR) Title 49 CFR part 222.21 train horn rules are in effect (Code of Federal Regulations, 2022). 49 CFR part 222.21 rules specify that locomotive engineers must sound their horn for at least 15 seconds, and for no more than 20 seconds in advance of all public grade crossings in a pattern of 2 long, 1 short, and 1 long blasts. This pattern must be repeated or prolonged until the lead locomotive or lead cab car occupies the grade crossing. Horn volume levels are required to be within the window of 96 to 110 dB. Optionally, as per Title 49 CFR part 222.33, train operators have the discretion to forego horn use if speeds are 15 miles per hour or less, and train crew members or flaggers are present to provide warning to nearby motorists (Code of Federal Regulations, 2022).

Table 6-1: South Bay Crossing Safety Equipment Inventory

	Length in Miles	Total Crossing Count	Mean Distance Between Crossings	Crossing Safety Equipment		
				*Fully Protected	**Partially Protected	No Active Equipment
BNSF Harbor Subdivision	12.4	26	0.48	26	0	0
UP El Segundo Industrial Lead	10.8	35	0.31	27	0	8
UP Torrance Industrial Lead	9.9	44	0.24	33	3	8

Source: United States Department of Transportation Federal Railroad Administration

*Gates, warnings lights, warning bells
**Warning lights, warning bells

Burlington Northern Santa Fe Harbor Subdivision

The BNSF Harbor Subdivision proceeds westbound from its origin at BNSF Watson Yard in the Los Angeles neighborhood of Wilmington. The mostly at-grade line then enters Harbor City's northeastern border via an overcrossing at Normandie Avenue. Continuing west-northwest approximately 9.5 miles through residential zones in Torrance, Redondo Beach, and Lawndale, the line terminates at the Chevron El Segundo Refinery. The Harbor Subdivision also services the ExxonMobil refinery in Torrance, and primarily operates as a petroleum service route. The line travels adjacent to the final leg of the LACMTA Green Line for approximately one mile between the Green Line's El Segundo Douglas and Redondo Beach terminus stations. This particular area is not located near any residential areas and is commercial and industrial. All 26 roadway crossings on this line are fully protected with mechanized gates, warning lights, and warning bells. Prior to the opening of the Alameda Corridor, the Chevron El Segundo Refinery leg existed as a spur route, with the main line continuing on through the city of Inglewood on its way to the Vernon rail yards. (United States Department of Transportation Federal Railroad Administration, 2022a) (Table 6-1).

Union Pacific El Segundo Industrial Lead

The UP El Segundo Industrial Lead begins where it separates from the UP Wilmington Subdivision at 105th Street in the Los Angeles neighborhood of Watts. Although railcar speed limits in this area are 40 miles per hour, typical speeds are in the 10 mile-per-hour range due to vehicular and pedestrian cross traffic. This portion of the Wilmington Subdivision rail line travels adjacent to the LACMTA Blue Line. After diverging from the Wilmington Subdivision, the El Segundo Industrial Lead continues westbound 1.8 miles where it enters a tunnel under I-105. Within this tunnel, the Torrance Industrial Lead splits off and begins its journey southbound. The El Segundo line exits the tunnel and then continues on through Hawthorne and Los Angeles County CDP Del Aire on its way to the Chevron El Segundo Refinery. Within the refinery property, the line converges and terminates with trackage from the Harbor Subdivision. This line travels through a mix of commercial, industrial, and residential zones, with 8 of its 35 roadway crossings having no active warning equipment (United States Department of Transportation Federal Railroad Administration, 2022a) (Table 6-1).

Union Pacific Torrance Industrial Lead

The third rail line in this study, the UP Torrance Industrial Lead, begins where it diverges from the El Segundo Industrial Lead in a tunnel under I-105. The line then travels south for approximately 8.5 miles through a mix of commercial, industrial, and residential zones in Los Angeles County CDPs Willowbrook and West Compton; city of Los Angeles neighborhood Harbor Gateway; and the cities of Gardena and Torrance where it terminates at United States Gypsum Company's Torrance rail yard. Customers serviced by this line are Robertson's Ready Mix Concrete in Willowbrook, Crenshaw Lumber in Gardena, Jones Chemical in Harbor Gateway, and United States Gypsum in Torrance. Three of the Torrance line’s 44 roadway crossings are partially protected with warning lights and warning bells, with 8 low-speed crossings that have no active equipment (United States Department of Transportation Federal Railroad Administration, 2022a) (Table 6-1).

Table 6-2: South Bay Rail Line Statistics

	Length in Miles	Total Crossing Count	*Crossing Adjacent Area Statistics				
			Commercial	Industrial	Residential	Park	School
BNSF Harbor Subdivision	12.4	26	61.5%	15.4%	73.1%	11.5%	11.5%
UP El Segundo Industrial Lead	10.8	35	54.3%	31.4%	77.1%	17.1%	17.1%
UP Torrance Industrial Lead	9.9	44	67.4%	9.3%	53.5%	7.0%	7.0%

Source: United States Department of Transportation Federal Railroad Administration

*Percentages may overlap due to crossings having multiple adjacent area types

Rail Noise Issues

When compared to other transportation modes, rail noise tends to have predominantly low frequency characteristics, which may underestimate perceived loudness when measured with A-weighted decibel (dBA) scales that emphasize a sensitivity to higher frequency sounds (Ogren *et al.*, 2017). In addition, as with most aircraft noise events, rail noise events are non-steady state and can be perceived differently by people when compared to steady state noise from sources like road traffic (Smith *et al.*, 2017). Similar to impacts from other transportation mode noise sources, rail noise impacts are inversely related to distance to the rail line or rail crossing.

Rail noise issues stem from three general categories: warning horns or whistles, crossing equipment, and noise generated from the train itself which can be airborne or through physical vibration. While some light rail and freight rail noise characteristics are similar, substantial differences can occur due to the variances in equipment that is used (Kasess *et al.*, 2013). The majority of light rail systems operate on electricity and generally do not utilize excessively large numbers of passenger cars. Freight rail, however, makes use of extreme duty diesel locomotives, with high-capacity rail cars that can be connected in large numbers. In addition, these locomotives utilize very loud warning horns, generate higher levels of ground-borne vibration, and tend to have fewer route frequencies when compared to passenger rail operations (Kasess *et al.*, 2013; Zannin and Bunn, 2014). Due to these differences, freight rail noise has been found to be more annoying than light rail (Sharp *et al.*, 2014).

In response to community complaints about train horn noise in the study area, a 2010 study by the City of Torrance evaluated FRA quiet zone requirements within the city. Implementation required additional raised medians, gates, and signals to prevent vehicles from bypassing existing safety equipment. Costs for the city were estimated to be between $10.9 and $13.5 million, which exceeded budget possibilities for the project. As any state or federal funding would require an actual motor vehicle safety improvement at each affected crossing, subsidies were not available for the implementation, which terminated the project due to budget constraints (City of Torrance, 2010).

Literature Review

In the published literature, only three freight rail line-specific HP studies were found, each of which examined rail proximity impacts on single-family home values. The first study was conducted in Cuyahoga County, Ohio (Simons and El Jaouhari, 2004), while the second study compared impacts among three counties in Ohio and Massachusetts (Clark, 2006). The third study, in Santa Marta, Columbia, focused on freight rail line impacts on nearby residential home prices (Chica-Olmo *et al.*, 2019).

In Cuyahoga County, Ohio, Simons and El Jaouhari (2004) found that impacts varied substantially when grouping homes into small, medium, and large square footages. Homes of less than 1,250 square feet were impacted by 5- to 7-percent reductions in value when located within 750 feet of a freight rail line. Homes that were between 1,251 and 1,700 square feet were negatively affected in value by around 5 percent when located between 251 and 500 feet from the line, with homes larger than 1,700 square feet showing no statistically significant impact. Proximity to gated crossings was also examined, but no conclusive results were observed.

Clark (2006) analyzed the effects from a 1991 Conrail decision to disregard existing train whistle bans in the cities where it operated. Aside from the study's primary hypothesis that train whistles would negatively impact nearby housing prices, it also determined freight rail proximity impacts based on distance to the rail line. Rail line proximity of up to 300 meters was found to have negative impacts in the 6.3- to 14-percent range depending on the neighborhood. Rail crossing proximity of up to 300 meters indicated negative impacts of 8.7 to 16 percent, and as much as 18.2 percent for distances up to 700 meters, depending on the neighborhood.

Finally, Chica-Olmo *et al.* (2019) used Spatial Autoregression (SAR), Spatial Error (SEM) and Regression Kriging (RK) models to study freight rail impacts in the coastal, tourist-centric city of Santa Marta, Columbia. Using Moran's *I* and Akaike information criterion (AIC) statistics, various weight matrix specifications were assessed to utilize optimal values. Focusing on single-family home sales in early 2016, the authors conclude that on average, values were negatively impacted between 14 and 23.7 percent for residences located within 230 meters of the freight rail line.

One HP study was found in the literature that focused specifically on train horn impacts. In this study, Bellinger (2006) examined 256 residential property transaction values between 1980 and 2004 in Wormleysburg, Pennsylvania. Model estimations resulted in an average $4,800 or 4.1 percent impact for each 10 dB of train horn noise, up to a range of 40 dB. This study also examined the results of a survey that was distributed in the area that focused on train horn noise. This Stated Preference study utilized a willingness-to-pay (WTP) question of how much residents would pay to eliminate train horn noise altogether. Results revealed an average monthly payment of between $13.06 and $30.18, which was interpreted to be the representative WTP dollar amount per adult resident in the household.

A number of freight rail annoyance level studies were also found in the published literature, including sleep disturbance studies (Pennig *et al.*, 2012; Elmenhorst *et al.*, 2012; Waddington *et al.*, 2015; Smith *et al.*, 2016). Health impacts have been investigated as well, including impacts related to psychomotor performance (Elmenhorst *et al.*, 2012), and heart issues (Ross *et al.*, 2012; Smith *et al.*, 2017).

These substantial health and economic impacts illustrate the need for additional focus into freight rail operations in urban areas. The literature reveals that minimal freight rail impact research has been conducted, despite the presence of extensive freight rail operations within heavily populated areas in both the United States and abroad. This study aims to fill this research gap by better understanding the economic impacts of freight rail operations in a densely populated metropolitan area, as it relates to residents’ WTP for residing in noise-affected zones.

Study Area and Data

Overview

Located within the South Bay region of Los Angeles County, the area designated for this study consists of the incorporated cities of El Segundo, Gardena, Hawthorne, Lawndale, Redondo Beach, Torrance; the Harbor City, Harbor Gateway, and Wilmington neighborhoods of the city of Los Angeles; and unincorporated Los Angeles County CDPs Alondra Park and Del Aire. The Harbor City and Harbor Gateway neighborhoods are part of the Los Angeles "Shoestring Strip", which is a narrow north-south area that was annexed by the city of Los Angeles in 1906 (Guinn, 1914). This strategic annexation allowed the city to maintain a direct jurisdictional connection between downtown Los Angeles to the north and the Port of Los Angeles to the south. Delineated portions of eastern Torrance and Gardena fall within the Harbor Gateway perimeter and are neither administrated nor supported by these two independent, incorporated municipalities; these annexed areas fall wholly under the jurisdiction of the city of Los Angeles. The study area consists of a mix of residential, commercial and industrial zones, with schools, parks, polycentric Central Business Districts (CBDs), and places of interest throughout.

The selection of this particular study area offers a unique opportunity to model freight rail noise impacts in a densely populated, major metropolitan area in the U.S. Despite the region having extensive transportation infrastructure in place, the study area is atypically unaffected by transit rail lines or air traffic. Single-family home types and neighborhood layouts are relatively homogeneous throughout the region making the area conducive to spatial modeling techniques. Additionally, the freight rail lines being studied have served solely as local service spur routes after the opening of the Alameda Corridor in 2002. These lines are no longer used as arterial through routes between the SPBP and regional Los Angeles railyards (Alameda Corridor

Transportation Authority, 2022). This provides a regular frequency of freight train movements as well as relative consistency in railcar load volumes.

Los Angeles County Office of the Assessor Dataset

The dataset for this study is a subset of the 171,475 geocoded Los Angeles County Office of the Assessor data described in Chapter 4. Using ArcMap, 7,152 observations were captured from the master dataset using study area city or neighborhood boundaries. Structural variables included in the master dataset were retained for this study. To represent elasticity and percent change in the model specification, log transformations were performed on the variables for price sold, structure square footage, and lot size. Temporal impact binary variables were generated to represent sale date by calendar quarter from 2010 Quarter 3 through 2014 Quarter 1, with 2014 Quarter being omitted as the reference category to avoid collinearity in the model specification.

HP neighborhood binary categorical variables represent delineation within the study area by incorporated city, Los Angeles County CDP, or city of Los Angeles neighborhood. These include Del Aire, El Segundo, Gardena, Harbor City, Harbor Gateway, Hawthorne, Lawndale, Redondo Beach, Torrance, and Wilmington, with Los Angeles County CDP Alondra Park omitted as the reference category. Binary variables representing school property distance buffers of up to 250 meters, and from 251 to 500 meters were generated, referencing Sah *et al.* (2016) who found that school proximity effects diminished at distances of 300 to 500 meters. Distance to the nearest beach recreation area was also represented with binary variables for distances of up to 150 meters, and from 151 to 300 meters (Landry and Hindsley, 2011; Catma, 2020). In addition, freeway accessibility was represented within 1,000-, 1,001- to 2,000-, and 2,001- to 3,000-meter network distances to the nearest onramp (Seo *et al.*, 2014). Finally, station accessibility variables for network distances of up to 400 meters, and for 401 to 800 meters were generated (Cervero and Duncan, 2002; Debrezion *et al.*, 2007; Hess and Almeida, 2007; Ransom, 2018).

Environmental variables were generated within ArcMap to represent proximity to nearby amenities or disamenities. As per Rahmatian and Cockerill (2004), influential proximity variables for the LAX property were generated for binary variable buffers of up to 1,000 meters, and for 1,001- to 2,000-meter distances. Binary road traffic impact variables were also generated for distances of up to 50-, 51- to 100-, 101- to 150-, and 151- to 200-meter distances to the nearest arterial roadway, and for up to 200 meters, and for 201- to 400-meter distances to the nearest freeway (Bowes and Ihlanfeldt, 2001; Li and Saphores, 2012; Seo *et al.*, 2014). Proximity to the LACMTA Green Line of up to 150 meters, and for 151 to 300 meters was represented with additional distance buffer variables (Bowes and Ihlanfeldt, 2001; Hess and Almeida, 2007; Diao *et al.*, 2016).

Finally, binary variables were generated for the environmental noise variables of interest, which are freight rail line distances of up to 150 meters, and 151 to 300 meters (Simons and El Jaouhari, 2004; Clark, 2006; Chica-Olmo *et al.*, 2019), along with freight rail crossing distances of up to 250, 251 to 500, and 501 to 750 meters (Bellinger, 2006; Clark, 2006).

Table 6-3: Structural Variable Summary Statistics

Variable	Mean	Std Dev	Min	Max
Sale price (463,504 median value)	524,295	259,354	90,000	1,979,019
Lot size (sq ft)	5,895.6	1,722.8	1,125	30,674
Building size (sq ft)	1,509.8	618.7	440	6,090
Bedrooms	3.1	0.8	1.0	8
Bathrooms	1.9	0.8	1.0	6
Pool on property	0.0556	0.2293	0	1
Age when sold (years)	61.4	16.4	2	121
Foreclosure sale	0.0098	0.0985	0	1
Resold within previous year	0.0299	0.1704	0	1
Sold during 2010 Quarter 3	0.0568	0.2314	0	1
Sold during 2010 Quarter 4	0.0566	0.2311	0	1
Sold during 2011 Quarter 1	0.0579	0.2335	0	1
Sold during 2011 Quarter 2	0.0684	0.2524	0	1
Sold during 2011 Quarter 3	0.0671	0.2502	0	1
Sold during 2011 Quarter 4	0.0710	0.2569	0	1
Sold during 2012 Quarter 1	0.0640	0.2448	0	1
Sold during 2012 Quarter 2	0.0600	0.2375	0	1
Sold during 2012 Quarter 3	0.0632	0.2433	0	1
Sold during 2012 Quarter 4	0.0612	0.2398	0	1
Sold during 2013 Quarter 1	0.0568	0.2314	0	1
Sold during 2013 Quarter 2	0.0800	0.2713	0	1
Sold during 2013 Quarter 3	0.0791	0.2700	0	1
Sold during 2013 Quarter 4	0.0617	0.2406	0	1
Sold during 2014 Quarter 1	0.0568	0.2314	0	1
Sold during 2014 Quarter 2	0.0412	0.1989	0	1

n=7,152

Table 6-4: Neighborhood Variable Summary Statistics

Variable	Mean	Std Dev	Min	Max
Nearest school property (up to 250m)	0.3270	0.4692	0	1
Nearest school property (251 to 500m)	0.3784	0.4850	0	1
Nearest beach recreation area (up to 150m)	0.0007	0.0264	0	1
Nearest beach recreation area (151 to 300m)	0.0041	0.0636	0	1
Nearest freeway onramp network distance (up to 1,000m)	0.2329	0.4227	0	1
Nearest freeway onramp network distance (1,001 to 2,000m)	0.2095	0.4069	0	1
Nearest freeway onramp network distance (2,001 to 3,000m)	0.2027	0.4021	0	1
Nearest light rail station network distance (up to 400m)	0.0025	0.0501	0	1
Nearest light rail station network distance (401 to 800m)	0.0176	0.1316	0	1
Alondra Park (LA County CDP)	0.0236	0.1519	0	1
Del Aire (LA County CDP)	0.0364	0.1872	0	1
El Segundo	0.0351	0.1840	0	1
Gardena	0.1054	0.3071	0	1
Harbor City neighborhood (City of Los Angeles)	0.0324	0.1772	0	1
Harbor Gateway neighborhood (City of Los Angeles)	0.0666	0.2493	0	1
Hawthorne	0.0963	0.2951	0	1
Lawndale	0.0324	0.1772	0	1
Lomita	0.0368	0.1882	0	1
Redondo Beach	0.1277	0.3337	0	1
Torrance	0.3357	0.4723	0	1
Wilmington neighborhood (City of Los Angeles)	0.0716	0.2578	0	1

n=7,152

Table 6-5: Environmental Variable Summary Statistics

Variable	Mean	Std Dev	Min	Max
LAX distance (Up to 1,000m)	0.0344	0.1823	0	1
LAX distance (1,001 to 2,000m)	0.0295	0.1692	0	1
Nearest arterial roadway distance (up to 50m)	0.0900	0.2863	0	1
Nearest arterial roadway distance (51 to 100m)	0.1475	0.3546	0	1
Nearest arterial roadway distance (101 to 150m)	0.1506	0.3577	0	1
Nearest arterial roadway distance (151 to 200m)	0.1356	0.3424	0	1
Nearest freeway distance (up to 200m)	0.0478	0.2134	0	1
Nearest freeway distance (201 to 400m)	0.0741	0.2620	0	1
Nearest light rail line distance (up to 150m)	0.0039	0.0625	0	1
Nearest light rail line distance (151 to 300m)	0.0080	0.0889	0	1
Nearest freight rail line distance (up to 150m)	0.0362	0.1868	0	1
Nearest freight rail line distance (151 to 300m)	0.0527	0.2235	0	1
Nearest freight rail crossing distance (up to 250m)	0.0461	0.2098	0	1
Nearest freight rail crossing distance (251 to 500m)	0.0735	0.2610	0	1
Nearest freight rail crossing distance (501 to 750m)	0.0924	0.2896	0	1

n=7,152

Dataset Diagnostics

Variance Inflation Factor multicollinearity diagnostics were performed on the independent dataset variables, resulting in a minimum value of 1.01, maximum of 4.43, and mean of 1.94. Below the generally accepted threshold of a value of 10, these values indicated minimal potential for multicollinearity issues within the model specifications, resulting in the retention of all original variables for the model specification.

Table 6-6: Variance Inflation Factor Multicollinearity Diagnostics

Variable	VIF	R-Squared	Variable	VIF	R-Squared
LnLotSqft	1.07	0.0613	Neigh8	1.43	0.3026
LnBldgSqft	3.88	0.7423	Neigh9	1.58	0.3686
Bed	2.08	0.5182	Neigh10	2.91	0.6569
Bath	3.18	0.6859	Neigh11	4.43	0.7744
Pool	1.03	0.0247	School1	1.54	0.3499
AgeSold	1.06	0.0555	School2	1.52	0.3439
Foreclosure	1.01	0.0102	Beach1	1.01	0.0090
Resold	1.05	0.0486	Beach2	1.04	0.0344
Q1	2.32	0.5696	LAX1	1.76	0.4323
Q2	2.32	0.5681	LAX2	1.33	0.2495
Q3	2.35	0.5736	Road1	1.13	0.1142
Q4	2.56	0.6101	Road2	1.18	0.1503
Q5	2.54	0.6056	Road3	1.17	0.1427
Q6	2.62	0.6186	Road4	1.14	0.1250
Q7	2.48	0.5975	Fwy1	1.44	0.3072
Q8	2.41	0.5853	Fwy2	1.44	0.3061
Q9	2.46	0.5935	Ramp1	2.56	0.6089
Q10	2.41	0.5854	Ramp2	1.91	0.4773
Q11	2.31	0.5680	Ramp3	1.60	0.3733
Q12	2.81	0.6437	LtRail1	1.27	0.2153
Q13	2.79	0.6412	LtRail2	1.31	0.2371
Q14	2.42	0.5864	Station1	1.20	0.1692
Q15	2.31	0.5675	Station2	1.22	0.1835
Neigh1	1.33	0.2480	Freight1	2.34	0.5734
Neigh2	1.67	0.4021	Freight2	2.10	0.5238
Neigh3	2.35	0.5736	FreightX1	2.99	0.6654
Neigh4	2.29	0.5625	FreightX2	1.64	0.3920
Neigh5	1.53	0.3451	FreightX3	1.20	0.1688
Neigh6	1.98	0.4958	*MEAN*	*1.94*	
Neigh7	2.42	0.5873			

Spatial Model

Following Anselin *et al.* (1996), an Ordinary Least Squares (OLS) model was estimated for baseline parameter values to generate residuals to be used for spatial dependence diagnostics. Moran's I, Lagrange Multiplier (LM), and Robust Lagrange Multiplier (LMR) tests were performed, with significant results for all spatial lag and spatial error term tests (Table 6-7). Based on these results, it was determined that spatial autocorrelation (SAC) was present in both the dependent variable and the error term, specifying a Spatial Autoregressive with Spatial Error (SARAR) model (Elhorst, 2010):

$$\begin{cases} \log(\boldsymbol{P}) = \rho \boldsymbol{W}\boldsymbol{P} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{u}, \\ \boldsymbol{u} = \lambda \boldsymbol{W}\boldsymbol{u} + \boldsymbol{\varepsilon}, \end{cases} \tag{18}$$

where:

- n designates the sample size and q the number of explanatory variables including a constant term;
- $\boldsymbol{P}$ is an $n \times 1$ vector of single-family residential property prices;
- ρ ($|\rho|<1$) is an unknown spatial lag parameter;
- λ ($|\lambda|<1$) is an unknown spatial error parameter;
- $\boldsymbol{W}$ is an $n \times n$ spatial weight matrix, which reflects spatial interactions;
- $\boldsymbol{X}$ is an $n \times q$ matrix of exogenous explanatory variables;
- $\boldsymbol{\beta}$ is a $q \times 1$ vector of unknown coefficients;
- $\boldsymbol{u}$ is an $n \times 1$ vector of correlated residuals; and
- $\boldsymbol{\varepsilon}$ is an $n \times 1$ vector of independently distributed errors with zero mean.

Table 6-7: Spatial Autocorrelation Diagnostics

Test	Statistic	p-value
Moran's *I*	0.3924	0.000
Lagrange Multiplier (Spatial lag)	2,305.67	0.000
Robust Lagrange Multiplier (Spatial lag)	266.52	0.001
Lagrange Multiplier (Spatial error)	2,335.58	0.000
Robust Lagrange Multiplier (Spatial error)	296.43	0.000

Results and Conclusions

Structural Variables

Model results indicate appropriate positive and negative values for lot and structure square footage, bedroom and bathroom count, presence of a pool, and age when sold. Outputs indicated significance across all three models on these parameters other than with the bedroom count variable. Foreclosure and resold status were negative and significant with all three models as well. Quarterly temporal variables showed an overall steady increase over time, and were significant across all quarters except for Quarter 1 of 2014 for all three models.

Neighborhood Variables

Neighborhood amenity variables for school proximity were not significant in any of the models run, but were positive and significant for beach proximity for both distance buffers up to 300 meters. Values were higher for the closer proximity, which agrees with higher prices for properties closer to the beach. Freeway onramp network distances were negative in parameter value, and were significant across all models and distances except for the two spatial models in the 1,000-meter or less buffer zone. This disamenity is in contrast to positive value findings by Seo *et al.*, 2014), and may be due to the fact that the South Bay area tends to be a destination zone in the polycentric greater Los Angeles area, and does not necessarily value freeway access as a positive amenity. Light rail network distance buffers were significant across all model estimations, and were negative for distances less than 400 meters, and positive for distances between 401 and 800 meters. This concurs with some studies that find that rail station traffic and noise tend to be a detriment, with walkability to the station being a positive attribute (Cervero and Duncan, 2002; Debrezion *et al.*, 2007; Hess and Almeida, 2007; Ransom, 2018). Finally, all three models indicated significance for all city/neighborhood variables, indicating expected positive value impacts over the reference neighborhood of Wilmington.

Environmental Variables

Environmental impact variables for distance to the nearest arterial roadway were negative and significant for distances of up to 50 meters, which was representative of arterial-facing properties. Only the OLS model showed significance in the 51- to 100-meter bandwidth, with no other distances showing significance with any of the models. Freeway proximity was negative and significant for all three models for both less than 200-meter areas and for 201- to 400-meter distances. Higher impacts were estimated for properties closer to a freeway, which indicates decreasing noise impacts as distances to the freeway increases. Light rail line distance impacts were positive and significant only for the OLS model, and showed higher positive values within 150 meters of the line. This might be attributed to accessibility benefit in certain areas, even though models indicated a negative value for network distances to the stations of less than 400 meters (Bowes & Ihlanfeldt, 2001).

Focusing on the variables of interest in this study, distance to freight rail lines were not statistically significant across all three models. Crossing distance buffers were significant only for the 251- to 500-meter distance, and were negative at -0.0396 for the OLS model, and -0.0242 for both ML and GS2SLS model outputs.

Table 6-8: Model Results - Structural Variables

Variable	OLS	ML	GS2SLS
LnLotSqft	0.1740***	0.1673***	0.0967***
LnBldgSqft	0.3667***	0.3225***	0.3164***
Bedrooms	0.0012	0.0018	0.0019
Bathrooms	0.0297***	0.0245***	0.0228***
Pool on property	0.0348***	0.0277***	0.0239***
Age when sold (years)	-0.0662***	-0.0553***	-0.0479***
Foreclosure sale	-0.0621**	-0.0501**	-0.0459**
Resold within previous year	-0.1029***	-0.1033***	-0.1050***
Sold during 2010 Quarter 3	-0.1392***	-0.1383***	-0.1372***
Sold during 2010 Quarter 4	-0.1735***	-0.1669***	-0.1569***
Sold during 2011 Quarter 1	-0.2163***	-0.2054***	-0.1982***
Sold during 2011 Quarter 2	-0.2045***	-0.2011***	-0.1969***
Sold during 2011 Quarter 3	-0.2274***	-0.2223***	-0.2190***
Sold during 2011 Quarter 4	-0.2609***	-0.2501***	-0.2400***
Sold during 2012 Quarter 1	-0.2680***	-0.2569***	-0.2481***
Sold during 2012 Quarter 2	-0.2327***	-0.2299***	-0.2225***
Sold during 2012 Quarter 3	-0.1939***	-0.1900***	-0.1861***
Sold during 2012 Quarter 4	-0.1846***	-0.1808***	-0.1722***
Sold during 2013 Quarter 1	-0.1495***	-0.1429***	-0.1436***
Sold during 2013 Quarter 2	-0.0691***	-0.0688***	-0.0676***
Sold during 2013 Quarter 3	-0.0436***	-0.0399***	-0.0369***
Sold during 2013 Quarter 4	-0.0445***	-0.0398***	-0.0386***
Sold during 2014 Quarter 1	-0.0253	-0.0224	-0.0218
Additional Parameters and Statistics			
Constant	8.8890	0.0996	1.6739
Spatial Lag Coefficient (λ)		0.5524*	0.6446*
Spatial Error Coefficient (ρ)		0.3953*	0.1862*
R^2	0.803		
Adjusted R^2	0.801		

*p<0.10, **p<0.05, ***p<0.01

Table 6-9: Model Results – Neighborhood Variables

Variable	OLS	ML	GS2SLS
Nearest school property (up to 250m)	-0.0090	-0.0066	-0.0049
Nearest school property (251-500m)	-0.0044	-0.0021	-0.0010
Nearest beach recreation area (up to 150m)	0.5756***	0.4455***	0.3725***
Nearest beach recreation area (151-300m)	0.3618***	0.2468***	0.1612***
Nearest freeway onramp network distance (up to 1,000m)	-0.1175***	-0.0872	-0.0113
Nearest freeway onramp network distance (1,001-2,000m)	-0.1474***	-0.0991***	-0.0220***
Nearest freeway onramp network distance (2,001-3,000m)	-0.1289***	-0.8345**	-0.0193***
Nearest light rail station network distance (up to 400m)	-0.1698***	-0.1255**	-0.0794*
Nearest light rail station network distance (401-800m)	0.0787***	0.0487**	0.0341*
Alondra Park (LA County CDP)	0.4001***	0.3313***	0.1485***
Del Aire (LA County CDP)	0.4613***	0.1777***	0.1576***
El Segundo	1.0010***	0.6060***	0.3027***
Gardena	0.1661***	0.0853***	0.0357***
Harbor City neighborhood (City of Los Angeles)	0.3279***	0.0767***	0.0661***
Harbor Gateway neighborhood (City of Los Angeles)	0.1786***	0.0313**	0.0236*
Hawthorne	0.2546***	0.0794***	0.0762***
Lawndale	0.2332***	0.0611***	0.0334**
Lomita	0.3922***	0.1880***	0.1135***
Redondo Beach	0.8352***	0.2593***	0.2778***
Torrance	0.6493***	0.4407***	0.2087***

*p<0.10, **p<0.05, ***p<0.01

Table 6-10: Model Results – Environmental Variables

Variable	OLS	ML	GS2SLS
LAX distance (up to 1,000m)	-0.0327	-0.0290	-0.0261
LAX distance (1,001-2,000m)	0.0036	-0.0109	-0.0109
Nearest arterial roadway distance (up to 50m)	-0.0702***	-0.0507***	-0.0506***
Nearest arterial roadway distance (51-100m)	-0.0229***	-0.0101	-0.0081
Nearest arterial roadway distance (101-150m)	-0.0062	0.0055	0.0048
Nearest arterial roadway distance (151-200m)	0.0046	0.0097	0.0098
Nearest freeway distance (up to 200m)	-0.0804***	-0.0442***	-0.0404***
Nearest freeway distance (201-400m)	-0.0689***	-0.0206***	-0.0203**
Nearest light rail line distance (up to 150m)	0.1484**	0.0401	0.0439
Nearest light rail line distance (151-300m)	0.0693**	0.0558	0.0400
Nearest freight rail line distance (up to 150m)	0.0151	0.0073	0.0066
Nearest freight rail line distance (151-300m)	0.0133	0.0035	0.0030
Nearest freight rail crossing distance (up to 250m)	-0.0157	-0.0335	-0.0348
Nearest freight rail crossing distance (251-500m)	-0.0396***	-0.0242**	-0.0242**
Nearest freight rail crossing distance (501-750m)	0.0328	-0.0035	-0.0063

*p<0.10, **p<0.05, ***p<0.01

Table 6-11: SARAR GS2SLS Average Direct and Indirect Impacts – Structural Variables

Variable	GS2SLS Parameter	ADI +	AII =	ATI
LnLotSqft	0.0967***	0.1036***	0.1685***	0.2721***
LnBldgSqft	0.3164***	0.3391***	0.5512***	0.8904***
Bedrooms	0.0019	0.0020	0.0033	0.0053
Bathrooms	0.0228***	0.0244***	0.0397***	0.0641***
Pool on property	0.0239***	0.0257***	0.0417***	0.0674***
Age when sold (years)	-0.0479***	-0.0514***	-0.0835***	-0.1349***
Foreclosure sale	-0.0459**	-0.0492**	-0.0800**	-0.1291**
Resold within previous year	-0.1050***	-0.1126***	-0.1830***	-0.2956***
Sold during 2010 Quarter 3	-0.1372***	-0.1471***	-0.2391***	-0.3861***
Sold during 2010 Quarter 4	-0.1569***	-0.1682***	-0.2734***	-0.4416***
Sold during 2011 Quarter 1	-0.1982***	-0.2124***	-0.3454***	-0.5578***
Sold during 2011 Quarter 2	-0.1969***	-0.2110***	-0.3431***	-0.5541***
Sold during 2011 Quarter 3	-0.2190***	-0.2347***	-0.3815***	-0.6162***
Sold during 2011 Quarter 4	-0.2400***	-0.2572***	-0.4181***	-0.6753***
Sold during 2012 Quarter 1	-0.2481***	-0.2660***	-0.4323***	-0.6983***
Sold during 2012 Quarter 2	-0.2225***	-0.2385***	-0.3877***	-0.6262***
Sold during 2012 Quarter 3	-0.1861***	-0.1995***	-0.3243***	-0.5238***
Sold during 2012 Quarter 4	-0.1722***	-0.1845***	-0.3000***	-0.4845***
Sold during 2013 Quarter 1	-0.1436***	-0.1539***	-0.2503***	-0.4042***
Sold during 2013 Quarter 2	-0.0676***	-0.0724***	-0.1178***	-0.1902***
Sold during 2013 Quarter 3	-0.0369***	-0.0396***	-0.0643***	-0.1039***
Sold during 2013 Quarter 4	-0.0386***	-0.0413***	-0.0672***	-0.1086***
Sold during 2014 Quarter 1	-0.0218	-0.0233	-0.0379	-0.0613

*p<0.10, **p<0.05, ***p<0.01

Table 6-12: SARAR GS2SLS Average Direct and Indirect Impacts – Neighborhood Variables

Variable	GS2SLS Parameter	ADI +	AII =	ATI
Nearest school property (up to 250m)	-0.0049	-0.0053	-0.0086	-0.0139
Nearest school property (251-500m)	-0.0010	-0.0011	-0.0018	-0.0029
Nearest beach recreation area (up to 150m)	0.3725***	0.3993***	0.6491***	1.0484***
Nearest beach recreation area (151-300m)	0.1612***	0.1727***	0.2808***	0.4535***
Nearest freeway onramp network distance (up to 1,000m)	-0.0113	-0.0121	-0.0197	-0.0318
Nearest freeway onramp network distance (1,001-2,000m)	-0.0220***	-0.0236***	-0.0383***	-0.0618***
Nearest freeway onramp network distance (2,001-3,000m)	-0.0193***	-0.0207***	-0.0337***	-0.0544***
Nearest light rail station network distance (up to 400m)	-0.0794*	-0.0851*	-0.1383*	-0.2234*
Nearest light rail station network distance (401-800m)	0.0341*	0.0365*	0.0594*	0.0959*
Alondra Park (LA County CDP)	0.1485***	0.1592***	0.2588***	0.4180***
Del Aire (LA County CDP)	0.1576***	0.1690***	0.2747***	0.4436***
El Segundo	0.3027***	0.3245***	0.5275***	0.8519***
Gardena	0.0357***	0.0383***	0.0623***	0.1006***
Harbor City neighborhood (City of Los Angeles)	0.0661***	0.0709***	0.1152***	0.1861***
Harbor Gateway neighborhood (City of Los Angeles)	0.0236*	0.0253*	0.0412*	0.0665*
Hawthorne	0.0762***	0.0816***	0.1327***	0.2143***
Lawndale	0.0334**	0.0358**	0.0581**	0.0939**
Lomita	0.1135***	0.1216***	0.1977***	0.3194***
Redondo Beach	0.2778***	0.2977***	0.4840***	0.7817***
Torrance	0.2087***	0.2236***	0.3636***	0.5872***

*p<0.10, **p<0.05, ***p<0.01

Table 6-13: SARAR GS2SLS Average Direct and Indirect Impacts – Environmental Variables

Variable	GS2SLS Parameter	ADI +	AII =	ATI
LAX distance (up to 1,000m)	-0.0261	-0.0279	-0.0454	-0.0733
LAX distance (1,001-2,000m)	-0.0109	-0.0117	-0.0189	-0.0306
Nearest arterial roadway distance (up to 50m)	-0.0506***	-0.0543***	-0.0882***	-0.1425***
Nearest arterial roadway distance (51-100m)	-0.0081	-0.0087	-0.0141	-0.0228
Nearest arterial roadway distance (101-150m)	0.0048	0.0052	0.0084	0.0135
Nearest arterial roadway distance (151-200m)	0.0098	0.0105	0.0171	0.0277
Nearest freeway distance (up to 200m)	-0.0404***	-0.0433***	-0.0704***	-0.1137***
Nearest freeway distance (201-400m)	-0.0203**	-0.0217**	-0.0353**	-0.0570**
Nearest light rail line distance (up to 150m)	0.0439	0.0448	0.0597	0.1045
Nearest light rail line distance (151-300m)	0.0400	0.0429	0.0697	0.1126
Nearest freight rail line distance (up to 150m)	0.0066	0.0070	0.0114	0.0185
Nearest freight rail line distance (151-300m)	0.0030	0.0033	0.0053	0.0086
Nearest freight rail crossing distance (up to 250m)	-0.0348	-0.0367	-0.0522	-0.0889
Nearest freight rail crossing distance (251-500m)	-0.0242**	-0.0218**	-0.0354**	-0.0573**
Nearest freight rail crossing distance (501-750m)	-0.0063	-0.0069	-0.0088	-0.0157

*p<0.10, **p<0.05, ***p<0.01

Table 6-14: SARAR GS2SLS Environmental Variable Average Impact Valuations

Variable	ATI Value	†Impact
LAX distance (up to 1,000m)	-0.0733	$ -33,975
LAX distance (1,001-2,000m)	-0.0306	$ -14,183
Nearest arterial roadway distance (up to 50m)	-0.1425***	$ -66,049
Nearest arterial roadway distance (51-100m)	-0.0228	$ -10,568
Nearest arterial roadway distance (101-150m)	0.0135	$ 6,257
Nearest arterial roadway distance (151-200m)	0.0277	$ 12,839
Nearest freeway distance (up to 200m)	-0.1137***	$ -52,700
Nearest freeway distance (201-400m)	-0.0570**	$ -26,420
Nearest light rail line distance (up to 150m)	0.1045	$ 48,436
Nearest light rail line distance (151-300m)	0.1126	$ 52,191
Nearest freight rail line distance (up to 150m)	0.0185	$ 8,575
Nearest freight rail line distance (151-300m)	0.0086	$ 3,986
Nearest freight rail crossing distance (up to 250m)	-0.0889	$ -41,206
Nearest freight rail crossing distance (251-500m)	-0.0573**	$ -26,559
Nearest freight rail crossing distance (501-750m)	-0.0157	$ -7,277

*p<0.10, **p<0.05, ***p<0.01

†Based on median sale price of $463,504

Conclusions

This study focuses on freight rail impacts on single-family residential prices in the South Bay region of Los Angeles County. While distance to actual freight rail lines were not significant in these modeling specifications, findings indicate that freight rail crossing equipment and train horns may be responsible for negative impacts on residences near roadway intersections. Calculating for spillover effects, this indicates impacts of up to -5.73% for distances between 251 and 500 meters for the GS2SLS SARAR model, which calculates to an average of -$26,559 based on the median sample price of $463,504. This is not dissimilar to findings by Clark (2006), who found rail crossing impacts of between -8.7% and -16% for distances up to 300 meters.

Future Research

Future research on this topic should include actual field measurements of noise levels, preferably inside affected residence locations, as railway noise level estimation can be mis-specified by geographical terrain and density, building construction and materials, and other environmental factors (Gidlof-Gunnarsson *et al.*, 2012; Ogren *et al.*, 2017). This could be combined with subjective survey data to correlate actual annoyance levels being experienced by residents (Licitra *et al.*, 2016). Data regarding actual rail traffic activity would allow for modeling of incident frequencies and magnitudes, which are important with non-steady state noise sources. Actual train horn use data would also be instrumental for future modeling, as train horn use is inconsistent and can vary per incident. Finally, C-weighted (dBC) low frequency-oriented analysis could be conducted alongside A-weighted dBA measurements, to better understand the low frequency vibration impacts that are characteristic to freight rail, when compared to other transportation noise sources (Table 6-13).

Table 6-15: A-weighted Versus C-weighted Corresponding Decibel Values

Center Frequency (Hz)	A-weighted Scale (dBA)	C-weighted Scale (dBC)
31.5	-39.4	-3.0
63	-26.2	-0.8
125	-16.1	-0.2
250	-8.6	0.0
500	-3.2	0.0
1,000	0.0	0.0
2,000	1.2	-0.2
4,000	1.0	-0.8
8,000	-1.1	-3.0

Table 6-16: Burlington Northern Santa Fe Harbor Subdivision Rail Crossings

City/Neighborhood	Rail Crossing	Lights	Bells	Gated	Speed Limit	Mile Post	Adjacent Area
Wilmington	BNSF Watson Yard (Origin)						
Carson	Lomita Blvd	Y	2	Y	10	26.61	Industrial
Carson	Wilmington Ave	Y	2	Y	20	26.36	Industrial, Residential
Wilmington	Lakme Ave	Y	2	Y	20	26.11	Residential
Wilmington	Broad Ave	Y	2	Y	20	26.04	Industrial, Residential
Carson	Avalon Blvd	Y	2	Y	20	25.94	Commercial, Residential
Carson	Figueroa St	Y	2	Y	20	24.79	Industrial
Torrance	Western Ave	Y	2	Y	20	23.03	Commercial, Residential
Torrance	Sepulveda Blvd	Y	3	Y	20	22.78	Commercial, Residential
Torrance	Border Ave	Y	2	Y	20	22.57	Residential
Torrance	Cabrillo Ave	Y	2	Y	20	22.49	Commercial, Park, Residential
Torrance	Arlington Ave	Y	2	Y	20	22.24	Commercial, Park, Residential
Torrance	Washington Ave	Y	2	Y	20	22.10	Commercial, Residential, School
Torrance	Carson St	Y	2	Y	20	21.60	Commercial, Residential, School
Torrance	Sonoma St	Y	2	Y	20	21.48	Commercial, Residential, School
Torrance	Pedestrian	N	N	N	20	21.36	Residential
Torrance	Torrance Blvd	Y	2	Y	20	21.24	Commercial, Residential
Redondo Beach	182nd St	Y	2	Y	20	18.38	Commercial, Park, Residential
Lawndale	170th St	Y	2	Y	20	17.62	Residential
Lawndale	162nd St	Y	2	Y	20	17.14	Residential
Lawndale	161st St	Y	2	Y	20	17.08	Residential
Lawndale	160th St	Y	2	Y	20	17.01	Residential
Lawndale	159th St	Y	2	Y	20	16.94	Commercial, Residential
Lawndale	Manhattan Beach Blvd	Y	3	Y	20	16.87	Commercial, Industrial
Lawndale	Inglewood Ave	Y	2	Y	20	16.74	Commercial, Industrial
Redondo Beach	Marine Ave	Y	2	Y	20	16.14	Commercial, Industrial
El Segundo	Douglas St	Y	2	Y	20	14.65	Commercial, Industrial
El Segundo	Sepulveda Blvd (Union Pacific trackage)	Y	2	Y	10	500.35	Commercial, Industrial
El Segundo	Chevron El Segundo Refinery (Terminus)						

Source: United States Department of Transportation Federal Railroad Administration

Table 6-17: Union Pacific El Segundo Industrial Lead Rail Crossings

City/Neighborhood	Rail Crossing	Lights	Bells	Gated	Speed Limit	Mile Post	Adjacent Area
Watts	(Feed from Wilmington Subdivision)				10	490.75	Park, School
Watts	108th St	Y	2	Y	10	490.94	Residential, School
Watts	109th St	N	N	N	10	491.02	Residential
Watts	110th St	N	N	N	10	491.12	Residential
Watts	Compton Ave	Y	2	Y	10	491.17	Commercial, Residential
Watts	Slater Ave	N	N	N	10	491.45	Residential, School
Watts/Green Meadows	Central Ave	Y	2	Y	10	491.62	Commercial
Green Meadows	Avalon Blvd	Y	2	Y	10	492.29	Commercial, Industrial, Residential
Green Meadows	Imperial Hwy	Y	4	Y	10	492.52	Commercial, Residential
Broadway-Manchester	San Pedro St	Y	4	Y	10	492.56	Commercial, Residential, School
Broadway-Manchester	Main St	Y	2	Y	10	492.83	Commercial, Industrial, Residential
Broadway-Manchester	Broadway	Y	2	Y	10	493.10	Industrial
Broadway-Manchester	Figueroa St	Y	2	Y	10	493.36	Commercial, Residential
Broadway-Manchester	Hoover St	Y	2	Y	10	493.61	Residential
Broadway-Manchester/ West Athens	Vermont Ave	Y	2	Y	10	493.88	Residential
West Athens	Budlong Ave	Y	2	Y	10	494.12	Residential
West Athens	Normandie Ave	Y	2	Y	10	494.38	Residential
West Athens/ Hawthorne	Van Ness Ave	Y	2	Y	10	495.46	Commercial, Park, Residential
Hawthorne	Pedestrian	N	N	N	10	495.93	Commercial, Industrial
Hawthorne	Crenshaw Blvd	Y	4	Y	10	495.99	Commercial, Industrial
Hawthorne	Northrop Ave (Spur)	Y	4	Y	10	496.45	Commercial, Industrial
Hawthorne	Prairie Ave	Y	4	Y	10	496.99	Commercial, Industrial
Hawthorne	York Ave	N	N	N	10	497.05	Commercial, Residential
Hawthorne	Oxford Ave	N	N	N	10	497.11	Residential
Hawthorne	Menlo Ave	N	N	N	10	497.18	Residential
Hawthorne	Freeman Ave	N	N	N	10	497.24	Residential
Hawthorne	Cedar Ave	N	N	N	10	497.30	Residential
Hawthorne	Birch Ave	Y	2	Y	10	497.36	Commercial, Residential
Hawthorne	Hawthorne Ave	Y	4	Y	10	497.50	Commercial, Industrial
Hawthorne	Grevillea Ave	Y	2	Y	10	497.63	Commercial, Residential
Hawthorne	Ramona Ave	Y	2	Y	10	497.76	Industrial, Residential, School
Hawthorne	Eucalyptus Ave	Y	2	Y	10	497.88	Industrial, Residential
Hawthorne	Inglewood Ave	Y	2	Y	10	498.01	Commercial, Industrial, Residential, School
Hawthorne	Pedestrian	N	N	N	10	498.17	School
Del Aire	El Segundo Blvd	Y	3	Y	10	498.50	Commercial, Residential
El Segundo	Aviation Blvd	Y	2	Y	10	499.15	Industrial, Residential
El Segundo	Douglas St	Y	2	Y	10	499.45	Commercial, Industrial
El Segundo	Sepulveda Blvd	Y	2	Y	10	500.35	Commercial, Industrial
El Segundo	Chevron El Segundo Refinery (Terminus)						

Source: United States Department of Transportation Federal Railroad Administration

Table 6-18: Union Pacific Torrance Industrial Lead Rail Crossings

City/Neighborhood	Rail Crossing	Lights	Bells	Gated	Speed Limit	Mile Post	Adjacent Area
Broadway-Manchester	(Feed from El Segundo Industrial Lead)				10	492.91	Tunnel
Broadway-Manchester	Broadway	Y	2	Y	10	493.10	Industrial
Broadway-Manchester	117th St	Y	2	Y	10	493.17	Industrial, Residential
Broadway-Manchester	120th St	Y	1	Y	10	493.44	Residential
Willowbrook	124th St	Y	2	Y	10	493.69	Park, Residential
Willowbrook	El Segundo Blvd	Y	2	Y	10	493.95	Commercial
Willowbrook	132nd St	Y	2	Y	10	494.23	Commercial
Willowbrook	135th St	Y	2	Y	10	494.45	Commercial
Willowbrook/ West Compton	Rosecrans Ave	Y	2	Y	10	494.96	Commercial
West Compton/ Harbor Gateway	Figueroa St	Y	2	Y	10	495.37	Commercial, Residential
Gardena	Vermont Ave	Y	2	Y	10	495.90	Commercial
Gardena	Redondo Beach Blvd	Y	2	Y	10	496.01	Commercial
Gardena	157th St	Y	2	Y	10	496.26	Commercial, Residential
Gardena	Alondra Blvd	Y	2	Y	10	496.51	Commercial, Residential
Gardena	164th St	Y	3	Y	10	496.70	Commercial
Gardena	Gardena Blvd	Y	2	Y	10	496.77	Commercial
Gardena	Berendo Ave	Y	2	Y	10	496.94	Residential
Gardena	166th St	Y	1	Y	10	497.22	Commercial, Residential
Gardena	Normandie Ave (Crenshaw Lumber Spur)	Y	2	Y	10	497.31	Commercial
Gardena	Brighton Ave (Crenshaw Lumber Spur)	N	N	N	10	497.37	Residential
Gardena	Halldale Ave (Crenshaw Lumber Spur)	Y	2	N	10	497.47	Residential
Gardena	Dalton Ave (Crenshaw Lumber Spur)	N	N	N	10	497.54	Residential
Gardena	Denker Ave (Crenshaw Lumber Spur)	Y	1	N	10	497.59	Residential
Gardena	Hobart Ave (Crenshaw Lumber Spur)	Y	1	N	10	497.77	Residential
Gardena	Western Ave (Crenshaw Lumber Spur)	Y	2	Y	10	497.83	Commercial
Gardena	168th St	Y	2	Y	10	497.33	Commercial, Residential
Gardena	Normandie Ave	Y	2	Y	10	497.42	Commercial, Residential
Gardena	Artesia Blvd	Y	2	Y	10	497.75	Commercial
Gardena	178th St	Y	2	Y	10	498.01	Commercial, School
Gardena	179th St	Y	2	Y	10	498.09	Residential, School
Gardena/ Harbor Gateway	182nd St	Y	2	Y	10	498.25	Residential, School
Harbor Gateway	186th St	Y	2	Y	10	498.51	Commercial, Residential
Harbor Gateway	190th St	Y	4	Y	10	498.77	Commercial
Harbor Gateway	Knox St	Y	4	Y	10	499.05	Commercial
Harbor Gateway	Francisco St	Y	4	Y	10	499.33	Commercial
Harbor Gateway	Torrance Blvd & Denker Ave	Y	3	Y	10	500.02	Commercial, Residential
Harbor Gateway/ Torrance	Western Ave	Y	2	Y	10	500.42	Commercial, Industrial
Torrance	Torrance Blvd	Y	1	Y	10	500.67	Commercial
Torrance	Cabrillo Ave	N	N	N	10	500.78	Commercial
Torrance	Torrance Blvd & Sartori Ave	N	N	N	10	500.88	Commercial
Torrance	Engracia Ave	N	N	N	10	500.92	Commercial
Torrance	Cravens Ave	N	N	N	10	501.02	Residential
Torrance	Arlington Ave	N	N	N	10	501.10	Commercial, Residential
Torrance	Portola Ave	N	N	N	10	501.20	Residential
Torrance	Dominguez Way	Y	2	Y	10	501.29	Industrial, Residential
Torrance	United States Gypsum (Terminus)						

Source: United States Department of Transportation Federal Railroad Administration

CHAPTER 7

Conclusions

This dissertation examined the impacts of transportation noise in two regions of Los Angeles County, California. An extensive literature research on the subject revealed a gap in the literature for research in the Southern California area on transportation noise impacts. This dissertation contributes to filling that gap by using spatial hedonic models (HP) to analyze impacts from operations near Los Angeles International Airport and from freight rail operations in the South Bay region of Los Angeles County. This is the first known study to utilize spatial modeling techniques to analyze transportation noise impacts in these locations.

The studies conclude that single-family home values are negatively affected when located in noise impacted areas -- specifically within CNEL 65 and CNEL 70 dBA zones near the airport, and within 500 meters of freight rail crossings. The results provide impact values that are similar to previously published findings, and improve on existing estimations that rely on fixed effect modeling techniques. In addition, this study was able to compare relatively similar datasets to investigate the influences of spatial homogeneity on spatial models across space in the context of geographically delineated zones. It found that when neighboring zones are similar, fixed effect delineations tend to show less significance with spatial models, as opposed to when neighboring zones are distinctly different. With OLS models however, fixed effect delineations almost always show strong significance, despite similarities with adjacent neighbors. This demonstrates the ability of spatial models to account for neighboring influences in the model specification.

Future Research

Future research should include actual sound measurements along with surveys to more accurately understand true annoyance levels in the community. This can provide improved modeling specifications that take noise characteristics into account, as various modes of noise along with variations in infrastructure can create major disparities in model outputs and their interpretation. Ultimately, these analyses can help policy makers and public health officials in their decision-making abilities in regard to transportation infrastructure planning and its associated health and socioeconomic impacts.

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