Will Urban Commuting Time Affect Housing Prices and Vehicle Emissions?

Final Report

TranLIVE

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16. Abstract

The transportation cost is an essential factor that impacts land and house values in urban areas. In a classical monocentric city model, residents who work in the Central Business District (CBD) are facing a trade-off between rent and commuting distance to the CBD. In most metropolitan areas, the real estates that are located in or close to a CBD are able to command a higher rent in equilibrium than those at the suburban areas. Nevertheless, longer distance may not always imply higher transpiration costs for commuting, since alternative commuting modes could shorten the physical distance by shortening commuting time or improving fuel consumption efficiency, such as riding on freeway instead of on local roads, or riding on public transportation rather than individual vehicle. This paper intends to explore how the average commuting time affects the housing price in four suburban cities in Texas, including Houston, Dallas-Ft Worth, San Antonio, and Austin, using real data from an online real estate database. The statistical relationships between the Median List Price (MLP) and the Average Commuting Time (ACT), after controlling family characteristics such as Median Household Income (MHI), are analyzed by linear regression. In addition, the social cost of urban sprawl when residents make a use of lower housing cost in suburban cities and spend more time on commuting to work was discussed. Results show that an increase in one additional minute on average commuting time raises 1.9 dollars less housing price per square foot (p-value: 0.038). The incurred costs in the form of significant vehicle emissions and highway congestion have important policy implications. The analytical framework and results in this paper could be references for research and practices in land use, transportation economics, transportation planning, transportation impact analyses, and real estate markets.

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ABSTRACT

The transportation cost is a very important factor that impacts land and house values in urban areas. In a classical monocentric city model, residents who work in the Central Business District (CBD) face a trade-off between rent and distance to the CBD. By considering the impact of transportation costs, real estates in or close to city center will be able to command a higher rent in equilibrium than those at the suburban areas.

This research uses real data from an online real estate database as examples to illustrate how the average commuting time affects the housing price in suburban cities in Texas (including Houston, Dallas-Ft Worth, San Antonio, and Austin). Relationships between the "median list price" and "average commuting time", after controlling family characteristics such as "median household income", are established. We also discuss the social cost of urban sprawl when residents make use of lower housing cost in suburban cities and spend more time commuting to work. The incurred cost in the form of significant vehicle emission and highway congestion has important policy implications. The analytical framework and results could be references for research and practices in land use, transportation economics, transportation planning, transportation impact analyses, and real estate markets.

Vehicle emissions are one of the major sources of urban air pollution and are also called mobile source emissions. A large amount of gross vehicle emissions is generated by vehicles commuting between residential homes and the workplace. Homebuyers generally prefer to purchase residential houses that are relatively less expensive, albeit at the cost of relatively longer commuting times. Consumers usually consider additional travel time, fuel consumption, and other personally concerned factors, with less

apprehension about the extra air pollution possibly generated. In cities with populations between 15,000 and 1,000,000, an increase of one additional minute of average commuting time is associated with a reduction of 1.9 dollars in housing price per square foot (p-value: 0.038). To account for the generation of additional air pollution, this research numerically characterizes factors related to air pollutants caused by additional travel time due to housing prices. Air pollutants such as CO, CO_2, NO_2, NO, NO_x and SO_2 as well as fuel consumption were estimated by MOVES (motor vehicle emissions simulator).

The results will be a useful reference to generate recommendations for more efficient reduction of mobile source air pollution in metropolitan areas through joint efforts by government, agencies, the public, and industry from multiple fields including environment protection, land use, housing markets, transportation management, and law enforcement.

EXECUTIVE SUMMARY

One of the most notable regularities of urban spatial structure is that, the price of residential housing decreases with the distance to the Central Business District (CBD), the farther away from the downtown, the lower the price of housing of equal size. Literature reviles that, after a long period during which house prices were stable, values of houses may decline by more than 8% per mile. Recognition of the existence of nonlinear land prices has an impact on the measurement of the rate at which land price declines with distance from the urban center.

In this report, the actual commuting time in urban area was retrieved from a comprehensive online real estate database. Admittedly, difference in commuting time does not fully account for difference in commuting cost if there is heterogeneity in resident's commuting modes. For instance, 40 minutes riding on the bus has the same time cost of driving 40 minutes on the highway, but the former has lower fuel cost (for passengers) than the latter. However, in our samples of suburban cities surrounding four metropolitan centers in Texas where majority of residents drive to work, the problem of heterogeneity in commuting mode is largely mitigated.

After quantifying the impact of commuting time on housing prices, the consequence of urban sprawl was analyzed when residents choose to live further away from the city center. Although residents are equally well-off living in the suburban areas as closer to CBD, there are hidden costs incurred in their choices, costs that not taken into account by residents but still imposed on the society as a whole. These hidden costs, named "externalities" in economics, mainly take two forms in this context: vehicle emission, highway congestion and air pollution. Travelling longer distance contributes significantly

to vehicle emission, a major source of air pollution. This problem is more severe in developing countries. According to a recent study in Proceedings of the National Academy of Sciences, which is widely cited by the press, severe pollution has slashed an average of 5.5 years from life expectancy in northern China, as toxic air has led to higher rates of stroke, heart disease and cancer. The cost of highway congestion is also worth mentioning. Texas' 10 largest cities had a combined congestion cost in excess of $12 billion dollars including delay, fuel and truck freight moving costs. In Britain, traffic congestion is costing the economy more than £4.3 billion a year, or £491 per car- commuting household, according to the survey by the Centre for Economics and Business Research and traffic information company Inrix.

In this report, the vehicle emission model MOVES is used to estimate air pollution emissions from mobile sources in eight counties within four major metropolitan areas in the State of Texas in United States. Differences of emissions for nonpeak and peak hours, as well as emission inventories per vehicle per minute in these counties in year 2004 and 2014 are compared.

This report conducted a case study in 86 Texas cities. Results show that for all the 86 cities in Texas, with one more minute of average commuting time, the median price decreases by 3.3 dollars while the average median list price in the sample is 94.3 dollars per square foot. If median household income is incorporated into regression, with one more minute of average commuting time, the median price decreases by 4.2 dollars, more than 4% of the average price. The p-value is close enough to zero (with a t-stat 3.9). Other control variables such as property tax and owners' share, are not affect the house price significantly. For 63 cities with populations between 15,000 and 1,000,000, one additional minute of average commuting time is associated with 1.9 dollars less housing price (p-value: 0.038).

During peak hours in 2014 within eight counties, one more additional minute of commuting generates 8.51 g of CO_2, 0.21 g of CO, 0.04 g of NO_x, and 0.04 g of NO_x. During nonpeak hours in 2014 within these eight counties, one more minute of commuting generates 6.72 g of CO_2, 0.14 g of CO, 0.03 g of NO, and 0.03 g of NO_X.

In general, this report quantified the impact of commuting time on housing prices; discussed the consequence of vehicle emissions from urban sprawl when residents choose to live further away from city center with longer commuting time to work; and contributed to the literature by providing theoretical explanation for economic vehicle emission and highway congestion mitigations. The statistical results from the case study could be very useful in land use, transportation economics, transportation planning, transportation impact analyses, and definitely the real estate market.

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CHAPTER 1

INTRODUCTION

1.1 Background of Research

It is well-known that urban spatial structure affects housing prices. There are many common regularities of urban spatial structure in almost all cities. One of the most notable regularities is in general the price of residential housing decreases with the distance to the Central Business District (CBD), the farther away from the downtown, the lower the price of housing of equal size. Table 1 presents the median list prices of houses in four suburban cities on the southwest of the Houston metropolitan area and their distances from city centers to the downtown of Houston. They are all linked to the downtown of Houston by the Highway US 59. The major difference among them is the distance to downtown via US 59. It is clear from Table 1 that the housing price declines as the distance to downtown increases. After a long period during which house prices were not affected by distance from the central business district, values now decline by more than 8% per mile stated by (McMillen, 2003). Recognition of the existence of nonlinear land prices has an impact on the measurement of the rate at which land price declines with distance from the urban center, said by Colwell *et al.* (1997).

Table 1. Distance to CBD and Housing Prices in Four Cities of Houston Metropolitan Area

City Name	Median List Price	Distance to Houston Downtown
Missouri	205,000	33.49
Stafford	219,900	34.45
Richmon	150,000	54.10
Rosenbe	125,000	58.12

(Sources: www.zillow.com and maps.google.com)

Figure 1. An Illustration of Distance and Housing Price. The yellow squares denote locations of the CBD and four cities. 1 is Downtown Houston, 2 is Missouri City, 3 is Sugar Land, 4 is Richmond, 5 is Rosenberg (The map was from www.google.com)

1.2 Objectives of Research

The background of the research presented above provided the context to define the objectives of this research.

We try to fill this gap in the literature by using the actual commuting time from a comprehensive online real estate database. Admittedly, difference in commuting time does not fully account for difference in commuting cost if there is heterogeneity in resident's commuting modes. For instance, 40 minutes riding on the bus has the same time cost of driving 40 minutes on the highway, but the former has lower fuel cost (for passengers) than the latter. However, in our samples of suburban cities surrounding four metropolitan centers in Texas where majority of residents drive to work, the problem of heterogeneity in commuting mode is largely mitigated.

After quantifying the impact of commuting time on housing prices, we move on to discuss the consequence of urban sprawl when residents choose to live further away from the city center and spend more time on commuting to work. Although residents are equally well-off living in the suburban areas as closer to CBD, there are hidden costs incurred in their choices, costs that not taken into account by residents but still imposed on the society as a whole. These hidden costs, named "externalities" in economics, mainly take two forms in this context: vehicle emission, highway congestion and air pollution. Travelling longer distance contributes significantly to vehicle emission, a major source of air pollution. This problem is more severe in developing countries. According to a recent study in Proceedings of the National Academy of Sciences, which is widely cited by the press, severe pollution has slashed an average of 5.5 years from life expectancy in northern China, as toxic air has led to higher rates of stroke, heart disease and cancer. The cost of highway congestion is also worth mentioning. In a testimony before the Texas House of Representatives, Dr. David Ellis (2013) referred to a report (Schrank *et al.*, 2012) in which it is estimated that Texas' 10 largest cities had a combined congestion cost in excess of $12 billion dollars including delay, fuel and truck freight moving costs. In Britain, traffic congestion is costing the economy more than £4.3 billion a year, or £491 per car-commuting household, according to the survey by the Centre for Economics and Business Research and traffic information company Inrix (2012).

The vehicle emission model MOVES is used to estimate air pollution emissions from mobile sources in eight counties within four major metropolitan areas in the State of Texas in United States. Differences of emissions for nonpeak and peak hours, as well as emission inventories per vehicle per minute in these counties in year 2004 and 2014 are compared.

The research objectives are summarized as follows:

1. Quantify the impact of commuting time on housing prices;
2. Discuss the consequence of urban sprawl when residents choose to live further away from city center and spend more time on commuting to work: vehicle emission and air pollution.
3. Contribute to the literature by providing theoretical explanation, readily available from economics, of vehicle emission and highway congestion.

1.3 Outline of the Study

This report is comprised of five chapters. The first chapter provides an overview of the problems, the research objectives, and the layout of the study. The second chapter presents literature review of a monocentric model for housing price and commuting time, as well as emission analysis with extra commuting time and effects of vehicle emission on air pollution. The third chapter describes the design of the study by introducing the methodology on collecting and analyzing the data. The fourth chapter presents and analyzes the results of the relationship between average commuting time and housing price; the extra vehicle emission due to extra commuting time; extra air pollution effects caused by extra emission. Finally, the fifth chapter provides the study conclusions and recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

The literature review is conducted from three perspectives in order to establish the context for the proposed research. First, a monocentric model for housing price and commuting time is presented. Second, emissions analysis with extra commuting time is provided. Third, effects of vehicle emissions on air pollution are calculated. Finally, the conclusions of the existing studies are summarized.

2.1 A Monocentric Model for Commuting Time and Housing Prices

Economic models to formulate this pattern originated in the works of William Alonso (1964), Richard Muth (1969), and Edwin Mills (1967). As in all economic models, there is a set of simplifying assumptions to capture the essential features of cities. First, the city is characterized as monocentric (see illustration in Figure 2). The only difference between any two locations is the distance to the CBD. Second, all the city's jobs are in the CBD, which is collapsed to a single point at the city center and takes no space since the objective is to analyze residential rather than business land use. Third, all households in the city are identical. They share the same preferences over consumption goods, and earn the same income from work at the CBD. Fourth, the city has a dense network of radial roads. The commuting cost is in proportion to the distance to CBD. The physical features of the roads that may make commuting cost a nonlinear function of travelling time are ignored in these models. We will discuss the details of the model in the next section.

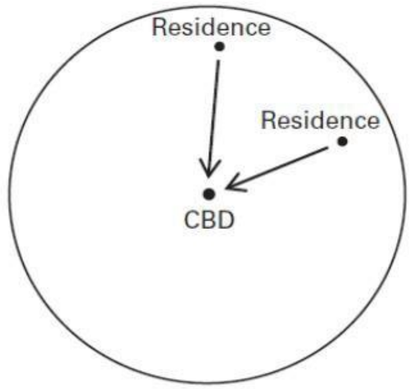


Figure 2. Radial Commuting.

In equilibrium, residents derive the same level of utility no matter their choice of residential location, because otherwise they have incentive to move and obtain higher level of utility. If they choose to live farther away from CBD, the price of land has to be cheaper to compensate for the unpleasant time cost incurred in commuting to work. It is one of the key predictions of these models and also what we test for empirically in this research.

This prediction is empirically tested in many papers. Grether and Mieszkowski (1974) is the first to study determinants of real estate values using a hedonic framework developed by Rosen (1974). They find that a house with average characteristics located on the boundary of New Haven, CT (around three miles from the CBD) as opposed to being one mile from the CBD will be sold for $200 less. A more recent paper by Chen and Chen *et al.* (2008) find location, specifically distance to the city center, as the primary determinant of housing price of all new commercial residential units in Shanghai, China.

Indirect evidence also highlights the importance of location in determining housing prices. If a new public transit system can reduce residents' commuting, then block groups where access to the new system is now available would experience a gain in housing prices, which is consistent with the aforementioned model's prediction. When a new light rail system was introduced in Charlotte, NC, across the four time periods prices of single-family houses closer to the light rail (0.25 miles) grew faster than those farther away from the light rail (1 mile) (Yan *et al.,* 2012). Another paper by Brandt and Maennig (2012) finds that access to public railway stations in Hamburg, Germany is associated with an increase of 4.6% in prices of surrounding condominiums.

2.2 Emission Analysis with Extra Commuting Time

Vehicle emissions are one of the major sources of urban air pollution and are also called mobile source emissions. A large amount of gross vehicle emissions is generated by vehicles commuting between residential homes and the workplace.

New vehicle engine technologies and new fuel types have reduced the amount of pollutants from each individual vehicle. However, mobile source pollution from roadway systems is still very high. This is because total emissions are also determined by VMT (vehicle miles traveled), which is significantly affected by travel routes, such as the commutes between residential areas (origins) and workplaces (destinations) (Qiao *et cl*., 2004).

MOVES (motor vehicle emissions simulator) is a computer program designed by the United States EPA (Environmental Protection Agency), which incorporates substantial new emissions test data and accounts for changes in vehicle technology and regulations as well as an improved understanding of in-use emission levels and the factors that influence them (Brodere, 2009; EPA, 2012). The MOVES also has a completely special software framework that includes many new features and provides much more flexibility for input and output options than MOBILE 6.2 (EPA, 2010). New input options in MOVES and changes in the way MOVES handles existing information may create significant new information burdens for states preparing submissions for State Implementation Plan (SIP) and conformity related purposes (EPA, 2010; EPA, 2012). Recently, the on-road vehicle emission testing equipment, such as PEMS (Portable Emission Measurement System) has been widely used to collect real time vehicle emissions and characterize the impacts of roadway design, traffic operations, and traffic activities (Younglove *et al*., 2005; Qiao *et al*., 2005). MOVES, even though has incorporated large amount of such on-road testing data, is however more suitable for the estimation of State and local inventories at national, county, and project levels.

Traffic congestion has been increasing dramatically in the U.S. and elsewhere over the past 20 years (World Bank, 2006; Schrank and Lomax, 2009). One of the reasons is that there are more commuters who prefer living further and adding the commuting time. More commuting time may cause traffic congestion and add vehicle emissions. Because congestion alters driving patterns, specifically causing frequent acceleration and deceleration in stop-and-go traffic, which increases emissions (Cappiello, 2002; Smit, 2006; TRB, 2002). Zhang *et al*. (2011) demonstrated that emissions varied with congestion type (rush hour congestion vs. work zone congestion), vehicle type (light-duty cars vs. heavy duty trucks), and pollutant type.

2.3 Effects of Vehicle Emission on Air Pollution

More commuting time may cause traffic congestion. Traffic is a major source of urban air pollution (TRB, 2002). The key issue is to what extend an emissions reduction can achieve from reduced congestions in urban area (Barth *et al.*, 2013). In many areas, vehicle emissions have become the dominant source of $PM_{2.5}$ (particulate matter less than 2.5 micrometers in aerodynamic diameter), PM_{10} (particulate matter less than 10 micrometers in aerodynamic diameter), nitrogen oxides (NO_x), hydrocarbons (HC) and carbon monoxide (CO), among other pollutants (TRB, 2002). In the U.S., mobile source emission and on-road vehicle emissions accounted for 53% and 30% of the national total for criteria pollutants, respectively (EPA, 2003), and on-road emissions contribute a larger share in urban areas where most people live. A European PM apportionment study concluded that road transport accounts for one-quarter to one-half of PM2.5 in a typical urban area, and that road transport is the most important source of NOx, CO, benzene and black carbon. Mobile sources also play an important role in tropospheric ozone formation due to emissions of volatile organic compounds (VOCs) and NO_x, which are precursors of ozone (TRB, 2002).

The motor vehicle engine emits many types of pollutants including nitrogen oxides (NOx), volatile organic compounds (VOCs), carbon monoxide (CO), carbon dioxide (CO_2), particulates, sulphur dioxide (SO_2) and lead. The impacts of exhaust emissions include acid deposition and air pollution, human health effects, global climate change and noise pollution (http://www.air-quality.org.uk/08.php, 2001). The emissions of NOx and HC can react with still air under sunlight to form toxic smog for humans, which lead to higher rates of stroke, heart disease and cancer (Li et al., 2016c). Besides, NOx is associated with the formation of acid rain. Further, recent studies found that drivers are exposed to hazard noise daily while riding on highways (Qiao et al, 2016; Li et al., 2015a). The hazard noise may damage drivers' sensitivity of hearing, raise significantly driving stress (Li et al., 2015b; Li et al., 2016a), and increase the risk of cardiovascular disease (Collingwood, 2013; Li et al., 2016b).

Concentrations of traffic-related air pollutants show strong spatial patterns (HEI, 2010). Two critical reviews (WHO, 2005; HEI, 2010) indicated that concentrations of NOx, black smoke and PM0.1 within 200 to 500 m of roadways far exceeded urban background; $PM_{2.5}$ and PM_{10} had somewhat higher concentrations than urban background; NO_2 had no evident spatial distribution; and higher concentrations of many pollutants were found in street canyons.

The increasing severity and duration of traffic congestion have the potential to greatly degrade air quality, particularly near large roadways (Schrank and Lomax, 2007). In addition, congestion can change driving patterns, resulting in an increased number of speedups, slowdowns, stops and starts, which increases emissions compared to "cruise" conditions, especially with high power acceleration. For example, Sjodin *et al*. (1998) showed up to 4-, 3- and 2-fold increases in CO, HC and NO_X emissions, respectively, with congestion (average speed of 13 mph compared to uncongested conditions (average speed, 38-44 mph).

Transportation contributes to the large amount of greenhouse gas emissions, especially for CO_2. According to the United States Environmental Protection Agency (EPA, 2007), 1,745.5 Million Metric Tons carbon dioxide CO_2 comes from transportation sources, accounting for 28% of such emissions. Transportation accounts for approximately one third of the United States' CO_2 emissions inventory. The transportation sector has dominated the growth in U.S. carbon dioxide emissions since 1990, accounting for 69 percent of the total increase in U.S. energy-related carbon dioxide emissions (EIA, 2009). In order to reduce future CO_2 emissions, transportation policy makers are looking for more efficient vehicles with the increased use of carbon-neutral alternative fuels.

2.4 Summary

The transportation cost is a very important factor that impacts land and house values in urban areas. In a classical monocentric city model, residents who work in the Central Business District (CBD) face a trade-off between rent and distance to the CBD. By considering the impact of transportation costs, real estates in or close to city center will be able to command a higher rent in equilibrium than those at the suburban areas. Recently, with the trend of urban sprawl, more commuters would like to commute longer time to get the cheaper housing prices. But limited literature review focuses on the impacts of commuting time on housing price and vehicle emissions.

This literature review is conducted from three perspectives in order to establish the context for the proposed research. First, a monocentric model for housing price and commuting time is presented. Second, emissions analysis with extra commuting time is provided. Third, effects of vehicle emissions on air pollution are calculated.

A major shortcoming of the existing literature is that distance is used as a proxy variable for the actual cost for commuters. Nevertheless, being further away from the CBD does not necessarily mean costing more (both time and fuel) to arrive at the CBD due to different commuting modes. For example, driving 20 miles on the freeway is probably less time-consuming and more fuel-efficient than driving 10 miles on local roads with frequent stop-and-go. In the meantime, there is little literature that calculates the relationship between emission amount and extra commuting time.

CHAPTER 3

DESIGN OF THE STUDY

3.1 Methodology

The model we use in this section is largely from Brueckner (2011). We assume city residents consume two goods: housing and "bread", which is a composite good covering the all consumption other than housing. Bread consumption is denoted by c, and since the price per unit is normalized to \$1, c gives dollars spent on bread (all goods other than housing). Housing consumption is denoted by q, but the physical units corresponding to q must be chosen. The problem is that housing is a complicated good, with a variety of characteristics that consumers value. The characteristics of housing include square footage of floor space in the dwelling, yard size, construction quality, age, and amenities (crime rates, for example). Although a dwelling is then best described by a vector of characteristics, the model requires that consumption be measured by a single number. The natural choice is square footage, the feature that consumers probably care about most. Thus, q represents the square feet of floor space in a dwelling. With this measurement choice, the price per unit of housing is then the price per square foot of floor space, denoted by p. The consumer's budget constraint, which equates expenditures on bread and housing to disposable income net of commuting cost, is

$$c + pq = y - tx \tag{1}$$

The budget constraint says that expenditure on bread (which equals c given bread's unitary price) plus expenditure on housing ("rent", or pq) equals disposable income. The consumer's utility function, which gives the satisfaction from consuming a particular (c,

q) bundle, is given by $U(c, q)$. The consumer chooses c and q to maximize utility subject to the budget constraint.

One of the regularities of urban spatial structure is that the price per square foot of housing floor space declines as distance to the CBD increases. In other words, p falls as x increases. The simple model we use in the research indeed predicts this regularity. This equilibrium condition in the model says that consumers must be equally well off at all locations, achieving the same utility regardless of where they live in the city. If this condition did not hold, then consumers in a low-utility area could gain by moving into a high-utility area. This incentive to move means that a locational equilibrium has not been attained. Utilities can be spatially uniform only if the price per unit of housing floor space falls as distance increases. Since higher commuting costs mean that disposable income falls as x increases, some offsetting benefit must be present to keep utility from falling. The offsetting benefit is a lower price per square foot of housing at greater distances. Then, even though consumers living far from the center have less money to spend (after paying high commuting costs) than those closer to the CBD, their money goes farther given a lower p , allowing them to be just as well off as people living closer in. The lower p thus compensates for the disadvantage of higher commuting costs at distant locations. This explanation makes it clear that the lower p at distant suburban locations serves as a compensating differential that reconciles suburban residents to their long and costly commutes.

While the compensating-differential perspective is the best way to think about spatial variation in p, another view that may seem easier to understand focuses on "demand." One might argue that the "demand" for suburban locations is lower than the demand for central locations given their high commuting cost. Lower demand then depresses the price of housing at locations far from the CBD, causing p to decline as x increases.

So far, the model's two main predictions are that the price per square foot of housing falls, and that size of dwellings rises, as distance to the CBD increases. These outcomes can be represented symbolically as follows:

$p \downarrow$ as $x \uparrow$, $q \uparrow$ as $x \uparrow$.

With these important conceptual considerations, several aspects of the preceding analysis deserve more discussion. The consumer has been portrayed as choosing her dwelling size on the basis of the prevailing price per square foot at a given location. Although most consumers aren't used to thinking about the price per square foot of housing (focusing instead on total rent), the model assumes that they implicitly recognize the existence of such a price in making decisions. For example, a small apartment with a high rent would be viewed as expensive by a consumer, but the individual would be implicitly reacting to the apartment's high rental price per square foot. Indeed, commercial space is always rented in this fashion, with a landlord quoting a rent per square foot and the tenant choosing a quantity of space. But one might then argue that residential tenants aren't offered such a quantity choice (they can't, after all, adjust the square footage of an apartment), making the model's portrayal of the choice of dwelling size seem unrealistic. The response is that the consumer's quantity preferences are ultimately reflected in the existing housing stock. In other words, the size of apartments built in a particular location is exactly the one that consumers prefer, given the prevailing price per square foot. Two additional conclusions can be drawn from consumer side of the model. The first concerns the nature of the curve relating the housing price p to distance. The curve is convex with the price falling at a decreasing rate as x increases (Figure 3). This conclusion follows from mathematical analysis, which shows that the slope of the housing-price curve is given by the following equation:

$$\frac{\partial p}{\partial x} = -\frac{t}{q} \tag{2}$$

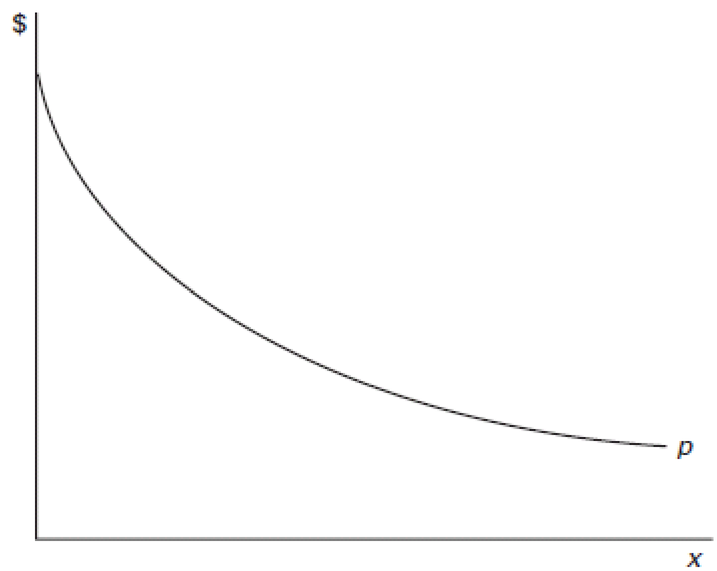


Figure 3. Housing Price and Distance to CBD

Therefore, the slope at any location is equal to the negative of commuting cost per mile divided by the dwelling size at that location. The convexity in Figure 3 follows because q increases with x, so that the–t/q ratio becomes less negative (and the curve flatter) as distance increases. The intuitive explanation is that at a suburban location where dwellings are large a small decline in the price per square foot is sufficient to generate enough housing-cost savings to compensate for an extra mile's commute. But at a central-city location, where dwellings are small, a larger decline in the price per square foot is needed to generate the required savings.

In the following sections, we will use data from suburban cities in Texas to test the predictions of per unit housing price and distance to CBD from this simple model.

3.2 Data Collection

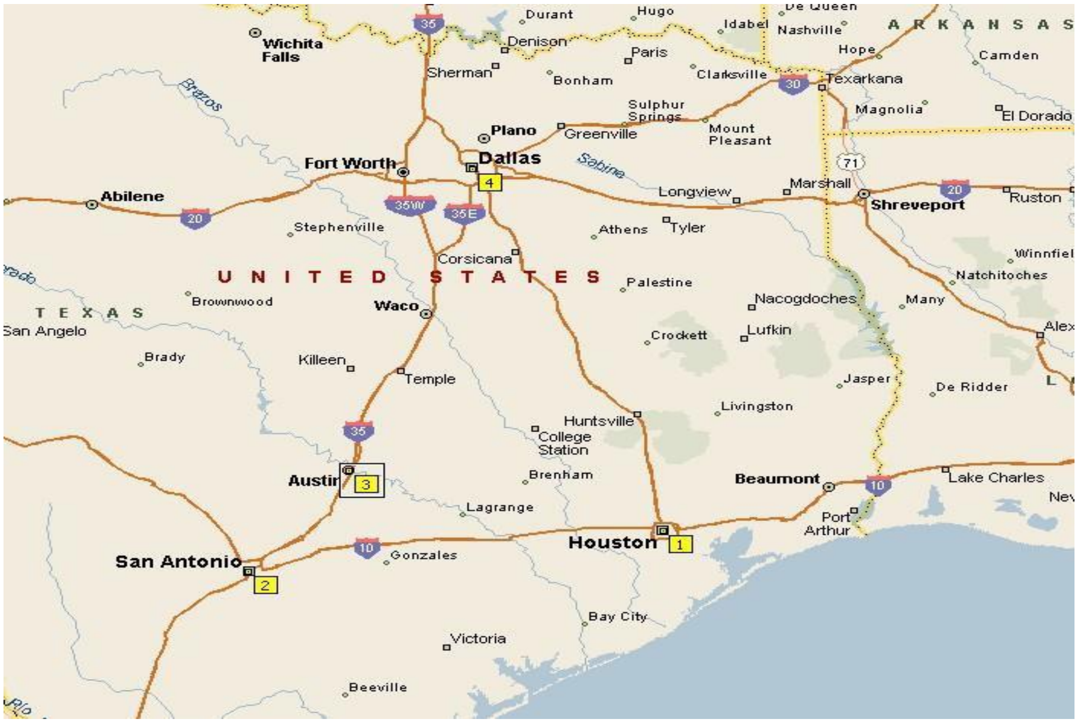
All data used in this research are from www.zillow.com. Zillow is an online real estate database that founded in 2005 and has data on 100 million homes across the United States. More importantly for this research, it has data at more aggregate level, such as median list price of homes as well as demographic information at the zip code level and city level, which are hard to find in other real estate databases. Uniquely in Zillow, it has average commuting time to work at the city level, a key variable in our following analysis. We also collect data of other important variables such as median household income, average household size, median age of households, population, median house square feet, ratio of owners versus renters, average year of houses when they were built and average property tax. Table 2 is the summary statistics of these variables.

Table 2. The Summary Statistic for all Cities Listed in Zillow Database

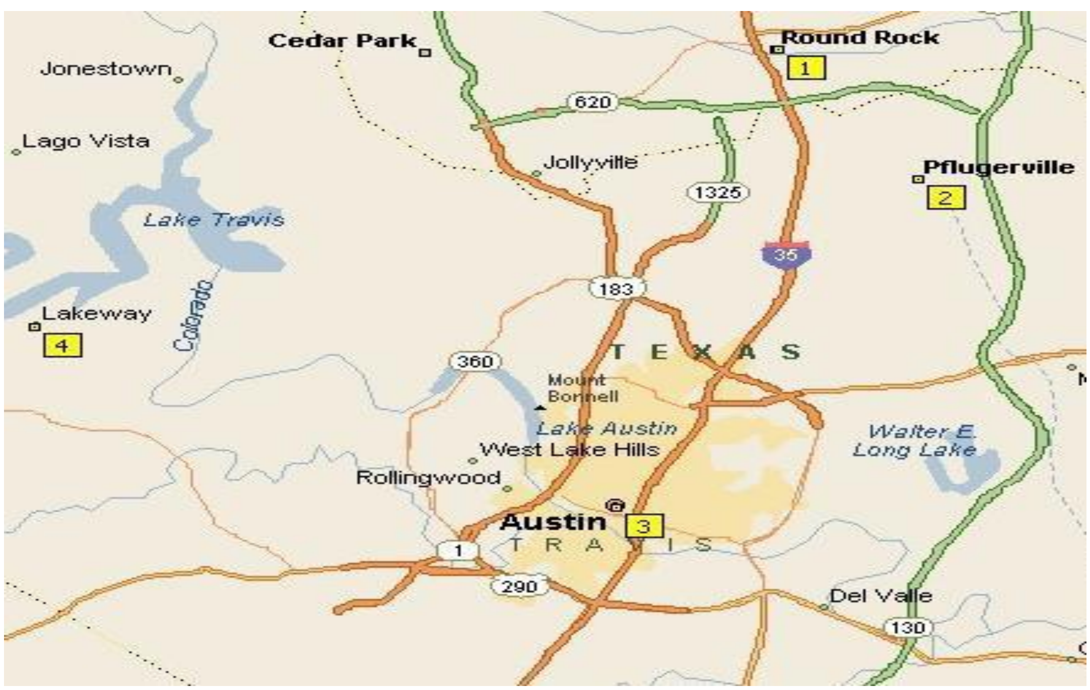
Index	Mean	Standard Deviation
Average Commute Time (minute)	27.5	3.5
Median List Price (Dollar)	186,970.9	158,850.3
Median Household Income (Dollar)	54,885.7	20,779.6
Median Age (Year)	33	2.4
Population (person)	117,743	311,299.9
Median Home Size (SqFt)	1,842.9	12.5
Average year Built (Year)	1,981	12.5
Property Tax (Dollar)	3,293.9	2,378.7

3.2.1 Data Collection on Commuting Time and Housing Prices

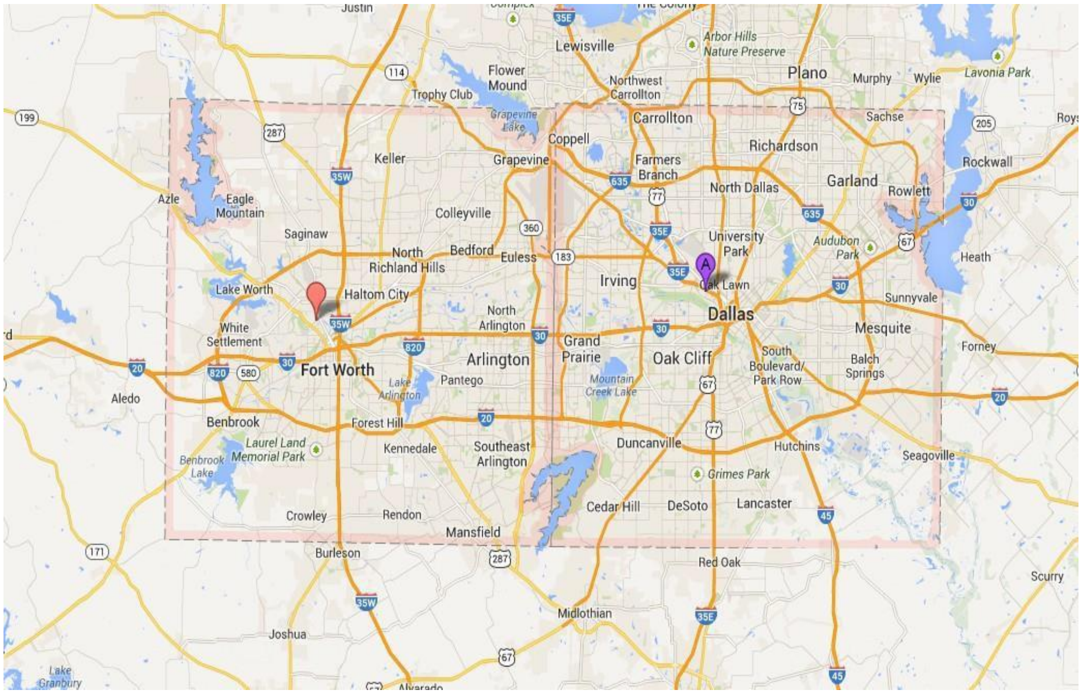
The reasons we choose the four largest metropolitan areas in Texas, Houston, Dallas/Ft Worth, San Antonio and Austin (illustrated in Figure 4), in our analysis are threefold. First, these metropolitan areas constitute more than 60% of total population in Texas in 2012. The counties where the metropolitan areas are located are among the most populous in the United States. For instance, Harris county and Dallas county are ranked 3rd and 9th respectively by population. The effect of urban spatial structure on housing prices in these areas also has implications for other large cities in the U.S. Second, housing prices in Texas were more robust than other states during the most recent financial crisis. Prices of housing in these four areas most likely reflect the fundamentals of housing market rather than speculative bubbles (McMillen 2002, Munneke 1995) Third, the number of cities for any one metropolitan area, which is the sample size, is too small to draw upon any stable statistical relationship. According to large sample theory, precise statistical inference can only be obtained when the sample size is large enough. Hence we use data from four metropolitan areas rather than focus on just one.



(a) Geometrical locations of the four Texas metropolitan areas. The four yellow squares denote: 1-Houston, 2-San Antonio, 3-Austin, 4-Dallas.

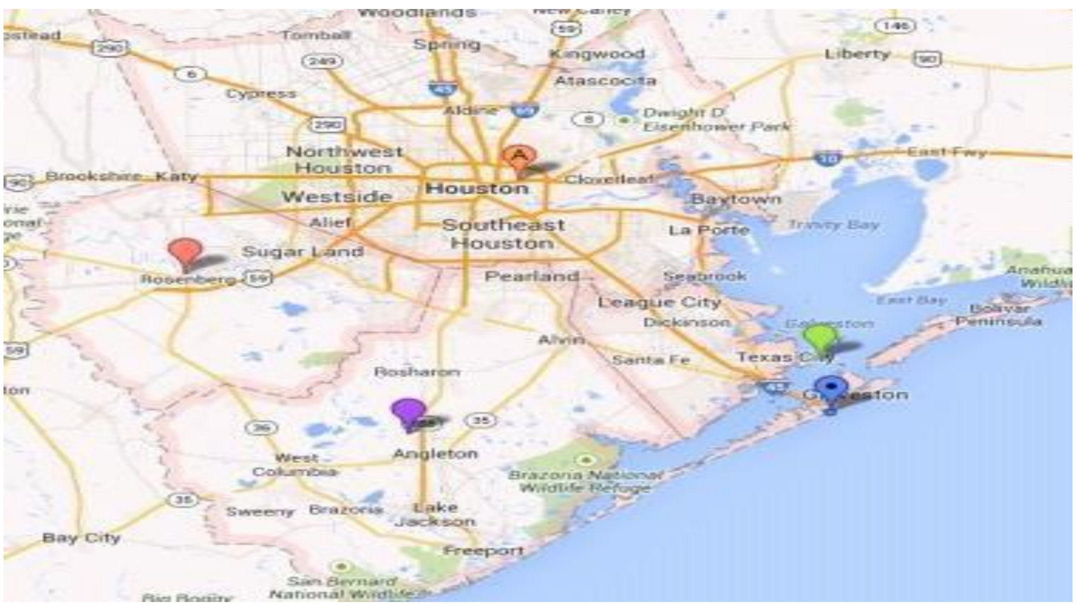


(b) Geolocation of Austin metropolitan area. The four yellow squares denote four cities in Travis County, where Austin resides.



(c) Geolocation of Dallas metropolitan area. The two counties where Dallas/FortWorth

Metro Area resides: Dallas county and Tarrant county



(d) Geolocation of Houston metropolitan area. The four counties where Houston Metro

Area resides: Brazoria county, Fort Bend county, Harris county and Galveston county

(e) Geolocation of San Antonio metropolitan area. The six yellow squares denote six cities in Bexar county, where San Antonio Metro Area resides. 1 Cibolo, 2 Converse, 3 Universal City, 4 Live Oak, 5 San Antonio, 6 Leon Valley

Figure 4. Four metropolitan areas in Texas.

3.2.2 Data Collection on Vehicle Emissions

3.2.2.1 Scope of Data Collection

The selected metropolitan areas in Texas are: Houston, Dallas/Ft. Worth, San Antonio and Austin (Figure 5). For example, Houston is the fourth largest city in the nation with a population of 2.162 million in 2013, and only New York City has more fortune 500 headquarters than Houston does (U.S. Census Bureau, 2010). The other three areas are also major metropolitan areas in Texas.

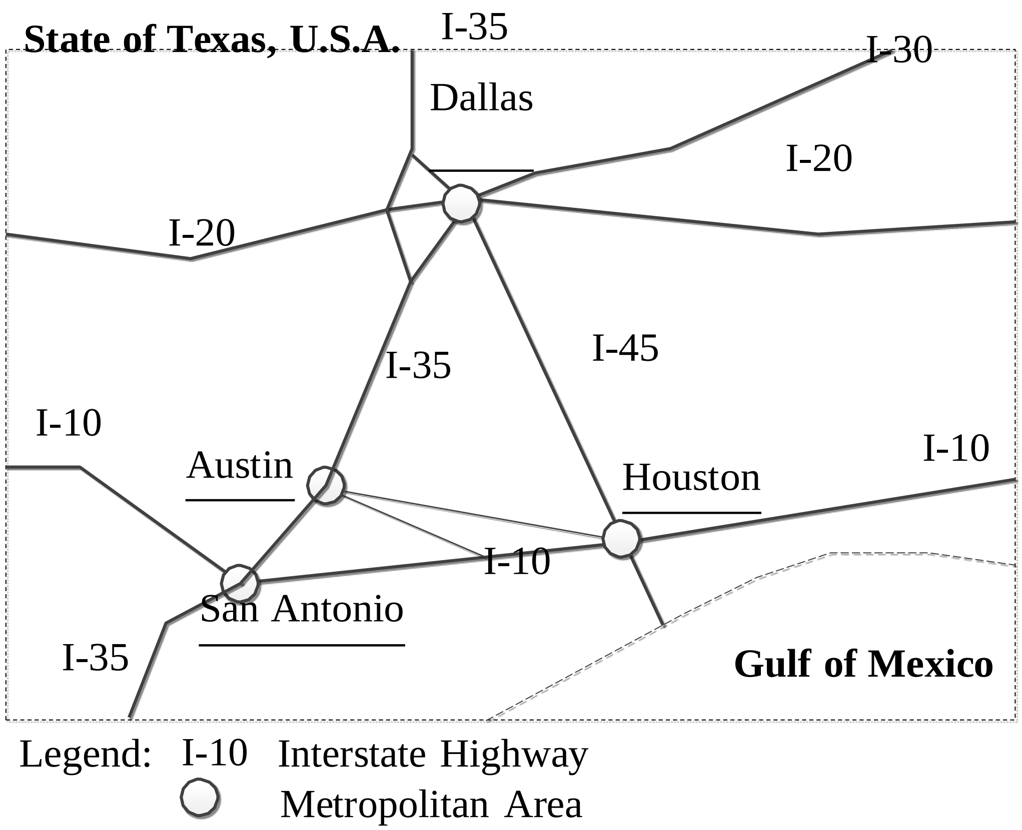


Figure 5. Geographic locations of the four metropolitan areas in the State of Texas, United States.

These four large metropolitan areas were selected for three reasons. First, they constitute more than 60% of the total population in Texas in 2012. The counties where the metropolitan areas are located are among the most populous in the United States. For example, Harris county and Dallas county rank the 3rd and the 9th, respectively by population in the nation. The effect of urban spatial structure on housing prices in these areas has also implications for other large cities in the US.

Second, housing prices in Texas were more robust than other states during the most recent financial crisis. Prices of housing in these four areas most likely reflected the fundamentals of the housing market rather than speculative bubbles.

Third, the number of cities for any single metropolitan area, which is with relatively smaller sample size, may not be sufficient to draw upon any stable statistical conclusion. According to the large sample theory, precise statistical inference can only be obtained when a sample size is sufficiently large. Hence, data from four metropolitan areas were used rather than focusing on just one area.

In practice, eight counties were included and comprised most of the territory. For Houston metropolitan area, the counties Brazoria, Fort Bend, Galveston, and Harris were selected; for Dallas/Fort Worth metropolitan area, the counties Dallas and Tarrant were selected; for Austin metropolitan area, the Travis County was selected; and for San Antonio metropolitan area, the Bexar County was selected. These county-level data were employed to synthesize the emission inventory of these eight counties.

The technical method is to employ the EPA newly approved model MOVES to estimate the county-level emission inventory during nonpeak hours and peak hours in 2004 and 2014.

Peak hour was from 7:00 a.m. to 7:59 am and nonpeak hour was selected as 13:00 pm to 13:59 pm. In order to focus on identifying air pollutant effects caused by extra commuting times, passenger cars were selected for the emission estimations.

3.2.2.2 MOVES step by step

In the "Scale" interface, "County and Inventory" was chosen.

In the "Time Spans" interface, for peak hour part, "hour, weekdays and time 7:00-7:59" are selected. Nonpeak hour part is "hour, weekdays and time 13:00-13:59". For those two parts. two different time periods are run separately: March 2004 and March 2014.

In the "Geographic Bounds" interface, "Texas and Harris County" was selected.

In the "Vehicles/Equipment-On Road Vehicle Equipment" interface, in "Fuels" panel "Gasoline" was selected, in "Source Use Types", all are chosen.

In the "Road type" interface, "all available road types" are selected. MOVES has five available road types:

1. Off-network
2. Rural Restricted Access
3. Rural Unrestricted Access
4. Urban Restricted Access
5. Urban Unrestricted Access

Start is captured, idle is extended, and resting evaporative emissions (e.g., parking areas)

2,3,4,5 Capture running emissions, including running evap: Restricted means restricted vehicle access, usually freeways and interstates；Unrestricted: all other roads (arterials, local, collector, etc.)

In the "Pollutants and processes" interface, CO, NO_x, NO, SO_2, Total Energy Consumption and Atmospheric CO_2" were selected.

In the "Output- General Output" interface, in "Units" section, following units were used: "Grams" under "Mass Units", "KiloJoules" under "Energy Units" and "Kilometers" under "Distance Units". In "Activity" section, "Distance Traveled and

Population" was chosen. In the "Output- Output Emission Detail" interface, in "Always" section, following elements are selected: "Time-Hour, Location-County and Pollutant"; in "For All Vehicle/Equipment Categories" section, "Model Type, Fuel Type and Emission Process"; in "On Road/Off Road" section. On Road/off Road; in "On road" Section, and "Road Type and Source Use Type"

3.3 Data Analysis on Commuting Time and Housing Prices

3.3.1 Data Processing

In our sample, we collected data for 86 cities from these four metropolitan areas. In practice, we first pick counties that consist most of the territory. For Houston, we pick Brazoria, Fort Bend, Galveston, and Harris County; for Dallas/Fort Worth, Dallas and Tarrant County; for Austin, Travis County, and for San Antonio, Bexar County. Note that not all cities of these counties are included in the sample. We drop cities with population less than 7,000 since it is likely that prices of housing in these small towns could be determined by idiosyncratic factors rather than common factors in larger cities.

In practice, eight counties were included and comprised most of the territory. For Houston metropolitan area, the counties Brazoria, Fort Bend, Galveston, and Harris were selected; for Dallas/Fort Worth metropolitan area, the counties Dallas and Tarrant were selected; for Austin metropolitan area, the Travis County was selected; and for San Antonio metropolitan area, the Bexar County was selected. These county-level data were employed to synthesize the emission inventory of these eight counties.

Table 3. A List of Cities Included in the Sample

Metropolitan Area	County	City	Population
Austin	Travis	Austin	773,906
		Lakeway	10,663
		Pflugerville	68,779
		Round Rock	136,046
Dallas	Dallas	Addison	12,340
		Balch Springs	25,666
		Carrollton	121,446
		Cedar Hill	46,599
		Coppell	37,422
		Dallas	1,206,228
		Desoto	51,012
		Duncanville	37,258
		Farmers Branch	28,719
		Garland	228,758
		Glenn Heights	9,227
		Grand Prairie	171,130
		Grapevine	45,922
		Irving	214,090
		Lancaster	37,995
		Lewisville	102,316
		Mesquite	138,033
		Richardson	98,089
		Rowlett	52,304
		Sachse	18,291
		Sunnyvale	7,354
		University Park	23,210
		Wylie	39,859
	Tarrant	Arlington	363,862
		Azle	9,596
		Bedford	46,476
		Benbrook	20,422
		Burleson	34,897
		Colleyville	23,409
		Euless	52,315
		Forest Hill	12,160
		Fort Worth	740,969
		Haltom City	43,177

		Hurst	36,252
		Keller	37,602
		Mansfield	56,438
		North Richland Hills	60,225
		Saginaw	21,758
		Southlake	28,368
		Watauga	22,275
		White Settlement	15,532
Houston	Brazoria	Alvin	22,270
		Angleton	15,827
		Brazoria	15,838
		Clute	11,291
		Freeport	11,723
		Lake Jackson	27,559
		Manvel	15,041
		Pearland	113,203
		Sweeny	8,604
		West Columbia	7,521
	Fort Bend	Missouri City	72,525
		Richmond	9,129
		Rosenberg	28,162
		Stafford	16,606
		Sugar Land	150,068
	Galveston	Friendswood	35,533
		Galveston	50,129
		La Marque	15,290
		League City	70,973
		Santa Fe	8,488
		Texas City	41,238
	Harris	Baytown	71,324
		Bellaire	16,498
		Deer Park	30,375
		Galena Park	8,667
		Houston	2,125,627
		Humble	13,781
		Katy	16,350
		La Porte	30,931
		Pasadena	144,074
		Seabrook	11,617
		South Houston	16,982
		Spring	54,324
		Webster	11,413
		West University Place	14,524
San Antonio	Bexar	Cibolo	25,521
		Converse	17,212

		Leon Valley	11,874
		Live Oak	13,022
		San Antonio	1,357,737
		Universal City	18,634

3.3.2 Regression Model

We run linear regressions to study the statistical relationship between average commuting time in a city and its median list price of houses. The regression specification is as follows:

$$Median\ List\ Price\ per\ sq\ foot_i = \alpha_0 + \beta_1 Average\ commuting\ time_1 + \beta_2 X + \epsilon_i \qquad (3)$$

Note that it is misleading to directly compare the median list price in houses in different cities given their average commuting time. As predicted in the aforementioned economic models, land is cheaper as distance to CBD increases. Households will take advantage of the cheaper land and buy/construct larger houses. Taking into account of this, we construct the median list price per square foot, which is median list price divided by median home size, and compare them across cities.

It is worth mentioning that the variable average commuting time measures the average time residents in the city spend on commuting to work, not the average distance to CBD as depicted in the models. In the real world, not all residents in suburban cities work in the CBD, especially in metropolitan areas of Texas where employment centers are geographically dispersed. Therefore, the average commuting time is a better measure of the actual time cost of living farther away than distance from CBD.

In the above regression, X is a set of control variables, included in the regression to control for other observable differences besides average commuting time to explain the prices of housing. An example is households' income. In a city where residents are richer, prices of housing will increase even the commuting time is the same because richer residents can afford more expensive houses and will bid up the price, which is the reason we want to control for it in the regression. ϵ_i, the error term, is included in the regression to account for the random disturbance to housing prices of unobserved differences across cities that affect housing prices but not unavailable to researchers, such as quality of public schools and crime rates. The error term is assumed to be subjected to a normal distribution.

3.4 Emission Analysis on Extra Commuting Time

Vehicle emission amount of 8 counties in Texas area in peak hour from 13:00 to 13:59 and nonpeak hour from 7:00 to 7:59 on March 2004 and March 2014 are calculated from MOVES.

Table 4, Table 5, Table 6, and Table 7 represents the total emission amount (Per hour) in the specific time.

Table 4. Vehicle Emission Amount during Peak Hour in March 2004

2004 peak	**CO2** (KiloTon)	**CO** (KiloTon)	**NO2** (KiloGram)	**NO** (KiloTon)	**NOx** (KiloTon)	**SO2** (KiloGram)	**TotalEnergy** (BillonJoules)	**Distance** KiloMiles
Brazoria	88.13	2.93	14.97	0.39	0.41	7.03	1.23	228.27
Fort Bend	141.20	4.63	23.88	0.61	0.64	11.26	1.96	354.18
Galveston	113.39	3.59	18.56	0.47	0.50	9.05	1.58	280.31
Harris	1654.30	49.05	250.78	6.52	6.83	131.96	23.02	4062.72
Dallas	1278.52	39.28	202.10	5.23	5.48	114.71	17.79	3102.50
Tarrant	805.02	25.06	127.51	3.30	3.46	72.23	11.20	1950.57
Travis	355.64	13.65	63.84	1.63	1.71	47.57	4.95	880.18
Bexar	628.95	25.06	116.93	2.98	3.12	99.26	8.75	1555.63
Total	5065.16	163.26	818.5	21.15	22.14	493.07	70.48	12414.35

Table 5. Vehicle Emission Amount during Peak Hour in March 2014

2014 peak	**CO2** (KiloTon)	**CO** (KiloTon)	**NO2** (KiloGram)	**NO** (KiloTon)	**NOx** (KiloTon)	**SO2** (KiloGram)	**TotalEnergy** (BillonJoules)	**Distance** KiloMiles
Brazoria	86.06	2.17	12.25	0.36	0.37	1.08	1.20	226.38
Fort Bend	137.93	3.42	19.64	0.56	0.59	1.73	1.92	351.24
Galveston	110.80	2.63	15.29	0.44	0.46	1.39	1.54	277.99
Harris	1616.39	38.69	223.40	6.38	6.66	20.39	22.49	4029.12
Dallas	1248.84	30.95	179.34	5.10	5.32	15.76	17.38	3076.85
Tarrant	786.21	19.77	113.13	3.22	3.36	9.92	10.94	1934.44
Travis	347.39	9.26	51.95	1.48	1.55	5.39	4.83	872.90
Bexar	614.35	16.60	92.81	2.64	2.76	9.54	8.55	1542.76
Total	4947.98	123.49	707.82	20.18	21.05	65.20	68.85	12311.68

Table 6. Vehicle Emission Amount during Nonpeak Hour in March 2004

,	**CO2** (KiloTon)	**CO** (KiloTon)	**NO2** (KiloGram)	**NO** (KiloTon)	**NOx** (KiloTon)	**SO2** (KiloGram)	**TotalEnergy** (BillonJoules)	**Distance** KiloMiles
Brazoria	78.06	2.13	14.62	0.37	0.39	6.23	1.09	214.39
Fort Bend	116.26	3.21	21.75	0.54	0.57	9.27	1.62	310.60
Galveston	91.49	2.52	16.69	0.42	0.44	7.30	1.27	239.15
Harris	1316.56	33.29	222.51	5.66	5.93	105.01	18.32	3419.01
Dallas	984.39	24.74	160.74	4.11	4.31	88.32	13.70	2586.10
Tarrant	619.58	15.61	101.09	2.59	2.71	55.59	8.62	1629.82
Travis	282.21	9.18	54.01	1.35	1.42	37.75	3.93	751.85
Bexar	498.82	17.16	102.37	2.56	2.68	78.72	6.94	1321.76
Total	3987.37	107.84	693.78	17.60	18.44	388.19	55.48	10472.67

Table 7. Vehicle Emission Amount during Nonpeak Hour in March 2014

2014non-peak	**CO2** (KiloTon)	**CO** (KiloTon)	**NO2** (KiloTon)	**NO** (KiloTon)	**NOx** (KiloTon)	**SO2** (KiloGram)	**TotalEnergy** (BillionJoules)	**Distance** (KiloMiles)
Brazoria	76.48	1.50	12.06	0.34	0.35	0.96	1.06	212.62
Fort Bend	113.92	2.28	18.02	0.50	0.52	1.44	1.59	308.03
Galveston	89.65	1.79	13.84	0.39	0.40	1.12	1.25	237.17
Harris	1290.19	25.71	199.73	5.56	5.81	16.28	17.95	3390.73
Dallas	964.19	19.04	142.93	4.01	4.19	12.16	13.42	2564.72
Tarrant	606.85	12.01	89.87	2.52	2.63	7.66	8.44	1616.34
Travis	276.47	5.94	44.16	1.23	1.29	4.29	3.85	745.63
Bexar	488.77	10.76	81.80	2.27	2.37	7.58	6.80	1310.82
Total	3906.52	79.04	602.40	16.83	17.57	51.49	54.36	10386.06

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Relationship Between Average Commuting Time and Housing Prices

4.1.1 Relationship Between Average Commuting Time and Housing Prices

The main results are shown in Equation (2). The sample size is 86 cities. There is a statistically significant relation between average commuting time and median list price per square foot of housing (for brevity, we will just use the term median list price hereafter). With one more minute of average commuting time, the median price decreases by 3.3 dollars while the average of median list price in the sample is 94.3 dollars per square foot. In other words, one additional minute of commuting time can account for more than 3% of the housing price per square foot. The p-value of the coefficient for average commuting time is 0.018, which means it is statistically significant at 2% level.

$$\text{Median List Price per sq foot}_i = 184\text{-}3.3\text{*Average Commuting Time}_i \tag{4}$$

4.1.2 Robustness Check

We also want to make sure the results are robust to incorporating more control variables. To do so, we add the variable median household income to the right hand side of the regression. The results are shown in Equation (3). Now the coefficient of average commuting time is even more significant in terms of magnitude. With one more minute of average commuting time, the median price decreases by 4.2 dollars, more than 4% of the average price. The p-value is close enough to zero (with a t-stat 3.9).

$$Median\ List\ Price\ per\ sq\ foot_1 = 140.8 - 4.2 * Average\ Commuting\ Time_i + 0.001 * Median\ Household\ Income_i \tag{5}$$

4.1.3 Regression Model by Adding More Independent Variables

We also try other control variables such as property tax and owners' share, and none of these affects the results significantly.

Bearing that in mind, we run a third regression eliminating not only these two outliers but also cities with population less than 15,000 and those more than 1,000,000. As explained earlier, housing prices in small town are more likely to reflect idiosyncrasy rather than the common factors in other larger cities. For cities with population more than one million such as Houston city (only part of Houston Metropolitan area), there is a lot heterogeneity of houses within the city ranging from skyscrapers to one-story apartments, while in suburban cities the majority of homes are single-family houses. The results of the third regression are shown in Equation (4). The sample size is reduced to 63 cities. One additional minute of average commuting time is associated with 1.9 dollars less housing price. The p-value is 0.038. We can see that across difference specifications and sample size the negative and significant relation between average commuting time and housing price persists.

$$Median\ List\ Price\ per\ sq\ foot_1 = 95.7 - 1.9 * Average\ Commuting\ Time_i + 0.001 * Median\ Household\ Income_i \tag{6}$$

4.2 Social Costs of Commuting Longer Distance

In the well-known metaphor “Tragedy of the Commons”, despite herders understanding that depleting the common resource is contrary to the group’s long-term best interests, acting independently and rationally out of each one’s self-interest they all choose to overgraze the grassland, which eventually leads to the depletion of a shared resource by the group. Similar to the metaphor, residents choose to drive longer distance even though they clearly know it contributes to vehicle emission and congestion, because they reap the full benefit of lower housing price but costs of air pollution and congestion are borne by other members in the society. This asymmetry in allocation of benefits and costs gives residents incentive to live further away.

Figure 5 illustrates the spatial setting. A freeway connects a suburb to the central city, which contains the urban area’s jobs. During the morning rush hour, a cluster of commuters travels down the freeway to work. The extent of rush-hour congestion on the freeway depends on how many commuters are present.

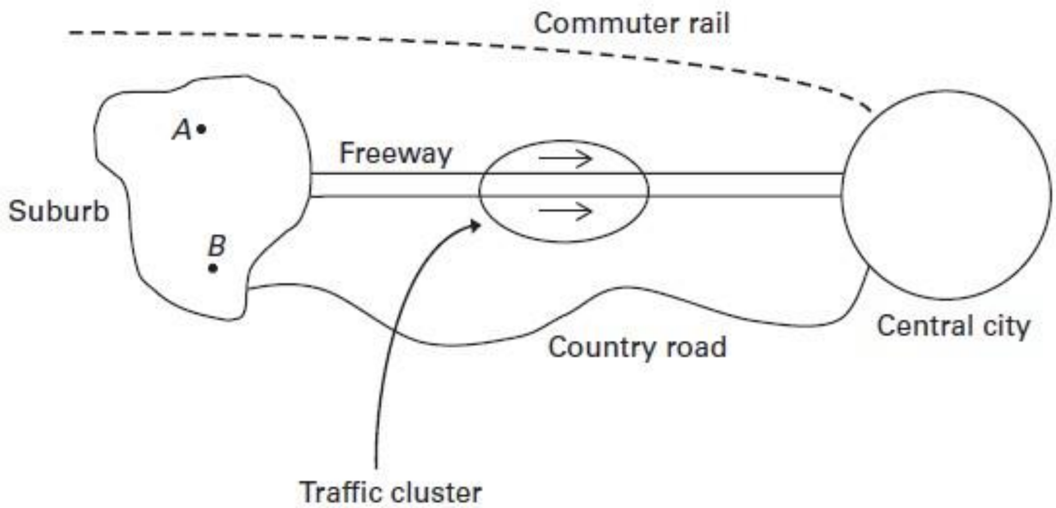


Figure 6. Map of a metropolitan area.

Let T denote the number of cars on the freeway, the relationship between the traffic speed s and T is illustrated in Figure 6. Speed is unaffected by the traffic volume as long as T is low. Because the freeway isn't congested, adding a car to the traffic cluster has no effect on s, and traffic continues to move at the speed limit. But when T rises above the freeway's design capacity, denoted by T, the traffic slows down and s falls. Speed drops sharply as T increases beyond T.

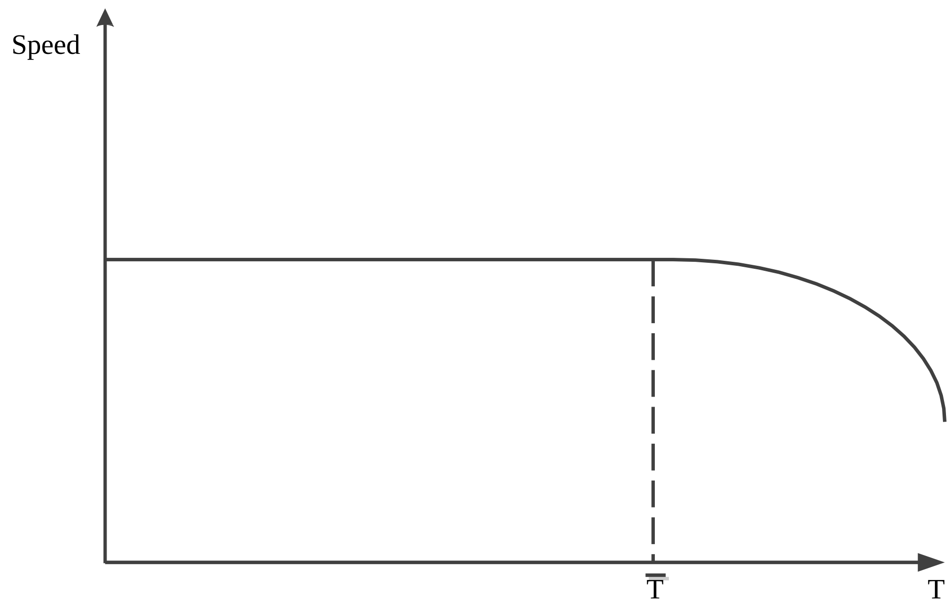


Figure 7. Speed profile with T.

To derive the connection between commuting cost and *T*, suppose that the money cost of the entire commute trip equals m. To derive the time cost, let *D* denote the length of the freeway in miles. Then the time duration of the trip is D / s hours, which equals the distance in miles divided by speed in miles per hour. If commuting time is valued at the hourly wage w, then time cost equals wD/ s. The total cost of the commute trip is then $g = m + wD/ s$.

When the freeway is uncongested, an increase in T has no effect on commuting cost. But over the congested range, a higher *T* leads to a reduction in the traffic speed s, which increases the trip's duration and thus its time cost (wD/ s in the g formula rises when s falls). Let commuting cost be written as a function of *T*, so that $g = g\ (T)$.

When the freeway is congested, the $g(T)$ function is upward sloping, and adding one more car (increasing T) raises each driver's commuting cost. This effect leads to a congestion externality. This aggregate cost equals $Tg(T)$, the number of cars times cost per car. When one more car is added to the freeway, the effect on aggregate cost is found by taking the derivative of this expression with respect to T. Using the product rule, this derivative is equal to

$$\frac{\mathrm{d}}{\mathrm{dT}}(\text{aggregate commuting cost}) = \mathrm{g(T)} + \mathrm{Tg^{'}(T)} \tag{7}$$

This formula shows that, when one more car is added to a congested freeway, aggregate costs rise for two reasons. First, the added car itself incurs a cost, equal to $g(T)$. Second, the added car imposes costs on all the existing cars on the freeway. The increase in cost for each of these cars is captured by the derivative $g'(T)$. Since T cars are present, the costs for all of them together rise by T times this amount, or $Tg'(T)$. This expression is the externality damage resulting from an added car, and it quantifies the congestion externality.

Since the above formula gives the increase in aggregate cost $Tg(T)$ when a car is added, it represents the marginal cost of an added car, denoted by MC. Corresponding to MC is an average cost, denoted by AC. Average cost equals aggregate cost divided by the number of cars, or $Tg(T)/T$, which is simply $g(T)$. Therefore, $AC = g(T)$, which is just the individual cost per car, while $MC = g(T) + T g'(T)$. Note that $MC = AC + T g'(T)$. In other words, $MC = AC$ + externality damage resulting from an added car.

Whilst the commuter only pays *AC*, his own commuting cost, other members of the society bears the externality incurred by his commuting.

An outcome of congestion is more vehicle emission produced, which is detrimental to public health. Quantifying the extent of vehicle emission in the suburban cities of Texas and its cost is beyond the scope of this research. Interested readers can refer to Fotouhi and Montazeri (2012), where a summarized pollution index is defined in varying traffic conditions in Equation (8), while the calculated pollution index under different traffic conditions are plotted in Figure 8.

$$\textit{Pollution index} = (\mathrm{CO} / 1 + \mathrm{HC} / 0.1 + \mathrm{NOx} / 0.06) / 3 \quad (8)$$

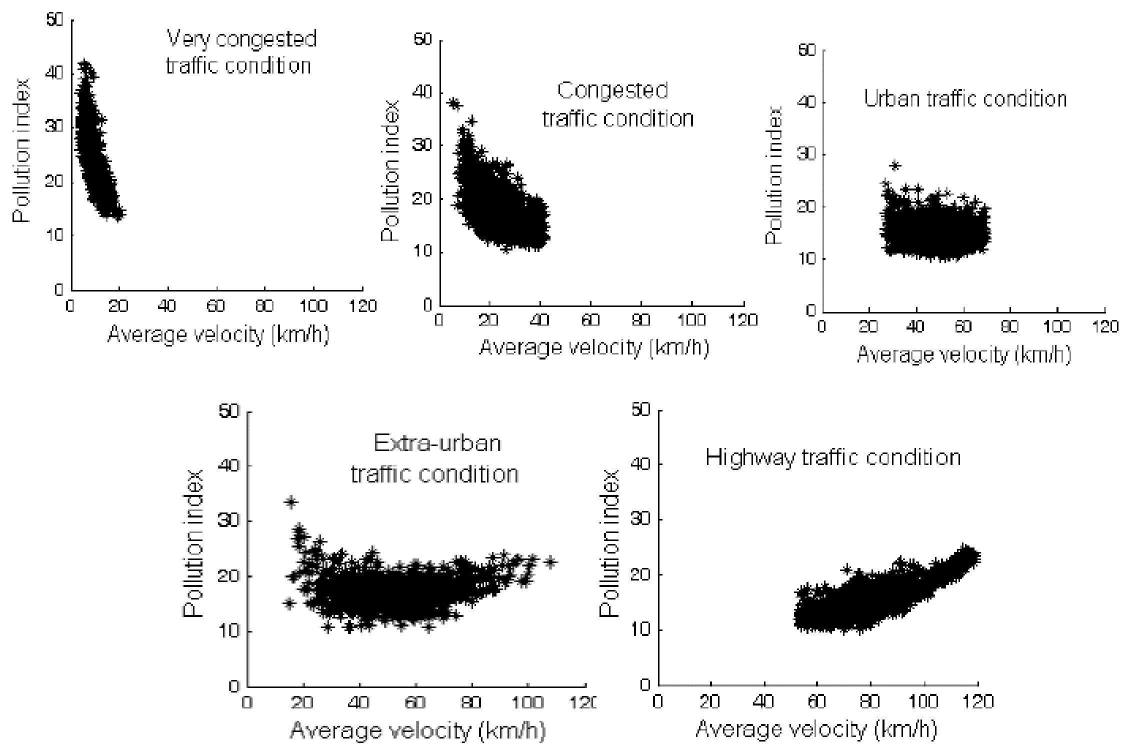


Figure 8. Pollution indexes in five different traffic conditions.

4.3 Extra Vehicle Emission Due to Extra Commuting Time

4.3.1 Changes in Total Vehicle Emission Over Time

Tables 8 and 9 show the changes in vehicle emission from 2004 to 2014. Table 1 shows changes during peak hours. Table 9 shows changes during nonpeak hours. Estimates for emission levels for eight counties decreased.

The decrease in emission reflects the economic recession, as there was less VMT in 2014 than in 2004, which was a year of high economic activity. Additionally, new vehicle engine technologies and new fuel sources have reduced the amount of pollutants from each individual vehicle when driving over the same distance during the same time period.

Table 8. Changes in vehicle emissions during peak hours in 2004 vs. 2014.

County	CO_2	CO	NO_2	NO	NO_x	SO_2	Total energy	Distance
Brazoria	-2.35%	-26.18%	-18.17%	-8.15%	-8.52%	-84.61%	-2.35%	-0.83%
Fort Bend	-2.32%	-26.10%	-17.73%	-7.97%	-8.34%	-84.62%	-2.32%	-0.83%
Galveston	-2.28%	-26.67%	-17.62%	-7.92%	-8.28%	-84.61%	-2.28%	-0.83%
Harris	-2.29%	-21.13%	-10.92%	-2.19%	-2.51%	-84.55%	-2.29%	-0.83%

Dallas	-2.32%	-21.22%	-11.26%	-2.64%	-2.96%	-86.26%	-2.32%	-0.83%
Tarrant	-2.34%	-21.13%	-11.28%	-2.65%	-2.97%	-86.26%	-2.34%	-0.83%
Travis	-2.32%	-32.16%	-18.62%	-9.04%	-9.40%	-88.67%	-2.32%	-0.83%
Bexar	-2.32%	-33.73%	-20.63%	-11.31%	-11.66%	-90.39%	-2.32%	-0.83%
Total	-2.31%	-24.36%	-13.53%	-4.59%	-4.92%	-86.78%	-2.31%	-0.83%

Table 9. Changes in vehicle emissions during nonpeak hours in 2004 vs. 2014.

County	**CO_2**	**CO**	**NO_2**	**NO**	**NO_x**	**SO_2**	**Total energy**	**Distance**
Brazoria	-2.03%	-29.34%	-17.48%	-7.93%	-8.30%	-84.56%	-2.03%	-0.83%
Fort Bend	-2.02%	-28.96%	-17.17%	-7.75%	-8.12%	-84.51%	-2.02%	-0.83%
Galveston	-2.02%	-28.91%	-17.08%	-7.69%	-8.05%	-84.61%	-2.02%	-0.83%
Harris	-2.00%	-22.77%	-10.24%	-1.74%	-2.07%	-84.50%	-2.00%	-0.83%
Dallas	-2.05%	-23.04%	-11.08%	-2.52%	-2.85%	-86.23%	-2.05%	-0.83%
Tarrant	-2.05%	-23.02%	-11.10%	-2.53%	-2.86%	-86.22%	-2.05%	-0.83%
Travis	-2.03%	-35.30%	-18.24%	-8.91%	-9.26%	-88.62%	-2.03%	-0.83%
Bexar	-2.01%	-37.32%	-20.10%	-11.09%	-11.43%	-90.37%	-2.01%	-0.83%
Total	-2.03%	-26.71%	-13.17%	-4.41%	-4.74%	-86.73%	-2.03%	-0.83%

4.3.2 Differences in Vehicle Emissions: Peak vs. Nonpeak

Table 10 shows that the differences in vehicle emissions during peak hours are much more than those in nonpeak hours in 2014. Table 11 shows that emissions in peak hours were much more than those in nonpeak hours in 2004. The numbers in Table 10 are slightly larger than the numbers in Table 11.

Table 10 shows that Harris County and Dallas County have higher numbers than other counties, while Brazoria had the lowest number of all eight counties. The higher numbers for Dallas County and Harris County reflect the higher population density in the area, and more emission in this area. Conversely, the lower the population density in an area, the less emission there is in an area.

Table 10. Differences in vehicle emissions between peak and nonpeak hours in 2014

County	CO_2	CO	NO_2	NO	NO_x	SO_2	Total energy	Distance
Brazoria	12.53%	43.92%	1.57%	5.74%	5.60%	12.59%	12.53%	6.47%
Fort Bend	21.08%	49.89%	9.04%	12.30%	12.19%	20.61%	21.08%	14.03%
Galveston	23.60%	46.96%	10.50%	13.35%	13.24%	23.95%	23.60%	17.21%
Harris	25.28%	50.47%	11.85%	14.77%	14.67%	25.28%	25.28%	18.83%
Dallas	29.52%	62.54%	25.48%	27.05%	27.00%	29.58%	29.52%	19.97%
Tarrant	29.56%	64.52%	25.88%	27.49%	27.43%	29.53%	29.56%	19.68%
Travis	25.65%	55.99%	17.64%	20.09%	20.01%	25.52%	25.65%	17.07%
Bexar	25.69%	54.34%	13.47%	16.32%	16.22%	25.74%	25.69%	17.69%
Total	26.66%	56.23%	17.50%	19.92%	19.83%	26.62%	26.66%	18.54%

Table 11. Differences in vehicle emission between peak and nonpeak hours in 2004.

County	CO_2	CO	NO_2	NO	NO_x	SO_2	Total energy	Distance
Brazoria	12.90%	37.77%	2.43%	5.99%	5.86%	12.95%	12.90%	6.47%
Fort Bend	21.45%	44.08%	9.79%	12.57%	12.46%	21.49%	21.45%	14.03%
Galveston	23.94%	42.47%	11.23%	13.62%	13.53%	24.00%	23.94%	17.21%

Harris	25.65%	47.35%	12.70%	15.29%	15.19%	25.66%	25.65%	18.83%
Dallas	29.88%	58.77%	25.74%	27.20%	27.15%	29.88%	29.88%	19.97%
Tarrant	29.93%	60.55%	26.13%	27.64%	27.59%	29.94%	29.93%	19.68%
Travis	26.02%	48.77%	18.19%	20.26%	20.18%	26.01%	26.02%	17.07%
Bexar	26.09%	45.99%	14.22%	16.62%	16.53%	26.09%	26.09%	17.69%
Total	27.03%	51.38%	17.99%	20.15%	20.07%	27.02%	27.03%	18.54%

A comparison between Tables 10 and 11 indicates that most of the numbers in Table 10 are slightly decreasing. This may reflect new vehicle engine technologies and new fuel sources that have already reduced the amount of pollutants from each individual vehicle over a given driving distance in the same time period.

This part numerically characterized air pollutants caused by additional travel time due to housing price factors. Preliminary results of air pollutants caused by additional travel time due to housing price factors were obtained. In recent years, since the economic recession from 2007, the economy has not returned to 2004 levels (although close to 2004 levels), and there have only been slight changes in housing prices, along with VMT (commuting by passenger cars) in the county, and population density. As such, there were only slight changes in emission inventories between 2004 and 2014.

4.3.3 Emission Amount per Vehicle per Minute Commuting Time

This part determined how much emission was generated in one minute per vehicle during peak hours and nonpeak hours. Rough estimates were determined based on the scope of this research.

We collected Houston number of vehicles per household, Texas number of vehicles per household and US number of vehicles per household which are provided by CLRSearch.com. We use the data of Texas number of vehicles per household to roughly calculated the total number of vehicles in Texas in 2010, which is 16,158,509.

Due to these metropolitan areas constitute roughly about 60% of total population in Texas in 2012. We assume that the vehicle numbers in theses 8 counties in 2004 and 2014 both constitute 60% of total number of vehicles in Texas in 2010, which is 9,695,105. Then emission amount per vehicle per minute is calculated.

Table 12. Emission amount and total energy per vehicle per minute in 2004 and 2014

Year and time period	**CO_2** (g)	**CO** (g)	**NO** (g)	**NO_x** (g)	**Total energy** (J)
2004 peak	8.71	0.28	0.04	0.04	121.16
2014 peak	8.51	0.21	0.03	0.04	118.36
2004 nonpeak	6.85	0.19	0.03	0.03	95.38
2014 nonpeak	6.72	0.14	0.03	0.03	93.45

Table 12 shows that in 2004, the difference in emission amount per vehicle per minute between peak hours and nonpeak hours was very large in terms of NO_2. The emission amount during peak hours was 51.38% more than that during nonpeak hours in 2004. In 2014, the result was 56.23%, and thus even larger.

In a comparison of emissions between 2004 and 2014 during peak hours, SO_2 and CO showed a large change. SO_2 dropped dramatically by 86.78% from 2004 to 2014 during peak hours, and by 86.73% from 2004 to 2014 in nonpeak hours. CO dropped by 24.36% from 2004 to 2014 during peak hours, and dropped by 26.71% from 2004 to 2014 during nonpeak hours.

During peak hours in 2014 within these eight counties, one more additional minute of commuting generates 8.51 g of CO_2, 0.21 g of CO, 0.04 g of NO, and 0.04 g of NO_x. During nonpeak hours in 2014 within these eight counties, one more minute of commuting generates 6.72 g of CO_2, 0.14 g of CO, 0.03 g of NO, and 0.03 g of NO_X.

CHAPTER 5

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

In this research, real estate data from 86 cities in the top four largest metropolitan areas in Texas (Houston, Dallas/Ft Worth, San Antonio and Austin) were analyzed. Counties that consist most of the territory were picked up while all cities with less than 7,000 populations were dropped off. Statistical analyses illustrating the relationships between housing price and commuting time were conducted and the associated formulas were established. The followings are several findings from statistics.

5.1 Impacts of Average Commuting Time on Housing Prices

- For all the 86 cities in Texas, with one more minute of average commuting time, the median price decreases by 3.3 dollars while the average median list price in the sample is 94.3 dollars per square foot.
- If median household income is incorporated into regression, with one more minute of average commuting time, the median price decreases by 4.2 dollars, more than 4% of the average price. The *p*-value is close enough to zero (with a *t*- stat 3.9).
- Other control variables such as property tax and owners' share, are not affect the house price significantly.
- For 63 cities with populations between 15,000 and 1,000,000, one additional minute of average commuting time is associated with 1.9 dollars less housing price (*p*-value: 0.038).

5.2 Impacts of Average Commuting Time on Vehicle Emissions

During peak hours in 2014 within these eight counties, one more additional minute of commuting generates 8.51 g of CO_2, 0.21 g of CO, 0.04 g of NO, and 0.04 g of NO_x. During nonpeak hours in 2014 within these eight counties, one more minute of commuting generates 6.72 g of CO_2, 0.14 g of CO, 0.03 g of NO, and 0.03 g of NO_X.

These statistical results could be very useful to research and practices in areas such as land use, transportation economics, transportation planning, transportation impact analyses, and definitely the real estate market.

REFERENCES

Air Pollution. 2001. http://www.air-quality.org.uk/08.php

Alonso, W. (1964). Location and Land Use. Harvard University Press.

Brodere, J. M. 2009. “E.P.A. MOVES to Curtail Greenhouse Gas Emissions.” The New York Times. http://www.nytimes.com/2009/10/01/science/earth/01epa.html. Published: September 30, 2009. Accessed January 6, 2015.

Brueckner, J. k. (2011). Lectures on Urban Economics, The MIT Press, Cambridge, Massachusetts, London, England, 2011.

Chen, J., and Q. J. Hao. (2008). The Impacts of Distance to CDB on Housing Prices in Shanghai: A Hedonic Analysis. Journal of Chinese Economic and Business Studies. Vol. 6, No. 3, pp 291-302.

Collingwood, J. 2013. The Physical Effects of Long - term stress. PsychCentral. http://psychcentral.com/lib/the-physicaleffects-of-long-term-stress/. (Accessed October 19, 2015)

Colwell, P. F., Munneke, H. J. (1997). The Structure of Urban Land Prices. *Journal of Urban Economics.* Vol41, pp 321-336.

EPA. 2003. National Air Quality and Emissions Trends Report, 2003 Special Studies Edition . Accessed October 4, 2007, http://www.epa.gov/air/airtrends/aqtrnd03/

EPA. 2007. Measuring the Air Quality and Transportation Impacts of Infill Development. Accessed June 14, 2013, http:// www.epa.gov/smartgrowth/pdf/transp_impacts_infill.pdf/.

Grether, D. M., and Mieszkowski, P.. (1974). Determinants of Real Estate Values. California Institute of Technology and Queen's University. Journal of Urban Economics 1, pp 127-146

Health effects institute, 2010. Traffic-Related Air Pollution: A Critical Review of the Literature on Emissions, Exposure, and Health Effects. Accessed on March 10, 2009, http://pubs.healtheffects.org/getfile.php?u=553

INRIX, 2012. Cebr economic cost of Gridlock report. http://www.inrix.com/pdf/Cebr_Economic_Cost_of_Gridlock_Report.pdf

Li, Q., F. Qiao, and L. Yu. 2015a. Testing of In-vehicle Noises when Driving on Freeways with Different Pavement Types. Publication in the Proceedings of the 107th Air & Waste Management Association (AWMA), June 22 - 25, 2015a. Raleigh, North Carolina, USA.

Li, Q., F. Qiao, and L. Yu. 2015b. Impacts of Pavement Types on In - vehicle Noise and Human Health. Journal of Air & Waste Management. 2016b. DOI: 10.1080/10962247.2015.1119217. http://www.tandfonline.com/doi/full/10.1080/10962247.2015.1119217. Vol. 66, Issue 1, Pp. 87 - 96. (Accessed on November 27, 2015).

Li, Q., F. Qiao, and L. Yu. 2016b. Impacts of Pavement Types on In - vehicle Noise and Human Health. Journal of Air & Waste Management. 2016b. DOI: 10.1080/10962247.2015.1119217. http://www.tandfonline.com/doi/full/10.1080/10962247.2015.1119217. Vol. 66, Issue 1, Pp. 87 - 96. (Accessed on November 27, 2015)

Li, Q., F. Qiao, and L. Yu. 2016c. Vehicle Emission Implications of Drivers Smart Advisory System for Traffic Operations in Work Zones. Journal of Air & Waste Management. 2016c. DOI:10.1080/10962247.2016.1140095. ISSN: 1096－2247 (Print) 2162－2906 (Online) Journal. Online access: http://www.tandfonline.com/doi/pdf/10.1080/10962247.2016.1140095. (Accessed on November 27, 2015)

Li, Q., Qiao, F., Qiao, Y., and Yu, L. 2016a. Impacts of Traffic Signal Coordination on In－vehicle Noises along an Arterial Road in Houston, USA. Publication in the Proceedings of the 11th Asia Pacific Transportation Development Conference and 29th ICTPA Annual Conference － Bridging the East and West: Theories and Practices of Transportation in the Asia Pacific. May 27-29, 2016a. Hsinchu, Taiwan. In Press

McMillen, D. P. (2003). The Return of Centralization to Chicago: Using Repeat Sales to Identify Changes in HouseP Distance Gradients. *Regional Science and Urban Economics*. pp 287–304.

Mills, E. (1967). An Aggregative Model of Resource Allocation in a Metropolitan Area. American Economic Review 57, pp197-210.

Muth, R. F. (1969). Cities and Housing. University of Chicago Press.

Qiao, F., and Yu, L. 2004. “An Alternative Approach to VMT Estimation: Combining Traffic Count and Link Attributes.” In Proceedings of the Transportation Research Board 83rd Annual Meeting CD-ROM, 11-5.

Qiao, F., Li, Q., and Yu, L. 2016. Neural Network Modeling of In-Vehicle Noises with Different Roadway Roughness. Publication in the 11th Asia Pacific Transportation Development Conference and 29th ICTPA Annual Conference - Bridging the East and West: Theories and Practices of Transportation in the Asia Pacific. May 27 - 29, 2016. Hsinchu, Taiwan. In Press.

Qiao, F., Liu, L., Long, W., and Yu, L. 2014. “Impacts of Average Commuting Time on Housing Prices in Texas Suburban Cities.” In Proceedings of the 93rd Transportation Research Board Annual Meeting, 14-1754.Washington, D.C., USA.

Qiao, F., Yu, L., and Vojtisek-Lom, M. 2005. “Collection and Evaluation of On-Road Vehicle Emission and Activity Data in Houston.” Transportation Research Record: Journal of the Transportation Research Board. Vol. 1941, pp 60-71.

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. The Journal of Political Economy, Vol. 82, No. 1, pp 34-55.

Schrank D, and Lomax T. The 2009 urban mobility report; 2009. Accessed February 6, 2010, http://tti.tamu.edu/documents/mobility_report_2009_wappx.pdf.

Sjodin, A., Persson, K., Andreasson, K., Arlander, B., and Galle, B., 1998. On-road emission factors derived from measurements in a traffic tunnel, International Journal of Vehicle Design 20(1-4): 147-158.

Transportation Research Board, 2002. The congestion mitigation and air quality improvement program: assessing 10 years of experience -- Special Report 264. National Academy Press: 45, 62-64.

U.S. Environmental Protection Agency. Apr. 2010. Technical Guidance on the Use of MOVES2010 for Emission Inventory Preparation in State Implementation Plans and Transportation Conformity. Washington, D.C., USA.

U.S. Environmental Protection Agency. Aug. 2012. Use of Data from Development of Emission Rates for the MOVES Model. Assessment and Standards Division Office of Transportation and Air Quality. Washington, D.C., USA.

U.S. Environmental Protection Agency. Jun. 2012. Motor Vehicle Emission Simulator (MOVES): Users Guide for MOVES2010b. Washington, D.C., USA.

U.S. Environmental Protection Agency. Nov. 2010. MOVES2010 Highway Vehicle, Population and Activity Data.. Washington, D.C., USA.

United States Census Bureau. 2010. “Houston Population 2014.” 2014 World Population Review. http://worldpopulationreview.com/us-cities/houston-population/. Accessed October 19, 2014.

World Bank, 2006. China: building institutions for sustainable urban transport. Accessed November 22, 2006, http://siteresources.worldbank.org/INTURBANTRANSPORT/Resources/340136-1152205421441/China-UT-AAA-Report-2006.pdf

.World Health Organization (WHO), 2005. Health effects of transport-related air pollution. Copenhagen, WHO Regional Office for Europe: 125-165.

Yan, S. S., E. Delmelle, and M. Duncan. (2012). The impact of a new light rail system on single-family property values in Charlotte, North Carolina. The Journal of Transport and Land Use. Vol. 5, No. 2, pp 60-67.

Younglove, T., Scora, G., and Barth, M. 2005. "Designing On-road Vehicle Test Programs for the Development of Effective Vehicle Emission Models." Transportation Research Record: Journal of the Transportation Research Board. Vol. 1941, pp 51-59.

Zhang, K., Batterman, S. and Dion, F. (2011). Vehicle emissions in congestion: Comparison of work zone, rush hour and free-flow conditions. Atmospheric Environment, 45 (2011) 1929-1939.