# Assessing Walkability Through Parking Prices*

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**Abstract**

This paper uses data on the price and location of garages to build a market-driven measure of walkability for New York City and Chicago. The concept is as follows: as drivers wish to park close to their destination, the cost of walking is embedded in parking prices. The paper lays out and estimates a theoretical model of price competition between garage operators that explains the dynamic between parking prices and the cost of walking. This model is later used as the framework to measure the cost of walking. Based on the estimated cost of walking, I calculate a Walkability Index that uses data on the location characteristics of all census tracts in New York City and Chicago. The Walkability Index presented in this paper combines several elements considered to affect walkability by the urban planning literature. The index shows a strong correlation with the proportion of non-car commuters.

**JEL Classification: O18, R12, R32, and R41**

*Keywords*: pedestrian-friendly, walkable, amenities, garages, parking, price competition, spatial panel.

## 1 Introduction

The last decade has seen a strong push towards pedestrian-friendly cities. From Barcelona's Superblocks to Oslo's downtown car restrictions, many cities worldwilde 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. 2007), pollution (Frank and Engelke 2005), street safety (DiMaggio and Li 2013 and McDonald et al. 2014), property values (Pivo and Fisher 2011 and Boyle et al. 2014), crime (Gilderbloom et al. 2015), and social fabric (Leyden (2003)), among other benefits. The

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existing evidence of positive outcomes is compelling enough to produce waves among some urban planners and city authorities that advocate increasingly for pedestrian-friendly cities, as described in Speck (2012).

Real estate research (e.g. Gilderbloom et al. 2015, Boyle et al. 2014), along with investments and policies aimed to build walkable streetscapes, raise the question of how to measure walkability. Current measures of walkability are based on the literature's consensus on the characteristics of a pedestrian-friendly area. For instance, the Walk Score uses proximity to different amenities to measure walkability —locations with a wide range of amenities nearby have a high score.[1] In the same vein, the National Walkability Index from the Environmental Protection Agency (EPA) combines characteristics like; street intersection density, the mix of land use (such as residential, office, industrial), and percentage of occupied housing to assess the degree of walkability. The way variables are selected and weighted in the Walk Score, the National Walkability Index, and other walkability measures is based on the authors' educated opinions. As such, these measures are subjective.

This paper produces an objective Walkability Index (WI), where variables are selected and weighted based on their relation with an indirect valuation of the cost of walking. As in other walkability measures, the WI bundles different locations' characteristics associated with pedestrian-friendly zones. However, unlike existing measures, the variable selection and weighting process depend on a market valuation, making the WI a market-driven index. To my knowledge, this is the first index of walkability that is based on an indirect valuation of people's willingness to walk obtained through market prices.

The assessment of the cost of walking used in this paper is based on 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 your next trip to an appointment, and 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 will be willing to pay more for spots closer to their destination and less for those further away. In this sense, the difference in prices is partially affected by the willingness-to-walk.

The reasons for using parking services to identify the effect of walking on prices is three-fold: 1) parking is differentiated by location, 2) parking is mostly homogeneous on features other than location, and 3) people walk after they park. As used in this paper, Price data from online platforms offer one extra advantage over prices offered on-site.[3] online customers avoid the cost of searching and cruising that is inherent to more traditional ways of parking, thus providing a cleaner relation between parking prices and the willingness-to-

[1]The Walk Score, considers amenities in a radius of 2 miles or less.
[2]Examples of this are spothero.com and parkwhiz.com.
[3]Prices on site are those offer to customer at the garage's physical address.

walk.

Using a novel spatial panel data set of parking services sold online, I estimate the theoretical model described in the paper. The result provides an approximation to the cost of walking. An approximation that is later used to weigh the importance of the location characteristic in the WI. In order 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 estimate the location price differential as the census tract effect in a hedonic price equation.

This paper provides estimates of the WI for New York City and Chicago. The proposed WI has a correlation above 60% with the proportion of workers who don't use their personal car for commuting.[4] This manuscript also provides some insight on the pricing behavior of garage operators. By the estimates of this paper, a one-dollar increase in prices by neighboring competitors produces an average hike in prices of five to ten cents. Finally, the paper uses data from Chicago's downtown area to show that competition in prices among garage operators fades as walkability decreases. This prediction that is consistent with the theoretical model.

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 two reviews previous works on walkability and the parking literature related to this work. Section three describes the theoretical model. Section four gives an example of the behavior predicted by the model in Chicago. Section five discusses how the econometric model adapts the data to the theoretical model. Section six describes the data set. Section seven explains and shows the numerical results. Section eight explores the validity of the WI by comparing projections of the WI with similar measures. Section nine discusses the paper's limitations along with some final remarks.

## 2 Previous Literature

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 physical activity. Frank et al. (2005) produce a walkability index that use the correlation between physical activity and the urban environment to weigh variables like; mix of land use, residential density, and intersection density, into one walkability index.[5] Measures that use physical activity can be affected by individual health and well-being concerns,

[4]This result only uses data for New York City.

[5]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

providing unreliable estimates of the effect of urban attributes on peoples' willingness-to-walk.

Another approach 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 four-way intersection, is twice that of three-way.[7]

Finally, there are measures of walkability that weigh location attributes uniformly. Porta and Renne (2005) focus on access to sidewalks, their measure depends on the fraction of the total area that is accessible through safe sidewalks. The larger the share of land accessible the more walkable the location. 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 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 mostly equal weights, all the 13 categories are then integrated in one final score that goes from zero to one hundred, where one hundred is the highest degree of walkability and zero the least.[9]

The impact of some of the measures of walkability mentioned above is significant. For instance, 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 the travel behavior of people in Montreal, Canada.[10] They find that all measures have a significant impact on the probability of walking trips regardless of their nature.[11]

Works like Manaugh and El-Geneidy (2011), Boyle et al. (2014), and Gilderbloom et al. (2015) provide support to a multi-dimensional 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

the highest explanatory power.

[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

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

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

variables should be included in the calculation of a walkability index, and how they should be weighted remains unaddressed until now.

This paper relies on a spatial competition approach to measure peoples 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 summary, in a symmetric equilibrium, a higher transportation cost leads to higher prices. Also, in an asymmetric framework, higher transportation cost 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 spaces at a given location depends on the cost of walking from the garage to the driver's destination. In this same line, empirical analysis of the off-street parking industry has found that the cost of walking segments the parking market, enabling monopolistic competition (see Froeb et al. 2003, Choné and Linnemer 2012, Lin and Wang 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 goes beyond this approach and assumes that the urban environment affects people's willingness to walk, and hence, their parking decisions—drivers can be deterred from using a garage if the cost of walking is increased by the location's unwelcoming surroundings.[12] The relation between the urban environment and the cost of walking, and how this relation is embedded in the price decisions of garage operators, produces the theoretical framework used in this paper as the blueprint of a market-driven measure of walkability.

# 3 The Flat City Model

Concentrations of pedestrians in promenades and downtown areas suggest that people are more likely to walk in places with certain characteristics. The model is built on the premise that willingness to walk changes across locations, affecting price competition among garage operators. The measure of walkability provided in this paper uses a spatial competition model of garages, where parking prices are a function of competitors' prices, the unit cost, and the cost of walking between competitors. To illustrate these relations, this paper uses a modified version of the model in Arnott (2006), where the cost of walking not only depends on the characteristics of the individual, but also on the location's attributes.

[12] One possible example of unwelcoming locations for pedestrians, are places surrounded by major highways or overpasses.

## 3.1 The Demand for Parking

Lets considers a flat city (i.e. with the same cost of moving in any direction) divided in small tracts, each formed by a few blocks laid in a uniform street grid. Each section is described by a vector of attributes $\Theta$. Garages are placed in fixed locations that are at equal distance from each other, their sole business is renting parking spots by the hour. Two types of clients rent those parking spots, discount customers and loyal customers. Loyal customers are drivers with strong preferences for one location; an example of this is every day commuters and customers with a high opportunity cost of time. There are many reasons why drivers prefer one garage above all, for instance, the garage is located in the same building as their work place or offer 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 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 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. The full price depends on the distance between garage and destination. Every parking lot is surrounded by a set of destinations for which, the parking lot in the center provides the lowest full price. These destination 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:

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

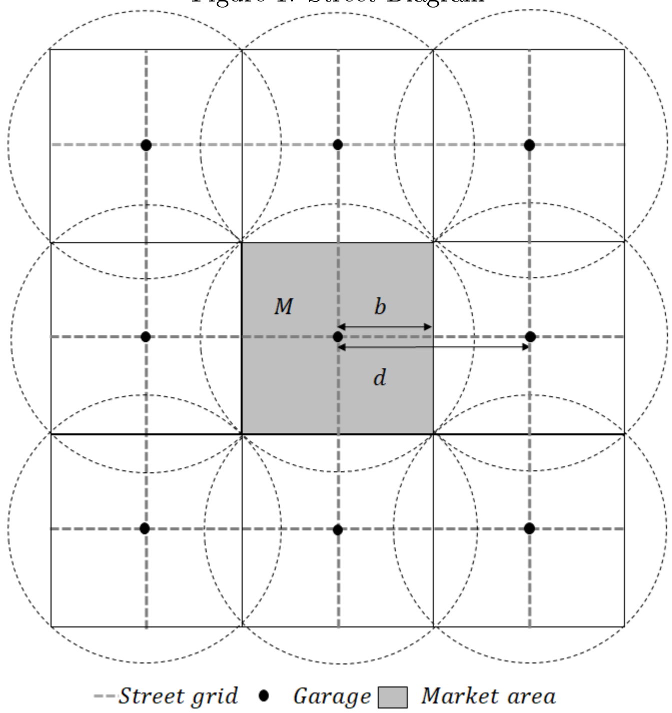
where $d$ is the distance between garages, $b$ is the distance from the garages to the edge of the market area, and $\bar{r}$ is the rate per unit of time charged by the neighboring garage (see figure 1).

The square street grid makes taxi-cab distance the relevant metric between two locations; this generates 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:

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

.

Figure 1: Street Diagram




## 3.2 Garage Operators

Loyal drivers pay a price that is above the cost of providing one parking spot. For the sake of simplicity, 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.[13] 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, so price at time $t$ is such that:[14]

[13]Loyal driver can have monthly contracts that charge low fix rates by hour. e.g. a $2000 monthly fee is less than a $3 per hour rate.

[14]In a high frequency framework, hour by hour, price by unit of time ($r$) and parking spot demand by unit of area ($D$)are the only variables that change.

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

subject to:

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

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

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

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 $\frac{dw(v,\Theta)}{T}$. From the relation in (3), it follows that in pedestrian-friendly locations ($w\,(v,\Theta) \approx 0$) price competition will represent a bigger share of the total price. As a consequence, price competition among garage operators is more fierce in walkable locations because of the lower cost of switching garages.

# 4 Prices, Disconnected 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:

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

Equation (4) describes how drivers might avoid parking at one place because prices are too high or because it is costly to walk from the garage to their destination. Let's think for instance of two neighboring locations called north side and south side. 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 disconnect between prices in the two locations, i.e. a change in the price of a garage on one side only affects competitors on that same side, despite of how close competitors are in the neighboring location.

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, among others. 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 week day 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) digs deeper into this issue by plotting the estimated weekend effects ($\beta_{j,\ WE}$) of the following model,

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

where $\mathbb{1}_{t,\ h}$ is the indicator functions of the $h$ hour of the day, and $\mathbb{1}_{t,\ WE}$ is an indicator function for the weekends. The X axis of figure (4) is the distanced to the City Business District (CBD).[15] Chicago's city hall is on the north side of Congress Parkway, so all garages on the north side are in the left hand side of figure (4) and garages on the south side are in the right hand side. Garages on the south side have a consistently smaller response to the weekend than their competitors on the north side, suggesting a disconnect between both locations. In the lights of the model, this disconnect 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; the second option is that 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 in the north side. This difference in behavior can be attributed to a more heterogeneous population of buildings and amenities that offer their own parking services. The north side has a mix of tall office buildings, theaters, hotels, and shopping areas, while the south side is more homogeneous. 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

Figure 2: Street Diagram

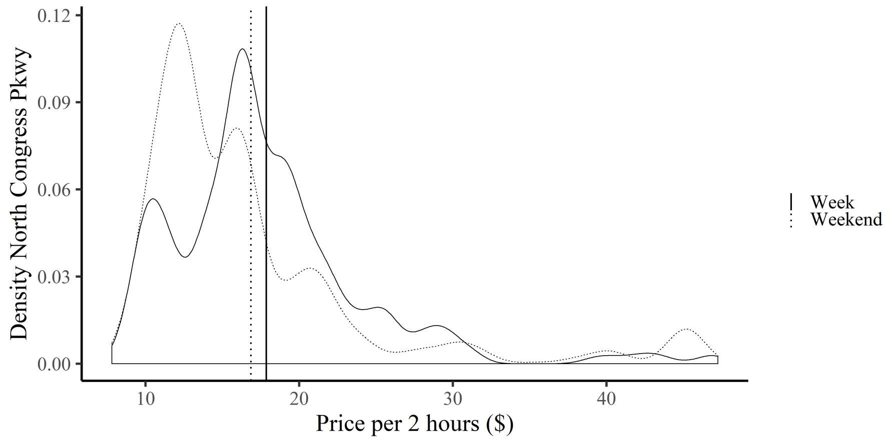



Figure 3: Street Diagram

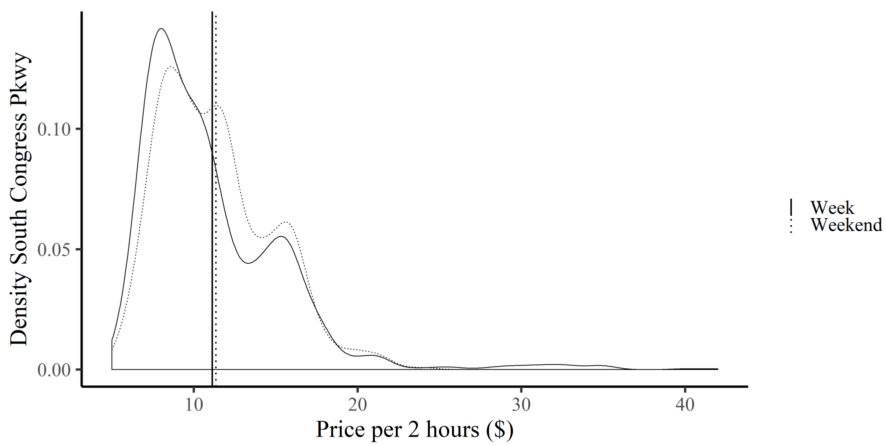
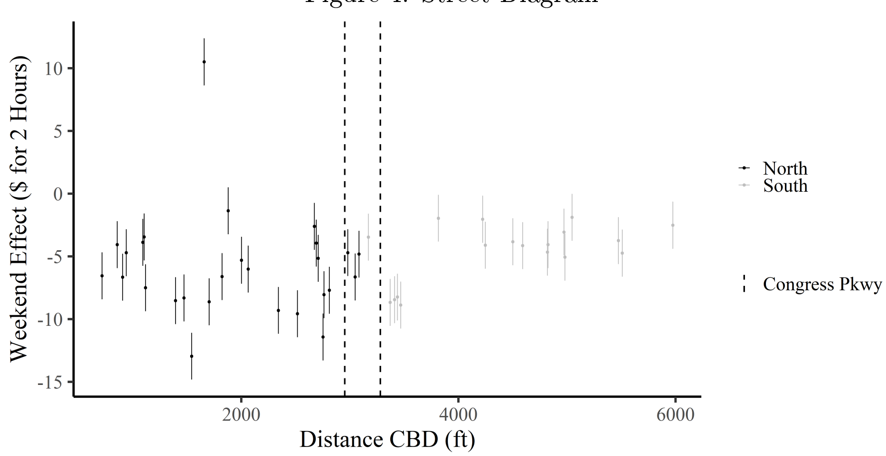



Figure 4: Street Diagram



serves a theater will have a higher opportunity cost during function days.

# 5 Estimation

## 5.1 Competitors and the $W$ Matrix

Expression (3) is built under symmetry and uniformity. Under this assumptions it is easy to isolate the competitors that define the market area of each garage. Cities however 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 $\alpha_i$ 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), i.e. estimates of $\lambda$ are expected to be equal or less than $1/3$.

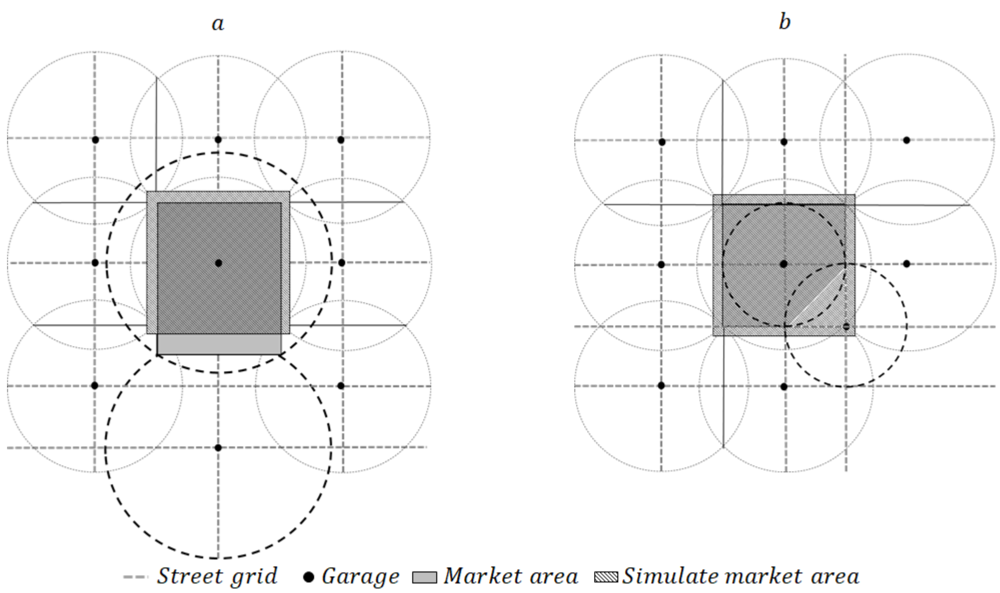
[15]CBD is defined as the location of the city hall.

Table (1) shows the estimates of $\lambda$ in equation (6) for different definitions of the threshold in the $W$ matrix. The results fluctuate between 0.05 and 0.11 all values bellow the 1/3 threshold imposed by the theoretical model. Furthermore, a simple hypothesis in the lower part of table (1) provide evidence that estimates of $\lambda$ are bellow 1/3, supporting the idea of a fuzzy price signal—$W_i r_t$ in equation (6) provides 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) |
| $\lambda$ | 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:

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

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

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

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

Vector $\rho$ is not a clean cut estimate of $\delta_\Theta$, as all elements in $\rho$ are multiplied by the same constant term $\left(\frac{2d^n}{3T}\right)$. However, since all terms in vector $\rho$ are equally affected by the same constant, they can be used as relative measures of the impact of $\Theta$ on the cost of walking, as show in section 7.

## 5.3 Controlling for the Unit Cost

Equation (3) draws a relation between the opportunity cost of long term contracts ($c$) and rates paid by discount drivers ($r$). One challenging element of this relation is that location characteristics can be correlated with the price of long term contracts, hence $\Theta_i$ is potentially correlated with $\eta_i$, making the OLS estimators of $\rho$ in equation (8) likely to be biased. The logic is simple: elements that affect the cost of walking can affect the the cost of providing one parking spot.[16] To alleviate this concern I use a property value differential that accounts for changes in rates driven by location characteristics. The differential is obtained by regressing property prices per square foot ($p$) on property characteristics ($X$) and a census tracts indicator ($\mu$), this is:

$$p_i = \beta_p X_i + \mu_j + \varepsilon_{pi},$$

where for each property $i$ in census tract $j$, $X$ accounts for the number of bedrooms and bathrooms, and $\mu_j$ is the census tract price differential.

Using $\hat{\alpha}$ as proxy of the cost of walking, I regress $\hat{\alpha}$ on the location characteristics ($\Theta$), using $\hat{\mu}$ as a control for location effects,

$$\hat{\alpha}_i = a + \beta_\alpha \hat{\mu}_j + \rho \Theta_i + \varepsilon_{\alpha i}. \tag{9}$$

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

Estimates of all parameters in equation (9) are presented in the appendix, table (2). A word of caution: despite controlling for property values, estimates of $\rho$ can still be confounded by the effect of $\Theta_i$ on $c_i$. Given the data available to me at the moment, I can't provide unbiased estimates of $\delta_\Theta$. Having said this, estimates of equation (9) should not be interpreted as measures of the impact of the urban environment on walkability.

# 6 Data

The model presented in section three 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 trough 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. Markets where operators publish their prices on billboards that are hard and costly to modify, and drivers cruise around the block trying to compare prices that, most of the time, are not visible from the street. A good example of this situation 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 hard to modify since they are printed on a billboard (pictures 3 and 5).

To estimate equation (6), I collected data on prices, location, and characteristics of 2331 parking lots listed on parkwiz.com. A website that rents off-street parking of 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 location with missing observations the data set is reduced to 903 locations with 119 observations per location.[17]

To weigh all location characteristics (intersection density, mixed land use, and proximity to amenities) in the WI, I estimated equation (9) using the following data:

- Intersection density at census tracts level (2010 census) form the United States Environmental Protection Agency (EPA).
- Mix of land use, commercial and housing in every census tracts (2010 census) from the EPA.

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

- The proximity of each parking location to thirteen different amenities[18], data collected using the Google places API.

- Real estate data for New York City and Chicago. The CoreLogic data set provides information on the price, location, and characteristics of the property (e.g. square fotage, number of bedrooms, number of bathrooms).

Finally, in order to test validity, the paper uses data on the proportion of non car commutes,[19] the Walk Score,[20] and the EPA's National Walkability Index, to check the relation of the WI with these variables.[21] Descriptive statistics of the data are provided in table (3) of the appendix.

# 7 The Walkability Index

Two major assumptions are established to limit the distortions rising from the confounding factors in equation (9), specially those related to the effect of $\Theta_i$ on $c_i$:

- No disamenities: All variables included in the WI are amenities.

- Equal bias: If estimates of $\rho$ are bias, the size of the bias is the same for all variables (all elements of $\rho$ are over estimated or all elements of $\rho$ are under estimated)

Under the no disamenities assumption, and in the lights of the theoretical model, a variable in $\Theta$ only has a negative effect on $\alpha$ ($\rho < 0$) if it reduces the cost of walking. Therefore, negative elements of $\hat{\rho}$ are related to variables that reduce the cost of walking. On the other hand, variables in $\Theta$ that have a positive effect on $\alpha$ ($\rho > 0$) are likely affect by the effect of $\Theta$ on $c$.

Under the equal sign bias assumption, estimates of $\hat{\rho}$ can be biased, but the relative weights they provide are consistent with the driver's valuation. Based on these assumptions, the proposed WI has the following formula:

[18] 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.

[19] from the Census Transportation Planning Products Service https://ctpp.transportation.org/.

[20] For more information visit www.walkscore.com/cities-and-neighborhoods/

[21] All data is at census tracts level.

$$\mathrm{wi} = |\underline{\hat{\rho}}|\underline{\Theta}, \tag{10}$$

where $\underline{\hat{\rho}}$ and $\underline{\Theta}$ are vectors that contain the subset of parameters and variables that have a negative correlation 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 with a weight of 2.11
- Mix of land use (entropy) with a weight of 1.17[22]
- 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 $\underline{\hat{\rho}}$ are used in absolute values for the sake of interpretation.

In order to further simplify the reading of the WI, the measure provide in equation (10) is divide by the maximum observed value and multiply by a 100:

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

Other than simplicity, this transformation brings two extra advantages:

1. It allows to get rid of the term $\left(\frac{2d^n}{3T}\right)$ as mentioned in section 5.2.[23]

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

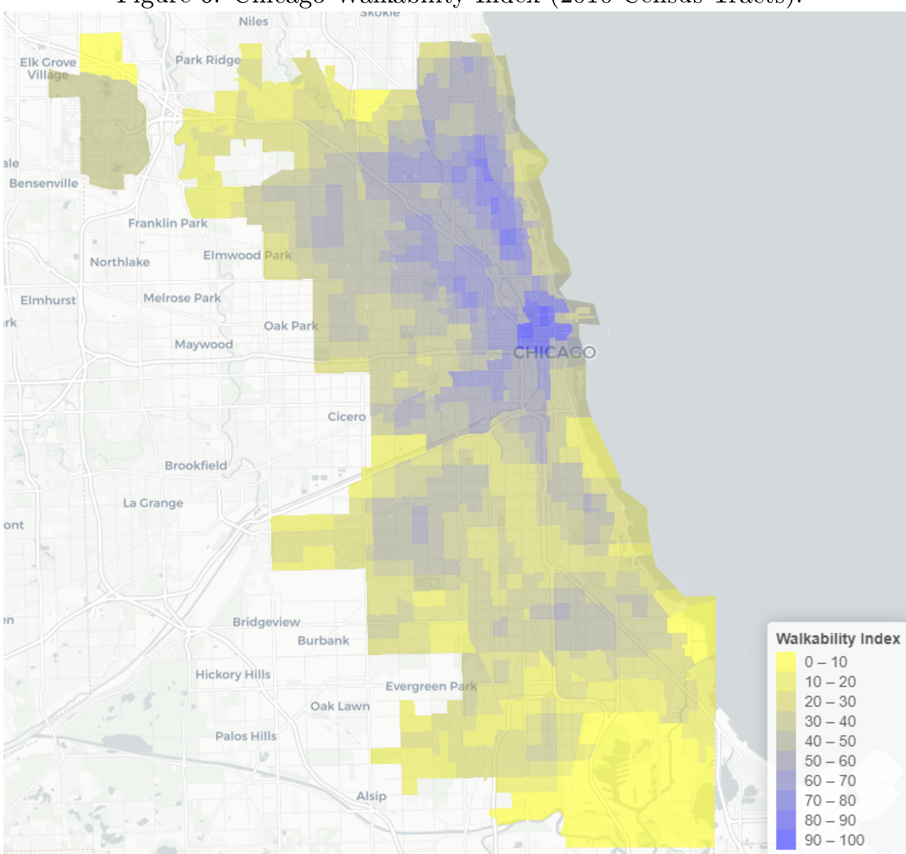
[23]Since $\rho = \frac{2d}{3T}\delta_\Theta$, $\mathrm{WI} = \frac{|\underline{\hat{\delta}_\Theta}|\Theta}{\max\left(|\underline{\hat{\delta}_\Theta}|\underline{\Theta}\right)} \times 100$

2. It gets rid of any proportional bias that equally affect all element of $\rho$.[24]

The measure of walkability provided here is intended to compare location. It should be read as an ordinal number, indicating that on location is more or less walkable than other but not by how much.[25]

Figures (6) and (7) presents projection of the WI for Chicago and New York City. The indicator shows that the most walkable areas are the loop in Chicago, and Midtown Manhattan and Brooklyn in New York. In both cases the city tends to become less walkable as one moves away from this areas, with some exceptions.

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

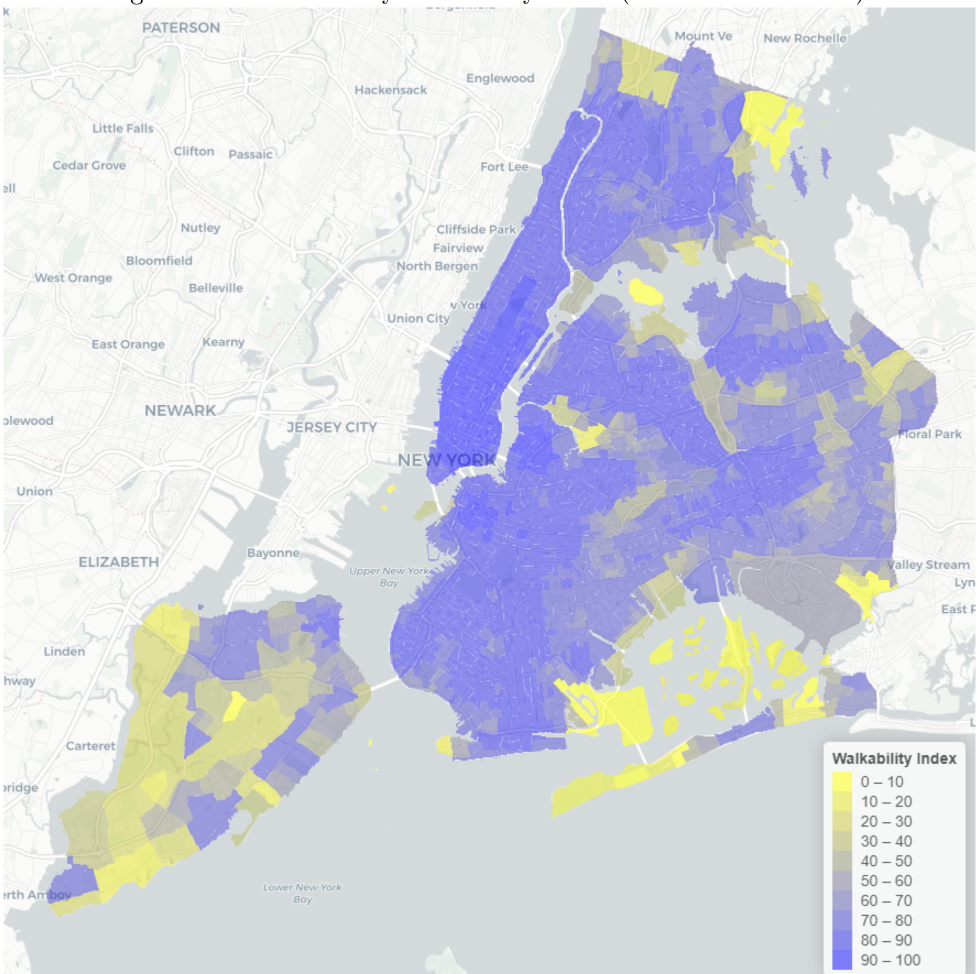



A more detailed version of this map can be found in
https://www.mauricio-arango.com/walkability-index-chi

[24]If $K$ is a proportional bias that equally affect all element of $\rho$, $\rho = K\frac{2d}{3T}\delta_\Theta$. Hence $\text{WI} = \frac{|\hat{\delta}_\Theta|\Theta}{\max\left(|\hat{\delta}_\Theta|\Theta\right)} \times 100$

[25]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 7: New York City Walkability Index (2010 Census Tracts).




A more detailed versions of this map can be found in
https://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 linked to walkability.

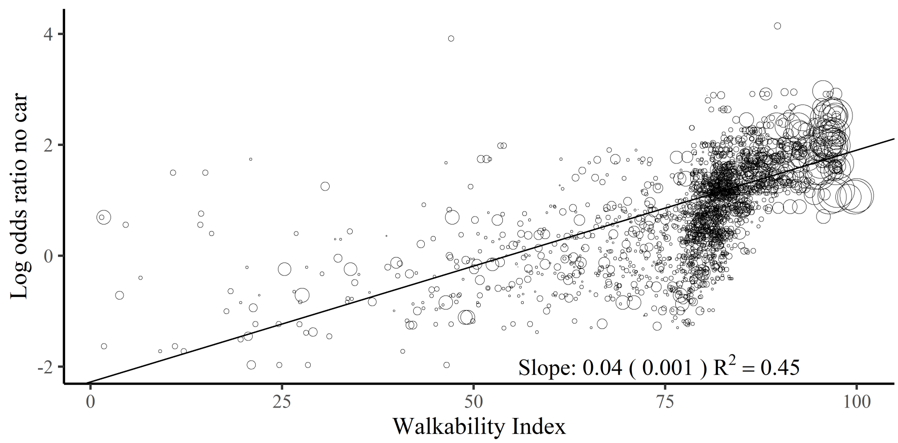
Figure (8) shows the relation between the WI and the log odds ratio of a no car commute for all census tracts in New York City. The correlation coefficient is above 0.65.[26] This connection is relevant as walking

[26]The regression and figure are weighted by the number of workers in each census tract.

is the first option for the last leg of a trip in public transit and other alternative means of transportation.[27]

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 correlations 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 form the fact that some variables used in the National Walkability Index —those that did not describe the physical attributes of a location—[28] where excluded from the WI.

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

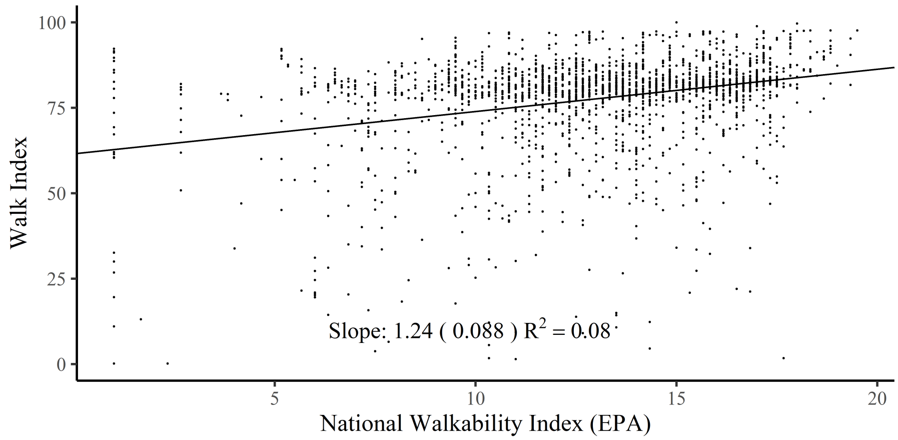



The size of the marker is proportional to the number of workers in each census tract. The regression is weighted by the number of workers in each census tract.

Figure 9: Walkability Index and The Walk Score


[27] Alternative to individual vehicle.
[28] 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 measure the cost of walking. Estimates of the cost of walking are 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 build in this paper has a strong positive correlation with the fraction of non car commuters in New York City.

The parameterization of the Walkability Index is built around the concept of willingness to walk. However, such a variable is unobservable. What this paper provides is a mere approximation using parking prices. This, along with the bias that might arise from possible omitted variables, limits the interpretation of the results presented in this manuscript. It is not the intention of this paper to prove causality nor to provide unbiased estimators. The results presented in this paper should be understood as a way to rank different characteristics of the urban environment based on their relation with driver's willingness to walk.

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# Appendix

Table 2: Estimates Equation (9)

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| Intercept | 53.41 | 12.55 | 4.26 | 0.00 |
| Tract price differential ($\mu$) | 2.63 | 0.28 | 9.36 | 0.00 |
| Street intersection density | 0 | 0 | -0.84 | 0.40 |
| Mix of use type | -1.17 | 1.45 | -0.81 | 0.42 |
| Number of grocery stores in one mile | -0.06 | 0.11 | -0.5 | 0.62 |
| Number of coffee shops in one mile | -0.2 | 0.15 | -1.37 | 0.17 |
| Number of movie theaters in one mile | 0.6 | 0.08 | 7.22 | 0.00 |
| Number of parks in one mile | 0.17 | 0.08 | 2.17 | 0.03 |
| Number of bookstores in one mile | -0.03 | 0.1 | -0.33 | 0.74 |
| Number of drug stores in one mile | 0.03 | 0.11 | 0.3 | 0.77 |
| Number of clothing stores in one mile | -0.31 | 0.06 | -5 | 0.00 |
| Number of restaurants in one mile | -2.11 | 0.74 | -2.83 | 0.00 |
| Number of bars in one mile | -0.02 | 0.17 | -0.11 | 0.91 |
| Number of schools in one mile | -0.17 | 0.35 | -0.5 | 0.62 |
| Number of libraries in one mile | -0.09 | 0.08 | -1.04 | 0.30 |
| Number of fitness centers in one mile | 0.52 | 0.13 | 3.92 | 0.00 |
| Number of hardware stores in one mile | 0.39 | 0.07 | 5.45 | 0.00 |

Table 3: 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