

# Assessing Walkability Through Parking Prices

Mauricio Arango\*

## Abstract

This paper uses the price and location of parking services offered online to construct a market-driven measure of walkability. The concept is as follows: since parking is a homogeneous service, price differences between two competing parking lots can be used to measure driver's willingness to walk from one location to another (cost of switching). Using a theoretical spatial competition model and a novel data of parking services offered online, that compiles garage's prices, location, and characteristics, this paper estimates a market-driven walkability index that can be applied to different cities across the United States.

**Preliminary and incomplete. Please do not cite or distribute without permission of the author.**

## 1 Introduction

The concept of walkability is embedded in most business districts and downtown areas in America. As a general rule, most valuable urban areas have a higher concentration of pedestrians than the rest of the city, a trend that has been recently fueled by increasing concerns on the environment, congestion, and public health. This trend has shaped many cities into more walkable environments raising the question of what makes a place pedestrian friendly. Existing measures of walkability have been structured around educated opinions, the variables included in each measure and the weight they receive reflect the author's concept of a pedestrian friendly environment. This paper sheds light on to this topic by using prices and characteristics of parking sold online to produce a market-driven measure of walkability.

The effect of walking on parking prices is a result of spacial competition, the concept is straightforward: Imagine you are planning your next day trip to an appointment and you are choosing where to park on an online prepaid parking platform. Several options appear in your computer or smartphone. Common sense dictates that most people will pick their parking spot based on the price and proximity to their 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, at least, partially affected by the willingness

---

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

to walk (walkability). This link becomes more clear when drivers use online parking platforms, since they avoid the cost of searching and cruising inherent to more traditional ways of parking. Ergo, online parking provides a cleaner identification of the willingness to walk. The reasons for using parking services to identify the effect of walking on prices are threefold: parking is differentiated by location, parking is mostly homogeneous on features other than location, and people walk after they park.

This paper estimates a model of spatial competition that describes how locations and prices of different garages can be used to measure driver’s willingness to walk. This measure is subsequently used to create a location walkability index (WI) that integrates different characteristics associated with pedestrian friendly zones. Variables are included and weighted in the index according to their correlation to the measure of willingness to walk, hence providing a market driven index of walkability. To my knowledge this is the first index of walkability that is based on people’s willingness to walk observed through market prices. This approach helps isolate the effect of the urban environment from health and well-being concerns that can bias measures based on physical activity. To produce such an indicator, this paper uses a novel high frequency data set of prices, amenities, and location of garages across the largest cities in America. The resulting index is meant to be a function of the urban environment, therefore it depends solely on the physical attributes of each location. This provides a measure of walkability that can be used in places not included in the original sample. After this introduction the rest of this paper 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 discusses how the econometric model adapts the data to the theoretical model, section five describes the data set, section six explains and shows the numerical results, and section seven concludes the paper.

## 2 Previous Literature

The methodology presented in this paper not only provides an objective measure of willingness to walk, it also summarizes some of the existing approaches in one indicator. Part of the work on the effects of the urban environment on walking have roots in the occupational and public health literature, this has produced a line of research that has placed emphasis on physical activity (walking). Frank et al. (2005) produce a walkability index (WI) that depends on the mix of land use, residential density, and intersection density. The authors use the relation between physical activity and the urban form to weight each variable in the total index.<sup>1</sup> Part of the idea behind this approach is that mixed use dense areas are more appealing to pedestrians than single-use low density areas.

Another important part of the literature uses the access to infrastructure as a measure of walkability. One important feature that enables safe walking

---

<sup>1</sup>The authors tested different sets of parameters and chose the one with the highest explanatory power of the physical activity.

is the presence of side walks is an important element. Porta and Renne (2005) produced a WI that depends on the fraction of the total area that is accessible through safe side walks. In the same vein, small blocks or high intersection density, is seen as a feature of pedestrian friendly areas since it allows for shorter trips. Kuzmyak et al. (2007) provide a measure of walkability that is a function of the intersection density and walk opportunities at a given location. Weights to walking opportunities depend on a rank of attractions given by a local survey, while intersections are weighted in a manner such that the weight of four-way intersection, is twice that of three-way and four-way intersection with a main road.

One popular approach is using walk opportunities for producing a WI. Under this concept a place is deemed walkable if common errands (opportunities) can be easily completed by walking. One good example of this is the the Walkscore® (WS).<sup>2</sup> The WS uses the distance to 13 different types of amenities (grocery stores, restaurants, coffee shops, bars, movie theaters, school, parks, library, bookstore, fitness, drug store, hardware store, and clothing and music store) to provide a pedestrian accessibility index. The closer a location is to an amenity in one of the 13 categories, the higher the WS. All the categories are then integrated in one final score that ranks from zero to one hundred, where one hundred is the highest degree of walkability.<sup>3</sup> The WS is a well known measure that has been used in works like Gilderbloom et al. (2015) and Boyle et al. (2014) to measure the impact of walkability on housing prices.

Manaugh and El-Geneidy (2011) examine the impact of the four WI indices described above (Frank et al. (2005), Porta and Renne (2005), Kuzmyak et al. (2007), and WS) on the travel behavior of people in the city of Montréal, Canada<sup>4</sup>. They find that all measures have a significant impact on the probability of walking trips regardless of their nature (school or shopping). This type of finding provides support to a multi-dimensional approach, where walkability depends on the access to infrastructure (e.g. intersection density, access to side-walks), characteristics of the urban environment (e.g. mix between commercial and residential use), and proximity to different amenities among other variables. However, the question of what variables should be include in the calculation of a WI, and how they should be weighted remains unsolved.

Models of spatial competition like Hotelling (1929) and Salop (1979) show the effect of transportation cost on pricing strategies. In a nutshell, in a symmetric equilibrium higher transportation cost leads to higher prices. 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 parking lot to the driver's destination, among other factors. This cost of walking is the transportation cost in spatial competition models. Empirical analysis of the off-street parking industry (Froeb et al. (2003), Choné and Linnemer (2012),

---

<sup>2</sup><https://www.walkscore.com>

<sup>3</sup>A place with a WS between 90 to 100 is denominated as a “Walker’s Paradise”, and 0 to 24 is a “Car Dependent” location

<sup>4</sup>The authors use the 2003 Montréal Origin–Destination survey.

Kobus et al. (2013), and Lin and Wang (2012)) incorporate the cost of walking as a factor that enables monopolistic competition.<sup>5</sup> This paper delves further into this concept identifying changes in the willingness to walk across location and then uses those differences to produce a WI.

### 3 The Flat City Model

The measure of walkability provided in this paper is built around the idea that parking prices are a function of competitors' prices, the unit cost, and the cost of walking between competitors. To illustrate this relation, this paper uses a modified version of the spatial competition model in Arnott (2006), and as such it uses a similar notation.<sup>6</sup> One important conceptual difference with most of the previous spatial competition literature is that this model accounts for a relation between the urban environment and peoples' willingness to walk. Spatial competition models usually portrait walking as the opportunity cost of time. This means that walking is a cost that depends solely on the characteristics of one individual, but not on the location's surroundings. However, an important body of literature supports the idea that the attributes of a location can affect people's desire to walk,<sup>7</sup> making some areas more walkable than others. For example, pedestrians might prefer to walk on a luminous, wide, busy sidewalk than in a dark, abandoned alley.

#### 3.1 The Demand for Parking

The model considers a flat city (i.e. with an equal cost of moving in any direction) that is divided in small homogeneous sections across which the demand for parking is uniform.<sup>8</sup> Each section is formed by a few blocks laid on a uniform grid. Parking lots are placed in fixed locations that are at equal distance from each other,<sup>9</sup> their business is renting parking spots by unit of time. Parking is regarded as a homogeneous service only differentiated by location, as a consequence drivers base their decision of parking in lot  $j$  at time  $t$ , on the cost per unit of time  $S_{jt}$  and the cost of walking to their destination. For the average driver the cost of walking one unit of distance in section  $i$  depends on the average cost of time,  $v$ , and a vector of attributes  $\Theta_i$  that describes the surroundings ( $w(v, \Theta_i)$ ). For an average driver that parks for  $T$  hours at a garage that is at distance  $x$  from their destination,<sup>10</sup> the full price of parking is

---

<sup>5</sup>See Inci (2015).

<sup>6</sup>Expressions like "full price of parking" and "market area" are also taken from the Arnott (2006).

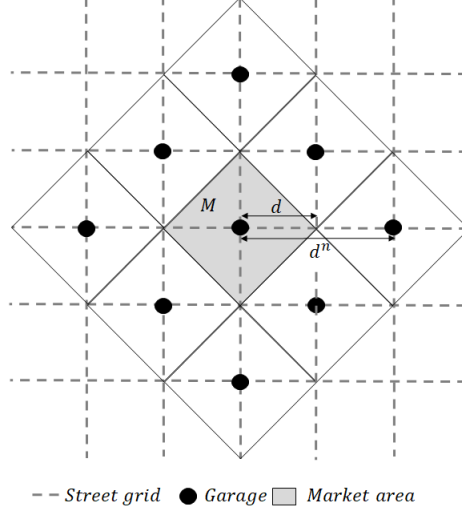
<sup>7</sup>,Some of it is mentioned in section 2, that

<sup>8</sup>This situation can be easily observed around parks, commercial streets (e.g. Michigan avenue in Chicago or 5th avenue in New York), and other locations where similar economic activities tend to group together.

<sup>9</sup>This even distribution of competitors across surface, is a direct consequence of the uniform distribution of the demand for parking. Further explanation of this result can be found in Tirole (1988) and Salop (1979).

<sup>10</sup>The driver must walk back and for to the garage.

Figure 1: Street Diagram



$$S_{jt}T + 2xw(v, \Theta_i).$$

### 3.1.1 Market Area

As the parking demand is driven by prices and distance, around each parking lot there is an area for which the parking lot has the lowest full price. This area is called the garage's market area ( $M$ ). For a parking lot  $j$  the border of the market area is at a distance  $d$ , where its full price equals that of a neighbor garage located at a distance  $d^n$ , that charges  $S_j^n$  per unit of time, this is:

$$S_{jt}T + 2dw(v, \Theta_i) = S_j^nT + 2(d^n - d)w(v, \Theta_i). \quad (1)$$

The uniform street grid makes taxi-cab distance the relevant metric between two locations, this generates market areas that are diamond shaped as shown in Figure (1). From equation (1) it follows that the market area is  $M_{ijt} =$

$$2 \left( \frac{(S_j^n - S_{jt})T}{4w(v, \Theta_i)} + \frac{d^n}{2} \right)^2.$$

## 3.2 Parking Pricing

The demand rate for parking spots per unit of area in location  $i$  at time  $t$  is  $D_{it}$ . Assuming that parking spots in location  $i$  are provided at a fixed unit cost  $C_j$ , the garage operator optimization problem is:

$$\max_{S_{jt}} \Pi_{jt} = S_{jt} M_{ijt} D_{it} T - C_j M_{ijt} D_{it} T$$

subject to

$$M_{ijt} = 2 \left( \frac{(S_{jt}^n - S_{jt}) T}{4w(v, \Theta_i)} + \frac{d^n}{2} \right)^2.$$

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

$$S_{jt} = \frac{2}{3} C_j + \frac{2d^n w(v, \Theta_i)}{3T} + \frac{1}{3} S_{jt}^n. \quad (2)$$

Equation (2) shows the effects of the unit cost, the cost of walking, and competitor's price on the garage operator pricing decision. In walkable areas the effect of price competition will represent a bigger share of the total price compared to less pedestrian friendly locations. In a way, price competition among garages is more fierce in walkable locations since the cost of switching is lower. Equation (2) assumes that in a high frequency time framework, price by unit of time is the only variable that changes. Despite being a reasonable assumption this structure groups the effect of the unit cost and the walking cost in the constant parameter. To disentangle these two effects this paper uses a linear cost structure similar to the one described in Shoup (2011), where the cost of one parking spot is determined by land values, construction cost, operation cost, and a set of amenities offered by each garage. Land values are assumed to be different for each location while construction cost and operation cost only change between cities. Land values are approximated based on the monocentric city model, where differences in values within the city are mainly driven by the distance to the city businesses district (DCBD). The cost structure is summarized in:

$$C_j = \gamma_{city} + \rho_{city} DCBD_j + \gamma_X X_j, \quad (3)$$

where  $\gamma_{city}$  accounts for construction cost, operation cost, and land values at the CBD of a given city,  $\rho_{city}$  is the gradient at which land values decrease around the CBD, and  $X_j$  a set of vectors that control for ammenities and services that might increase the cost of providing one parking spot.

For the cost of walking I used a set of variables often found in walkability measures, those can be divided in three groups: access to infrastructure, characteristics of the urban environment, and proximity to different amenities assuming a linear structure yields

$$w_i = v_{city} + \beta \Theta_i \quad (4)$$

Section 4.2 provides a better description of variables included in  $\Theta_i$ . Important factors like sidewalks and its condition, along with the presence of trees and other variables, were not available to me at the time hence they were not included.

## 4 Competitors, the $W$ Matrix, and The Walkability Index

### 4.1 Competitors and the $W$ Matrix

Expression (2) is build around an assumption of symmetry, where all that competitors charge the same price and are evenly distributed across each location, situation that is rarely found in urban areas. To finesse this difficulty I use a spatial panel model with a  $W$  matrix that, average the prices of competitors are weighting each price by the inverse of the distance. This produces the average competitor that defines the market area. Also the  $W$  matrix only accounts for competitors located in a small radius, making the uniform demand assumption more tenable. The resulting regression equation is:

$$S_{jt} = \alpha_j + \lambda W_j S_t + \varepsilon_{jt}, \quad (5)$$

where  $\alpha_j$  accounts for the unit cost plus the cost of walking of the average driver in  $j$ 's location, and  $W_j$  is the  $j^{\text{th}}$  row of matrix  $W$ , that is the  $n \times n$  spatial weight matrix, that has zeros in the diagonal, values of  $W_{jk} = \frac{1}{d_{jk}}$  for every location  $k$  within one quarter of a mile from garage  $j$ , and zeros in all other locations.

### 4.2 Walkability Index

I use the time fixed effects in equation (5) to weight the effects of the urban environment ( $\Theta_i$ ) on the walking cost. Equation (3) provides a proxy of the unit cost of each garage, adding equations (3) and (4) establish a way to separate the two types of cost embedded in  $\alpha_i$ , The resulting regression equation is:<sup>11</sup>

$$\hat{\alpha}_j = \gamma_{city} + \gamma_X X_j + \rho_{city} DCBD_j + \beta^I \Theta_i^I + \beta^U \Theta_i^U + \beta^A \Theta_i^A + \varepsilon_j, \quad (6)$$

where  $\gamma_{city}$  accounts for the effect of the operation cost, construction cost, land values at the CBD, and the average value of time.  $\beta^I$ ,  $\beta^U$ ,  $\beta^A$ ,  $\Theta_i^I$ ,  $\Theta_i^U$ , and  $\Theta_i^A$  are subsets of  $\beta$  and  $\Theta_i$ . Each subset is associated with a group of features of the urban environment as described bellow:

- $\Theta_i^I$ : Street intersection density
- $\Theta_i^U$ : Mix of employment types in a block group (such as retail, office or industrial)
- $\Theta_i^A$  13 different variables that indicate the number of grocery stores, restaurants, coffee shops, bars, movie theaters, schools, parks, libraries, bookstores, fitness centers, drug stores, hardware stores , and clothing and music stores, within a quarter of a mile.

---

<sup>11</sup>This expression approximates the first two terms on the right hand side of equation (2).

After estimating equation (6) I use negative values of  $\beta$  to produce a WI that goes from 1 to 10, been ten the highest degree of walkability .

$$WI_i = (\beta^{I,<0}\Theta_i^I + \beta^{U,<0}\Theta_i^U + \beta^{A,<0}\Theta_i^A) \frac{10}{\max(WI)} \quad (7)$$

## 5 Data

The model presented in section 3 describes a situation where parking lot operators can easily change prices with no menu cost. Prices are also easily observable, eliminating the cost of cruising for parking. This two conditions are meet by online parking platforms, where garages can change prices at no cos; and all the information about prices, location, and amenities, is free and accessible to all costumers with an internet enable device. On the other hand, the model is not a good fit for more traditional parking 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. In line with the above, to estimate equation (5) 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 US.

Information on prices and availability was collected every hour during a one month period (from July 25th 2019 to August 25th 2019). 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 period of data collection 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 reduces to 903 locations with 119 observations per location.<sup>12</sup>

To weight the effect of infrastructure, mixed use, and the proximity to different amenities in the WI, I estimate of equation (6) using the following data:

- Infrastructure: intersection density at census block level (2010 census) form the United States Environmental Protection Agency (EPA).
- Urban environment: mix of commercial use, housing occupancy, and portion of workers that carpool in every census block (2010 census) from the EPA.
- The proximity of each parking location to 13 different amenities<sup>13</sup>, data collected using the Google places API.

<sup>12</sup>The 119 observations are the result of using 17 hours (6:00 am to 11:00 pm) for the 7 days of the week.

<sup>13</sup>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.



The DCB of each parking lot is measured as the euclidean distance to the city-hall of each cities but New York, where the CBD is assumed to be located at the Empire State Building.<sup>14</sup>

## 6 Results

Table 1 presents the results of estimating (5). Columns 1 and 2 show the estimations for different definitions of the  $W$  matrix, column in column 1 every one within a half a kilometer is defined as a neighbor (competitor), while in columns 2 the radius of the definition is increased to 0.75 kilometers. Other definitions of the  $W$  matrix (1 km and 1.5 km radius), had no difference with the 0.75 kms radius matrix, therefore they where not included. Both columns of table 1 show a relative robustness to different definitions of the  $W$  matrix, not only in the parameter  $\lambda$ , but on the mean and standard deviation of the individual time-invariant effects.

Table 1: Land values and observable characteristics I.		
Dependent Variable: Price of 2 hours parking		
Radius W matrix in miles	0.50	0.75
	(1)	(2)
Price neighbor competitors, different radius	0.5046 (0.0121)	0.5052 (0.0121)
Average value fixed effects	11.5274 (0.4875)	11.5190 (0.4875)
$R^2$	0.3375	0.3363
Number observations	107,457	107,457

### 6.1 Walkability Index

To build the WI I need to estimate equation (6). It is worth saying that the intention of this exercise is not to provide unbiased estimators. The objective is to obtain a relative ranking of characteristic based on their relation with the willingness to walk. Having said this, the underlying assumption of this exercise is that the bias is the same across all variables in the vector of location's characteristics ( $\Theta$ ).

Table 2 shows the estimation and parametrization of the Walkability Index (WI). Columns 1 and 2 show the estimations with and without controls, while column 3 shows the maximum values of the variables. The maximum values are used in the reweighting described in equation (??), process that yields the parameterization presented in column 4. Since the only interest is on variables associated with a lower cost of walking, the WI only uses the negative parameters. Despite a few changes in the order of magnitude, columns 1

<sup>14</sup>A similar assumption is found in Albouy et al. (2018)..

and 2 are reasonably similar, therefore the parameterization of the WI seems to be robust to the inclusion of different controls. Figure (2) uses the parameters in column 4 of Table 2 to map the results of the WI in all the census tracts of New York city. The indicator shows that the most walkable areas are lower Manhattan and Brooklyn, the city becomes less walkable as one moves away from this area, specially in locations that are closed to large highways. A more detailed version of this map can be found in <https://sites.google.com/view/mauricioarango/walkability-index-nyc>

Figure 2: New York City Walking Index (2010 Census Tracts).

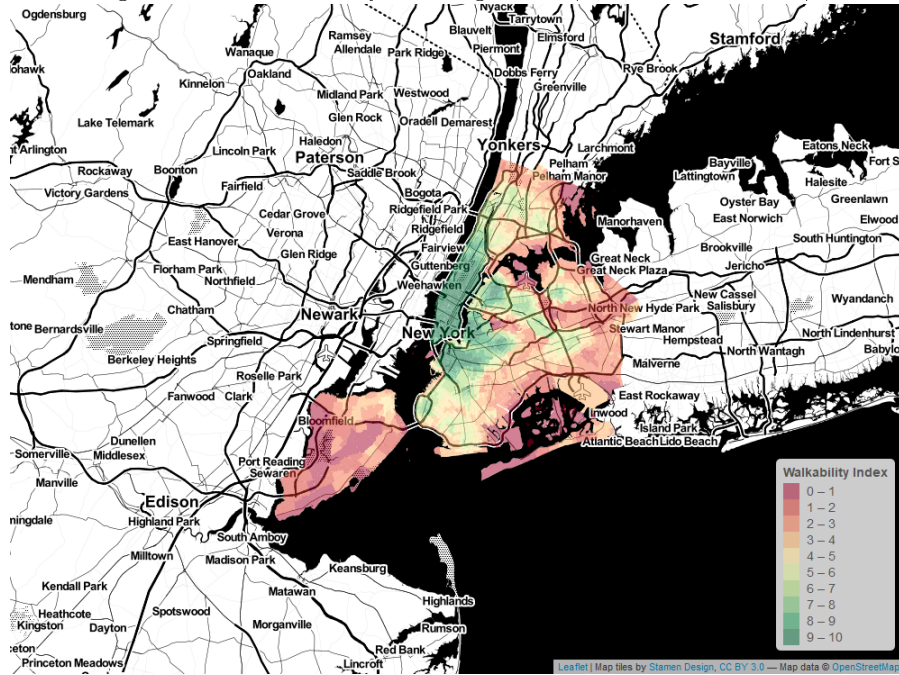


Table 2: Walkability Index.

	Dependent Variable: $\hat{\alpha}_i$		WI parameters
	Estimation	Maximum value	
	(1)	(2)	(3)
Number of restaurants	-1.08 (0.63)	-0.84 (0.61)	8.71
Number of drugstores	-0.95 (0.41)	-0.92 (0.39)	4.9
Number of bars	-0.72 (0.48)	-0.73 (0.47)	6.99
Street intersection density	-0.5 (0.38)	-0.56 (0.35)	8.18
Number of schools	-0.25 (0.42)	-0.24 (0.39)	5.49
Number of hardware stores	-0.18 (0.37)	-0.23 (0.35)	7.78
Predicted commute mode split	-0.17 (0.32)	-0.08 (0.31)	0.16
Number of bookstores	-0.05 (0.41)	-0.14 (0.39)	6.46
Mix use and occupied housing	-0.00 (0.77)	-0.04 (0.73)	6.46
Number of music stores	0.12 (0.38)	0.15 (0.37)	
Number of libraries	0.22 (0.35)	0.29 (0.34)	
Number of movie theaters	0.23 (0.4)	0.25 (0.37)	
Number of fitness centers	0.62 (0.41)	0.64 (0.41)	
Number of grocery stores	0.63 (0.45)	0.5 (0.42)	
Mix of employment types	0.64 (0.76)	0.36 (0.72)	
Number of parking lots	0.66 (0.33)	0.68 (0.32)	
Number of coffee shops	0.89 (0.53)	0.77 (0.51)	
Controls for unit cost	Yes	No	
$R^2$	0.06	0.03	
Number observations	903	903	

## 7 Conclusions

Existing measures of walkability are not built around the concept of willingness to walk. This often produces measures that describe how feasible is to leave with no car or how often people engage in physical activity, which tends to ignore the relation between the urban environment and the cost of walking. This paper uses a spatial competition model of off-street parking, to measure the cost of walking between competing garages. This is used to propose and parameterize a market driven walkability index that depends on the location's characteristics. The resulting index summarizes some of the existing measures of walkability, and describes a convenient and objective way to include new characteristics in future measures.

## References

- Albouy, D., Ehrlich, G., and Shin, M. (2018). Metropolitan land values. *Rev. Econ. Stat.*, 100(3):454–466.
- Arnott, R. (2006). Spatial competition between parking garages and downtown parking policy. *Transp. Policy*, 13(6):458–469.
- Boyle, A., Barrilleaux, C., and Scheller, D. (2014). Does Walkability Influence Housing Prices? *Soc. Sci. Q.*, 95(3):852–867.
- Choné, P. and Linnemer, L. (2012). A Treatment Effect Method for Merger Analysis with an Application to Parking Prices in Paris. *J. Ind. Econ.*, 60(4):631–656.
- Frank, L. D., Schmid, T. L., Sallis, J. F., Chapman, J., and Saelens, B. E. (2005). Linking objectively measured physical activity with objectively measured urban form: Findings from SMARTRAQ. In *Am. J. Prev. Med.*, volume 28, pages 117–125.
- Froeb, L., Tschantz, S., and Crooke, P. (2003). Bertrand competition with capacity constraints: mergers among parking lots. *J. Econom.*, 113(1):49–67.
- Gilderbloom, J. I., Riggs, W. W., and Meares, W. L. (2015). Does walkability matter? An examination of walkability's impact on housing values, foreclosures and crime. *Cities*, 42(PA):13–24.
- Inci, E. (2015). A review of the economics of parking. *Econ. Transp.*, 4(1-2):50–63.
- Kobus, M. B., Gutiérrez-i Puigarnau, E., Rietveld, P., and Van Ommeren, J. N. (2013). The on-street parking premium and car drivers' choice between street and garage parking. *Reg. Sci. Urban Econ.*, 43(2):395–403.

- Kuzmyak, J., Baber, C., and Savory, D. (2007). Use of Walk Opportunities Index to Quantify Local Accessibility. *Transp. Res. Rec. J. Transp. Res. Board*, 1977:145–153.
- Lin, H. and Wang, Y. (2012). Competition and Price Discrimination in the Parking Garage Industry. *SSRN Electron. J.*
- Manaugh, K. and El-Geneidy, A. (2011). Validating walkability indices: How do different households respond to the walkability of their neighborhood? *Transp. Res. Part D Transp. Environ.*, 16(4):309–315.
- Porta, S. and Renne, J. L. (2005). Linking urban design to sustainability: Formal indicators of social urban sustainability field research in Perth, Western Australia. *Urban Des. Int.*, 10(1):51–64.
- Salop, S. C. (1979). Monopolistic Competition with Outside Goods. Technical Report 1.