Mobility Investment Priorities Project

Assessing Economic Benefits of Walkability in Austin, Texas

September 2013

mobility INVESTMENT PRIORITIES

Texas A&M Transportation Institute

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Assessing Economic Benefits of Walkability in Austin, Texas

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TABLE OF CONTENTS

LIST OF FIGURES

Page

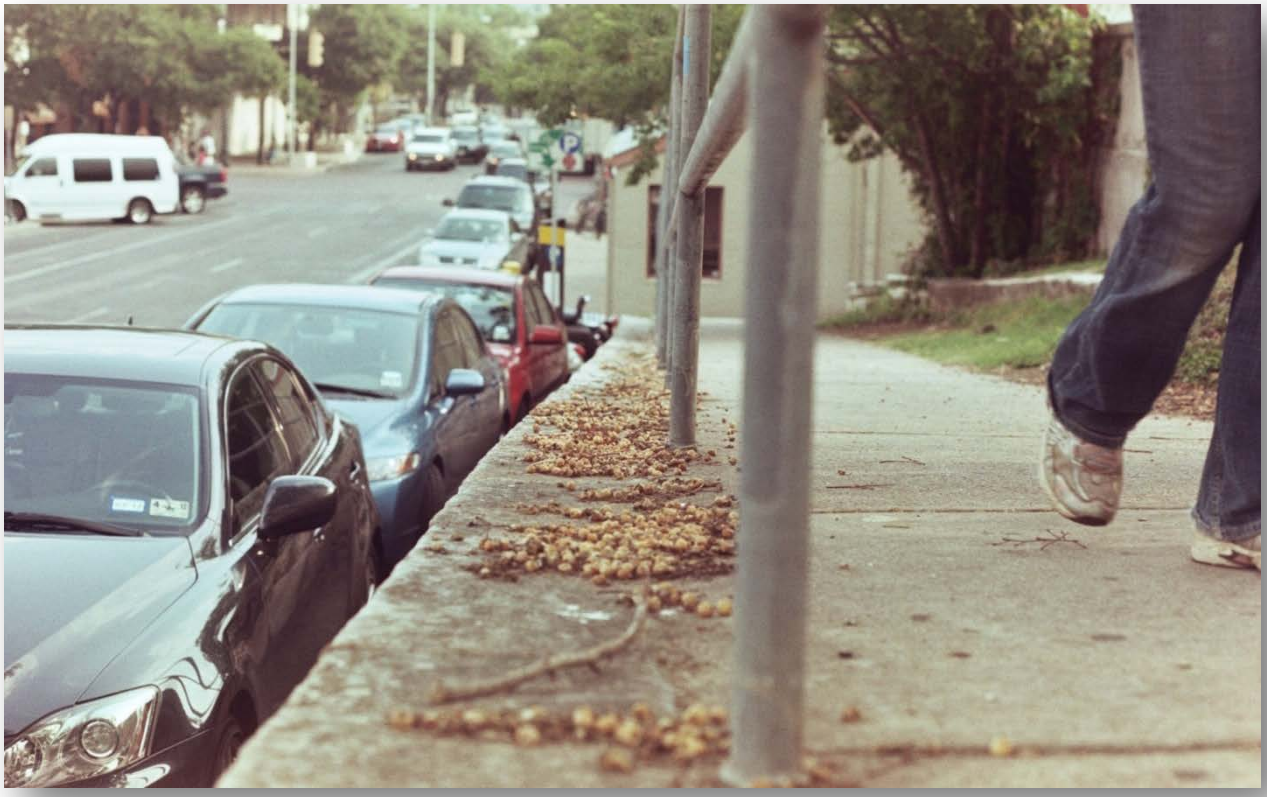
LIST OF TABLES

Page

ABSTRACT

Transportation planners and policymakers have been promoting neighborhood walkability in pursuit of smart growth goals and reduction in carbon-intensive travel. Despite broad support for the benefits of walkable communities, the links between walkability and economic outcomes, such as residential property values, are still poorly understood. This project investigated the impact of walkability on residential property values by analyzing the 2010 through 2012 sale transactions in Austin, Texas. Three types of residential properties were analyzed: single-family homes, condominiums, and multifamily properties. We compared the performance of two different walkability measurements—Street Smart Walk Score based on actual walking paths, as well as the more commonly used Walk Score that assumes direct (i.e., bird flight) paths. We evaluated how the premiums of walkable neighborhoods depend on built environment features and other neighborhood factors including safety, street connectivity, and density of sidewalks, as well as various socio-demographic factors. Our results suggest that it may be unrealistic to expect immediate economic returns on investments made to increase walkability in what are commonly referred to as "car dependent neighborhoods." However, walkability may have several other social benefits, and it appears there may be benefits to constructing new neighborhoods with walkable features. The results from this project could help state and local governments make informed decisions that maximize the benefit of investments in promoting walkable communities and active transportation.

Keywords: walkability, Walk Score, Street Smart Walk Score, hedonic pricing method, property values, spatial regression, fixed-effects, active transportation.



1.0 INTRODUCTION

Walking, as an active transportation mode, helps individuals increase fitness and reduce risks of developing cardiovascular diseases, depression, and even some types of cancers (Killingsworth & Lamming, 2001; Litman, 2003). Impact of neighborhood walkability on physical activity has been documented by some studies (Ding et al., 2011; Feng et al., 2010; Saelens & Handy, 2008). Transportation planners and policymakers in the US are increasingly promoting neighborhood walkability in pursuit of smart growth and reduction in carbon intensive travel. However, the links between neighborhood walkability and economic outcomes, such as residential property values, are still poorly understood.

This paper investigates the impact of walkability on residential property values by analyzing the 2010 through 2012 residential property sale transactions in Austin, Texas. We compared the performance of two different walkability measurements: Street Smart Walk Score, which is based on actual walk paths, and the conventional Walk Score, which is based on a direct path (or bird flight distance). We evaluated how the premiums of walkable neighborhoods depend on local built environment and other neighborhood features including safety, street connectivity, and density of sidewalks, as well as various socio-demographic factors. In order to control for the spatial autocorrelation effects that refer to the influences of neighboring properties on the property value, we estimated the spatial regression model and explored how the results would change if different modeling methods are employed.

The results from this study could help state and local governments make informed decisions that maximize the benefit of investments in promoting walkable communities and active transportation.

We provide a brief overview about recent studies on benefits and measurements of neighborhood walkability in the next Section. Sections 3 and 4 introduce our data and methodology, respectively. Sections 5 to 7 present the results for the single-family, condominium, and multifamily markets, respectively. Section 8 concludes this study.

2.0 BACKGROUND AND LITERATURE REVIEW

2.1 Measuring Walkability

The academic community has focused its attention to the correlates among neighborhood walkability, physical activity, and health outcomes since the 2000s (Frank et al., 2005; Killingsworth & Lamming, 2001; Saelens & Handy, 2008; Saelens, Sallis, & Frank, 2003). Researchers have developed a number of methods for measuring walkability, such as Walk Score, Neighborhood Environment Walkability Scale (NEWS), Composite Walkability Index (CPI), and the Irvine-Minnesota Inventory (IMI). While there has yet to be a consensus about how to best measure neighborhood walkability, different measurement tools could serve various aspects of policy development. Generally speaking, measurements of neighborhood walkability fall into three interrelated categories: observation-based measurement of the built environment, survey-based measurement of perception, and objective measurement of amenity densities.

The **observation-based measurements**, such as CPI and IMI, serve as audit tools to examine and summarize various features of the built environment. A wide array of audit instruments have been developed to measure walking and cycling behavior (for more detail on the different instruments refer to Moudon and Lee, 2003). These instruments have identified nearly 200 built environment features that are linked with active living; the IMI alone include 160 inventory items, divided into different types of measures including accessibility, pleasurability, perceived safety from traffic, and perceived safety from crime (Day et al., 2006). While the traditional focus of these audits has been on accessibility measures for walking and cycling (such as the 4 D's: density, diversity, design and destinations), many also include questions on perceptions on traffic safety and crime and attitudes toward walking and cycling behavior.

The **perception-based measurements**, such as NEWS, examine neighborhood walkability scales based on response to survey questions. This tool was introduced by Saelens et al. (2003) and has been implemented by many researchers since then (Brownson et al., 2004; Cerin et al., 2008; Cerin et al., 2006; Gebel et al., 2011). Perception-based measurements focus on the perceived attributes of the built environment rather than the objective measures of the built environment. For example, in the NEWS instrument, perceived attributes to be correlated with physical activity are included in the survey, and subscales were devised to assess perception of environmental characteristics such as land use mix, connectivity, and safety (Cerin et al., 2006). These perception measures can be validated with observation-based instruments to determine whether resident perception of walkability in the neighborhood corresponds with observable characteristics.

Finally, the **objective measures** often rely on geographic/spatial analytical tools such as the Geographic Information Systems (GIS) to assess the built-environment characteristics, such as density of neighborhood amenities, street connectivity and land use mix. The most widely-used measure in this category is Walk Score, which assesses the density of the nearby walkable destinations (usually within one mile) to derive a walkability score for a specific location (Cortright, 2009; Litman, 2003; Pivo & Fisher, 2011; Rauterkus & Miller, 2011). These destinations include amenities such as retail businesses, recreational points of interest, and schools. Conventional Walk Score uses Euclidean (also referred to as bird flight) distances to amenities to generate walkability scores while the recently released Street Smart

Walk Score uses the actual street network to calculate the routing distance. Walk Score (or Street Smart Walk Score) is simple and easy for the public to access. For example, there is a mobile phone application, the information is publicly available and one can obtain a walkability score for any US address at www.walkscore.com.

2.2 Economic Benefits of Walkability

Research examining walkable communities has primarily focused on the environmental and public health aspects of walking, while the economic benefits of walkable communities has largely been overlooked until recently. Litman (2003) examines the value of walkability in terms of consumer cost savings, more efficient land use, reductions in health care costs, and increased economic development. In another study conducted by researchers at the Urban Land Institute, it was determined that homebuyers were willing to pay a premium for walkable neighborhoods compared to conventional suburban neighborhoods (Eppli & Tu, 1999). Other studies have found that reductions in traffic speeds through traffic calming increased residential home values (Litman, 1999).

There have been a few studies using the hedonic pricing model to determine how neighborhood walkability, measured by Walk Score, influences home values (Cortright, 2009), residential land values (Rauterkus & Miller, 2011) and commercial property values (Pivo & Fisher, 2011). They generally agree that increased walkability is correlated with higher property values; however, these studies are subject to some key limitations. First, spatial autocorrelation was not taken into account in their models, which may lead to biased estimation results. Second, they relied on the conventional Walk Score which does not account for the street network characteristics, a key aspect in the criticisms of cul-de-sac neighborhoods. Third, their results were point estimates in nature, which provided limited information on how various factors (e.g., socio-demographic, connectivity of streets, safety) may influence the premiums for walkability.

In this project, the data and methodology allow us to address the above limitations. We analyzed the premiums for walkability for single-family, condominium and multifamily housing markets separately, using both Walk Score and the Street Smart Walk Score. Our analytical methods allow us to control for the spatial autocorrelation effects.

3.0 DATA

We analyzed residential property sale transactions from January 2010 to November 2012 in the city of Austin, Texas (USA). The housing markets analyzed in this study include the single-family housing market (21,687 sale transactions in total), the condominium market (each condominium was sold as a separate property; 3899 sale transactions in total), and the multifamily property market (number of units is 2 or larger for each property; 836 sale transactions in total). Tables 1, 2 and 3 present the summary statistics of variables incorporated in our modeling analysis for the three markets respectively. We decided to analyze no more than three years of housing market data to avoid the risk of compromising market equilibrium[1] (Maclennan, 1977).

[1] In economics, market equilibrium refers to a state where the supply and demand forces are well balanced.

3.1 Housing Data

Our housing transaction variables are based on the Multiple Listing Service (MLS) data of home sales provided by the Austin Board of REALTORS®. The MLS data include detailed information about the properties such as the usable area, lot size, built year, numbers of bedrooms, full bathrooms, half bathrooms, stories and garage spaces, as well as binary variables about whether a property has a pool, view, and waterfront location. A majority of housing records were geocoded with reference to the shapefile of the Travis County parcel locations provided by the Travis Central Appraisal District; the rest of the housing records were geocoded in ArcGIS 10 using the address information of the properties. In order to protect the confidentiality of the MLS data provided by the Austin Board of REALTORS®, we decided not to disclose the maps showing specific locations of these housing records; instead, we use Figures 1, 2 and 3 to illustrate the number of records for each census tract in the city of Austin.

3.2 Neighborhood Data

We collected roadway and railroad network shapefiles from ESRI Inc., the provider of the ArcGIS software. We derived the major road intersections from the roadway network shapefile data. Capital Metropolitan Transportation Authority (Capital Metro) provided the locational information of their rail (MetroRail) stations. The Texas Department of Education provided the school quality data. The city of Austin provided shapefiles showing various neighborhood amenities including lakes. We decided to exclude proximities to other neighborhood amenities other than lakes as they are already counted in our walkability measurement (see Carr et al., 2011 for a list of amenities measured by Walk Score).

Various socio-demographic variables, such as race/ethnicity, age, education, poverty level and income, were extracted from the 2007 to 2011 American Community Survey 5-year estimates, at the 2010 Census Block Group level. Our population density and employment density data, summarized for the 2008 Traffic Analysis Zone level, were provided by the Capital Area Metropolitan Planning Organization.[2]

The city of Austin also provided the Geographic Information Systems (GIS) shapefile data about crime rates, traffic collision locations, street nodes, sidewalk network and street network with speed limit information. Within one mile of each single-family home, we calculated the number of violent crimes, property crimes, traffic collisions involving pedestrians, number of street nodes, total length of sidewalks, and average speed limit. A one-mile radius was chosen because our walkability measurement, Walk Score, is determined mainly based on proximities to amenities within one mile (Carr et al., 2011).

[2] The Traffic Analysis Zones, or TAZs, are commonly used by Metropolitan Planning Organizations in the US for model and forecast travel demand and traffic flows. A TAZ is defined based on the road network with some socio-economic considerations.

Table 1: Summary Statistics for Single-Family Market Analysis

Variable Definition and Unit	Mean	Std. Dev.	Min	Max
Home sale price, $1000	302.58	199.43	63.00	1480.00
Structural characteristics				
Usable area, sq. ft.	2149.12	921.17	357.04	8718.76
Lot area, acre	0.28	0.41	0.03	17.07
House age at the year of sale, year	27.70	20.96	0.01	126.00
Number of days on market	98.04	80.50	1.00	1253.00
Number of bedrooms	3.41	0.76	1.00	11.00
Number of full bathrooms	2.20	0.72	1.00	9.00
Number of half bathrooms	0.38	0.51	0.00	9.00
Binary: 1 = Having 2 or more stories	0.44	0.50	0.00	1.00
Binary: 1 = Having 1 or more garage spaces	0.77	0.42	0.00	1.00
Binary: 1 = Having pool	0.09	0.29	0.00	1.00
Binary: 1 = Having view	0.27	0.45	0.00	1.00
Binary: 1 = Located on the waterfront	0.01	0.12	0.00	1.00
Binary: 1 = Large/medium tree on parcel	0.81	0.39	0.00	1.00
Neighborhood variables				
Network distance to state capitol, mile	24.19	11.91	1.01	55.94
Network distance to major road intersection, mile	1.15	0.71	0.01	4.99
Network distance to nearest MetroRail station, mile	6.08	3.86	0.16	15.77
Direct distance to nearest lake, mile	0.47	0.31	0.00	1.75
School accountability indicator in the past year, 0–100	75.28	14.98	28.00	96.00
Binary: 1 = highway within quarter mile	0.49	0.50	0.00	1.00
Binary: 1 = railroad within quarter mile	0.10	0.30	0.00	1.00
Street Smart Walk Score, 0–100	29.05	24.48	0.00	99.00
Walk Score, 0–100	39.61	22.07	0.00	98.00
Covariates				
Percent of African American, 0–100	5.42	7.75	0.00	62.80
Percent of Asian, 0–100	6.42	6.42	0.00	35.41
Percent of non-White Hispanic, 0–100	23.81	18.35	1.56	89.30
Percent of other non-White, 0–100	2.29	0.72	0.29	4.15
Percent of under 18 years, 0–100	23.85	7.37	1.09	46.22
Percent of 65 years or older, 0–100	8.69	5.55	0.36	38.07
Percent of college degree holders, 0–100	77.43	18.58	4.54	100.00
Percent of population in poverty, 0–100	4.71	6.16	0.00	69.35
Per capita income, $1000	39.81	19.14	6.63	135.06
Population density, 1000 persons/sq. mile	3.69	2.28	0.01	23.18
Job density, 1000 jobs/sq. mile	1.32	1.95	0.00	51.35
Number of violent crimes within 1 mile	58.74	93.61	0.00	685.00
Number of property crimes within 1 mile	779.07	833.78	0.00	4716.00
Number of collisions involving pedestrians within 1 mile	3.80	5.34	0.00	54.33
Number of street nodes within 1 mile	233.97	108.02	8.00	623.00
Total length of sidewalk within 1 mile, mile	65.85	26.35	0.00	136.88
Average speed limit within 1 mile, km/hour	32.47	3.18	25.31	53.47

Note: This summary table is based on our final sample of 21,687 sale transactions from January 2010 to November 2012 in the city of Austin, Texas, USA. The quarter mile threshold for highway and railroad was selected following findings from Li and Saphores (2012a). Population and job densities were calculated based on the 2008 Traffic Analysis Zone developed by the Capital Area Metropolitan Planning Organization.

Table 2: Summary Statistics for Condominium Market Analysis

Variable Definition and Unit	Mean	Std. Dev.	Min	Max
Home sale price, $1000	208.17	130.30	33.40	830.00
Structural characteristics				
Usable area, sq. ft.	1162.65	495.75	344.99	3771.87
Lot area, acre	0.19	1.13	0.00	14.51
Home age at the year of sale, year	20.93	15.17	0.01	90.00
Number of days on market	116.28	98.13	1.00	1149.00
Number of bedrooms	1.92	0.71	1.00	5.00
Number of full bathrooms	1.64	0.57	1.00	4.00
Number of half bathrooms	0.30	0.46	0.00	2.00
Binary: 1 = Having 2 or more stories	0.37	0.48	0.00	1.00
Binary: 1 = Having 1 or more garage spaces	0.32	0.46	0.00	1.00
Binary: 1 = Having pool	0.48	0.50	0.00	1.00
Binary: 1 = Having view	0.48	0.50	0.00	1.00
Binary: 1 = Located on the waterfront	0.04	0.20	0.00	1.00
Binary: 1 = Large/medium trees on parcel	0.54	0.50	0.00	1.00
Neighborhood variables				
Network distance to state capitol, mile	4.97	3.99	0.07	20.26
Network distance to nearest major road intersection, mile	0.60	0.45	0.00	3.35
Network distance to nearest MetroRail station, mile	3.39	2.70	0.07	14.43
Direct distance to nearest lake, mile	0.38	0.29	0.00	1.43
School accountability indicator in the past year, 0–100	74.04	11.15	28.00	96.00
Binary: 1 = highway within quarter mile	0.81	0.39	0.00	1.00
Binary: 1 = railroad within quarter mile	0.15	0.36	0.00	1.00
Street Smart Walk Score, 0–100	59.40	28.93	0.00	100.00
Walk Score, 0–100	64.12	22.87	6.00	100.00
Covariates Interacting with Walkability				
Percent of African American, 0–100	5.13	5.76	0.00	46.03
Percent of Asian, 0–100	6.41	6.42	0.15	35.41
Percent of non-White Hispanic, 0–100	22.04	17.22	4.20	87.16
Percent of other non-White, 0–100	2.36	0.72	0.58	4.53
Percent of under 18 years, 0–100	14.11	9.39	0.09	41.36
Percent of 65 years or older, 0–100	8.13	6.81	0.00	38.07
Percent of college degree holders, 0–100	79.63	17.42	18.40	100.00
Percent of population in poverty, 0–100	14.35	18.71	0.00	79.38
Per capita income, $1000	43.28	26.54	1.74	126.44
Population density, 1000 persons/sq. mile	5.95	5.01	0.08	23.18
Job density, 1000 jobs/sq. mile	6.10	13.13	0.01	136.24
Number of violent crimes within 1 mile	140.94	154.90	0.00	708.33
Number of property crimes within 1 mile	1961.70	1420.94	0.33	5003.33
Number of collisions involving pedestrians within 1 mile	15.56	17.93	0.00	65.33
Number of street nodes within 1 mile	336.64	146.34	12.00	616.00
Total length of sidewalk within 1 mile, mile	85.63	29.19	0.00	135.20
Average speed limit within 1 mile , mile/hour	34.63	2.99	25.83	47.15

Note: This summary table is based on our final sample of 3899 condominium sale transactions from January 2010 to November 2012 in the city of Austin, Texas, USA. The quarter mile threshold for highway and railroad was selected following findings from Li and Saphores (2012a). Population and job densities were calculated based on the 2008 Traffic Analysis Zone developed by the Capital Area Metropolitan Planning Organization.

Table 3: Summary Statistics for Multifamily Market Analysis

Variable Definition and Unit	Mean	Std. Dev.	Min	Max
Home sale price, $1000	191.75	90.87	54.90	620.00
Structural characteristics				
Usable area, sq. ft.	218.25	72.17	78.04	692.66
Lot area, acre	871.10	325.10	263.05	6029.82
Home age at the year of sale, year	32.78	12.95	3.00	104.00
Number of days on market	97.93	85.57	8.00	658.00
Number of bedrooms	5.16	1.61	1.00	12.00
Number of full bathrooms	3.37	1.25	2.00	8.00
Number of half bathrooms	0.65	1.21	0.00	8.00
Binary: 1 = Having 2 or more stories	0.44	0.50	0.00	1.00
Binary: 1 = Having 1 or more garage spaces	0.34	0.47	0.00	1.00
Binary: 1 = Having pool	0.01	0.09	0.00	1.00
Binary: 1 = Having view	0.04	0.21	0.00	1.00
Binary: 1 = Large/medium trees on parcel	0.38	0.49	0.00	1.00
Neighborhood variables				
Network distance to state capitol, mile	6.78	2.88	1.29	15.57
Network distance to nearest major road intersection, mile	0.79	0.40	0.05	2.13
Network distance to nearest MetroRail station, mile	4.28	2.51	0.18	11.29
Direct distance to nearest lake, mile	0.47	0.35	0.00	1.46
School accountability indicator in the past year, 0–100	64.51	14.18	28.00	96.00
Binary: 1 = highway within quarter mile	0.56	0.50	0.00	1.00
Binary: 1 = railroad within quarter mile	0.16	0.36	0.00	1.00
Street Smart Walk Score, 0–100	42.05	19.35	0.00	99.00
Walk Score, 0–100	53.03	16.35	12.00	86.00
Covariates Interacting with Walkability				
Percent of African American, 0–100	8.63	8.68	0.00	44.23
Percent of Asian, 0–100	2.63	3.60	0.06	35.41
Percent of non-White Hispanic, 0–100	41.98	23.32	5.86	87.45
Percent of other non-White, 0–100	2.21	0.88	0.44	4.15
Percent of under 18 years, 0–100	23.17	8.58	4.96	41.93
Percent of 65 years or older, 0–100	7.17	4.85	1.48	26.09
Percent of college degree holders, 0–100	60.52	23.08	4.54	100.00
Percent of population in poverty, 0–100	9.94	8.87	0.00	38.32
Per capita income, $1000	25.64	12.80	8.75	76.63
Population density, 1000 persons/sq. mile	5.53	2.20	0.14	11.38
Job density, 1000 jobs/sq. mile	2.09	2.13	0.07	11.52
Number of violent crimes within 1 mile	137.49	117.50	0.67	625.33
Number of property crimes within 1 mile	1484.07	843.80	5.00	3947.67
Number of collisions involving pedestrians within 1 mile	7.53	5.13	0.00	24.33
Number of street nodes within 1 mile	276.94	69.30	42.00	559.00
Total length of sidewalk within 1 mile, mile	78.07	16.35	18.99	123.63
Average speed limit within 1 mile , mile/hour	33.96	3.37	27.40	42.99

Note: This summary table is based on our final sample of 836 multifamily sale transactions from January 2010 to November 2012 in the city of Austin, Texas, USA. The quarter mile threshold for highway and railroad was selected following findings from Li and Saphores (2012a). Population and job densities were calculated based on the 2008 Traffic Analysis Zone developed by the Capital Area Metropolitan Planning Organization.

Figure 1: Sample Locations for Single-Family Housing Market Analysis

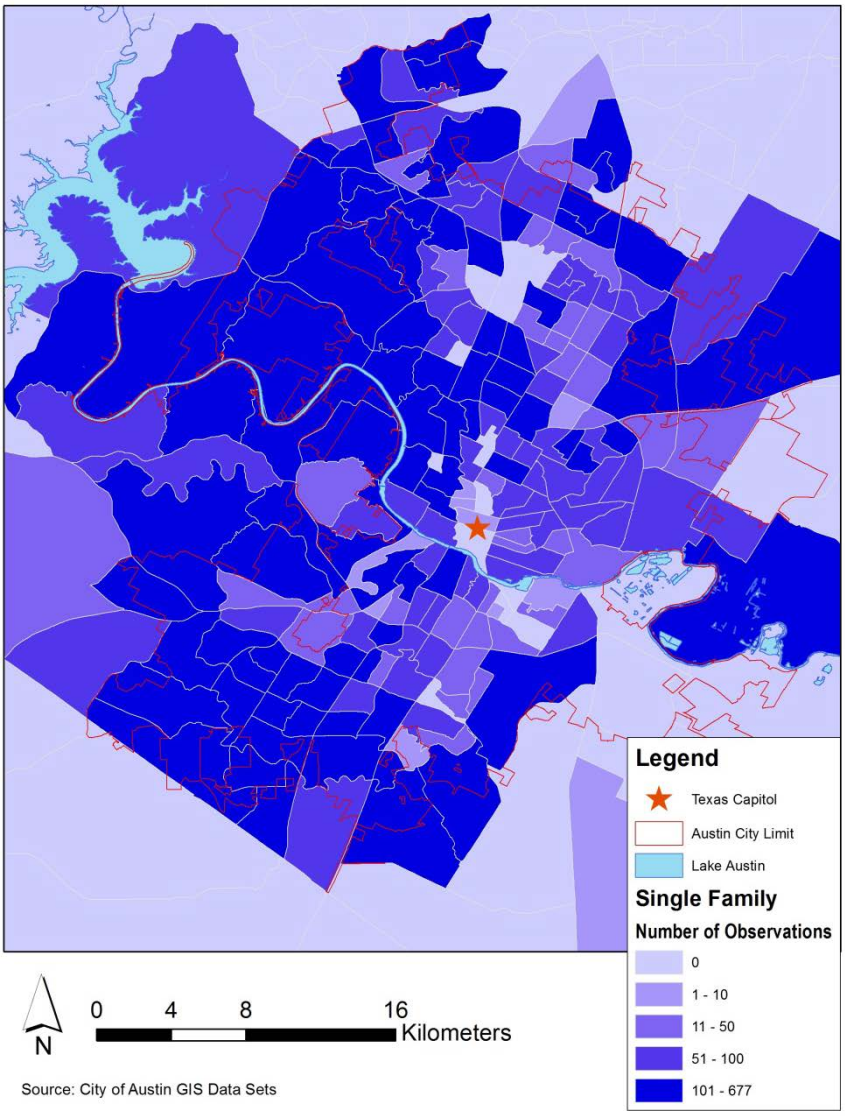
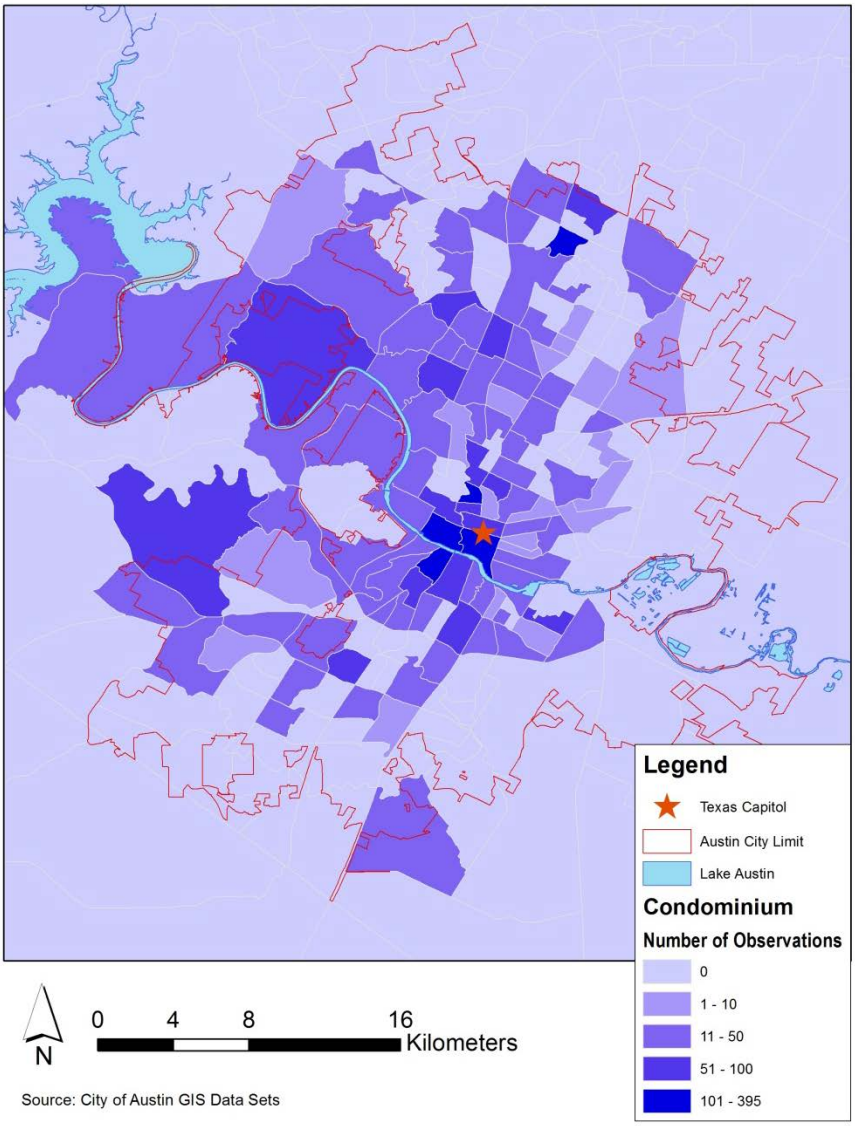
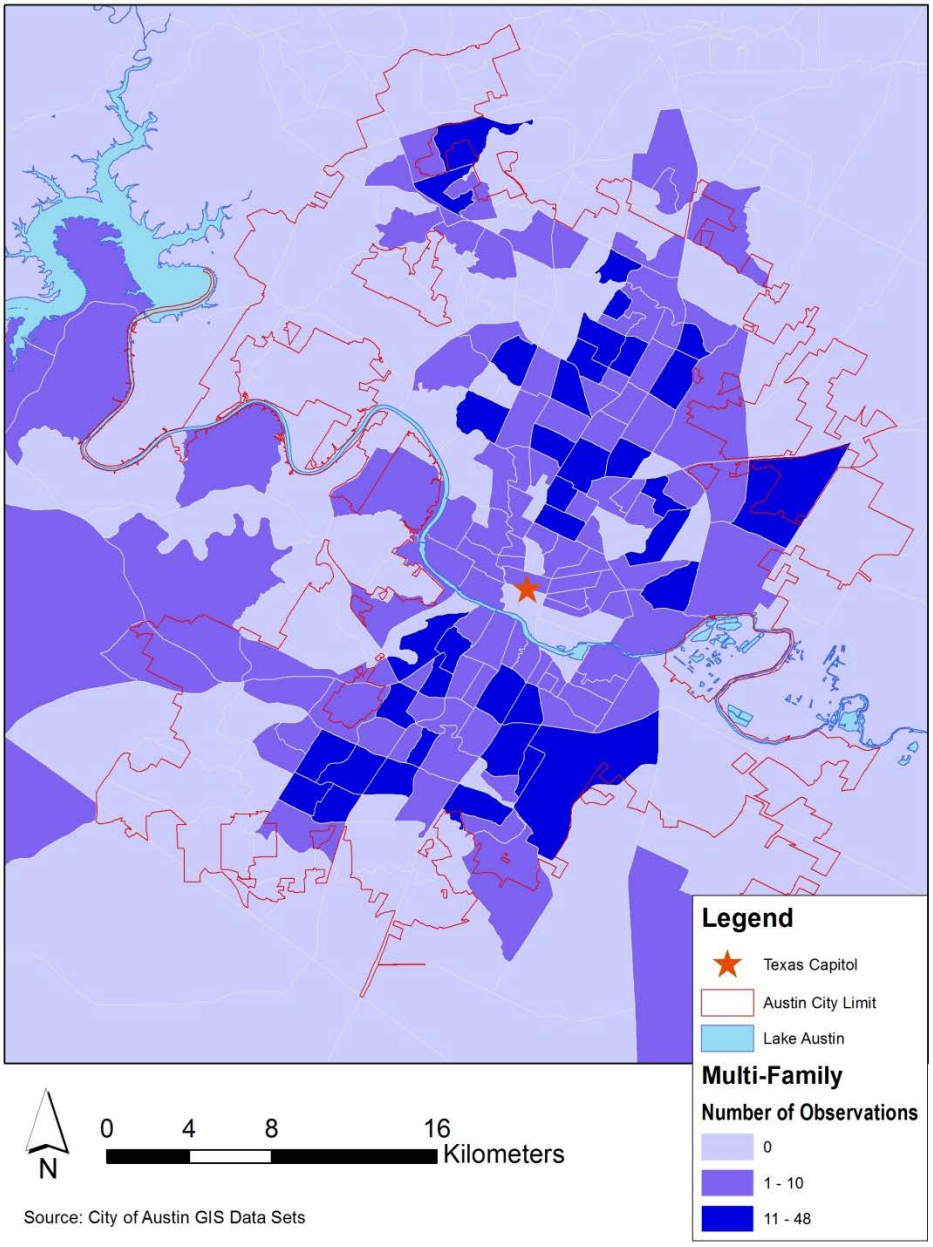


Figure 2: Sample Locations for Condominium Market Analysis



Source: City of Austin GIS Data Sets

Figure 3: Sample Locations for Multifamily Market Analysis



Source: City of Austin GIS Data Sets

3.3 Walkability Data

We calculated a Walk Score for each home in our sample. A Walk Score (WS) is a number between 0 and 100 that describes neighborhood walkability for an address. Walk Score is developed and maintained by Front Seat (www.frontseat.org), a civil software company, with funding support from the Rockefeller Foundation and the Robert Wood Johnson Foundation (WalkScore.com, 2013c). It is available to the public through www.walkscore.com. The neighborhood walkability for an entered address is generated through an algorithm which, based on the Google AJAX Search application program interface (API), identifies amenities in close proximity to this address (Carr et al., 2011). Thirteen categories of amenities are included in the calculation of Walk Score: grocery stores, coffee shops, restaurants, bars, movie theatres, schools, parks, libraries, book stores, fitness centers, drug stores, hardware stores, clothing/music stores (Carr et al., 2011). Points are awarded based on direct distances (without regard to the actual walking distance) to the nearest amenity in each category if it is located within 1 mile.

Public health researchers have documented evidence which have justified the reliability and validity of using Walk Score to measure neighborhood walkability (Carr, Dunsiger, & Marcus, 2010; Carr et al., 2011; Duncan et al., 2011; Duncan et al., 2013). Walk Score has also gained substantial public popularity: according to WalkScore.com (2013b), as of April 2013, Walk Score is listed on more than 20,000 real estate sites and with more than a quarter billion Walk Score records.

The Walk Score (WS) is a non-network walkability measurement of accessibility to amenities; it is measured on direct distances (bird flight) without considering the street network routing. In addition to Walk Score, we also obtained the Street Smart Walk Score (SSWS), which is calculated with a similar algorithm to the standard Walk Score, except that the points were calculated on the street routing distances (WalkScore.com, 2013a). SSWS was recently developed jointly by Front Seat, Walk Score Advisory Board and Dr. Larry Frank from the University of British Columbia, with funding support from the Robert Wood Johnson Foundation (WalkScore.com, 2013a).

Following Carr et al. (2011) and Duncan et al. (2013), we categorize our sample properties into five categories based on their Street Smart Walk Score (SSWS):

- Car-dependent (Driving Only): SSWS = 0 to 24; virtually no neighborhood destinations within walking range;
- Car-dependent (Only a Few Walking Destinations): SSWS = 25 to 49; residents must drive or take public transportation for most of their errands;
- Somewhat walkable: SSWS = 50 to 69; some amenities are within walking distance, but many daily trips rely other modes other than walking;
- Very walkable: SSWS = 70 to 89; it is possible to get by without a car;
- Walkers' paradise: SSWS = 90 to 100; most errands can be accomplished by walking; many people get by without owning a car.

4.0 METHODS

Our main analytical framework was the hedonic pricing method (HPM). Proposed by Rosen (1974), HPM generates implicit prices of environmental amenities and disamenities by analyzing variation in housing prices within an urban area (Redfearn, 2008). Our hedonic pricing framework is as follows:

$$\ln(p_i) = f(\mathbf{S}_i, \mathbf{N}_i, \mathbf{R}_i, \varepsilon_i) \quad (1)$$

where p_i is the sale price of property *i*; $\mathbf{S}_i$ and $\mathbf{N}_i$ are vectors of structural and neighborhood characteristics, respectively, for *i*; $\mathbf{R}_i$ is a vector of walkability related variables for *i*; and ε_i is the error term.

Using the HPM, we were able to identify the benefits of walkability to property values by controlling for the structural and neighborhood characteristics. In order to control for the spatial autocorrelation effects which refer to the influences of neighboring properties on the property value, we estimated the spatial regression model and explored how the results would change if different modeling methods are employed. Our results were generated by using the statistical package developed by Drukker, Peng, Prucha, and Raciborski (2011).We provide details of our analytical methodology in Exhibit A.

5.0 RESULTS AND DISCUSSION REGARDING THE SINGLE-FAMILY HOUSING MARKET

5.1 Walk Score vs. Street Smart Walk Score

Figure 4 compares the premiums for walkability estimated with Walk Score (WS) and the Street Smart Walk Score (SSWS). SSWS is valued higher than the WS for 60 percent (12,894) of the sample properties.[3] On average, the premium for SSWS is 0.0091 higher than that of WS.[4] Therefore, based on our evidence, single-family home buyers think about their potential walk paths to destinations they might wish to walk to before they purchase a home. While previous hedonic studies (Cortright, 2009; Pivo & Fisher, 2011; Rauterkus & Miller, 2011) on the economic values of walkability relied on the conventional Walk Score (perhaps due to the easy availability), this study suggests that the measurement of walkability should consider street network density and connectivity. In this section, we report the results generated with SSWS (Table 4).

The coefficients of 34 monthly binary variables (February 2010 to November 2012) were not reported in Table 4. However, they showed some interesting real estate market conditions in the city of Austin during the study period. Compared to the benchmark of January 2010, housing prices from February 2010 to September 2010 were 0.22 to 3.57 percent higher. Generally speaking, the prices were on a slight decline trend from August 2010 to February 2012, while the market gradually warmed starting in March 2012.

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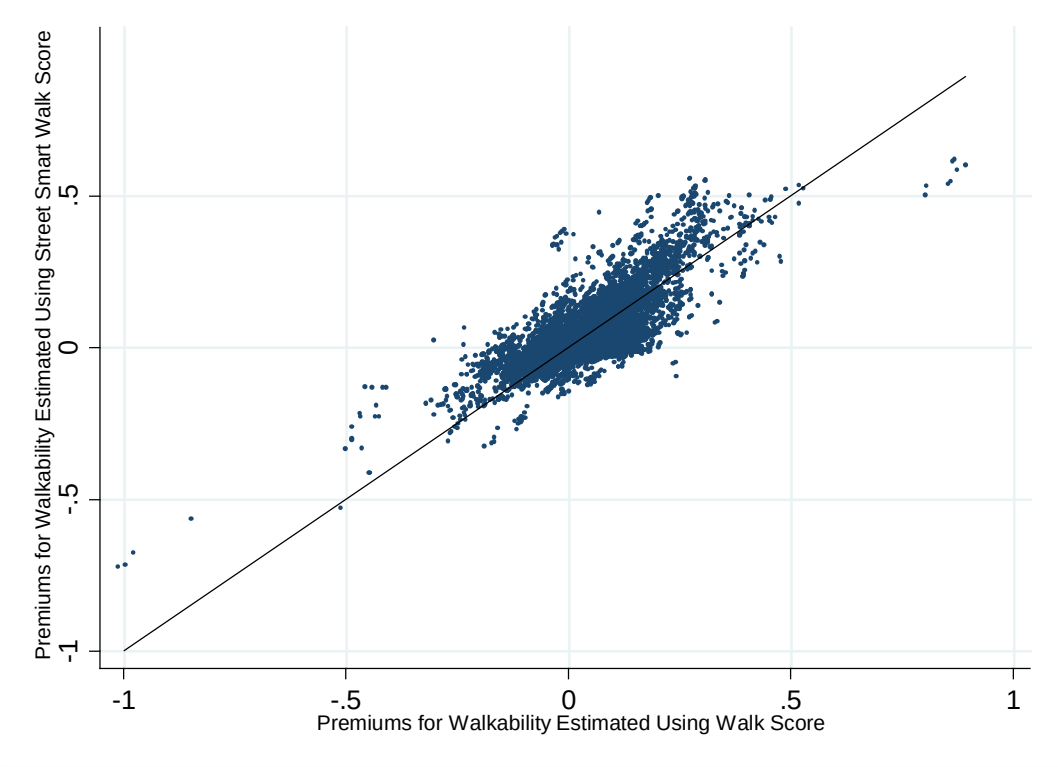
[3] The detailed results estimated with SSWS are reported in Table 4. The results estimated with WS, which are not reported in this paper for brevity, will be provided upon request.

[4] For example, suppose a 1 percent increase in WS would lead to x percent increase in the property value; then 1 percent increase in SSWS would lead to (x+0.0091) percent increase in the property value.

Figure 4: Comparing Premiums for Walk Score and Street Smart Walk Score (Single-Family Housing Market)



5.2 Structural and Neighborhood Characteristics

The effects of structural characteristics on single-family property values were highly significant and generally had expected signs. Property value would increase by 0.64 percent for each 1 percent increase in the use area and by 0.10 percent for a 1 percent increase in the lot size. On average, when keeping all other factors constant, property value would increase by 3.30 percent for an additional full bathroom and 5.79 percent for an additional half bathroom.[5] On average, for a one-year increase in home age, the home value decreased by 0.13 percent.

The transaction sales data showed that the price of a home decreased by 0.03 percent when its time on the market increased by 1 percent. This is understandable given that the longer a home stays on the market, the more likely a seller decreases the asking price; by closing the deal sooner, the seller would avoid additional costs such as property taxes, utilities, and landscape maintenance. Some buyers may also have a negative perception about property that is on the market for a long time.

[5] These marginal benefits were calculated based on the sample averages: 2.2020 full bathrooms, and 0.3801 half bathrooms.

Table 4: Estimation Results from Single-Family Market Analysis

Variable Names	Coefficients	Rob.SE	Variable Names	Coefficients	Rob.SE
Structural characteristics			*Walkability*		
Log(use area)	0.6436***	0.0080	Normalized Street Smart Walk Score	−0.0141***	0.0043
Log(lot area)	0.0964***	0.0034	Square of norm. SSWS	0.0178***	0.0043
Log(age)	−0.0352***	0.0011			
Log(time on market)	−0.0255***	0.0021	*Interaction terms: normalized walkability with*		
Log(number of bedrooms)	−0.0246***	0.0084	*within normalized variables*		
Square of Log(number of bedrooms)	−0.0023**	0.0011	Percent of African American, 0–100	0.0062	0.0038
Log(number of full bathrooms)	0.0726***	0.0033	Percent of Asian, 0–100	−0.0229***	0.0043
Log(number of half bathrooms)	0.0220***	0.0038	Percent of non-White Hispanic, 0–100	0.0598***	0.0119
Binary: 1 = Having 2 or more stories	−0.0585***	0.0042	Percent of other non-White, 0–100	0.0080	0.0139
Binary: 1 = Having 1 or more garage spaces	0.0272***	0.0048	Percent of under 18 years, 0–100	0.0381**	0.0169
Binary: 1 = Having pool	0.0878***	0.0053	Percent of 65 years or older, 0–100	0.0056	0.0076
Binary: 1 = Having view	0.0354***	0.0035	Percent of college degree holders, 0–100	0.1309***	0.0375
Binary: 1 = Located on the waterfront	0.1121***	0.0127	Percent of population in poverty, 0–100	−0.0072**	0.0032
Binary: 1 = Large/medium tree on parcel	0.0365***	0.0037	Per capita income, $	−0.0076	0.0104
			Population per square mile	0.0255***	0.0059
Neighborhood variables			Employment per square mile	−0.0014	0.0015
Log(network distance to state capitol)	−0.0531**	0.0248	Violent crime rate within 1 mile	−0.0274***	0.0050
Log(network distance to major road intersct.)	0.0147***	0.0037	Property crime rate within 1 mile	0.0270***	0.0100
Log(network distance to MetroRail station)	0.0385***	0.0132	Pedestrian accident rate within 1mile	0.0065	0.0049
Log(direct distance to lake)	−0.0142***	0.0023	Street connectivity within 1 mile	0.0705***	0.0198
Log(school quality)	0.0942***	0.0169	Total length of sidewalk within 1 mile	−0.0994***	0.0216
Binary: 1 = highway within 400 meters	−0.0008	0.0034	Average speed limit within 1 mile	0.0603*	0.0343
Binary: 1 = railroad within 400 meters	−0.0321***	0.0063			
Normalized violent crime rate within 1 mile	−0.0315***	0.0072			
Normalized property crime rate within 1 mile	0.0393***	0.0123	Constant	−1.8235	1.1599
Normalized pedestrian accident within 1 mile	0.0067	0.0079	Spatial lag coefficient for price	−2.3001***	0.0966
Normalized average speed limit within 1 mile	0.1074***	0.0329	Spatial lag coefficient for error term	0.9477***	0.0028
			Number of observations	21687	

*Note: The results, based on our final sample of 21,687 single-family sale transactions, were estimated by the Cliff-Ord model as illustrated by Equation (2) in Exhibit A. The selected spatial weight matrix allows all properties located in the same census block group to have equal weights of influences on each other. The dependent variable is the natural logarithm of the home sale price. Table 1 presents definitions and summary statistics of the relevant variables. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively. For brevity, we do not report the results for the monthly binary variables and the spatial lag coefficients of selected independent variables.*

Compared to similar properties without it, property values would benefit by 2.72 percent for having a garage, 8.78 percent for having a pool on the parcel, 3.54 percent for having a view and 3.65 percent for having large or medium sized trees. Waterfront location was highly valued by Austin single-family home residents, commanding a premium of 11.21 percent. Interestingly, homes with 2 or more stories would be less desirable, selling for 5.85 percent less than similar one-story homes. However, this was likely a regional characteristic due to the long and hot summers in Austin. Single-story homes would need less energy for cooling compared to multistory homes. Proximity to transportation infrastructure usually had two contrasting effects on property values: a positive effect because of the convenience, and a negative effect because of nuisances such as congestion, air pollution and noise. In our data, increasing proximity to the nearest major road intersection by 1 percent had a slight (0.01 percent) negative impact on property values; homes within a quarter mile of railroad tracks were 3.21 percent less valuable than similar homes located further away from railroad tracks. On the other hand, proximity to the nearest MetroRail station affected property values in a different direction: a 1 percent increase in proximity to the station increased property values by 0.04 percent. A 1 percent increase in the average speed limit within 1 mile of a property increased property values by 0.11 percent.

As expected, a 1 percent increase in school quality would increase property value by 0.10 percent. Both types of crime rates had significant impacts on property values, but in opposite directions: Increased violent crime rate significantly damaged property values, while a higher property crime rate increased property values. Such a pattern was also observed by Bowes (2007) and Li and Saphores (2012b). As expected, single-family properties located closer to the state capitol would have a higher property value.

5.3 Effects of Walkability on Single-Family Property Values

The effects of walkability on property values are interpreted as “elasticities”: if the elasticity is x, then a 1 percent increase in walkability would increase property values by x percent. As shown in Table 5, the average (or median) elasticities for the two car-dependent neighborhoods are both negative; they become positive for properties located in the neighborhoods which are at least somewhat walkable (walk scores above 50).

More precisely, the SSWS would show a benefit for 7,481 (35 percent) of the total 21,687 properties in our sample. As illustrated in Figure 5, the marginal benefit of walkability on property values was generally higher for homes located in more walkable neighborhoods. Most of the home sales in with walk scores above 60 showed an increase in home value for higher walk scores, and if the walk score is above 80, a higher sales price was virtually assured.

Table 5: Effects of Walkability on Single-Family Property Values

	Number of Properties	Average SSWS	Median SSWS	Average Premium	Median Premium
Car-Dependent (driving only); SSWS = 0–24	11,550	9.8929	9	−0.0135	−0.0107
Car-Dependent (only a few walking destinations); SSWS = 25–49	5,308	36.1375	36	−0.0061	−0.0095
Somewhat Walkable; SSWS = 50–69	2,963	59.1478	59	0.0369	0.0312
Very Walkable; SSWS = 70–89	1,669	78.1198	78	0.1579	0.1565
Walkers' Paradise; SSWS = 90–100	197	92.6294	92	0.3680	0.3753
Whole Sample	21,687	29.0481	22	0.0119	−0.0070

Note: SSWS is short for Street Smart Walk Score; the premium for walkability is measured as the elasticity of the property value with respect to SSWS (e.g., 0.2932 means for 1 percent increase in SSWS, the property value would increase by 0.2932 percent).

5.4 Other Important Explanatory Factors

The effects of walkability on single-family property values are influenced by several factors that were analyzed as a part of this report.

- Race / Ethnicity – Hispanic home purchasers were willing to pay the highest premium for increased neighborhood walkability, followed by African Americans and Caucasians. Asian buyers showed the lowest willingness to pay for walkability among all the groups.
- Age – Neighborhoods with higher proportion of youth (under 18 years old) demanded higher premiums for walkability. This echoed the finding by L. Frank, Kerr, Chapman, and Sallis (2007) that access to recreation or open space was the most important urban form variable related to walking frequencies of youth. A larger than average percentage of population over 65 years also increased the premium for walkability, even though the impact was not statistically significant. According to Naumann et al. (2009), seniors with more confidence in walking than driving was an important factor in the decision to choose walking.
- Education – Neighborhoods with higher percentage of population with college degrees demanded higher premiums for walkability.
- Poverty – Having higher poverty rate significantly decreased the premium for walkability; this was expected, as persons in poverty may have decreased ability (rather than willingness) to pay for walkability due to financial constraints.

- Density – A higher population density significantly increased the premium for walkability. However, a higher employment density decreased the premium by a very small magnitude,[6] and the effect was not statistically significant.
- Crime – The premium of walkability was significantly lower in neighborhoods with high violent crime rates, but was enhanced in neighborhoods with high property crime rates. Such a pattern, as noted above, was similar to the results by Bowes (2007) and Li and Saphores (2012b).
- Pedestrian Collision Rate – The premium of walkability was higher for properties located in a neighborhood with higher pedestrian collision rates, but the effect was not significant. The pedestrian accident rate may act as a proxy for increased pedestrian exposure, suggesting that these neighborhoods have high pedestrian activity.

Figure 5: Distribution of Premiums for Walkability (Single-Family Housing Market)

- Street Connectivity – Previous studies found that street connectivity was an important factor in influencing walking behavior (Oakes, Forsyth, & Schmitz, 2007; Owen et al., 2004; Saelens & Handy, 2008; Saelens et al., 2003), could significantly increase the premium of walkability by expanding the choice of routing.
- Sidewalk – We found that having a higher total length of sidewalk in the neighborhood decreased the premium for walkability. While this may be counterintuitive at first, this is probably due to the building codes for newer subdivisions in Austin. These tend to be more

[6] The correlation between population density and employment density is 0.2541, which is much lower than we expected.

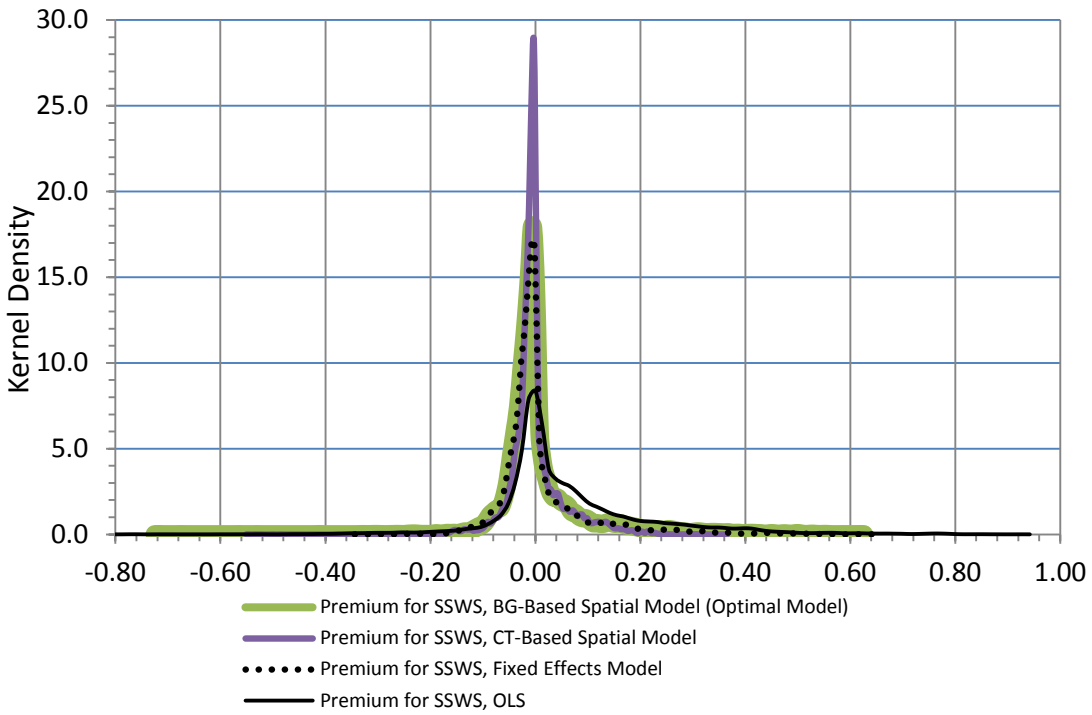
spread out with fewer nearby destinations, but are more likely to have sidewalks mandated by zoning ordinance. In contrast, the older, more compact neighborhoods in East Austin, for example, often lack sidewalk infrastructure.

- Speed Limit – The premium of walkability on property values was higher when the average speed limit within 1 mile increased.

5.5 Robustness of Results

In order to ensure robustness of results, we also estimated Equation (2) in Exhibit A by using the census tract (2010 Census) to define the neighborhood such that all neighbors located in the same census tract would have the same weights of influence on each other. In addition, we estimated a fixed-effects model by adding the 182 census block group binary variables to Equation (1). [7] In Figure 6, we compare the premiums for walkability estimated using different modeling approaches. The distributions of the premiums for walkability estimated from the two spatial hedonic models and the fixed-effects model are generally consistent, confirming the robustness of our results.

Figure 6: Robustness of Results (Single-Family Housing Market Analysis)



Note: The premium for walkability is measured as the elasticity of the property value with respect to Street Smart Walk Score (e.g., 0.2932 means for 1 percent increase in SSWS, the property value would increase by 0.2932 percent). The thickest line represents the distribution of the premiums for walkability estimated by the optimal model, as illustrated by Equation (2) in Exhibit A.

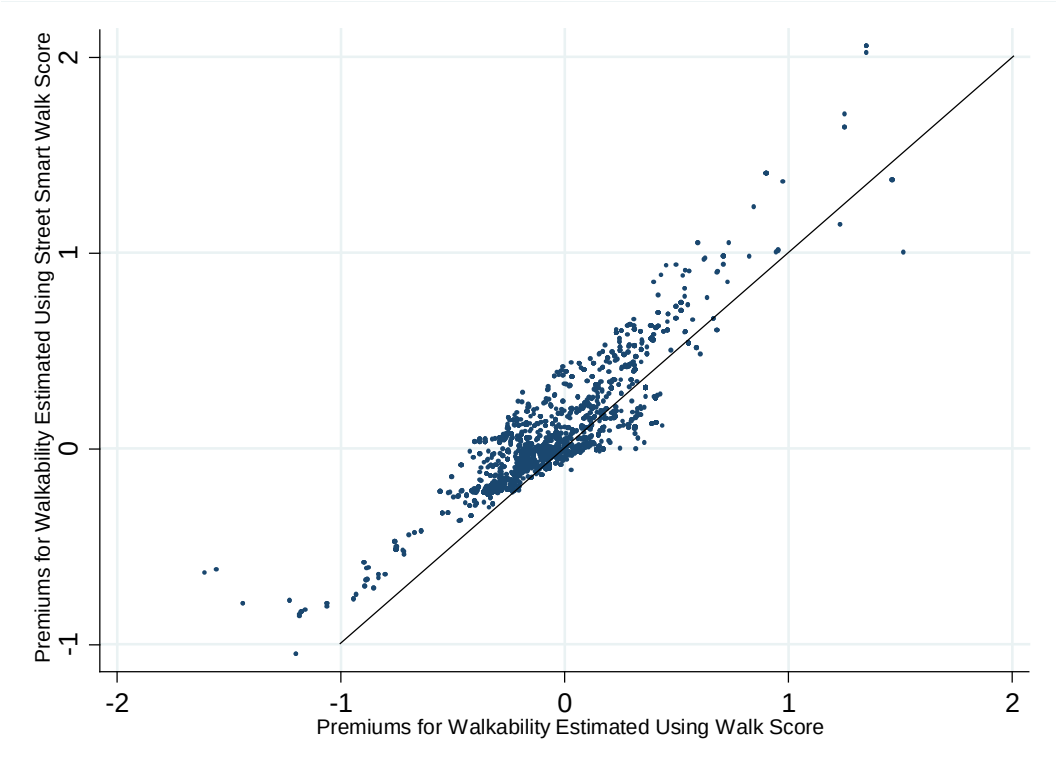
[7] For a census block group binary variable, its value would be 1 if a property is located in that block group; 0 otherwise. We also estimated the census tract based fixed-effects model and obtained similar results with the census block group based model.

6.0 RESULTS AND DISCUSSION REGARDING THE CONDOMINIUM MARKET

6.1 Walk Score vs. Street Smart Walk Score

Figure 7 compares the premiums for walkability estimated with the two different types of measurements: Street Smart Walk Score vs. Walk Score.[8] Points above the dividing line represent the condominium properties where the premium for SSWS is valued higher than that for WS which does not account for the characteristics of street networks. Those points make up 78 percent (3022) of the total 3899 condominium properties. On average, the premium for SSWS is 0.1063 higher than that for WS.[9] Our results show that the characteristics of street networks and routing choices matter to residents in terms of walking to different destinations. While previous hedonic studies (Cortright, 2009; Pivo & Fisher, 2011; Rauterkus & Miller, 2011) on the economic values of walkability relied on the conventional Walk Score, this study suggests that the measurement of walkability should consider street network density and connectivity. We report the results generated with SSWS (Table 6).

Figure 7: Comparing Premiums for Walk Score and Street Smart Walk Score (Condominium Market)



[8] The detailed results estimated with SSWS are reported in Table 6. The results estimated with WS, which are not reported in this paper for brevity, will be provided upon request.

[9] For example, suppose 1 percent increase in WS would lead to x percent increase in the property value; then 1 percent increase in SSWS would lead to (x+0.1063) percent increase in the property value.

For brevity, we do not report the estimated coefficients of the monthly binary variables in Table 6. Generally speaking, the condominium prices in Austin did not change significantly from January 2010 to May 2012, but the prices were on a rising trend during the second half of 2012.

6.2 Structural and Neighborhood Characteristics

Keeping all other factors constant, a condominium would be sold at a significantly higher price if it has larger user areas, a good view, more full bathrooms, one or more garage spaces, or is located at the waterfront. Its property value would significantly decrease as it ages, stays longer on the market, or has two or more stories. Surprisingly, having more half bathrooms would harm a condominium's property values.

Proximity to the nearest major road intersection or MetroRail station would significantly benefit a condominium property's value. The higher traffic collision rate involving pedestrians is also positively associated with property values, likely due to the reason that such a rate is closely related to the number of active pedestrians in the neighborhood. As expected, a condominium would enjoy a price premium for being located closer to a lake, or in an area with a lower violent crime rate. A shorter distance to the state capitol would have a negative impact on a condominium's property value,[10] possibly due to nuisances such as congestion and inconvenience of parking.

[10] The network distance to the state capitol also shows a positive sign in the fixed-effects model and the spatial regression model using the census tract to generate the spatial weight matrix.

Table 6: Estimation Results from Condominium Market Analysis

Variable Names	Coefficients	Rob.SE	Variable Names	Coefficients	Rob.SE
Structural characteristics			*Walkability*		
Log(use area)	0.8474***	0.0198	Normalized Street Smart Walk Score	0.0578**	0.0279
Log(lot area)	0.0042	0.0050	Square of norm. SSWS	0.1918***	0.0527
Log(age)	−0.0632***	0.0028			
Log(time on market)	−0.0124***	0.0044	*Interaction terms: normalized walkability with*		
Log(number of bedrooms)	0.0042	0.0218	*with normalized covariates*		
Square of Log(number of bedrooms)	−0.0058	0.0046	Percent of African American	0.2405***	0.0301
Log(number of full bathrooms)	0.0173*	0.0103	Percent of Asian	0.0760**	0.0357
Log(number of half bathrooms)	−0.0289**	0.0115	Percent of non-White Hispanic	0.1928**	0.0797
Binary: 1 = Having 2 or more stories	−0.0246**	0.0107	Percent of other non-White	−0.2380**	0.0927
Binary: 1 = Having 1 or more garage spaces	0.0928***	0.0093	Percent of under 18 years	−0.0113	0.0684
Binary: 1 = Having pool	0.0037	0.0075	Percent of 65 years or older	0.0126	0.0378
Binary: 1 = Having view	0.0594***	0.0076	Percent of college degree holders	0.4435**	0.2262
Binary: 1 = Located on the waterfront	0.0844***	0.0175	Percent of population in poverty	−0.2192***	0.0371
Binary: 1 = Large/medium tree on parcel	−0.0043	0.0072	Per capita income	−0.1585***	0.0612
			Population density	0.1335***	0.0401
Neighborhood variables			Job density	0.0082*	0.0046
Log(network distance to state capitol)	0.0633**	0.0308	Violent crime rate within 1 mile	−0.2643***	0.0515
Log(network distance to major road intersct.)	−0.0246***	0.0090	Property crime rate within 1 mile	0.0579	0.1453
Log(network distance to MetroRail station)	−0.0410**	0.0195	Pedestrian accident rate within 1 mile	0.1822**	0.0719
Log(direct distance to lake)	−0.0193**	0.0076	Street connectivity within 1 mile	0.9117***	0.1589
Log(school quality)	0.0475	0.0667	Tot. length of sidewalk within 1 mile	−1.3077***	0.1712
Binary: 1 = highway within 1/4 mile	0.0238	0.0170	Average speed limit within 1 mile	−0.6837***	0.2291
Binary: 1 = railroad within 1/4 mile	−0.0223	0.0164			
Norm. violent crime rate within 1 mile	−0.1705***	0.0328	Constant	2.2432**	1.0557
Norm. property crime rate within 1 mile	−0.0196	0.0790	Spatial lag coefficient for price	−0.4100***	0.1349
Norm. pedestrian collision within 1 mile	0.1717***	0.0430	Spatial lag coefficient for error term	0.8285***	0.0228
Norm. average speed limit within 1 mile	−0.1321	0.1579	Number of observations	3899	

*Note: The results, based on our final sample of 3899 condominium sale transactions, were estimated by the Cliff-Ord model as illustrated by Equation (2) in Exhibit A. The selected spatial weight matrix allows all properties located in the same census block group to have equal weights of influences on each other. The dependent variable is the natural logarithm of the home sale price. Table 1 presents definitions and summary statistics of the relevant variables. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively. For brevity, we do not report the results for the monthly binary variables and the spatial lag coefficients of selected independent variables*

6.3 Effects of Walkability on Condominium Property Values

The effects of walkability on property values are interpreted as "elasticities": if the elasticity is x, then a 1 percent increase in walkability would increase property values by x percent.

On average, 1 percent increase in neighborhood walkability would increase a condominium's property value by 0.1033 percent. Increasing walkability would benefit property values for 57 percent (2231) among the total 3,899 condominiums in our sample. As shown in Table 7, the impact of walkability on condominium property values depends on the current neighborhood walkability levels. In a car-dependent driving only neighborhood (SSWS = 0–24), increased walkability would yield a slightly negative effect on property values. However, for condominiums located in neighborhoods with higher walkability ratings, increased walkability would become beneficial to property values. On average, 1 percent improvement in walkability would increase the property value by 0.0322 percent for a condominium if it is located in a car-dependent neighborhood with only a few walking destinations (SSWS = 25–49), 0.0430 percent for a somewhat walkable neighborhood (SSWS = 50–69), 0.1322 percent for a very walkable neighborhood (SSWS = 70–89) and 0.2932 percent for Walkers' Paradise (SSWS = 90–100).

Table 7: Effects of Walkability on Condominium Property Values

	Number of Condos	Average SSWS	Median SSWS	Average Premium	Median Premium
Car-Dependent (driving only); SSWS = 0–24	597	13.0921	13	−0.0175	−0.0268
Car-Dependent (only a few walking destinations); SSWS = 25–49	863	36.2619	36	0.0322	0.0085
Somewhat Walkable; SSWS = 50–69	744	60.2836	60	0.0430	0.0051
Very Walkable; SSWS = 70–89	892	80.5325	82	0.1322	0.0754
Walkers' Paradise; SSWS = 90–100	803	94.3985	94	0.2932	0.3493
Whole Sample	3899	59.3993	63	0.1033	0.0382

Note: SSWS is short for Street Smart Walk Score; the premium for walkability is measured as the elasticity of the property value with respect to SSWS (e.g., 0.2932 means for 1 percent increase in SSWS, the property value would increase by 0.2932 percent).

6.4 Other Important Explanatory Factors

Various socio-demographic and environment factors influence the premium for walkability in the condominium market.

- Race / Ethnicity – Among all racial/ethnic groups, African Americans would be willing to pay the highest premium for neighborhood walkability, followed by non-white Hispanics, Asians, and Caucasians.
- Education – Residents from neighborhoods with a higher proportion of college degree holders would demand higher premium for walkability.

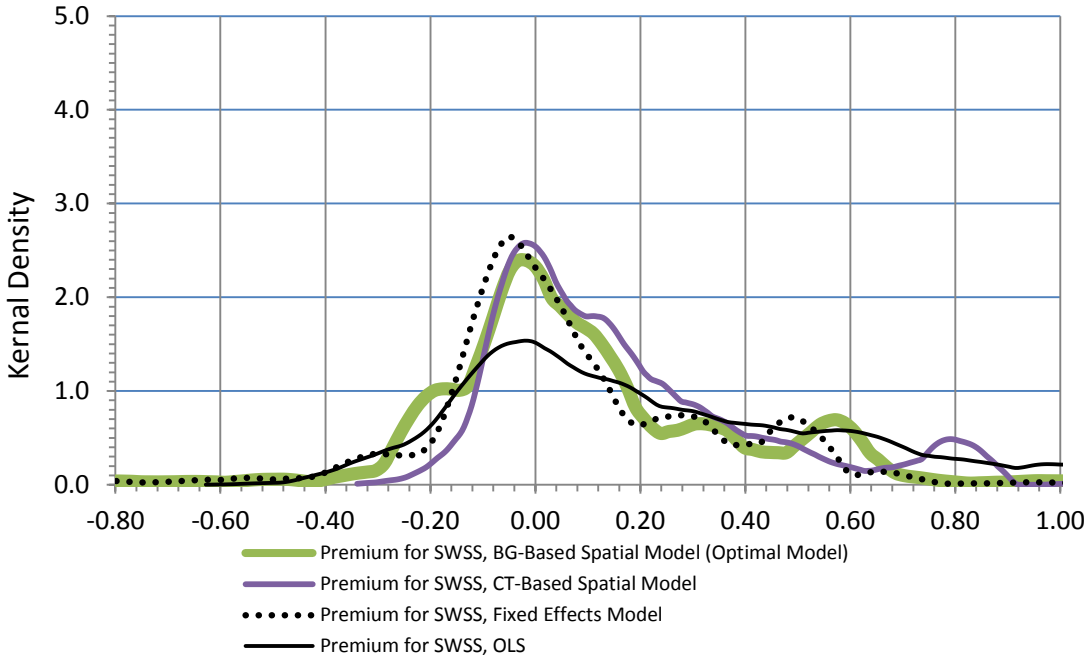
- Poverty – Having a higher than average poverty rate would significantly decrease the elasticity of walkability, as persons in poverty may have decreased willingness to pay for walkability due to financial constraints. However, when keeping the poverty rate and other factors constant, having lower per capita income would significantly increase condominium residents' willingness to pay for walkability.[11]
- Density – Higher population density or employment density would lead to increases in the walkability premium. Increased population or employment density may lead to higher congestion levels on roadways, so that residents may favor walking as an active transportation mode or transit which may also require access/egress walking trips.
- Crime – The premium for walkability would be significantly compromised in neighborhoods with high violent crime rates, as previous studies (Joh, Nguyen, & Boarnet, 2012; McDonald, 2008) have found that violent crime rates are negatively associated with walking activities. On the other hand, property crime rates may positively enhance the premium of walkability. The contrasting effects by these two crime rates were also observed by some previous hedonic studies (Bowes, 2007; Li and Saphores, 2012b).
- Pedestrian Collision Rate – Interestingly, we found that the pedestrian collision rate is positively associated with the premium for walkability; the pedestrian collision rate may partly indicate levels of pedestrian activities.
- Street Connectivity – Consistent with previous studies on street connectivity and walking (Oakes et al., 2007; Owen et al., 2004; Saelens & Handy, 2008; Saelens et al., 2003), we found that increased street connectivity could significantly increase the premium for walkability by expanding the choice of routing.
- Sidewalk – Counter-intuitively, the average total length of sidewalk is negatively associated with Austin condominium residents' willingness to pay for walkability. This is probably due to the fact that newer subdivisions in Austin tend to be more spread out with fewer nearby destinations, but will likely have sidewalks due to requirement in zoning regulations.
- Speed Limit – A higher speed limit within one mile would significantly harm the premium for walkability, mainly due to the safety concerns as discussed in previous studies (Moudon & Lee, 2003; Zhu & Lee, 2008).

6.5 Robustness of Results

We performed the robustness checks using an approach similar to that described in Section 5.4. In Figure 8, we compare the premiums for walkability estimated using different modeling approaches. The distributions of the premiums for walkability estimated from the two spatial hedonic models and the fixed-effects model are generally consistent, confirming the robustness of our results.

[11] We decided to include both poverty rate and per capita income covariates in our model after confirming that the correlation between these two variables was not extremely high (−0.4103).

Figure 8: Robustness of Results (Condominium Market Analysis)



Note: The premium for walkability is measured as the elasticity of the property value with respect to Street Smart Walk Score (e.g., 0.2932 means for 1 percent increase in SSWS, the property value would increase by 0.2932 percent). The thickest line represents the distribution of the premiums for walkability estimated by the optimal model, as illustrated by Equation (2) in Exhibit A.

7.0 RESULTS AND DISCUSSION REGARDING THE MULTIFAMILY HOUSING MARKET

7.1 Walk Score vs. Street Smart Walk Score

Figure 9 compares the premiums for walkability estimated with the two different types of measurements: Street Smart Walk Score and Walk Score. Points above the dividing line represent the multifamily building properties where the premium for SSWS is valued higher than that for WS, which does not account for the characteristics of street networks. Those points comprise 75 percent (630) of the total 836 multifamily building properties. On average, the premium for SSWS is 0.1864 higher than that for WS. Our multifamily analysis shows, once again (similar to the single-family and the condominium analysis), that the characteristics of street networks and routing choices matter to residents in terms of walking to different destinations. In this section, we report the results generated with SSWS (Table 8).

Figure 9: Comparing Premiums for Walk Score and Street Smart Walk Score (Multifamily Housing Market)

Note: The values on both axes are estimated by the optimal model approach—the Cliff-Ord model as illustrated by Equation (2) in Exhibit A. Points above the dividing line represent the MFB units where the premium for Street Smart Walk Score is valued higher than Walk Score.

7.2 Structural and Neighborhood Characteristics

Keeping all other factors constant, a multifamily building (MFB) would be sold at a significantly higher price if it has larger use and lot areas, more full bathrooms, and one or more garage spaces. Its property value would significantly decrease as the building ages. Interestingly, MFBs would be sold at a higher price the longer it stays on the market. Other structural characteristics, such as the number of bedrooms and having a view, did not significantly impact property values.

The most robust neighborhood factor impacting the sale price of MFBs is the school quality of the neighborhood. Proximity to the lake was also a significant positive factor for MFB property values, although its magnitude is much less than school quality. As expected, factors negatively associated with property values included property crime and proximity to the railroad tracks. Proximity to the state capitol has a positive impact on property values, suggesting that buyers were willing to pay a premium to live closer to downtown. Other neighborhood factors that were significant at the 10 percent level included distance to the MetroRail station (properties closer to the MetroRail station enjoyed a premium in property values) and average speed limit within one mile (increase in speed limit negatively impacted MFB property values).

Table 8: Estimation Results from Multifamily Housing Analysis

Variable Names	Coefficients	Rob.SE	Variable Names	Coefficients	Rob.SE
Structural characteristics			*Walkability*		
Log(use area)	0.4558***	0.0562	Normalized network walkability	−0.0353	0.0377
Log(lot area)	0.1003***	0.0294	Square of norm. network walkability	0.1093***	0.0402
Log(age)	−0.1759***	0.0187			
Log(time on market)	0.0181**	0.0093	*Interaction terms: normalized walkability with*		
Log(number of bedrooms)	−0.0219	0.0274	*within normalized variables*		
Square of Log(number of bedrooms)	0.0001	0.0021	Percent of African American, 0–100	−0.0479	0.0293
Log(number of full bathrooms)	0.0190**	0.0091	Percent of Asian, 0–100, 0–100	0.0016	0.0132
Log(number of half bathrooms)	−0.0100	0.0081	Percent of non-White Hispanic, 0–100	−0.0274	0.0971
Binary: 1 = Having 2 or more stories	−0.0261	0.0223	Percent of other non-White, 0–100	0.0156.	0.0536
Binary: 1 = Having 1 or more garage spaces	0.0569***	0.0182	Percent of under 18 years, 0–100	0.1420	0.1108
Binary: 1 = Having pool	−0.0342	0.739	Percent of 65 years or older, 0–100	0.0246	0.0293
Binary: 1 = Having view	−0.0433	0.0372	Percent of college degree holders, 0–100	0.0093	0.1818
Binary: 1 = Large/medium tree on parcel	−0.0004	0.0142	Percent of population in poverty, 0–100	−0.0354*	0.0185
			Per capita income	−0.0999*	0.0588
			Population per square mile	−0.0135	0.0547
Neighborhood variables			Employment per square mile	0.0299**	0.0139
Log(network distance to state capitol)	−0.5924***	0.2164	Violent crime rate within 1 mile	0.0671	0.0466
Log(network distance to major road intersct.)	0.0067	0.0257	Property crime rate within 1 mile	−0.0221	0.0997
Log(network distance to MetroRail station)	−0.1619*	0.0967	Pedestrian accident rate within 1mile	−0.0161	0.0554
Log(direct distance to lake)	0.0319**	0.0136	Street connectivity within 1 mile	0.1949	0.1486
Log(school quality)	0.2512***	0.0866	Total length of sidewalk within 1 mile	−0.4544**	0.2088
Binary: 1 = highway within 1/4 mile	−0.0034	0.0231	Average speed limit within 1 mile	−0.3586	0.2650
Binary: 1 = railroad within 1/4 mile	−0.0624**	0.0318			
Normalized violent crime rate within 1 mile	0.0515	0.0793			
Normalized property crime rate within 1 mile	−0.2830**	0.1354	Constant	1.0503	0.6604
Normalized pedestrian collision within 1 mile	0.1176	0.0737	Spatial lag coefficient for price	0.6803***	0.0609
Normalized average speed limit within 1mile	−0.5382*	0.3093	Spatial lag coefficient for error term	−0.6905**	0.2730
			Number of observations	836	

*Note: The results, based on our final sample of 836 multifamily building sale transactions, were estimated by the Cliff-Ord model as illustrated by Equation (2). The selected spatial weight matrix allows all properties located in the same census block group to have equal weights of influences on each other. The dependent variable is the natural logarithm of the home sale price. Table 1 presents definitions and summary statistics of the relevant variables. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively. For brevity, we do not report the results for the monthly binary variables and the spatial lag coefficients of selected independent variables.*

7.3 Effects of Walkability on Multifamily Property Values

On average, 1 percent increase in neighborhood walkability would increase a MFB's property value by only 0.0045 percent. Increasing walkability would benefit property values for 35 percent (294) among the total 836 MFBs in our sample. As shown in Table 9, the impact of walkability on MFB property values depends on the neighborhood walkability levels. In both car-dependent neighborhood categories (SSWS = 0–49), increased walkability would have a slightly negative effect on property values. However, for MFBs located in neighborhoods with higher walkability ratings, increased walkability would become beneficial to property values. On average, 1 percent improvement in walkability would increase the property value by 0.1043 percent for a somewhat walkable neighborhood (SSWS = 50–69), 0.0155 percent for a very walkable neighborhood (SSWS = 70–89) and 0.3339 percent for a walkers' paradise (SSWS = 90–100). Surprisingly, the property value premium for a very walkable neighborhood was lower than a somewhat walkable neighborhood.

Table 9: Effects of Walkability on Multifamily Property Values

	Number of MFB	Average SSWS	Median SSWS	Average Premium	Median Premium
Car-Dependent (driving only); SSWS = 0–24	171	15.9415	17	−0.0512	−0.0505
Car-Dependent (only a few walking destinations); SSWS = 25–49	376	37.4069	38	−0.0322	−0.0468
Somewhat Walkable; SSWS = 50–69	202	57.7327	58	0.1043	0.0680
Very Walkable; SSWS = 70–89	80	75.6375	74.5	0.0155	−0.0238
Walkers' Paradise; SSWS = 90–100	7	93.2857	93	0.3339	0.3094
Whole Sample	836	42.0538	41	0.0045	−.0255

Note: SSWS is short for Street Smart Walk Score; the premium for walkability is measured as the elasticity of the property value with respect to SSWS (e.g., 0.3339 means for 1 percent increase in SSWS, the property value would increase by 0.3339 percent).

7.4 Other Important Explanatory Factors

Socio-demographic factors did not appear to influence the premium for walkability with the exceptions of percentage of persons in poverty and per capita income (albeit these factors were significant only at the 10 percent level). Race and ethnicity were not significant factors impacting the premium for walkability in our model. Above average poverty rates decreased the elasticity of walkability, suggesting that persons in poverty are less willing to pay for improvement in walkability. Similarly, having lower per capita income decreased MFB residents' willingness to pay for walkability.

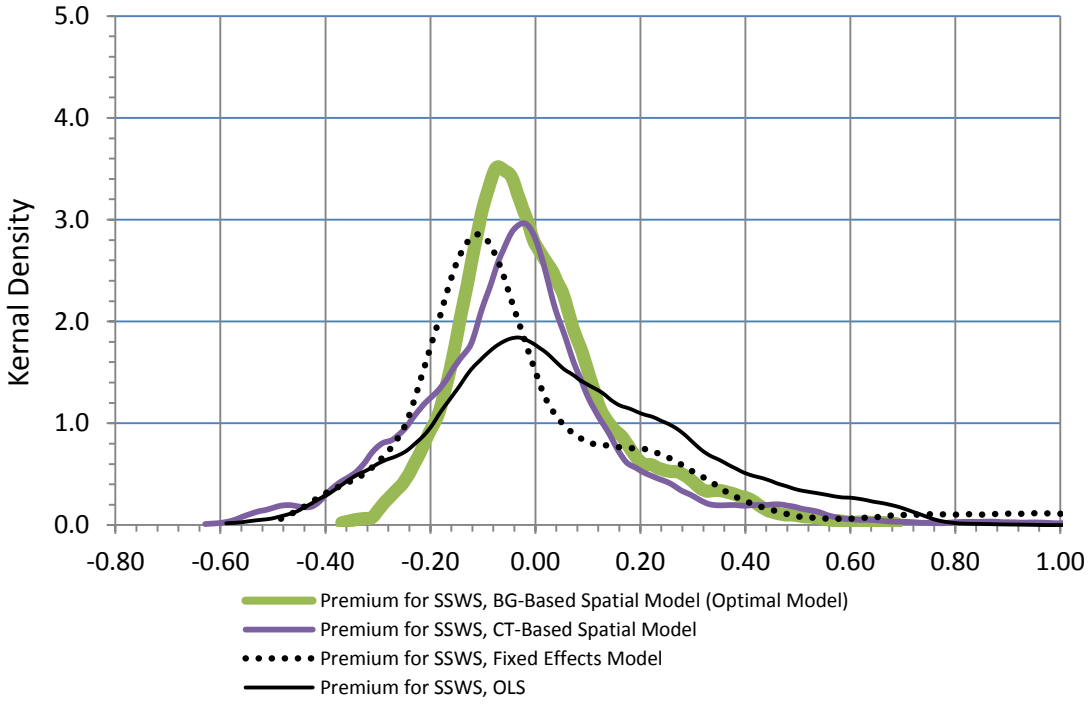
Higher employment density would lead to increases in premium for walkability, although higher population density was not a significant factor. This supports previous studies showing that areas with higher commercial densities generate more walking trips (Boarnet et al., 2011; Joh et al., 2008). However, crime rates did not appear to significantly impact the premium for walkability for MFBs. While

pedestrian collision rate did not significantly impact the premium for walkability, the average total length of sidewalk is negatively associated with walkability premiums for Austin MFB residents. While this appears counter-intuitive, sidewalk presence does not equate to sidewalk use, and areas with long stretches of sidewalks tend to be in newer and more spread out neighborhoods. Other factors such as street connectivity and average speed limits did not appear to significantly impact walkability premiums for MFBs.

7.5 Robustness of Results

We performed the robustness checks using an approach similar to that described in Section 5.4. In Figure 10, we compare the premiums for walkability estimated using different modeling approaches. The distributions of the premiums for walkability estimated from the two spatial hedonic models and the fixed-effects model are generally consistent, confirming the robustness of our results.

Figure 10: Robustness of Results (Multifamily Market Analysis)



Note: The premium for walkability is measured as the elasticity of the property value with respect to SSWS (e.g., 0.3339 means for 1 percent increase in SSWS, the property value would increase by 0.3339 percent). The thickest line represents the distribution of the premiums for walkability estimated by the optimal model, as illustrated by Equation (2).

8.0 CONCLUDING REMARKS

In this study, we investigated the effects of walkability on property values by analyzing three types of housing markets (i.e., single-family homes, condominiums and multifamily homes) in the city of Austin. Key attributes and findings include:

- We used the Street Smart Walk Score as a network-based walkability measurement and found that residents valued street networks in which routing is convenient.
- In order to control for the spatial autocorrelation effects and obtain unbiased estimations, we implemented the Cliff-Ord spatial regression model. We compared our results with those from other modeling approaches confirmed the robustness of our results.
- We investigated how economic values of walkability were influenced by social and built environment characteristics.
- Our results suggest that it may be unrealistic to expect immediate economic returns on investments made to increase walkability in what are commonly referred to as "car dependent neighborhoods". However, walkability may have several other social benefits and it appears there may be benefits to constructing new neighborhoods with walkable features.

Our findings illustrate the potential economic benefits of improving walkability, in addition to the environmental and public health benefits. On this account, we suggest that if improving neighborhood walkability is a goal for communities, the biggest home (and therefore tax) value payoff will be in already walkable neighborhoods. The results indicate that an investment in sidewalks or paths that link a set of homes in a walkable neighborhood to a desirable destination will yield a greater home price increase than a similar investment in a generally non-walkable neighborhood. Rather than getting every neighborhood to some level of walkability, the data suggest the biggest payoffs are in neighborhoods where residents are already inclined to walk. Single-family homes in locations where a car is more likely to be an optional, rather than a required element, show home value increases at twice the rate for a given walkability increase than homes in the next most walkable locations. And the effect of walkability improvements in those 'next most walkable' homes are five times greater than the group of homes with walkability scores below them. The potential economic benefits of walkability also extend to condominiums and multifamily housing as well, with the greatest increase in property values in neighborhoods that are already somewhat walkable.

This research has important policy implications. Given the fiscal constraints facing TxDOT and municipal governments in Texas and throughout the nation, promoting walkability solely on environmental and health benefits may not resonate for policymakers as much as the potential for economic benefits. Our findings show that allocating funding for walkability improvements on neighborhoods where walking is a likely result will yield the greatest dividends for cities through increased property tax revenue as well as increased walking, cycling, and transit use.

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EXHIBIT A: METHODOLOGY

According to Rosen (1974), a valid hedonic framework requires strong assumptions, including market equilibrium, continuum of products, perfect competition and perfect information for buyers and sellers. Maclennan (1977) found that equilibrium could be generally assumed when there is no severe shock in the market. Meese and Wallace (1997) found that the real estate market could adjust quickly to small shocks. We found no severe shock in the market during our study period of January 2010 to November 2012, likely due to the general good health of the Texas economy. Therefore, market equilibrium could be assumed in our study. The assumption of product continuum could also be reasonably satisfied, because of our large sample size and inclusion of various socio-economic covariates. The standard of "perfect information for buyers and sellers" could be guaranteed as information related to the home sales could be easily accessed through the internet and professional realtors, and home inspection is also a common practice. However, it is difficult to justify the "perfect competition" assumption. Fortunately, according to recent theoretical insights by Bajari and Benkard (2005), the demand side of a market could ensure a function connecting price and the characteristics of products even when the market is not perfectly competitive.

Following Redfearn (2008) and Kuminoff et al. (2010), we conducted a Box-Cox transformation test for the price and continuous structural characteristics and obtained a very low power parameter for each of the three housing markets. Therefore, we performed logarithm transformations on the sale price as well as on most continuous structural and neighborhood variables.

Previous hedonic studies of walkability using Walk Score (Cortright, 2009; Pivo & Fisher, 2011; Rauterkus & Miller, 2011) may be subject to biases from omitted variables and spatial autocorrelation effects (SAE). Property values are determined in the real estate market through a complex mechanism and are subject to various factors; therefore hedonic modeling efforts may be subject to empirical challenges from the omitted variable bias and spatial autocorrelation effects. When some of the factors are omitted in the modeling efforts and they are correlated with existing explanatory variables, then the estimation results may be biased and inconsistent (Kennedy, 2003). The SAE may exist when the value of a property is influenced by market values and other characteristics of neighboring properties; omitted variables may also be spatially correlated and cause SAE in the error terms (Case, 1991). Failure to control for spatial autocorrelation effects would lead to biased and inconsistent estimation (Anselin, 1988).

In addition to extensive data collection, we added 34 monthly binary variables (February 2010 to November 2012) in our models to control for market factors.

We performed Moran's I test using the toolbox provided by LeSage (2010) in order to identify the existence of the SAE in our sample. Our Moran's I test provides strong evidence for existence of SAE for each of the three housing markets. Therefore, instead of Ordinary Least Squares, we rely on the spatial hedonic modeling approach, which could reduce the risk of having omitted neighborhood variables and control for SAE as well (Anselin, 1988; Brasington & Hite, 2005; Pace & LeSage, 2008). The following section will provide details of our spatial modeling methods.

We utilized the Lagrange Multiplier Testing Suite by Lacombe (2013) to test whether the SAE exists in the dependent variable or in the error terms. The LM tests results show that the SAE exist in both the dependent variable and in the error terms for each of three markets. Therefore, we decide to estimate the Cliff-Ord spatial hedonic model (Anselin, 1988; Arraiz et al., 2010; Cliff & Ord, 1981; Saphores & Li, 2012) as follows:

$$\begin{cases} \mathbf{ln(P)} = \lambda \cdot \mathbf{W} \cdot \mathbf{ln(P)} + \mathbf{S} \cdot \boldsymbol{\beta}_{\mathbf{S}} + \mathbf{N} \cdot \boldsymbol{\beta}_{\mathbf{N}} + \mathbf{R} \cdot \boldsymbol{\beta}_{\mathbf{R}} + \mathbf{W} \cdot \mathbf{L} \cdot \boldsymbol{\beta}_{\mathbf{L}} + \boldsymbol{\varepsilon}, \\ \boldsymbol{\varepsilon} = \rho \cdot \mathbf{W} \cdot \boldsymbol{\varepsilon} + \mathbf{u}, \end{cases} \tag{2}$$

where

- $\mathbf{ln(P)}$ is a vector of logarithm transformed sale prices;
- $\mathbf{W}$ is a spatial weight matrix;
- $\mathbf{S}$ is a matrix of structural characteristics and monthly binary variables;
- $\mathbf{N}$ is a matrix of neighborhood characteristics;
- $\mathbf{R}$ is a matrix of walkability variable, its square term and the interaction terms (as done by Anderson and West, 2006, and Saphores and Li, 2012) with socio-demographic and walking infrastructure variables;
- $\mathbf{L}$ is a matrix of variables combining $\mathbf{S}$, $\mathbf{N}$, and $\mathbf{R}$ except for the square and interaction terms;
- $\boldsymbol{\beta}_{\mathbf{S}}$, $\boldsymbol{\beta}_{\mathbf{N}}$, $\boldsymbol{\beta}_{\mathbf{R}}$, and $\boldsymbol{\beta}_{\mathbf{L}}$ are vectors of coefficients;
- $\boldsymbol{\varepsilon}$ is a vector of error terms;
- $\mathbf{u} \sim N(0, \sigma^2 \mathbf{I}_n)$ is a vector of error terms without spatial autocorrelation effects.
- λ and ρ are spatial coefficients.

In order to simplify the interpretation of results, we follow the linear transformation methods implemented by Anderson and West (2006) and Saphores and Li (2012), and normalize walkability and its covariates as:

$$\tilde{r}_{ki} = \frac{r_{ki} - \overline{r}_k}{\overline{r}_k} \tag{3}$$

where

- r_{ki} is the original value of variable r_k for property *i*, $k \in \{1, 2, 3, ..., 18\}$;
- $\overline{r}_k$ is the sample mean of the variable r_k;
- $\tilde{r}_{ki}$ is the transformed value of variable r_k for property *i*.

For a property *i,* the component matrix $\mathbf{R} \cdot \boldsymbol{\beta}_{\mathbf{R}}$ in Equation (2) could be written as:

$$\left(\mathbf{R} \cdot \boldsymbol{\beta}_{\mathbf{R}}\right)_i = \tilde{x}_i \left[\beta_0 + \beta_1 \tilde{x}_i + \tilde{\mathbf{Z}}_{\mathbf{i}} \boldsymbol{\delta}\right] \tag{4}$$

where

- $\tilde{x}_i$ is the quantified walkability measurement for property *i*;
- $\tilde{\mathbf{Z}}_{\mathbf{i}}$ is the *i*th row of the matrix of socio-demographic and built environment variables for property *i*;

- $\boldsymbol{\delta}$ is a vector of estimated coefficients for the interaction terms between walkability and the covariates.

The elasticity of price with respect to walkability for property *i* is

$$\begin{cases} e_i^*, & \text{if } \lambda = 0 \\ v_i^* = \mathbf{V}_{ii} e_i^* + \lambda^{-1}(\mathbf{V}_{ii} - 1)(1 + \tilde{x}_i)\beta_{l,x}, & \text{if } \lambda \neq 0 \end{cases} \tag{5}$$

where

- $e_i^* = (1 + \tilde{x}_i)\left[\beta_0 + 2\beta_1 \tilde{x}_i + \tilde{\mathbf{Z}}_\mathbf{i}\boldsymbol{\delta}\right]$;
- $\mathbf{V}_{ii}$ is the component at the *i*th row and *i*th column of matrix $\mathbf{V} \equiv (\mathbf{I} - \lambda \mathbf{W})^{-1}$;
- $\beta_{l,x}$ is the coefficient of the spatially lagged term of walkability.

Following Saphores and Li (2012), we interpret e_i^* as a direct effect and v_i^* as the total effect.

For property *i*, the elasticity of price with respect to a transformed continuous variable *j*, is

$$\begin{cases} e_{j,i}, & \text{if } \lambda = 0 \\ v_{j,i} = \mathbf{V}_{ii} e_{j,i} + \lambda^{-1}(\mathbf{V}_{ii} - 1)\beta_{l,j}, & \text{if } \lambda \neq 0 \end{cases} \tag{6}$$

The effect of changing the value from 1 to 0 on value of the property *i* is:

$$\ln(p_i^1) - \ln(\mathrm{p}_i^0) = \begin{cases} e_{j,i}, & \text{if } \lambda = 0 \\ v_{j,i} = \mathbf{V}_{ii} e_{j,i} + \lambda^{-1}(\mathbf{V}_{ii} - 1)\beta_{l,j}, & \text{if } \lambda \neq 0 \end{cases} \tag{7}$$

For Equation (6) and (7):

- $e_{j,i}$ the direct effect, is the estimated coefficient;
- $v_{j,i}$ is the total effect;
- $\beta_{l,j}$ is the coefficient of the spatially lagged term of the variable *j.*

Following Saphores and Li (2012), we construct a continuity spatial weight matrix so that all neighbors located within the same census block group (2010 Census) would have the same weight of impact on one's property value. Our continuity matrix is doubly stochastic in nature so that the sum of each row or column is equal to 1. According to Pace and LeSage (2009), a doubly stochastic matrix generates the best linear unbiased estimation with smoothing in spatial regression models.

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