# Parking Prices, Cruising, and Congestion *

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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, as drivers that curbside park 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 on-street parking is allowed. I further exploit the data's variation over time and location to analyze how strong the incentives to park on-street are and how different the behavior of garage operators and city officials is. The data shows that most drivers have a significant incentive to cruise in search of on-street parking; and that prices and supply of meters and garages are high at the city center and lower further away.

**JEL Codes:** R40, R41, R48, R58

**Keywords:** On-street Parking, Traffic Congestion, Garages, Prices

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# 1 Introduction

On March 30th 1930 the New York Times reported that an ordinance that reduced on-street parking in downtown Philadelphia had "speeded up traffic".[1] Two years before that, a 1927 survey conducted in Detroit reported that between 19% and 34% of the traffic in two downtown locations was cruising for parking.[2] Searching for parking (cruising) has been a concern in American cities since the dawn of the car era. The struggle is so ubiquitous and alive today that it has found its way into sitcoms (Seinfeld),[3] songs (Spaced by Loudon Wainwright III),[4] and newspaper articles (Why the Fight Over Parking in New York Is "Like the Hunger Games").[5] Searching for curbside parking produces a negative externality as the person that is cruising increases congestion, slowing everyone else on the road. Garages provide a partial solution to this issue since cruising in a garage does not affect street traffic. However, garages tend to be more expensive than on-street parking, creating an incentive to cruise for curbside parking among drivers with low willingness to pay.

In this paper, I turn to the parking market and traffic data of New York City (NYC) to map and assess the costs of on-street parking. To do this, I (i) build a theoretical model that connects on-street parking with cruising and traffic speed; (ii) map the location, price, and supply of parking services and how they change through the day; (iii) quantify the effect of on-street parking on traffic speed; and (iv) map and assess the demand, consumer surplus, congestion cost, and search cost produced by on-street parking.

The analysis starts by focusing on the microeconomics of the parking market through a theoretical model. The model shows how the price gap between on-street and off-street parking, the traffic speed, the duration of the parking period, and the probability of finding an empty spot are critical elements of the demand for on-street parking.

The model recognizes two costs linked to on-street parking: search cost and congestion. Search cost refers to the time spent cruising for parking. Only drivers that park on-street bear the search cost. On the other hand, congestion is a negative externality that affects all drivers on the road.

[1] "PHILADELPHIA PLAN CUTS PARKING EVIL", The New York Times Archives (TimesMachine).
[2] See Simpson (1927)
[3] Seinfeld season 3 episode 22, The Parking Space.
[4] Album: Haven't Got the Blues (Yet).
[5] By Christina Goldbaum, January 5, 2021 in the New York Times.

The connection is as follows; demand for curbside parking increases traffic as drivers searching for curbside spots are part of the stock of cars circulating on the street. The model is limited to search cost and congestion for simplicity, ignoring other possible social costs. This assumption means that in the theoretical model, garages provide parking services with no social cost.

The second part of the document focuses on analyzing the time and location of factors that affect the cost and benefits of on-street parking. For this assessment, the paper uses new and existing data on three subjects: congestion (traffic speed), the supply of on-street parking, and the price gap between on-street and off-street parking (incentive to curbside park). It is of particular interest the new data on parking supply. This novel data not only serves the central objective of measuring the effects of on-street parking on traffic. It also contributes to the discussion on the space dedicated to cars in cities. In this matter, the paper estimates the number of on-street spaces, both metered and free of charge, supplied by the City of New York. In addition, this part of the analysis describes how different types of parking services—free, metered, and garages—are distributed across the city and how prices and supply change during the day. Thus, the analysis in this section serves two objectives: understand the behavior of garage operators and city officials when supplying parking services, and provide the insight needed to understand the identification strategy used for measuring the effect of on-street parking on traffic speed.

The paper then moves to quantify the relation between on-street parking and traffic speed. To do this, I look at changes in the supply of free on-street parking imposed by restrictions marked on traffic signs. One example of these changes is sweeping signs; street sweeping limits parking in parts of the city at different times as cars have to move to give room to street sweepers. The location and schedule of sweepers are marked on traffic signs around the city. Reducing the supply of on-street parking makes it harder to find a spot open, extending the search period. Consequently, the expected drop in demand—due to a higher non-monetary cost of searching for parking—reduces the number of vehicles cruising, easing traffic, and increasing the average speed.

Quantifying the effect of on-street parking on traffic speed is a challenging endeavor for three main reasons. First, city officials modify the supply and price of on-street parking in an endogenous way—some parking spots are banned, and meters are enforced during high congestion hours. Second, the location of meters and free on-street parking is not random; meters can be found in both local and arterial streets, while free parking is a common feature of lower-order streets. Third, the traffic of each road is different as it is affected by the idiosyncrasies of each location (e.g., amenities and infrastructure like grocery stores and traffic lights can affect traffic speed).

To address these challenges, I use a difference-in-difference approach that exploits variations in traffic speed over time and location. In doing this, I use controls for location, time, and type of parking. The degree of disaggregation provided by the difference-in-difference regressions allows me to isolate the effect of on-street parking on traffic speed. An effect that otherwise remains hidden in the aggregated data under cyclical components and other relevant divers 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. Other parts of the welfare analysis are bound to a city-level aggregation due to data limitations.

To perform the welfare analysis and project it to locations beyond my sample, I require some population characteristics and a price forecast model. Assessments on the population income, type of commute, and other relevant characteristics are collected from the census data, the American Community Survey, and transportation reports issued by the city and the state of New York. To forecast the price of garages outside of my price sample, I use a spatial autoregressive model. The model is built under the idea that garage prices are affected by neighboring competitors. To build the weight matrix in the spatial autoregressive model, I borough the concept of cross-validation from the machine learning literature. Using cross-validation allows me to build a weight matrix consistent with the performance objective of this part of the paper—having good out-of-sample estimates.

I split the paper's findings into three groups: measurement facts, statistical claims, and welfare estimates. Measurement facts are characteristics of the supply of parking based on the novel data used in the paper. For instance, I add to the debate on the urban space dedicated to cars by showing that the supply of free on-street parking is more than four times that of metered parking and more than double the supply of paid parking (meters + garages). Another interesting finding is that city officials price meters similarly to how private garage operators manage prices. Nevertheless, differences in rates between meters and garages persist, creating a significant incentive to park on-street.

Statistical claims are estimated causal effects based on new and existing data. These results focus on the relation between on-street parking and traffic. As predicted by the theoretical model, there is a negative relation between on-street parking and traffic speed. I find that free on-street parking reduces average traffic speed by 0.15 to 0.18 MPH. During rush hour, these changes can represent drops in the average speed of more than 1% and more than 3% in the slowest locations. Those results show to be robust to the different specifications and checks performed in this paper.

Welfare estimates are cost-benefit assessments based on the theoretical model and the paper's estimates. My findings produce two main welfare estimates. The first comes from the cruising incentives—the price gap between on-street parking and off-street parking. The paper estimates that, given the differences in prices between on-street and off-street parking, more than 80% of New Yorkers have an incentive to cruise for parking in locations where both types of parking are available. This last situation is especially true in congested areas close to the city center if I only account for free parking (e.g., Midtown and lower Manhattan). On the other hand, if I only account for metered parking, the largest incentive to park on-street is outside the city center.

The second welfare estimate is an assessment of the cost produced by drivers searching for parking. A back-of-the-envelope calculation shows that the average car commuter in NYC losses one minute on every round trip due to drivers searching for on-street parking. Given the number of drivers commuting and visiting the city, I reckon that more than 46,000 hours or $1,430,000 are lost every day due to congestion produced by this type of cruising.

After this introduction and motivation the rest of the paper goes 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 from the parking supply. Section 4 presents the data on parking, traffic, and population. Section 5 describes the location and dynamics of the supply and prices of parking. Section 6 discusses the estimation strategy and results. Section 7 maps and assesses the costs and benefits of on-street parking. Section 8 concludes.

## 2 Background

Donald Shoup's book, "The High Cost of Free Parking" (Shoup, 2005), revitalized an old discussion: why is there so much parking, and why we charge so little for it? This question remains valid in today's cities, where the space per person keeps shrinking while the area dedicated to cars remains unchanged for the most part. Extensive literature, written before and after Shoup's book, has provided a strong theoretical framework aimed to explain the economics behind parking (Vikrey, 1994, Glazer and Niskanen, 1992, Arnott and Rowse, 1999, Anderson and de Palma, 2004, Arnott, 2006, and Arnott and Rowse, 2009 to mention some). Important results like the notion of parking as a service prone to the tragedy of the commons, and the latent externalities of providing parking at low cost, are common ground in this body of literature. However, despite the broad consensus, the lack of data has made it hard to measure inefficiencies and externalities linked to the parking market.[6]

Free parking and fixed meter rates found in most American cities entail that the way drivers "pay" for a spot is different between on-street and off-street parking. For instance, 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 search and walk for a cheaper curbside spot. Furthermore, as the city owns all curbside spaces, the cost of providing this service is bear by all taxpayers.

Occupying a curbside spot in a saturated location,[7] has unintended consequences on other drivers: it increases congestion and cruising, costs that are rarely associated with off-street parking.[8] As a consequence, the difference in prices between on-street and off-street parking reflects, at least

[6]Often the best measurements available are numerical exercises calibrated to match anecdotal evidence.
[7]As in Arnott and Rowse (2009) curbside parking is saturated if "the occupancy rate is 100%".
[8]The terms on-street and off-street parking are used as synonyms of curbside and garage parking respectively.

partially, the underlying externalities of curbside parking. This result is embedded in the theoretical work of Anderson and de Palma (2004), and Arnott and Rowse (2009), among others. In the simpler versions of their model, private garage operators can allocate parking in a socially optimal way. This conclusion quickly fades as the models grow in complexity. However, the wedge between tariffs of garages and curbside parking accounts, at least partially, for the externalities of underpriced curbside parking.[9] This paper builds on this framework, providing an indicator of the externalities caused by the low price of off-street parking. For this, I use novel panel data on garage services sold online.[10] The online garage industry provides a unique opportunity to identify the effect of searching and cruising on parking prices. The reason is simple: online platforms like Parkwhiz and SpotHero eliminate the search cost as all data on availability, price, and facilities can be easily accessed 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 it less attractive to park on-street. In line with this, an important body of the theoretical literature claims that increasing the meter rates is socially optimal. For instance, the theory predicts that charging the market rate at the meter—the same rate as garages—will eliminate cruising (Shoup, 2006), or produce a social optimum (Anderson and de Palma, 2004). 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."

One of the main conclusions of this paper is that the nature of the inefficiencies related to curbside parking changes across the urban environment. The supply and demand of parking are not homogeneous within a city; spots tend to be more scarce, and hence more costly, in downtown areas than in the outskirts of a town. As such, a saturation of curbside parking, congestion, and other externalities related to a high search cost, are distinctive phenomenons of downtown areas. This paper maps curbside parking inefficiencies for NYC. These results are then matched with the supply of on-street parking to estimate the welfare losses caused by underpriced curbside parking. This allows to reckon the social dividends of increasing meter tariffs and seize the effect of increasing

[9]The price gap accounts for the externalities that can be internalized by the garage operator

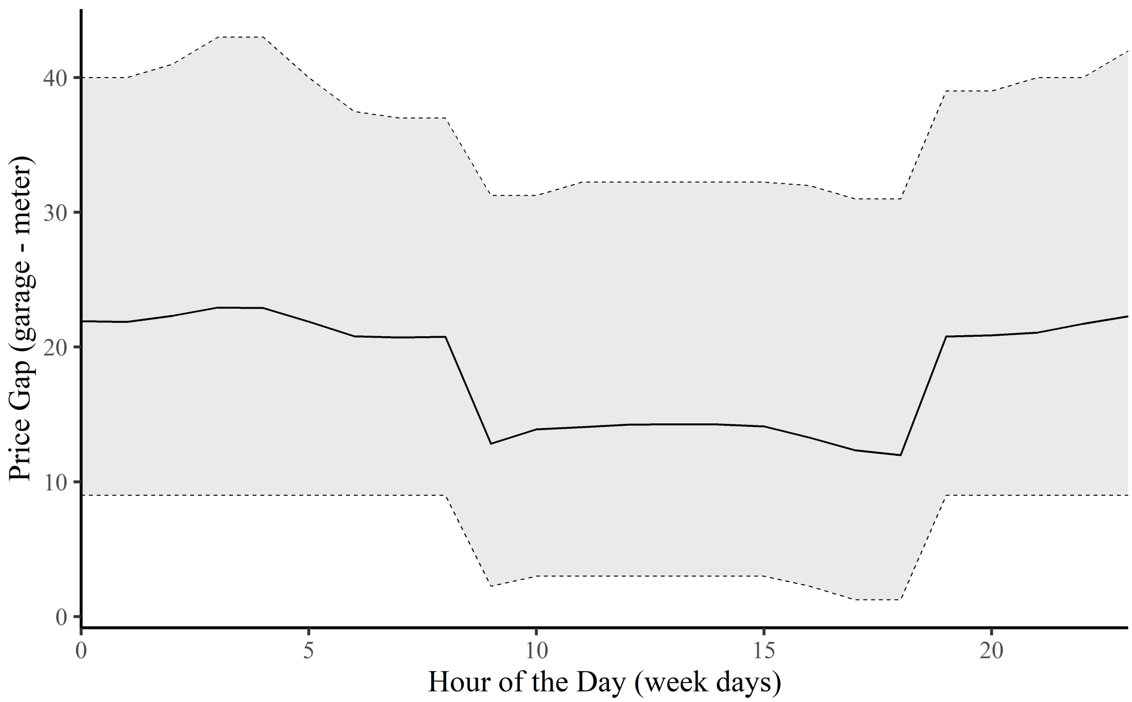
[10]The term garage services sold online refers to parking services sold, using applications and websites like ParkWhiz.com.

those tariffs in different locations.

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

This relative scarcity of parking reflects in prices. Shoup (2006) documented that NYC had the largest price gap between curb and off-street parking in a sample of 20 American cities. Figure 1 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 a two hours is positive and around \$20 for most of the day, with some extreme cases where the price difference can stretch to more than \$40. Even in a city like New York, where the income by the hour is around \$37, parking on-street can represent substantial savings for many New Yorkers.

Figure 1: Two Hour Price Gap NYC (garages - meters).
Median, 5th and 95th Percentiles.




# 3 Theoretical Model

The model is set in a city where all streets are laid in a uniform grid. Drivers visiting one block have two options: park on the curb or in a garage. In both cases drivers park in the same block, so the cost of walking to their destination is fairly equal in both options. Parking is assumed to be a homogeneous good, i.e. on-street parking and off-street parking are equal in all characteristics other than price, making price and location the only drivers of the demand.

## 3.1 Drivers

Drivers decide between parking in a garage that charges $r_g$ per unit of time or park on-street and pay $r_m$ at the meter. The parking decision is based on the full price of each option—the rate plus search cost. Garage operators only accept drivers when they have availability, making the search cost close 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 as they can't afford to cruise for parking. Aware of this, garage operators charge a rate higher than that offer at the meter, pushing drivers with low time valuations to park on-street.

The process of searching for on-street parking follows what Arnott and Williams (2017) calls a binomial process. Drivers cruising expect to find an empty spot with a probability $p$; this means that on average they have to inspect $\frac{1}{p}$ spots before finding one empty. The time spent inspecting each spot is an inverse function of the traffic speed ($S$). The length of each parking space is normalized to one,[11] so that the cost of cruising is equal to $\frac{v}{Sp}$. A driver is indifferent between on-street and off-street parking if her valuation of time $\bar{v}$ is such that the full price of off-street and on-street parking is the same:

$$r_g l = r_m l + \frac{\bar{v}}{Sp}, \tag{1}$$

where $l$ is the average length of the parking period.

From equation (1) follows that any driver with a value of time bellow $\bar{v} = (r_g - r_m)\, lSp$, will decide to park on-street, while people with a time valuation above this threshold will decide to park in a garage. Assuming that on average 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:

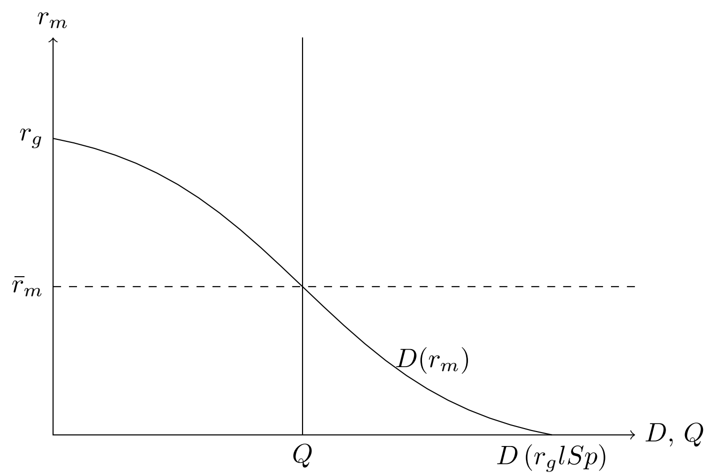
$$D = F(\bar{v})\, X. \tag{2}$$

Figure 2 provides an illustration of the on-street market where $Q$ is the fixed parking supply per city block. When meter rates are equal or greater than $r_g$the demand for on-street parking

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

equals zero as all drivers prefer to park in a garage where the search cost is zero. The demand for on-street parking reaches its maximum value when $r_m = 0$, i.e. when searching is the sole cost of on-street parking.[12]

Figure 2: On-street Parking Supply and Demand.




### 3.2 Congestion

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

The fundamental diagram of traffic governs traffic on the street, hence speed ($S$) is a decreasing function of vehicle density:

$$S = S\left(\frac{T+D}{J}\right). \tag{3}$$

### 3.3 Garage Operators

The demand for off-street parking is given by the complement of the CDF function $\left(1 - F\left(\bar{v}\right)\right) X$. Knowing this, garage operators set prices to maximize profit. Under the assumption that the CDF

[12] $\bar{r}_m$ is the equilibrium rate, any price above will cause excess supply, and any price bellow excess demand.

is log concave, it can be shown that the profit maximizing garage rate is such that:

$$r_g = c + \frac{1 - F(\bar{v})}{f(\bar{v})} \frac{1}{lSp} \tag{4}$$

Equation (4) shows that the optimal rate equals the unit cost ($c$), plus the inverse of the hazard function $\left(\frac{1-F(\bar{v})}{f(\bar{v})}\right)$, times the search period ($\frac{1}{Sp}$), times the vacancy rate ($\frac{1}{l}$). The structure of the best response function means that garage prices are high when: the unit cost is high, most drivers have a high time valuation, the search period is long, or the length of the parking period is short. The sensibility or garage rates to changes on $l$, $S$, and $p$ depends on how concentrated are time valuations around the threshold value $\bar{v}$. If drivers with a time valuation equal to $\bar{v}$ are a small share of all drivers with a time valuation equal or greater than $\bar{v}$; garage prices will be very sensible to changes on $l$, $S$, and $p$, as garage operators can adjust prices without loosing to many clients.[13]

## 3.4 Consumer Surplus

For a set of prices $\bar{r}_m$ and $r_g$, the consumer surplus of drivers that park on-street is given by the integral of the demand function ($X \int_{\bar{r}_m}^{r_g} F((r_g - r_m) lSp) \, dr_m$), as long as the demand ($D$) is less than the supply ($Q$). If the demand for on-street parking is greater than the supply ($D > Q$), only $Q$ drivers get a spot, so the consumer surplus is $Q \int_{\bar{r}_m}^{r_g} F((r_g - r_m) lp) \, dr_m$. In both cases, the consumer surplus per custumer is the same:

$$\text{Consumer surplus per driver} = \int_{\bar{r}_m}^{r_g} F((r_g - r_m) lSp) \, dr_m.$$

## 3.5 Search Cost

Assuming that on-street empty spots are distributed uniformly around the block, the probability ($p$) of finding one empty spot is $p = \frac{Q-D}{Q}$. As only drivers with a valuation of time below $\bar{v}$ park

[13] In this context, the inverse of the hazard rate, also known as Mills ratio, determines how sensible are garage prices to changes in the length of the search period ($\frac{1}{Sp}$), or vacancy rate ($\frac{1}{l}$).

on-street, only they bear the cost of cruising, this is:

$$\text{Search cost per driver} = \frac{Q}{S\left(Q - F\left(\bar{v}\right)X\right)} \int\limits_{0}^{\bar{v}} vf\left(v\right)dv.$$

### 3.6 Congestion Cost

Drivers in transit take $L/S$ units of time traveling through a street segment of length $L$. One driver cruising reduces the traffic speed by $S'/J$ in the same segment. All drivers on that street segment are affected by this reduction in speed, so the congestion cost to the average driver is given by:

$$\text{Congestion cost per driver} = \frac{LS'}{S^2 J} \int\limits_{0}^{\infty} vf\left(v\right)dv,$$

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

### 3.7 The Cost of Walking

Equation (1) 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 results for blocks that have on-street parking but no garage; a common situation given that garages are not as ubiquitous as on-street parking. To address this issue I introduce walking to equation (1).

It is often the case that the off-street option is located in a different block, this situation entails walking back and forth from the parking block to the destination block. To account for this 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, so equation ( 1) can be re-write as:

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

$w$ limits the garage's market, as any distance $d^*$ such that the walking cost $w(d^*, v)$ is above $\frac{1}{2}\left((r_m - r_g)l + \frac{\bar{v}}{Sp}\right)$ makes the garage to far to be a viable parking option. Most papers limit the market area to a 0.2 mile radius (Choné and Linnemer, 2012, Lin and Wang, 2015, and Inci, 2015).

The 0.2 mile radius represents a relatively low cost if I only account for the time spent walking; if humans walk at an average speed of 3 miles per hour, they can cover the 0.2 miles in 4 minutes, therefore the cost will be just 1/15 of an hourly wage. Further more, authors like Kobus et al. (2013) value the time spend walking at one third of the wage. In line with this, I settle for a theoretical model that only uses the cost of walking to limit the market area of garage.

## 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 two: parking and traffic data. Parking data accounts for three different types of parking: garages, metered on-street, and free on-street. The data is obtained from a mix of public and private sources, as explained below. On the other hand, traffic speed data comes from a unique source, the Uber Movement website. At the 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. Two thousand twenty data was also available. However, to avoid possible noise from the SARS COVID-19 pandemic, I only use the year 2019.

Matching the data from the different sources came with challenges from both the time and space dimensions. From the spatial point of view, matching the data is challenging as streets, curbs, and garages are contiguous to each other but not under the same coordinates. To bridge this challenge, I decided on blocks as the aggregation unit for the spatial dimension. Blocks provide fairly granular data consistent with the idea of cruising around the block—to minimize the length of the walk; drivers tend to search for parking in small areas surrounding their destination.[14]

Most of the challenges in matching the time of the different data sets came from Uber's traffic speed data. Uber Movement data entails two significant restrictions. The first is simple; at the moment of my query, traffic speed data was 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

[14] Similar assumptions are implicit in Anderson and de Palma, 2004 and Arnott, 2006.

comes from the lack of dates in the traffic speed data—the panel contains the speed, location, and hour of every trip but doesn't have the date. To bridge this difficulty and better match traffic and parking data, I do the following: I only use parking data from Monday to Friday, as I assume that most Uber trips happen during weekdays. For each block I average traffic speed and garage prices of every hour of the day, yielding 24 observations per block that mostly describe the behavior of these two variables 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 day of the week. This last measure helps provide a better match between the traffic speed data and the on-street parking supply.

A broad set of sources was used to build the parking data set, all of which are described below. 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 signals. This lack of signals is especially true in residential and low congestion areas. The absence of some of those parking locations is not a concern as they are very unlikely to cause congestion—residents parking on their driveways or garages do not cruise as drivers cruising on an empty street do not create congestion

- **Garages supply:** Using the register of licensed business provided by the City of New York Open Data portal, I build a data set with the locations and capacity of all licensed garages and parking lots in NYC (Figure 5). A few locations needed amendments since they registered coordinates outside NYC. These amendments were made using the business's address, Google Maps, and Google Street View.

- **Garages prices:** Using Parkwhiz.com I obtained the prices of a subset of garages that account for approximately 51% of the total universe of licensed garages in the sample period. Data was obtained through an hour by hour web scraping process that lasted over one year (July 2019 to July 2020).

- **Traffic signs:** NYC Department of Transportation offers a detailed map of the text and location of all traffic signs in the city through 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 those signs to build the inventory of free on-street parking. The signs also indicated at what time parking was allowed and when meters were enforced. Luckily many signs are the same, and so are their descriptions or "types". I found more than 1,200 different types of signs that mark the time of parking or meters. I used these signs to make dummy variables that indicate when parking is allowed and when meters are enforced in each location.[15]

- **Paid on-street parking:** NYC Department of Transportation offers a detailed map of the price and curves where metered parking is permitted through the City of New York Open Data portal(Figure 6). The time frame for meter enforcement was procured from traffic signs in each location, as done with free on-street parking. Since the data provided by the city only describes the segment of the curb that is available for parking, I used an average length of 18 feet, that is the recommended length of an interior stall by the Transportation Engineering Agency,[16] to estimate of the number of spaces.

- **Free on-street parking (signalized):** The City of New York does not provide an inventory of the free parking provided across the city. However, one can be build one using the no parking and parking traffic signs —traffic signs that forbid parking in a time laps allow parking during the rest of the day. By connecting those signs, I'm 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. The remaining segments are the curbs where parking is free at a given time. Traffic signals mark the area where one can park but not the number of spaces. To estimate the number of spaces, I assume an 18 feet length for every spot.[17]. In a cross-comparison of this map with other private source—SpotAngels.com and Parkopedia.com—the map shows a strong consistency with no visible differences.

[15] Many discrepancies that lead to illogical results—such as typos or poor wording— were solved by looking at the traffic sign on Google Street View.

[16] See "Parking Tutorials" at https://www.sddc.army.mil/sites/TEA.

[17] The same length used with metered parking

# 5 Parking Supply, Prices, and Traffic Speed

Not every street in NYC is congested, nor busy streets are 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 of four variables: traffic speed, parking prices, and the supply of on-street and off-street parking. The data patterns in this section not only describe the behavior of city officials and garage operators, they also provide insight into the reasoning behind the identification strategy presented in section 6.

## 5.1 Parking Supply and Location

To understand how on-street parking affects traffic, it is important to know where is the supply located and how it is priced. 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) that provides a model where all drivers visit the same desirable location; the city business district (CBD). Like in the monocentric city model (Beesley and Alonso, 1966, Muth, 1969, and Mills, 1967), parking prices in Anderson and de Palma (2004) get higher as locations get closer to the CBD. Figure 8 shows evidence of a gradient consistent with a monocentric city approach, as prices drop when the distance to the CBD (DCBD) increases.[18] 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 a similar behavior to that of private garages. Figure 9 plots meter rates and DCBD. The type of plot is different due to the discontinuity of meter rates. Unlike garages, meteres are divided into six prices 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 raters ($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 10 show

[18] 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)

how garages are concentrated arround the CBD. Figure 10 is a little deciving as longer distances from the CBD imply larger ring areas where more garages can be located. Figure 11 addresses this issue and shows the garage density per square mile. The result is consistent with previews findings. If the CBD is a common desirable location, private parking providers allocate around it. Figure 12 shows the percentage of blocks with meters and the distance to the CBD. The result is similar to that in figure 11; the closer to the CBD the higher the meter density.

The supply of free on-street parking behaves in a different way to that of meters and garages. The differences go beyond prices. The supply of free on-street parking is more spread across the city. Figure 13 shows the percentage of blocks with free-of-charge on-street parking around the CBD. Unlike with garages and meters, there is no step gradient. On the contrary, in the first 5 miles from the CBD the percentage of blocks with on-street parking increases, result that is likely driven by the increasing presence of residential buildings in the areas farther away from the CBD. The percentage starts to drop in the outskirt of the city, where blocks are larger and industrial and green areas are more common.

The finding mentioned above show how the supply of meters and garages have similar spatial characteristics in both quantity and prices. Meanwhile, free on-street parking behaves in a very different way. The above suggests that city officials manage metered parking in a manner similar to that of private providers, while free parking follows a different set of rules.

## 5.2 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 cities' inhabitants, specially during week days. This behavior has an important impact on traffic and the decisions regarding the supply and price of parking. Figure 14 shows the hour by hour behavior of traffic speed during the day. The pattern should be familiar as it relates to rush hour with two low speed kinks at 8 am and 5 pm. Figure 14 shows this behavior by plotting the $\alpha_{S,h}$ obtained from estimating equation:

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

As with traffic speed, garage prices show that garage operators pricing behavior is consistent with the usual 9 am to 5 pm work schedule. Figure (15) 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:

$$\ln\left(r_{g,ih}\right) = \alpha_{r,i} + \alpha_{r,h} + \varepsilon_{r,ih}. \tag{5}$$

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

Similar to garage operator, city officials adjust the supply and price of on-street parking during the day. Figure 16 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. A similar behavior can be observe in figure 17 that show most meters are enforced when traffic is the slowest.

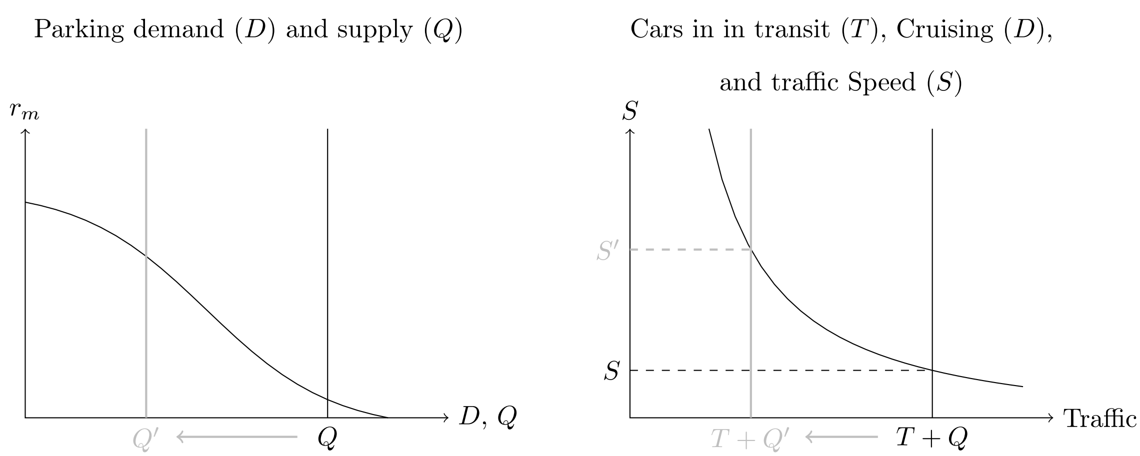
Figures 16 and 17 provides a good example of how aggregated data can hide the negative relation between on-street parking and traffic speed; at first sight it seems that there is a positive relation between the supply of on-street parking and traffic speed, as the city reduces the supply during period of high congestion. A more desegregated analysis allows to separate some location specific and cyclical components that can confound the effect of increasing on-street parking and traffic speed.

Figure 18 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 higher speed than blocks with on-street parking. The difference in speed looks non significant due to high variance, however, high variance across location can mask within location significant effects. Section 6 presents an identification strategy that addresses this issues.

# 6 Estimation

To measure the effect of on-street parking on traffic I use within day changes in the supply of parking at each location. Changes in the supply of parking are reported by the traffic signs in each location. In the light of the theoretical model, modifying the number of parking spots available affects traffic speed through a change in the number of drivers cruising. Closing the curb for parking reduces the probability of finding an empty spot ($p$), so it 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 less drivers cruising, lower traffic density, hence higher traffic speed. Figure 3 illustrates the effects of reducing on-street parking on traffic speed based on the theoretical model.

Figure 3: Reducing On-street parking Supply and Traffic Speed




To gauge the effect of changing the supply of on-street parking on traffic speed, I use a difference-in-difference strategy that exploits the variation in time and space of traffic and free on-street parking supply. A difference-in-difference approach allows to control for the time and location factors described in section 5. The strategy leads to the following regression equation:

$$S_{ih} = \alpha_i + \alpha_h + \gamma_i + \beta_F \times \mathbb{I}_{\text{free parking},ih} + X_{ih}\beta_X + \varepsilon_{F,ih}, \tag{6}$$

where $\alpha_i$ are the fixed effects that account for the unique characteristics of every block, $\alpha_h$ is the vector of the hour of the day fixed effects, $\gamma_i$ controls for the type of parking available at each location,[19] $\mathbb{I}_{\text{free parking},ih}$ 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 $X_{MC}$) and spill over effects ($X_{NP}$) as describe bellow:

- 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 $X_{NP} = \begin{cases} 1 & \text{Neighbor blocks offer any type of on-street parking (free or metered)} \\ 0 & \text{Otherwise} \end{cases}$

Table 2 shows the result of estimating equation (6). Standard error are cluster at the borough by hour level. Clustering at the borough level follows the physical barriers created by the Hudson river, which creates subsystems of street grids within each borough.

Results in Table 2 show that allowing on-street parking in one block can reduce speed by 0.15 to 0.22 miles per hour which is roughly a 0.8%-1.5% speed reduction during rush hour. The estimates show to be fairly consistent to the introduction of the different controls transition periods and spillover effects, as shown in columns 2 to 4.

## 6.1 Robustness

A reasonable concern with estimates in Table 2 is that the results can be driven by a phenomenon other than daily changes in the supply of on-street parking. The concern is especially worrisome due

[19] $\gamma_i$ is a vector of two dummy variables $\gamma_{F,i}$ and $\gamma_{M,i}$. $\gamma_{F,i}$ is equal to 1 if location $i$ only has free parking available, zero to otherwise. $\gamma_{M,i}$ is equal to 1 if location $i$ only has metered parking available, zero to otherwise. This means that the reference category are locations with both types of on-steet parking.

to the ciclicality of traffic and time consistency in changes of the parking supply—if all commuters drive by one location at time $h$ and coincidentally traffic signs modify parking in that location at the same time, the estimator will wrongly estimate a significant effect of parking supply on traffic.

To alleviate concerns on this issue a preform a placebo test for a random sample of location that have no on-street parking (fake treatment group). The time at which curbside parking is permitted (parking schedule) changes across location. This makes the assigning of the falsification test a non-trivial task. My strategy to assign the falsification test consist of using the five most common on-street parking schedules in my traffic sign survey; from 10 am to 7 am next day, 11 am to 8 am, 11 am to 7 am, 1 pm to 10 am, and 2 pm to 10 am.[20] Using these five different schedules I create dummy variables that are then assigned to the randomly picked 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 factor can exist in smaller groups. this correlation can lead to smaller standard errors and miss leading conclusions. To address this issue, Table 4 clusters errors at the census tract level. The result shows standard errors similar to those in table 2. The result is encouraging given that census tracts is one of the smallest granularities plausible for this exercise.[21]

# 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 6, and a set of observations and calibrated parameters obtained form, Census data, government reports, and other papers. The effect on welfare can be decomposed in three elements: the consumer surplus ($CS$), the time spend cruising ($TC$), and traffic delays caused by divers cruising ($TD$). The expressions of theses three factors are

[20] In all cases the last hour marks the end of the parking period next day. E.g. 2 pm to 10 am means that there is no curb parking between 11 am and 1 pm

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

as follow:

$$CS = \begin{cases} X \int_{\bar{r}_m}^{r_g} F\left(\left(r_g - r_m\right) lp\right) dr_m & \text{if } D \leq Q \\ Q \int_{\bar{r}_m}^{r_g} F\left(\left(r_g - r_m\right) lp\right) dr_m & \text{if } D > Q \end{cases}$$

$$TC = \begin{cases} F\left(\bar{v}\right) X \frac{Q}{S(Q - F(\bar{v})X)} \int_0^{\bar{v}} v f\left(v\right) dv & \text{if } D \leq Q \\ Q \frac{Q}{S(Q - F(\bar{v})X)} \int_0^{\bar{v}} v f\left(v\right) dv & \text{if } D > Q \end{cases}$$

$$TD = \frac{L}{S\left(\frac{T+D}{W}\right)}$$

The estimates of $CS$, $TC$, and $TD$ depend of the type of visitor of each block, specifically on their time valuation. This information is unobservable to me, hence I provide estimates based on the characteristics of the average New Yorker as described in section 7.1. Estimates of $CS$ and $TC$ require the price of garages in all locations. Since I only have the price of garages that belong to the prices sample (PS), I build a forecast for locations where the price is missing. This forecast is based on a spatial model described in section 7.2.

The results of the welfare analysis are divided in two: a granular assessment of the incentives to park on-street in each block (section 7.3), and back of the envelop calculation of the welfare effects of on-street parking in a representative block (section 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 hour to estimate the distribution of the value of time. The census office provides data by deciles of the income distribution. I use maximum likelihood to fit a log normal distribution to the average income of each decile. Figure 20 shows the observed deciles and fitted cumulative distribution function (CDF), and table 7 summarizes the descriptive statistics of the fitted distribution. A similar approach can be found in Hall (2021).

The distribution of the value of time allows to calculate the proportion of drivers that choose to park on-street. To approximate the mass of visitor per block I use different sources of data on the number of residents, workers, and daily car visitors, those sources are: the 2019 American Community Survey (ACS), 2010 US Census, 2016 New York City Screenline Traffic Flow report, and the 2018 NYC Mobility report.

- The 2019 ACS reports that 37 % workers in NYC use their cars for commute within the city.
- The US bureau of labor statistics reported an average of 4,650,180 nonagricultural employees during 2019.
- 1,128,260 vehicles from outside the city visited NYC daily according to the 2016 New York City Screenline Traffic Flow report.
- 8,336,817 is the projected population of NYC in 2010. Using the spatial distribution of the 2010 Census, the average NYC blocked housed 214 people.
- in 2019 the average NYC household was form by 2.2 people and owned 0.9 cars according to the ACS.
- 53% of residents parked on-street according to the 2018 NYC Mobility report.

## 7.2 Predicting Garage Prices

The block-by-block analysis of the incentives to curb park is limited to blocks where both options, garage and on-street parking, are available. To forecast the garage price in blocks where there are garages that are out of the PS, I use a spatial autoregressive model. The concept is as follows: as parking is a fairly homogeneous good in all characteristics but location. Garage operators engage in price competition among their closest competitors. As a consequence the price at one location are determined by neighboring garages:

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

where $W$ is the spatial contiguity matrix under an equal weight criterion, this is:

$$W = \begin{bmatrix} 0 & w_{1,2} & \cdots & w_{1,n} \\ w_{2,1} & 0 & & w_{2,n} \\ \vdots & & \ddots & \vdots \\ w_{n,1} & \cdots & w_{n,n-1} & 0 \end{bmatrix} \quad \text{where:} \quad \begin{array}{l} w_{ij} = \frac{1}{k} \text{ if block } j \text{ is among the } k \text{ closest blocks} \\ w_{ij} = 0 \text{ else.} \end{array} \tag{7}$$

For the $W$ matrix in (7), I picked a criterion of equal weight for all near garages. This criterion is picked under the idea that competitors tend to be among the closest neighbors. However, no neighbor can be single out by the researcher, as the most important competitor. The difficulty to single 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 sensible to the competitor's pricing scheme. A 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 neighbor $k$ in matrix $W$, I borrow the concept of cross-validation from the machine learning literature. Figure 21 plots the Mean Square Error (MSE) of the ten-fold cross-validation exercise for eight different definitions of the $W$ matrix—eight different values of $k$, from 3 to 10. To produce the ten-fold cross-validation exercises the PS is organized from north to south and split in ten groups of similar size.[22] Using nine of the ten groups I forecast the prices of the left out observations and record the MSE. This exercises 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 21 shows how the MSE plateaus after $k = 7$, suggesting no major gains in forecasting performance when using $W$ matrices with $k$ greater than seven. In a similar way, table 5 uses the full PS to show that the estimates of $\rho$ 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

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

for the out-of-sample forecast.

### 7.3 On-street Parking Incentives

The market area of each garage extends beyond its block. I assume the radius of the market is the length of the long side of two average Manhattan blocks (roughly 0.16 miles). This definition affects blocks that have no garage but are neighbors of a block that has a garage. In this case the effective garage rate is equal to that of the closest block.

Figure 19 shows the map percentage of drivers that are willing to park on-street in each block ($F(v)$). This number is based on the estimated income distribution, the average price gap between on-street and off-street parking, a parking period of 2 hours (papers like Arnott, 2006 and Arnott and Rowse, 2009 use the same parking period), and an expected cruising period of 10 minutes (Shoup, 2006 and Hampshire and Shoup, 2018 review a handful of studies that calculate cruising time in NYC between 3.8 and 13.9 minutes). The map shows that in most locations where garages ad curbside parking are an option more than 80% of New Yorkers are willing to park on-street. Further more the incentive to park is greater in congested areas like Midtown and lower Manhattan.

### 7.4 Consumer Surplus, Search Cost, and Traffic Delays

As with other public services, on-street parking provides a big benefit to few and a small cost to many—a few drivers benefit from parking at a low rate while many face slightly longer travel times. I assume a standard Manhattan block (830 by 220 ft) that has parking on the 2 street sides but not on the avenue side. this produces roughly 88 spot if I account for the 20 feet gap between the parking area and the intersection as recommended by the Federal Highway Administration.[23] Using the data above I calculate that in the average block residents occupies 30 spots and workers occupy 24 spots during the day and. Leaving 34 spots for visitors during the day. The average parking period is 2 hours and that drivers expect to cruise for around 10 minutes. In a block with both on-street and off-street parking, where the price gap between the two services of $18 dollars

[23]See www.pedbikesafe.org

for a 2 hour period, 93% of visitors will decide to park on-street.This yields an average consumer surplus and an average search cost per driver of $17 and $3.

Drivers in transit that pass by the block are delayed by cruisers, at an average speed of 15 MPH, a driver transiting the long side of the block can lose more than half a second. The above means that to offset the benefits of one driver parking on-street more than 5400 drivers have to drive by the by the block. a number that can be meet in some congested NYC streets.

# 8 Conclusions

For decades on-street parking has been subsidized under the pretexts that it improves the business of merchants. Despite having a strong body of theoretical literature that highlights the downsides of curbside parking the lack of data has limit the empirical analysis to specific projects an locations within cities. This paper sheds light into these topics by using city wide data to map an asses the cost and benefits of on-street parking in New York City.

The simulations in this paper estimates that the price difference between curbside and garages is such that in most of the city more than 80% of drivers are willing to cruising in search of on-street parking. Cruising creates congestion, a negative externality that is bear by all drivers on the road. My results show that on-street parking reduces traffic speed. The effect of is small but significant. Using meters can cut the effect of on-street parking on traffic speed by one half, as it closes the breach between the two prices.

This paper focuses on the congestion congestion cost of curbside parking. other possible externalities, both positive and negative, are ignored for the sake of simplicity, hence the analysis is short of comprehensive. A more complete analysis should look at the effects of on-street parking on economic activity, pollution, and potential used of the space dedicated to cars.

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Table 1: Summary Statistics New York City

| | Min (1) | $1^{st}$ quartile (2) | Median (3) | Mean (4) | $3^{rd}$ quartile (5) | Max (6) |
|---|---|---|---|---|---|---|
| Speed (MPH) | 4.074 | 14.265 | 16.528 | 16.805 | 19.089 | 56.869 |
| Income by hour ($) | 0.048 | 0.624 | 1.205 | 3.167 | 2.608 | 18.617 |
| Prices | | | | | | |
| Garage prices ($ two hours) | 2.000 | 15.043 | 19.889 | 21.246 | 25.108 | 89.298 |
| Parking meter prices ($ two hours) | 3.000 | 3.000 | 4.000 | 6.195 | 10.750 | 12.000 |
| Location, Distance to the City Business District (DCBD) | | | | | | |
| Garages DCBD (miles) | 0.112 | 1.045 | 2.102 | 2.575 | 3.184 | 13.965 |
| Parking meters DCBD (miles) | 1.092 | 2.376 | 4.772 | 4.655 | 6.834 | 8.195 |
| Free on-street parking DCBD (miles) | 0.100 | 5.625 | 11.150 | 11.150 | 16.675 | 22.200 |

Notes: Speed data form Uber trips during the fourth quarter of 2019. Data available at Uber Movement website. Garage prices data was web scraped from Parkwhiz.com during the fourth quarter of 2019. Parking meter prices and location provided by the City of New York Open Data portal. Garages location was obtained from the register of licensed business provided by the City of New York Open Data portal. The sampel is limited to garages operating during the second half of 2019. The location of free on-street parking was obtained by analyzing all traffic sings in New York City. The City of New York Open Data portal offers a detailed map of the text and location of all traffic signs in the city

Table 2: 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 $h$ | $-0.15^{***}$ | $-0.16^{***}$ | $-0.18^{***}$ | $-0.18^{***}$ |
| | (0.04) | (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. Neighboring census blocks are defined as any census blocks that share a common border. Standard errors are clustered at the borough by hour level.

Table 3

| 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 |

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

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 am to 9 am, 9 am to 10 am, 8 am to 10 am, 11 am to 12 am, and 11 am to 1 pm).

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. Neighboring census blocks are defined as any census blocks that share a common border. Standard errors are clustered at the census tract by hour level.

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) |
| $\rho$ | 0.586*** | 0.651*** | 0.693*** | 0.726*** |
| | (0.028) | (0.028) | (0.028) | (0.028) |
| Nagelkerke pseudo $R^2$ | 0.327 | 0.363 | 0.379 | 0.393 |
| 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) |
| $\rho$ | 0.747*** | 0.770*** | 0.786*** | 0.798*** |
| | (0.028) | (0.027) | (0.027) | (0.027) |
| Nagelkerke pseudo $R^2$ | 0.400 | 0.412 | 0.414 | 0.418 |
| Observations | 787 | 787 | 787 | 787 |

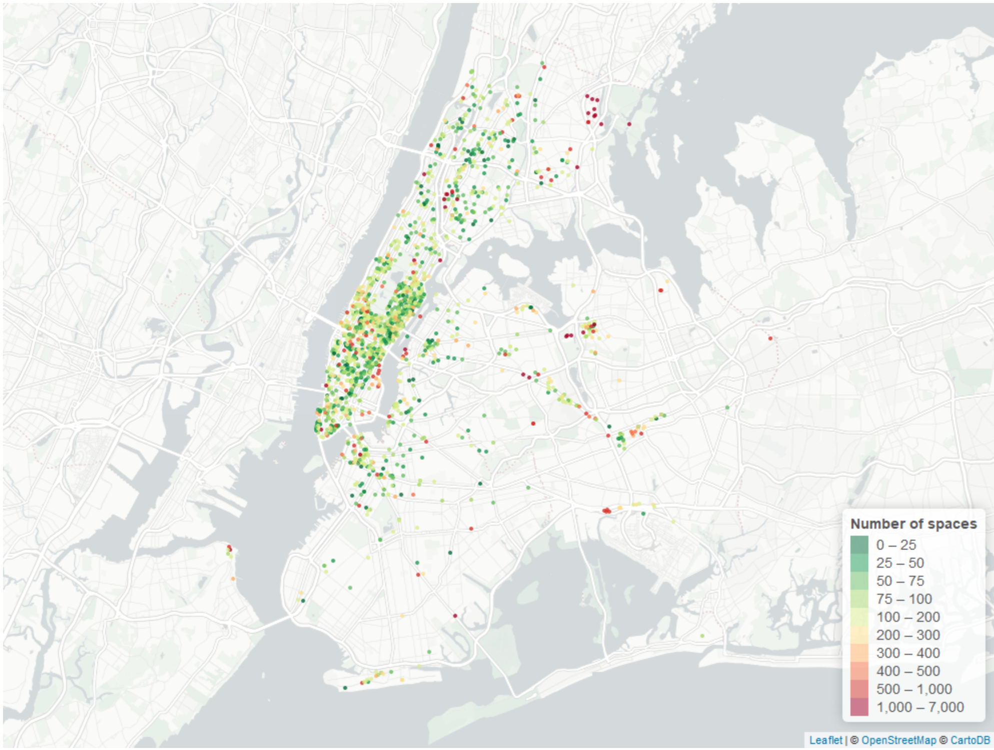
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 6: Value of One Hour of Time Based on Income Distribution

| Mean | Median | Variance | 2$^{\text{nd}}$ Decile | 9$^{\text{th}}$ Decile |
|---|---|---|---|---|
| 37.51 | 11.87 | 12636.16 | 1.70- 3.31 | 42.56- 82.94 |

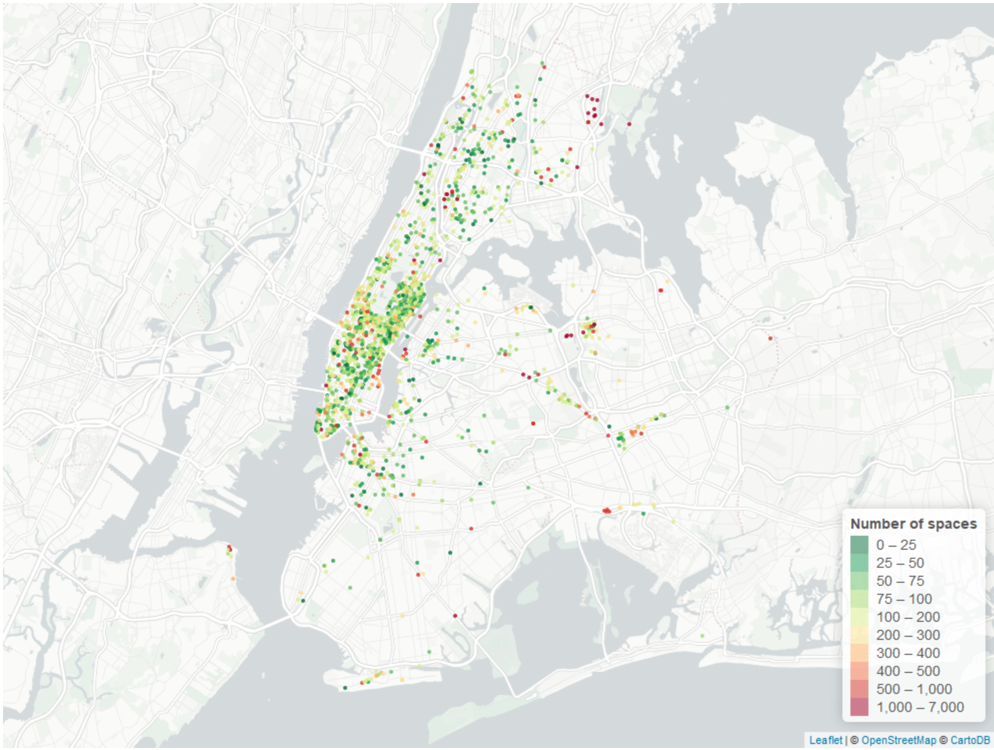
Table 7: Example of Parking Signs Used to Build the Hour by Hour Inventory of Free On-street Parking

Figure 4: Garages NYC.



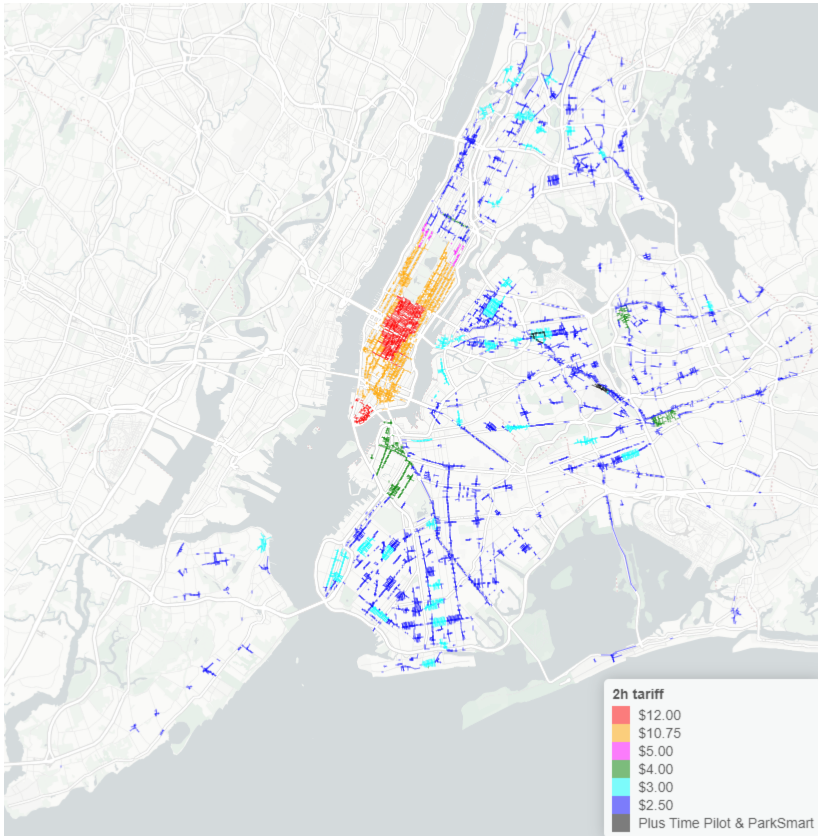

Full detailed map:`https://marangoisa.github.io/NYCGarages`

Figure 5: Garages NYC.



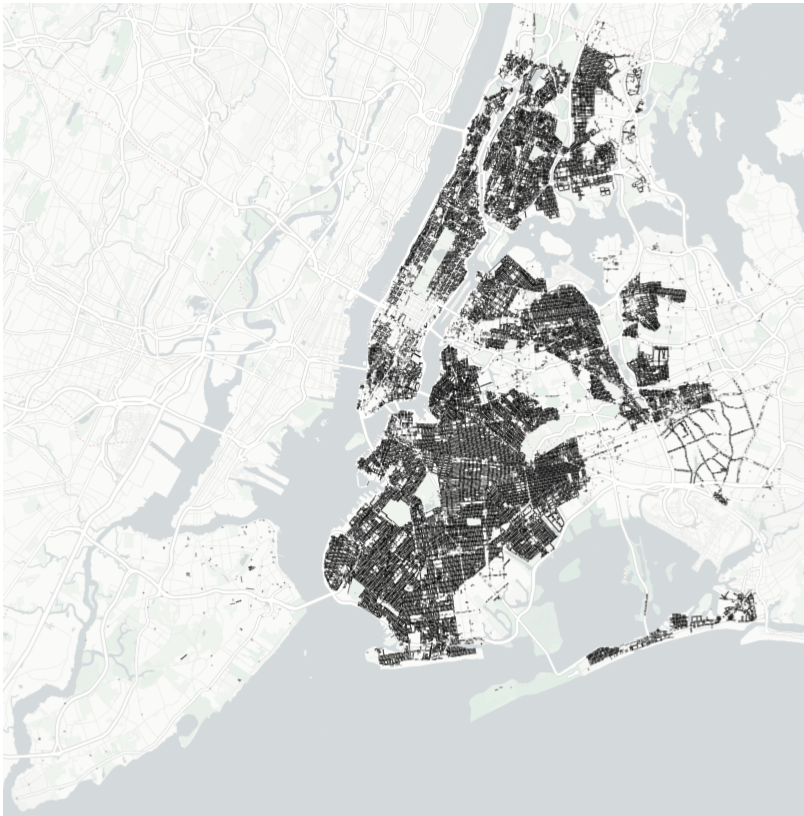

Full detailed map:https://marangoisa.github.io/NYCGarages

Figure 6: .




Full detailed map:https://marangoisa.github.io/NYCMeter.html

Figure 7: Free Parking NYC.



Full detailed map:https://marangoisa.github.io/NYCFree.html

Figure 8: Garage Prices and Distribution Across NYC

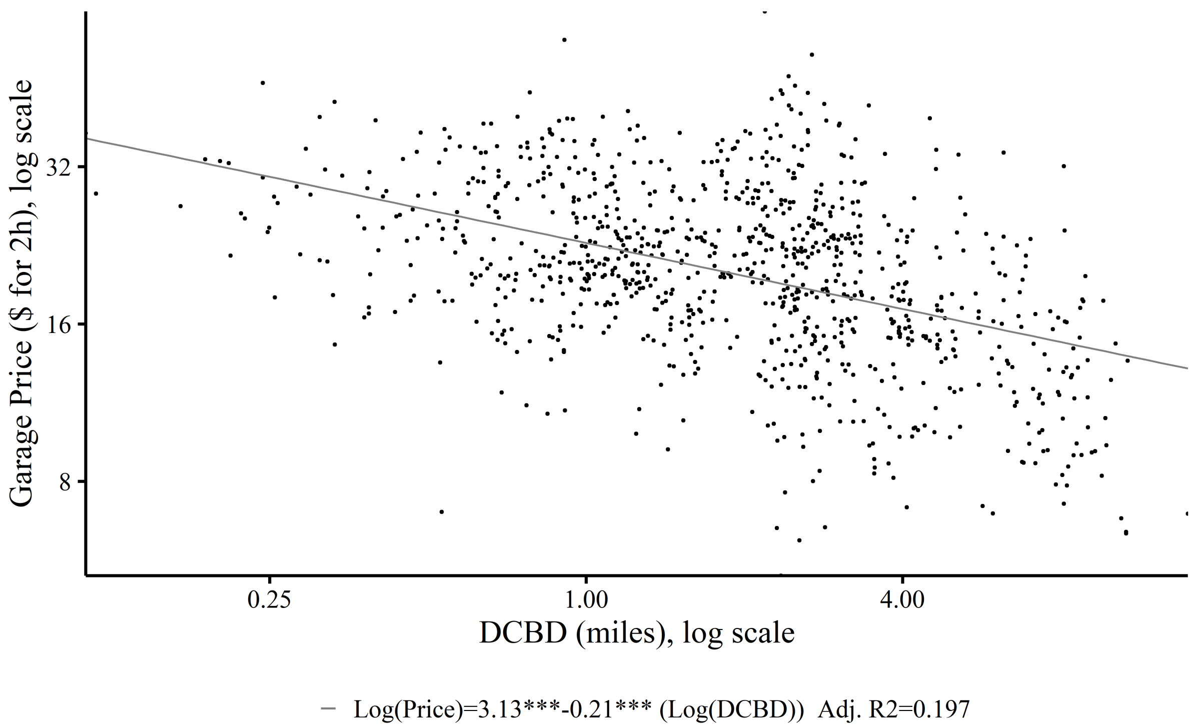


Figure 9: Meter Prices and Distribution Across NYC

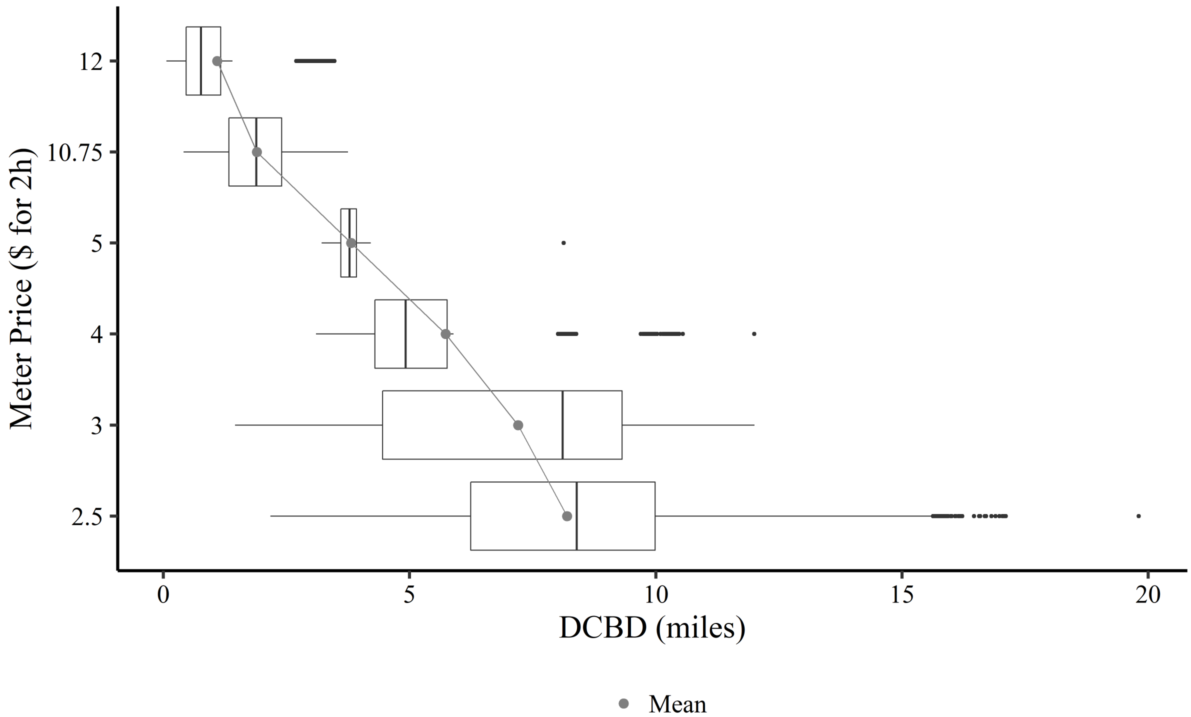


Figure 10: Distribution Garages Across NYC

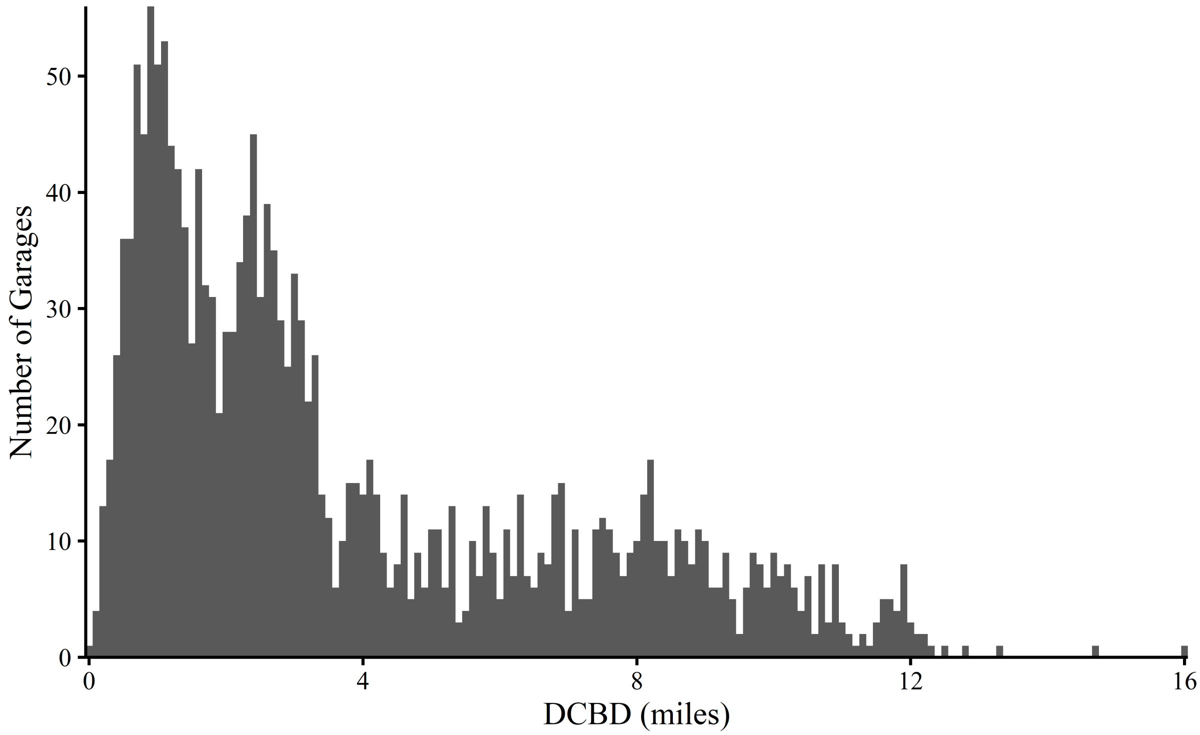


Figure 11: Distribution Garage Density Across NYC

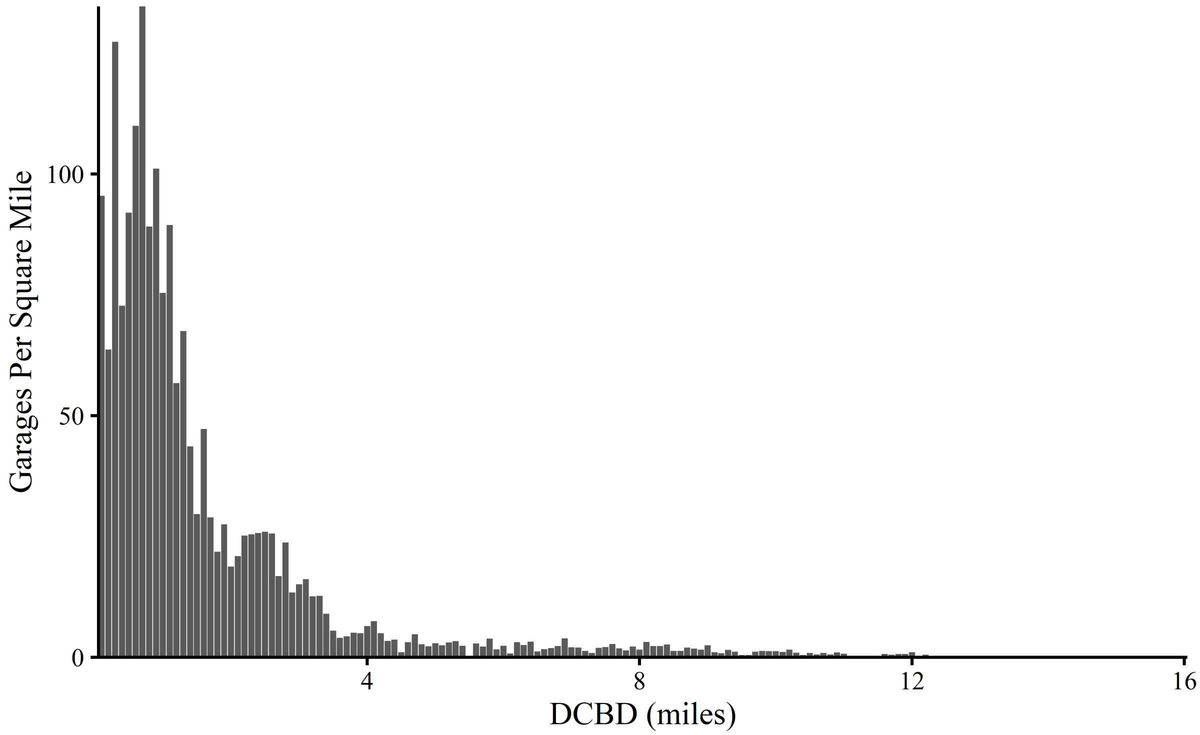


Figure 12: Distribution Meters Across NYC

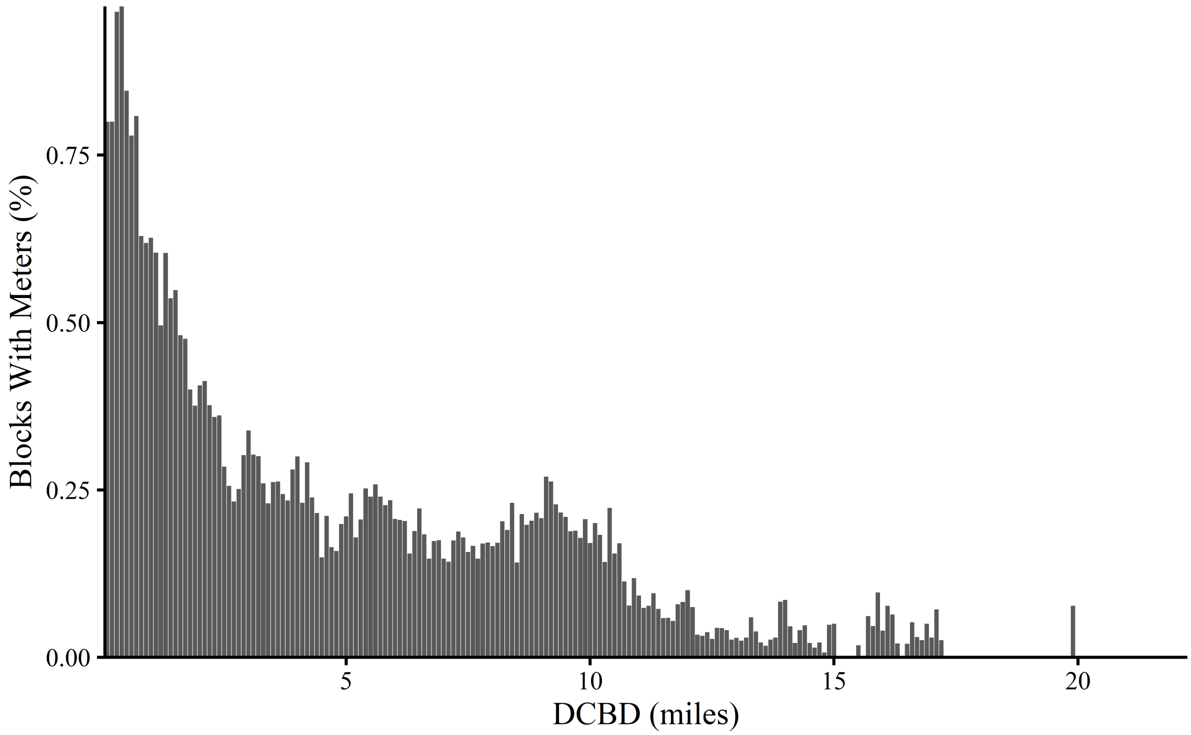


Figure 13: Distribution On-street Parking Across NYC

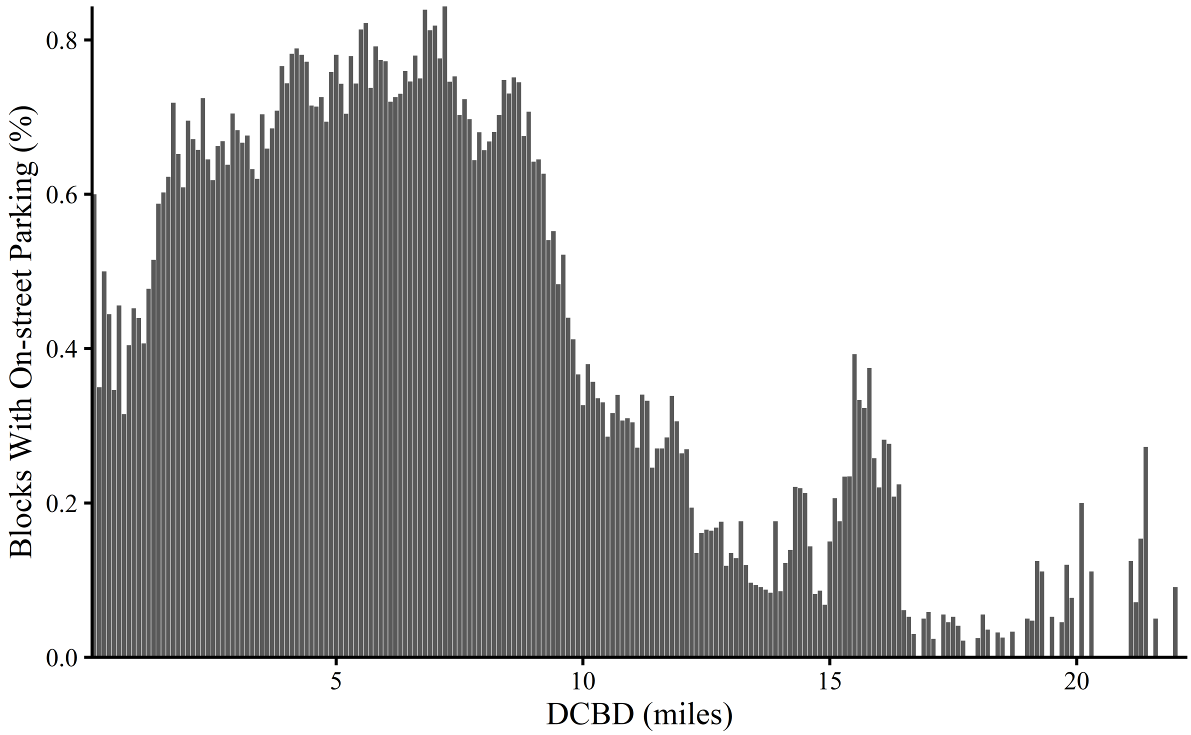


Figure 14: Hour of the Day Effect on Traffic Speed (Weekdays)

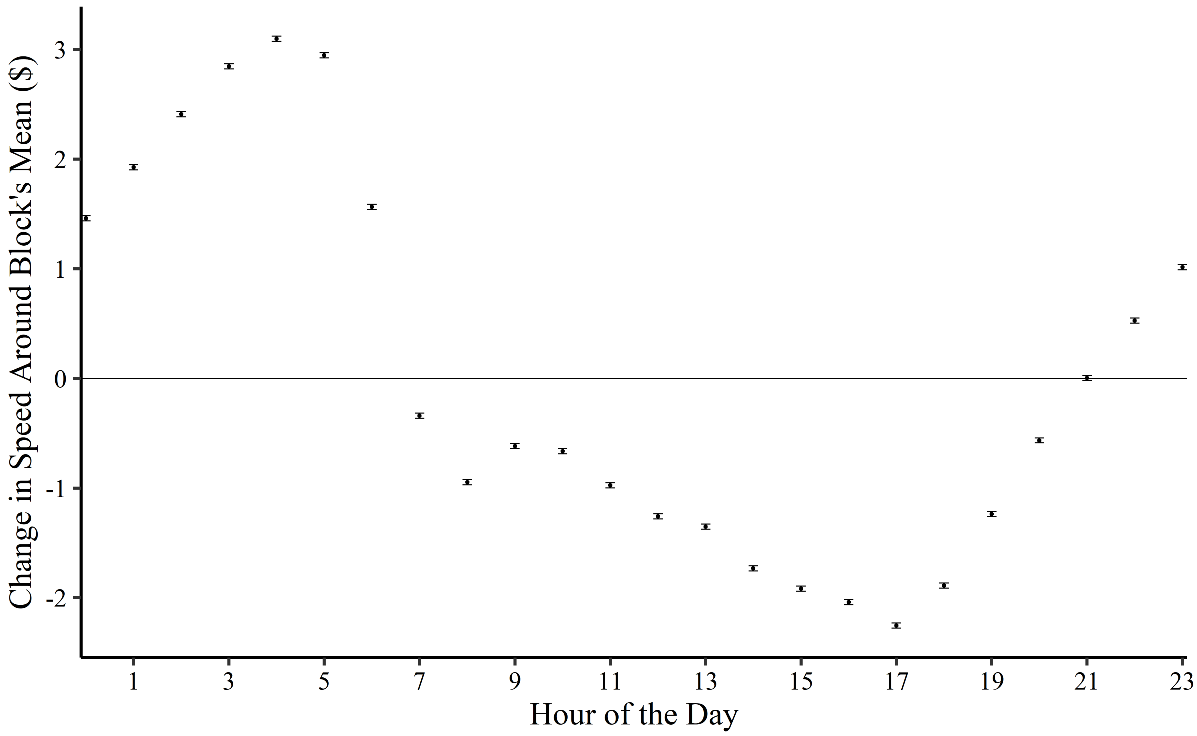


Figure 15: Hour of the Day Effect on Garage Prices During (Weekdays)

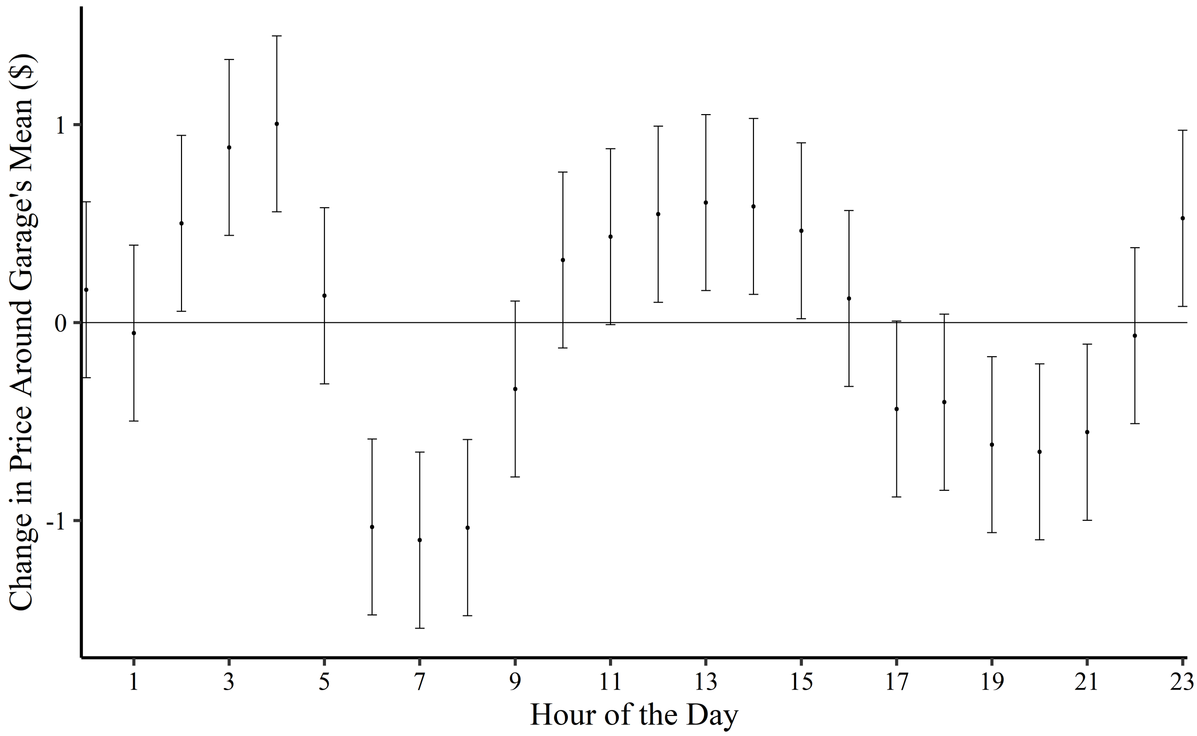


Figure 16: Traffic Speed and Share of On-street Parking Available

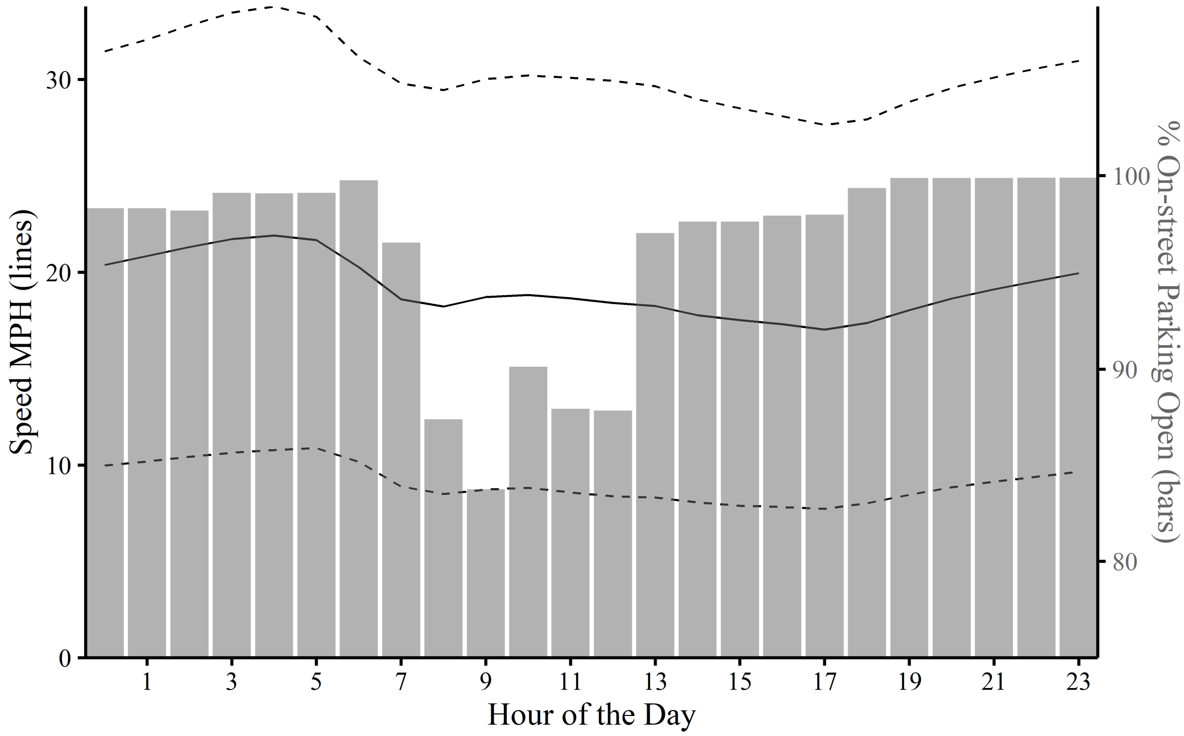


Figure 17: Traffic Speed and Share of Meters Enforced

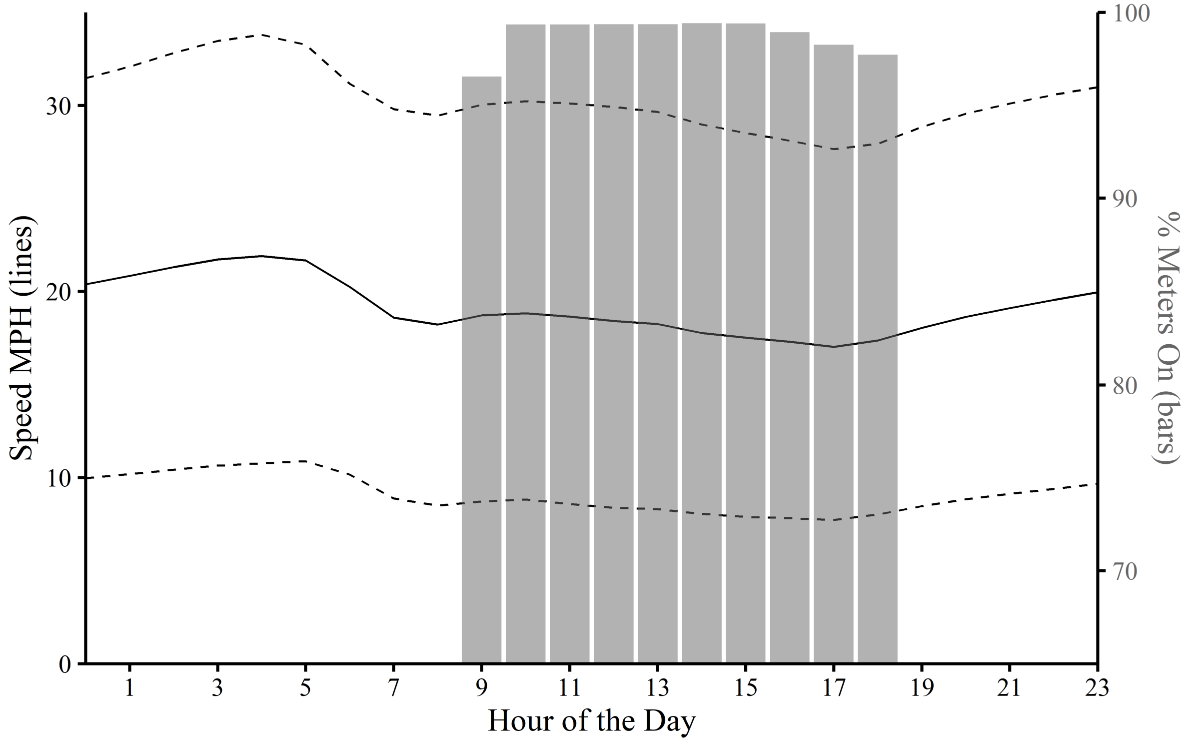


Figure 18: Traffic Speed, Blocks With and Without On-street Parking

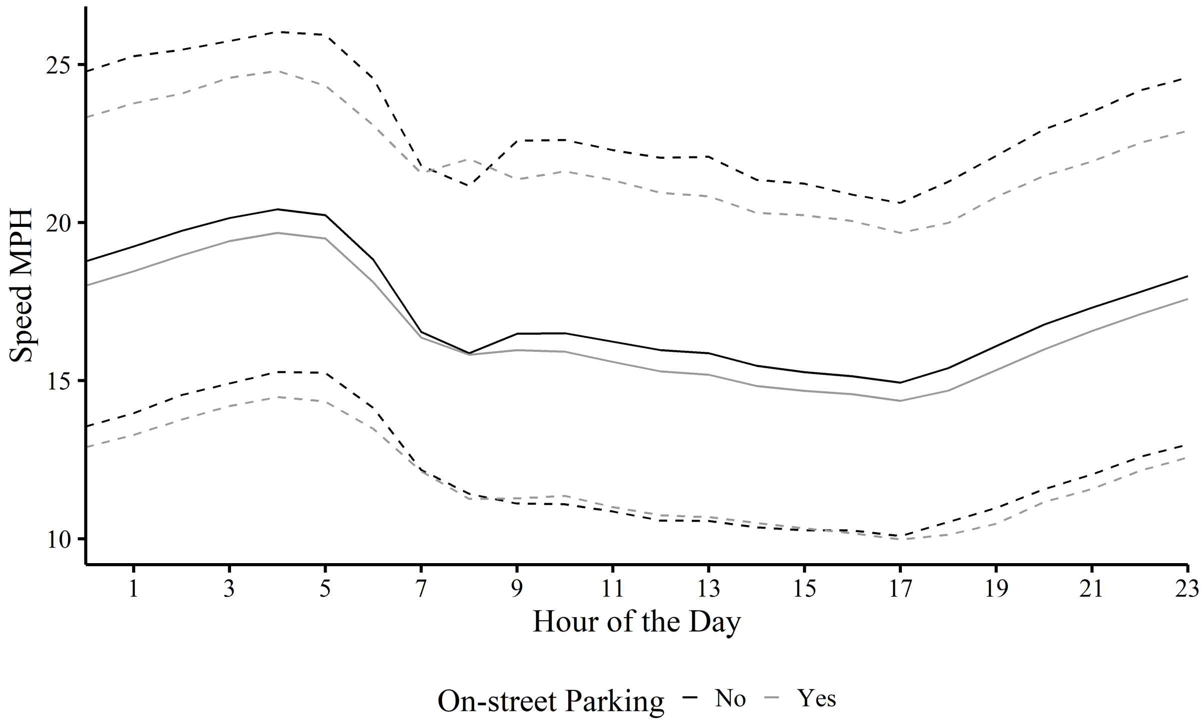


Figure 19: Percentage Of Drivers Willing to Park On-street

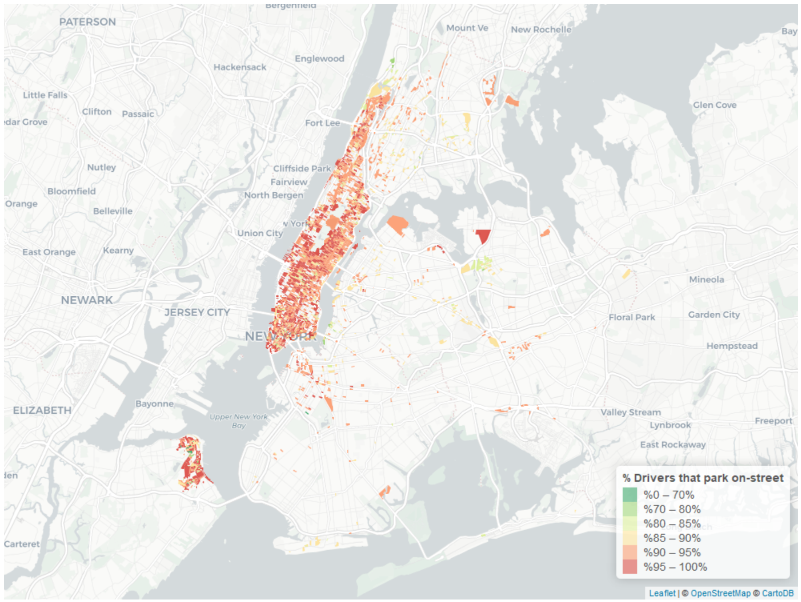


Figure 20: Income Deciles and Estimated CDF

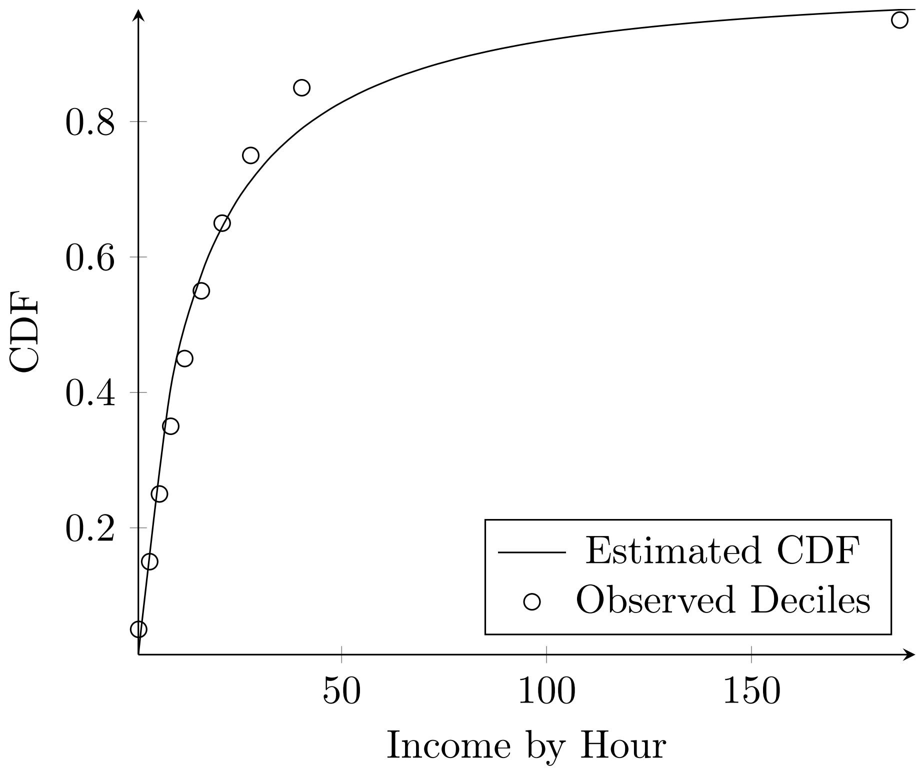


Figure 21: Cross-Validation Exercise $W$ Matrix ($k$ neighbors, and Mean Square Error)

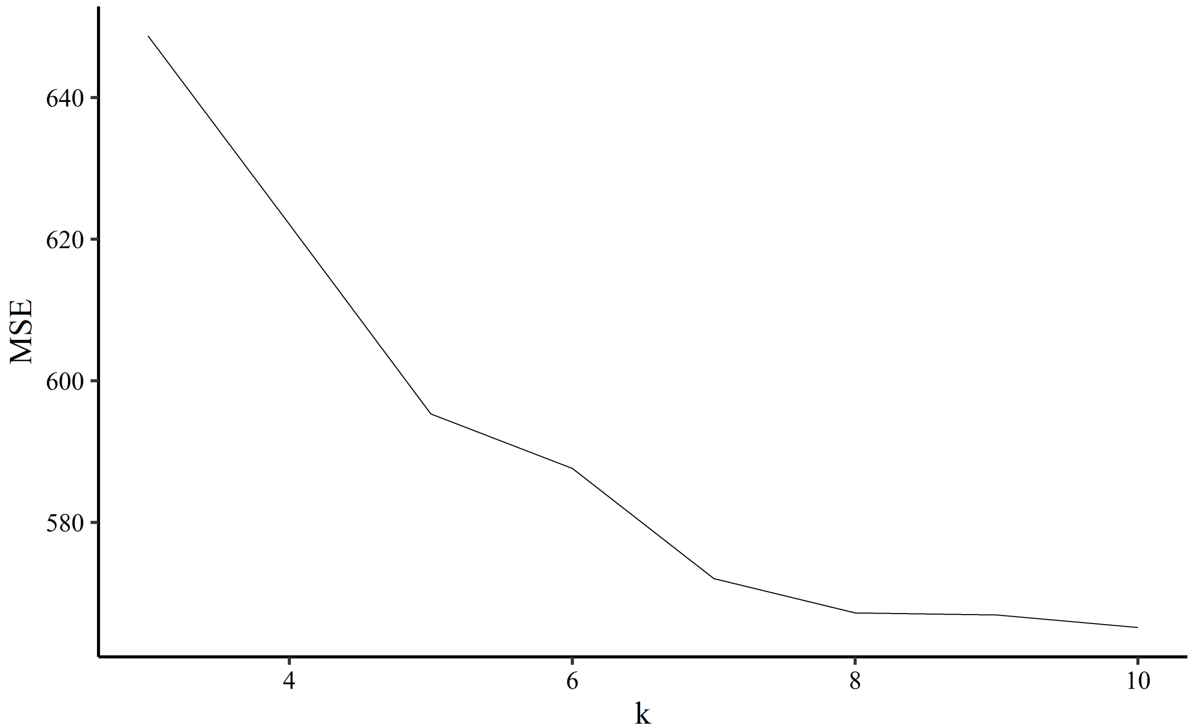


Figure 22: Traffic Speed Manhattan.