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Matthew H. SHAPIRO

Singapore Management University, mshapiro@smu.edu.sg

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DENSITY OF DEMAND AND THE CONSUMER BENEFIT FROM UBER

Matthew H. Shapiro*

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Abstract

Uber has attracted the attention of economists and policy makers for its innovations in the taxicab market and its potential for significant consumer welfare gains. The size of this gain depends in part on whether these innovations permit transactions previously costly or infeasible. Using New York City — the largest taxi market in the country — as its context, this paper estimates the level of any technological advantage Uber has over hail taxis in matching to consumers. I combine publicly available transportation data with data scraped from Uber and traffic cameras to estimate a model of the demand for transportation services and imbed it in a spatial equilibrium framework in which Uber and taxis compete for customers. I find that Uber’s matching advantage depends on the density of the market and translates into highly heterogeneous benefits to customers across the city. In consumer welfare terms, I estimate that the introduction of Uber added only \$0.10 per ride in the densest parts of New York but over \$1.00 in the least dense. These results, combined with the high volume of substitution from taxis to Uber in central Manhattan, imply Uber’s appeal in its densest market has depended significantly on advantages independent from its matching technology, including its lower regulatory burden.

1 Introduction

Since the company’s founding in 2009, Uber and the ride-sharing business at large have transformed the once stagnant taxi cab market. Recent research by [Cohen et al. \(2016\)](#) estimates that Uber delivered a consumer surplus of nearly \$6.8 billion dollars to the United States in 2015 alone. The magnitude and distribution of these consumer benefits, however, depend in large part on whether

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Uber can facilitate transactions that were otherwise cost prohibitive or impossible under existing services. In this paper I propose that Uber’s technological advantage in matching consumers over these existing taxis highly depends on a market’s density of potential demand. For New York City, I find that this advantage shrinks significantly with density. The technology difference translates to highly heterogeneous consumer surplus gains from Uber; I estimate that they vary by over a factor of ten from the least dense to most dense areas in the study.

One of Uber’s principal innovations in the transportation market is the way the platform matches consumers to drivers. Compared to a system in which people must physically hail a taxi, Uber’s technology has effectively allowed potential customers to hail cabs blocks or miles from their location. While telephone-based dispatch services offered an analogous service, Uber and similar companies refined the system by using geo-positioning to minimize the time a customer must wait for a driver. How advantageous this system is over hailing, however, depends on a market’s geography. In very dense markets, like central Manhattan, where vacant cabs drive through most streets frequently, physically waving down a taxi can result in a match quickly. By comparison the same customer may wait longer for the contracted Uber. The Uber driver must navigate to her location and try to identify the correct person to pick up on a busy street. This simple intuition drives the central hypothesis of the paper. Uber’s technology in matching consumers is advantageous in less dense markets but evaporates and can even be detrimental in highly dense areas.

This paper quantifies the technological matching advantage Uber has over taxis, the extent to which it depends on a market’s density of potential demand, and the implications for the consumer value of Uber in these different areas. The New York City taxi market has an ideal setting to study this relationship. Besides being the largest taxi market in the United States, the city features wide variation in density from central Manhattan to less dense Manhattan and the outer boroughs.¹ This geography offers key variation across which to contrast the demand for taxis and Uber.

To study the development of the market I use publicly available trip-level data on the pickups of taxis and for-hire vehicles like Uber. These rich records permit a study of the New York over both space and time. I augment this dataset with two unique sources on consumer wait times for Uber and taxis. In the first I scraped the Uber app on a simulated Android phone to collect wait time and surge price data for that service in 47 locations across the city at different times of day. For taxis I follow [Frechette, Lizzeri and Salz \(2016\)](#) in using the pickup data to estimate a measure of the time consumers wait for taxis. I calculate these wait times at a granular level with respect to location and time, and discipline these estimates by using scraped traffic feeds to record the frequency of taxi traffic at key intersections throughout the city. I treat these wait times as the interface the consumer has to each of these platforms’ technologies. Simple patterns in the trends of Uber and taxis over time in conjunction with these wait times delivers a hint at the major result of the paper. In the less dense parts of NYC, the taxi market has expanded with the growth of

¹Approximately 20% of US taxi cab drivers are based out of New York and the city hosted 10% of Uber’s 2 billion global rides in 2016.

Uber. The wait times for an Uber in these areas are much lower than for taxis. In Manhattan, however, Uber has cannibalized the share of taxis in the market without much overall expansion. In these same areas, the wait time for an Uber is often no better or even worse than for a taxi.

These stark findings motivate a model with a focus on controlling for geographic heterogeneity to isolate the effects of density. I break up this modeling problem into two parts. In the first, I develop a standard discrete choice demand model for transportation in granular submarkets of New York City. The demand model incorporates not only taxi and Uber but also alternative transportation choices, most importantly public transit options. Another important feature of the demand side is that I permit unobserved heterogeneity in the tastes for different choices across the city. This heterogeneity allows the model to capture consumer preferences for Uber over alternatives that I cannot directly model, such as better quality vehicles or the ability for consumers to screen drivers. All of these features are critical to ensure that I can separate out the demand for taxis as a function of geographic density from the quality of these outside options in the particular submarket. Because consumers do not care about technology differences across taxi and Uber per se but rather the prices and wait times they experience, both of which I measure directly, I estimate this portion of the model separately from supply.

The results from this demand model deliver immediate results on the change of consumer surplus from Uber across density. Following the methodology of the new product literature (see [Petrin \(2002\)](#)), I compare my time of study in 2016 to market data from 2013 as a baseline when Uber did not exist.² I estimate a \$0.10 per ride compensating variation to Uber riders giving up their Uber in the densest parts of the city but up to \$1.00 per ride to Uber riders in the least dense markets. As a percent of revenue per rides in the same area, values range from approximately 2% to 10%.

The second part of the model, the supply side, adds several features. The first is to estimate the relative efficiency of taxis versus Uber in areas of different density. This efficiency is a key set of parameters in the structural model. The second is to allow for equilibrium counterfactuals that test whether the consumer surplus brought by Uber is driven by technology or the strict regulatory regime capping the number of yellow taxis at levels below that which Uber operates. The supply model I employ is an extension of the spatial equilibrium model introduced by [Buchholz \(2017\)](#) building off the oblivious equilibrium framework of [Weintraub, Benkard and Van Roy \(2008\)](#). The model itself, however, differs in two critical ways. First, I allow alternative platforms — in this case Uber — to exist in the same market as taxis. Second, I leverage the model and my collected data on wait times to estimate taxi matching efficiency in each of the submarkets I study rather than imposing it as the same for the entire city or large subregions of the city. This alteration alone is essential to allow the efficiency of taxi matching to change with submarket density. A key result from the estimation of this model is that matching efficiency for taxi cabs is indeed highly

²Uber technically did operate in the city already. Section 2 makes the argument that Uber’s presence was small enough at that time to ignore its impact on the market.

correlated with market density.

The counterfactuals fed to the supply model focus on tracking welfare and service quality changes from alterations to the taxi regulatory regime. In one key counterfactual I replace every Uber with a yellow taxi to determine the net impact on service quality by simply allowing yellow cabs to sidestep quota regulations. I find yellow taxis decidedly cannot replace Uber to match the same service quality measured in wait times, particularly in the less dense areas of the city. The result highlights that Uber offers genuine technological change in the less dense markets, where previous transactions with taxis were infeasible. In the densest markets of the city, matching technology is insufficient to explain why consumers have switched from taxi to Uber. Measuring service quality as wait times alone yields a result that dense markets would be better off with taxis replacing Uber.

Another principal counterfactual assesses a real policy in consideration in the debate around NYC transportation services. In this counterfactual I introduce a congestion tax on Uber for pickups in parts of Manhattan. Although I assume the incidence falls entirely on Uber, consumers in Manhattan substitute back to taxis as Uber service quality diminishes for a given volume of demand. Ultimately, the cost is born by the outer areas of New York since the tax reduces how much Manhattan can subsidize Uber drivers' operations in the outer parts of the city, and they exit the market.³

To my knowledge this paper is the first to discuss the magnitude and geography-based distribution of the welfare benefits offered by Uber's matching technology. It is not, however, the first to evaluate the consumer welfare impact of having a better matching technology for taxi-like services in New York. The closely related work of [Frechette, Lizzeri and Salz \(2016\)](#) and [Buchholz \(2017\)](#) both develop models of the taxi market in NYC. [Frechette, Lizzeri and Salz \(2016\)](#) explores this question through an aggregate model of the market to measure the cost of search frictions. In counterfactual simulations of the market, they introduce an Uber-like matching system by having a dispatcher link potential consumers to the closest cab within a mile. This paper builds off their findings in several dimensions. This work has the benefit of data on both Uber and taxis. The data allow me to explicitly model heterogeneity in the demand for these two services along more than just the wait time. On the supply side the data are crucial for estimating the relative efficiency of these two platforms across densities. Ultimately, a key finding from this paper mirrors a major result from their counterfactuals. They show that a dispatching system is a larger improvement over the existing technology when demand is thinner across the course of the day. This paper makes the same claim but across locations in the city.

The model in [Buchholz \(2017\)](#), in contrast, allows rich spatial heterogeneity in the market for taxis. In a counterfactual the research simulates the introduction of a more efficient matching technology by assuming that cabs can perfectly reach customers in each of several locations across

³As recently as March 2018 NYC policy makers have considered congestion taxes of the form proposed at the end of this paper. See <https://www.nytimes.com/2018/03/31/nyregion/congestion-pricing-new-york.html>.

the city. This paper shows, however, that the value of these services depends on several qualities of these different submarkets. One crucial advantage that Uber has over taxis, for example, is to match with consumers far from their current location. The incremental value of this difference over regular taxis depends on the density of the location, per the results in this paper. The real Uber matching system can also be disadvantageous in some locations, an aspect missed by modeling Uber as a hail cab with better efficiency. The value of Uber’s matching technology also depends on the substitutability of taxis with alternative forms of transportation. How elastic customer response is to better matching depends on these outside options, which I explicitly control by estimating demand for a full model of a city’s transportation services.

Recent research has also leveraged Uber data to directly measure the value of the company and its impact on the taxi industry. [Cohen et al. \(2016\)](#) estimates an aggregate measure of the consumer surplus generated by Uber. They suggest Uber has generated a potential \$6.8 billion consumer surplus in the United States for 2015 alone. The result cannot account for significant intra-city and inter-city variance in this surplus. Additionally, total surplus changes depend on Uber’s impact on existing services over time. Depending on whether Uber expands the market for taxi services or simply displaces it, welfare gains estimated from short-term analysis may be mitigated by accounting for the quality of alternatives. Other research quantifies the benefits of Uber to the labor side of the market. [Hall and Krueger \(2015\)](#) and [Chen et al. \(2017\)](#) identify and quantify the labor-side welfare impact from Uber’s flexible supply model, in contrast to traditional cab systems that work on fixed shift times.

This research additionally complements a recent explosion of research around both Uber and the taxicab industry, a few of which directly contrast Uber with traditional taxis. [Cramer and Krueger \(2016\)](#) look at the dimension of utilization rate, how often a cab is occupied, as a measure of Uber’s relative efficiency. While not directly modeling these effects, they attribute utilization differences to the matching technology, Uber’s scale, regulations, and the flexible supply model. Notably, they find Uber’s utilization rate is significantly higher in all cities, save NYC. This paper models the first three of those forces though using expansion rather than utilization as a performative measure. [Berger, Chen and Frey \(2017\)](#) examine the interaction of Uber and incumbents through the lens of employment and earnings. Their results contrast with a story of Uber rapidly destroying incumbents in the market, a result echoed in the NYC taxi market particularly. [Bian \(2017\)](#) focuses on the existence of network effects in the matching processes for these platforms. To some extent I capture this effect by allowing matching efficiency to vary with the scale of transactions; consumers may indirectly respond to the size of the “network” through the waiting time.

Naturally, Uber’s signature surge pricing has itself been the subject of intense study. While I currently treat surge pricing as exogenously set by Uber in my estimation, other papers endogenize their problem. [Castillo, Knoepfle and Weyl \(2017\)](#) find surge pricing solves a problem inherent in dispatch models of taxi operation — in contrast to street hail models. Flexible prices can deter

demand from growing beyond supply capacity, thus preventing hypercongestion. [Bimpikis, Candon and Daniela \(2016\)](#) focus on the more familiar allocative role of surge pricing. They highlight the increasingly important role surge pricing plays in the profitability of *unbalanced* markets, in which some areas of the market feature much higher levels of demand than others at a given price. Both pieces of research suggest that the “non-matching” innovations Uber brought to the market, dynamic pricing and the flexible supply side, could be critical to its sustainability.⁴

For transportation policy makers this literature and the new results developed in this paper might inform the vigor with which they try to regulate Uber and similar ride-sharing services. If the difference from existing taxis — granted few cities feature incumbents of the style in NYC — is largely in regulation avoidance, incumbents have little to fear from regulating ride-sharing services on equal footing. As of the time of writing, New York City has already begun moving in this direction. The city has lowered the barriers between incumbents and Uber on the supply side by introducing a universal taxi license. In contrast London has taken more aggressive steps to ban Uber entirely.

The paper proceeds as follows. Section 2 offers a brief overview of the recent history of taxi services in NYC and a larger view of Uber’s expansion and regulatory fights across the country. In this section I also describe my methodology for collecting price and wait time data for taxis and Uber; I then use it to develop descriptive evidence of the impact of Uber on the existing taxi market. Sections 3 and 4 present the demand and supply models to take it to the data. Section 5 presents the results from this estimation along with counterfactual analysis. Finally, Section 6 concludes with thoughts on future research.

2 Evolution of Uber and Taxis in the New York City Market

While the last five years have brought volatility to the New York City transportation market, two key platforms have emerged (or remained): traditional street-hail taxis, which I will refer to as taxis, and Uber. This section will briefly describe the broader changes in the market over these past several years. The focus then moves to taxis and Uber, describing their operation and the regulatory regime they face. Here, I explain my method of constructing prices and wait times to explore quality differences between the two platforms.

The section provides evidence of two key facts. The market for cab services has expanded but the magnitude of that expansion is highly correlated with an area’s geographic density. Additionally, Uber has largely displaced traditional taxis in dense markets while contributing to an expanding market elsewhere. These two facts lay the groundwork for identifying the magnitude of Uber’s technological advantage over traditional taxis in the structural model.

⁴Enormous subsidies from cheap financial capital are likely critical as well. I am not familiar with any research isolating this dimension.

2.1 Brief Description of the Market

Prior to Uber’s launch into the NYC market in May 2011, taxicab services were split primarily between street-hail yellow taxis and pre-arranged dispatched cabs, known as for-hire vehicles (FHV). The Taxi and Limousine Commission (TLC) governed these two segments markedly differently. FHV are restricted from picking up street hails (legally) but operated under comparatively free circumstances. Hard caps did and do not exist for FHV nor are companies operating FHV subject to strict price controls. In practice NYC has long had many more FHV than hail cabs, but they were still far less ubiquitous on the road. While hail cabs completed hundreds of thousands of trips per day, FHV completed on average about 20 or 30 thousand.

In contrast hail taxis are highly regulated. Two regulations through the period of interest are of particular importance. The first is the infamous medallion system limiting the number of yellow taxis on the road. From 2011 to the present day, the number of available medallions has fluctuated from 13,237 to 13,587. Because these medallions are required for the operation of yellow cabs and, until recently, in high demand, they became famous for their prices peaking in 2014 at over \$1 million. For independent medallion owners, mandated to be around 40% of the market, the entrance costs are obvious; for cab drivers leasing cabs from corporate owners, the costs are passed down in the required weekly leasing payment, itself regulated by the TLC to prevent gouging drivers. The second important regulation are the strict price controls on ride fares.

The cap on the number of medallions and the stagnant FHV market left many parts of the city poorly serviced. Then Mayor Bloomberg perceived the problem as significant enough in early 2011, perhaps notably before the arrival of Uber, to warrant an initiative to improve taxi service in the outer boroughs.⁵ The solution, Boro (or “green”) cabs, first hit the roads in August 2013. Many were simply converted livery cabs previously falling under the umbrella of FHV regulation.

For the purpose of this paper, green cabs also face two important regulations. These cabs can operate exactly like street hail yellow taxis, including the price regime, except at John F. Kennedy and LaGuardia Airports and in Manhattan below East 96th and West 110th Streets.⁶ Figure 1 illustrates this exclusion zone over a map of the city. The second is that green cab vehicle licenses are capped, like yellow taxis, but they are available for a fixed fee. In the first year the TLC made 6,000 available for a price of \$1,500. Every year thereafter licenses were available at a price of \$3,000.⁷ These regulations introduce a type of taxi with identical technology but a lower cost to enter the market, and, importantly, the geographic restrictions introduced a new supply of taxis in

⁵This initiative actually came a year after the arrival of Uber. The State of the City address in January 2011 was the first acknowledgement of outer borough service as a priority: “Why shouldn’t someone in the Bronx, Brooklyn, Queens, or Staten Island be able to hail a legal cab on the street? 97 percent of yellow cab pick-ups happen in Manhattan or at the airports — even though 80 percent of New Yorkers live outside of Manhattan.”

⁶These cabs, unlike yellow taxis, can also continue to serve pre-dispatched rides from their base. My data only include the hail rides they complete.

⁷Although there is an overall cap of 18,000 green cabs, only about 8,000 have been purchased to the present day; hence, the supply cap has not been binding.

areas once scarcely visited by yellow taxis.

Uber, of course, significantly differs from both yellow and green taxis in terms of matching technology and regulation.⁸ Uber drivers are prohibited from picking up street hails, though the dispatching model of ride-sharing companies circumvents that process by using the a phone app to make the match. While Uber drivers in New York City do not face the same legal operating costs as taxi drivers, they are still more regulated than drivers from other cities.⁹ First, Uber is regulated just as any FHV is, and drivers must obtain a special license through the same process. Uber itself must also operate through base stations and satisfy the same administrative costs and burdens as other FHV companies. These similarities allay concerns that driver quality might be an unobserved, but important, difference between Uber and taxis.¹⁰ Table 1 summarizes the key differences across yellow and green taxis and Uber.

The regulatory systems for these three platforms coalesce to create uneven relative costs for the different taxi technologies across New York City. In the green taxi exclusion zone of Manhattan, the hail technology requires a hefty fee, in the form of the medallion, to pick up potential consumers. The Uber model, along with other ride-sharing services, completely avoid this cost. Past the exclusion zone, the different technologies are on a more level playing field.

2.2 Mapping the Growth of Uber Over Time

Uber’s ubiquity may be enough to convince one of the magnitude of Uber’s operation in NYC. Figure 2 illustrates its expansion in terms of total monthly pickups over time. These data come from the TLC, which publishes detailed trip-level data for green and yellow taxis and, since 2015, pickup location by taxi zone and time data for FHV, including Uber. The figure delineates two important cutoffs. The first is the introduction of green cabs in July 2013; it sees a steady rise in its pickups for about six months before largely flatlining, despite the availability of more permits after August 2014. The second is January 2015 when FHV data, including for Uber, is first consistently available. Lyft, which I can also separate from the rest of the FHV data, is part of the “Other FHV” category and a relatively small operation compared to Uber in this time period. The big takeaway, however, is Uber’s performance compared to the yellow taxis over this time period. From when I first have data on Uber pickups in April 2014 — these early data are not available consistently through to 2015 — to July 2016, yellow taxis shrank from twenty-six times the operation of Uber to two times the size.

⁸App-based matching services for taxis first arrived for taxis in September 2015. CMT and Verifone, the two credit card operators covering approximately 8,000 covering approximately 14,000 yellow and green taxis, respectively, licensed different companies for their apps. Unfortunately, it is unclear what the uptake on these services has been. They were unsuccessful enough to require relaunching the programs in April 2016 toward the end of the period of interest.

⁹See Kleiner (2017).

¹⁰Hall et al. (2017) explicitly tests for quality differences in Uber drivers potentially arising by NYC regulations and find little evidence of a difference.

The story is incomplete, however, without looking at Uber’s expansion across the city and the relationship of its growth with market density. Ideally, I would measure density as the number of potential consumers per unit of area and time. Ignoring the dimension of time, this ideal measure is particularly farfetched to obtain in New York because of the notorious difficulty in measuring the movement of population over the course of the day. These challenges motivate restrictions I introduce later in the paper to limit the demand analysis to morning commuters. For now I use a different proxy for the potential density of demand, capturing relative geographic density across the city. In particular I use zoning data from New York’s Property Land Use Tax Lot Output (PLUTO) to calculate the ratio of building space to the surface area of each taxi zone. Figure 7 depicts this measure overlaying the city.¹¹ As a cursory check for the usefulness of this measure, I note that it is positively correlated with the total taxi pickups normalized by the size of each taxi zone in Figure 8. In the model sections of this paper I will distinguish between this geographic density and transaction density, the latter referring to the volume of matches in a given area and time and can be considered analogous to market scale.

As seen in Figure 7 the exclusion zone marker, denoted by the thick black line, provides a natural break for a cursory analysis to compare the development of the taxi market in areas of different geographic density. The green exclusion zone, i.e. most of Manhattan, is, geographically, the densest part of the city while density drops off quickly in the other boroughs. Figures 3a and 3b map monthly pickup data by taxi or FHV type for pickups originating inside and outside the green cab exclusion zone, respectively. Outside of the exclusion zone, Uber is the largest platform in the market by July 2016 and the growth has, largely, not been at the expense of yellow and green taxis. Inside the exclusion zone, Uber remains the smaller competitor but has gained at the expense of the yellow taxis. Year-on-year monthly pickup growth inside the exclusion zone from 2015 to 2016 is, on average, slightly higher than 5% and outside the zone upward of 40%. Even in absolute terms growth is higher outside the exclusion zone by a factor of 2. By the end of the second quarter of 2016, Uber served approximately the same number of rides in and out of the exclusion zone but commanded a larger market share in most taxi zones outside (see Figure 9).

In Appendix D.1 I conduct a more granular analysis of the relationship between patterns in the market and density with observations at the level of taxi zone. The two key facts from the wider analysis hold even at finer levels. First, the market for taxi-like services has expanded relatively more in less dense zones of the city. Second, Uber and taxis are nearly perfect substitutes, in terms of 1:1 replacement of rides from yellow taxis to Uber, over time in the most dense zones.

These trends paint a stark picture that motivates the theory in this paper. In the city’s geographically densest markets, those in the exclusion zone, overall growth is minimal and hence Uber’s gains come at the expense of yellow taxis. Enough consumers prefer Uber to taxi to switch, but the offering is not sufficiently valuable relative to alternatives to draw from other sources of

¹¹I also carried out the analysis from this section using the ratio of building space to the length of road bordering and running through the area. The change results in no qualitative differences.

transportation. Outside this area yellow and, importantly, green service plateaus early despite the latter operating below its supply cap. The ascendancy of Uber and ride-sharing services in these sparse areas do not cannibalize existing business but is part of pure expansion. A natural hypothesis to draw is that potential green cab drivers found it insufficiently profitable to service areas that Uber can or was insufficiently attractive to generate the demand.¹²

2.3 Constructing Wait and Price Data for Uber and Taxis

The two key pieces of ride quality data by which consumers in this paper compare Uber and taxis are their prices and wait times. Unfortunately, only price data for taxis are readily available. Trip-level data from the TLC break down various components of each ride, like trip distance and time and, most relevantly, total trip fare. Additionally, because the taxi fare structure is fixed, I can approximate the cost of counterfactual rides with decent accuracy. The following sections detail how I collect the remaining price and wait data.

2.3.1 Uber Wait Times and Price

The trip records provided by the TLC for FHV, which include Uber, do not provide the same information on prices. While Uber has a fixed fare structure for each of its products, its well-known *surge pricing* mechanism multiplies these prices in locations with especially heavy demand, relative to the available supply. Since these fees are quite substantial relative to baseline prices, controlling for them as best as possible is necessary for demand estimation.

To collect price information for Uber, I emulated an Android phone and automated the process of feeding the Uber app locations throughout New York City over the period of March to June 2016. I could then scrape the relevant data from the app itself. Every hour and a half, I scraped the expected wait time — then labeled “ETA” in the app — and surge price, which at the time showed up as a “[#]x” warning before agreeing to the contract. Appendix C.1 has more details on this process. To interpolate wait times at locations and times of day not sampled I used a simple inverse distance weighting method over time and space sampling only points not separated by bodies of water.¹³ I use the same method of interpolation for surge prices with a more significant drop off to account for the sharper change in surge prices by area and over time.¹⁴

Besides interpolation another potential source of measurement error is the accuracy of the data reported to the consumer, i.e. the information I collect via scraping. Cohen et al. (2016) reveal that actual surge prices charged are slightly different than the prices shown to consumers. They

¹²One caveat about reading expansion from the available data is that new entrants may have cannibalized business from community vans, like “dollar vans.” These services are more comparable to public transit than taxis.

¹³Future versions of this paper will employ a more sophisticated distance metric using actual travel distance for the spatial dimension.

¹⁴Uber uses zones, unknown to me, to set surge prices so it less reasonable to assume a smooth transition of prices over locations. On the temporal dimension surge prices are highly volatile (see Diakopoulos (2015)).

report, however, these differences are marginal. Further, since consumers have no way to learn “true” price, this issue should not affect their transportation decision. On the other hand if wait times are consistently over or under-estimated, this error will be unaccounted for when I use these data in the demand estimation.

2.3.2 Taxi Wait Times

The final piece of critical information is the wait time for taxis. [Frechette, Lizzeri and Salz \(2016\)](#) is the first paper of which I am aware that attempts to convert the raw TLC data into information on how long consumers must wait for taxis. Two issues prevent me from adopting their methodology wholesale. First, this paper’s research question revolves around spatial heterogeneity in the competition of taxis and Uber; hence, I need a metric for wait times at a fairly granular level. Second, the data available from the TLC has changed in the intervening years. Fitting their simulated model requires knowledge of the search time for each cab. For the data available in that time period, it was possible to track cabs over the course of the day. Since 2013 the TLC removed these identifiers because of privacy concerns. Without the ability to track a cab, the data do not indicate how much time each taxi spent searching for a new passenger.

In my adjusted procedure I generate a probabilistic count of taxis on each of New York’s street segments throughout the day.¹⁵ I use this count to estimate how long it takes for a vacant cab to pass through each segment without a pickup. Ideally, I would know precisely when customers arrive on a street segment to determine the time for a cab to pass them. This procedure does not assume a structure on customer arrival and measures wait time as how long a marginal consumer on each segment would have to wait for a cab to arrive. Hence, in reality some consumers in the data might be more or less “lucky” in catching a cab than what I measure. Since I cannot follow individual cabs, instead I keep track of how far the taxi could have traveled in an allotted time. Within this travel area is every possible route the cab could have taken based on a street map of NYC. For tracking purposes subsequent pickups are randomly assigned to any cab that could have made it to the location in time. This assignment generates a guess of the path of cabs between drop off and pickup. The full details of this algorithm and the additions that follow are described in [Appendix C.2](#).

To improve the guess of which paths vacant taxis took, I scraped traffic camera data available publicly via the New York City Department of Transportation.¹⁶ [Figure 10](#) marks each camera location by a blue dot. I captured a roughly continuous feed — each camera updates a still image approximately every 4 or 5 seconds — for every camera 6 times a day with an additional measurement on Fridays and Saturdays for the months of September and December 2015 as well as June 2016.¹⁷ On average I captured 600 images from each half hour block per camera. To follow a

¹⁵The area I track is limited to the areas covered in the estimation portion of the paper (see [Figure 12](#)).

¹⁶Source: <http://nyctmc.org>

¹⁷The specific times I started the camera captures were 3 AM, 9 AM, 12 AM, 2 PM, 5 PM, and 10 PM. I also

single camera for the entire two month period requires processing approximately 200,000 images. I spent the equivalent of 2 months working time selectively processing the images of roughly 150 cameras across the city.¹⁸ Figure 11 shows a screen capture of the program I put together to process the images from the cameras. The key questions are those asking about “new and empty” taxis, that is, those marked vacant by a light atop the taxi in the image.

2.4 Contrasting Taxi and Uber

With taxi and Uber prices and wait times calculated, I close the section by contrasting these two services in select parts of the city. Figure 4 highlights a few popular origins and destinations to contrast the price and wait time for taxis and Uber over the course of the day using 2016 prices. The taxi price in the image is the median for all observed trips in March 2016. Uber prices are calculated using the fare structure at the time, the average weekday surge price for the time of day, and the median trip distance and time. Reported wait times are the average weekday wait for the time of day; note that they do not depend on the destination.

A few facts are obvious. Uber is typically cheaper, but it depends on the surge price at the time. They do not, however, always bear the advantage in wait time. In Williamsburg, a less geographically dense location outside of Manhattan, the wait time for an Uber is on average lower across the day, even though both green and yellow taxis can pick up there. In Manhattan, particularly the locations I have chosen, Uber’s advantage depends on the time of day. The wait for taxis is higher during the shift changes around 5AM/PM but otherwise lower on average. While these wait times are functions of the market outcome and not the matching process alone, they may hint at the conditions driving the patterns from Figures 3a and 3b. From the wait perspective alone, Uber is hardly better and often worse than taxis in the most dense markets of the city. These are also the areas of the city where the competition between Uber and taxi has exhibited business stealing. Other factors may drive taxi customers to Uber, but they are not sufficient to grow the market. Meanwhile, in the outer boroughs, or at least in the Williamsburg neighborhood of Brooklyn, Uber offers substantial improvement in this quality dimension. The outer boroughs are also where there has been a significant expansion of the market.

I conclude by noting a significant competitive advantage Uber, and other non regulated companies, have against taxi companies: the ability to change fare structures. Uber has had two major rate cuts in the past several years. The first in July 2014 made the prices of the cheap UberX option roughly comparable to traditional taxis. The second in February 2016 solidified Uber’s price advantage. Figure 5 compares the actual price of all yellow taxi trips in March 2015 at the captured 8 PM on Friday and Saturday.

¹⁸For the curious, or sympathetic, reader I first attempted to process the images using machine learning-based computer vision programs. Unfortunately, that these cameras produce static images rather than a video feed confounded my best attempts at that solution. Additionally, it proved difficult to consistently determine whether a cab’s vacancy light is on in areas of vastly different lighting. In future work the program I plan to outsource the processing of the cameras I missed and check the work I did to further refine my wait time measurements.

indicated locations against a fitted Uber trip cost.¹⁹ At this point slightly more than half of Uber trips would have been cheaper than taxis. The difference between a more or less expensive ride largely depends on the time and distance of each trip since Uber charges by the minute and mile differently than taxis. Figure 6 illustrates the same distribution but in March 2016. After the price drop in February 2016 few Uber rides would have been more expensive than the same taxi trip. The “surge price tail” drives most of the cases where taxis are cheaper.

While I will not be modeling Uber’s decision to change its fare structure, the difference in and out of the exclusion zone to this February 2016 highlight each market’s capacity to grow. In Manhattan the effect of the price change is a bump in rides that follows an increase in rides for all taxis in February 2016. Meanwhile the period was followed by stagnant growth relative to the previous year, which did not feature a price change. One might worry that the price drop has a hollow effect because of the negative impact it has on supply. The expansion pattern outside of the exclusion zone, however, nullifies this argument. February 2016 marked an inflection point in the growth rate of Uber in these areas of the city. This differential response emphasizes the need to model the demand for these services with attention to heterogeneity across the city.

3 Structural Model

In this section I develop a structural spatial model of the NYC transportation market. The model features two sets of decision makers. On the demand side consumers arrive in separate zones across the city at specific times and make a discrete decision in their choice of transportation to a pre-determined destination. These choices are not limited to taxis and Uber, but also include the city’s public transportation network. On the supply side I do not model the decision-making process of the principal governing taxi and Uber drivers — the medallion owners or the division of Uber governing decisions for NYC — rather I focus on the search decisions of the drivers themselves. This portion of the model is an extension of Buchholz (2017), allowing multiple, here two, taxi platforms to interact with each other as their respective drivers search for customers throughout the city. The immediate purpose of explicitly modeling the supply side of the market is to generate the distribution of cabs over the course of the day, figures which are not observable from the available data, and estimate the efficiency with which taxis match to consumers in areas of different geographic and transaction density.

3.1 Demand

Define a sub-market of New York as a zone l and time period t . The entire market for New York City is the collection of zones L and time periods throughout the day T . In a given sub-market I define the maximum potential demand \tilde{Q}_l^t , that is the total number of consumers who are looking

¹⁹The figure uses the surge price profile from 2016, but in practice affects a small percentage of rides.

for a ride in l at t . At time t a fraction of those consumers in l , $\gamma^t(l, l')$, seek to travel to location l' . Note also that $\sum_{l'} \gamma^t(l, l') = 1$.

A consumer i in zone l traveling to l' faces a choice set C of transportation options to complete the journey. These options may include public transit, taxis, Uber, walking, or an outside option, depending on availability. Both green and yellow taxis are considered part of the same choice.²⁰ Although standard for the literature, I justify the assumption that consumers typically only use one transportation option per trip in Appendix D.2. Besides the characteristics of the options, the choice might also depend on consumer i 's income bracket g . The utility this particular consumer derives from choosing option $j \in C$ has the following form:

$$\begin{aligned} u_{ij}^t &= \alpha_{g(i)} p_j^t(l_i, l'_i) + \beta_w w_j^t(l_i, l'_i) + X_j^t(l_i, l'_i) \beta + \xi_j^t(l_i) + \varepsilon_{ij}^t \\ &\equiv V_{ij}^t + \varepsilon_{ij}^t \end{aligned} \quad (1)$$

Going forward I will suppress these time superscripts. p_j is the cost in dollars of taking the transit choice from l_i to l'_i . $\alpha_g(i)$, the marginal utility of money and hence value of time, depends on the commuter's income bracket, g . w_j is the associated waiting time, that is time not in transit, the commuter must expend with this transit choice. X_j is a vector of other trip characteristics, including the travel time and associated walking distance. The way consumers in this model can respond to congestion both explicit in counterfactuals and in reality is through the travel time term, as congestion will impact the travel time for Uber and taxis. ξ_j is transit choice-location-time unobserved demand. This term may reflect latent time-area preferences for the transit choice or unobserved qualities of the transit choice common regardless of location. For example, if consumers have a taste for a greater relative taste for Uber in the morning to avoid waiting in the cold, this preference would be picked up by ξ_j . Finally, ε_{ij} is an additional idiosyncratic taste shock. Consumer i then chooses option j if and only if

$$u_{ij} \geq u_{ik}, \forall k \in C$$

In total this utility model features parameters of interest $\theta_d = (\alpha', \beta_w, \beta')$.

Following the standard process from the discrete choice literature, this decision can be summarized as a choice probability. Let A_{ij} be the set of $\varepsilon_i = (\varepsilon_{0i}, \dots, \varepsilon_{Ji})$ rationalizing choice j , that is $A_{ij} = \{\varepsilon_i | u_{ij} \geq u_{ik}, \forall k \in C\}$. The probability commuter i chooses transit option j is then $q_i(j; \theta_d)$, where

$$q_i(j; \theta_d) = \int_{A_{ij}} dP(\varepsilon_i) \quad (2)$$

Apart from the destination, the only distinguishing feature of each consumer is her income. Let

²⁰This simplification requires the consumer who wants a taxi would take either a yellow or green taxi, whichever responded to the hail first. It is possible consumers with a penchant for one color wait longer for the ride of their desired choice, but that seems out of character for New Yorkers.

$f_l(d_i)$ be the distribution of income classifications in location l . I assume this distribution is fixed for the location regardless of time of day *and the destination*. Then the share and total quantity of consumers traveling from l to location k who choose j is, respectively,

$$q_{lk}(j; \theta_d) = \int_{\{i|l'_i=k\}} q_i(j; \theta_d) f_l(d_i) d(i) \quad (3)$$

$$Q_{lk}(j; \theta_d) = \tilde{Q}_l \gamma(l, k) q_{lk}(j; \theta_d) \quad (4)$$

For the entire sub-market l (at time t), the share of consumers who choose j is then

$$q_l(j; \theta_d) = \sum_k \gamma(l, k) q_{lk}(j; \theta_d) \quad (5)$$

$$Q_l(j; \theta_d) = \tilde{Q}_l q_l(j; \theta_d) \quad (6)$$

Assumptions in the estimation section will permit an explicit formulation for Equation 2 and its dependents.

Demand in the Supply Model

In the supply model, taxi and Uber drivers take most features of each location in the city as exogenous. For example, subway and bus schedules and their impact on a consumer's choice decision is an exogenous feature of each time and location. To drivers the relevant demand information is $Q_{lk}^t(j; \theta_d)$ for $j \in \{Uber, Taxi\}$, where l and k are the origin and destination, respectively. To emphasize that price and wait time are relative qualities of Uber and taxi that can change over the course time²¹, one can rewrite this function as $q_j(p, w|l, k, t)$, where p and w are vectors of the price and wait time for the two taxi platforms, for each $j \in \{Uber, Taxi\}$. $q_j(p, w|l, t)$ is the same function integrated over destinations.

The supply model proceeds by describing the searching and matching procedure for taxis and Uber. The setup largely follows Buchholz (2017) with a few critical differences. First, I explicitly contrast the matching technology of an Uber and taxi. Additionally their matching efficiency depends on the area of the city they serve. Finally, the model predicts consumer wait times in the submarkets across the city thus allowing consumer demand to respond to changes in service quality in counterfactuals.

3.2 Supply

There is a fixed supply of yellow taxis, green taxis, and Uber cars operating throughout the city. These totals are denoted V_x , V_g , and V_u , respectively. Taxi and Uber drivers operate among the locations L of New York. I assume drivers, regardless of platform, attempt to maximize individual

²¹Whereas Uber and taxis have no impact on the quality of other transit options in the area, for example.

profits by picking up passengers over the course of a shift. Both Uber's system of loosely ride-based commission and taxi's system of weekly lease payments from drivers to owners are consistent with this goal. Throughout the day, composed of distinct five-minute time periods $t = \{1, \dots, T\}$, vacant cabs search for consumers and occupied cabs travel to the destination location designated by their passenger. Any two locations $l, k \in L$ in the city are linked by a distance δ_{lk} and a time to travel τ_{lk} , the latter of which can change with the volume of traffic in the adjoining areas. τ_{ll} will denote an additional time to travel within a location for Uber only.

Arrival of Passengers

Having discussed demand in the previous section, I begin by fitting it into the supply model. To accommodate that the total number of consumers looking for rides in a particular submarket is likely not deterministic, I let \tilde{Q}_l^t be the parameter of a Poisson distribution. In combination with the shares derived from the demand model, *on average* the demand function for taxis and Uber will be

$$Q_j(p, w|l, t) = \tilde{Q}_l^t \gamma^t(l, k) q_j(p, w|l, k, t) \quad (7)$$

for $j \in \{Taxi, Uber\}$ where $\gamma^t(l, k)$ is the location transition matrix introduced in the demand section. Holding fixed (p, w) , the Poisson setup allows random variation in the scale of demand but not the relative demand between Uber and taxis. I assume that drivers for all platforms are aware of the distributions of \tilde{Q}_l^t across the city over time and the demand parameters θ_d , i.e. they have enough information to form expectations over $Q_j(p, w|l, t)$. For now I again rewrite these functions for simplicity; denote $Q_{l,u}^t$ the demand for Ubers and $Q_{l,b}^t$ the demand for taxis in location l at time t .²²

Searching

I start with the discussion of the matching process for taxis, both green and yellow. The critical difference in their operation compared to Uber is the process by which they match to consumers.

Consider a period t and location $l \in L$. Each location l is also associated with a dummy x_l , which takes a value of 1 when green taxis are not allowed to pick up in that area. The number of vacant taxis in location l at the beginning of the period is given by $v_{l,b}^t = (1 - x_l)v_{l,g}^t + v_{l,x}^t$, where $v_{l,g}^t$ and $v_{l,x}^t$ are the number of vacant green and yellow taxis, respectively.

Taxis can only match with potential passengers within the same location. This process is

$$m_b^t(v_{l,b}^t, Q_{l,b}^t) = v_{l,b}^t \left(1 - \left(1 - \frac{\alpha_l^t}{v_{l,b}^t} \right)^{Q_{l,b}^t} \right) \quad (8)$$

²²Recall I assume consumers are indifferent between hailing a yellow or green taxi.

Note that every location has a different efficiency parameter

$$\alpha_l^t = f_l(m_b^t) \quad (9)$$

which can be further specified as a function of the area and the scale, or transaction density, of the market. Section 4 will introduce assumptions on the form to make it tractable in estimation. Critically this function imposes no forced relationship between geographic density and efficiency.

Suppressing time the expected probability of finding a passenger from the perspective of a cab in a period is

$$p_{l,b} = \frac{E_{Q_{l,b}}[m_b(v_{l,b}, Q_{l,b})|\tilde{Q}_l]}{v_{l,b}}$$

Passengers in l seeking to travel to k , however, are not indifferent between traditional taxis and Uber. Therefore, I also specify the joint probability of finding a match and that match traveling to location k . Let $q_b(l, k) \equiv q_b(p, w|l, k, t)$, suppressing the t , that is the share of consumers who prefer taxis conditional on traveling from l to k .

$$p_{lk,b} = \frac{q_b(l, k)}{\sum_k q_b(l, k)} p_{l,b} \quad (10)$$

Hence $p_{lk,b}$ is the probability that a cab is matched to a passenger and that passenger requests to be taken to location k . Clearly $\sum_k p_{lk,b} = p_{l,b}$, the probability of matching at all.

From the perspective of a consumer, we can derive a similar expected probability of being matched to a taxi.

$$p_{l,c} = E_{Q_{l,b}} \left[\frac{m_b(v_{l,b}, Q_{l,b})}{Q_{l,b}} | \tilde{Q}_l \right] \quad (11)$$

Note that the expectation is still over the total consumers who have arrived, and it is assumed the number of vehicles which will pass through the location at the time is known. This probability yields an expected wait time for the consumer to match a taxi. If $p_{l,c}$ were constant over time it would be given by the mean of the geometric distribution, i.e.

$$w_{l,b} = 1/p_{l,c}$$

measured in terms of the number of periods. Because $p_{l,c}$ adjusts with time, however, I can approximate the wait time using a survival function. Let $S_l^t(x)$ be the probability of matching in the x th period after initial arrival in period t :

$$S_l^t(x) = p_{l,c}^{x+t} * \prod_{k=1}^{x-1} (1 - p_{l,c}^{k+t}) \quad (12)$$

assuming that $x + t \leq T$ else it is 0. The expected wait time (in terms of number of periods) is

then approximated by

$$w_{l,b}^t = \sum_{k=1}^{\bar{T}} k * S_l^t(k) \quad (13)$$

where necessarily $t + \bar{T} \leq T$. Note consumers waiting for taxis are assumed to disappear if they are not matched in their own period (and potentially born anew in the next period), but it is still possible to calculate the time it would have taken to catch a cab.

The first key difference between an Uber and taxi is an Uber driver need not be in the same location as a potential passenger to match to her. Indeed, their dispatching technology is the central focus of their potential advantage over taxis. I *assume that Uber permits guaranteed matching* at the expense of variation in the time needed for Uber to get to its passenger. With taxis there is uncertainty whether a match will be made but once the taxi is contracted the customer is in the cab. Although Uber assigns customers to the nearest vacant driver, at least at the time the paper covers, the model will not specify the location of Uber vehicles with enough precision to replicate reality. Therefore, I impose a rule to approximate this process.

At a given time $v_u = \{v_{l,u}\}_l$ describes the distribution of vacant Uber cabs across any of the locations in the city. Likewise, $Q_u = \{Q_{l,u}\}_u$ is demand across the city.²³ The share of consumers in l matched to an Uber in location k is given by the logit form

$$p_{l,c}^k = \frac{\exp(v_k/(1 + \tau_{lk})\mathbb{1}(\tau_{lk} \leq \bar{\tau}))}{1 + \sum_{k'} \exp(v_{k'}/(1 + \tau_{lk'})\mathbb{1}(\tau_{lk'} \leq \bar{\tau}))} \quad (14)$$

where locations with a larger mass of vacant cabs and closer are likeliest to be the source of the match. $\bar{\tau}$ is the farthest distance an Uber would be dispatched for a pickup. Hence the probability an Uber in location k is assigned to a passenger in location l is determined by

$$p_{l,u}^k = (Q_{l,u}/v_{k,u})p_{l,c}^k \quad (15)$$

Again, let $q_u(l, k) \equiv q_u(p, w|l, k, t)$, the share of consumers who prefer Uber conditional on traveling from l to k . Then

$$p_{lk,u}^{k'} = \frac{q_u(l, k)}{\sum_k q_u(l, k)} p_{l,u}^{k'} \quad (16)$$

is the probability an Uber in location k' is matched to consumer in l requesting to be taken to location k . Note I do not allow Uber drivers to reject rides.²⁴

²³Since mid 2016 Uber has begun assigning passengers to non-vacant cabs. Presumably, it would be a straightforward extension to consider here, where all Uber cabs, occupied or otherwise would be considered for the match, with the wait time also accounting for the time to drop off the last customer. That is a needless complication for the period of consideration, though.

²⁴Ge et al. (2016) show that drivers do indeed discriminate against passengers. This would be relevant to consumers in my model if consumers in certain areas have to wait longer in ways not captured by the estimate given by the Uber app. The data I collected on wait times prior to finalizing the transaction, however, do not allow me to determine if approximated (pre-finalization) and actual wait times differentially diverge depending on one's location.

It straightforward to check that every passenger will indeed be matched, that is

$$Q_{l,u} = \sum_l p_{l,u}^k v_{k,u}$$

The result of this assignment process is how long a passenger must wait for the contracted Uber and how long the Uber must drive (at its expense) to pick up that passenger. I assume when a consumer opens the Uber app to observe the wait time, the observer is marginal and sees the average result of the process above, that is

$$w_{l,u} = \sum_k \tau_{lk} p_{l,u}^k \quad (17)$$

Congestion

A final implication of the search behavior of taxis and Uber drivers is their impact on congestion throughout the city. I model this impact by allowing transit speeds across zones to differ with the level of taxis and Ubers searching in each of the zones. Consider two proximal taxi zones l and k ,

$$\tau_{lk}^t = g_{lk} \left(\sum_j (v_{l,j}^t + e_{l,j}^t), \sum_j (v_{k,j}^t + e_{k,j}^t) \right) \quad (18)$$

where e designates the count of employed cabs and g a function that can depend on the zone pair. τ_{lk}^t for locations that are not proximal remain the shortest route between l and k , considering the changes from traffic. In Section 4 I introduce assumptions on the function to estimate it independent of the rest of the model. In counterfactual simulations consumers will then respond to congestion through their preferences on travel time.

Static Profits

I assume drivers on all platforms are only paid for rides.²⁵ The fare structure, however, depends on the type of platform. For taxis the fare structure is set by regulations with a fixed price of ϕ_b and distance-based fare π_b . Hence profits for a ride taking a passenger from l to k are

$$\Pi_{lk}^x = \phi_b + \pi_b \delta_{lk} - c_{lk}$$

where c_{ij} are the costs, i.e. fuel, of travel on the trip. For green cabs I make the adjustment

$$\Pi_{lk}^g = (1 - x_l) [\phi_b + \pi_b \delta_{lk} - c_{lk}]$$

²⁵In reality Uber has flexibility around this assumption I cannot capture. In the short-run Uber might offer driver incentives detached from the fare structure.

that is, I force profits for green cabs to be 0 in areas where they should not pick up.

Uber's fare structure is slightly different. In addition to a commission taken from revenue, Uber utilizes surge prices, which multiply revenues by some factor, and time-based fares. Hence profits for a ride taking a passenger from l to k are

$$\Pi_{lk}^u(s) = \kappa \times s \times [\phi_u + \pi_{u,1}\delta_{lk} + \pi_{u,2}\tau_{lk}] - c_{lk}$$

where $s \geq 1$ is the surge factor and κ is the commission.²⁶

States and Payoffs

Ultimately, the interesting behavior of the taxis in the model is the decision of where to locate in their search for passengers. The object of interest from this model is the state of the world S encapsulating the location of taxis and Uber at any given time and driving this behavior. All cabs keep track of 7 sets of states. First is cab i 's own location at t , l_i^t for cab i . The rest of the market is captured by the count of vacant green, yellow, and Uber taxis in each location, $v_{l,g}^t, v_{l,x}^t, v_{l,u}^t$, respectively, and the count of cabs in transit $e_{k,g}^t$, etc., where k indexes the number of periods until the cab arrives at its destination. Finally, the drivers keep track of the distribution of surge prices s_l^t . For the estimation I assume the distribution of surge prices are known in advance, not an unreasonable assumption in the medium run if surge prices follow general daily patterns.

Hence, the full state for any cab i is

$$S_i^t = \{l_i^t, \{v_{l,j}^t\}_{j,l}, \{e_{l,j}^t\}_{j,l}, \{s_l^t\}_l\}$$

I assume all vacant drivers have a belief on the complete state $S = \{S_i^t\}_{i,t}$. While it is a stretch to assume that taxis have knowledge of surge prices, it is more reasonable that they form an expectation of it over time. Nonetheless, I do not model this dimension of uncertainty for now. Given S , taxis can then evaluate the expected dynamic value of any location l .

$$V_{l,b}^t(S) = E_{p_l|\bar{Q}_l, S^t} \left[\sum_k p_{lk,b}^t \left(\Pi_{lk}^b + V_{k,b}^{t+\tau_{lk}} \right) + \right. \\ \left. \left(1 - \sum_k p_{lk,b}^t \right) E_{\varepsilon_k^{t+1}} \left[\max_{k \in C(l)} V_{k,b}^{t+\tau_{lk}} - c_{lk} + \varepsilon_k \right] \right] \quad (19)$$

for $b \in \{x, g\}$. Note that $C(l)$ is the choice set of alternative locations given a cab starts in l . $C(l)$ includes all adjacent, i.e. proximal, locations and l itself. The first half of the expectation is the probability that in location l the taxi makes a match and is sent to location k with a passenger.

²⁶Because I do not currently model the decision of Uber as a platform, this s is taken as exogenous and read from data by location and time of day as explained in Section 2.3.

The second half of the expectation is the probability that it makes no match within the time period and must make a decision about where to search next by maximizing the net present value of profits. I allow an additive idiosyncratic shock ε to that decision, which follows the extreme value distribution, useful both for modeling the search choice decision and capturing unobserved heterogeneity in searches.

Uber cabs have a different value function by nature of the matching assignment process.

$$V_{l,u}^t(S) = E_{p_l|\tilde{Q}_l,S^t} \left[\sum_k \sum_{k'} p_{kk',u}^{l,t} \left(\Pi_{kk'}^u(s_k^t) - c_{lk} + V_{k',u}^{t+\tau_{lk}+\tau_{kk'}} \right) + \right. \\ \left. (1 - \sum_k \sum_{k'} p_{kk',u}^{l,t}) E_{\varepsilon_k^{t+1}} \left[\max_{k \in C(l)} V_{k,b}^{t+\tau_{lk}} - c_{lk} + \varepsilon_k \right] \right] \quad (20)$$

The major difference is in the first term. The first probability after the summation is the probability that an Uber in location l at t is matched to a consumer in location k who requests a destination in k' . Two additional differences from taxis are that the payoff from the trip depends on the surge price of the customer's location and, even after match is made, the driver faces a cost in traveling from location l to the pickup point in k . The time superscripts on the continuation value are also slightly different. Taxis are idle only during the search process. Uber drivers are idle both while searching and while picking up passengers. These differences identify what could be one heuristic for how cab drivers make their decisions. A first-order concern for taxis is the probability they will find a match in a given area. That concern is supplanted by the idle time for an Uber driver, as described in [Castillo, Knoepfle and Weyl \(2017\)](#).

Choice Problem and Transition Beliefs

The critical choice problem facing drivers is where to search in the event they do not get matched in period t . Save the form of the continuation value, the decision problem faced in Equations 19 and 20 are identical. Both unmatched Uber drivers and taxis in location l solve the following problem

$$k^* = \arg \max_{k \in C(l)} \left(V_{k,j}^{t+\tau_{lk}} - c_{lk} + \varepsilon_k \right) \quad (21)$$

where $C(l)$ is the lists of location adjacent to l . Although the problem is the same for $j \in \{b, u\}$, the motivations for moving are not. While we expect taxis to search to maximize their probability of matching, the related incentive for an Uber driver is to minimize the distance they would need to travel upon being matched to a consumer.

Because ε is assumed to follow the Extreme Value I distribution with scale σ_ε , the probability

of choosing a particular search location k is given by the logit formula

$$\sigma_{l,j}(k|S^t) = \frac{\exp(E[V_{k,j}^{t+\tau_{lk}} - c_{lk}|S^t])}{\sum_{k' \in C(l)} \exp(E[V_{k',j}^{t+\tau_{lk'}} - c_{lk'}|S^t])} \quad (22)$$

for a cab of type j starting in location l . For any type of cab in location l at t , then, this function determines the optimal movement to new locations. Designate that vector $\sigma_{l,j}^t$. There are then three matrices to determine the entire transition matrix for empty cabs σ_j^t .

3.3 Equilibrium

To ensure the tractability of the model, I utilize the oblivious equilibrium concept of [Weintraub, Benkard and Van Roy \(2008\)](#) adapted for the taxi industry in [Buchholz \(2017\)](#). I assume that drivers of all cab types hold beliefs over competitors of all other cab types regarding both their policy functions and spatial distribution. Along with complete knowledge of demand and the surge price schedule, every driver can project the evolution of the state S^t over the course of the day. Let Σ^t denote this transition belief for the state at time t .

The **equilibrium** is the set of states $\{S^t\}$, transition beliefs Σ^t , policy functions σ_j^t for all j and t given an initial state S^0 and the total number of cabs V_j for $j \in \{x, g, u\}$ such that the following conditions hold

1. Taxis match in each location l at the start of period t according to Equation 8. They transition according to $p_{lk,b}^t$ once conditioned on matching. Uber drivers also match and are assigned customers according to Equation 15 with transitions conditional on contracting defined by Equation 16. Together these transitions determine the aggregate movement of occupied cabs. Let $\nu(e_j^{t+1}|e_j^t, m^t, p_u^t)$ be the transition kernel where e_j^t is the distribution of cabs of type j at time t , p_u^t is the assignment of Uber drivers to passengers across all locations, and m^t are taxi matches.
2. Vacant drivers at the end of every period move according to the solution of Equation 21, that is $\sigma_j^t(S^t, \tilde{\Sigma}^t)$ based on the state and beliefs for all cab types, where $\tilde{\cdot}$ denotes beliefs. Let $\mu(v_j^{t+1}|v_j^t, \tilde{\sigma}_j^t, S^t)$ be the transition kernel of vacant taxis.
3. The realized state transition is the combined movement for employed and vacant cabs, along with the exogenous change in surge prices, s^t . Hence $\Sigma(S^{t+1}/s^{t+1}|S^t/s^t) = \nu(e_j^{t+1}|e_j^t, m^t, p_u^t) + \mu(v_j^{t+1}|v_j^t, \tilde{\sigma}_j^t, S^t)$.
4. Rational expectations ensure that $\Sigma^t = \tilde{\Sigma}^t$ for all t .

Existence follows from the standard arguments.

4 Data and Estimation

Estimation of the model proceeds in three steps. Because I measure price and wait times directly, I estimate demand separately as the first step of this procedure. I then integrate Equations 4 and 6 into the estimation of the supply model. Finally, the congestion and efficiency term functions are estimated at the end.

This section proceeds by describing the data and estimation procedure for demand. It concludes by repeating the exercise for supply.

4.1 Demand

Rather than modeling the transit demand for the entire city throughout the day, I make two limitations on the scope of the estimation. The first is that I estimate the demand system based on Monday through Thursday morning commuting patterns. The reason for this limitation is multifold. Residency population distributions are more accurate representations of the actual distribution of population on weekday mornings. Second, other than what the MTA can track through card users, the census publishes the most persistent datasets on transit choice, but those choices are limited to morning commutes. Finally, changes to the transit system can influence a consumer's extra-marginal decision about making a trip. I lack the data to meaningfully estimate a model that captures this dimension. In modeling morning commutes, which are more likely to occur with regularity, I can mitigate this particular issue. Additionally, granular data exist linking home and work locations. I explain extending the demand estimates beyond these commuting times in the discussion of the supply model.

The second limitation reduces the geographic scope of the estimation. Its purpose is simply to avoid areas with near zero shares of taxi users. Figure 12 shows the extent of the coverage. In total 129 taxi zones, or 350 census tracts, are included. One concern is that these areas are some of the most dense in the city. Because the matching efficiency for taxis will be estimated for each zone in the supply section, it should not bias those estimates. Results reported over measures of density, however, will obviously be truncated to these higher density locations.

This model is not one of a daily choice problem for each consumer. Rather, as details of the data sources lay out, I model the *typical* choice a consumer would make on her way to work. The major assumption is that the demand parameters governing the consumer problem for morning commute trips will also apply to any another trips taken in the day.²⁷

²⁷This assumption is not entirely out of left field, but a particular concern is that, say, consumers are more wait time elastic in their choices for the morning commute.

Data Sources

Three sources of data constitute the consumer choice data for the demand estimation. The first is the 2008 New York Customer Travel Survey conducted by the Metropolitan Transportation Authority (MTA) over the period of May through November 2008. While the period covered is long before the key time period of interest in mid-2016, the dataset offers more extensive details on transit behavior and rider demographics than any other available.²⁸ The survey provides the typical work transit mode of over 10,000 people living in the five boroughs of New York. In addition to their transit choice the survey takers indicate the census tract of their home and work, time of departure, and income bracket. These observations are designated $M = \{M_i\}_{i=1}^{N_1}$.

The next set of choice data, from the American Community Survey, allow for the construction of choice shares at the temporospatial divisions outlined in the model section. The 5-year surveys report estimates of transit choice by the time of departure in 30-minute to 1-hour blocks and by census tract. I require the construction of shares for two time periods, 2008 and 2015.²⁹ I can then aggregate the tract data up to the taxi-zone level. The long horizon in calculating the estimates of these shares is the principal disadvantage in using this dataset. In an environment I have speculated has changed significantly over the past several years, 5-year estimates dampen the extent of the transformation. Additionally, the ACS does report taxi service usage but does not distinguish between different types of taxis. These observations are designated $B = \{B_i\}_{i=1}^{N_2}$.

To augment the ACS data, the final set of choice data utilizes the yellow, green, and Uber pickup data from the TLC already exhibited elsewhere in the paper. As alluded to in the discussion of the other datasets, I favor this source over the ACS for its ability to differentiate between traditional taxis and Uber and the potential to take advantage of daily variations in the characteristics — and choice — of these two products. These variations are arguably more subject to change from day to day than those impacting the choice to take public transit or walk. The unfortunate shortcoming is that I am unable to distinguish work commuters from other passengers. In the main body of the paper I attempt to tease out which rides are morning commutes, the details of which are in Appendix C.4.³⁰ I use observations from the end of March 2016 through June 2016, corresponding to the period during which I collected characteristic data for Uber rides, and designate these observations $K = \{K_i\}_{i=1}^{N_3}$. A summary of these data sources is in Table 2.

The observable trip characteristics in the demand model are travel times, walking distance, price, and wait times. Nearly every characteristic depends on the starting location, the destination, and the time of departure. Consider a taxi trip I observed at 9:00AM from location l to location k . Of the menu of choices, the only characteristics read off data are the price and traveling time for the

²⁸Future versions of this paper will certainly take advantage of updated transit surveys. The National Household Travel Survey for 2016 to '17 is slated for release in 2018, for example. The ACS Public Use Microdata Sample also includes rich demographics but obscures home and work locations in geographies too large to be useful in this context.

²⁹The 2015 data can be updated to 2016 as soon as the Census Bureau releases it in late 2017.

³⁰In future robustness tests I will check the impact on the demand parameters by dropping this filtering.

taxi. Every other characteristic must be simulated. Table 3 summarizes which characteristics are observed or simulated when the choice is the observed choice.

To simulate travel times for any choice, I use a mix of OpenTripPlanner and a separately built graph of NYC’s road network. OpenTripPlanner provides directions similar to Google Maps, but trips can be planned around an arbitrary public transit schedule. Since my data are now historic, this feature was important to accurately reflect the contemporaneous schedules. Appendix C.5 further details its usage and application to vehicle-based choices. I also use this program to gauge walking distances. I assume for vehicle-based choices that the walking distance is negligible.

Prices and wait times are the final characteristics and the only two observable characteristics differentiating Uber from taxis. Prices for public transit are calculated using contemporaneous prices along each route simulated. Section 2 described the process for gathering price and wait times for taxis and Uber. The route planner also generates wait times for public transit options.

An additional assumption I impose on the data is that all Uber rides I observe are through UberX, the most popular choice at the time. Although I collected price and wait time for all of Uber’s choice offerings in New York City, The TLC dataset does not distinguish which type of Uber passengers used to complete a particular ride.

The final sources to address concern individual characteristics, destinations, and income. I simulate income at the census tract level — sub-geographies of taxi zones — using 5-year ACS data. I use the Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) for 2014 to simulate home tract-to-work tract commute flows for later periods, and the Census Transportation Planning Product (CTPP) estimated based on ACS data from 2006 to 2010 for the 2008 period. These two datasets are used to empirically estimate the origin-destination matrix $\gamma(l, k)$.

Estimation Procedure

To estimate the model in Section 3, I require a few additional assumptions. First, I assume ε_{ij} are iid across individuals but multivariate normal across products, following the set up in Goolsbee and Petrin (2004). Hence ε_i follows the distribution below

$$\varepsilon_i = \begin{bmatrix} \varepsilon_{tran} - \varepsilon_0 \\ \varepsilon_{taxi} - \varepsilon_0 \\ \varepsilon_{uber} - \varepsilon_0 \\ \varepsilon_{walk} - \varepsilon_0 \end{bmatrix} \sim MVN \left(0, \begin{bmatrix} 1 & \sigma_{tr,tx} & \sigma_{tr,u} & \sigma_{tr,w} \\ \cdots & \sigma_{tx}^2 & \sigma_{tx,u} & \sigma_{tx,w} \\ & \cdots & \sigma_u^2 & \sigma_{u,w} \\ & & \cdots & \sigma_w^2 \end{bmatrix} \right) \quad (23)$$

or $\varepsilon_i \sim MVN(0, \Omega)$, introducing an additional six demand parameters. I depart from the standard logit setup because of the striking and close substitution from yellow taxis to Uber laid out Section 2. The second assumption, worth restating here, is that (θ_d, Ω) govern preferences in all time periods covered.

Given the first assumption I can calculate predicted shares for each market, here defined as 30-minute blocks (t) for each of the taxi zones (l) covered in Figure 12 for each separate month in March to June 2016. For each taxi zone l , ns individuals are simulated *for each census tract*, so each taxi zone is partitioned by census tracts $l = \{l^1, \dots, l^n\}$. Income is drawn independently for each of the simulated consumers according to the distribution $f_{l^i}(d_i)$, where d_i is the vector of indicators for income bracket in the census tract. The desired destination tract k^i is also drawn independently based on $\gamma(l^i, k^i)$, pinned down empirically with data described in the previous section. Each of the ns individuals is then assigned a time-of-departure block by weights generated from ACS data. Let $\pi_l^t(l^i)$ be the fraction of departures in time block t originating from tract l^i . Given (θ_d, Ω) , predicted market shares for the zone are

$$q_l^t(j; \theta_d, \Omega) = \sum_k \pi_l^t(l^k) \left[\frac{1}{ns} \sum_{k_i=1}^{ns} \int_{A_{k_i j}} dP(\varepsilon_i) \right] \quad (24)$$

with the integral computation here over the MVN idiosyncratic errors.

I proceed with the standard technique introduced by Berry (1994) to “concentrate out” $\{\xi_j^t(l)\}_j$, the unobserved choice taste parameters for each market. Shares are constructed for these markets in 2008 and 2016 using the ACS data and denoted $q_l^{t, DATA}(j)$.

Before the inversion, I make a slight alteration to Equation 1 to account for a peculiarity with the wait times. For taxis and Uber the wait time is independent of the destination. I split up wait time into two additive components $w_j(l, l') = [d_j w_j(l) + (1 - d_j) w_j(l, l')]$, where d_j is an indicator for a taxi-like choice. I can then define $\delta_j(l; \theta_d, \Omega) = \beta_w d_j w_j(l) + \xi_j(l)$. Typically, the Berry inversion carries the extra value of reducing the parameter space by the terms linear in δ . In this case β_w still remains in the form $\beta_w(1 - d_j) w_j(l, l')$, but, the inversion still plays two important roles in this estimation. First, isolating w for taxis and Uber in a linear equation introduces an opportunity to instrument wait times to handle with endogeneity concerns. Unfortunately, the same technique cannot be used with price — price is always a function of the starting point and destination — but controlling for the component of the error, a location-time-specific taste for Uber, that is likely correlated with price can mitigate endogeneity concerns if not directly address it. For all other transit choices, prices and wait times should not be meaningfully responsive to these unobserved tastes.

The Berry technique in this case requires the restriction that shares in the data match predicted shares from the model at the half-hour, taxi-zone block level. That is,

$$q_l^{t, DATA}(j) - q_l^t(j; \theta_d, \Omega, \delta) = 0 \quad \forall j, l, t \quad (25)$$

Berry (1994) demonstrates that for each (θ_d, Ω) , there exists a unique $\delta(\theta_d, \Omega)$ for Equation 25 to hold. Given this restriction I utilize four sets of moments to identify the demand parameters.

The first set of moments are the score of a maximum simulated likelihood estimator using the travel survey data M . Unlike the following sets of moments, these are less sensitive to simulation errors. Let $j(i)$ denote the work commute choice of individual i . From equation 2

$$L(\theta_d, \Omega; M) = \frac{1}{N_1} \sum_{i=1}^{N_1} w_i * \log q_i(j(i); \theta_d, \Omega)$$

where w_i is the sample weight for observation i . The score of the log likelihood function yields $|\{\theta_d, \Omega\}|$ moment conditions

$$E[\psi_1(\theta_{d0}, \Omega_0, M_i)] \equiv E\left[\frac{\partial L(\theta_{d0}, \Omega_0; M_i)}{\partial \theta_{d0}}\right] = 0 \quad (26)$$

with corresponding sample moment at arbitrary (θ_d, Ω) , $\frac{1}{N_1} \sum_{i=1}^{N_1} \psi_1(\theta_d, \Omega, M_i)$.

The next set of moments match aggregate income statistics in the ACS by commuting choice, similar to the matching moments used in Petrin (2002). In its 5-year data the ACS reports a breakdown of transit choices by income. The sample statistics to match are read straight off the data and denoted by

$$\hat{q}_{l^i kj} \equiv \hat{q}_i(\text{income}_r \in [\aleph_k, \aleph_{k+1}] | r \text{ uses option } j \text{ for transit})$$

for location l^i . Let the population analog be $\mu_{l^i kj}$. The corresponding statistics generated by aggregate model predictions are derived by the following equation.

$$q_{l^i kj}(\text{income}_r \in [\aleph_k, \aleph_{k+1}] | r \text{ uses option } j \text{ for transit}; \theta_d, \Omega) = \frac{\sum_{r=1}^{ns} \left[\mathbb{1}(\text{income}_r \in [\aleph_k, \aleph_{k+1}]) \int_{A_{rj}} dP(\varepsilon_r) \right]}{\sum_{r=1}^{ns} \int_{A_{rj}} dP(\varepsilon_r)}$$

for the simulated individuals r corresponding to tract l^i . The moment restriction imposes that at the true parameter the model's aggregated statistic and the population should be equal.

$$E[\psi_2(\theta_{d0}, \Omega_0, B_i)] \equiv \mu_{l^i kj} - q_{l^i kj}(\text{income}_r \in [\aleph_k, \aleph_{k+1}] | r \text{ uses option } j \text{ for transit}; \theta_{d0}, \Omega_0) = 0 \quad (27)$$

for all j, k and tracts.

The third set takes advantage of the much richer data for taxi and Uber usage, relative to the other transit options. The set roughly attempts to pin down the elements of Ω . The first method tracks unexpected disturbances in the subway lines — historic records are available for most Manhattan lines — that create delays (and hence wait times) for commuters who would

typically take the subway.³¹ For those days I measure the substitution toward taxis and Uber. Denote $\hat{\Delta}_{lj}^e$ the change in the share of $j \in Taxi, Uber$ from the change in wait time on the subway, that is an empirical measure of the cross wait elasticity without holding fixed all the other factors likely to have changed from the disturbance day e . Let $\Delta_{lj}^e(\theta_d, \Omega)$ be the same measure from the model replicating the observed characteristics from the event day. On average over all events E , these measures should match.

The second method utilizes day-to-day variation in the wait times between taxi and Uber. The procedure follows the same set up as the subway method. Here, I define an event — these are more uncommon than subway delays — as deviations from long-term average wait times for taxi cabs. I estimate an empirical measure of the cross wait elasticity as with the subway and force the model to match that on average.

$$E[\psi_3(\theta_{d0}, \Omega_0, K_i)] \equiv \frac{1}{|E|} \sum_{e=0}^{|E|} \hat{\Delta}_{lj}^e - \Delta_{lj}^e(\theta_d, \Omega) = 0 \quad (28)$$

The final set of moments are simply instruments on the wait time in the linear equation for $\delta(\theta_d, \Omega)$. I adapt instruments from [Frechette, Lizzeri and Salz \(2016\)](#) and measure average traffic speeds in rings one and two zones away from each location l at the specified time block t , denoted Z_l^t .³² These traffic speeds should be correlated with wait times of both Uber and taxis but not otherwise affecting the choice. Hence,

$$E[\psi_4(\theta_{d0}, \Omega_0, B_i)] \equiv E[\xi_{lj}^t(\theta_{d0}, \Omega_0) Z_{lj}^t] = 0 \quad (29)$$

for all l, t and $j \in \{Taxi, Uber\}$ where $\xi_{lj}^t(\theta)$ is the value of ξ implied from the share inversion for a given value of θ .

GMM Estimator

The sets of moments can be stacked into a single vector. Formally, it is assumed that θ_{d0}, Ω_0 uniquely satisfies

$$E[\psi(\theta_{d0}, \Omega_0, M, B, K)] = E \begin{bmatrix} \psi_1(\theta_{d0}, \Omega_0, M) \\ \psi_2(\theta_{d0}, \Omega_0, B) \\ \psi_3(\theta_{d0}, \Omega_0, K) \\ \psi_4(\theta_{d0}, \Omega_0, B) \end{bmatrix} = 0 \quad (30)$$

³¹Note also this time period is before disturbances were the exception not the rule.

³²Relevant comments I received in seminars and hope to include in future iterations of this paper are better instruments to put here. First, as I argue in this very paper, traffic speeds impact demand. A better instrument would be unexpected changes to traffic speeds, like through accidents. Alternatively it is well documented how weather acts like a supply shifter in this market.

with sample analog $\hat{\psi}(\theta_d, \Omega, M, B, K)$. The GMM estimate $(\hat{\theta}_d, \hat{\Omega})$ is the solution the following criterion function

$$\hat{\theta}_d, \hat{\Omega} = \arg \min_{\theta_d, \Omega} \hat{\psi}(\theta_d, \Omega)' W \hat{\psi}(\theta_d, \Omega)$$

where W is the weighting matrix derived via Hansen (1982). To calculate standard errors, I follow the adjustment on the standard formula offered by Goolsbee and Petrin (2004) to manage sampling errors in the observed market shares.

4.2 Supply

Data and Setting

For the supply estimation I focus on the area covered by the demand estimation, illustrated in Figure 12. While I could extend the coverage area, limiting myself and the cabs to these locations allows me to most fully take advantage of the demand derived from the first stage of the estimation. The day is played out over the course of 5-minute periods from 6am to 4pm Monday through Friday every month of March through June 2016. I assume all taxis play the same strategy for a time period in a given month. To account for the fact that Uber is still expanding over the time period, particularly outside of Manhattan, I re-solve for the relative demand of taxis and Uber using the available price and wait data each month. Location-time-level unobserved preferences are assumed fixed for the entire period.

Extending the results from the demand model to apply here requires one additional assumption. The unobserved demand tastes $\xi_j^t(l)$ for each transportation type are only estimated for times covered by the demand model, that is up to noon. Since the greatest volatility in these values is across l rather than t within a fixed month, I substitute in the average unobserved taste for each location l beyond noon. In future robustness work, I can limit the supply analysis to the first half of the day at the expense of forcing taxis out of their shifts artificially early.

The second complication to address is the matter of total supply on the road for the various services. Yellow taxis follow the standard 5 to 5 work shift, the timing of which motivates the daily 6am to 4pm simulation. Based on advertisements for green cab shift partners on the website *nycitycab.com*, I assume green cabs largely follow the same shift pattern. The TLC also publishes records for the average green and yellow cabs on the road for each month, a record that I use as the assumed number of cabs under operation that month.

Uber drivers, on the other hand, have flexible shifts. The number of cabs on the road weekly is bounded on the high end by TLC reports indicating the unique vehicle dispatches from each of the FHV bases in New York, including the Uber bases. Considering the result in Hall and Krueger (2015) that as of 2014 nearly 42% of NYC UberX drivers drive less than 15 hours a week — barely a full shift — anything close to the upper bound as the number of Uber vehicles on the road during

the day would be any overestimate. Instead I look to the pickup data itself to form a first guess at a bound on supply. I look for the maximal simultaneous (within 5 minutes) pickups on a day and average it for the month. Approximating the “consistent” supply on the road V_u , however, is built into the estimation procedure.

There are several components of the model I can directly construct using data. First $\gamma^t(l, k)$, the transition probability for time t I treat differently in this section than the last. Since the period of interest covers more than morning commutes, I need an approximation of destination preferences outside the time period. Relying on the fact that Uber and taxis are close substitutes, I estimate $\gamma^t(l, k)$ using *old* yellow and green taxi data from 2013 before Uber took a chunk out of their businesses. In areas outside of Manhattan the precision of these estimates decline with the observed trips taken. However, as detailed in the model section, riders are not indifferent between Uber and taxi conditional on a destination. I use the current demand model to pin down their relative preference.

The other model parameters read from data are profits. Travel distances are approximated by observed taxi rides between locations, as are travel times. While travel times are determined in the model, for the estimation these travel times are estimated using actual travel times read from the taxi data. The cost of operation scales with distances traveled and by mile is the average monthly fuel cost against the average fuel economy of the taxi fleet. The final component for profits are surge prices for Uber. The estimation period is precisely the time for which I collected surge prices from the Uber app, March to June 2016. Finally, I assume $\bar{\tau}$ in Equation 14 is 16, based on the observation in data that no wait time for Uber was ever over 16 minutes. Finally, the commission rate for Uber, $\kappa = 0.238$, is based on the estimates reported in [Castillo, Knoepfle and Weyl \(2017\)](#), which uses data from Uber in Manhattan.

Estimation

For a given vector of parameters $\theta_s = (\sigma_\varepsilon, \{\alpha_l^t\}, \{\tilde{Q}_l^t\}, V_u)$ I need to solve the equilibrium. Here, I follow the oblivious equilibrium procedure developed under [Weintraub, Benkard and Van Roy \(2008\)](#) to significantly simplify this procedure.

I assume the city is serviced by enough of every type of taxi to treat them as a continuum. Under this assumption transition probabilities become deterministic; the predicted transition paths throughout the day are thus also deterministic. The value of this insight from the oblivious equilibrium literature is that every driver need not keep track of or have beliefs on the behavior of all drivers when making their own search decisions. Instead each driver makes decisions conditional on industry averages.

Let $S_0 = \{S_0^t\}_t$ be the initial guess of the state with S_r the state for each iteration of the algorithm. Denote $m_{l,j}^t$ the matches of type j in location l . The only adaptation to the algorithm from [Buchholz \(2017\)](#) is to check for convergence of all taxi types and Uber.

Algorithm 1: Equilibrium Algorithm

```

1 Set  $r = 0$  and  $\tilde{Q} = \tilde{Q}_0$  generated by the fixed point algorithm described
2 Use the guess of  $S_r^T$  to calculate  $V_j^T(S_r^T, \tilde{Q}^T)$  for all  $j \in \{x, g, u\}$ 
3 for  $t = T - 1$  to 1 do
4   Guess  $S_r^t$  to calculate  $V_j^t(S_r^t, \tilde{Q}^t) \forall j$ 
5   for  $t=1$  to  $T-1$  do
6     Derive  $\sigma_r(k|S_r^t)$  for all  $t, j, l$ 
7     Realized transitions and  $\sigma$  yield the actual state  $\tilde{S}^{t+1}$ 
8     Update the state  $S_{r+1}^{t+1}$  for the next period using  $\tilde{S}^{t+1}$ 
9     Update continuation values  $V_j^{t+1}(S_{r+1}^{t+1})$ 
10    Set  $r = r + 1$ 
11  end
12 end
13 while  $|V_{j,r}^t - V_{j,r-1}^t| > \varepsilon \quad \forall t, j$  do
14   Repeat 4 to 11
15 end

```

To derive \tilde{Q} for a guess of the parameters $\{\theta_s/\tilde{Q}_l^t\}$, I feed a guess to the Equilibrium Algorithm and use the distribution of taxis (not Uber) to invert \tilde{Q} from Equation 8. I repeat the process to convergence.

For the other parameters $\{\theta_s/\tilde{Q}_l^t\}$ I use simulated method of moments. I match the average vacancy time for cabs, the utilization rate, and wait times. Uber wait times and the average utilization rate taken from Cramer and Krueger (2016) address the scale of Uber. The more vehicles on the road, the lower the utilization rate, for a given level of rides. But, clearly wait times also change as a function of the number of Uber drivers on the road. Since demand in this portion of the estimation is not responsive to changes in wait times approximated by the model (but rather the wait times in data), more Uber cabs should unambiguously decrease wait times.

In Section 3 I detailed how matching probabilities are linked to wait times. Because these wait times are estimated in terms of periods, I convert it to a continuous value by assuming that the probability of being matched within any five-minute period t is uniform conditional on being matched in that period. Matching taxi wait times pins down α_l^t . To estimate the function for α_l^t , I assume a simple form for Equation 9

$$\alpha_l^t = \alpha_l + \theta^{t'} \alpha_{tod} + \alpha_{dens} m_{l,b}^t + \varepsilon_l^t \quad (31)$$

where t indexes the time and θ^t is a vector of time-of-day dummies. Additionally, the number of matches are adjusted for the street access area of the location. β_{dens} should capture the relationship of transactional density with matching efficiency, while α_l is a location fixed effect that may pick up factors like street layout. The nature of the market helps identify this density term; near the green

exclusion border there is an artificial glut of supply from the green taxis. Figure 13 demonstrates a large drop off in the share of Uber pickups around the green exclusion border. Assuming conditions are similar around the border, this hints at a larger available supply from competitors, in particular green and yellow taxis.

Finally, I estimate the congestion function from Equation 18 after assuming the following form

$$\tau_{lk}^t = \beta_{lk} + \theta^t \beta_{tod} + \beta_l traf_l^t + \beta_k traf_k^t + \varepsilon_{lk}^t$$

where $traf_l^t = (v_{l,j}^t + e_{l,j}^t)$ for $j \in \{x, g, u\}$. Each route between proximal zones can have a separate intercept, which I estimate as a fixed effect.

5 Results and Discussion

5.1 Model Estimates

The parameter estimates from the model appear in several tables and figures in the Appendix. Tables 4 and 5 present the result of the demand-side estimation. Table 6 presents the result for the estimated volume of Uber cabs, the degree of uncertainty σ_ε governing the location decision of taxi and Uber drivers, and the estimate of transaction density on efficiency α_{dens} .

A few validating and interesting facts emerge from the demand estimates alone. First, price elasticities, as conventional wisdom would posit, diminish with income. This fairly general pattern is reflected in the estimates for α_g in Table 4. Additionally, consumers do not value all time equally. Consumers penalize waiting time much more significantly than travel time, a finding reflected in transportation literature. Finally, the off-diagonal components in Table 5 reflect inherent substitutability of different transit choices. Expectedly, Uber and taxis have the highest degree of substitutability even controlling for the fact that the quality of service they offer, in terms of price and wait time, is already quite similar in most areas of the city.

Figure 14 is another attempt at validating the results from the demand estimation. The figure maps the average taxi wait time elasticity in each taxi zone covered by the estimation. Quite sensibly, the areas with better substitutes have the highest elasticities along the dimension of wait time. This pattern also appears to be reflected down the central axis of Manhattan where most of the subway lines run. This figure, in part, previews one part of the value of Uber in different parts of the city. In Manhattan consumers can easily substitute away from Uber were it to disappear. In other areas of the city, where Uber has a larger share of traffic, we would expect these consumers to be hit by both a much sharper drop in the market quality (along wait time) and also have a lower wait elasticity.

The final supply results are presented in Figure 15 and should be taken along with the result that $\alpha_{dens} = .0048$. These figure maps the residual parameters (α_l) from Equation 31 over building

to ground density with values normalized by the maximum. Despite controlling for transactional density, I still find $\text{corr}(\alpha_l, \text{density}_l) > 0$.³³ The residual values range from 0.34 to 1.32. To get a sense of their meaning fix the transactional density at 0, and suppose an area had 100 potential and 100 potential cabs. In the location with $\alpha_l = 0.34$, we would expect 29 matches. In the location with $\alpha_l = 1.32$, we would predict only 73.5 matches.

To account for the role of transactional density in efficiency via α_{dens} , consider the zone with the most transactions per unit area per 5 minutes. Appropriately, this zone contains Penn Station, which has anywhere from 50 to over 250 pickups per 5 minute period per square mile over the course of the day. α_l for this zone is 0.92. Absent any transactional density, the matching function would predict 60 matches with 100 cabs and 100 consumers. Ignoring time of day effects, the predicted matches accounting for the transactional density ranges from 68 to 88. Hence the transactional density alone improves efficiency in a particular area by 20%. All other zones, by definition, do not receive close to the same boost in efficiency from transactional density.

5.2 Welfare Analysis and Counterfactuals

The supply results alone in Figure 15 combined with the impact of transactional density present a stark estimate of the relative advantage Uber’s technology might have over taxis. This section attempts to determine the significance of this relative advantage from the perspective of consumers across different parts of the market. I then tease out the importance of Uber’s different matching regime in servicing the city through a series of counterfactuals that change the regulatory burden on yellow taxis. Finally, I consider a set of regulations geared toward leveling the playing field between taxis and Uber through geographic restrictions and congestion taxes. Table 7 summarizes the spatially heterogeneous results of the counterfactuals separated out by density quantiles.

First, to avoid having all welfare results depend too heavily on the supply model, I carry out a standard welfare analysis dependent solely on the estimated demand model. Following the tactic of Petrin (2002), I treat Uber as a new product category introduced to the market by the period of analysis in March to June 2016. I compare the welfare of consumers choosing Uber to their alternative in a baseline year 2013, when I assume Uber is still a small platform in the market. Technically, Uber entered New York in May 2011, but, as I argued in Section 2, the scope of the operation even as late as early 2014 was negligible compared to yellow taxis. Finally, I break down the compensating variation per ride for each of the 143 zones in the analysis.

In extrema, these compensating variation values range from \$1.00 per ride in eastern Queens, where it is approximately 10% of revenue from the ride, to \$.10 per ride in central Manhattan, where it is approximately 2% of revenue from the ride. Figure 16 illustrates the range of results for all the zones in the study over a map of the city. Figure 17 depicts the same information smoothed out over the measure of geographic density. In total the change in consumer surplus per day for

³³Earlier versions of the paper in which I set $\alpha_l^t = \alpha_l$ exhibited a much stronger correlation.

these riders works out to be \$73,000 for an average total of 120,000 transactions per day, a factor of 10 difference from the estimates in [Cohen et al. \(2016\)](#).³⁴ In Table 7, the results from the exercise are recorded under “C1”.

5.2.1 Taxi Entry Policy Counterfactuals

The counterfactual exercises proceed in a series of steps to understand the importance of Uber’s technology itself, versus its relatively high level of supply, in providing service to different markets in the city. For every counterfactual I start from the previous baseline and “shock” the system with the particular regulatory adjustment for that counterfactual. Unlike in the supply estimation, demand and supply interact with each other in the determination of the new equilibrium. I handle this problem through the following algorithm.

Algorithm 2: Counterfactual Algorithm

- 1 Shock the system with a regulatory change, e.g. eliminating Uber
 - 2 Holding fixed the demand system, allow cabs to re-optimize their location decisions
 - 3 Re-calculate the wait times and congestion based on these decisions
 - 4 Feed the wait times and travel times back into the demand system and allow consumers to re-optimize
 - 5 Repeat 2-4 until convergence
-

Three remaining issues are unaccounted for in these counterfactuals. The first is the potential evolution of unobserved tastes for taxis once the regulatory change has been applied. I simply hold these unobserved tastes fixed at the average daily level per taxi zone as of June 2016. The second issue is that I have no proof guaranteeing convergence. While computationally that has not been issue at the current parameter values, I intend to address this potential problem in the future. Finally, a multiplicity of equilibria are a near certainty in this setting because of the feedback from demand to supply and vice versa. I am only presenting one potential new equilibrium. Future robustness work may require testing the sensitivity of the equilibria.

The first of these counterfactuals (“C2” in Table 7) is meant to replicate the results of the previous welfare analysis conducted, along with simulating the now unlikely possibility of banning Uber in New York as London has done. I ban Uber as of March 2016 and re-solve the model. The welfare changes here approximate those from the demand-based analysis and serve as a sanity check for using the supply model in further counterfactuals. Figure 18 maps the relative difference in the calculations across the zones in the city. While the qualitative pattern of the welfare

³⁴I cannot directly assess the contrast in these findings. One theoretical difference, however, is in the demand model used to generate price elasticities. My paper estimates demand on longer term transit choice decisions, which should yield consumers with higher price elasticity than in [Cohen et al. \(2016\)](#). Higher price elasticity would also translate to a lower consumer surplus. Second, this work demonstrates that where *in a city* consumers are sampled can impact one’s estimate of the value of Uber (or any new transit option).

patterns is somewhat different than the in the baseline welfare calculation, the quartile averages across density groups are fairly similar. The results do suggest, however, that modeled congestion, as a countervailing force against taxis congregating in the densest areas of the city, may be *too* strong. Compared to models without congestion in earlier versions of the paper, the calculated compensating variation in Manhattan is higher and likewise lower outside Manhattan. Looking at the change in rides, the percentage declines (or in the best case, growth) in Manhattan are worse than before. Congestion pushes taxi cabs out of attractive dense locations, and, in this case, that effect could be over shooting the real impact.³⁵

The final counterfactual (“C3” in Table 7) in this section asks how many yellow taxis would be needed to at least match the service quality (gauged by wait time) consumers have in the initial data. I again carry out this counterfactual by adding a stock of yellow taxis weighted by the initial distribution of cabs from the previous counterfactual. Because of network externalities there are infinite possible equilibria resulting from this regulatory change. I choose to handle it by adding an additional 500 taxis, allow the model to reach an equilibrium, and I then add the next 500. Ultimately, I find New York City would require 32,000 additional yellow taxis; note that this quantity is greater than the 21,356 Uber cabs previously servicing the market.³⁶ The result is born from two factors. First, enough yellow taxis must enter the densest markets to make the less dense markets relatively more appealing. Additionally, because of yellow taxis’ technological disadvantage in the outer boroughs, more are required to achieve the same level of service quality from the baseline number of Uber cabs.³⁷ Finally, note that this analysis makes no claim about the profitability of these routes. Depending on the outside options for these drivers, the market may never achieve this level service even were the regulatory cap on yellow taxis to completely disappear.

5.3 Counterfactuals on Uber Restrictions and a Congestion Tax

For the counterfactuals in this section, I consider a set of less draconian policies geared toward evening the playing field between Uber and taxis. As I discussed in Section 2 Uber’s unfair regulatory advantage stems from being able to pick up passengers in Manhattan at no additional cost. The old technology requires a high fee to pick up in these areas through the medallion system. Hence, in the section I simulate two counterfactuals: one in which Uber is banned from picking up in the green exclusion zone. The other implements a tax on pickups for Uber for every pickup in the green exclusion zone.

The simulation of these counterfactuals is slightly different than for the previous set. Obviously,

³⁵In earlier versions of the paper, not accounting for congestion, the difference was larger across quartiles. The convergence across the specifications is encouraging evidence of the supply framework. On the other hand the qualitative patterns of benefits diverge more than in previous models.

³⁶Without congestion this estimate approached 36,500.

³⁷A corollary counterfactual in the works is redoing this problem but adding only “green” taxis. Green taxis eliminate the first factor driving up this number; that is their service starts in less dense markets.

both Uber and taxis are searching in the city simultaneously. Because Uber continues to operate, I need an additional assumption on counterfactual surge prices. For now, I assume that the surge pricing scheme stays constant. Future iterations will estimate a surge price function much like the for congestion in Equation 18.

In the first counterfactual Uber is banned from picking up in the green exclusion zone. Because the goal of this exercise is to assess how much Uber relies on Manhattan to “subsidize” its operations in the outer boroughs, I introduce an additional profit condition in the algorithm, described below. The welfare results of the simulation are reported by density quantile in Table 7 as “C4”. A naive

Algorithm 3: CF Algorithm Banning Uber from Manhattan

```

1 while the current average profit of Uber drivers is less than the original average profit do
2   Remove 100 Uber drivers
3   Shock the system with the regulatory change
4   Holding fixed the demand system, allow cabs and Uber to re-optimize their location
   decisions
5   Re-calculate the wait times and congestion based on these decisions
6   Feed the wait times and travel times back into the demand system and allow
   consumers to re-optimize
7 end

```

baseline for the findings would be to claim that 50% of the Uber drivers would exit the market after the implementation of the Manhattan ban, since, as of June 2016, about half of Uber pickups are in Manhattan. The ban has a further effect, however, as not being able to pick up in Manhattan makes traveling from Bronx to the other boroughs, or vice versa, more expensive in expectation to Uber drivers because of the higher idle time. As a result, Queens and Brooklyn actually enjoy a higher quantity of Uber while Bronx disproportionately suffers. In the end 65% of Uber drivers exit the market. While the result does suggest a disproportionate revenue value from access to the dense Manhattan market, part of the result is mixed in with the value of Manhattan as a low-idle time bridge between the boroughs.³⁸ More importantly, the high cost to Manhattan consumers — the welfare cost mirrors that in the C2 — suggests there might be room for a tax not born entirely by Uber drivers, as I propose in the final counterfactual.

The final counterfactual implements a tax on Uber for pickups in the green exclusion zone. For a given tax level, I calculate the new equilibrium as in the previous algorithm. I adjust the tax searching over a discrete grid of \$0.10 increments starting from \$1.00. For simplicity I assume the tax incidence fall on the drivers, that is Uber does not adjust its prices. I continue to raise the tax until the shift revenue of yellow taxis matches the level from June 2013, an approximately \$100

³⁸Another valuable counterfactual would be to allow Uber drivers to pay a fee for access to Manhattan. This set up parallels the congestion tax in the final counterfactual and also more cleanly assesses the value of this Manhattan subsidy.

difference.³⁹ The welfare results are reported in Table 7 as “C5.” Ultimately, the algorithm settles on a tax of \$2.50. Like in the previous counterfactual the areas hurt most by the policy are those in the outer areas of the city, even though the tax does not target them. The tax, however, functions similar to a ban in that the revenue value to Uber drivers from access to Manhattan is, by design, dampened.

5.4 Concluding Comment

Underpinning all these results is the relative advantage and disadvantage of a hailing taxi’s technology to Uber’s dispatching system across markets of varying density. Taken together they offer an answer to the question underlying this paper: has Uber’s success been born from “technology” or its ability to field supply in a way traditional taxis are often prohibited from doing? In New York City, the answer is clear; it depends on the density of the market. In New York’s densest markets, Uber offers little if any advantage with its technology; unobservable consumer preference — which may be indeed be a knowable characteristic Uber manipulates but I cannot measure — drives consumers to its platform. Yellow taxi service could itself yield the same quality rides. Elsewhere, the old hailing technology is simply insufficient to service the market at the same level of efficiency as Uber or similar services; the counterfactual illustrating the much higher quantity of yellow taxis required to match the baseline service demonstrates this result.

The second set of counterfactuals highlight a separate result about the benefits from Uber. First in cities of densities similar to the outer boroughs, assuming all other transit options the same, the benefit from Uber would likely be lower. These cities would not benefit from the high revenue value rooted in denser areas. On the other hand, Uber has the ability to adjust the costs to drivers in each of these markets. Extending these results to other markets thus remains an open problem. The corollary is that the clear cut case of business stealing I presented in Section 2 is less evident at the level of the whole market. The rents extracted from old taxi drivers in Manhattan are, in part, transferred to consumers in the outer boroughs.

6 Conclusion

Uber is the face of a sea change in the transportation industry. Uber’s incredible inroads into the historically stagnant taxi market serves as decent evidence of this perspective. How beneficial the new technology in matching consumers Uber has brought to the market, however, is an open question. On the surface the ability to hail a taxi from a phone is but an incremental change to traditional dispatch services. This paper proposes that the size of the benefit offered by Uber’s technology is a function of the density of the market it is serving. In the densest of markets hail

³⁹An alternative planner might adjust the tax with actual concern for congestion. In the future I could run the same procedure to have traffic speeds reach parity with June 2013 levels. I find average difference of around 3mph.

taxi services, which match consumers to drivers through physical contact, can actually generate lower waiting times for consumers than Uber’s dispatching program. Using New York City as the context, I find that the introduction of Uber to the market has consumer welfare benefits that vary by a factor of ten from the most dense to least dense locations studied.

To study the development of the market I use publicly available trip-level data on the pickups of taxis and for-hire vehicles like Uber. These rich records permit a study of the New York City market over both space and time. I augment this dataset with two unique sources on consumer wait times for Uber and taxis. In the first I scraped the Uber app on a simulated Android phone to collect wait time and surge price data for that service in 47 locations across the city at different times of day. For taxis I follow [Frechette, Lizzeri and Salz \(2016\)](#) in using the pickup data to estimate a measure of the time consumers wait for taxis. The data allow me to estimate a discrete choice of model of demand for multiple types of transportation services in the city and imbed it in a spatial equilibrium supply model in which Uber and taxis simultaneously. Controlling for spatial heterogeneity in demand for Uber and taxis and the quality of alternative transit options is critical in separating out the effects of market density from other conflating factors.

The relative technological advantage of Uber in less dense areas manifests itself in several ways. First, the estimated consumer surplus per ride from Uber in the least dense areas of the city outweigh those in the most dense by a factor of ten. In terms of revenue from this rides, the consumer surplus ranges 2% to 10%. Second, if indeed Uber had no technological advantage over taxis, one could remove the supply cap from yellow and green taxis and acquire a similar level of service, as measured by wait times. I explore this possibility in two counterfactuals easing the supply cap on yellow cabs in the absence of Uber. The results from both suggest that a much higher volume of yellow taxi capital would be required in the market to provide the same level of service to the outer boroughs, the less dense parts of NYC, as Uber had as of June 2016.

The paper also opens the door to several more specific questions about Uber but also the innovations in the transportation market at large. Notably, this paper does not account for other technological differences between Uber and alternative services including other app-based competitors. For example, how much does the quick drop-in, drop-out system of supply specifically contribute to the welfare generated by Uber? The advantage from this system may exist independent of density. This paper also skirts around the critical question of the magnitude of scale economies in these markets, as demonstrated by [Bian \(2017\)](#). With more reliable data on the supply side for Uber, the framework developed in this paper could easily be extended to reliably answer that question. How easy it is to achieve scale is relevant to further understanding the nature of free entry in this market. Will new entrants eventually drive platform profits to zero? Alternatively Uber’s early expansion through ample financial capital may have been its true advantage and given the company an insurmountable advantage.

Using the framework developed in this paper, however, a number of additional applications are

already under development. The first was accounting for the impact of supply growth on congestion. New York has already begun considering implementing a congestion tax to deal with perceived problems of traffic growth from ride-sharing services in the city. This work includes preliminary results incorporating congestion into service quality through transit times and assessing the impact of such a policy. The second extension is modeling the e-hail technology in use by an increasing number of taxis. In Israel, for example, Gett is exclusively an app that links consumers to existing taxis. As the use of this technology grows, the differences between taxis and Uber diminish, but the latter still has the principal advantage of being a flexible and centralized platform. In the context of what this paper can do, I can isolate the role of surge pricing, a feature taxis could not replicate, in the service quality provided by Uber.

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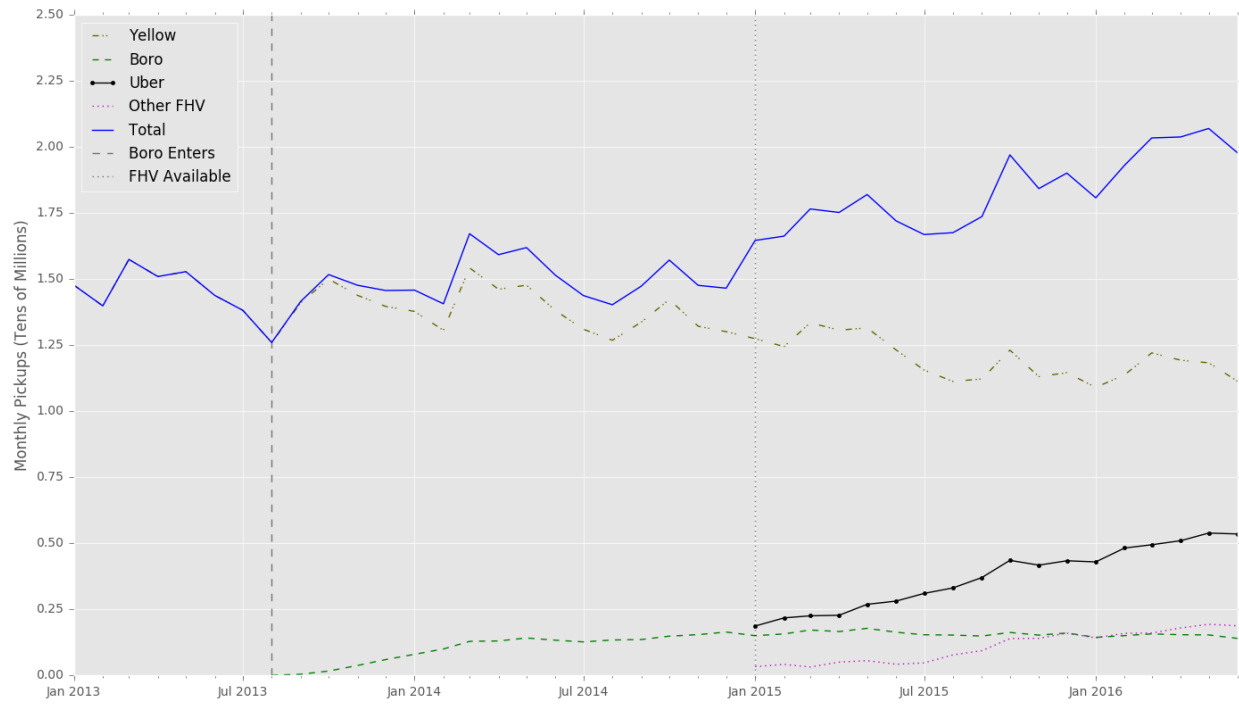
A Figures

Figure 1: **Exclusion Zones for Taxi Service in NYC**



Note: Divisions in the map are different taxi zones, the unit of analysis for most of the paper. The exclusion zone for Green cabs is the hatched area over Manhattan. Green cabs additionally cannot serve as “hail” cabs at JFK and LaGuardia. Pickups at these locations must be pre-arranged. In the non-exclusionary zone — save the airports — green cabs can pick up street hails.

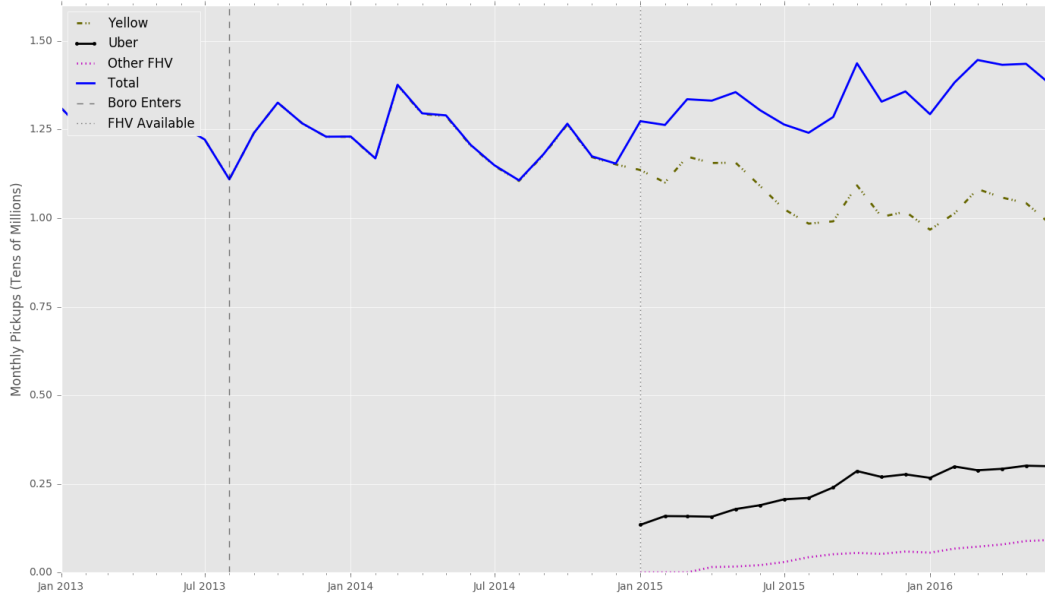
Figure 2: Monthly Pickups by Cab Type



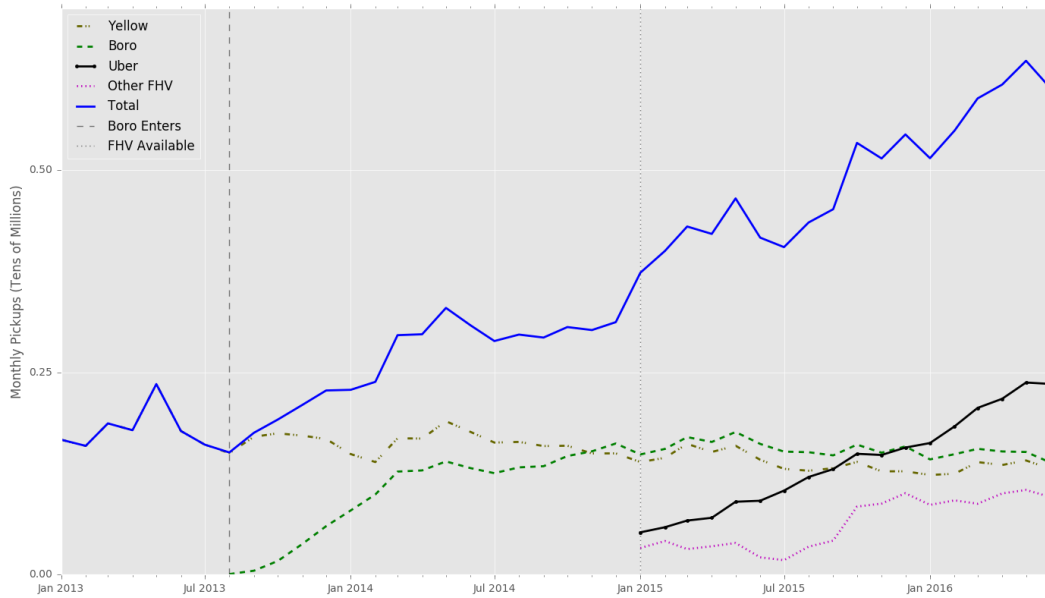
Note: The two vertical lines denote, respectively, the introduction of green tax in August 2013 and the availability of FHV data in January 2015. Lyft and Uber entered the NYC market before January 2015 but FHV data are only available continuously at this date. Therefore, the total pickups are measured consistently before and after January 2015 but not across that date.

Figure 3: Monthly Pickups by Cab Type and Zone

(a) Pickups in the Green Cab Exclusion Zone

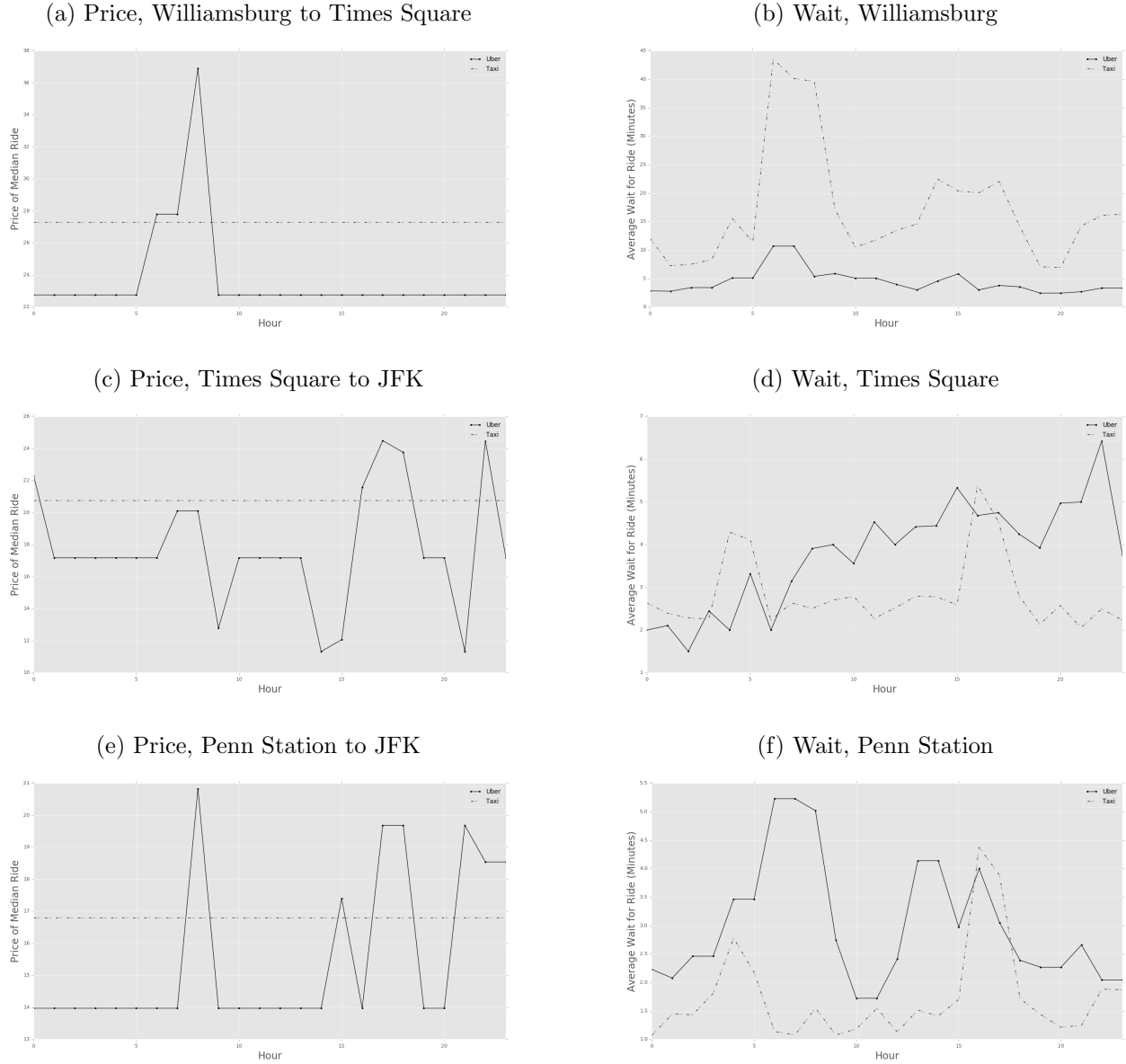


(b) Pickups Outside the Green Cab Exclusion Zone



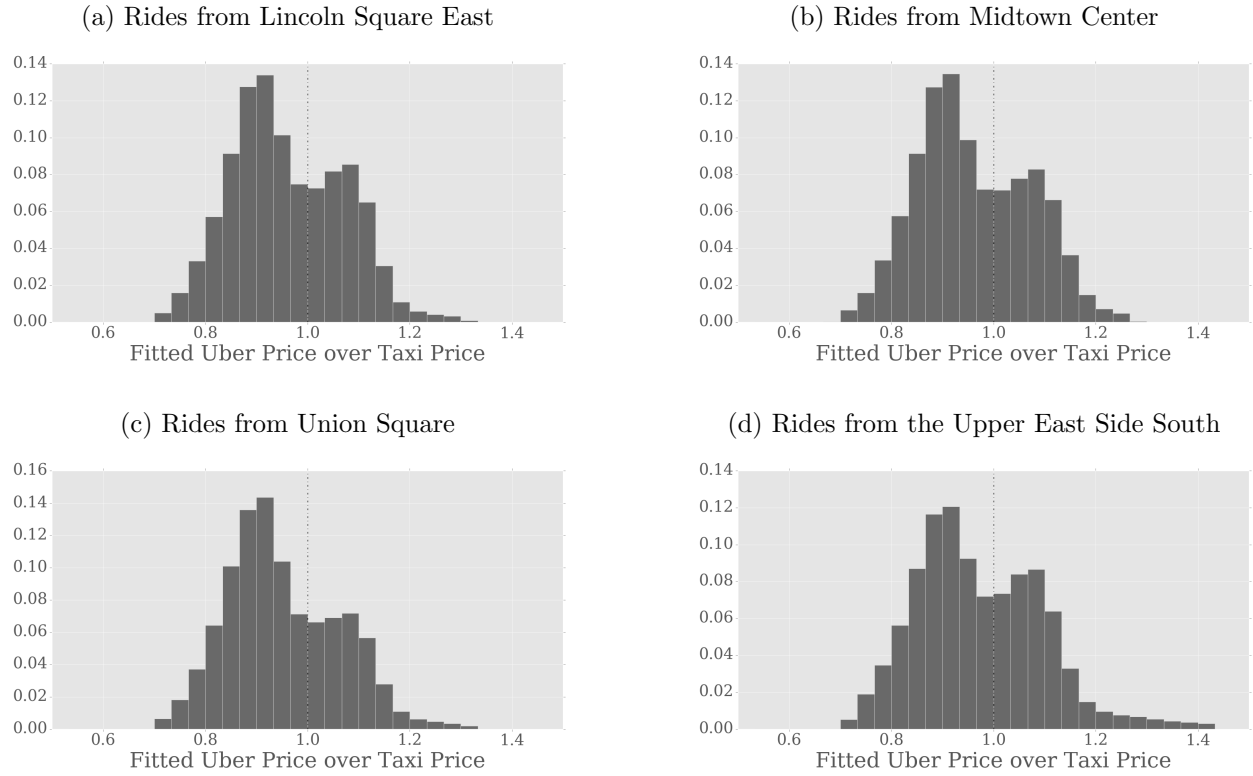
Note: The two vertical lines denote, respectively, the introduction of green taxis in August 2013 and the availability of FHV data in January 2015. Lyft and Uber entered the NYC market before January 2015 but FHV data are only available continuously at this date. Therefore, the total pickups are measured consistently before and after January 2015 but not across that date.

Figure 4: **Comparison of Uber and Taxi Price and Wait Times**



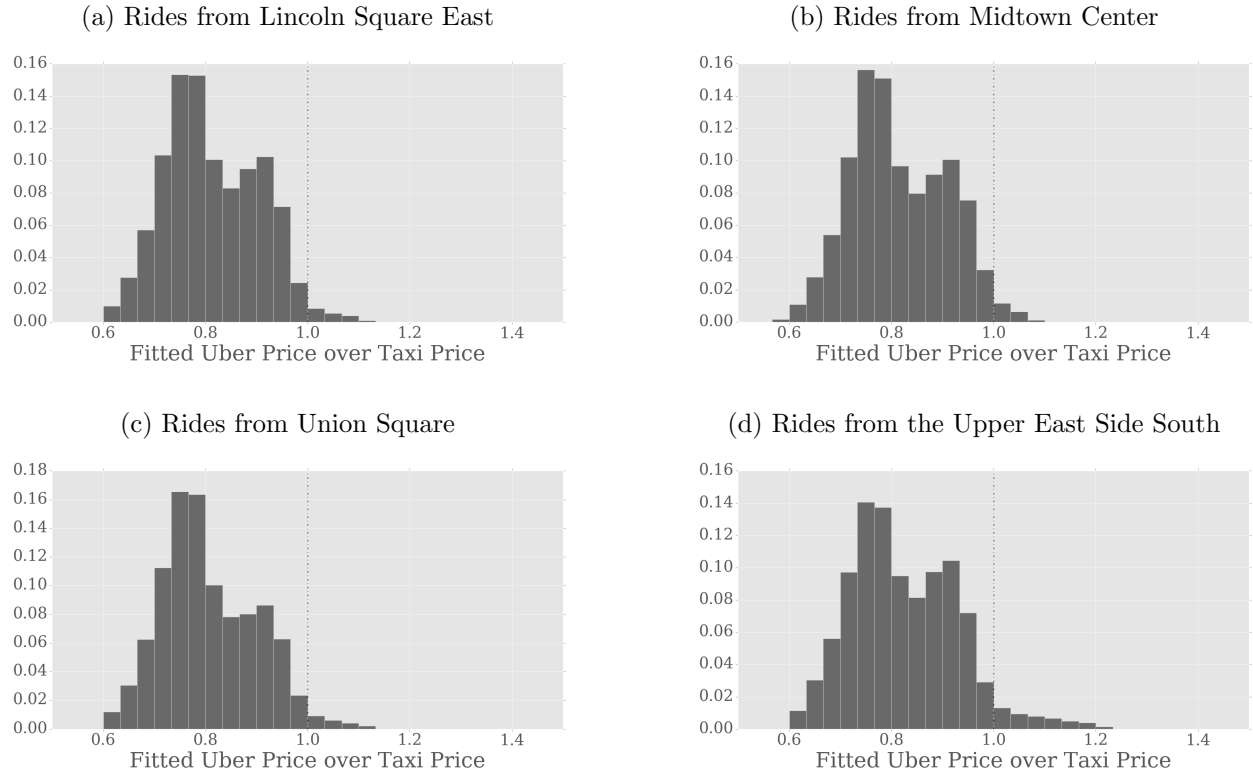
Note: The image contrasts prices and wait times for Uber (solid line) and taxis (dotted line) in different areas of the city. Times Square and Penn Station are stand ins for “dense” parts of the city. Williamsburg represents a less dense part of the city. Taxi prices are read from data. Uber prices are estimated using the recorded surge and the median trip time and distance for rides at that time of day. Taxi wait times are estimated via the process described in the text. Uber wait times are the average wait recorded from weekday trips at that time.

Figure 5: **Distribution of the Relative Price of Uber and Taxi, 2015**



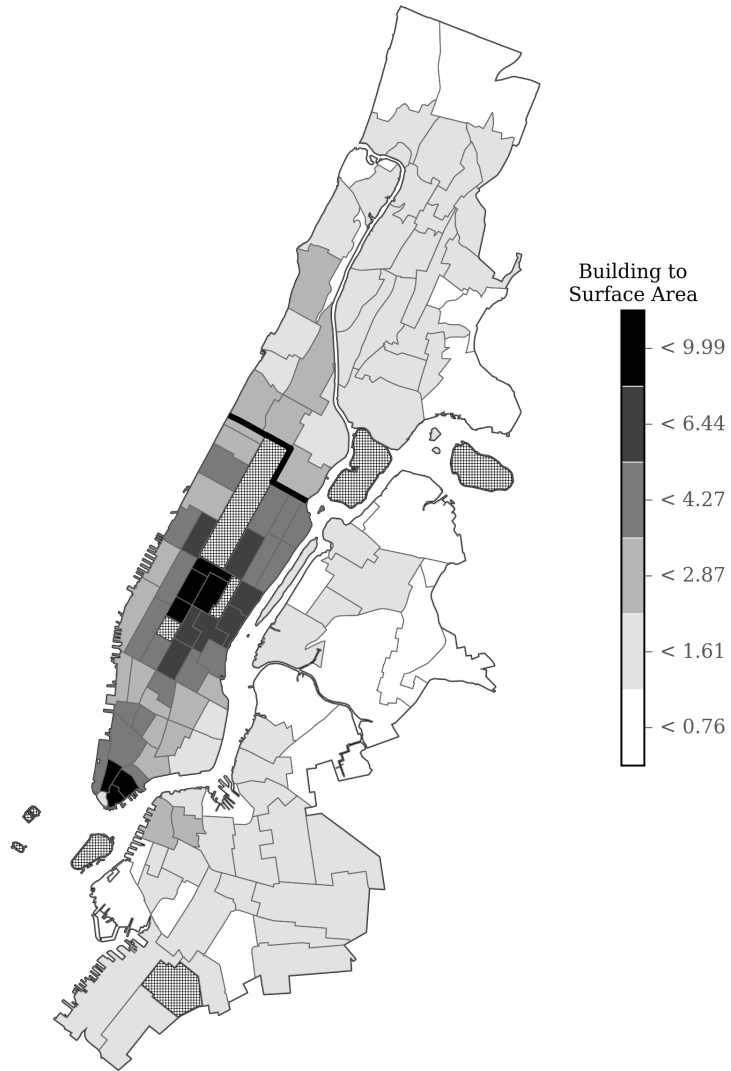
Note: Each graph presents the frequency distribution of the ratio of Uber prices to taxi prices for trips originating in the specified location. A dotted line appears at 1.0 where the two prices are equal. The mass of the plot above 1.0 are trips which would have been more expensive to take with Uber than with taxi. For each location Uber prices are estimated using the realized trip distance and time for rides in the taxi trip records. The surge price profile uses averages calculated for each weekday and hour, but from 2016. These estimated prices are compared to total fares, including tip, from realized trips in the taxi trip records.

Figure 6: **Distribution of the Relative Price of Uber and Taxi, 2016**



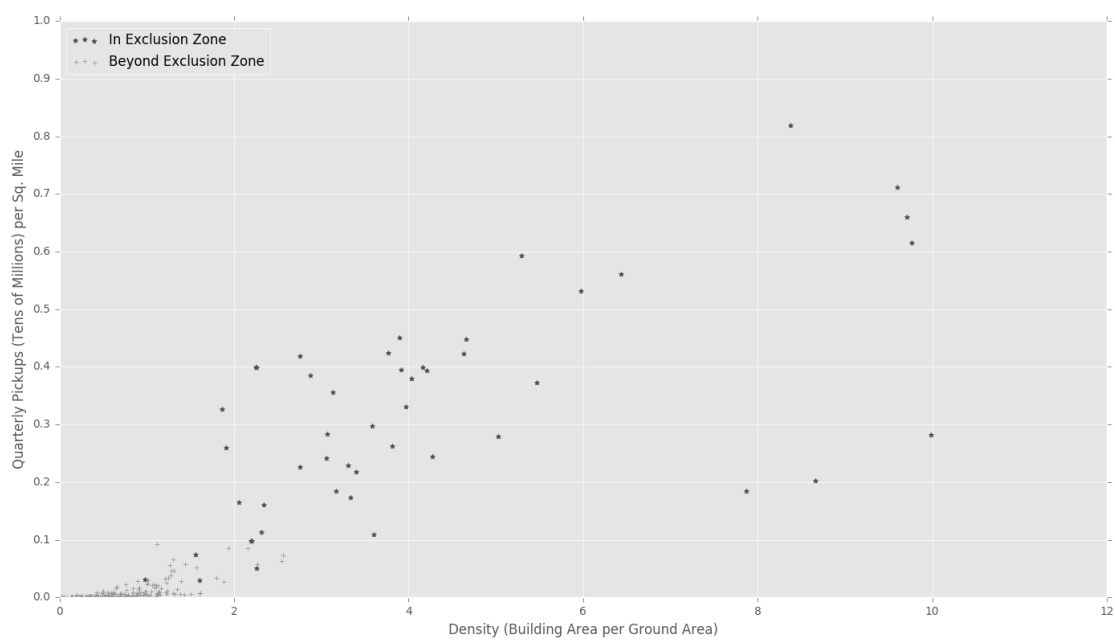
Note: Each graph presents the frequency distribution of the ratio of Uber prices to taxi prices for trips originating in the specified location. A dotted line appears at 1.0 where the two prices are equal. The mass of the plot above 1.0 are trips which would have been more expensive to take with Uber than with taxi. For each location Uber prices are estimated using the realized trip distance and time for rides in the taxi trip records. The surge price profile uses averages calculated for each weekday and hour, but from 2016. These estimated prices are compared to total fares, including tip, from realized trips in the taxi trip records.

Figure 7: **Geographic Density Measure over NYC**



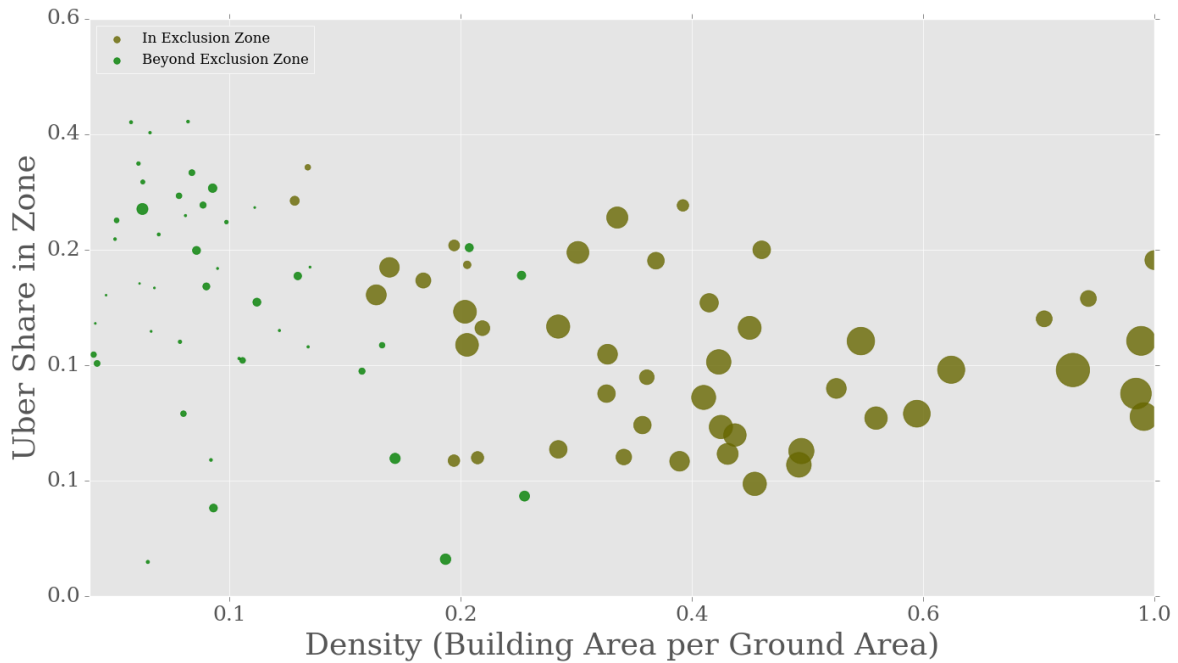
Note: Divisions in the map are different taxi zones, the unit of analysis for most of the paper. The boundary or the exclusion zone is denoted by a thick black line in northern Manhattan, south of which green cabs cannot pick up passengers. Density is measured by the total building area over the ground area in the particular zone. Checkered areas are excluded from analysis in the spatial auto-regressive models in Appendix [D.1](#). *Source:* NYC Planning *PLUTO*

Figure 8: **Total Pickups by Taxi Zone, Q1 2016**



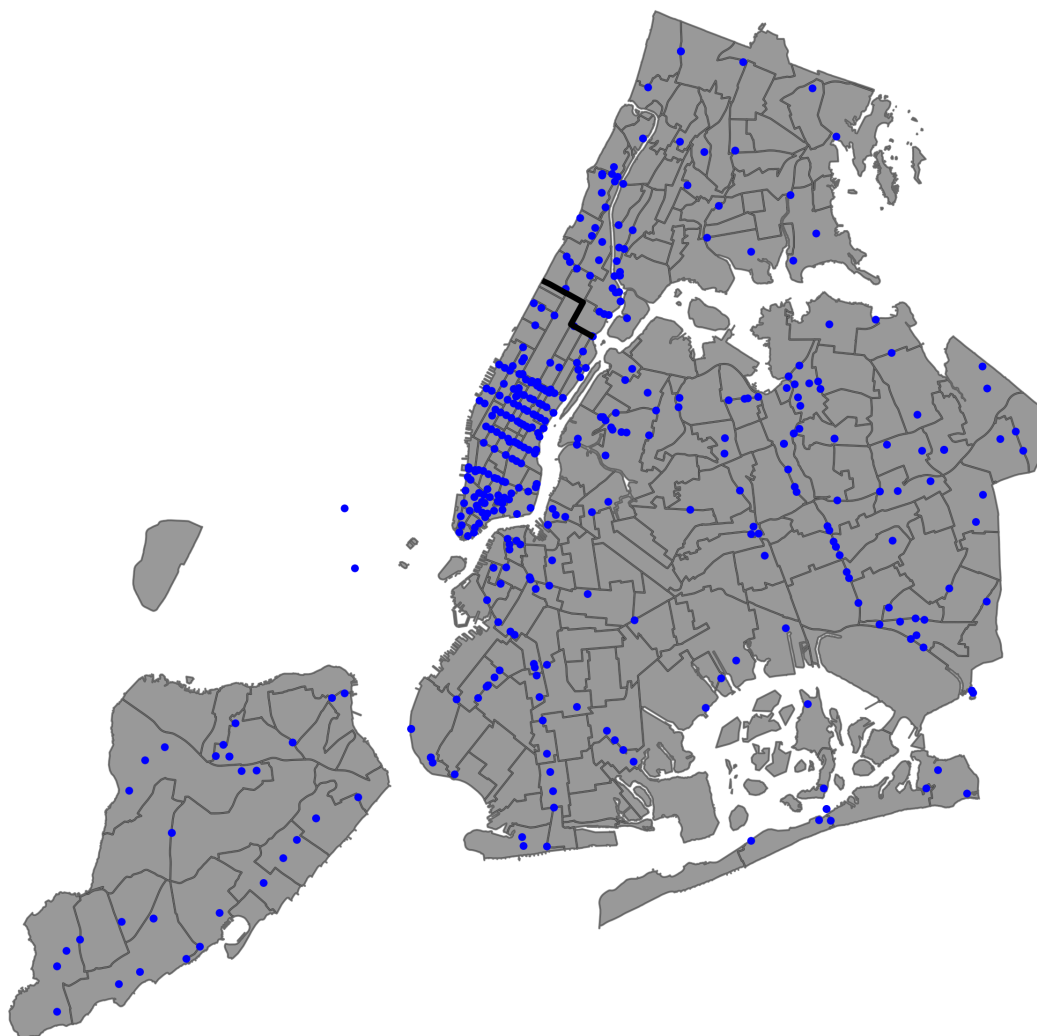
Notes: Observations are organized by density measured as total building area over ground area. Pickups are normalized to pickups per square mile in the zone to account for significant variation in taxi zone size.

Figure 9: Uber Share of Transit Market by Density, Q2 2016



Note: This is a log-log graph of share on density normalized between 0 and 1. Observations are organized by density measured as total building area over ground area at the level of a taxi zone. Share is measured as the share of pickups Uber made over all FHV, yellow taxi, and green taxi trips in the same area for the second quarter of 2016. Point sizes reflect the relative total volume of rides in the period of interest.


Figure 10: **Traffic Camera Locations**



Note: Each blue dot is the location of a traffic camera from which I scraped images in September and December 2015. In this version of the paper not all locations were processed at all times because of manual constraints. Additionally, camera locations in the outer boroughs tend to overlook highways rather than local streets.

Figure 11: **Sample of Traffic Camera Image Processing**

Time Taken: 2015-09-30 04:03:01
Seconds Since Last: 4.0
Facing South 2015-09-30 04:02:59



←

Previous Image

44 of 2046

Next Image

→

Find that cab!

Please answer the following questions based on the image to the left.

How many taxis (including parked) are in the image?

How many of these are green?

How many empty taxis (including parked) are in the image?

How many of these are green?

How many new taxis (not in previous) are in the image?

How many of these are green?

How many new and empty taxis (not in previous) are in the image?

How many of these are green?

How many parked taxis are in the image?

How many of these are green?

How many taxis became filled in this image?

How many of these are green?

Were the answers to these questions clear to observe (y or n)?

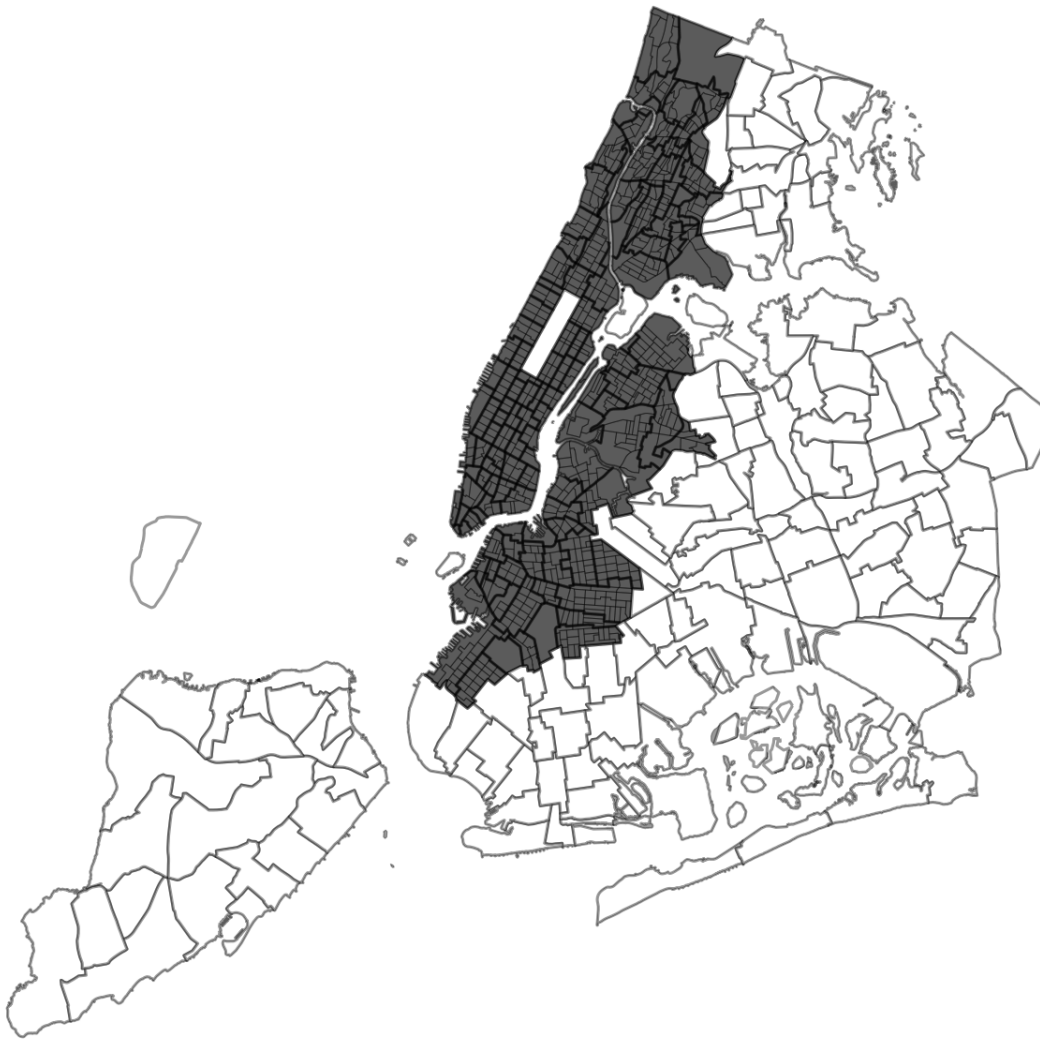
☐ Yes

☒ No

Submit

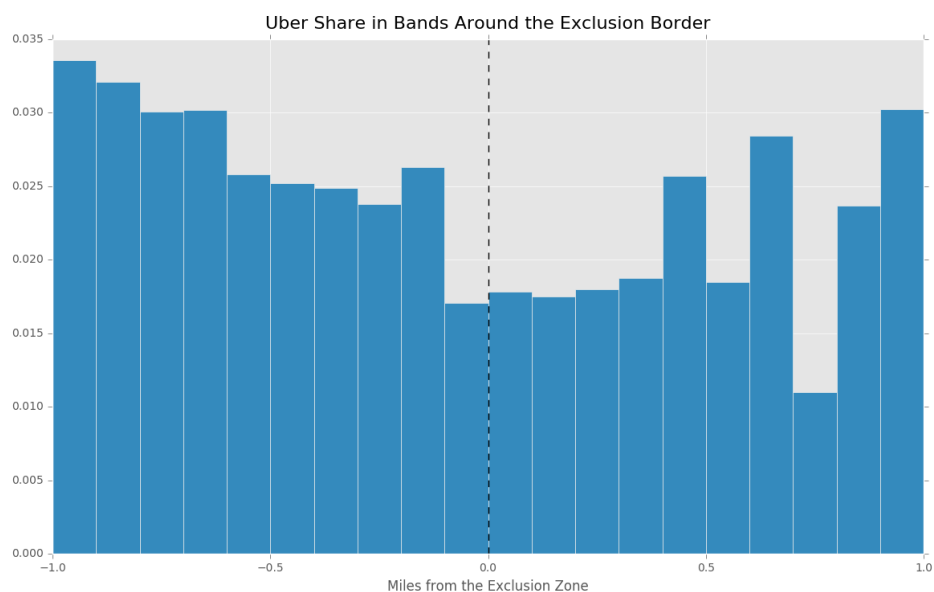
Note: This image is a screenshot of the program developed to process the scraped feeds from New York City traffic cameras. Taxi vacancy is determined by the taxi light atop the cab; hence, processing is more prone to errors in daytime. The red box surrounds the taxi in the image, but it is not part of the original program.

Figure 12: **Zones Included in the Estimation**



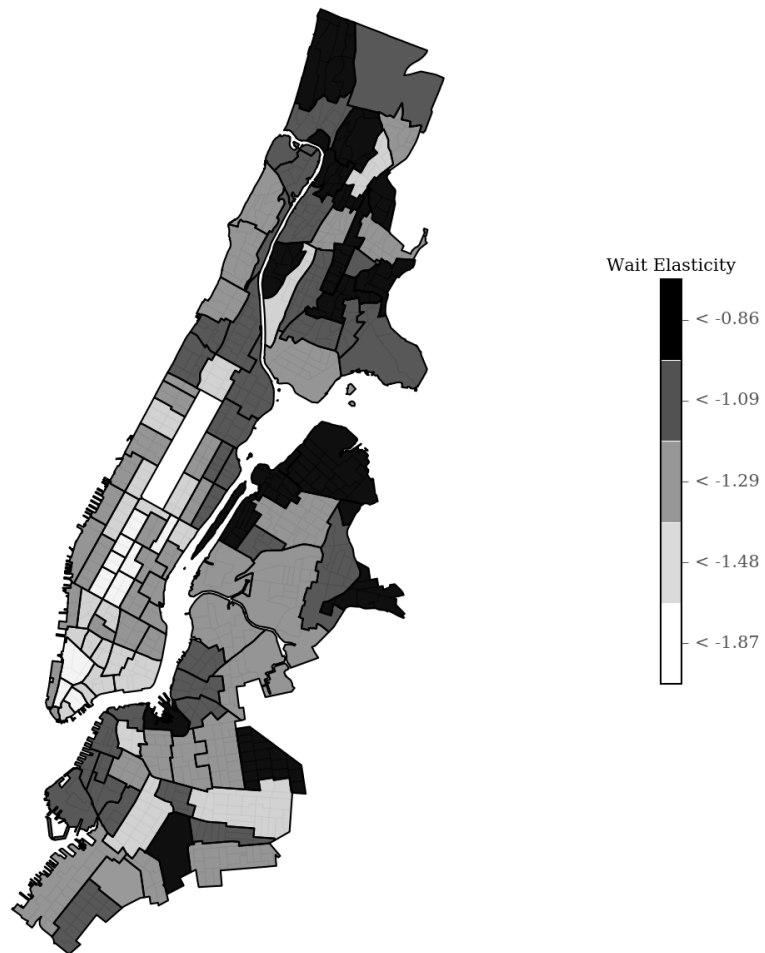
Note: Zones explicitly modeled in the demand analysis are shaded gray. Census tracts are outlined in dimmed gray while taxi zones are separated by dark gray.

Figure 13: Uber's Share of Pickups Around the Exclusion Border, Q3 2014



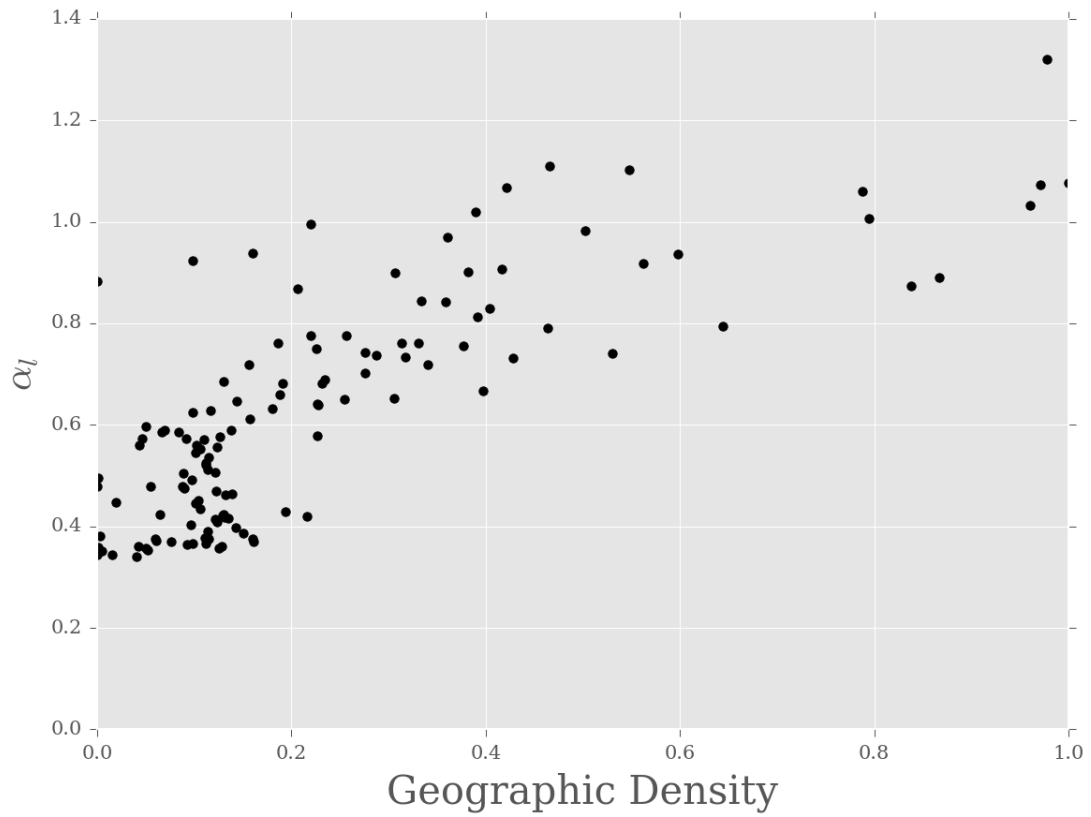
Note: Shares are initially calculated by census tract; data from an earlier period when Uber pickups are available by census tract is used for this figure only. Each tract identified by its distance from the green exclusion border based on its centroid. Shares in each bin are then weighted by the total pickups. Pick up assignment issues at the border precisely likely yield this strange drop off in the bin right before the exclusion zone. It is also possible green taxis are not heavily penalized for infinitesimal infractions.

Figure 14: Average Estimated Taxi Wait Time Elasticity by Area



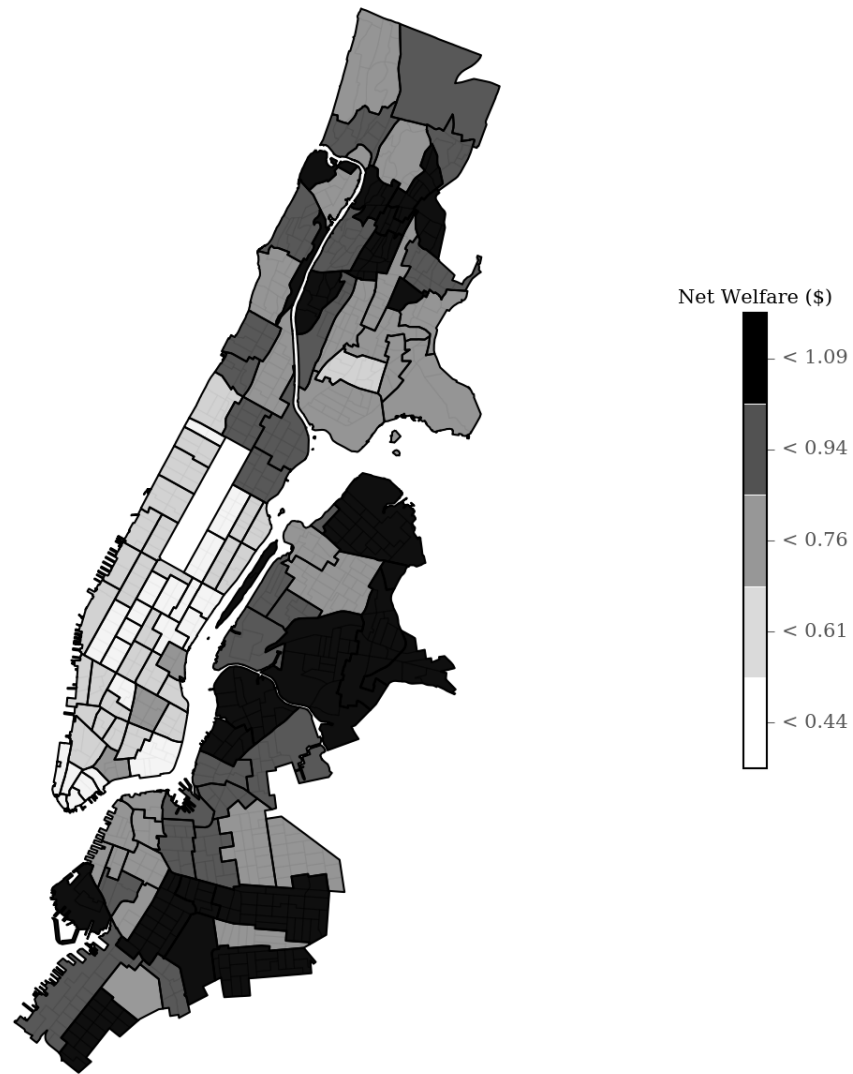
Note: The map measures the average taxi wait time elasticity for consumers included in the demand analysis using the variables' values in June 2016.

Figure 15: **Estimated α_l Parameters over Density**



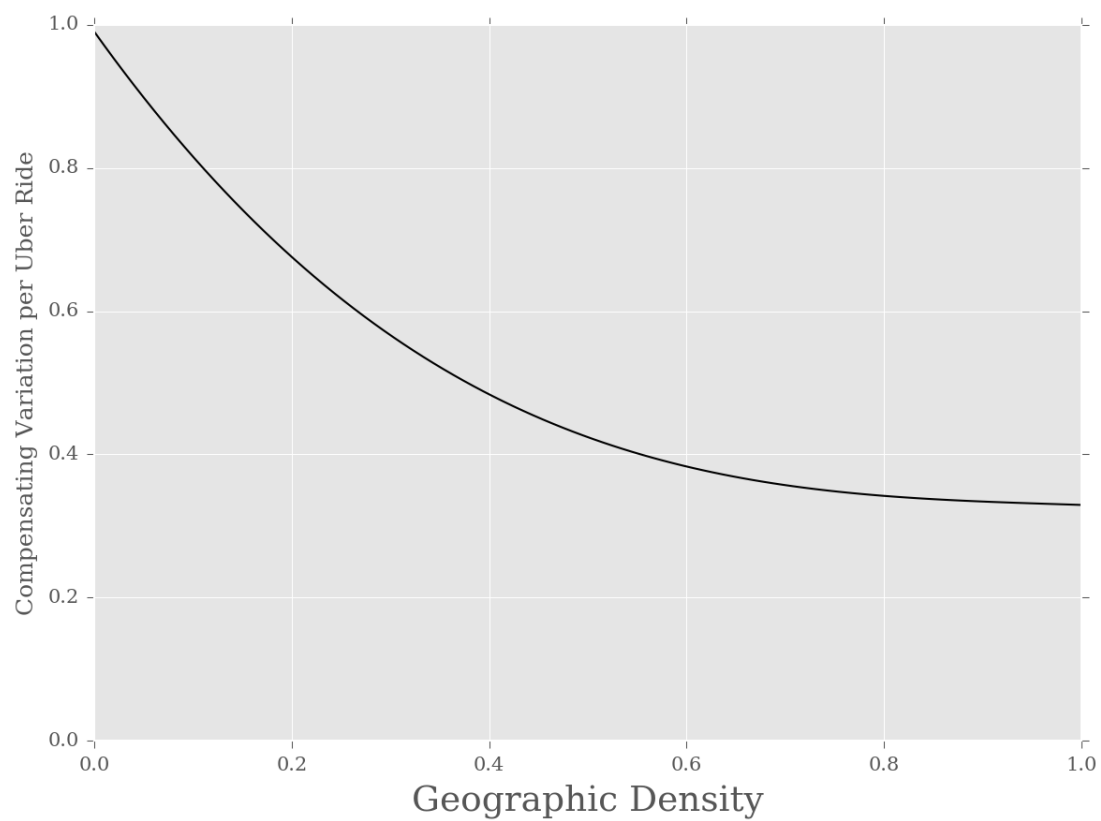
Note: Density is measured by the total building area over the ground area in the particular zone. Here density has been normalized to be between 0 and 1, to emphasize the relative difference across taxi zones. Each dot represents the fitted α_l for the location with that density.

Figure 16: **Compensating Variation per Uber Ride, 2013 to 2016**



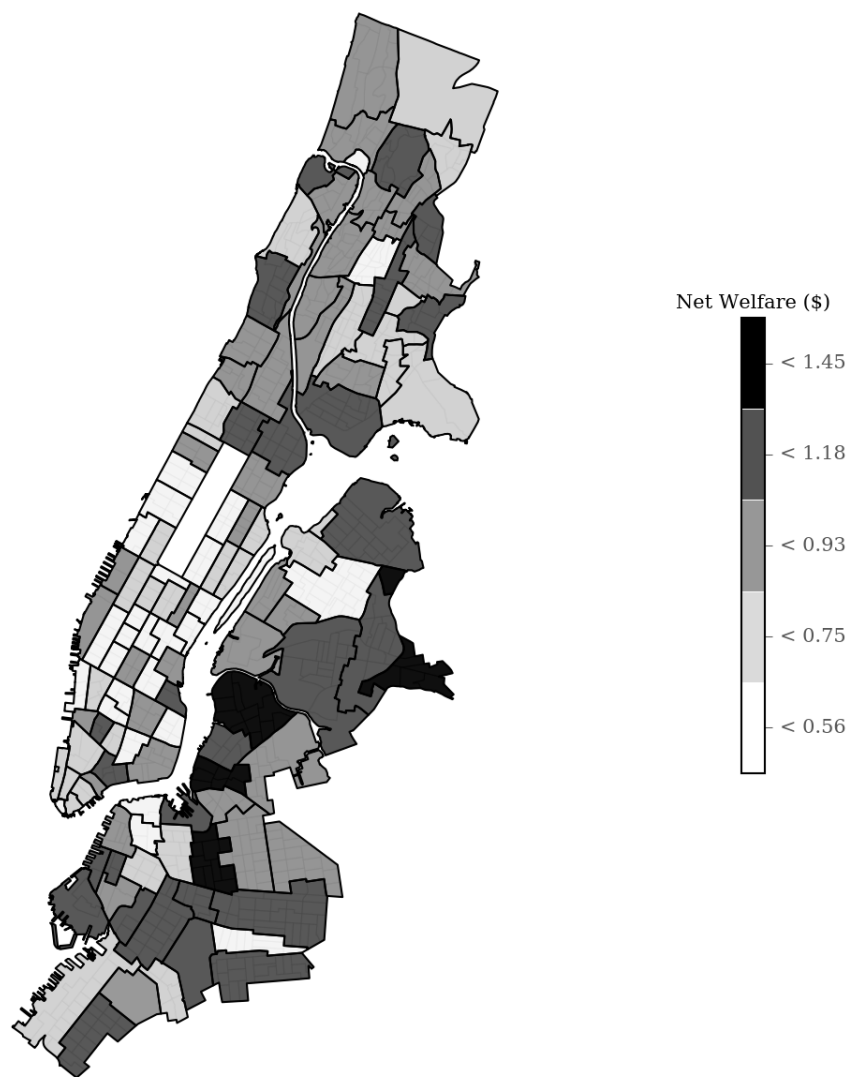
Note: The map illustrates the average change in consumer welfare (in \$) per ride for Uber riders in each of the zones of the map. This change in welfare was measured by calculating the welfare of the rider in 2016 compared to her choice set in 2013, taken as the period “before Uber.”

Figure 17: **Fitted Compensating Variation over Geographic Density**



Note: The figure rearranges the data from Figure 16 along geographic density. The underlying data were fitted using a 3rd-degree polynomial.

Figure 18: **Compensating Variation per Uber Ride, After Banning Uber**



Note: The map illustrates the average change in consumer welfare (in \$) per ride for Uber riders in each of the zones of the map. This change in welfare was measured by calculating the welfare of the rider in 2016 compared to her choice set after Uber is eliminated from the market. Note, unlike with the first measurement using 2013 data as the “counterfactual”, the quality of other non-taxi services do not change here.

B Tables

Table 1: **Comparison of Taxi / Uber Platforms**

Type	In Operation	Matching	Supply Cap	Entrance Fee	Geo. Limited
Yellow	–	Hail	Binding	High	No
Green	Aug. 2013	Hail	Not Binding	Low	Yes
Uber	May 2011	Dispatch	No Cap	Lowest	No

Notes: While Uber began operations in New York in May 2011, the scale of its operations only began to close the gap with yellow taxis in late 2014.

Table 2: **Data Summary: Transit Choice**

Source	Date Range	Variables	Observations
ACS	2008, 2015	Choice, Time of Departure (ToD)	5600
MTA Travel Survey	05/2008 - 11/2008	Choice, Demographics, ToD	10580
TLC Pickup Data	03/2016 - 06/2016	Choice, Choice Characteristics, ToD	7.5m

Notes: The observations for “ACS” are the number of markets for which shares are generated. There are 8 half-hour time periods for 350 census tracts for two years. In the estimation the tract shares are aggregated to taxi zones.

Table 3: **Data Summary: Transit Characteristics**

	Wait Time	Travel Time	Price	Walking Distance
Taxi	Simulated	Data	Data	0
Uber	Data	Simulated	Data, Simulated	0
Walking	0	Simulated	0	Simulated
Public Transit	Simulated	Simulated	Simulated	Simulated

Notes: For each choice and characteristic, I list whether it is read off data or simulated when the choice is an observed choice. Assume whenever a choice is counterfactual, its characteristics are simulated as described in the text. A “0” denotes that field is always assumed negligible.

Table 4: **Demand Estimation Results**

Parameter	Estimate	Standard Error
(baseline) α_0	-0.0433	0.0015
($25K \leq inc < 50K$) α_2	-0.0428	0.0014
($inc < 75K$) α_3	-0.0359	0.0015
($inc < 100K$) α_4	-0.0337	0.0019
($inc < 150K$) α_5	-0.0287	0.0023
($inc < 200K$) α_6	-0.0282	0.0034
($inc > 200K$) α_7	-0.0208	0.0043
β_{wait}	-0.0104	0.0012
β_{time}	-0.0006	0.0000
β_{walk}	-0.0001	0.0000

Table 5: **Demand Estimation Results**

Parameter	Estimate	Standard Error
σ_{tx}^2	1.224	0.568
σ_u^2	1.315	0.492
σ_w^2	3.145	1.231
$\sigma_{tr,tx}$	0.789	0.346
$\sigma_{tr,u}$	0.894	0.278
$\sigma_{tr,w}$	1.186	0.512
$\sigma_{tx,u}$	1.532	0.167
$\sigma_{tx,w}$	0.632	0.291
$\sigma_{u,w}$	0.831	0.354

Table 6: **Supply Estimation Results**

Parameter	Estimate
σ_ε	1.315
V_u	21356
α_{dens}	0.0048

Notes: I currently omit the standard errors because the correct formulation requires accounting for the impact of the first-round (and in the case of α_{dens} , second-round) estimates on the variance of variables estimated later. To calculate the standard errors by bootstrap will be saved for the end of the research process.

Table 7: **Summary of Changes in Each Counterfactual, by Density Quartile**

CF	Variable	In Exclusion Zone				Outside Exclusion Zone			
		1Q	2Q	3Q	4Q	1Q	2Q	3Q	4Q
C1	Welfare	0.52	0.52	0.45	0.38	0.94	0.81	0.85	0.79
C2	Welfare	0.65	0.67	0.60	0.57	0.90	0.70	0.74	0.70
	Total Rides	-44.8	-23.9	-7.34	0.53	-96.4	-79.2	-71.3	-52.5
C3	Welfare	0.42	0.44	0.44	0.38	0.51	0.46	0.48	0.41
	Total Rides	-20.2	-15.4	-2.1	6.30	-43.2	-30.1	-33.5	-20.5
C4	Welfare	0.64	0.68	0.60	0.62	0.15	0.13	0.15	0.11
C5	Welfare	0.30	0.28	0.15	0.16	0.05	0.08	0.02	0.07

Notes: Measures are simple, that is unweighted, averages of the average for each zone over the course of a simulated day. Welfare is measured as the compensating variation per ride for an Uber passenger. Changes in rides are reported in average percent changes, again unweighted by initial pickups. All changes are relative to the baseline in June 2016.

C Data Sources and Construction

This appendix goes into more detail about the collection and scope of raw data sources. The following appendix explains how these data are transformed for use in the model estimation.

C.1 Collecting Uber and Lyft Characteristic Data

To collect information on the characteristics of Uber services (and Lyft), I emulated two Android phones set up with the applications (app) for Uber and Lyft from March through June 2016. Figure 19 depicts the Uber app from the time of collection.⁴⁰ I automated the applications to feed the apps the locations depicted in Figure 20 at specific times throughout the collection period. The Uber app ran every hour and a half, and the Lyft every forty-five minutes. Locations were sampled in the same sequence for every run but in an order to minimize the time between collecting information for each general area.

For Uber I collected data on UberPOOL, UberX, UberXL, Uber BLACK, and Uber SUV, though I use the low-cost UberX as the de facto Uber choice. Specifically, I scraped the information visible in Figure 19. The ETA, i.e. “wait time” was of particular interest. Once the automator “clicked” SET PICKUP LOCATION, the app revealed the surge multiplier.

I also collected data on Lyft Standard, Lyft Plus, and Lyft Courier, using Lyft Standard as the de facto Lyft choice. I managed to capture the web traffic from the Lyft app in which details on the pricing scheme for the particular ride — Lyft had no visible surge multiplier like Uber — and wait time were available.

⁴⁰The Uber has updated their application for significant changes since mid 2016. A critical, and perhaps behavior-changing, update was to report estimated ride prices before confirming the process. At this time the application only reported the minimum fare, seen in the figure, and the surge price multiplier.

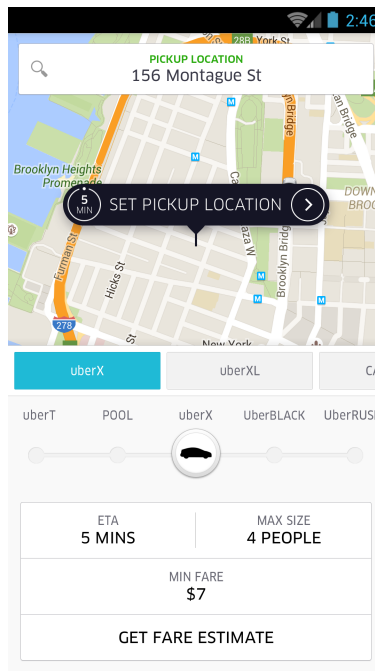


Figure 19: Image Captured from Uber Application



Figure 20: Locations Sampled for Scraping in NYC

C.2 Constructing Wait Time Data

Before delving into the specific method to simulate wait times, I first illustrate how I would use information on cab movements and images from traffic cameras in an idealized setting to deliver a probabilistic count of the taxi in each location. Figure 21 depicts a stylized city with one taxi. The cab starts on green (node L) at time 0, after completing a drop off, and ends at red (node A) at time 5 for its next pick up. Traversing any street segment takes one time period.

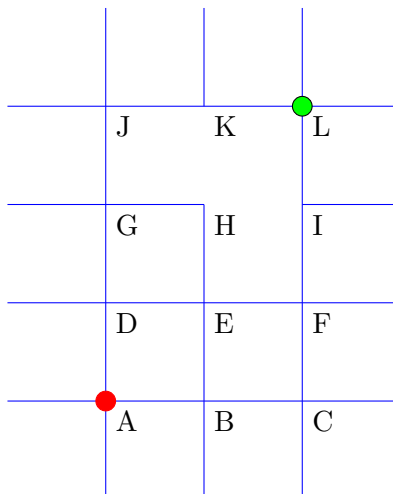


Figure 21: **Stylized City with One Taxi**

The first step is to consider the potential streets the taxi could have crossed. Given I know travel time, the start, and the end of the trip, the cab could have taken the following routes: LKJGDA, LIFCBA, LIFEDA, LIFEBA. I assume at first each of these time-consistent routes is equally likely. Therefore, for example, the probability a cab was on street segment LI at this time is 75%. With additional taxis, I could develop an estimate of the expected time between two cabs passing on segment LI. This would be the construction of the wait time for a consumer on street segment LI. In the simplest case, suppose I observe a repeat of the same trip every six periods. The expected wait time in periods comes from the survival analog of an exponential distribution with rate parameter $.75 * 1/6$. Similarly, the expected wait time on segment LK would be 24 periods.

The addition of traffic cameras helps pin down what route the taxi is taking. Suppose I now have access to cameras at every intersection in the city. At $t = 4$ I find a taxi crossing node D. This additional information narrows down the possible routes this cab could have taken down to only LKJGDA. I can in turn use this information to refine my estimate of the wait time for passengers throughout the city.

Taking this procedure to the full data steps quite far from the idealized example, but the intuition of converting the probabilistic positions of taxis into consumer wait times remains the same. Three particular sets of features distinguish reality from the idyllic city in Figure 21. First,

many thousands of taxis are simultaneously searching the city. Second, since 2013, the taxi pick up and drop off data from the TLC does not permit tracking taxis over the course of the day. This is irrelevant in the simple example, but potentially important in a city with more than two taxis. Third, the roads of New York City are significantly more complicated and permit far more route permutations between two points in a given time.

The following algorithm details the procedure by which I estimate wait times. In brief the procedure works by checking how far a cab can get without picking up another passenger. Once a potential cab is assigned a next pickup, the latter of which I observe in data, probability weights are assigned to segments in the fashion described in the simple example. The role of the camera images are similar to how the pickups are used. Both sets of data essentially tag locations and times for when a cab must be in that location.

The algorithm accelerates time t by one minute through every iteration. Once a cab c makes a drop off, it is assigned a vintage starting at zero. The next period it is assigned to all street segments accessible within one minute. Naturally, the areas it could be in any period explode quickly, so two assumptions help with tractability: cabs cannot double back and are disappeared after 20 periods if they are not assigned pickup or a camera tag. The object V , a matrix of size L , the number of locations, by 20 keeps track of a count of assigned cabs by vintage for each location. For each active cab in the algorithm, I track c_s , the starting location, and vintage c_v . These two are sufficient information to determine where the cab could have traveled in the time period. Finally, P is matrix of size L by T , the number of time periods, holding the probabilistic count of cabs in each location at each time in the day. After the algorithm runs for the desired period of time (4 AM to 4 AM in my sample), wait times throughout the day are constructed using the probabilistic locations of cabs through an approximation of the survival function). The algorithm “burns in” using an arbitrary day to generate a starting C . I typically choose Sunday to prepare the algorithm to run for the weekdays.

With P , it is straightforward to calculate wait times with an approximated survival function. The calculation follows formula in Equation 12 with the probability of a cab passing through the segment in any t using the weights in P and checking up to $x = 60$.

One issue with extending this algorithm to other time periods is that I only have camera images processed from the end of 2015. To extend the value of the camera information, I assume that the marginal impact of the camera data on P uncovers a propensity for cabs to travel certain routes and street segments.⁴¹ To capture this effect, I run the algorithm twice in the relevant months of 2015; I run it once with the camera data and once without. For each time period, the relative difference in the probability counts of each street segment I take as something analogous to a fixed effect for that time period. I then apply this same weighting to P for periods when the camera data is not available.

⁴¹I am implicitly, and now explicitly, assuming that these favored routes do not change with the entrance of competitors.

Algorithm 4: Taxi Wait Time Algorithm

```
1 Set  $t = 0$ 
2 while  $t < T$  do
3   Check drop offs at time  $t$  and update the first column of  $V$ 
4   Assign all pickups to an arbitrary taxi in the location with priority to the oldest vintage
5   Subtract these cabs from  $V$ 
6   Update  $P$  by evenly weighting the routes the cab could take from  $c_s(l)$  to  $c_v(l)$ 
7   Assign camera images to an arbitrary taxi with priority
8   Update  $P$  by evenly weighting the routes the cab could take from  $c_s(l)$  to  $c_v(l)$ 
9   Reset these cabs as vintage 0 and reset its starting location
10  Increment cab vintages and update  $V$ 
11  Remove all vintage 21 cabs
12  Set  $t = t + 1$ 
13 end
```

One concern about this procedure is that it lacks any measure of external validity. This is an important issue to revisit in future iterations of this work.

C.3 Classifying For-Hire Vehicle Data

The pickup data for FHV's provided by the TLC does not explicitly list which company the consumer contracted for the ride. It does, however, list the base station linked to the particular ride. The TLC provides separate documentation with the name of the company operating each base station as well the name ("doing business as") under which that station operations. I separate Uber pickups from pickups of other FHV companies on the criterion that "Uber" appears in the DBA name of the linked base station.

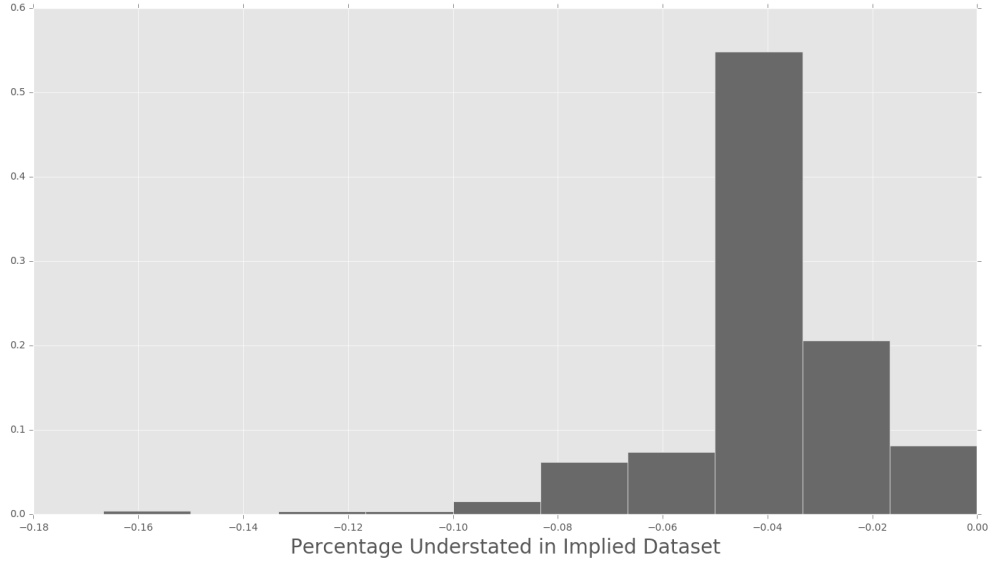
A lucky quirk in the TLC release of data allows me to check the veracity of this methodology. The TLC released a separate dataset of exclusively Uber pickups for only the first six months of 2015, a time period also covered by my standard FHV dataset. For the purpose of this comparison, I will call the Uber data from the full FHV dataset "implied Uber" and the other dataset "true Uber."

The first check compares the total Uber and implied Uber pickups on any given day. On average the implied Uber dataset yields 3.6% fewer rides than the true dataset. At worst it missed 4.1% and at best 3.2%. Hence, in a given day the implied Uber dataset tends to understate the total pickups. In the demand estimation this should manifest as a slightly underestimated unobserved quality term for Uber. But, one might worry still that the bias is not random with respect to time of day or location. The next two tests check this issue.

Unsurprisingly, for both the location- and time-based comparisons the implied Uber dataset uniformly understates the total pickups. By location the implied dataset on average yields 3.9% fewer rides than the true dataset. At best the two datasets perfectly match up, but at worst the

implied dataset misses up to 16.7% of the rides in the true dataset. Figure 22 shows the distribution of the understatement. Fortunately the vast majority of locations feature deviations of a similar magnitude. Finally, I checked the difference between the two datasets by half-hour segments of the day. On average the implied dataset gives 3.6% fewer rides than the true dataset. The range of the deviations is otherwise tight; at best the understatement is 3.3% and at worst 4.2%.

Figure 22: **Deviation of Implied Uber Dataset from True Dataset**



Note: The frequency distribution is calculated using deviations at locations as individual observations.

C.4 Determining Morning Taxi Commutes

For a fine granularity, e.g. census tracts, the American Community Survey does not report taxi usage separately from other means of transit. Along with the fact that the ACS data is taken over a long period of time and the personal vehicle segment of the transportation market is rapidly changing, I instead opt to construct commuting data from the rich TLC data set. Unfortunately, the dataset does not distinguish between the purpose of various trips. This section describes the procedure to extract commuting data from the raw TLC trip information.

I use the an algorithm to sort through the taxi commute observations and determine which should be classified as work rides based on two criteria:

1. the “same” ride appears in the dataset within γ_1 days; and
2. the “same” ride appears on that day within γ_2 hours of the first day.

To be explicit designate a trip record as $r_{ll'}^{dt}$, where l designates the identified starting census tract, l' designates the ending tract, d is the date, and t is the time of day. Only rides associated with

the same starting and ending tract pair are compared so we can drop the ll' notation. Let R be the set of all trip records which will be compared. For each record $r^{dt} \in R$, the algorithm extracts a subset $R^{dt} = \{r^{ij} \in R : i \in [d - \gamma_1, d + \gamma_1], j \in [t - \gamma_2, t + \gamma_2]\}$. If R^{dt} is not the empty set, record r^{dt} is designated a commuting trip.

Ultimately, “typical” commuting choices are of interest, rather than day-to-day decisions. To convert the trip-level commuting designations into a tract-level measure of cab usage comparable to the data available from the census, a measure of “typical” cab usage is constructed. I simply take the average number of commute trips per day over an extended period of time.

To calibrate the parameters γ_1 and γ_2 , I match predicted taxi commute usage to PUMS-calculated usage for 2009 to 2012, prior to the introduction of green cabs, by year and PUMA in lower Manhattan, i.e. the yellow-taxi exclusive zone depicted in Figure 1. Designate $\mathcal{L} = \{\bar{l}\}$ the set of PUMAs, which is itself a collection of tracts. Let $f_t(l, \gamma_1, \gamma_2)$ be the number of typical taxi commuters identified by the algorithm for tract l in year t and $f_t^{Data}(\bar{l})$ the commuters identified by PUMS data for PUMA \bar{l} . γ_1 and γ_2 are the solution to the following minimization problem.

$$\begin{aligned} & \underset{\gamma_1, \gamma_2}{\text{minimize}} && \sum_t \sum_{\bar{l}} \left(\sum_{l \in \bar{l}} f_t(l, \gamma_1, \gamma_2) - f_t^{Data}(\bar{l}) \right)^2 \\ & \text{subject to} && \gamma_1 \in \mathbb{Z} \end{aligned} \tag{32}$$

The algorithm works on the assumption that people generally leave for work at the same time of day while not necessarily taking a cab every day.

For Uber, I conduct the same exercise using 2014 data in which the TLC-released Uber data is comparable to that available for yellow taxis. I then lump Uber rides in with those of traditional taxis and re-solve Equation 32 matching 2014 PUMS data. Because later Uber data does not include the destination of the trip, I am unable to use these parameters in later years to tease out which Uber trips are allegedly for morning commutes. Instead I calculate the fraction of trips identified in 2014 as commuting trips and assume that fraction holds over time.

C.5 Routing

An important feature of the choice dataset is the time each option takes and how much walking is required as part of that choice. Unfortunately, little of this information is available in the datasets. The one partial exception is that the TLC data does note the time taken to complete realized taxi trips. For walking, transit, driving, and for-hire vehicles in areas with few recorded trips, I use a mix of OpenTripPlanner — an open-source route planning program, much like Google Maps — and a separately built graph of NYC’s road network, based on the LION geographic database of NYC streets. ⁴²

⁴²From source <http://www1.nyc.gov/site/planning/data-maps/open-data/dwn-lion.page>

Mechanically OpenTripPlanner functions similarly enough to Google Maps that it is not worth detailed explanation. A key difference, however, is that the former can be used with arbitrary public transit schedules stored in the General Transit Feed Specification (GTFS) format. For 2016, for example, I utilize the transit schedules published for 2016. While historic, off-schedule delays could also be incorporated, they have not at this time.⁴³

Three pieces of data are fed into the routing program: starting location, ending location, and time of departure. Simulated and survey individuals assigned to a census tract are assumed to start from the centroid of their tract and travel to the centroid of their work tract. Individuals in the travel survey start their trip at the time indicated in the survey while simulated individuals leave at the start of their designated half hour slot. One concern might be that the rough departure assignment overstates the waiting time. For example, I assume a commuter leaves her house at 9:00AM for a proximal train leaving at 9:15AM. Like Google Maps Directions, the wait time at the beginning of the trip is shaved off. Only the time waiting for transfers counts toward the total wait time for that trip.

Vehicle trips are routed through a custom-made graph of New York City’s street network. Simulated and survey individuals are again assumed to start from the centroid of their tract and travel to the centroid of their work tract. Unlike OpenTripPlanner, however, traffic speeds are approximated using data on cab travel time from when the trip was taken.

D General Appendix

D.1 Uber’s Expansion Pattern Across Geographies

This appendix expands on Section 2 by linking changes in the NYC taxi market more closely to density in parts of the city. Again, I use the ratio of building area to ground area in the various taxi zones of the city as the measure of density. Figure 7 depicts density using this metric. Ultimately, this density measure is inappropriate for areas where people congregate in wide space, e.g. parks, and where people magically appear, e.g. airports and train terminals. These zones are thus eliminated from the analysis in this section and noted by a checkered overlay in Figure 7.

I use this measure of density to illustrate two key facts about Uber’s expansion from 2014 to 2016. The first is that market activity in area has grown in terms of total pickups with the sparsity of that area. In the densest areas Uber simply substitutes the existing incumbents. The second notes that Uber dominates in the sparsest areas and most of its growth since 2014 has been redirected to these locales. These results are preliminary evidence of the relative technology position of Uber and incumbents across areas of different density.

The analysis proceeds under the framework of spatial autoregressive models with a spatial lag.

⁴³On average one rests on the hope that the official schedules are correct, but the NYC MTA is becoming more notorious for its delays.

The model is attractive because of several issues present which exacerbate the potential for bias introduced by spatial correlation. First, incumbent taxis and Uber both benefit from local scale and the primary units of analysis, the taxi zones, are not isolated from each other. Unobserved characteristics impacting the variables of interest surely spill over these geographic boundaries. Second, the key regressor, density, is also highly spatially correlated. The general model for these regressions is

$$Y_i = \beta X_i + \rho WY_i + \varepsilon_i \quad (33)$$

The elements in the neighborhood matrix W are defined by

$$w_{ij} = \begin{cases} 1 & \text{if } i \text{ borders } j \\ 0 & \text{if } i = j \\ 0 & \text{all other cases} \end{cases} \quad (34)$$

with ρ serving as the spatial correlation parameter. The unit of analysis is all taxi zones not excluded by the criterion mentioned above for each month January to June 2015 and 2016. Table 8 offers relevant summary statistics for the regressions in and out of the green exclusion zone.

Table 8: **Summary Statistics for SAR**

	Inside the Exclusion Zone			Outside the Exclusion Zone		
	Mean	5th Pctile	95th Pctile	Mean	5th Pctile	95th Pctile
Density	4.212	1.579	9.651	0.687	0.007	1.492
Daily Rides ^a	36945	4861	82343	934	6	5162
Y-Y Growth ^b	5.08%	-2.76%	19.01%	233%	4.28%	1136%
Uber Share ^c	23.5%	14.8%	39.0%	69.6%	25.2%	98.1%

^a Total daily rides per sq mile by zone, as of March 2016

^b Percent change in total rides from March 2015 to 2016

^c Uber share of pickups per zone as of March 2016

The second two rows of Table 8 describe the regressands for the two regression specifications. Beside the spatial lag of the regressand, each of the regressions additionally fit a quadratic function of density, after density has been normalized to be between 1 and 0, and a dummy for whether the zone is in the green exclusion zone. I fit a quadratic of density rather than a single term because patterns between the variables of interest and density tend to break down in the most extreme dense and least dense zones. The results of all specifications are reported in Table 9.

The first specification is reported in the first column of Table 9. The regression establishes the link between zone density and growth. Less dense markets have enjoyed greater growth over the time period. These results hold accounting both for the starting level of rides (“Lag Total”), which appears to be irrelevant, along with the exclusion zone dummy. The fitted function on density is a U shape but for densities lower than .15 (roughly 1.5 in unadjusted terms) the predicted growth is

higher than the densest area. As clear from Table 8, most zones in the outer boroughs fit into this category.

The second specification examines how tightly the substitutions between Uber with yellow and green taxis (called incumbents in Table 9 over time follows from the density of the area. The dependent variable in this set of regressions is the total change — not percent — in Uber rides from 2015 to 2016 in the given month and taxi zone. The additional regressands are the change in yellow and green taxis over the same time period and that term interacted with density. The key variables of interest in this regression are these two terms. If Uber and taxis were perfect substitutes in all locations, the regression would yield -1 on the “incumbent change term”. If instead substitution increases with density the interaction term should be negative. A coefficient of -1 on this term would imply that Uber and taxis approach perfect substitutes in the densest market. Column 2 in Table 9 shows the latter is indeed the result. In the least dense locations of NYC the interaction term is dominated by the incumbent change term and Uber tends to growth with taxis. In the most dense locations incumbent and Uber growth tend to move in opposite directions with an expected rate of substitution of .67 taxis for each new Uber in the most dense market.

Table 9: **SAR Regressions**

	Y-Y Total Growth	Uber Pickup Change
Density	-16.635**	34305.88***
Density ²	14.455**	-14361.21
Exclusion Zone	1.192	-4320.52**
Lag Total	0.000	
Taxi Change		0.314***
Taxi*Density		-0.982***
ρ	0.698***	0.446***
N	1536	1536

Notes: *** $p < 0.01$, ** $p < .05$, * $p < .1$; Observations are at the month- and taxi zone-level for January to June over the period 2015 to 2016. The measure of density defined as zone building area to ground area has been normalized to be between 0 and 1 or these regressions. Taxis are defined as yellow or green taxis in these regressions.

D.2 Transportation Habits

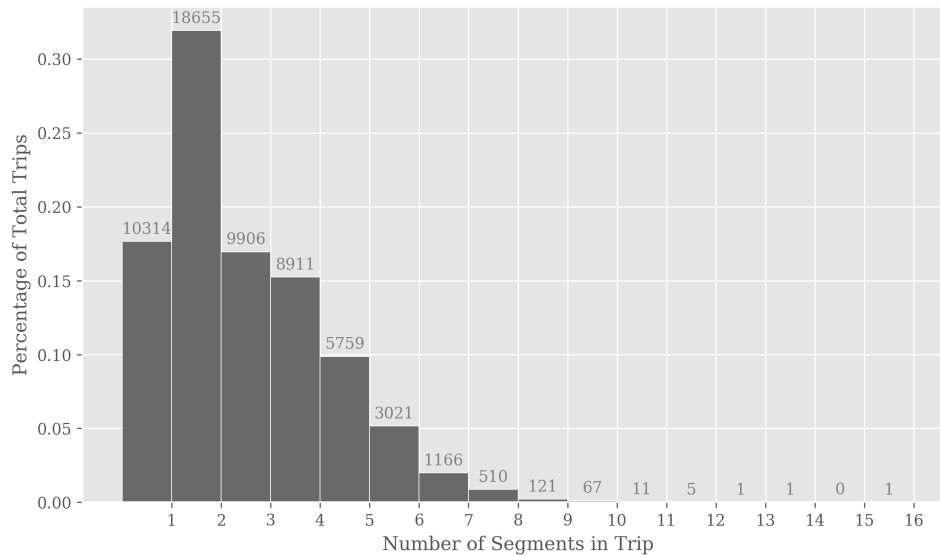
An important assumption in the consumer choice model is that consumers choose a single mode of transit to travel from their origin to their destination. The assumption guarantees a potential consumer’s choice set can be reasonably modeled as a single form of transportation.⁴⁴

⁴⁴One issue that arises from multi-modal transit is the question where mode transitions occur in a trip and the implications for cost, travel time, etc.

To test this assumption I use a transportation survey the Metropolitan Transit Authority conducted over a random sample of NYC residents in mid-to-late 2008. The samples were taken to roughly match demographics and residence distributions across the five boroughs in NYC and within community districts, with locations verified by the participants' home addresses. Over 13,000 households, or 16,000 people, were interviewed with each person offering details on an average of 2 trips, including transit method(s) and destination and origin. These households also provided demographic details and other relevant information, e.g. what kind of MTA card they hold.

Most importantly, the transit survey allows participants to list up to 16 transit segments used to get from origin to destination; a segment change might occur when a passenger switches from one mode of transit to a second or simple at an event like a bus transfer. Figure 23 groups the 58,452 recorded trips by the number of segments.

Figure 23: **Recorded Trips Grouped by Number of Segments**



This figure includes segments where passengers, for example, walk from home to their bus stop. Walking to transit nodes is explicitly modeled so Figure 24 presents the same data without walking segments. Nearly 90% of trips feature only one or two segments. The problem of modeling a consumer's choice set is further reduced by noting that indeed most trips are monomodal. Table 10 illustrates that monomodal, exclusive walking, make up almost 85% of the total sample.

Figure 24: Recorded Trips by Number of Segments, Excluding Walking

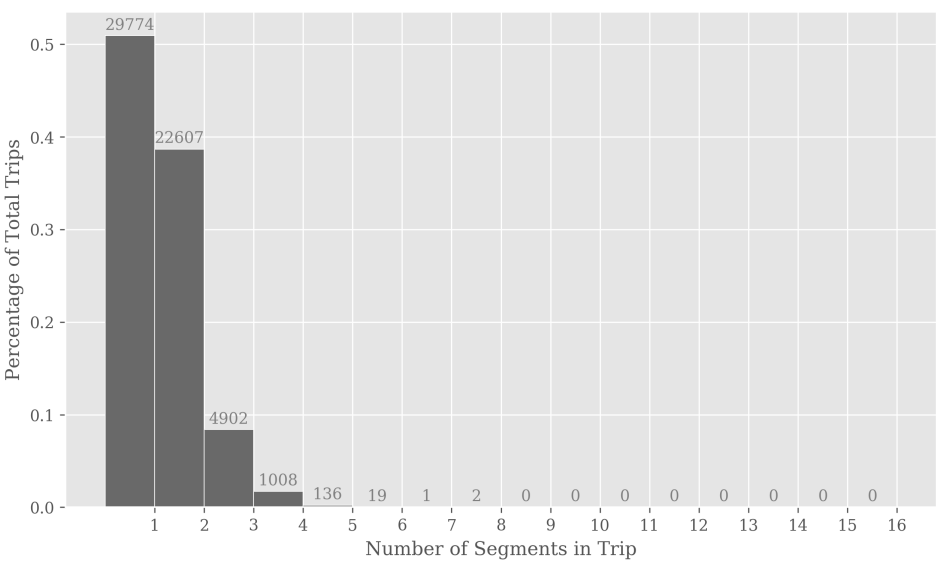


Table 10: Count by Number of Modes

	Unrestricted	Without Walking
1	24594	48434
2	24545	5543
3	8144	493
4+	1169	73