Parking, Cruising, and Congestion *

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Job Market Paper

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Abstract

This paper uses a novel block-by-block panel data set of garages, traffic speed, meters, and free-of-charge curbside parking to map and assess the effects of on-street parking on traffic in New York City. The analysis starts with a theoretical model that rationalizes the connection between parking prices and traffic. The model shows how expensive garages and cheap curbside parking increase traffic volume because drivers that park curbside must cruise in search of parking. Based on the theoretical model, I follow a difference-in-differences approach to measure the effects of on-street parking on traffic speed. Estimates of the model show a significant speed reduction when free-of-charge on-street parking is allowed. I further exploit variation in the data over time and space to analyze how low curbside rates induce drivers to park on the street. The data show that most drivers have a significant incentive to cruise in search of on-street parking, especially in congested locations like Manhattan below 96$^{\text{th}}$ street.

JEL Codes: R40, R41, R48, R58

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1 Introduction

Searching for parking has been a concern in American cities since the dawn of the car era. On March 30, 1930, the *New York Times* reported that an ordinance that reduced on-street parking in downtown Philadelphia "speeded up traffic."[1] Two years earlier, a 1927 survey conducted in Detroit reported that between 19% and 34% of the traffic in two downtown locations was cruising for parking.[2] The struggle to find parking is so ubiquitous that it has found its way into popular culture—sitcoms and songs describe drivers fighting for a space as a common picture of the urban landscape.[3] Recently, the rise of ride-hailing services and the increase in car demand due to the COVID-19 pandemic have made cruising and parking a growing concern of city officials throughout the United States.[4] The allocation process of curbside parking (cruising for parking) produces a negative externality as the person that is cruising increases congestion and thus slows traffic. Garages provide a partial solution to this problem because cruising in a garage does not affect street traffic. However, parking in a garage is usually more expensive than on-street parking, which creates an incentive to cruise for curbside parking among drivers with low willingness to pay.

In this paper, I examine the parking market and traffic data of New York City (NYC) to map and assess the costs of on-street parking.[5] My study involves (i) building a theoretical model that connects on-street parking with cruising and traffic speed; (ii) quantifying the effect of on-street parking on traffic speed; (iii) mapping the location, price, and supply of parking services and how they change through the day; and (iv) mapping and assessing the demand, consumer surplus, congestion cost, and search cost produced by on-street parking.

The analysis first focuses on the microeconomics of the parking market through a theoretical model. The model highlights the critical elements of the demand for on-street parking, including the price gap between on-street and off-street parking, the traffic speed, the duration of the parking

[1] Reported in *New York Times* Philadelphia Plan Cuts Parking Evil, Davies (1930).

[2] See Simpson (1927).

[3] "The Parking Space," season 3, episode 22, of the television show *Seinfeld*; "Spaced" by Loudon Wainwright III on the album *Haven't Got the Blues (Yet)*.

[4] The following newspaper articles attest to cruising-congestion concern: Why the Fight Over Parking in New York Is "Like the Hunger Games", Goldbaum (2021); The Ride-Hail Utopia That Got Stuck in Traffic, Brown (2020); In Win for Uber, Lyft, Judge Strikes Down New York City's Cruising Cap, Bellon (2019); and Chicago Approves Traffic Congestion Tax on Ride-hailing Services, Staff (2019).

[5] The terms on-street and off-street parking are used as synonyms of curbside and garage parking, respectively.

period, and the probability of finding an empty spot. The model recognizes two costs linked to on-street parking: search cost and congestion. Search cost refers to the time spent cruising for parking, and it is entirely borne by the drivers parking on-street. In contrast, congestion is a negative externality that affects all drivers on the road, no matter where they park.

The paper next focuses on quantifying the relation between on-street parking and traffic speed. For this analysis, I consider changes in the supply of free-of-charge on-street parking (hereafter free on-street parking) due to restrictions posted on parking signs. As an example, street sweeping signs (see Figure 1) limit parking in parts of the city at different times because vehicles cannot be parked where they block street sweepers. Using parking signs, I build an inventory of the time and location of curbside spots that I later matched with Uber traffic speed records to produce a panel data set.

Quantifying the effect of on-street parking on traffic speed is a challenging endeavor for three main reasons. First, city officials enforce meters and reduce the supply of free on-street parking during rush hour; this behavior hides the effect of cruising for parking in the aggregated data. Second, the location of free on-street parking is not random; free parking is a common feature of lower-order streets, which is a differentiation factor that can introduce selection bias. Third, the traffic of each road is affected by the idiosyncrasies of each location, for example, amenities and infrastructure such as grocery stores and traffic lights.

To address the challenges mentioned above, I use a difference-in-difference approach that exploits variations in parking supply and traffic speed over time and space. My approach includes controls for time, type of street, and location. These controls and the disaggregated data allow me to isolate the effect of on-street parking from potential confounders. I document parallel trends that argue to the comparability of locations with and without on-street parking. To deal with endogeneity concerns, I consider different variations of the baseline model. Consistency in the estimates across the different specifications suggests that the potential endogeneity bias is small. Finally, I provide an hour-by-hour approach that addresses possible nonlinearities in the congestion-speed relationship described by the Macroscopic Fundamental Diagram of Traffic.

The last part of the manuscript is a welfare analysis of the effects of on-street parking on NYC's drivers. The welfare assessment is based on the framework provided in the theoretical model. The model accounts for the benefits drivers get from parking on-street, the search cost they bear, and the congestion externality produced by cruising. In this part of the paper, I exploit the spatial variation of the price data to show how the demand for different types of parking changes across the city.

To perform the welfare analysis and project it to locations beyond my sample I require some population characteristics, estimates of the value of time, and a price forecast model. Estimates of the value of time, type of commute, and other relevant population characteristics are based on data collected from the American Community Survey, and reports issued by the city of New York. To forecast the price of garages outside my sample, I use spatial econometrics methods based on the idea that garage prices are affected by neighboring competitors. I borrow the concept of cross-validation from the machine learning literature to pin the otherwise discretionary parameters in the spatial model. Using cross-validation allows me to have estimates consistent with the out-of-sample performance objective of the spatial model.

I split the paper's findings into statistical claims and measurement facts. The first type of statistical claim is estimates of causal effects between on-street parking and traffic speed. As predicted by the theoretical model, I find that free on-street parking reduces the average traffic speed. The drop in speed changes during the day, as the congestion technology is nonlinear. The strongest effect is observed during the peak of rush hour, at 5:00 p.m. At this time, having free on-street parking can reduce traffic speed by more than 2 miles per hour (MPH). This is a 15% drop in speed that can cost car commuters $700 million dollars in losses every year.

The second type of statistical claim is the proportion of drivers willing to park on-street. Based on the theoretical model, the income distribution, and the price gap between on-street and off-street parking, I estimate that around 90% of drivers are willing to cruise in search of free on-street parking. This estimate changes across the city and type of parking, as prices of meters and garages are different across locations. The proportion of drivers willing to cruise for parking is high in congested locations like Manhattan below 96^{th} street, and lower in areas farther from the city centers. Measurement facts are observations based on characteristics of the supply of parking obtained from the novel data used in the paper. Using these data, I estimate that free on-street parking is the most abundant type of parking among the three categories measured—free on-street, metered, and garages. Furthermore, the number of free on-street spaces is around four times that of metered parking and close to double the number of paid spots (meters + garages). Other measurement facts describe the price and supply of parking provided by city officials and garage operators; the supply of meters and garages is concentrated in the city center, while free parking is spread across the city.

This paper belongs to different bodies of literature. The paper contributes to the transportation and congestion literature by estimating the city-wide effect of on-street parking on traffic. Existing papers, such as Pierce and Shoup (2013), Millard-Ball et al. (2014), Krishnamurthy and Ngo (2020), and Dalla Chiara and Goodchild (2020), focus on more narrow locations and use smaller samples. The paper also contributes to the parking literature because it provides estimates based on a theoretical parking model. Previous works (Arnott and Rowse 1999; Anderson and de Palma 2004; Arnott 2006; Arnott and Inci 2006; Arnott and Rowse 2009; Inci et al. 2017) rely on numerical simulations since data were lacking. Observations on the behavior of garage operators and city officials are also contributions to the parking literature. Finally, the estimates on the space used for parking make this work part of the literature on the land dedicated to cars. Unlike existing literature (Shoup 2005; Scharnhorst 2018; Bunten and Rolheiser 2020a), my parking inventory uses parking signs to account for the time and location of parking.

The rest of the paper proceeds as follows. Section 2 provides the background on the parking literature and parking dynamics in NYC. Section 3 explains the theoretical model that connects parking prices with traffic, speed, and the costs and benefits of the parking supply. Section 4 presents the data on parking, traffic, and population. Section 5 discusses the estimation strategy and results. Section 6 describes the location and dynamics of the supply and prices of parking. Section 7 maps and assesses the costs and benefits of on-street parking. Section 8 concludes.

2 Background

In his book *The High Cost of Free Parking*, Shoup (2005) revitalized an old discussion arising from the following question: Why is there so much parking, and why is so little charged for it? This question remains valid in many of today's cities, where the space per person keeps shrinking while the area per car remains unchanged thanks to building codes and city ordinances. Extensive literature, written before and after Shoup's book, provides a strong theoretical framework aimed at explaining the economics behind parking (Vikrey 1994; Glazer and Niskanen 1992; Arnott and Rowse 1999; Anderson and de Palma 2004; Arnott 2006; Arnott and Rowse 2009). Important results such as the notion of parking as a service prone to the tragedy of the commons and the externalities of providing parking at low cost (overuse of parking and congestion from cars cruising) serve as a foundation for this body of literature. However, despite the broad consensus, the lack of data has hindered measurement of the inefficiencies and externalities linked to the parking market.[6]

The free parking and fixed meter rates found in most American cities entail differences in the way drivers "pay" for a spot is different between on-street and off-street parking. Drivers looking to park in the downtown of a major city usually face a trade-off between paying a hefty price for a garage close to their destination or having to search for and walk from a cheaper curbside spot. Since the city owns all curbside spaces, the cost of providing on-street parking at no charge is an opportunity cost borne by all taxpayers. For instance in 2018 the NYC Department of Transportation reported $228 million in parking meter revenue.[7]

Occupying a curbside spot in a saturated location has unintended consequences for all drivers, as cars cruising for parking increase the search period and street congestion.[8] The theoretical work of Anderson and de Palma (2004) and Arnott and Rowse (2009) shows how garage operators internalize the search cost externality. In the simplest versions of their models, private garage operators' parking allocation is socially optimal. This conclusion quickly fades as the models grow in complexity. However, the price gap between garages and curbside parking partially accounts for the

[6] Often the only measurements available are numerical exercises calibrated to match anecdotal evidence.

[7] (Letter Report on the Department Of Transportation's Administration of the Collection of Cash Revenue from Parking Meters.

[8] As in Arnott and Rowse (2009), curbside parking is saturated if "the occupancy rate is 100%."

externalities of underpriced curbside parking. This paper builds on this concept, providing a measurement of the demand for on-street parking that indicates the location of potential externalities caused by the low price of on-street parking. For this, I use the price and location of on-street parking and a novel panel data on garage services sold online.[9] The online garage industry is a good fit for this task, as prices are net of the search cost. The reason is simple: online platforms such as Parkwhiz and SpotHero eliminate the search cost, as all data on availability and prices are easily accessible from an internet-enabled phone or computer.

One common result of the theoretical parking literature is that higher meter rates reduce cruising and congestion, as expensive meters make parking on-street less attractive. In line with this, an important body of the theoretical literature claims that increasing the meter rates is socially optimal. Shoup (2006) shows that charging the market rate at the meter—the same rate as garages—will eliminate cruising. In Anderson and de Palma (2004), equating meter rates with those of garages produces a social optimum. Arnott and Inci (2006) find that "it is efficient to raise the on-street parking fee to the point where cruising for parking is eliminated without parking becoming unsaturated."

The scarcity of parking and the large price gap between on-street parking and garages make NYC a case of great interest to the parking allocation question. Relative to other American cities, parking in NYC is scarce; Scharnhorst (2018) estimates that NYC has only 0.6 parking spaces per household, while cities such as Philadelphia, Seattle, and Des Moines have 3.7, 5.2, and 19.4 spots per household, respectively. In the same vein, Bunten and Rolheiser (2020b) report that the area dedicated to parking in Manhattan is much less than that of Phoenix, despite having similar populations. The authors document a remarkable difference; the parking area in Phoenix adds up to more than twice that in Manhattan.

This relative scarcity of parking is reflected in prices. Shoup (2006) documents that NYC has the largest price gap between curb and off-street parking in a sample of 20 American cities. Figure 2 uses new data on parking prices to show the evolution of the price gap during the day. The findings are consistent with those reported by Shoup. The price gap for 2 hours is positive and around $20

[9] The term *garage services sold online* refers to parking services sold, using applications and websites such as ParkWhiz.com.

for most of the day, with some extreme cases in which the price difference can extend to more than \$40. Even in New York, where the average income by hour is above the national average, parking on-street can represent substantial savings for many New Yorkers.

3 Theoretical Model

The model is set in a densely populated area of a city where all streets are laid in a uniform grid. Drivers visiting one block have three options: park in a garage, at the meter, or in a free spot. Metered and free spots are on-street parking, while garages are off-street parking. Garages, meters, and free on-street parking are equally distributed across the city, so drivers face having to walk similar distances to their destinations no matter the type of parking they choose. Drivers' decision process is limited to the kind of parking, meaning that outside options are irrelevant because they are too costly.[10] Finally, parking is a homogeneous good; that is, on-street parking and off-street parking are equal in all characteristics other than price, making price the only argument of the demand function. The objective of this section is to model the relation between traffic speed and parking. In this vein, I make some simplification assumptions to keep a clean, simple relation. All simplification assumptions are explained in the following subsections.

3.1 Drivers

Drivers arriving at one block decide between parking in a garage that charges r_g per unit of time, park on-street and pay r_m at the meter, or look for a free on-street spot. Drivers make their parking decisions based on each option's full price—the rate plus search cost. Garage operators only accept drivers when they have availability, making the search cost equal to zero. On the other hand, drivers that park on-street have to cruise for parking, making the demand for on-street parking a function of the personal value of time (v). Consequently, drivers with a high time valuation will park in a garage because they cannot afford to cruise. Aware of this, garage operators charge a rate higher than that offered at the meter, pushing drivers with low time valuations to park on-street.

[10]Examples of this are drivers with fixed destinations—for example, medical patients, clients of a lawyer, or members of a club—that live far from public transit.

Drivers parking on-street expect to find an empty spot with a fixed probability (p_m) if the spot is metered and (p_f) if it is free. The process of searching for on-street parking follows what Arnott and Williams (2017) call a binomial process. Drivers cruising for metered ($i = m$) or free parking ($i = f$), expect to inspect $\frac{1}{p_i}$ spots before finding one empty. The time spent inspecting one parking spot is equal to the time used to drive by each space at traffic speed (S). The length of each parking space is normalized to one,[11] so drivers expect to cruise for $\frac{1}{Sp_i}$. Hence, the cost of cruising is equal to $\frac{v}{Sp_i}$.

Drivers compare the cost of all parking options. A driver parking in a garage pays r_g per unit of time and parks immediately without cruising. Meanwhile, a driver parking on-street parks with a probability p_i or keeps cruising with a probability $1 - p_i$. The cost of both on-street parking options is described by the following Bellman equations:[12]

$$C_{m,t} = p_m \left(\frac{1}{S_t p_m} v + r_m l \right) + (1 - p_m)\, C_{m,t+1}, \tag{1}$$

$$C_{f,t} = p_f \left(\frac{1}{S_t p_f} v \right) + (1 - p_f)\, C_{f,t+1}, \tag{2}$$

where $C_{m,t}$ is the cost of parking at the meter at time t, $C_{f,t}$ is the cost of parking at a free space, and l is the length of the parking period. This period is the time a driver needs to complete their visit to the block, which is assumed to be fixed.[13] Assuming the searching period is less than one hour, it is reasonable to think that traffic conditions change little, making $S_t = S_{t+1}$. As shown in Appendix A solving Equations (1) and (2) yield the following results:

$$C_m = \frac{1}{S p_m} v + r_m l \tag{3}$$

[11]Under this assumption, speed is in units of the length of a parking space (i.e., the number of spaces a driver cover per unit of time).

[12]The discount factor in the Bellman equation is assumed to be 1, since cruising periods are relatively short (less than one day).

[13]Fixing the value of l allows avoiding corner solutions where all drivers park in a garage and cut their visit short to compensate for the higher cost of parking. In this context, l should be understood as the minimum amount of time needed to complete the driver's visit to the block, for example, the time needed to complete a doctor's visit or a similar appointment that cannot be cut short.

$$C_f = \frac{1}{Sp_f} v \tag{4}$$

A driver is indifferent between two types of parking if their valuation of time $\bar{v}$ is such that the full price of both options is the same. That is, a driver for whom $C_m = C_f$ is indifferent between parking at the meter or in a free spot, and a driver for whom $r_g l = C_m$ is indifferent between parking on-street or in a garage. These two comparisons along with expressions (3) and (4) can be used to obtain the two threshold values that determine the demand for each type of parking:

$$\bar{v}_m = \frac{lSr_m p_f p_m}{p_m - p_f}, \tag{5}$$

$$\bar{v}_g = (r_g - r_m)\, lSp_m, \tag{6}$$

Equations (5) and (6) provide the time valuation thresholds that determine the demand of each type of parking:

- $\bar{v}_g < v$, drivers that park in a garage
- $\bar{v}_m < v < \bar{v}_g$, drivers that cruise in search of a metered space
- $v < \bar{v}_m$, drivers that cruise in search of a free-of-charge space

The difference between p_m and p_f has to be sufficiently large for drivers to use the meters. Appendix B shows that $\frac{r_m}{r_g} < 1 - \frac{p_f}{p_m}$ is a sufficient condition for having $\bar{v}_g > \bar{v}_m$ and $\bar{v}_m > 0$. It follows from Equation (6) that if $r_m \geq r_g$ drivers will only use garage and free parking.[14] To avoid this result, I assume city officials set $r_m \leq r_g$. Under this condition, $\bar{v}_g$ is the relevant threshold for the on-street parking demand, as all drivers with a valuation of time below $\bar{v}_g$ will park in a metered or free spot. Figure 3 illustrates this situation by showing the probability distribution function of v, the threshold value $\bar{v}_g$, and the fraction of drivers that park on-street and in a garage. Assuming a block receives X visitors per unit of time and that the cumulative distribution function (CDF) of v is $F(v)$, the demand for curbside parking is given by:

[14] $r_m \geq r_g$ yields an unreasonable negative value of time threshold v_g.

$$D = F(\bar{v}_g)\, X. \tag{7}$$

Figure 4 illustrates the equilibrium of the on-street market in a city block with a fixed supply of parking spots Q. When meter rates are equal or greater than r_g, the demand for on-street parking equals zero because all drivers prefer to park in a garage where there is no search cost. The demand for on-street parking reaches its maximum value when $r_m = 0$, which is when searching is the sole cost of on-street parking. $\bar{r}_m$ is the equilibrium rate, any price above $\bar{r}_m$ will cause excess supply, and any price below will cause excess demand.

3.2 Congestion

Each city block gets D vehicles cruising per unit of time. These vehicles drive along with those in transit (T), producing a car density equal to $\frac{T+D}{J}$, where J is the street capacity.

Streets are connected in a network where the congestion effects of cars ripple through the whole street grid. The Macroscopic Fundamental Diagram of Traffic (MFDT, see Daganzo 2007 and Geroliminis and Daganzo 2008) governs car flow, so speed (S) is a decreasing function of vehicle density:

$$S = S\left(\frac{T + \theta_D D}{J}\right), \tag{8}$$

where θ_D is the effect of cars cruising on traffic volume relative to that of cars in transit.

3.3 Garage Operators

The demand for off-street parking is given by the complement of the CDF function $(1 - F(\bar{v}_g))\, X$. Knowing this, garage operators set prices to maximize profit. Assuming that the CDF is log-concave, the first order condition yields that the profit-maximizing garage rate is:[15]

$$r_g = c + \frac{1 - F(\bar{v}_g)}{f(\bar{v}_g)} \frac{1}{lSp_m}. \tag{9}$$

Equation (9) shows that the price charged by garages equals the unit cost (c), plus the inverse of the hazard function $\left(\frac{1-F(\bar{v}_g)}{f(\bar{v}_g)}\right)$, times the search period $\left(\frac{1}{Sp_m}\right)$, times the vacancy rate $\left(\frac{1}{l}\right)$. The sensitivity of garage rates to changes in l, S, and p_m depends on how concentrated time valuations around the threshold value $\bar{v}_g$ are. If drivers with a time valuation equal to $\bar{v}_g$ are a small share of all drivers with a time valuation equal to or greater than $\bar{v}_g$; garage prices will be very sensitive to changes in l, S, and p_m, as garage operators can adjust prices without losing too many clients.[16]

3.4 Consumer Surplus

For a set of prices $\bar{r}_m$ and r_g such that all metered and free spaces (Q_m and Q_f) are occupied,[17] the consumer surplus (CS) of drivers that park at a meter is $\left(Q_m \int_{\bar{r}_m}^{r_g} F((r_g - r_m) lSp_m) \, dr_m\right)$. For drivers that cruise for free-parking, the consumer surplus is given by $\left(Q_f \int_0^{\bar{r}_m} F\left(\frac{Slr_m p_f p_m}{p_m - p_f}\right) dr_m\right)$. Dividing both consumer surplus expressions by the number of spots and adding them yields:

$$CS \text{ per driver parking on-street} = \int_{\bar{r}_m}^{r_g} F((r_g - r_m) lSp_m) \, dr_m + \int_0^{\bar{r}_m} F\left(\frac{Slr_m p_f p_m}{p_m - p_f}\right) dr_m. \tag{10}$$

3.5 Search Cost

Assuming that on-street empty spots are distributed uniformly around the block ($i = f, m$), the probability (p_i) of finding one empty spot is equal to the proportion of available spaces $\left(p_i = \frac{Q_i - D_i}{Q_i}\right)$. As only drivers with a valuation of time below $\bar{v}_i$ park on-street, only they bear the cost of cruising, which is

[15] Log-concavity is a reasonable assumption, as many distribution functions have log-concave CDFs, particularly the log-normal distribution function later used in this paper (see Bagnoli and Bergstrom 2005).

[16] In other words, the inverse of the hazard rate, also known as the Mills ratio, determines how sensitive garage prices are to changes in the length of the search period $\left(\frac{1}{Sp_m}\right)$ or the vacancy rate $\left(\frac{1}{l}\right)$.

[17] The assumption of having all on-street spots occupied is consistent with the need for cruising.

$$\text{Search cost per driver parking on-street} = \frac{Q_i}{S\left(Q_i - F\left(\bar{v}_i\right)X\right)} \int_0^{\bar{v}_i} vf\left(v\right)dv.$$

3.6 Congestion Cost

For a driver in transit, the average trip has a length L and it takes L/S units of time to complete it at traffic speed. One driver cruising reduces the traffic speed by S'/J in the same segment. The MFDT governs traffic, so all drivers on the road experience a drop in speed that increases by $\left(\frac{S'}{SJ}\right)$ times their travel time, so the congestion cost (CC) is given by the following:

$$CC \text{ per driver} = \frac{LS'}{S^2 J} \int_0^{\infty} vf\left(v\right)dv, \tag{11}$$

where $\int_0^{\infty} vf\left(v\right)dv$ is the expected value of time of all drivers on the road.

3.7 Welfare Gain

The threshold values given by Equations (5) and (6) depend on the cruising time; hence, the consumer surplus is net of the search cost. In consequence, the welfare gain per driver from having on-street parking (WG) is the weighted difference of the consumer surplus from Equation (10) and the congestion cost from Equation (11):

$$WG = \theta_m \int_{\bar{r}_m}^{r_g} F\left(\left(r_g - r_m\right)lSp\right)dr_m + \theta_f \int_0^{\bar{r}_m} F\left(\frac{Slr_m p_f p_m}{p_m - p_f}\right)dr_m - \frac{LS'}{S^2 J} \int_0^{\infty} vf\left(v\right)dv,$$

where θ_m and θ_f are the proportion of drivers that park in metered and free spots.

3.8 The Cost of Walking

Equation (6) is built on the idea that on-street and off-street parking are located in the same block. As such, it does not provide a result for blocks that have on-street parking but no garage, which is a common situation given that garages are not as ubiquitous as on-street parking. To increase the coverage of my analysis to locations that have no garages but have one nearby, I assume that garages provide parking services to the nearby blocks as long as the cost of walking is low. To include this feature in the model, I introduce walking into Equation (6).

I assume that the cost of walking (w) is a function of the distance between the parking and destination blocks (d), and the value of time. This cost adds up to the full price of on-street parking. The cost has to be added twice as drivers have to walk back and forth, so Equation (6) can be re-written as

$$r_g l + 2w(d,v) = r_m l + \frac{\bar{v}}{Sp_m}.$$

w limits the garage's market area, as the garage is not a viable option to destination located at any distance equal or greater than d^*, where d^* is such that the walking cost $w(d^*,v)$ is above $\frac{1}{2}\left((r_m - r_g)l + \frac{\bar{v}}{Sp_m}\right)$. Most papers limit the market area to a 0.2- to 0.6-mile radius (Choné and Linnemer 2012; Lin and Wang 2015; Inci 2015). The 0.6-mile radius represents a relatively low cost if I only account for the time spent walking—if people walk at an average speed of 3 MPH, they can cover the 0.6 miles in 12 minutes and the cost will be just 1/5 of an hourly wage. Furthermore, authors such as Kobus et al. (2013) value the time spent walking at one-third of the wage since walking is considered a pleasant activity. Based on the above, I use the 0.6-mile radius to determine the garage's market area.[18] Nevertheless, as the cost of walking is fairly small, it is excluded from all other calculations.

4 Data

This section describes the sources and characteristics of the panel data used in this paper. The panel contains hour-by-hour data for all census blocks in NYC (hereafter blocks). The data set is divided into parking and traffic data. Parking data account for three different types of parking: garages, metered on-street, and free on-street. I use a mix of public and private sources, as explained in this section. Traffic speed data come from a unique source, the Uber Movement website. At the

[18]The market area or area of influence includes the locations (blocks) where the garage is close enough to be a competitive option for drivers.

moment of my query, Uber provided anonymized data on the time, location, and speed of 2,634,421 trips that happened in NYC during the last quarter of 2019. Figure 5 maps the average speed of all streets in the sample. Data for 2020 are also available. However, to avoid possible noise from the COVID-19 pandemic, I only use data for 2019.

Matching the data from the different sources presents challenges from both the time and space dimensions. From the spatial point of view, matching the data is complicated because streets, curbs, and garages are contiguous to each other but not under the same coordinates. To bridge this difficulty, I used blocks as the aggregation unit for the spatial dimension. Blocks provide high granularity data consistent with the idea of cruising around the block or a small group of blocks.[19]

Most of the challenges in matching the time of the different data sets come from Uber's traffic speed data. Uber Movement data entail two significant restrictions. The first is simple; at the moment of my query, traffic speed data were only available for the last quarter of the year. This constraint meant that all data had to be limited to the same time frame. The second restriction comes from the lack of dates in the traffic speed data—the panel contains the speed, location, and hour of every trip but does not have the date. I do the following to address this issue. First, I only use parking data from Monday to Friday, assuming that most Uber trips happen during weekdays.[20] Second, for each block I average traffic speed and garage prices for every hour of the day,[21] yielding 24 observations per block. Under the assumption that most trips happen during weekdays, the data describe the traffic speed during an average weekday. Last, I only use data on the supply of on-street parking from locations with the same parking rules for every weekday, so parking supply data are consistent with traffic speed data.[22]

I only use locations with parking signs, as I can only be certain of the parking schedule on a block if there is a parking sign. Blocks with no parking sign may or may not have on-street parking.[23] Since I only use locations with parking signs, and traffic data are averaged at the hour

[19]Drivers tend to search for parking in small areas surrounding their destination to minimize the length of the walk; similar assumptions are implicit in Anderson and de Palma 2004 and Arnott and Williams 2017.

[20]Five of every seven days are weekdays.

[21]For instance, speed at time h in block i is the average of all trips that pass by block i at time h.

[22]Locations with parking signs that only enforce parking some weekdays—for example, no parking Monday to Thursday, or no parking Tuesdays and Thursday—are left out from the data used in the regression exercise.

[23]I found this information by using Google Street View and doing in situ verification.

level,[24] the panel is balanced.

I used a broad set of sources to build the parking data set, all of which are described below. It is important to mention that not all parking in NYC is in this data set; driveways and private residential garages are not included. Furthermore, some of the on-street parking lacks traffic signs. This lack of signs is especially true in residential and low congestion areas. However, the absence of some of those parking locations is not a concern because they are very unlikely to cause high congestion—residents parking in their driveways or garages do not cruise and drivers cruising on an empty street do not create congestion.

- **Free on-street parking (signalized):** The City of New York does not provide an inventory of the free on-street parking provided across the city. However, it is possible to build one by using parking signs. The NYC Department of Transportation offers a detailed map of the text and location of all traffic signs in the city. The data are available at the City of New York Open Data portal. Of all the traffic signs, I found 20,750 with the word parking or a parking symbol printed. I use these signs to build the inventory of free on-street parking. By connecting those parking signs, I am able to map the curbs where parking is permitted. I then use the city map of metered parking to subtract all locations with paid on-street parking. I use the text on parking sign to make dummy variables that indicate when parking is allowed and when meters are enforced in each location.[25] To estimate the number of spaces, I assume an 18-foot length for every spot. Eighteen feet is the length recommended by the Transportation Engineering Agency.[26] Figure 6 maps the location of all curbs with on-street parking. In a cross-comparison of this map with other private sources—SpotAngels.com and Parkopedia.com—no major differences were observed.

- **Paid on-street parking:** The NYC Department of Transportation offers a detailed map of the curbs where metered parking is permitted through the City of New York Open Data

[24] An observation at time h is the average of all observations time h during one quarter.

[25] Many signs are tagged with the same text in their description, so I could separate them into 1,200 different groups. All discrepancies that lead to illogical results—such as typos or poor wording—were solved by looking at the traffic sign on Google Street View.

[26] See TEA "Parking Tutorials".

portal. The data contain the price but not the time when meters are enforced. The time frame for meter enforcement was procured by checking the parking signs in each location, as done with free on-street parking. Since the data provided by the city only describe the segment of the curb that is available for parking, I used a length of 18 feet to estimate the number of spaces.[27] Figure 7 maps the location and prices of all curbs with metered on-street parking.

- **Garage supply:** Using the register of licensed businesses provided by the City of New York Open Data portal, I built a data set with the locations and capacity of all licensed garages and parking lots in NYC (Figure 8). A few places needed amendments since they registered coordinates outside NYC. To do these amendments I used the business's address, Google Maps, and Google Street View. Figure 8 maps the location and capacity of all registered garages. For garage prices I web-scraped Parkwhiz.com for data over one year (July 2019 to July 2020). This process provided me with the hour-by-hour prices of a subset of garages accounting for 51% of all licensed garages.

5 Empirical Strategy

To measure the effect of on-street parking on traffic, I use within-day changes in the parking supply on each block. Under the theoretical model, modifying the number of parking spots affects traffic speed through changes in the number of drivers cruising. The closing of the curb to parking reduces the probability of finding an empty spot and thus increase the time spent cruising. Longer cruising periods make it costly to park on-street, reducing the demand for curbside parking. A lower demand for on-street parking means fewer drivers cruising, lower traffic density, and higher traffic speed. Figure 9 illustrates the effects of reducing on-street parking on traffic speed based on the theoretical model.

[27] The same length used with free on-street parking parking.

5.1 Challenges and Identification Assumptions

Assessing the effect of on-street parking on traffic speed comes with challenges. The first obstacle is that city officials reduce the supply of on-street parking during the high congestion period. This behavior transforms the aggregated data in a way that suggests a relation opposite to that predicted by the theoretical model—the model predicts that increasing on-street parking reduces traffic speed while city officials reduce on-street during the slow traffic periods. Figure 10 shows the traffic speed and percentage of curbs where parking is allowed for every hour of the day. Most temporary parking restrictions start at 7:00 a.m. and end at 5:00 p.m. In this period the speed drops along with the percentage of curbs available for parking. Outside the 7:00 a.m. to 5:00 p.m. period, almost all the temporary parking restrictions are lifted. This pattern is depicted in Figure 10, where the curbside availability remains close to 100% between 6:00 p.m. and 6:00 a.m.

Another obstacle to estimating curbside parking effects on traffic is the group and idiosyncratic characteristics of city blocks with free on-street parking. Free on-street parking is usually found on lower order streets, while metered parking is a feature of main streets and avenues. This group difference is a potential confounder, as it affects the traffic speed. Similarly, street idiosyncrasies such as amenities and infrastructure have an impact on the traffic flow and speed recorded in each block.

The objective of the identification strategy is to estimate the effect of on-street parking by comparing blocks where traffic speed is affected by group and individual characteristics. To do this, I use a difference-in-difference strategy that exploits the variation in time and space of traffic and free on-street parking supply. This approach allows me to control for the time and location factors described above.

The difference-in-difference strategy relies on the assumption of parallel trends. Providing evidence of the viability of this assumption is important in defining treatment and control groups. Splitting the sample between treatment and control groups is not straightforward as blocks alternate between having and not having on-street parking throughout the day. To provide a clean comparison, I focus on the period when most changes occur—7:00 a.m. and 5:00 p.m. Based on this time frame, I define having free on-street parking as the treatment, and I explore the effects of moving back and forth between the treated and nontreated groups.

Using the 7:00 a.m. and 5:00 p.m. thresholds, I take a 10-hour period (5 hours before and 5 hours after each threshold) and compare a subsample of blocks that have a changed supply of parking with blocks that do not have a changed supply. Five hours before and after are the largest symmetric pre- and post-treatment periods possible given the 10-hour interval. Figure 11 provides raw graphical evidence of parallel trends before and after both thresholds. In this same spirit, Appendix Figure **??** provides the aggregated comparison of all blocks in the sample. Again, the evidence is consistent with that shown in Figure 11 as both groups, blocks with and without free on-street parking, show parallel trends during the day.

Using the same subsample and thresholds of the raw parallel trend analysis above, Figure 12 shows an hour-by-hour event study analysis of the difference in means between the treated and nontreated groups. The evidence supports the no pretrend assumption, as there is no significant difference between the treated and nontreated groups before changes in the parking supply. This result holds at both thresholds: when the supply of parking drops (7:00 a.m.) and when the supply of parking increases (5:00 p.m.). The event study provides further evidence of how aggregated data hide the effect of on-street parking on traffic speed. Evidence that supports the disaggregated analysis is described in the following section.

5.2 Econometric Model

The identification strategy leads to a linear approximation of Equation (8) that yields the following regression equation:

$$S_{ih} = \alpha_i + \alpha_h + \gamma_i + \beta_F \mathbb{I}\{\text{free parking}_{ih}\} + \beta_X X_{ih} \beta_X + \varepsilon_{F,ih}, \tag{12}$$

where α_i are the fixed effects that account for the unique characteristics of every block; α_h is the vector of the hour of the day fixed effects; γ_i controls for the type of parking available at each location; $\mathbb{I}\{\text{free parking}_{ih}\}$ is the indicator function that is equal to 1 when there is free on-street parking in location i at time h; and X is a set of dummy variables that act as controls for transition periods (X_{NY}, X_{YN}, and X_{MC}), spill over effects (X_{NP}), and type of parking (X_{FR} and X_{ME}) as described below:

- No parking to parking $X_{NY} = \begin{cases} 1 & \text{Switch from not allowing to allowing parking} \\ 0 & \text{Otherwise} \end{cases}$
- Parking to no parking $X_{YN} = \begin{cases} 1 & \text{Switch from allowing to not allowing parking} \\ 0 & \text{Otherwise} \end{cases}$
- Musical chairs $X_{MC} = \begin{cases} 1 & \text{Switch from allowing to not allowing parking and back in less than on hour} \\ 0 & \text{Otherwise} \end{cases}$
- Neighbor block parking $X_{NP} = \begin{cases} 1 & \text{Neighbor blocks offer any type of on-street parking (free or metered)} \\ 0 & \text{Otherwise} \end{cases}$
- Free on-street parking $X_{FR} = \begin{cases} 1 & \text{Only has free parking} \\ 0 & \text{Otherwise} \end{cases}$
- Metered on-street parking $X_{ME} = \begin{cases} 1 & \text{Only has metered parking} \\ 0 & \text{Otherwise} \end{cases}$

Equation (12) assumes the congestion technology from Equation (8) can be approximated with a linear equation. This assumption averages the effect of cruising during high and low congestion periods. The effect of on-street parking on traffic speed is unlikely to be constant as the congestion technology is unlikely to be linear. To estimate changes in β_F through the day, I estimate an hour-by-hour cross-section version of Equation (12):

$$S_i = \alpha_{ih} + \beta_{Fh}\mathbb{I}\{\text{free parking}_i\} + \beta_{Xh}X_i + \varepsilon_{F,i}, \tag{13}$$

where β_{Fh} is the parameter of interest that reflects the effect of on-street parking on congestion at time h. I limit the regressions of Equation (13) to the 7:00 a.m. to 5:00 p.m. period, as there is little to no variance in the supply of free on-street parking beyond this time period (see Figure 10).

5.3 Results

Table 2 shows the result of estimating Equation (12). Standard errors are clustered at the borough level by hour. Clustering at the borough level follows the physical barriers created by the Hudson River. The idea behind this type of clustering is that physical barriers define systems of streets, each governed by the MFDT.

Results in Table 2 show that allowing on-street parking in one block can reduce speed by 0.15 to 0.22 MPH. Estimates are small as they bundle every hour of the day. The estimates are consistent with the introduction of the different types of controls, as shown in columns 2 to 4. Results in Table 2 bundle together the effect of cruising during high congestion and low congestion periods; as such, they are expected to be small.

Figure 13 shows the estimates of Equation 13 between 7:00 a.m. and 5:00 p.m. The figure shows greater effects than Table 2 as it allows for nonlinearities during rush hour. The results show how the effect of cruising on traffic speed becomes more significant through the day, reaching its peak at 5:00 p.m. As with Table 2, standard errors are clustered at the borough level.

The drop in speed shown in Figure 13 represents a significant loss of time for commuters that drive. For example, a commuter that leaves for work at 8:00 a.m. and drives back at 5:00 p.m. loses 7 minutes on average due to drivers cruising for parking (2 minutes in the morning and 5 minutes in the afternoon).[28] Those minutes add up to around 32 hours every year, and multiplied by the number of car commuters and their value of time, those hours represent roughly $700 million in losses.[29] This number is an underestimation as it overlooks other vehicles on the road, such as buses and for-hire vehicles, as well as other types of drivers.

[28] At 8:00 a.m. the loss in speed is 0.9 MPH and the average speed is 16 MPH, so the trip is 5% longer owing to cars cruising. At 5:00 p.m. the drop in speed is 2.3 MPH and the average speed is 14.6 MPH so the trip is 15% longer owing to cars cruising. If the average one-way car commute is around 36 minutes (from the Census' Public Use Microdata Areas PUMAs), the time loss is close to 7 minutes a day.

[29] According to the U.S. Bureau of Labor Statistics, 4,650,180 NYC residents worked in NYC during 2019. The PUMAs data reported that in 2019, 29% of NYC commuters drove to work (Table B08105A: Means of Transportation to Work). To calculate the value of time I use the formula from the U.S. Department of Transportation described in Section 7.1.

5.4 Robustness

A reasonable concern with estimates in Table 2 is that the results could be driven by a phenomenon other than daily changes in the supply of on-street parking. The concern is especially worrisome due to the cyclicality of traffic and parking supply. For example, the estimator will wrongly estimate a significant effect of parking supply on traffic if all commuters drive by one location at time h and, coincidentally, parking signs modify parking in that location at the same time.

To alleviate concerns on this issue, I perform a placebo test for a random sample of locations that have no on-street parking (fake treatment group). The parking schedule (when parking is permitted) changes across locations. This makes the assignment of the falsification test a nontrivial task. My strategy to assign the falsification test consists of using the five most common on-street parking schedules in my traffic sign survey: from 10:00 a.m. to 7:00 a.m. next day, 11:00 a.m. to 8:00 a.m., 11:00 a.m. to 7:00 a.m., 1:00 p.m. to 10:00 a.m., and 2:00 p.m. to 10:00 a.m.[30] Using these five different schedules, I create dummy variables that I later assign to the randomly selected fake treatment group. Table 3 presents the estimates of the placebo tests. The table shows no significant effect in any time frame as expected.

Clustering in Table 2 is done at the borough level. Correlation of unobservable factors can exist in smaller groups. This correlation can lead to smaller standard errors and misleading conclusions. To address this issue, Table 4 clusters errors at the census tract level. The table shows standard errors similar to those in Table 2. The results are encouraging given that census tracts are one of the smallest granularities possible for this exercise.[31]

6 Parking Supply, Prices, and Traffic Speed

Not every street in NYC is congested, nor are busy streets always congested. Traffic and the supply of parking are factors that change across space and time. This section looks at the dynamics during the day and across the city for four variables: traffic speed, parking prices, and the supply of

[30] In all cases the last hour marks the end of the parking period next day. For example, 2:00 p.m. to 10:00 a.m. means that there is no curb parking between 11:00 a.m. and 1:00 p.m.

[31] As the data set is built at the census block level, technically data can be clustered at the census block group level, however, this would leave groups with very few observations.

on-street and off-street parking. The data patterns in this section describe the behavior of city officials and garage operators. The analysis also provides further insight into the reasoning behind the identification strategy presented in section 5.

6.1 Parking Supply and Location

To understand how on-street parking affects traffic, it is important to know the location and price of the parking supply. The model in Section 3 ignores this question as it focuses on the demand dynamics within a block. The model assumes that the garage's location is fixed as the cost of relocating is prohibitive. In this subsection I rely on the work of Anderson and de Palma (2004), which provides a model in which all drivers visit the same desirable location; the city business district (CBD). As in the monocentric city model (Alonso 1964; Muth 1969; Mills 1967), parking prices in Anderson and de Palma (2004) become higher as locations get closer to the CBD. Figure 14 shows evidence of a gradient consistent with a monocentric city approach, as prices drop when the distance to the CBD (DCBD) increases.[32] The relation between the logs of prices and the DCBD is significant, and the correlation between the two variables is higher than 0.4.

Meter rates show behavior similar to that of private garages. Figure 15 plots meter rates and DCBD. The type of plot is different due to the discontinuity of meter rates. Unlike garages, meters have six price zones with a fixed price for each zone. The relation between meter prices and the DCBD is also negative. Higher meter rates ($12 and $10.75) are mostly in blocks closer to the CBD, while lower rates ($2.5 and $3) are more common in blocks more than 5 miles away from the CBD.

The number of garages is also consistent with the monocentric demand model. Figure 16 shows how garages are concentrated around the CBD.[33] The result is consistent with previous findings. If the CBD is a common desirable location, private parking providers allocate around it. Figure 16 also shows the percentage of blocks with meters. The result is similar to that of garages: the closer

[32] I use the location of the Empire State Building as the CBD. A similar definition of the CBD of NYC can be found in Albouy et al. (2018).

[33] A density measure provides a better description, as it controls for the area. This approach is relevant because longer distances from the CBD imply larger ring areas that can contain more garages.

to the CBD, the higher the meter density.

The supply of free on-street parking behaves differently from that of meters and garages. For instance, free on-street parking is more spread across the city. Figure 17 shows the percentage of blocks with free on-street parking around the CBD. In contrast to garages and meters, there is no step gradient. In the first 5 miles from the CBD, the percentage of blocks with on-street parking increases, and this result is likely driven by the increasing presence of residential buildings in the areas farther from the CBD. The percentage starts to drop in the outskirts of the city, where blocks are larger and industrial and green areas are more common.

These findings on the price and distribution of parking show how the supply of meters and that of garages have similar spatial characteristics in both quantity and prices. Free on-street parking, however, follows its own set of rules.

6.2 Speed and Prices During the Day

Traffic speed and garage prices have a cyclical behavior during the day. This cyclicality is related to the daily routines of a city's inhabitants, especially during weekdays. This behavior has an important impact on traffic and the decisions regarding the supply and price of parking. Figure A.1 shows the hour-by-hour behavior of traffic speed during the day. The pattern relates to rush hour with two low-speed kinks at 8:00 a.m. and 5:00 p.m. Figure A.1 shows this behavior by plotting the $\alpha_{S,h}$ obtained from estimating:

$$S_{ih} = \alpha_{S,i} + \alpha_{S,h} + \varepsilon_{S,ih}.$$

As with traffic speed, garage prices show that garage operators' pricing behavior is consistent with the usual 9:00 a.m. to 5:00 p.m. work schedule. Figure A.2 has the same approach used with traffic speed; it plots the hour of the day effects ($\alpha_{r,h}$) obtained from estimating the following equation:

$$\ln\left(r_{g,ih}\right) = \alpha_{r,i} + \alpha_{r,h} + \varepsilon_{r,ih}.$$

The waving behavior shows that the lower prices are offered between 6:00 a.m. and 8:00 a.m. (early birds) and in the 5:00 p.m. to 9:00 p.m. span—after office hours.

Similar to garage operators, city officials adjust the supply and price of on-street parking during the day. Figure 10 shows how the percentage of available parking declines during the day and increases back at night. This cyclical behavior partially matches the drop in traffic speed observed during the first half of the day. Similar behavior is observed in Figure 18, which shows how most meters are enforced when traffic is the slowest.

Figures 10 and 18 provide a good example of how aggregated data can hide the negative relation between on-street parking and traffic speed. At first glance, the figure shows a positive relation between the supply of on-street parking and traffic speed, as the city reduces the supply during periods of high congestion. In this figure, location-specific and cyclical components confound the effect of increasing on-street parking and traffic speed. A more desegregated analysis allows separating some location-specific and cyclical components that can confound the effect of increasing on-street parking and traffic speed, as shown in Section 5.

Figure **??** shows the dynamics of traffic speed in blocks with and without on-street parking during the day. Blocks with no on-street parking consistently show a higher speed than blocks with on-street parking. The difference in speed looks nonsignificant owing to high variance. However, high variance across locations can mask within-location significant effects. Section 5 presents an identification strategy that addresses this issue.

7 Welfare Analysis

The welfare analysis is based on the theoretical model described in Section 3, estimates of the effect of on-street parking on traffic speed from Section 5, and a set of observations and calibrated parameters obtained from census data, government reports, and other papers. I also estimate the value of time distribution function for drivers in NYC and forecast the price of garages outside my sample using a spatial econometric approach.[34] The results of the welfare analysis are divided into

[34] Since I only have the price for a subset of all garages in NYC (prices sample), I build a forecast for locations where the price is missing.

a granular assessment of the incentives to park on-street in each block (Section 7.3) and a city-level back-of-the-envelop calculation of the welfare effects of on-street parking (Section 7.4). Sections 7.1 and 7.2 lay the foundation for the necessary estimates and provide the forecast needed to produce the results in sections 7.3 and 7.4.

7.1 Distribution of the Value of Time and the Demand for On-street Parking

Following the recommendations of the U.S. Department of Transportation, I use the household income by the hour to estimate the distribution of the value of time. The Department of Transportation uses a formula where individuals are assumed to work 8 hours a day 5 days a week, and their value of travel time is calculated as 50% average hourly income.[35] The 50% assumption is consistent with some of the existing literature as documented in Belenky (2011).

The NYC Independent Budget Office provides personal income data by deciles.[36] To approximate the CDF of the value of time $F(v)$, I use maximum likelihood to fit a log-normal distribution to the average of each income decile. The estimation yields a log-normal distribution with a mean of 37 and variance of 12,636. A similar approach can be found in Hall (2021). Figure 19 shows the observed deciles and the fitted CDF.

7.2 Predicting Garage Prices

Equation (7) describes the demand for curbside parking in blocks where both options, garage and on-street parking, are available. Not all blocks in NYC have a garage, nor do I have the prices of all garages in NYC (my sample has 51% of all garages in NYC). To expand the on-street parking demand analysis, I do two things. First, following Section 3.8, I define 0.6-mile-radius market areas, which are areas where garages offer a viable parking option to any visiting driver. Second, I forecast garage prices in blocks with garages outside my sample. For this, I use a spatial autoregressive model under the idea that garage operators engage in price competition with their closest competitors.

[35] The average hourly income is calculated as the yearly income divided by 2,080 hours worked in a 9:00 a.m. to 5:00 p.m. work schedule (8 hours a day, 5 days a week, 52 weeks), see Belenky (2011).

[36] I use 2019 data from the Independent Budget.

Assuming parking is a homogeneous service, the price at one location is determined by neighboring garages:

$$r_g = \rho W r_g + \mu + \epsilon,$$

where W is the spatial contiguity matrix under an equal weight criterion, which is

$$W = \begin{bmatrix} 0 & w_{1,2} & \cdots & w_{1,n} \\ w_{2,1} & 0 & & w_{2,n} \\ \vdots & & \ddots & \vdots \\ w_{n,1} & \cdots & w_{n,n-1} & 0 \end{bmatrix} \quad \text{where:} \quad \begin{array}{l} w_{ij} = \frac{1}{k} \text{ if block } j \text{ is among the } k \text{ closest blocks} \\ w_{ij} = 0 \text{ else.} \end{array} \tag{14}$$

For the W matrix in (14), I picked a criterion of equal weight for all near garages. This criterion is based on the idea that competitors ought to be among the closest neighbors, but that no neighbor can be singled out as the most important competitor. The difficulty in singling out the most important competitor comes from unobserved idiosyncrasies. For instance, a garage might have a deal with a nearby office building that provides a captive market, making the garage operator less sensitive to the competitor's pricing scheme. The second advantage of this criterion is that it provides a simple structure that facilitates the calculations needed for the forecast ($(I - \rho W)^{-1}$).

To pick the number of neighbors k in matrix W, I borrow the concept of cross-validation from the machine learning literature. Figure A.4 plots the mean square error (MSE) of the 10-fold cross-validation exercise for eight different definitions of the W matrix—eight different values of k, from 3 to 10. The sample is organized from north to south and split into 10 groups of similar size to produce the 10-fold cross-validation exercises.[37] Using 9 of the 10 groups, I forecast the prices of the left-out observations and record the MSE. This exercise is then replicated nine more times, each time leaving out a different group. The MSE serves as a measure of the out-of-sample performance of the model. This is relevant as the objective is to produce the best out-of-sample forecast.

Figure A.4 in the Appendix, shows how the MSE plateaus after $k = 7$, suggesting no major

[37] There are a few small differences in the group size of no more than three observations. The reason for this is that some garages close to the latitude cutoffs have no neighbors within their group, so they are left out.

gains in forecasting performance when using W matrices with k greater than seven. Similarly, Table 5 uses the full sample to show that the estimates of ρ change little when the W matrix accounts for more than seven neighbors (panel B). For this reason, I chose $k = 7$ as the preferred structure of the W matrix for the out-of-sample forecast.

7.3 On-street Parking Demand

Figures 20 and 21 map the percentage of drivers that are willing to park on-street in each block ($F(\bar{v})$). Figure 20 compares garages and free curbside parking, and Figure 21 compares garages and meters. Numbers in the map are based on the estimated income distribution (F) and a numeric approximation to $\bar{v}$ in Equation (6).

To calculate $\bar{v}$, I do the following. First, using observed and forecasted prices,[38] I calculate the average daily price gap between on-street and off-street parking in each location for a 2-hour period (papers including Arnott 2006 and Arnott and Rowse 2009 also use a 2-hour period). Second, the expected cruising period $\left(\frac{1}{Sp_m}\right)$ is assumed to be 10 minutes for cars looking for metered parking,[39] and 20 minutes for cars looking for free parking.[40]

Figure 20 shows that in most locations where garages and free curbside parking are an option, more than 90% of New Yorkers are expected to cruise for on-street parking, especially in Manhattan below 96th Street. However, the story changes as we compare garages and meters. Figure 21 shows the expected percentage of drivers willing to cruise for parking when all on-street parking is metered. If I limit my analysis to only locations with meters and assume all spots are metered, the percentage of drivers willing to park on-street drops from 94% to 83%.

7.4 Consumer Surplus, Search Cost, and Traffic Delays

In this section I conduct a back-of-the-envelope calculation of the cost and benefits of on-street parking based on the consumer surplus (Equation 10), search cost (Equation 3.5), and congestion

[38]For garages in the sample, I used observed prices; for locations out of the sample, I used forecasted prices.

[39]Shoup 2006 review a handful of studies that calculate cruising time in NYC to be between 7.9 and 13.9 minutes.

[40]Millard-Ball et al. 2014 estimate that the increase in prices from the San Francisco SFpark program reduce the average cruising distance by one half.

cost (Equation 11). For this assessment I use the parameters and estimates discussed in section (7.1). The calculations are done hour-by-hour as prices, traffic speed, and the effect of on-street parking changes throughout the day.

On-street parking is a service that provides a significant benefit to some and a small cost to many—a few drivers benefit from parking at a low rate, while many others face longer travel times. In view of this, the consumer surplus, the search cost, and the congestion cost have to be reweighted because they affect different populations; the consumer surplus and search cost only affect drivers that park on-street, while congestion affects everyone on the road. I do the reweighting based on the 2018 and 2019 NYC Mobility Reports.[41]

According to the survey in the 2019 NYC Mobility Report, 44.2% of trips are in vehicles that use the street grid—30.2% use cars, 11.5% bus, and 2.5% for-hire vehicles.[42] This means that cars represent 68% of all trips that use the street grid. Among car owners, 53% declared they parked on-street, according to the 2018 NYC Mobility Report. Hence, for every user of the street grid, there are 0.36 users of on-street parking. Finally, I use the weighted average of metered and free on-street parking to provide a unique number for the consumer surplus and search cost. According to my estimates, 81% of on-street spots are free, and the remaining 19% are metered.

Under the theoretical model, gains from on-street parking can be measured as the difference between the consumer surplus and the congestion cost, as the search cost is embedded into the consumer surplus. Figure 22 shows the hour-by-hour gains by comparing the two variables through the day. To simulate the congestion cost and consumer surplus, I use the structure described in Equations (10) and (11); the distribution of the value of time estimated in Section 7.1; the calibrated values described in Section 7.3; and the weights mentioned in the paragraph above. The figure shows how the gains from on-street parking drop through the day as the gap between the consumer surplus and the congestion cost narrows. The main reason behind this outcome is that the price gap between garages and on-street parking is relatively stable while the congestion grows steadily throughout the day.

[41] 2018 NYC Mobility Report and 2019 NYC Mobility Report.

[42] This percentage ignores bicycle riders as they can avoid car congestion.

8 Conclusions

For decades on-street parking has been subsidized under the pretext that it improves the business of merchants. However, despite a substantial body of theoretical literature that highlights the downsides of curbside parking, the lack of data has limited the empirical analysis to specific projects and locations within cities. This paper sheds light on these topics by using city-wide data to map and assess the cost of on-street parking in NYC.

The paper estimates a negative effect of curbside parking on traffic. Cars cruising for parking create congestion that slows down traffic. By the paper's estimates, a car commuter that drives into the city at 8:00 a.m. and drives back to their home at 5:00 p.m. can lose 7 minutes a day or 32 hours a year. Multiplying this result by the average value of time and the number of commuters yields $700 million in losses every year. The number is an underestimation since it does not account for transit users, drivers other than commuters, and other users of the street grid.

The effect of curbside parking on traffic changes throughout the day because the congestion technology is not linear. A car cruising during rush hour has a worse impact on traffic than a car cruising in an empty street. The paper estimates that on-street parking has the largest effect on traffic speed at 5:00 p.m., the peak of rush hour. Offering on-street parking at 5:00 p.m. can reduce traffic speed by 2 MPH, which represents a 15% average drop in speed.

I produce a set of simulations based on the theoretical model and the estimated demand for on-street parking. The results show that the prices charged by garages are so high that more than 90% of drivers are willing to cruise in search of on-street parking. This high demand for on-street parking is concentrated in congested locations of the city. The simulations show that the percentage of drivers that cruise for parking drops significantly if all on-street parking is metered at current prices.

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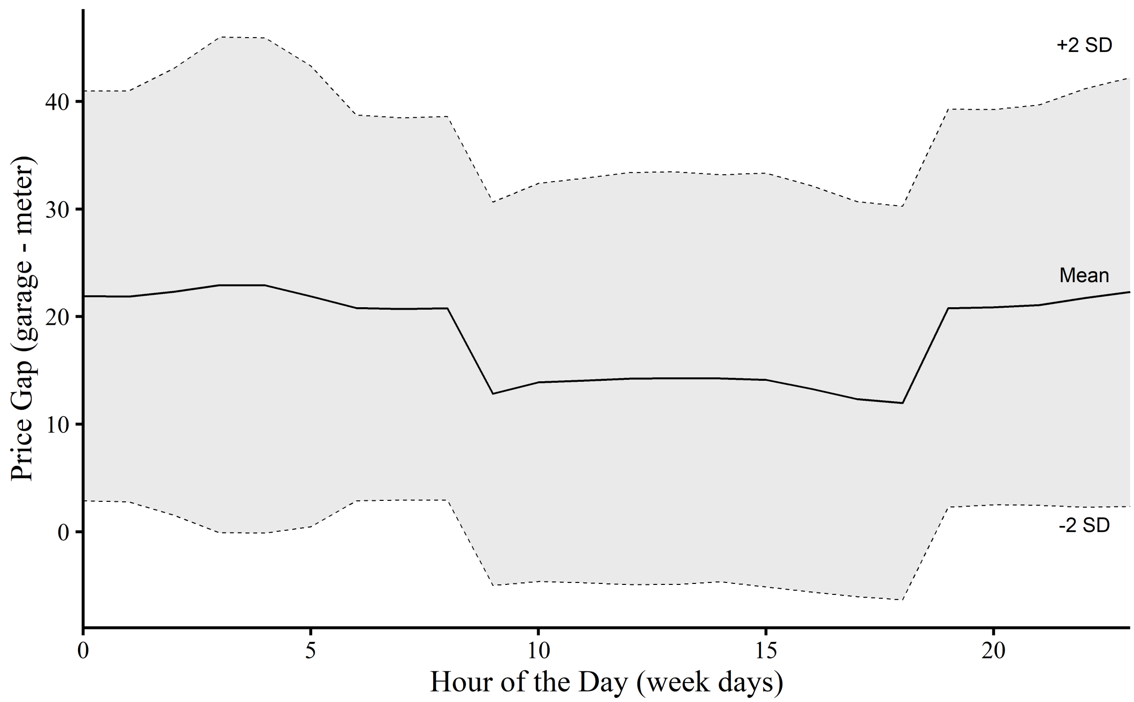
Figure 1: Example of Parking Signs in New York City
Parking Signs are Used to Build the Hour-by-hour Inventory of Free On-street Parking

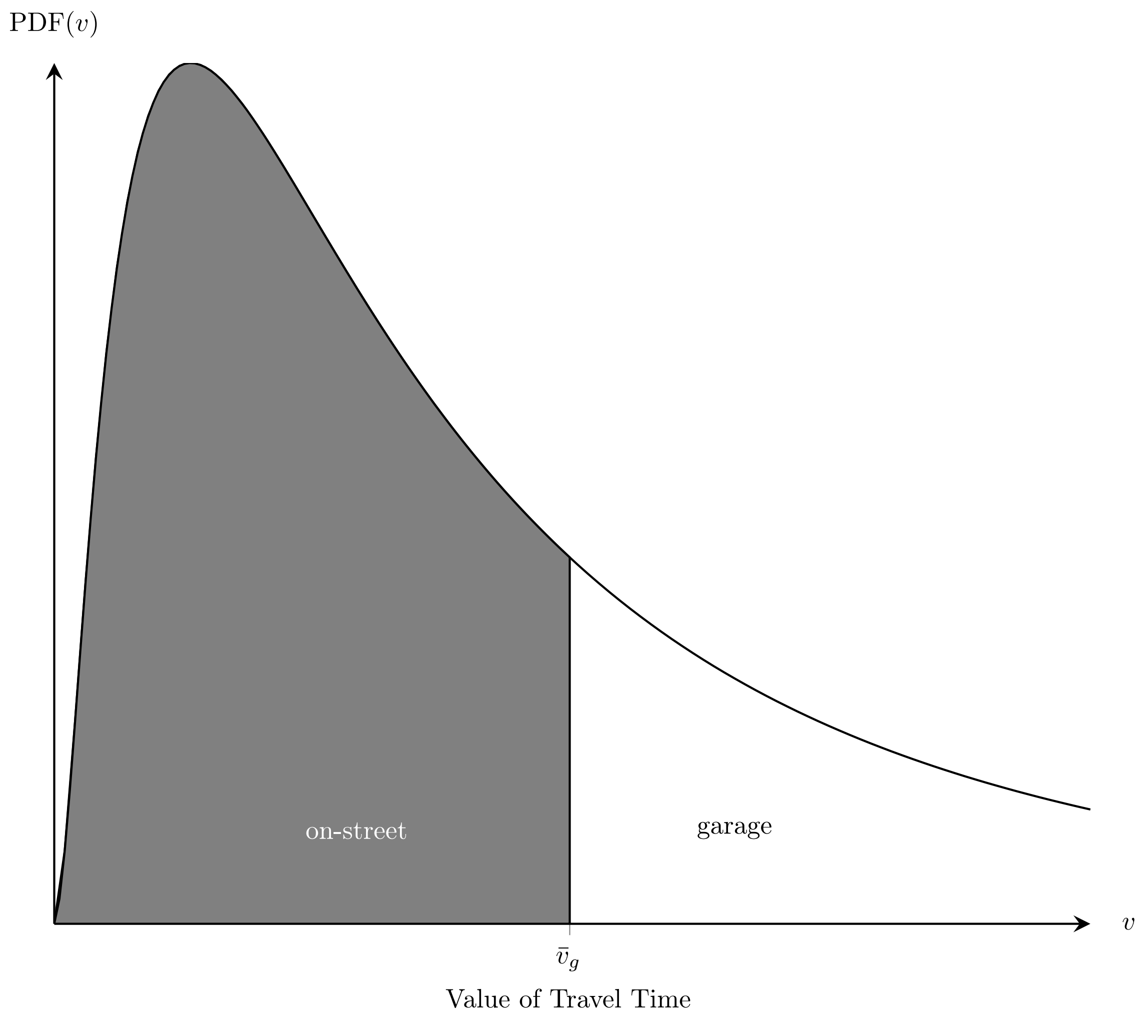
Notes: The two figures are examples of parking signs used to build the panel data of free parking in New York City. The city provides a map with the location and text on all traffic sign. I select all traffic signs that say something about parking and interpret their message. Based on these parking signs, I mark the location and schedule of on-street parking.

Figure 2: On-street Parking Savings, Two Hour Price Gap NYC
Garages ($) - Meters ($), Mean and 2 Standard Deviations (SD)



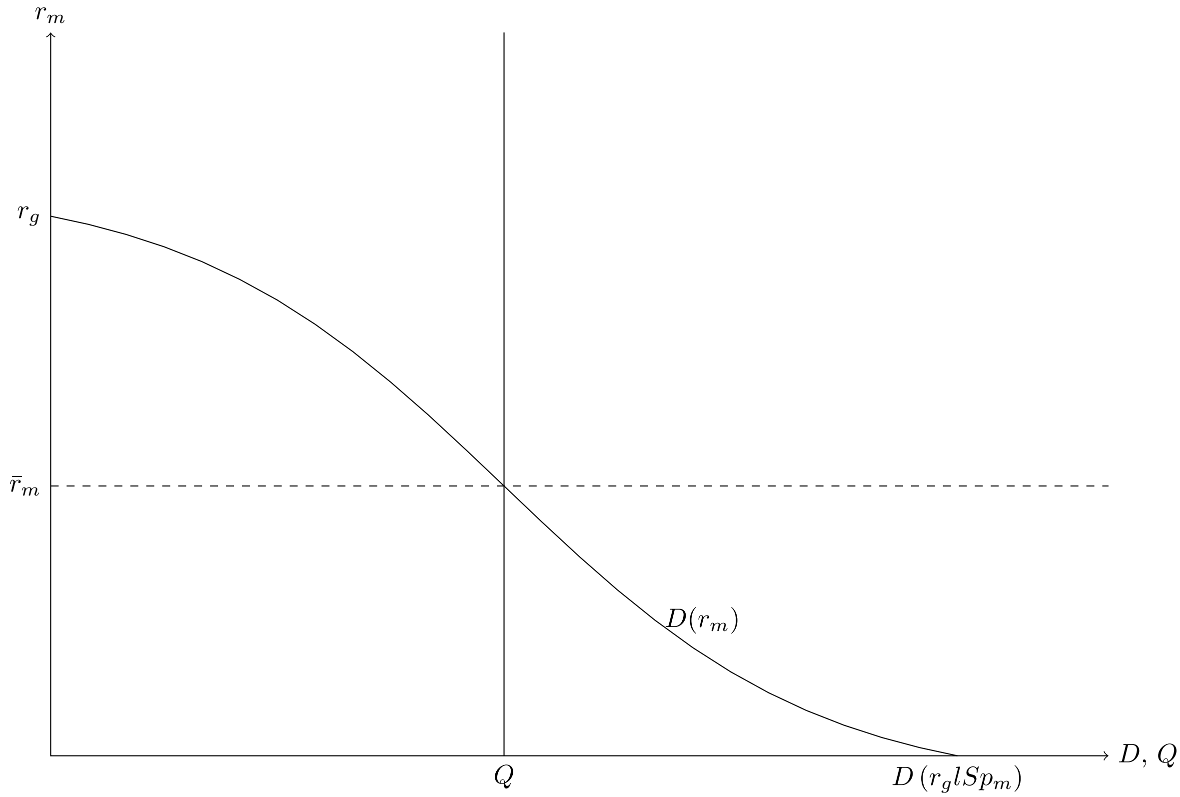
Notes: The figure shows the difference in prices between on-street parking and garages for a 2-hour period—saving from on-street parking. The data represent the average weekday for 955 locations with garages in New York City in the fourth quarter of 2019. The price gap changes during the day as garage operators modify prices and meters move from being enforced to being unenforced.

Figure 3: Type of Parking and the Value of Time
(Areas = Proportion of Drivers that Park On-street or in a Garage)



Notes: The figure shows the probability distribution function (PDF) of the value of time (v). Divers with a high time valuation ($v > \bar{v}_g$) park in a garage as they cannot afford to cruise for parking. Drivers with a low time valuation ($v < \bar{v}_g$) cruise for parking in search of a cheaper option. The integral below the curve represents the proportion of drivers that park on-street (left of $\bar{v}_g$) and that park in a garage (right of $\bar{v}_g$). $\bar{v}_g$ is the threshold value obtained from Equation (6).

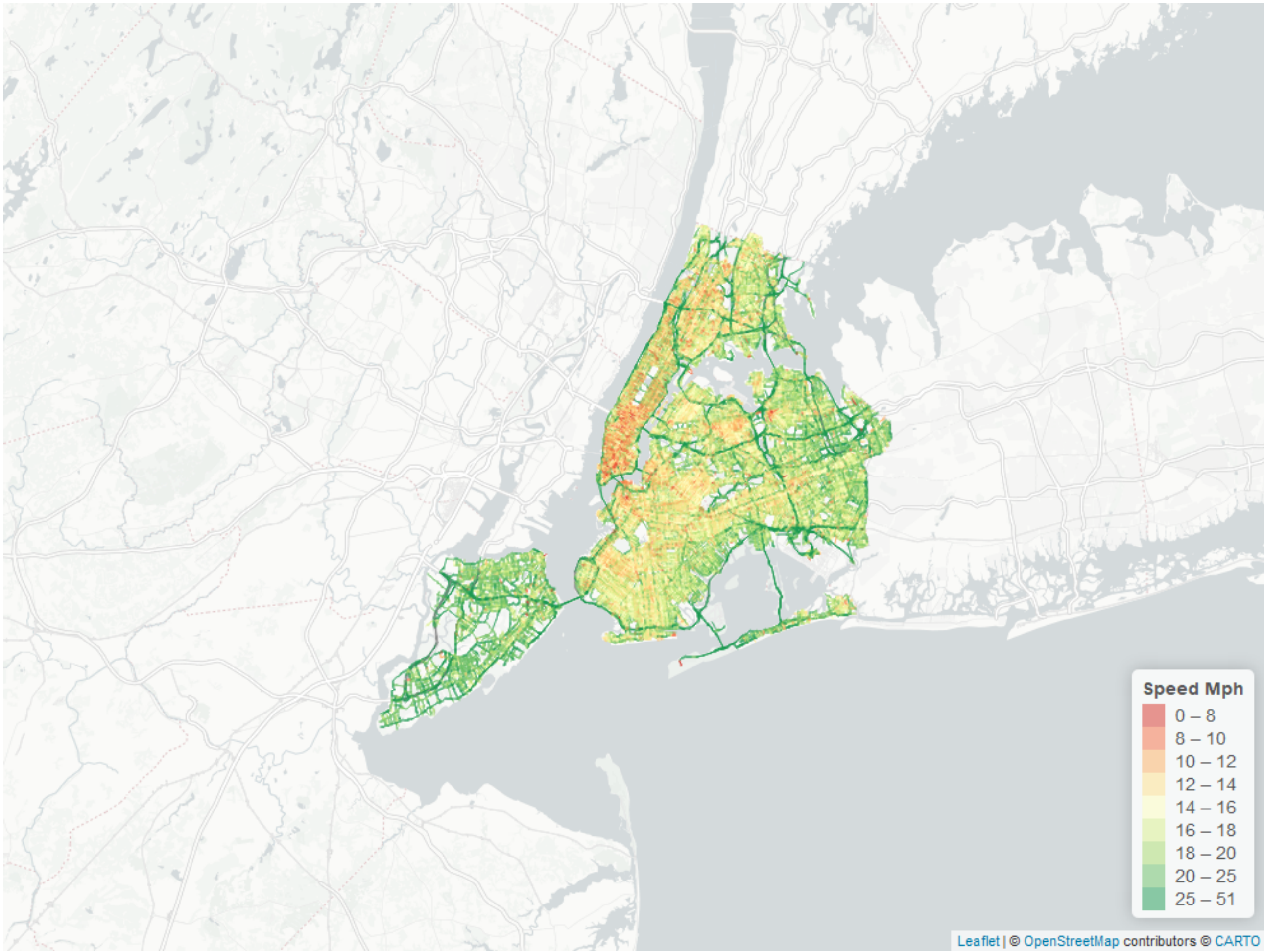
Figure 4: On-street Parking Supply (Q), Demand (D), and Meter Prices (r_m)



Notes: The demand for on-street parking is the cumulative distribution function of the value of time evaluated at threshold value $\bar{v}_g$ (CDF($\bar{v}_g$)) times the number of visitors that drive.[43] As such, the on-street parking demand is a function of meter prices r_m. If prices are equal to or greater than garage prices (r_g), the demand is zero. If meter prices are zero, the demand for on-street parking is a function of garage rates, length of the parking period (l), traffic speed (S), and the probability of finding an empty spot (p_m).

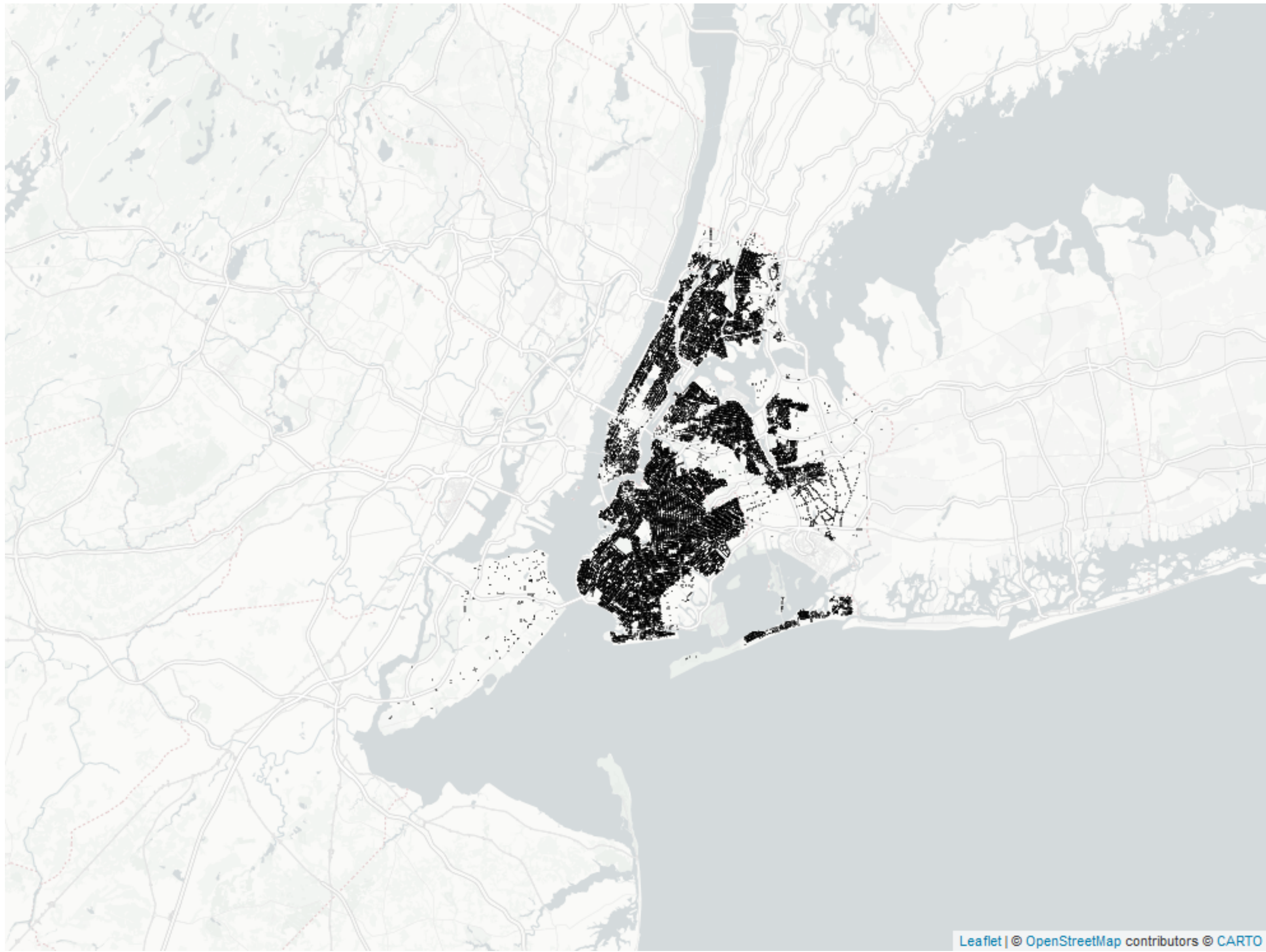
[43] $\bar{v}_g$ is the threshold value obtained from Equation (6.

Figure 5: Average Traffic Speed in New York City
(Sample: 2,634,421 Uber Trips, Fourth Quarter 2019)



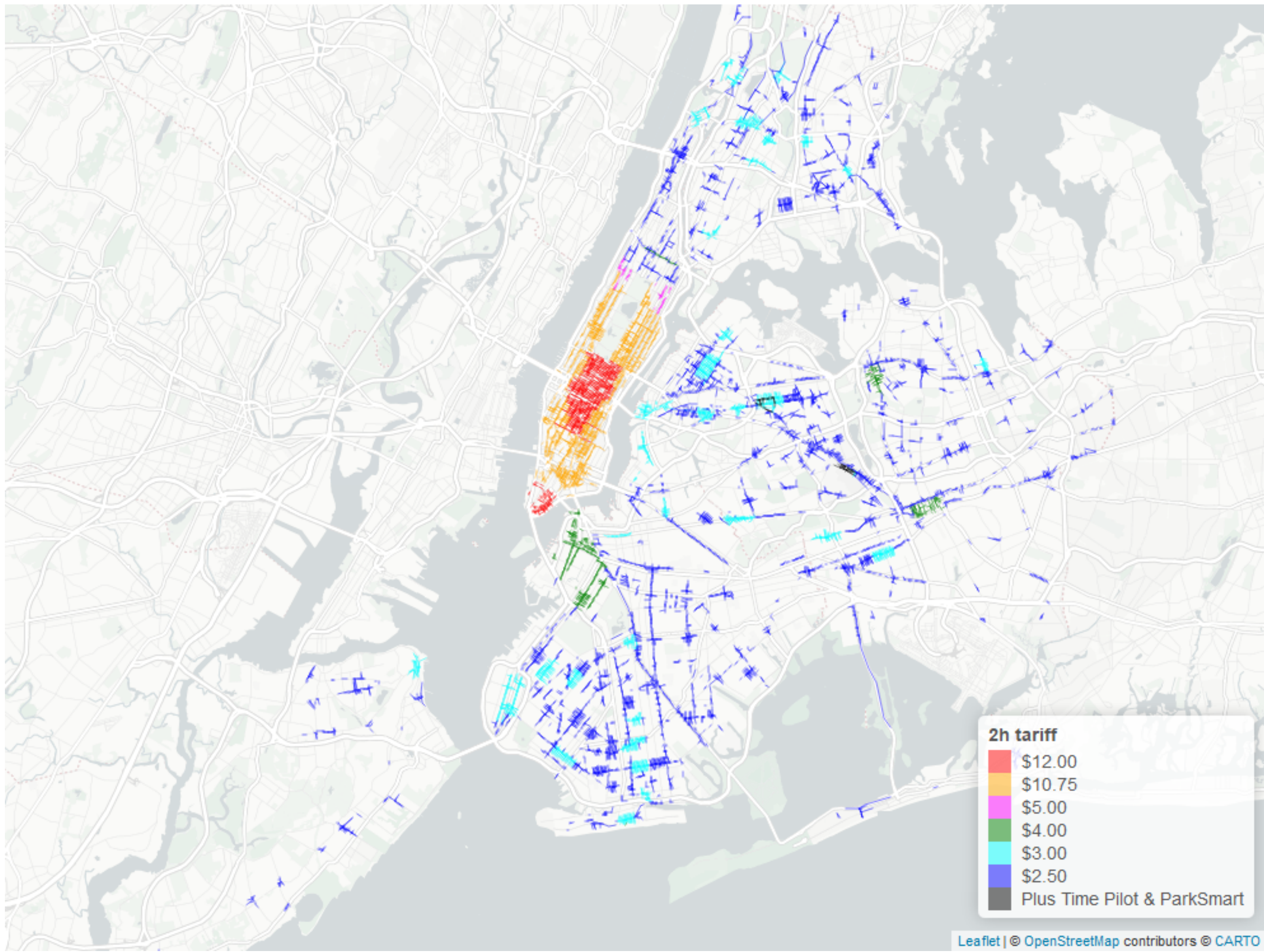
Note: the map shows the average speed of 2,634,421 anonymous Uber trips during the fourth quarter of 2019. The data mark the street segment, speed, and hour but not the day.

Figure 6: Free-of-charge On-street Parking in New York City
For a detailed map click here



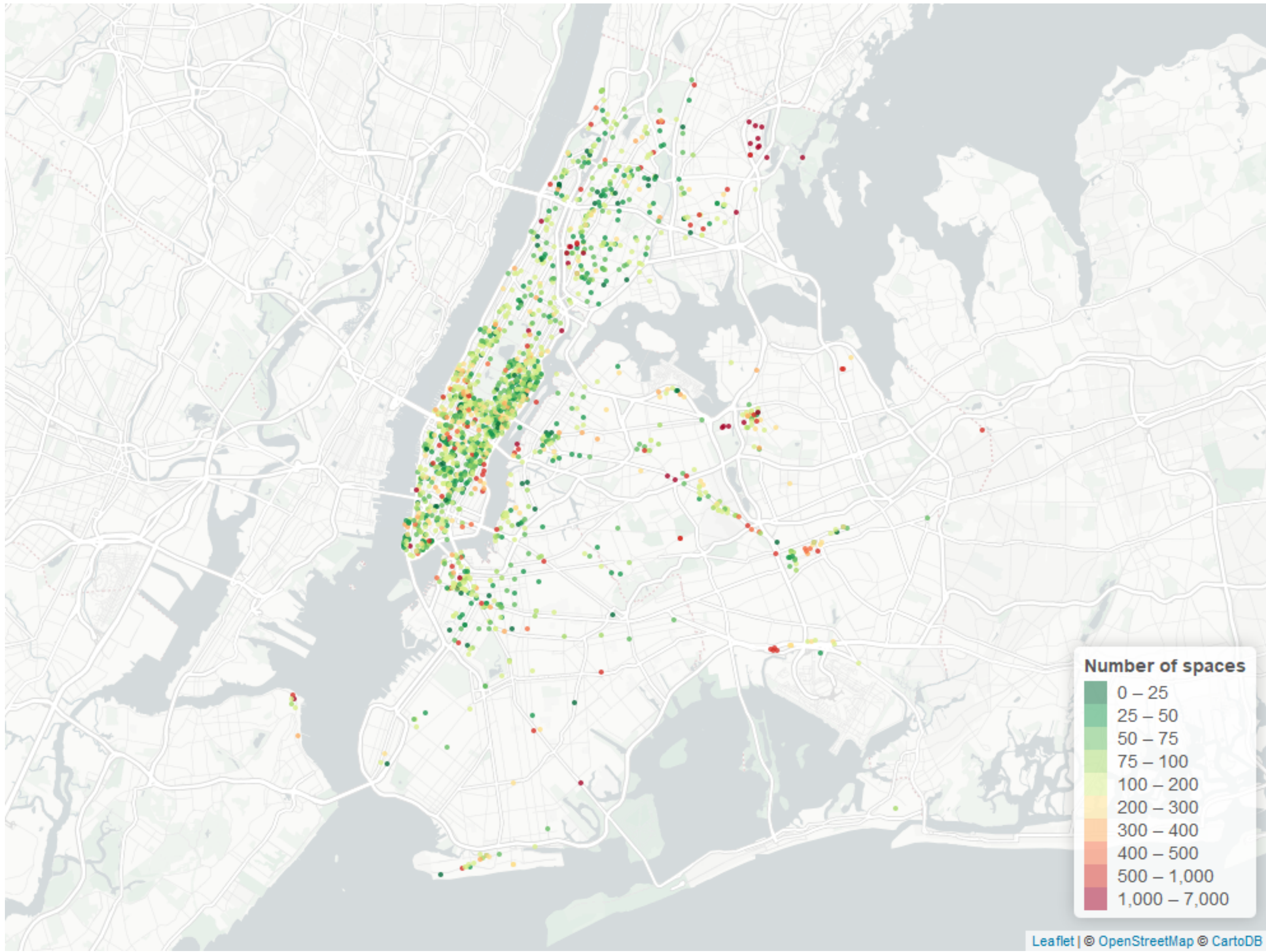
Notes: Map of all free-of-charge on-street parking in New York City. Map build connecting the location of parking sign on the same curb segment.

Figure 7: Metered Parking New York City, Location and Prices
For a detailed map click here



Notes: Map of all metered on-street parking in New York City and the price for a 2-hour period.

Figure 8: Garages New York City, Location and Number of Spaces
For a detailed map click here



Notes: Map of all licensed garages in New York City and the space capacity declared in the license.

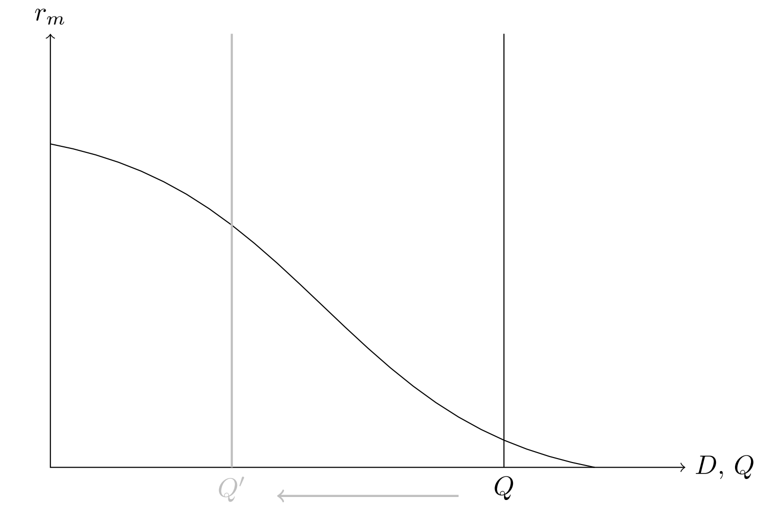
Table 1: Summary Statistics New York City

	1st quartile (1)	Median (2)	Mean (3)	3rd quartile (4)	SD (5)
Drives					
Speed (MPH)	14.265	16.528	16.805	19.089	3.710
Length car commute (min)	20.000	30.000	36.437	45.000	24.195
Prices ($ two hours)					
Garage prices	15.043	19.889	21.246	25.108	8.965
Parking meter prices	3.000	4.000	6.195	10.750	3.690
Location, Distance to the City Business District (DCBD) in miles					
Garages DCBD	1.045	2.102	2.575	3.184	2.120
Parking meters DCBD	2.376	4.772	4.655	6.834	2.870
Free on-street parking DCBD	5.625	11.150	11.150	16.675	6.423
Annual income ($ thousands)					
Car commuter	27.000	50.000	66.485	82.000	77.940
All tax payers	12.975	28.578	66.585	54.255	115.485

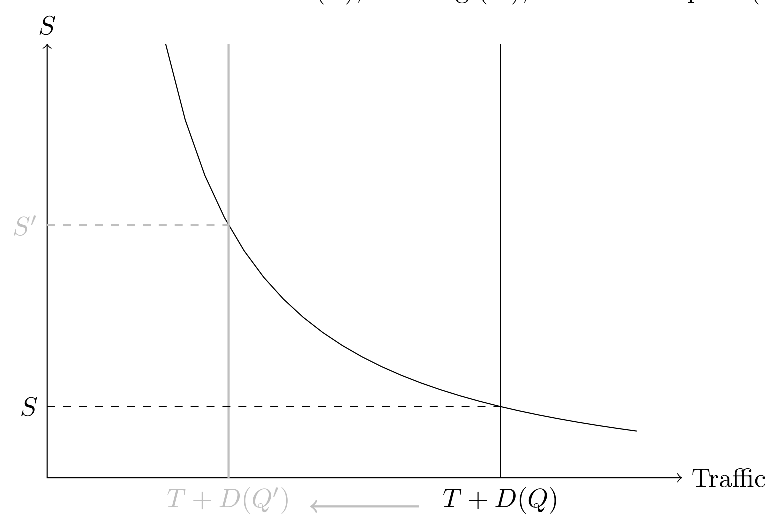
Notes: Speed data in miles per hour (MPH) from Uber trips completed during the fourth quarter of 2019. Data available at Uber Movement website. Length of car commutes in minutes. New York City data from the Census' Public Use Microdata Areas (PUMAs). Garage prices data web scraped from Parkwhiz.com during the fourth quarter of 2019. Parking meter prices and location provided by the New York City Open Data portal. Garage locations were obtained from the register of licensed business provided by the City of New York Open Data portal. The sample is limited to garages operating during the second half of 2019. The location of free on-street parking was obtained by analyzing all traffic signs in New York City. The City of New York Open Data portal offers a detailed map of the text and location of all parking signs in the city. Annual income for car commuters is the 12-month salary income of car commuters in the New York City PUMAs data set. Annual income for all tax payers is taken from income deciles documented by the New York City Independent Budget Office.

Figure 9: Reducing On-street Parking Supply and Traffic Speed

Panel A. Parking demand (D), Supply (Q), and Meter Prices (r_m)



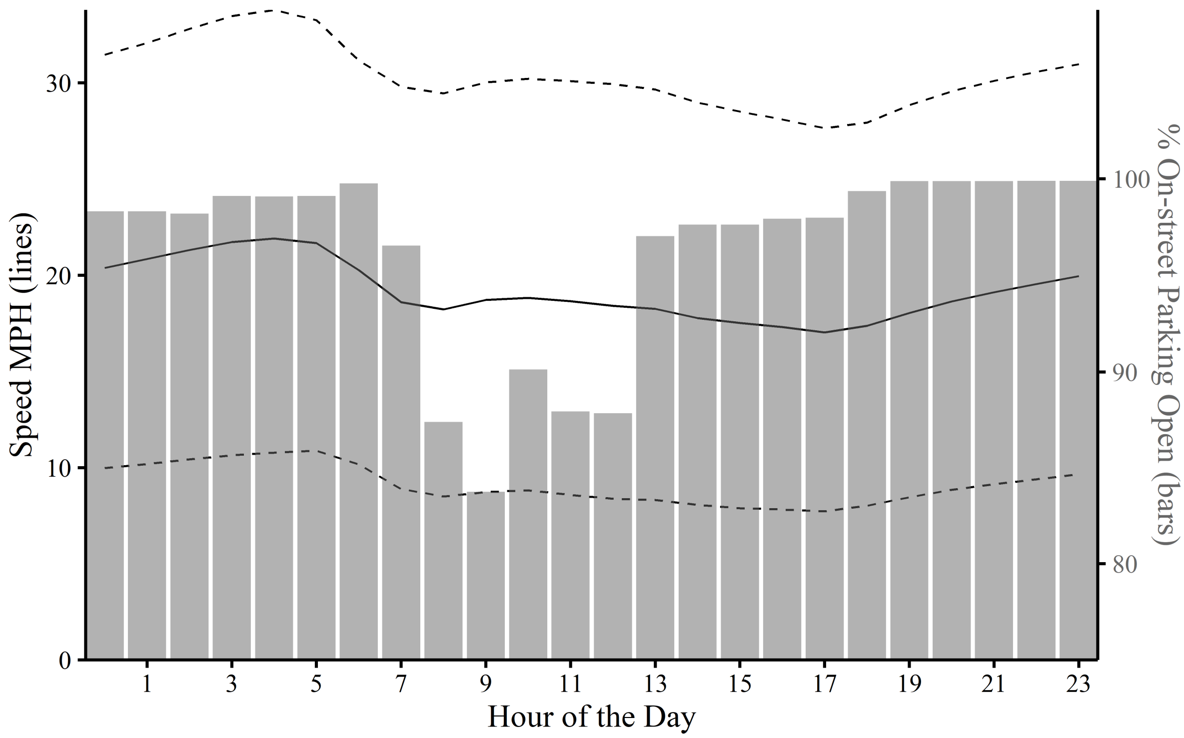
Panel B. Cars in in Transit (T), Cruising (D), and Traffic Speed (S)



Notes: Panel A illustrates a reduction of the supply in the on-street parking market. Q and Q' are the initial and final situations.

Panel B shows the effect of reducing the supply of on-street on traffic speed. The number of cars cruising equals the demand for on-street parking (D). The demand for on-street parking drops with the supply; a lower supply implies a higher cost of curbside parking through longer search periods, hence a smaller number of cars cruising.

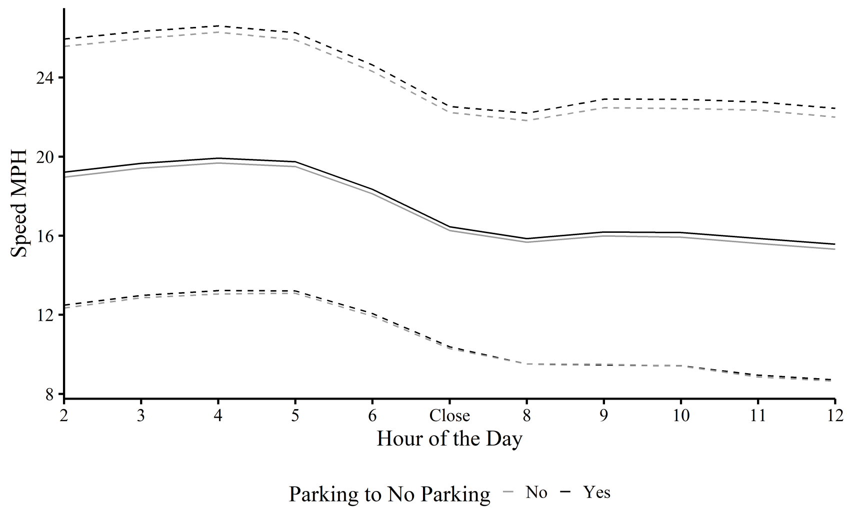
Figure 10: Traffic Speed and On-street Parking (Hour-by-hour)
Speed (Lines, Mean and 2 SD), On-street Parking (Bars, Percentages Allowed)



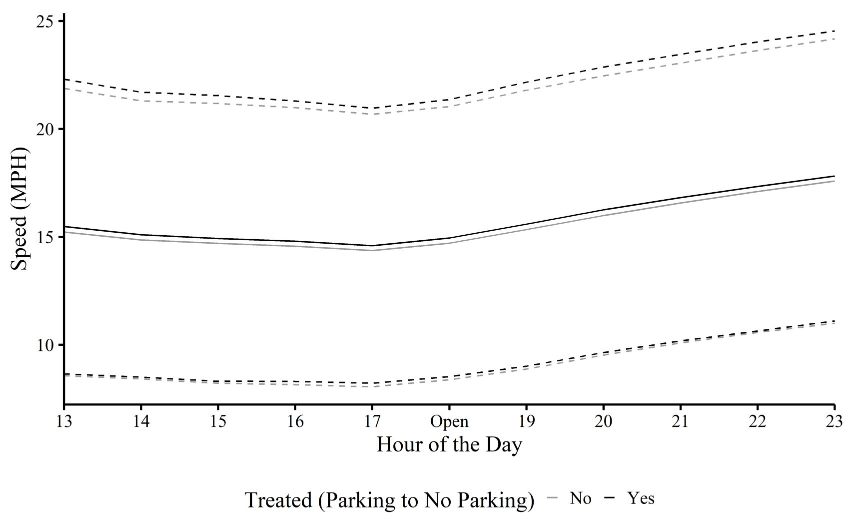
Notes: The figure shows how aggregated data hide the effect of on-street parking on traffic speed as city officials reduce parking during high congestion periods. Lines are the average traffic speed (continuous line) with a two-standard-deviation (SD, discontinuous lines) interval (left axis). Bars are the percentage of curb segments where free-of-charge on-street parking is allowed (right axis). The percentage is relative to the length of all curb segments where on-street parking is allowed at some time during the day.

Figure 11: Traffic Speed Parallel Trends (Mean and 2 SD)
Treated: Change in Parking Supply, Control: No Change

A. 7 am. Change From Parking to No Parking



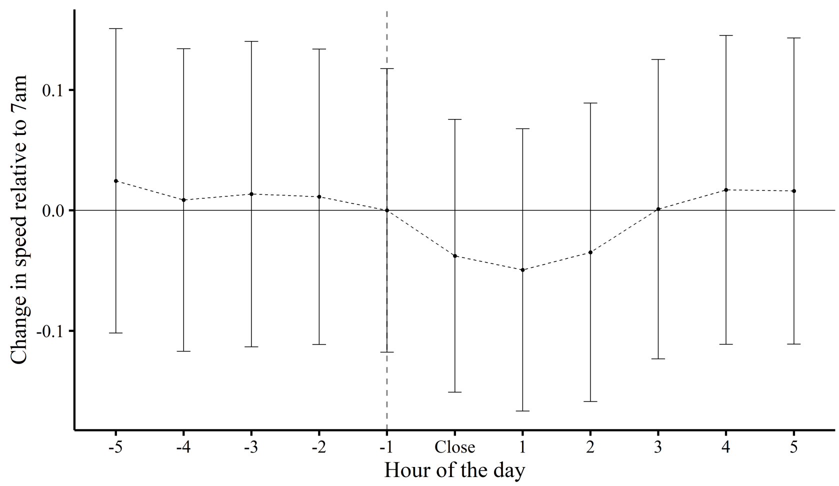
B. 5 pm. Change From No Parking to Parking



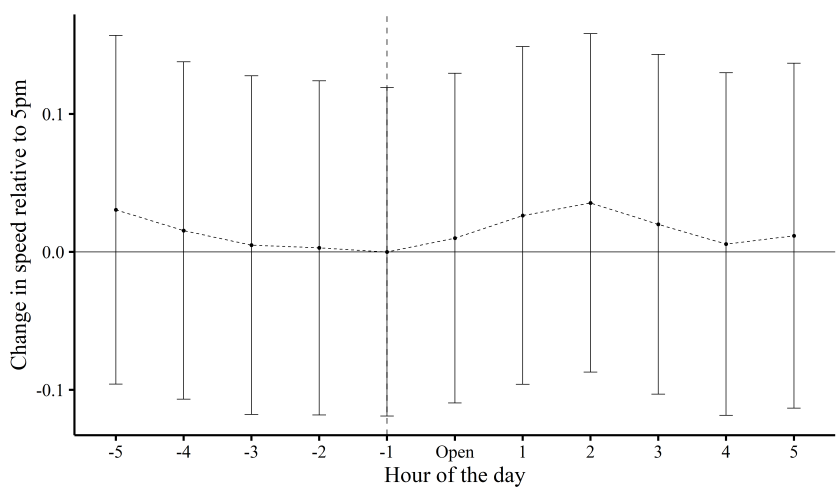
Notes: Panels A and B are based on a subsample of census blocks. The treated group decreases supply of parking at 7:00 a.m. and increases it back after 5:00 p.m. The control group keeps parking available before and after the two time thresholds. Both figures compare the hour-by-hour average speed (continuous line) and the two-standard-deviation interval (discontinuous lines) of the treated and control groups. Raw averages provide evidence of parallel trends.

Figure 12: Difference in Means, Traffic Speed Pretrends (Estimate & 95% Confidence Interval)
Treated: Change in Parking Supply, Control: No Change

A. 7 am. Change From Parking to No Parking

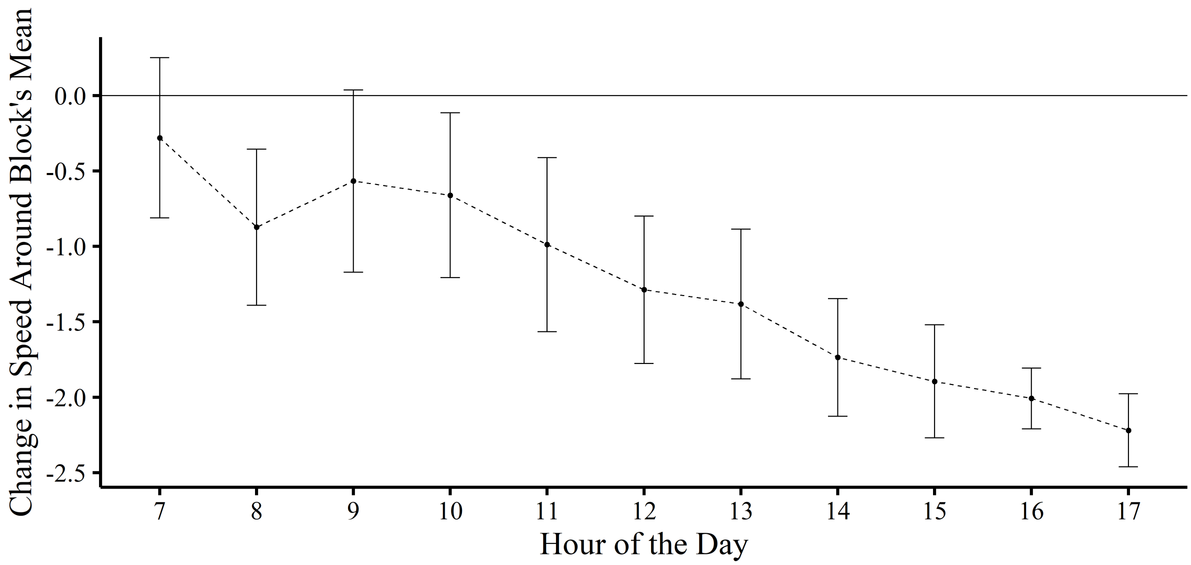


B. 5 pm. Change From No Parking to Parking



Notes: Panels A and B are based on a subsample of census blocks. The treated group decreases supply of parking at 7:00 a.m. and increases it back after 5:00 p.m. The control group keeps parking available before and after both time thresholds. Both panels plot the t-statistic for the hour-by-hour difference in means of the average speed between treated and nontreated groups. There is no evidence of pretrends as the two panels show no significant difference between the two groups previous to the two time thresholds.

Figure 13: Hour by Hour Effect of Free On-Street Parking on Traffic Speed



Notes: The figure shows the estimates and 95% confidence interval. Nonlinearities in the relationship between volume and traffic speed (congestion technology) yield different effects through the day as a car cruising has a greater impact on a congested street than on an empty road.

Table 2: Aggregated Effect of Free On-street Parking on Traffic Speed (Weekdays)

Dependent variable:	Average speed (MPH) at time h			
	(1)	(2)	(3)	(4)
Free on-street parking at time h	-0.15^{***}	-0.16^{***}	-0.18^{***}	-0.18^{***}
	(0.04)	(0.05)	(0.06)	(0.07)
Control dummy variables				
Census block fix effects	Yes	Yes	Yes	Yes
Hour of the day fix effects	Yes	Yes	Yes	Yes
Metered parking available	No	Yes	Yes	Yes
Transition period dummies	No	No	Yes	Yes
Neighbor blocks with on-street parking	No	No	No	Yes
Adjusted R^2	0.87	0.87	0.87	0.87
Observations	161541	161541	161541	161541

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Notes: Sample of census blocks with free on-street parking, metered parking, or both. The time dimension (h) hour-by-hour data for an average weekday. A neighboring census block is defined as any census block that shares a common border. Standard errors are clustered at the borough by hour level.

Table 3: Placebo Test

Dependent variable	Traffic speed (MPH)				
Available parking time frame	10am-7am	11am-8am	11am-7am	1pm-10am	2pm-10am
	(1)	(2)	(3)	(4)	(5)
Placebo	0.006	0.024	0.014	0.015	0.008
(Free on-street parking at time h)	(0.017)	(0.017)	(0.014)	(0.017)	(0.014)
Control dummy variables					
Census block fix effects	Yes	Yes	Yes	Yes	Yes
Hour of the day fix effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.812	0.812	0.812	0.812	0.812
Observations	625549	625549	625549	625549	625549

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Notes: Placebo test for the effect of free on-street parking on traffic speed. The test is run using a randomly selected fake treatment group—block with no off-street parking—and five of the most common curbside parking restrictions (no parking from 8:00 a.m. to 9:00 a.m., from 9:00 a.m. to 10:00 a.m., from 8:00 a.m. to 10:00 a.m., from 11:00 a.m. to 12:00 a.m., and from 11:00 a.m. to 1:00 p.m.).

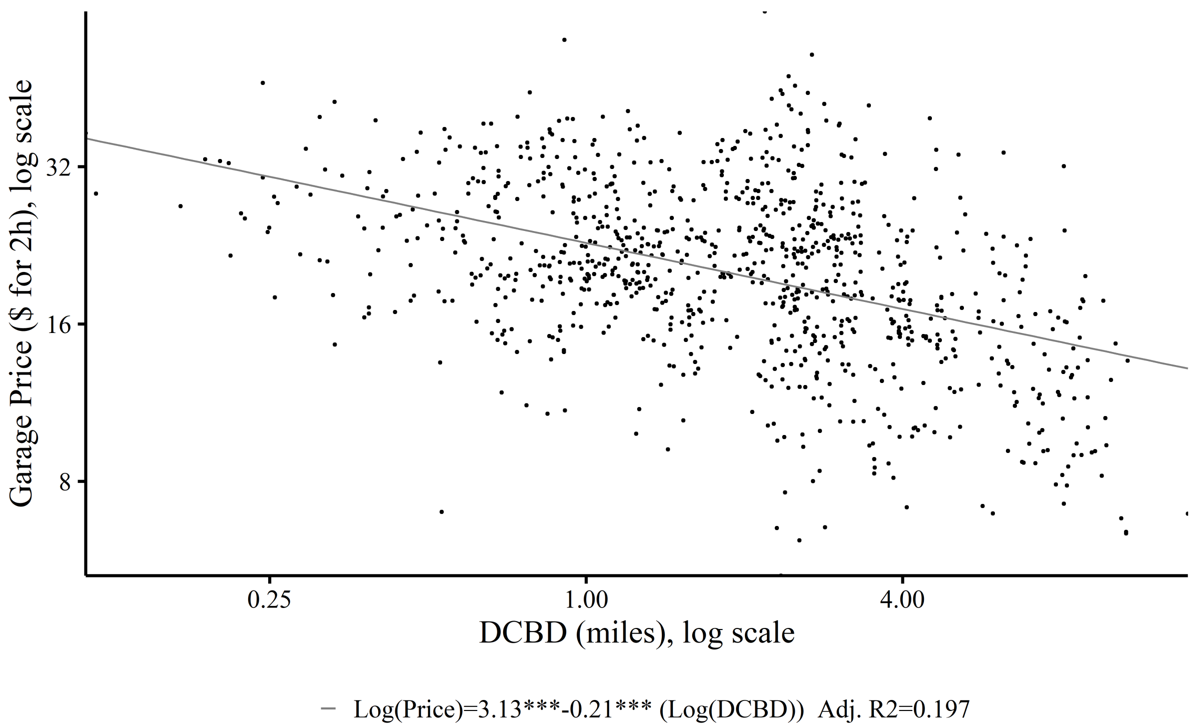
Table 4: Cluster at Census Tract Level, Effect of Free On-street Parking on Traffic Speed During Weekdays

Dependent variable:	Average speed (MPH) at time h			
	(1)	(2)	(3)	(4)
Free on-street parking at time h	-0.15^{***}	-0.16^{***}	-0.18^{***}	-0.18^{***}
	(0.02)	(0.02)	(0.03)	(0.02)
Control dummy variables				
Census block fix effects	Yes	Yes	Yes	Yes
Hour of the day fix effects	Yes	Yes	Yes	Yes
Metered parking available	No	Yes	Yes	Yes
Transition period dummies	No	No	Yes	Yes
Neighbor blocks with on-street parking	No	No	No	Yes
Adjusted R^2	0.87	0.87	0.87	0.87
Observations	161541	161541	161541	161541

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

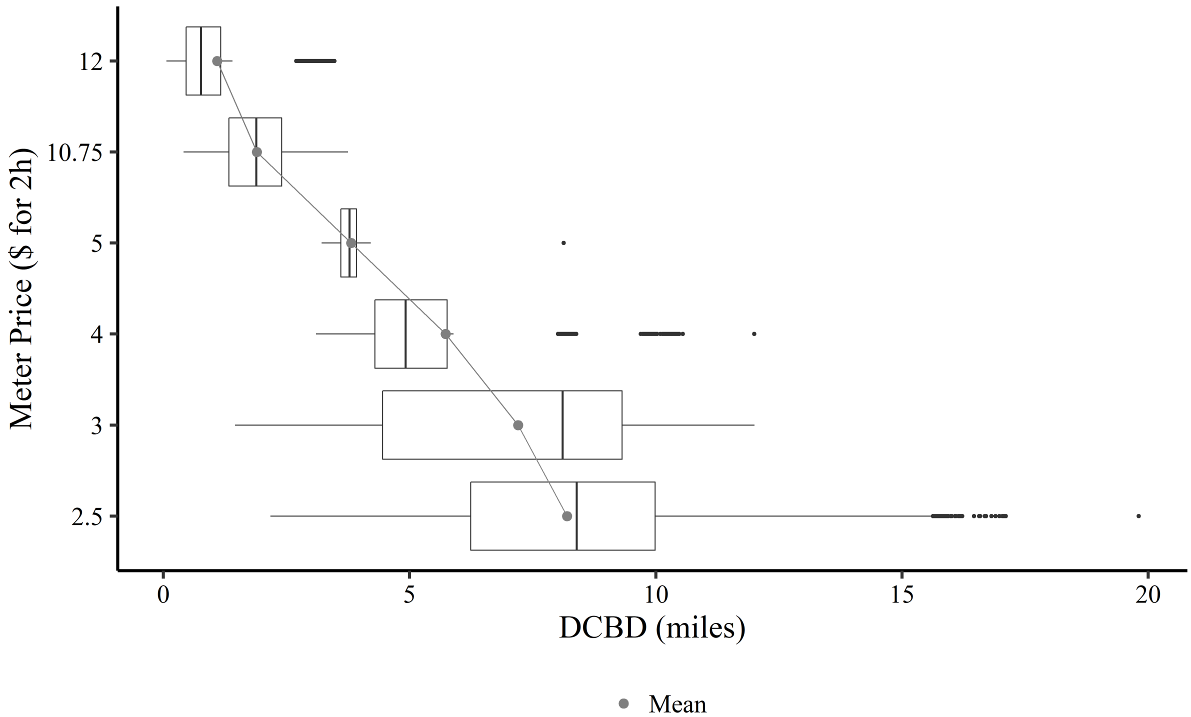
Notes: Sample of census blocks with free on-street parking, metered parking, or both. The time dimension (h) hour-by-hour data for an average weekday. A neighboring census block is defined as any census block that shares a common border. Standard errors are clustered at the census tract by hour level.

Figure 14: Garage Prices and Distance to New York City Center



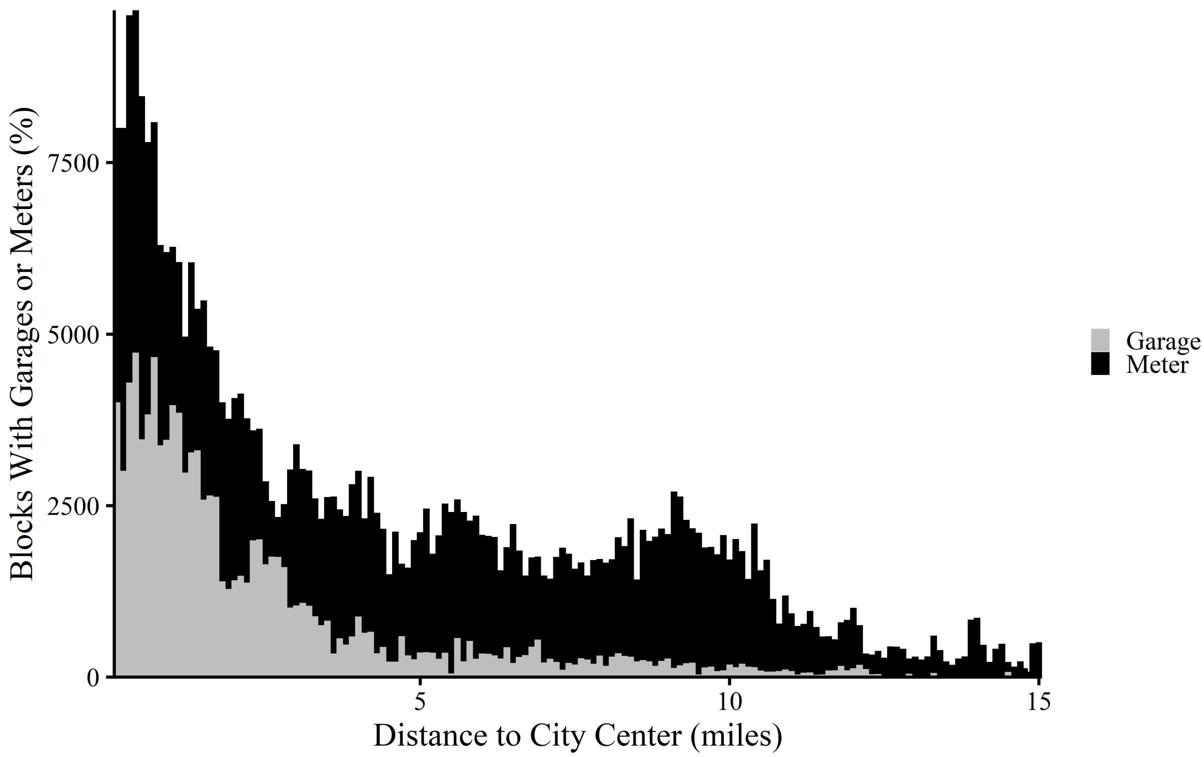
Notes: Garage prices and distance in miles to the city business district (DCBD). The figure shows evidence of consistency with the monocentric city model (Alonso 1964; Muth 1969; Mills 1967). The relation is negative and is statistically significant. The correlation is higher than 0.44. Figure is in Log scales.

Figure 15: Meter Prices and Distance to the City Center, New York City



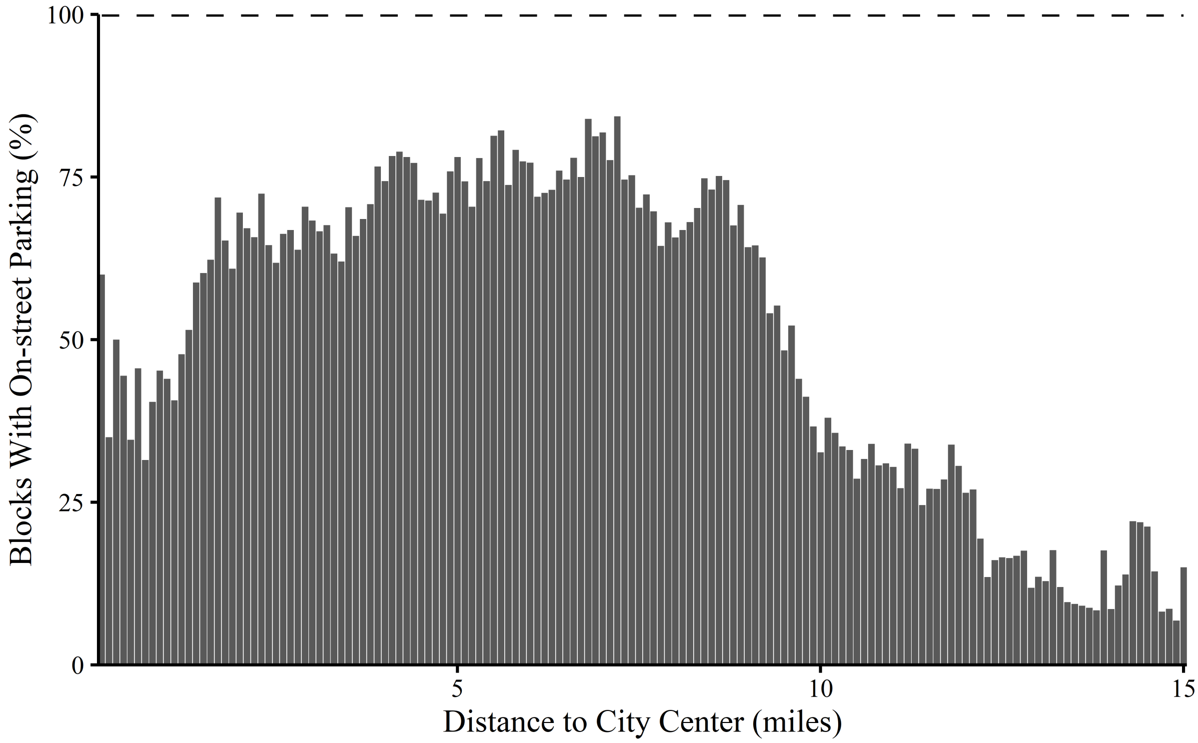
Notes: Meter Prices and distance to the city business district (DCBD). The figure shows evidence of consistency with the monocentric city model (Alonso 1964; Muth 1969; Mills 1967).

Figure 16: Concentration of Garages, Metered Parking, and Distance to the City Center, New York City



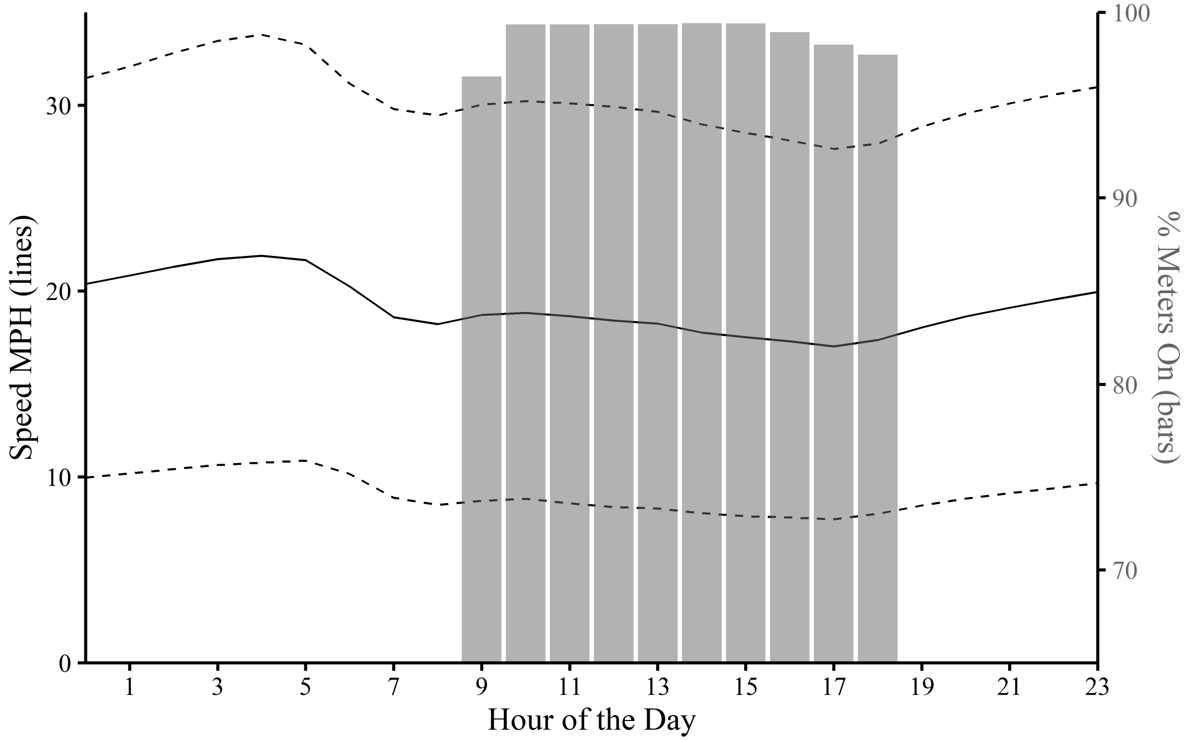
Notes: Percentage of blocks with garages (light gray), percentage of blocks with metered parking (black), and distance to the city business district (DCBD). The figure shows evidence of consistency with the monocentric city model (Alonso 1964; Muth 1969; Mills 1967).

Figure 17: Concentration of Free-of-Charge On-street Parking and Distance to the City Center
New York City



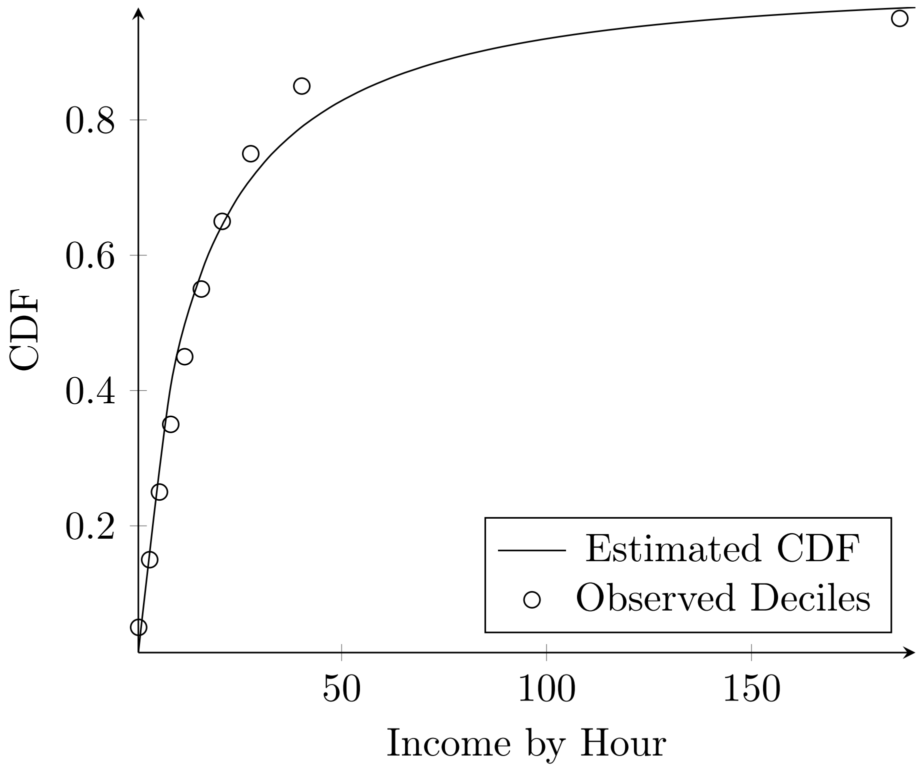
Notes: Percentage of blocks with free-of-charge on-street parking and distance to the city business district (DCBD). Unlike garage and metered parking (figure 16), free-of-charge on-street parking is spread across the city with a low concentration in the business district.

Figure 18: Traffic Speed and Share of Meters Enforced
Speed (Lines, Mean and 2 SD), On-street Parking (Bars, Percentage of Meters Enforced)



Notes: The average traffic speed (continuous line) with a two-standard-deviation interval (SD, discontinuous lines) use the left axis. Bars are the share of meters enforced (right axis). The vertical axis on the right starts at 60% to show variations in the 9:00 a.m. to 6:00 p.m. period. Enforcement of meters outside the 9:00 a.m. to 6:00 p.m. period is minimal.

Figure 19: Income Deciles and the Estimated Cumulative Distribution Function (CDF)
(Log-normal)



Notes: Circles are the income deciles as reported by the New York City Independent Budget Office year 2018. The line is the log-normal cumulative distribution function for a fitted using maximum likelihood.

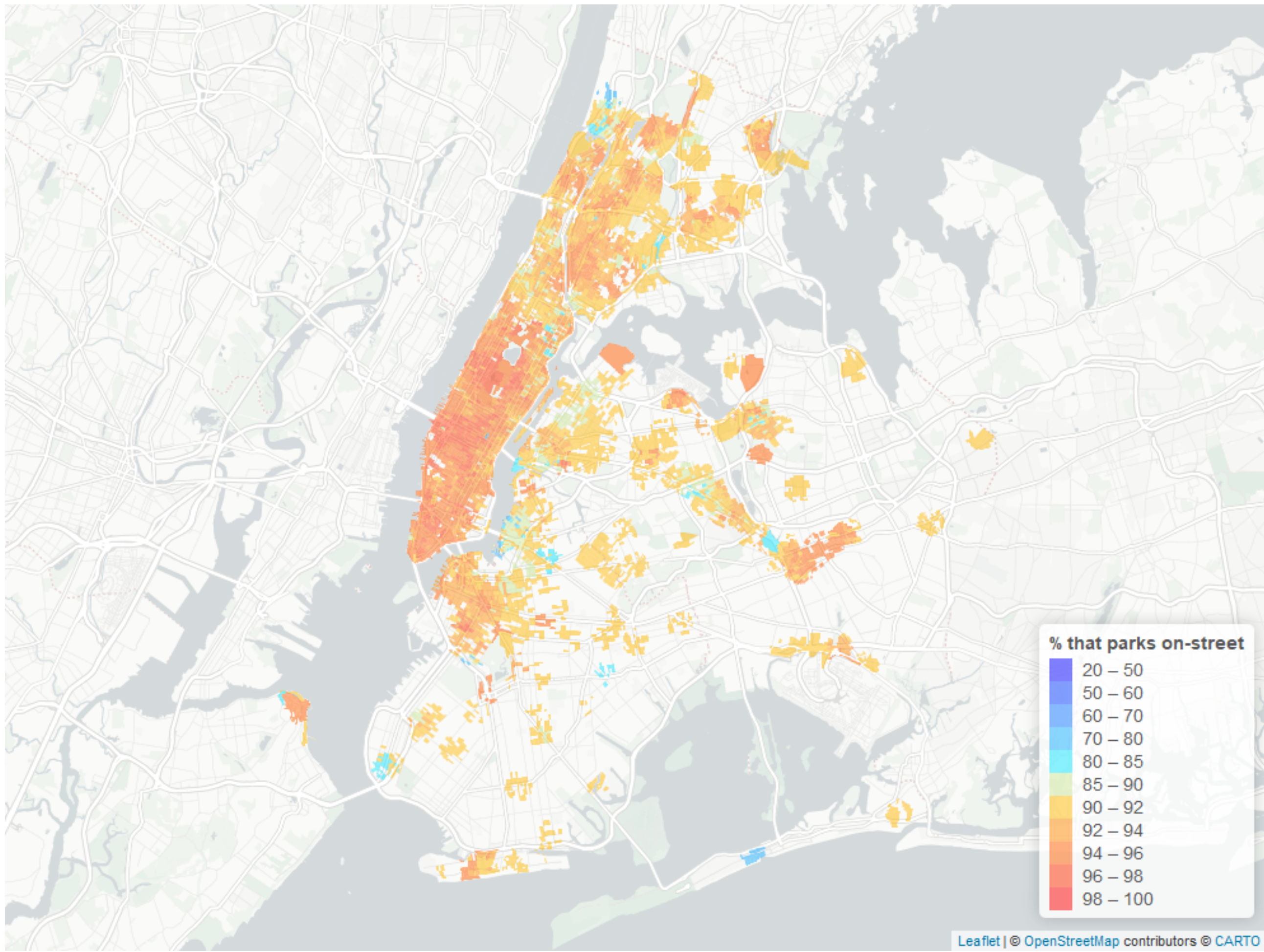
Table 5: Garage Prices, Spatial Autoregressive Model

Panel A				
Dependent variable	Garage prices (Census block average)			
Number of neighbors (k)	3	4	5	6
	(1)	(2)	(3)	(4)
ρ	0.586***	0.651***	0.693***	0.726***
	(0.028)	(0.028)	(0.028)	(0.028)
Observations	787	787	787	787
Panel B				
Dependent variable	Garage prices (Census block average)			
Number of neighbors (k)	7	8	9	10
	(1)	(2)	(3)	(4)
ρ	0.747***	0.770***	0.786***	0.798***
	(0.028)	(0.027)	(0.027)	(0.027)
Observations	787	787	787	787

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

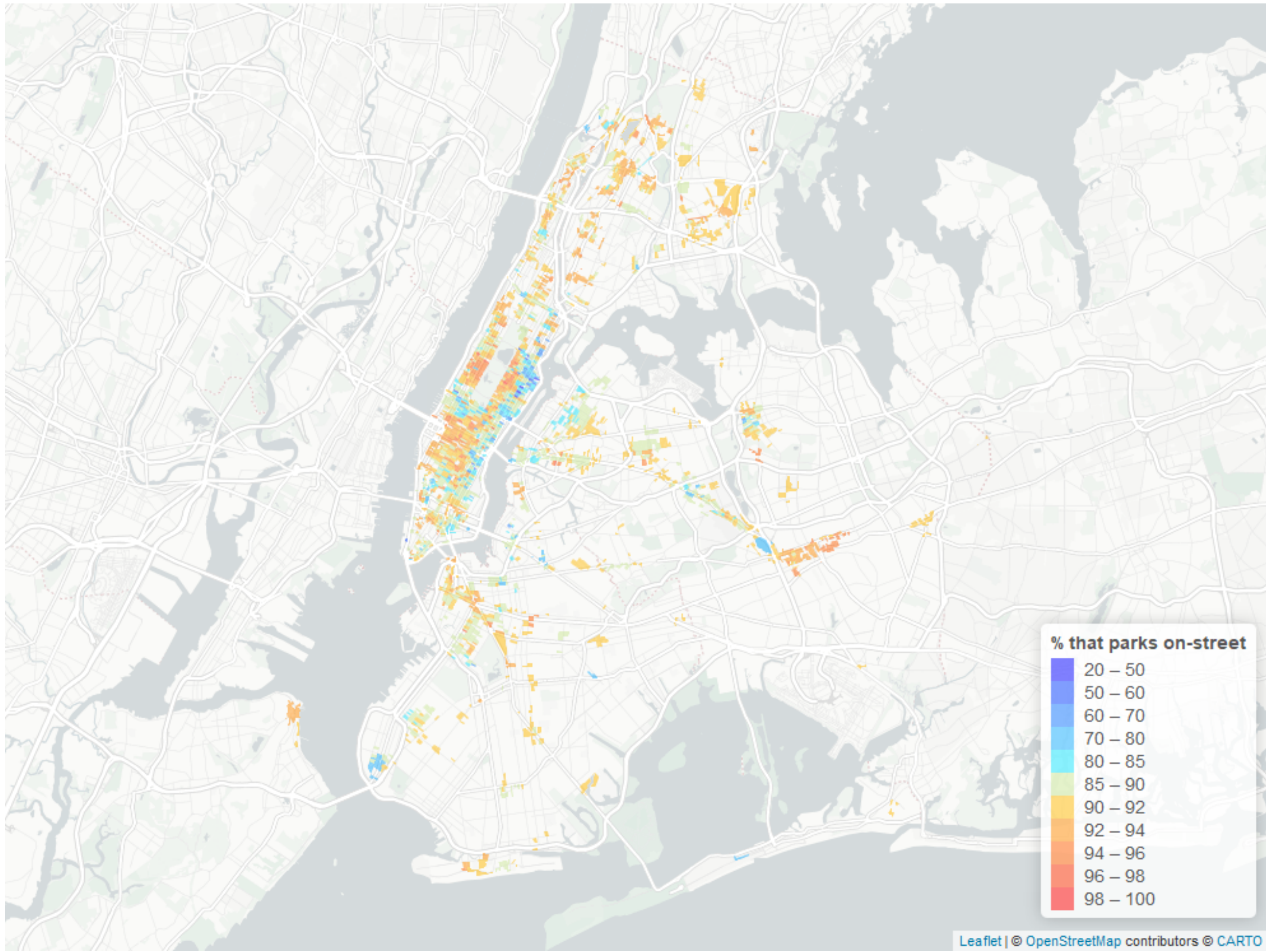
Notes: I use a spatial autoregressive model to forecast the price of garages out of my sample. The k neighbors are defined as the k closest locations by euclidean distance. The optimal number of neighbors in the weight matrix W is selected using 10-fold cross-validation as described in Section 7.2.

Figure 20: On-street Parking Savings, Percentage of Drivers Willing to Cruise for Free On-street Parking Based on Garage Prices and Income by Hour. For a detailed map click here



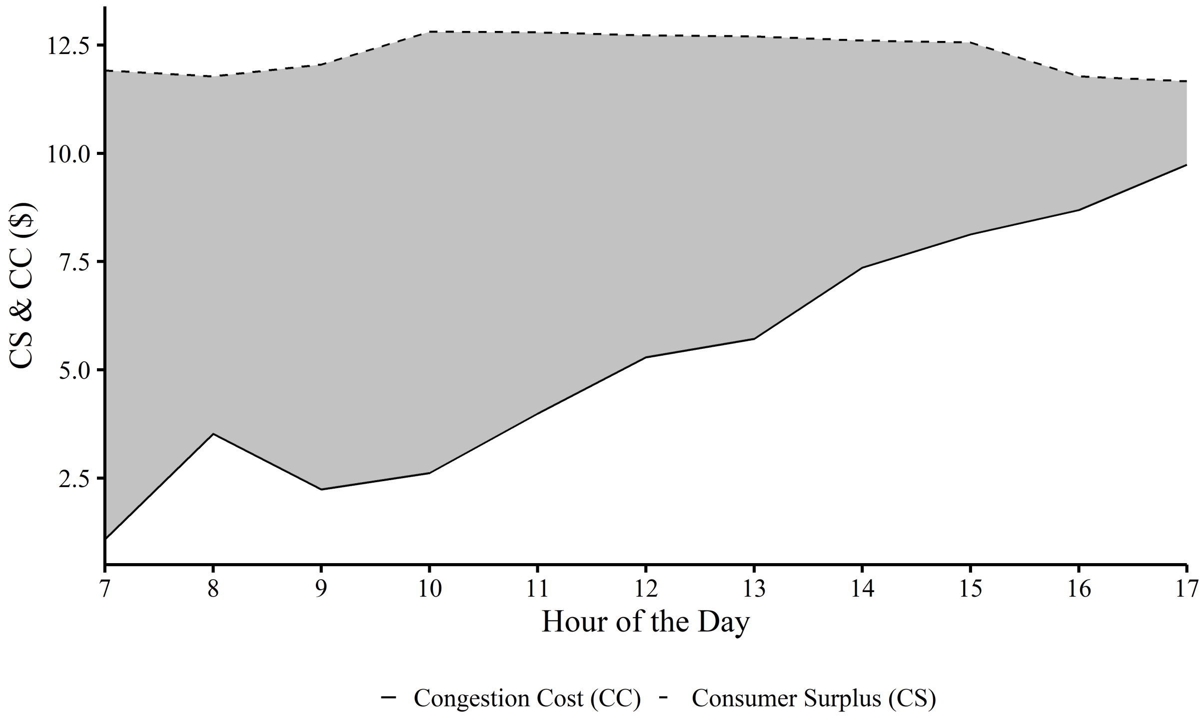
Notes: The census block map uses the estimated distribution function of the income by hour, locations of garage and metered parking, the price gap between meters and garages, and a set of calibrated parameters (section 7.3), to calculate the percentage of drivers willing to park on-street free-of-charge.

Figure 21: Percentage of Drivers Willing to Cruise for Metered On-street Parking
Based on the Price Gap Between Meters and Garages and the Income by Hour. For a detailed map click here



Notes: The census block map uses the estimated distribution function of the income by hour, locations of garage and metered parking, the price gap between meters and garages, and a set of calibrated parameters (section 7.3), to calculate the percentage of drivers willing to park on-street at the meter.

Figure 22: Welfare Gains from On-street Parking Measured in Dollars



Notes: The gap between the consumer surplus (CS) and congestion cost (CC) is the welfare gain from on-street parking. CS changes through the day due to changes in garage prices. Changes in CS are driven by the delay in traffic caused by on-street parking (Figure 13). To calculate CS and CC, I use the structure from the theoretical model (Equations 10 and 11); the distribution of the value of time estimated in section 7.1; the calibrated values described in Section 7.3; and the proportion of road users that park on-street (value based on the 2018 NYC Mobility Report).

Appendix

A Bellman Equation

It is reasonable to think that traffic conditions change little during the cruising period, transforming equation (1) and (2) into:

$$C_m = p_m \left(\frac{1}{Sp_m} v + r_m l \right) + (1 - p_m) \, C_m, \tag{15}$$

$$C_f = p_f \left(\frac{1}{Sp_f} v \right) + (1 - p_f) \, C_f, \tag{16}$$

Equations (15) and (16) can be rewritten as follows:

$$C_m = p_m \left(\frac{1}{Sp_m} v + r_m l \right) \sum_{i=0}^{\infty} (1 - p_m)^i \tag{17}$$

$$C_f = p_f \left(\frac{1}{Sp_f} v \right)) \sum_{i=0}^{\infty} (1 - p_f)^i \tag{18}$$

Since $(0 < 1 - pi < 1)$ Expression (17) and (18) are the two geometric series that yield the results in (3) and (4).[44]

[44]Note that if $S = 1 + (1 - p_i) + (1 - p_i)^2 + \ldots$, $S - S(1 - p_i) = 1$, hence $S = \frac{1}{p_i}$.

B Theoretical Model Sufficient Conditions

Claim: $\frac{r_m}{r_g} < 1 - \frac{p_f}{p_m}$ is a sufficient condition for having $\bar{v}_m > 0$.

Proof:

- $\frac{r_m}{r_g} > 0$ as r_m and r_g are both positive price. This means that $\left(1 - \frac{p_f}{p_m}\right) > 0$ hence $p_m > p_f$.
- $p_m > p_f$ implies that $\bar{v}_m > 0$ as $S > 0$, $l > 0$, $p_m > 0$, and $p_f > 0$.[45]

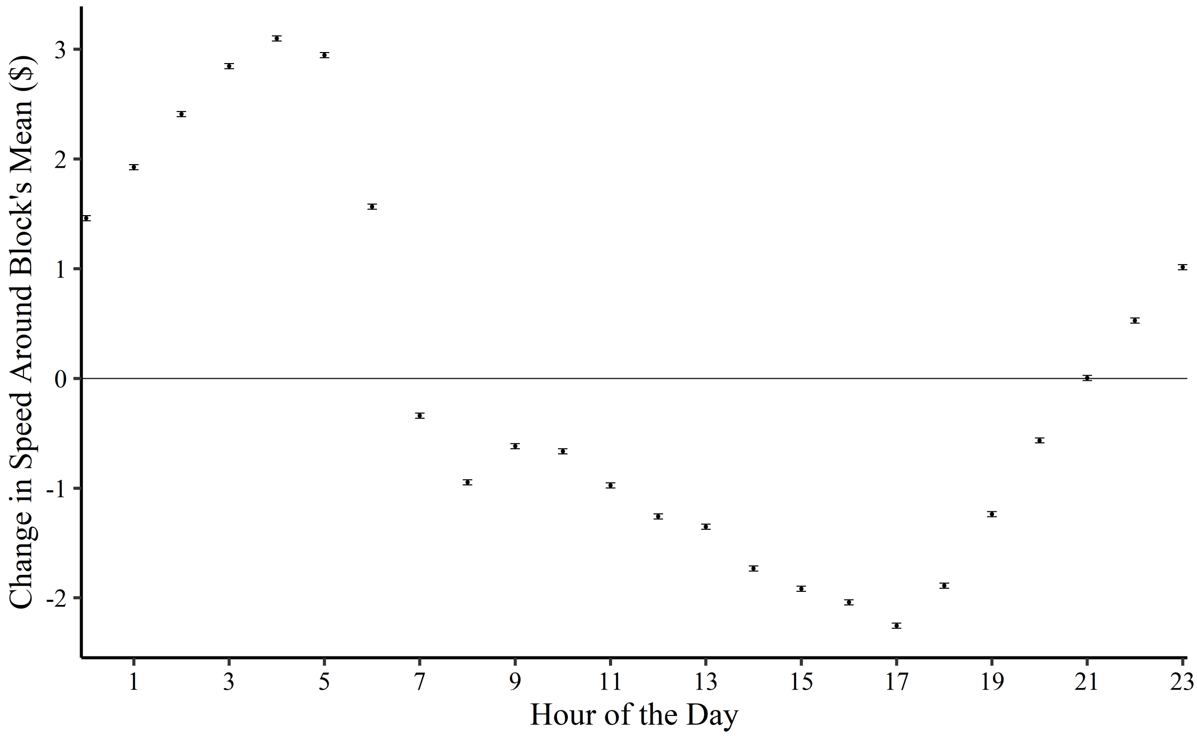
Claim: $\frac{r_m}{r_g} < 1 - \frac{p_f}{p_m}$ is a sufficient condition for having $\bar{v}_g > \bar{v}_m$

Proof:

$$\begin{aligned}
\frac{r_m}{r_g} &< \; < 1 - \frac{p_f}{p_m} \\
\frac{p_m r_m}{p_m - p_f} &< r_g \\
\frac{p_m r_m}{p_m - p_f} - r_m &< r_g - r_m \\
lSr_m \frac{p_f r_m}{p_m - p_f} &< lSr_m \left(r_g - r_m\right) \\
\bar{v}_m &< \bar{v}_g \text{ Q.E.D.}
\end{aligned}$$

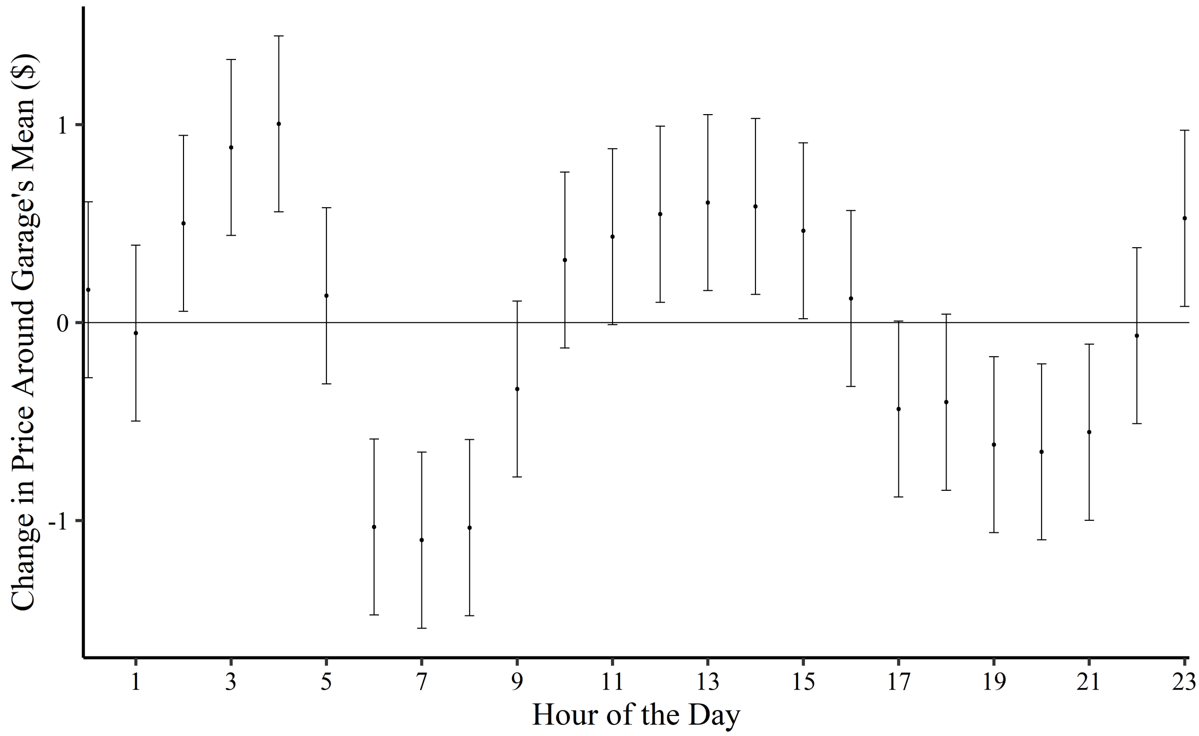
[45]Speed (S), length of the parking period (l), and the probability of an open metered spot (p_m) are positive.

Figure A.1: Hour of the Day Fixed Effect, Traffic Speed (Weekdays)



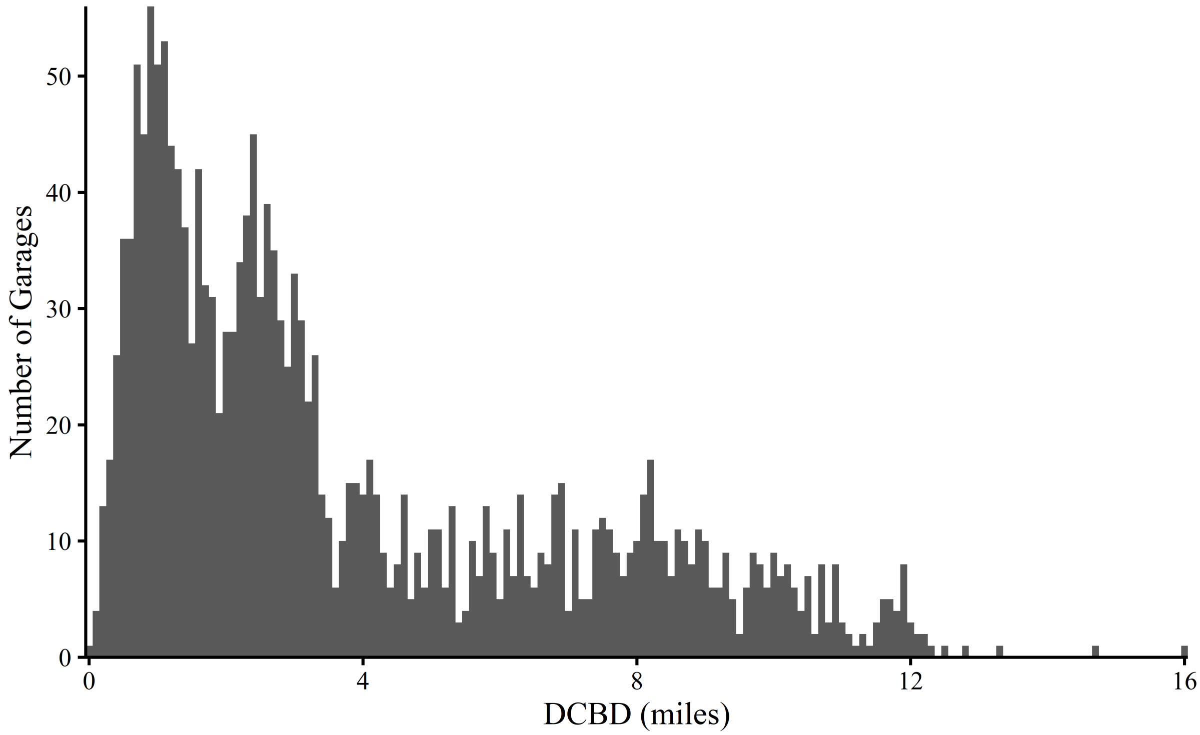
Notes: The figure shows the values $\alpha_{S,h}$ of from estimating $S_{ih} = \alpha_{S,i} + \alpha_{S,h} + \varepsilon_{S,ih}$. Where S_{ih} is the speed at location i at hour of the day h.

Figure A.2: Hour of the Day Fixed Effects, Garage Prices During (Weekdays)



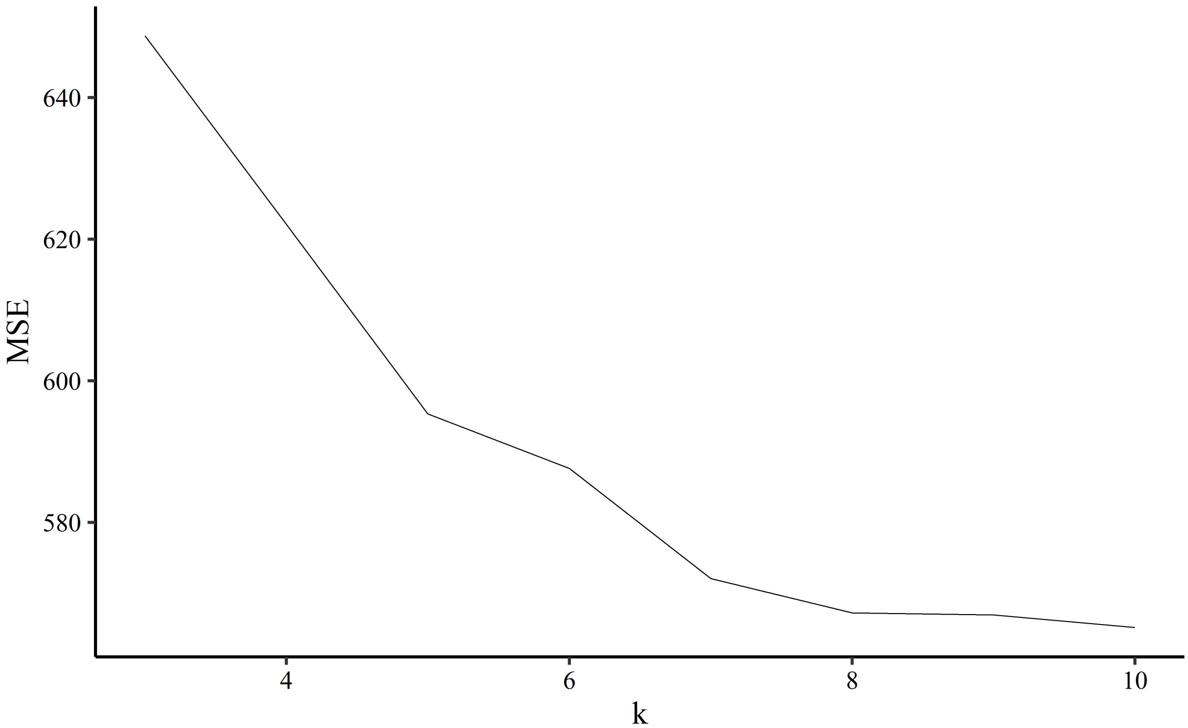
The figure shows the values $\alpha_{S,h}$ of from estimating $\ln(r_{g,ih}) = \alpha_{r,i} + \alpha_{r,h} + \varepsilon_{r,ih}$. Where $r_{g,ih}$ is the garage price for a 2-hour period at location i at hour of the day h.

Figure A.3: Distribution of Garages and Distance to the City Center, New York City



Notes: Number of garages and distance to the city business district (DCBD) in miles.

Figure A.4: Cross-Validation Exercise W Matrix (k neighbors, and Mean Square Error)



Notes: Average Mean Square Error (MSE) of the out-of-sample forecast for the ten fold cross validation exercise using different numbers of neighbors k.