Assessing Walkability Through Parking Prices*

Mauricio Arango†

Abstract

This paper uses data on the price and location of parking garages to build a market-driven measure of walkability for New York City and Chicago. The measure is based on a theoretical model of price competition between garage operators that shows how the cost of walking is embedded in parking prices. I use the framework and estimates of the theoretical model to build a proxy f the cost of walking. The proxy is later used to combine variables that characterize pedestrian friendliness—according to the existing literature—into a walkability index. The Walkability Index proposed in this paper strongly correlates with the proportion of no-car commuters in New York City and other variables often associated with walkability.

JEL Classification: O18, R12, R32, and R41

Keywords: Pedestrian-friendly, Walkability, Garages, Parking, Spatial competition, Spatial panel.

1 Introduction

From Barcelona's Superblocks to Oslo's downtown car restrictions, many cities worldwide are shaping their downtown areas into more walkable places. The trend towards walkability is fueled by concerns for the environment, congestion, public health, and a desire for vibrant downtowns that stimulate the local economies. Existing literature has linked walkability with positive outcomes in health (Doyle et al. 2006), pollution (Frank and Engelke 2005), street safety (DiMaggio and Li 2013 and McDonald et al. 2014), and property values (Pivo and Fisher 2011, Boyle et al. 2014, and Gilderbloom et al. 2015), among other benefits.[1] Some of the research mentioned above uses existing walkability measures—as the Walk Score and Walkability Index from the Environmental Protection Agency—to gauge the impact of pedestrian-friendliness on property values, pollution, and other outcomes. These measures assess walkability by bundling into one index a set of variables that describe characteristics related to pedestrian-friendly zones (e.g., proximity to parks, coffee shops, access to sidewalks, and intersection density, among other factors). Choosing what variables form the index and the weight they receive is a process that depends heavily on the author's educated opinion, making the result a subjective measure of walkability.

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†University of Illinois Urbana-Champaign. email: arangoi2@illinois.edu

[1] For more on the benefit of walkable cities see Speck (2012).

In this paper I propose a Walkability Index (WI), where variables are selected and weighted based on their relationship with an implicit valuation of the inconvenience (cost) of walking. This implicit valuation is embedded in parking garage prices—drivers are willing to pay more for parking close to their destination, as they aim for shorter walks (a more detailed explanation is provided in the theoretical model). Since the valuation of the cost of walking is built based on a market price, I call the WI a market-driven index. As in other walkability measures, the WI bundles different locations' characteristics associated with pedestrian-friendly zones (e.g., number of restaurants, the mix of land use, and the number of coffee shops, among others). Unlike existing measures, variables are weighted accordingly to their relation with drivers' implicit valuation of the cost of walking—i.e., a variable strongly related with the cost of walking receives a larger weight than that of a variable with a weak relationship.

The analysis starts by laying out the theoretical framework. The assessment of the cost of walking used in this paper is built around an economic model of spatial competition between garage operators. The theoretical model shows how the cost of walking is embedded in parking prices. The concept is straightforward: imagine you are planning a trip to an appointment; you are choosing where to park on an online prepaid parking platform.[2] Several options appear on your computer or smartphone. Common sense dictates that you are likely to pick your parking spot based on the price and proximity to your destination; drivers are willing to pay more for spots closer to their destination and less for those further away. Garage operators account for this behavior by adding drivers' willingness-to-walk in the price's best response function. Hence, the cost of walking is part of the price charged by garage operators.

Using a novel spatial panel dataset of parking services sold online, I estimate the price's best response function. The result provides a proxy to the cost of walking. To isolate the cost of walking from other factors that can affect the average cost of parking, I control for real estate values using the location price differential—I calculate the location price differential as the census tract fixed effect in a hedonic price equation for properties in New York City and Chicago. I then use the proxy to estimate the relationship of variables that describe location characteristics with the cost of walking. Finally, the estimated parameters are used to ponder the variables that form the WI.[3]

The reasons for using parking services to identify the effect of walking on prices is three-fold: 1) parking is differentiated by location and price, 2) parking is mostly homogeneous on other features (limiting confounding effects), and 3) people walk after they park. Price data from online platforms offer one extra advantage over prices offered on-site;[4] online customers avoid the cost of searching that is inherent to more traditional ways

[2]Examples of this are spothero.com and parkwhiz.com.

[3]The estimated parameters used in this study are meant to be understood as mere relative weights since this is not a causal inference study. The sole goal of this paper is to propose a strategy to objectively asses walkability.

[4]Prices on site are those offer to customer at the garage's physical address.

of parking, thus providing a cleaner relation between parking prices and the willingness-to-walk.

This paper provides estimates of the WI for New York City and Chicago. The proposed WI has a strong correlation with variables that relate to walkability—e.g., the Walk Score and the proportion of workers that commute by means of transportation other than their personal car.[5] This manuscript also provides some insight on the pricing behavior of garage operators by putting empirical flesh on the theoretical model. I use data from Chicago's downtown area to show how competition in prices among garage operators fades as walkability decreases. Also, the estimates of the price's best response function show that a one dollar increase in prices by neighboring competitors produces an average hike in prices of five to ten cents; a result that is evidence of a competitive market.

Due to data limitations, projections of the index are provided only for New York City and Chicago. However, the methodology described in the paper can be applied to cities outside of the original sample as there are no city-specific effects. After this introduction, the rest of the manuscript goes as follows: section 2 reviews previous works on walkability and the parking literature related to this work. Section 3 describes the theoretical model. Section 4 gives an example of the behavior predicted by the model. Section 5 discusses how the econometric model adapts the data to the theoretical model. Section 6 describes the data set. Section 7 explains and shows the numerical results. Section 8 explores the validity of the WI by comparing projections of the WI with similar measures. Lastly, section 9 discusses the paper's limitations along with some final remarks.

2 Previous Literature

Virtually all measures of walkability bundle different variables associated with pedestrian-friendly places into one index. The process used to select and weight variables is what changes. One approach to this process is using surveys to weigh the importance of urban attributes in the walkability index. Kuzmyak et al. (2007) provide a measure of walkability that accounts for access to amenities (walk opportunities) and intersection density at a given location.[6] The weight assigned to each walking opportunity depends on a rank of attractions given by a local survey. Meanwhile, intersections are weighted in a manner such that the weight of a four-way intersection is twice that of a three-way.[7]

A third way is assuming equal weights for all attributes in the walkability measure (uniform method). One popular measure in this category is the Walk Score.[8] The concept behind the Walk Score is simple; a place is deemed walkable if common errands can be easily completed by walking. The Walk Score uses the

[5]These two result only uses data for New York City.

[6]Intersection density is usually deemed a positive factor, as it enables shorter trips through possible shortcuts.

[7]Four-way intersection with a main road received the same weight of a three-way intersection.

[8]walkscore.com

distance to 13 different types of amenities (grocery stores, restaurants, coffee shops, bars, movie theaters, schools, parks, libraries, bookstores, gyms, drug stores, hardware stores, and clothing and music stores) to provide a pedestrian accessibility index. The closer a location is to one of the 13 amenities, the higher the Walk Score. Using equal weights, all the 13 categories are then integrated into one final score that goes from zero to one hundred, where one hundred is the highest degree of walkability and zero the lowest.[9]

Measures that use surveys and the uniform method bind different variables into one index (multidimensional approach). Works like Manaugh and El-Geneidy (2011), Boyle et al. (2014), and Gilderbloom et al. (2015) provide support to a multidimensional approach, where walkability depends on the access to infrastructure (e.g., intersection density or access to sidewalks), characteristics of the urban environment (e.g., mix between commercial and residential use), and proximity to different amenities. However, the questions of what variables should be included in the calculation of a walkability index and how they should be weighted remain unaddressed until now.

Part of the work on the effects of the urban environment on walking has roots in the occupational and public health literature. This background has produced an emphasis on walking as exercise. Frank et al. (2005) produce a walkability index that uses the correlation between physical activity and the urban environment to weigh different variables into one walkability index (those variables are: mix of land use, residential density, and intersection density).[10] Despite being reasonable, measures that use physical activity can be affected by individual health and well-being concerns, providing unreliable estimates of the relation between urban attributes and peoples' willingness-to-walk.

The impact of some of the measures of walkability mentioned above is significant: the Walk Score is not only displayed in real estate websites like Zillow.com, it has also been used in works such as Gilderbloom et al. (2015) and Boyle et al. (2014) to measure the impact of walkability on housing prices. Another example of the impact of these measures can be found in Manaugh and El-Geneidy (2011). In this article, the authors examine the impact of the four walkability indexes described above (Frank et al. 2005, Porta and Renne 2005, Kuzmyak et al. 2007, and the Walk Score) on travel behavior of people in Montreal, Canada.[11] They find that all measures have a significant impact on the probability of walking trips regardless of their nature.[12]

This paper relies on a spatial competition approach that measures people's willingness-to-walk. Models of spatial competition, such as Hotelling (1929) and Salop (1979), show the effect of transportation cost on vendors' pricing strategies. In a nutshell, in a symmetric equilibrium higher transportation costs lead to

[9]A place with a Walkscore between 90 to 100 is labeled as a "Walker's Paradise", and 0 to 24 is a "Car Dependent" location.

[10]This approach is based on the notion that dense areas with a mixed use are more appealing to pedestrians than single-use low density areas. Using physical activity as the target, the authors tested different sets of parameters and chose the one with the highest explanatory power.

[11]The authors use the 2003 Montreal Origin–Destination survey.

[12]The authors consider two types of trips: school or shopping.

higher prices. Also, in an asymmetric framework, higher transportation costs can lead to higher differences in prices between locations. Froeb et al. (2003) and Arnott (2006) use this type of spatial competition framework to analyze the behavior of garage operators. In their models, the demand for parking spots depends on the cost of walking from the garage to the driver's destination. In line with this, there is evidence of the link between the walking cost and the differences in prices between locations; papers on this topic have found that the cost of walking segments the parking market, enabling monopolistic competition among garage operators (see Froeb et al. 2003, Choné and Linnemer 2012, Kobus et al. 2013, and Inci 2015).

In general, the parking literature assumes the cost of walking is the opportunity cost of time (see Arnott and Rowse 1999, Arnott and Inci 2006, Arnott and Rowse 2009, and Anderson and de Palma 2004 among others). This paper assumes that the urban environment affects people's willingness-to-walk, hence influencing their parking decisions—drivers can be deterred from using a garage if the cost of walking to their destination is increased by the location's unwelcoming surroundings.[13] The relation between the urban environment, the cost of walking, and how this relation is embedded in the price decisions of garage operators is at the heart of the theoretical framework used in this paper to produce a market-driven measure of walkability.

3 The Flat City Model

The model presented in this section is built on the premise that willingness-to-walk changes across locations—the concentrations of pedestrians in promenades and downtown areas suggest that people are more likely to walk in places with some characteristics. Drivers' willingness-to-walk affects prices charged by garage operators; garage operators in pedestrian-friendly zones can attract customers by lowering prices, while operators in unfriendly locations achieve little by cutting prices. To illustrate these relations, I use a modified version of the model in Arnott (2006), where the cost of walking is a function of the location's attributes.

3.1 The Demand for Parking

Consider a flat city (i.e., with the same cost of moving in any direction) divided into small tracts, each formed by a few blocks laid in a uniform street grid. Each tract is described by a vector of attributes Θ. Garages are placed in fixed locations that are at equal distance from each other,[14] their sole business is renting parking spots by the hour. Two types of clients rent these parking spots: discount customers and loyal customers. Loyal customers are drivers with strong preferences for one location; an example of this is everyday commuters and customers with a high opportunity cost of time. There are many reasons why

[13] One possible example of unwelcoming locations for pedestrians, are places surrounded by major highways or overpasses.
[14] This is a consequence of the uniform demand for parking within each tract.

drivers prefer one garage above all; for instance, the garage is located in the same building as their workplace or offers amenities valued by customers (e.g., valet parking, elevators, or outlets for electric vehicles). On the other hand, discount customers are drivers that shop around looking for low prices. They regard parking as a homogeneous service only differentiated by price and location. Hence their parking decision is based on the cost per unit of time (r) and the cost of walking (w) back and forth to their destination. For the average discount driver, the cost of walking one unit of distance depends on the average cost of time (v) and the location's characteristics ($w(v, \Theta)$). Then, if the average discount driver parks for T hours at a garage that is at a distance x from their destination, the full price of parking is $rT + 2xw(v, \Theta)$.

3.1.1 Market Area

Discount drivers choose the garage with the lowest full price. Every garage is surrounded by a group of destinations for which the garage is the closest parking provider. For some of these destinations—the closest ones—the garage offers the lowest full price. These destinations are within the garage's market area (M), as named in Arnott (2006). A destination is located at the border of the market area if the full price of two garages is equal, this is:

$$rT + 2bw = \bar{r}T + 2(d - b)w, \tag{1}$$

where d is the distance between garages, b is the distance from the garages to the edge of the market area, and $\bar{r}$ is the rate per unit of time charged by the neighboring garage (see figure 1).

The square street grid makes taxi-cab distance the relevant metric between two locations. This layout and the uniform distribution of garages generate square-shaped market areas, as shown in figure (1). Using the shape of the market area and equation (1), it follows that the market area is:

$$M = 4\left(\frac{(\bar{r} - r)T}{4w} + \frac{d}{2}\right)^2.$$

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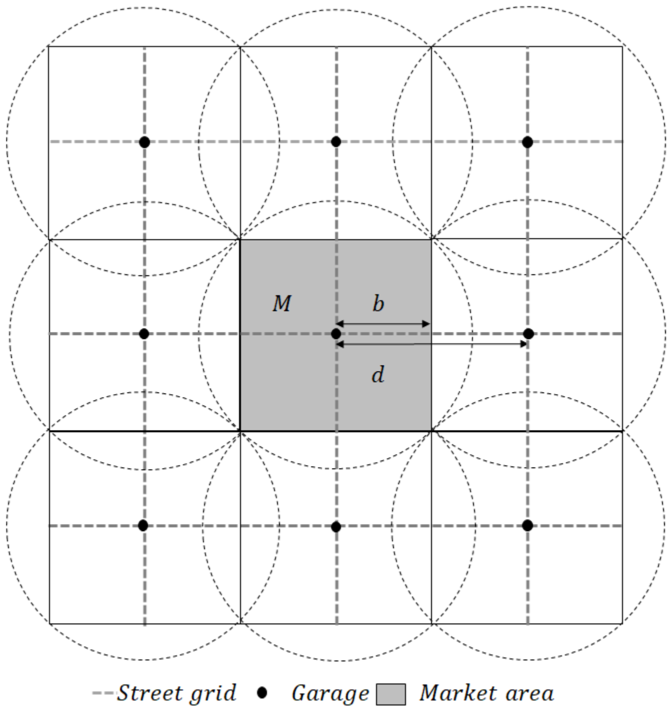
Figure 1: Street Diagram



3.2 Garage Operators

For the sake of simplicity, I assume that garage operators can always rent a spot to a loyal customer. Hence the price paid by those customers (c) constitutes the opportunity cost of renting a spot to a discount driver.[15] Discount drivers visit a wide range of businesses and amenities (coffee shops, doctors' offices, and parks, among many others), making the demand for parking spots per unit of area (D) uniformly distributed within each tract. The representative garage operator takes the demand for parking and the competitor's price as exogenous; visits to each tract and hence parking demand is driven by amenities and not by parking prices. Under this framework, the profit maximization problem, at time t, is described by:[16]

$$\max_{r_t} \ \Pi_t = r_t M D_t T - c M D_t T$$

subject to:

$$M = 4\left(\frac{(\bar{r}_t - r_t)\,T}{4w\,(v,\Theta)} + \frac{d}{2}\right)^2. \tag{2}$$

[15]An implicit assumption is that loyal customers pay a price that is above the cost of providing one parking spot.
[16]In a high frequency framework—hour by hour—the only variables that change are: price by unit of time (r) and parking spot demand by unit of area (D).

Solving the garage operator optimization problem yields the price best response function:

$$r_t = \frac{2}{3}\left(c + \frac{dw\left(v,\Theta\right)}{T}\right) + \frac{1}{3}\bar{r}_t. \tag{3}$$

Equation (3) shows how parking prices are a function of one dynamic factor: competitor's price $(\bar{r}_t)$, and two static factors: the opportunity cost (c) and the cost of walking $\left(\frac{dw(v,\Theta)}{T}\right)$. From the relation in (3), it follows that in pedestrian-friendly locations $(w\left(v,\Theta\right) \approx 0)$ price competition $\left(\frac{\bar{r}_t}{3}\right)$ will represent a larger share of the total price. Consequently, price competition among garage operators is fiercer in walkable locations because of the lower cost of switching garages.

4 Prices, Segmented Markets, and Walkability

The situation described in section 3.1 can be summarized by saying that drivers park in garage i at time t, if and only if it offers the lowest full price:

$$\begin{gathered} r_{i,t}T + 2bw\left(v,\Theta_i\right) \leq \min\left(r_{j,t}T + 2\left(d-b\right)w\left(v,\Theta_j\right)\right) \\ \forall i \neq j. \end{gathered} \tag{4}$$

Equation (4) describes how drivers avoid parking at garage j because prices are too high or because it is costly to walk from the garage to their destination. Let's think of two neighboring locations called north and south. The two locations are divided by a barrier that makes moving between locations costly, e.g., a highway or overpass that makes walking unpleasant. The cost of crossing this barrier can be such that visitors of one location can't be lured by lower prices to cross to the other side. In this case, the physical barrier creates a market segmentation that disconnects prices in the two locations—no matter how close competitors are, changes in the price of a garage only affect competitors on the same side of the barrier.

A situation like the one described above can be found in Chicago's downtown, in the area surrounding Congress Parkway. Readers familiar with downtown Chicago will recognize that north of Congress Parkway is Chicago's main business area. It has important buildings like the Willis Tower, the Board of Trade, and city hall. South of the Congress Parkway is a less busy and more residential area. The average two-hour price for an off-street spot north of Congress Parkway is lower during weekends as the demand by weekday commuters is reduced (figure 2). Meanwhile, the weekend effect is not observed south of Congress Parkway (figure 3). The result not only suggests that garages on the south side are less affected by changes during the weekend, but that there is little competition between garages on the north and south sides, even if they are close to each other.

Figure (4) looks deeper into the weekend effect by plotting the estimates of $\beta_{j,\ WE}$ from the following model,

$$r_{j,t} = \beta_j + \beta_{j,\ WE} 1_{t,\ WE} + \sum_{h=3}^{18} \beta_h 1_{t,\ h} + \sum_{h=3}^{18} \beta_{h\ WE} 1_{t,\ h} 1_{t,\ WE} + \epsilon_{j,t}, \tag{5}$$

where $1_{t,\ h}$ is the indicator functions of the h hour of the day, and $1_{t,\ WE}$ is an indicator function for the weekends. The X-axis of figure (4) is distanced to the City Business District (CBD).[17] Chicago's CBD is on the north side of Congress Parkway, so all garages on the north side are on the left-hand side of figure (4), and garages on the south side are on the right-hand side. Garages on the south side have a consistently smaller response to the weekend effect than their competitors on the north side, suggesting a disconnect between both locations. By no mean this exercise is proof of causality. However, in the lights of the model this disconnect in prices can be the consequence of two things: The discount offered by garages on the south side is such that it leaves little to no room to reduce prices during the weekend, or garages south of Congress Parkway only engage in competition with each other. In both cases the effect of crossing and walking south of Congress Parkway is evident.

Figure (4) shows a higher dispersion of the weekend effect on the north side. One potential reason for this is that the north side has a diverse mix between tall office buildings, theaters, hotels, and shopping areas. In contrast, the south side is a more homogeneous area mainly populated by residential buildings. The heterogeneous mix of buildings and amenities affects the opportunity cost of garage operators. For example, a garage located in the basement of a tall office building has a high opportunity cost during weekdays and a low opportunity cost during weekends. Meanwhile, a garage that serves a theater will have a higher opportunity cost during show days.

5 Estimation

The strategy to produce the WI has two elements: isolating the proxy of the cost of walking and weighing each location characteristic on the WI based on its relationship with the proxy. To isolate the proxy of the cost of walking I estimate a spatial approximation of equation (3) as described in section 5.1. I then run a regression of the proxy of the cost of walking and the location characteristic to calculate the weighs used to produce the WI (section 5.2).

[17]CBD is defined as the location of the city hall.

Figure 2: Street Diagram

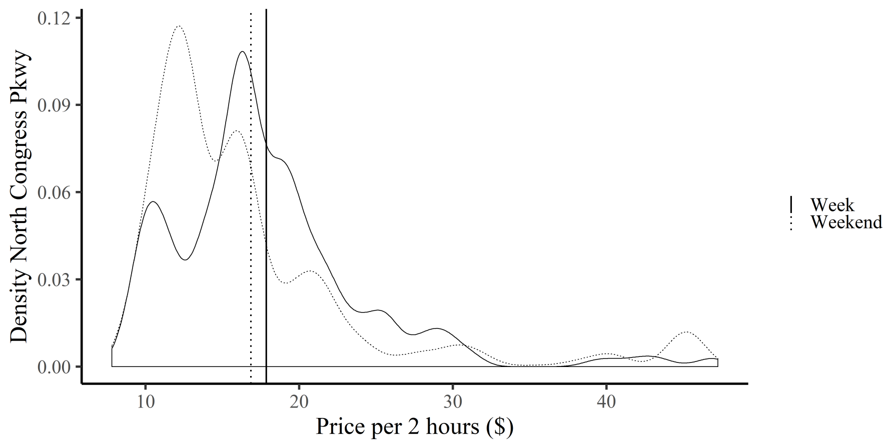


Figure 3: Street Diagram

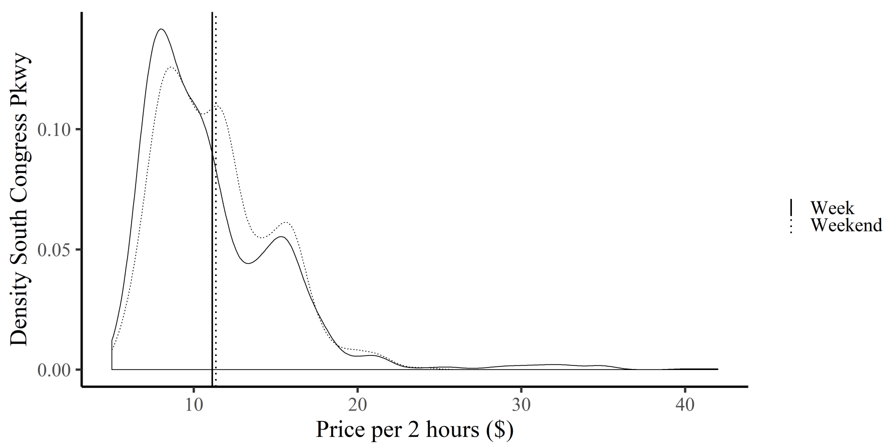
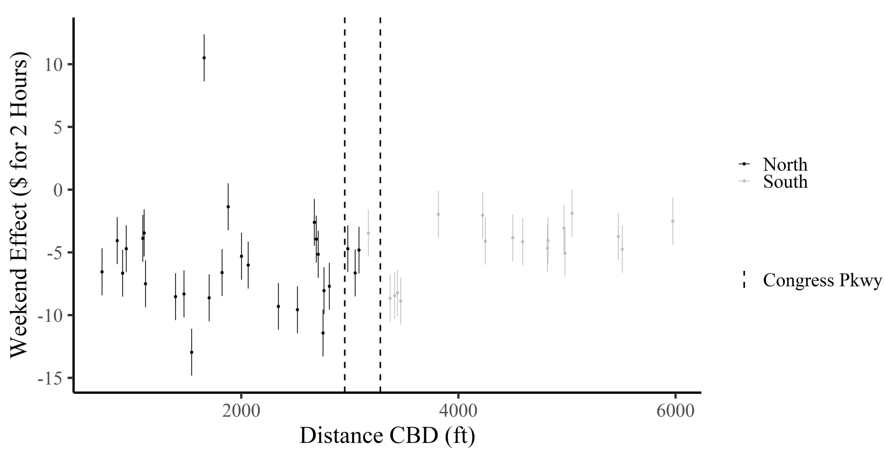


Figure 4: Street Diagram



5.1 Prices Best Response

Expression (3) assumes symmetry and uniformity. Under these assumptions it is easy to isolate the competitors that define the market area of each garage—the only competitors relevant are the closest in each direction. However, cities are irregular, making symmetry and uniformity more a novelty than a rule. To finesse this difficulty, I simulate an average competitor that defines the market area of each garage. The average competitor is built based on the price of surrounding parking lots. Each competitor j is weighted by $1/d_{ij}$, where d_{ij} is the distance between garage i and competitor j. In order to produce the average competitor, I define a W matrix that weighs the prices of each competitor within a radius of length d:

$$W = \begin{bmatrix} 0 & W_{1,2} & \cdots & W_{1,n} \\ W_{2,1} & 0 & & \vdots \\ \vdots & & \ddots & W_{n-1,n} \\ W_{n,1} & \cdots & W_{n,n-1} & 0 \end{bmatrix}$$

$$W_{jk} = \begin{cases} W_{ij} = \frac{1}{d_{jk}} \text{ if } d_{ij} \leq d \\ W_{ij} = 0 \text{ if } d_{ij} > d \end{cases} .$$

Using the definition of W to represent expression (3) in a spatial panel framework, yields the following regression equation:

$$r_{it} = \alpha_i + \lambda W_i r_t + \varepsilon_{it}, \tag{6}$$

where α_i accounts for the unit cost plus the cost of walking of the average driver $\left(\alpha_i = \frac{2}{3}c_i + \frac{2d^n w_i(v,\Theta_i)}{3T}\right)$.

This approach uses a simulated market area that can differ from the real one. Figure (5) illustrates two simple examples of this situation, where the gray polygon represents the real market area, and the stripes square the simulated market area used in equation (6). As both areas can differ, it is reasonable to assume that the price signal of the average competitor has a smaller effect on r_{it} than that predicted in equation (3)—hence, estimates of λ are expected to be equal to or less than $1/3$.

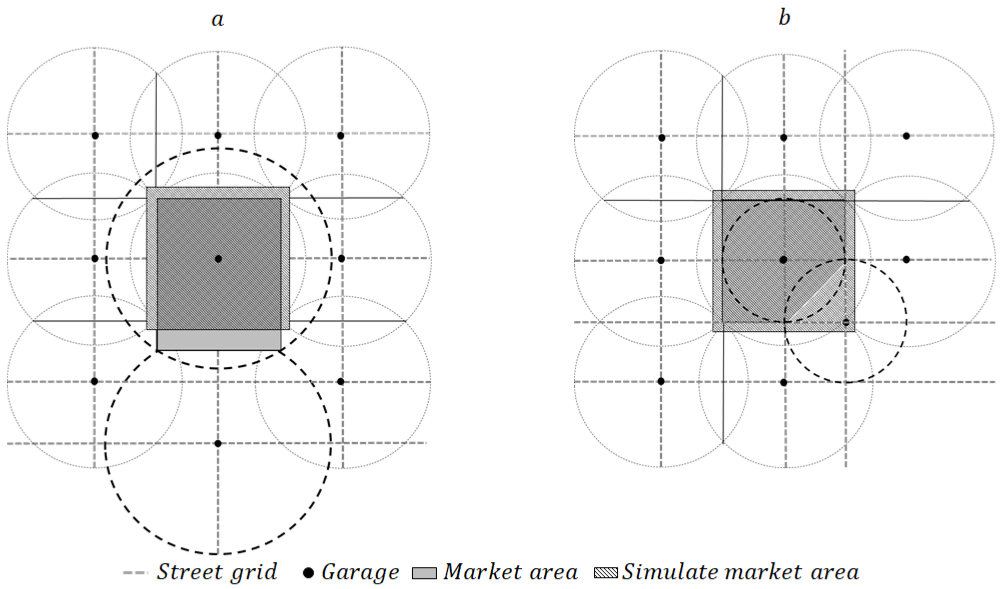
Table (1) shows the estimates of λ in equation (6) for different definitions of the threshold in the W matrix. The results fluctuate between 0.05 and 0.11 all values below the $1/3$ threshold imposed by the theoretical model. Furthermore, a simple hypothesis test provides evidence that estimates of λ are below $1/3$, supporting the idea of a fuzzy price signal—$W_i r_t$ in equation (6) is an imperfect approach to $\bar{r}_t$ in equation (3).

Table 1: Estimates Best response Function.

Different Definitions of the W Matrix by Distance Thresholds

	W distance thresholds (miles)			
	0.25	0.5	0.75	1
	(1)	(2)	(3)	(4)
λ	0.05	0.05	0.11	0.09
	(0.00)	(0.01)	(0.01)	(0.01)
P-val $\lambda \leq 1/3$	>0.99	>0.99	>0.99	>0.99
R^2	0.80	0.82	0.78	0.80

Figure 5: Street Diagram



5.2 Cost of Walking

As described before, the cost of walking one unit of distance depends on the opportunity cost of time and the characteristics of a location $(w(v, \Theta))$. Assuming that a first-order Taylor expansion around the origin provides a good approximation of w yields that:

$$w_i = \frac{\partial w}{\partial v} v + \frac{\partial w}{\partial \Theta} \Theta_i + \varepsilon_{wi}, \tag{7}$$

where $\frac{\partial w}{\partial \Theta}$ is a vector that contains the partial derivatives of w with respect to each variable in Θ, and ε_{wi} is the difference between the first-order approximation and the cost of walking. From (3), (6), and (7) follows that:

$$\hat{\alpha}_i = a + \mu_i + \rho\Theta_i + \eta_i, \tag{8}$$

where $a = \frac{2d}{3T}\frac{\partial w}{\partial v}v$, $\rho = \frac{2d}{3T}\frac{\partial w}{\partial \Theta}$, $\mu_i = \frac{2}{3}c_i$, and $\eta_i = \frac{2d}{3T}\varepsilon_{wi}$.

Vector ρ provides a measure of the impact of Θ on the cost of walking, as all elements in ρ ar multiplied by $\left(\frac{2d}{3T}\right)$, and since $\left(\frac{2d}{3T}\right) > 0$, ρ can be used as relative measures of the impact of Θ on the cost of walking, as shown in section 7.

5.2.1 Controls, Real Estate Values (μ)

To control for the unit cost of one parking spot (opportunity cost c) I use the census tract real estate value differential (μ). Controlling for μ mitigates potential bias of the OLS estimators of ρ in equation (8)—Location characteristics (Θ) that affect the cost of walking (w), can be correlated with the price of long term contracts (c) causing omitted variable bias.[18]

To Calculate μ I estimate a hedonic equation of real estate values where the price (p) of property i in census tract j, is a function of property characteristics (X_i) and a census tracts indicator (μ_j), this is:

$$p_i = \beta_p X_i + \mu_j + \varepsilon_{pi}.. \tag{9}$$

Estimates of equation (9) are presented in table (2) in the appendix.

5.2.2 Location Characteristics and the Cost of Walking

To calculate the weight of each location characteristic on the WI, I estimate the following equation:

$$\hat{\alpha}_i = a + \beta_\alpha \hat{\mu}_j + \rho\Theta_i + \varepsilon_{\alpha i}, \tag{10}$$

where $\hat{\alpha}$ is a proxy of the cost of walking, (Θ) a vector of location characteristics, and $\hat{\mu}$ a location property value differential,

Estimates of all parameters in equation (10) are presented in the appendix in table (3). A word of caution: despite controlling for property values, estimates of ρ can still be confounded by the effect of Θ_i on c_i. Given the data available to me at the moment, I can't provide unbiased estimates of $\frac{\partial w}{\partial \Theta}$. Having said this,

[18]For example: charming pedestrian-friendly locations can attract firms that pay high wages (e.g., financial institutions or law firms). High incomes employees can afford expensive long term parking contracts increasing the opportunity cost of renting to a discount driver.

estimates of equation (10) should not be interpreted as measures of the impact of the urban environment on walkability.

6 Data

The model presented in section 3 describes a market where prices can be easily observed and modified at no cost. Online parking platforms meet these two conditions: garage operators can conveniently change prices through the platform, and all the information about prices, location, and amenities, is free and accessible to all customers with an internet-enabled devices. On the other hand, the model is not a good fit for more traditional parking markets—this is markets where operators publish their prices on billboards that are costly to modify, and drivers cruise around the block comparing garage prices from billboards, that often are not visible from the street. A good example of this traditional parking market is shown in the appendix; figure (11) shows pictures of different garages in Chicago where prices are too far to be seen from the street (pictures 1, 2, 4, and 5), or prices are costly to modify since they are printed on a billboard (pictures 3 and 5).

In line with the above, I use data from online platforms that rent parking. To estimate equation (6), I collected data on prices, location, and characteristics of 2331 parking lots listed on parkwhiz.com; a website that rents off-street parking offered by different providers in all major cities in the United States. Information on prices and availability was collected every hour during 2 months (from July 25th 2019 to August 25th 2020). The dates of the data collection process provide a sample with no major seasonal irregularities like significant changes in the weather or big holidays. Since most locations were unavailable at some time during the data collection period, the original data set has several missing values. In order to obtain a balanced panel, I used the average price for every hour of the week between 6:00 am and 11:00 pm. After drooping all locations with missing observations, the data set is reduced to 903 locations with 119 observations per location.[19]

To weigh all location characteristics (intersection density, mixed land use, and proximity to 13 different amenities) in the WI, I estimated equation (10) using the following data:

Variables in Θ

- Intersection density at census tracts level (2010 census) from the United States Environmental Protection Agency (EPA).

[19] The 119 observations are the result of using 17 hours (6:00 am to 11:00 pm) for the 7 days of the week.

- Mix of land use, commercial and housing in every census tracts (2010 census) from the EPA.
- The proximity of each garage to thirteen different amenities[20], data collected using the Google places API.

Element in μ

- The values of μ for each location are obtained by estimating equation (9) using CoreLogic real estate data for New York City and Chicago. The data set provides the location, square footage, number of bedrooms, number of bathrooms, and other characteristics of 221,094 real state transactions.

Finally, in order to test the validity of the WI, the paper uses data on the proportion of no-car commutes,[21] the Walk Score,[22] and the EPA's National Walkability Index to check the correlation between the WI and these variables.[23] Descriptive statistics of the data are provided in table (4) of the appendix.

7 The Walkability Index

In this section I use the estimates of ρ in equation (10) to build the WI. The existing literature predicts that all variables in Θ reduce the cost of walking, hence all parameters in ρ should be negative. My results show something different; some parameters are negative and some are positive. There are many reasons why parameters in ρ can take positive values,[24] however this discussion goes beyond the reach of this paper as this is not a causal inference study. In order to avoid contradicting some of the existing literature with insufficient evidence, I only use variables with a negative parameter in vector ρ to build the WI. Based on the above, I define $\underline{\hat{\rho}}$ as the subset with all the negative values in $\hat{\rho}$. Following this definition, the proposed WI has the following formula:

$$\text{wi} = |\underline{\hat{\rho}}|\underline{\Theta}, \tag{11}$$

where $\underline{\Theta}$ is the vector that contains the subset of variables that have a negative relation ($\hat{\rho} < 0$) with the proxy of the cost of walking ($\hat{\alpha}$). This selection process leads to the following set of variables ($\underline{\Theta}$) and weights ($|\underline{\hat{\rho}}|$) that form the WI:

- Number of restaurants in one mile with a weight of 2.11

[20] Those amenities are: grocery stores, restaurants, coffee shops, bars, movie theaters, schools, parks, libraries, bookstores, fitness centers, drug stores, hardware stores , and clothing and music stores.
[21] from the Census Transportation Planning Products Service https://ctpp.transportation.org/.
[22] For more information visit www.walkscore.com/cities-and-neighborhoods/
[23] All data is at census tracts level.
[24] e.g., bias estimators or genuine negative relations.

- Mix of land use, entropy,[25] with a weight of 1.17
- Number of clothing stores in one mile with a weight of 0.31
- Number of coffee shops in one mile with a weight of 0.20
- Number of libraries in one mile with a weight of 0.09
- Number of grocery stores in one mile with a weight of 0.06
- Number of book stores in one mile with a weight of 0.03
- Number of bars in one mile with a weight of 0.02

Values of $\hat{\rho}$ are used in absolute values for the sake of interpretation. In order to further simplify the reading of the WI, I modified the measure provided in equation (11) into an equivalent indicator that goes from 0 to 100 by using the following transformation:

$$\mathrm{WI} = \frac{\mathrm{wi}}{\max(\mathrm{wi})} \times 100.$$

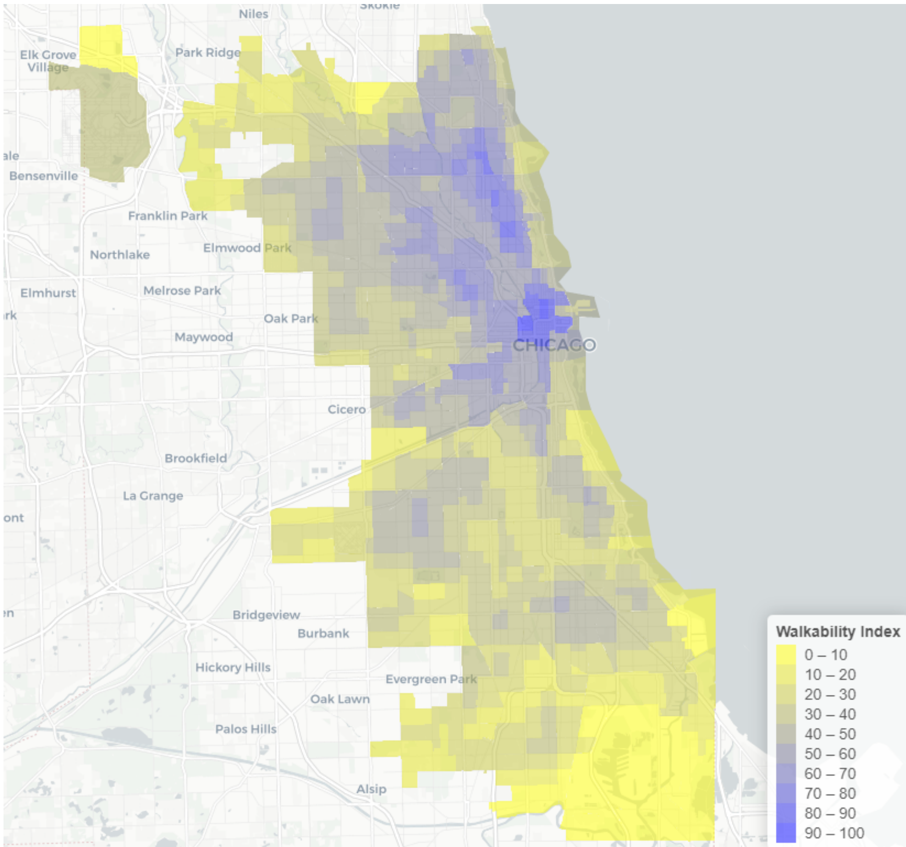
The measure of walkability provided here is compares locations. As such,it should be read as an ordinal number, indicating that on location is more or less walkable than other but not by how much.[26]

Figures (6) and (7) present projections of the WI for Chicago and New York City. The indicator shows that the most walkable areas are the loop in Chicago, Midtown Manhattan, and Brooklyn in New York. In all cases, the city tends to become less walkable as one moves away from these areas.

[25] Measure of entropy calculated by the EPA using eight different categories. For more information see variable D2b_E8Mix at www.epa.gov/smartgrowth/smart-location-mapping

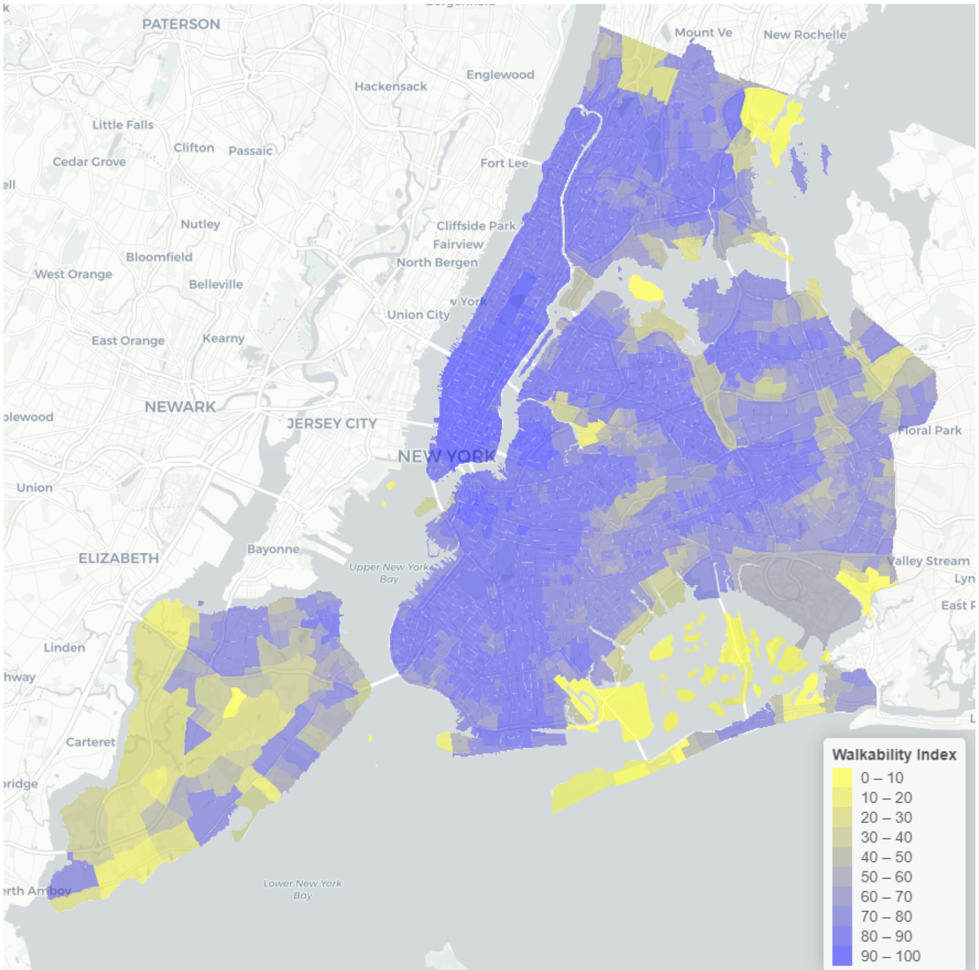
[26] For example if location A has a WI of 60 and location B a WI of 66, the WI indicates that location B is more walkable than A, but not that location B is 10% more walkable than A

Figure 6: Chicago Walkability Index (2010 Census Tracts).



A more detailed version of this map can be found in www.mauricio-arango.com/walkability-index-chi

Figure 7: New York City Walkability Index (2010 Census Tracts).



A more detailed versions of this map can be found in www.mauricio-arango.com/walkability-index-nyc

8 Validating the Walkability Index

As willingness to walk is an unobservable variable there is no unique way to prove the validity of any walkability measure. One plausible way of checking the coherence of the WI is by looking at its relation to other variables related to walkability.

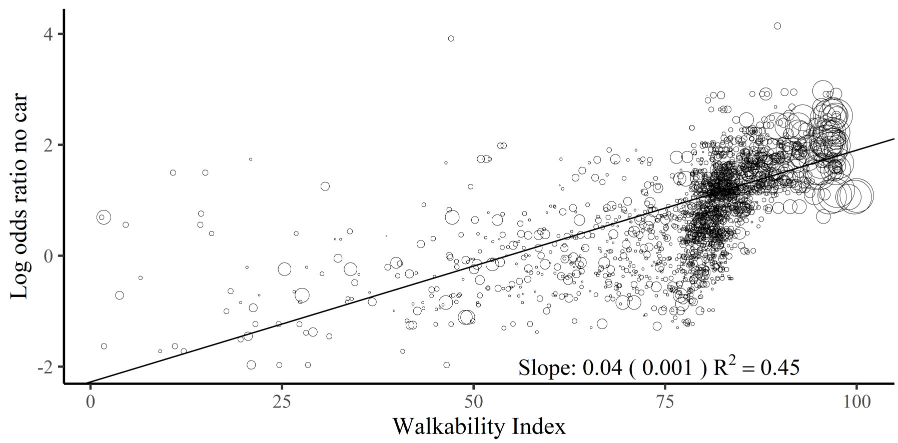
Figure (8) shows the relation between the WI and the log odds ratio of a no-car commute for all census tracts in New York City.[27] The correlation coefficient is above 0.65. This connection is relevant as walking is the first option for the last leg of a trip in public transit and other alternative means of transportation.[28]

Figure (9) compares the WI with the Walk Score, and figure (10) compares the WI with the EPA's National Walkability Index. The correlation coefficient between the WI and Walk Score is 0.82. This strong

[27] The regression and figure are weighted by the number of workers in each census tract.
[28] Alternative to individual vehicle.

correlation is consistent with the fact that some of the amenities used in the Walk Score are present in the WI, but with different weights. On the other hand, the WI shows a weak correlation with the National Walkability Index. Part of this divergence comes from the fact that some variables used in the National Walkability Index—those that do not describe the physical attributes of a location—where excluded from the WI.[29]

Figure 8: Walkability Index and Percentage of No-Car Commuters by Census Tract in New York City

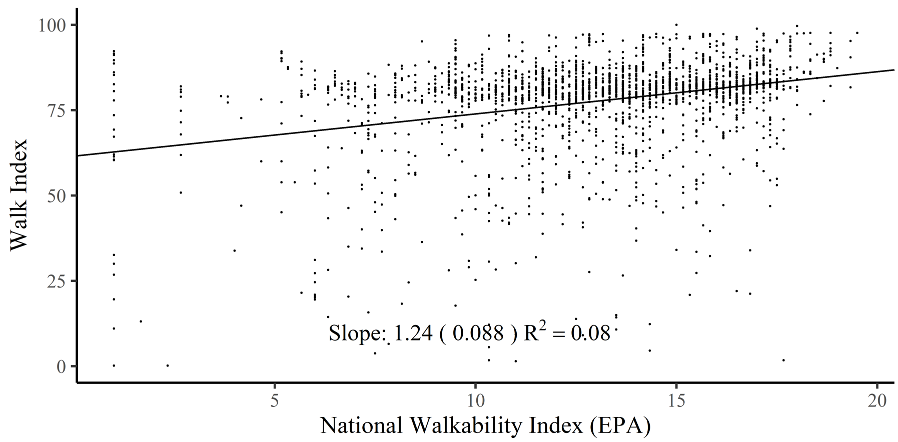


The size of the marker is proportional to the number of workers in each census tract. The regression is weighted by the number of workers in each census tract.

Figure 9: Walkability Index and The Walk Score

[29]e.g., Predicted commute mode and proportion of workers that carpool.

Figure 10: Walkability Index and The National Walkability Index



9 Final Remarks

This paper uses estimates of a spatial competition model of garage operators to produce a proxy of the cost of walking. The proxy of the cost of walking is used to parameterize a market-driven Walkability Index that depends on the characteristics of each location. The resulting index summarizes some of the existing theories and measures of walkability.The used methodology can be applied in cities outside of the original sample. This methodology also provides an objective way to include new characteristics in future measures. A simple validation exercise shows that the Walkability Index built in this paper has a strong positive correlation with other measures of walkability and with the fraction of no-car commuters in New York City. The objective of this paper is to propose an objetive way to build a Walkability Index. It is not the intention of this paper to prove causality nor to provide unbiased estimators.

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Appendix

Table 2: Estimates Equation (9)

	Estimate	Std. Error
Square footage	77.52	1.50
Number of bathrooms	112776.69	1498.21
Number of bedrooms	4446.63	725.76
Adjusted R^2		0.49
Number of observations		221094

Table 3: Estimates Equation (10)

	Estimate	Std. Error
Intercept	53.41	12.55
Tract price differential (μ)	2.63	0.28
Street intersection density	0	0
Mix of use type	-1.17	1.45
Number of grocery stores in one mile	-0.06	0.11
Number of coffee shops in one mile	-0.2	0.15
Number of movie theaters in one mile	0.6	0.08
Number of parks in one mile	0.17	0.08
Number of bookstores in one mile	-0.03	0.1
Number of drug stores in one mile	0.03	0.11
Number of clothing stores in one mile	-0.31	0.06
Number of restaurants in one mile	-2.11	0.74
Number of bars in one mile	-0.02	0.17
Number of schools in one mile	-0.17	0.35
Number of libraries in one mile	-0.09	0.08
Number of fitness centers in one mile	0.52	0.13
Number of hardware stores in one mile	0.39	0.07

Table 4: Descriptive Statistics

	Mean (1)	Median (2)	SD (3)	Min (4)	Max (5)
Mix of employment types and occupied housing	0.63	0.66	0.18	0.03	0.96
Mix of employment types	0.64	0.68	0.17	0	0.93
Street intersection density	128.65	100.34	129.63	0	1155.68
Number of grocery stores	3.26	3	2.52	0	14
Number of coffe shops	5.09	4	3.84	0	20
Number of movie theater	1.13	0	1.76	0	13
Number of parks	1.51	1	1.46	0	9
Number of bookstores	1.53	1	1.67	0	10
Number of drugstores	2	2	1.8	0	8
Number of clothing stores	1.27	0	2.43	0	19
Number of restaurants	10.89	11	5.44	0	20
umber of bars	7.37	7	5.15	0	20
Number of schools	6.13	6	4.29	0	20
Number of libraries	1.85	1	2.17	0	12
Number of fitness center	3.4	3	2.94	0	17
Number of hardware stores	0.92	0	1.24	0	7

Figure 11: On-the-spot Parking Price