ABSTRACT

Title of Dissertation: ESSAYS ON EMPIRICAL
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This dissertation broadly focuses on two topics in spatial competition. The first two chapters examine the role of regulation in growing shared micromobility market in Washington, DC. The third chapter looks at the fixed broadband market in Wisconsin, USA, and tries to offer insights into the observed spatial pattern of infrastructure upgrades by the incumbents in relation to the entry threat.

In the first chapter, I build and estimate a model of shared micromobility market. The demand side of the market is represented by a standard random utility model. In order to estimate consumer preferences over price and non-price characteristics, I borrow a novel method that accounts for the observed zero market shares in the data. The supply side of the market is represented by a dynamic discrete choice incomplete information game. It is well-known that equilibrium calculation and estimation of these kinds of games are challenging. I employ a variety of concepts and methods that help accommodate those challenges to recover unobserved cost components for scooter operators.

The second chapter builds on the model and estimation results from the first chapter. In this chapter, I conduct counterfactual exercises to analyze the welfare effects of regulation on Washington, DC micromobility market due to local authorities. I specifically focus on two scenarios. In the first scenario, I explore the effect of a policy that promotes equity in dockless vehicle use. I do so by implementing a subsidy to dockless vehicle use in low income neighborhoods. In the second scenario, I explore how welfare outcomes change when the local authority grants fewer permits of operation in the market.

The third chapter aims to explore competitive practices in the fixed broadband industry in the United States. I find that in the face of potential entry by fiber ISPs, incumbent cable modem ISPs strategically invest in upgrading their existing infrastructure. I do so by looking at two kinds of local markets: threatened vs unthreatened by the entry of a fiber ISP. I show that incumbents' network upgrade decisions are monotonic in market size in unthreatened markets while I establish a non-monotonic relation in threatened markets. This evidence is in line with the existing empirical literature on entry deterrence that suggests entry deterring behavior might be unnecessary in smaller markets and a pointless effort in larger markets. In contrast, medium-sized markets could still be a battleground where the incumbent may be able to affect the future competitive environment to a greater degree. Moreover, I employ a discrete hazard model to show that local markets where network upgrades by cable incumbents had already taken place are more likely to receive their first fiber ISP during the sample period.

ESSAYS ON EMPIRICAL INDUSTRIAL ORGANIZATION

by

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Dissertation submitted to the Faculty of the Graduate School of the
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Dedication

Dedicated to the loving memory of my father, Nadir Ertürk.

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I owe my gratitude to all the people who have made this thesis possible. Most importantly, I would like to offer my sincere gratitude to Prof. Andrew Sweeting. He has been more than generous with his excellent guidance, valuable time, and his patience. I admire his professionalism and dedication, and hope that many graduate students in the future will get a chance to learn from him.

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Chapter 1: Regulation in Micromobility Markets: Model and Estimation

1.1 Introduction

Chapter 1 aims to take a look into the shared mobility market in Washington, DC. Specifically, I am interested in the market for shared scooters. In order to analyze this market, I follow a formal modeling approach and set up a demand and supply model of shared scooter market. I recover the key parameters of consumer preferences and scooter operator costs through estimation of this model. The insights from the estimation implemented in this chapter will be used in Chapter 2 to quantify the welfare effects of various aspects of regulation imposed on these markets by the local transportation authority.

In the recent years, many cities around the world have opened their streets to dockless scooters in hopes to offer an environmentally-friendly solution to cover the gap between transit stops and initial/final destinations in local transportation, also known as the first/last mile problem. However, the presence of scooters on the streets has sparked public debate among the residents of cities that welcomed them. The main points of skepticism revolve around the safety issues and parking violations (Sun, 2018). Faced with these concerns, local transportation authorities have responded in a multitude of ways. These responses include, but are not limited to, limiting the number of operators, putting restrictions on fleet sizes, increasing penalties for parking violations, charging higher operation fees for companies, and imposing speed limits on vehicles.

Given that the regulators have power to shape the spatial distribution of vehicles through restrictions mentioned above, efficiency becomes a first-order concern. In relation to this, another interesting restriction on the scooter companies in Washington, DC, from an economic standpoint, is that the pricing on scooter trips is required to be uniform. It is well-known that shared mobility providers such as the ride-share platforms have complex pricing algorithms at their disposal to help them balance demand and supply across time and space. Scooter operators, on the other hand, given the competitive environment that they are subject to, resort to (environmentally and financially) costly fleet rebalancing activities throughout the day in whack-a-mole fashion. Data used in this chapter suggests that for every mile of scooter trip, on average 0.26 miles of rebalancing activity is undertaken, using a conservative measure. In light of this observation, I build a model that will allow me to address the potential effects of regulation in this market. I will use rebalancing activities as a key feature of the supply side model.

Drawing lessons from the existing literature, I first build a theoretical model of the demand side. Following the standard tools in the literature, I set up a differentiated products demand system using nested logit. I estimate the nested logit model using the standard Berry, Levinsohn, and Pakes (1995) method in conjunction with a novel technique developed by Gandhi et al (2020) to account for the prevalence of zero market shares in the data. The implementation of this technique is important because the standard practice in the literature is to use ad hoc fixes to deal with zero market shares. The estimation uncovers riders' preferences over price and non-price determinants of demand. Then, I set up a dynamic discrete choice supply model that captures the unique features of the setting such as rebalancing activities, the dependence of supply of vehicles at a particular location on the origin/destination preferences of riders, and competition. Scooter operators will maximize discounted future profits over choices of rebalancing. Having the computational burden of solving and estimating this dynamic model with large state space in mind, I will make several assumptions. I will adopt the oblivious equilibrium introduced by Weintraub, Benkard, and Van Roy (2008) as the working equilibrium concept. Moreover, I will decentralize operator decision making to some extent by allowing local managers to make decisions over smaller geographical areas rather than allowing a single agent to optimize over the whole city. I use the nested pseudo likelihood procedure (NPL) by Aguirregaibiria and Mira (2007) to estimate the supply model. The estimation will recover the unobserved costs of rebalancing, maintenance, and visibility. The empirical part of this chapter will rely on a high frequency data collected over a month from Washington, DC. Data consists of trips by riders and rebalancing activities undertaken by scooter operators.

Chapter 1 is organized as follows: In Section 2, I give an overview of the related literature. Next, I describe the market background and the data used. In Section 4, I present the model of demand and supply. I discuss the equilibrium concept and solution methods to obtain the equilibrium. I talk about specifics of estimation of the model and the present results in Section 5 and present concluding remarks in Section 6.

1.2 Related literature

I relate to and draw lessons from two broad strands of literature in this chapter: (i) shared mobility markets, (ii) structural models of dynamic discrete choice.

As the proliferation of shared economy becomes an undeniable trend, there is a growing body of literature both in economics and in operations research that investigates shared mobility services markets. Various aspects of these markets were put under scrutiny such as competition and consumer preferences in addition to descriptive studies of micromobility usage patterns. To my knowledge, this is the first empirical study on dockless vehicles with high frequency data in economics literature.

In operations research, He et al. (2020) take on the case of London bike share system and study consumer preferences over station network. They model choice sets for riders to include both origin and destination stations, rather than individual stations. This allows them to capture the network structure of the system. They use their estimates derived from the choice model to compare welfare outcomes of current station density in contrast to alternative station expansion proposals. Similarly, Kabra et al. (2019) look at how improving station accessibility and bike availability improve ridership in Paris bike share system using a demand model.

Cao et al. (2018) study competition between two dockless bike service providers, ofo and Mobike, in China. Using aggregate data that describes trips and staggered entry patterns across regions, they argue that the arrival of an entrant expands the market for the incumbent. Moreover, this expansion effect dominates the market stealing effect that is due to incumbent's old customers' switch to the entrant. They also set up a model of demand and supply to demonstrate the plausibility of this phenomenon in the presence of positive network effects.

Also notably, McKenzie (2019) suggests that there are substantial differences in spatial and temporal patterns of dockless versus docked shared mobility options. The main result that emerges is that users tend to prefer dockless vehicles for leisurely activities more than so for commuting. Qin et al. (2019) provide evidence on the how introduction of dockless vehicles reduces traffic congestion during rush hour. Gu et al. (2019) study the evolution of dockless shared bike systems in China. Allem and Majmundar (2019) give an overview of safety concerns associated with dockless scooters. Chu et al. (2019) argue that the presence of bike share systems leads to reduction in housing premiums by alleviating the first/last mile problem.

The second line of literature this chapter relates to is the literature on dynamic discrete choice models. In this chapter, I set up a theoretical model of the supply side of the shared mobility market where scooter operators maximize expected profits through their rebalancing actions. There is a vast existing literature on dynamic choice models involving oligopolies and the appropriate estimation models that allow inferences based on these models. In particular Bajari, Benkard, and Levin (2007), Pakes, Ostrovsky, and Berry (2007), Aguirregabiria and Mira (2007) present methods that allow the estimation of structural parameters without having to undertake the computational burden of calculating the Markov perfect equilibrium repeatedly. Here, when it comes to the estimation of model parameters, I follow Aguirregabiria and Mira (2007) nested pseudo likelihood (NPL) procedure. This procedure relies on an alternative representation of the Markov perfect equilibrium of the underlying dynamic incomplete information game as a fixed point of the best response mapping in the space of players' choice probabilities.

Although the NPL procedure greatly reduces the computational cost of the estimation of the model parameters, as it will be discussed in the next sections, the dimensions of the problem I deal with still make it nearly impossible to rely on the Markov perfect equilibrium as the working equilibrium concept. Instead, I make use of the oblivious equilibrium concept following Weintraub, Benkard, and Van Roy (2008). Oblivious equilibrium is an approximation to the Markov perfect equilibrium where each player makes decisions based on their own state and the long-run average state of other players. In other words, unlike Markov perfect equilibrium, players no longer take their competitors' current state into account when making their decisions. Adopting the oblivious equilibrium concept reduces the curse of dimensionality problem I face to a great extent. In addition, I take one more step toward easing the computational complexity of the problem by assuming that the scooter operators delegate local managers that make decisions over a smaller geographical region. This approach is due to Aguirregabiria and Ho (2010). Thanks to this approach, every agent in the model have to follow their own state over a smaller geographical region, rather than every operator following their own state over the whole city.

1.3 Market overview and data

In this section, I give an overview of the shared micromobility markets. I describe the regulatory environment that shapes both general and day-to-day operations of micromobility providers in Washington, DC. I also describe the data used in this chapter.

1.3.1 Shared dockless scooter market background

A typical scooter trip works as follows: A potential rider has to use Company X's mobile application if they wish to hire a vehicle that is operated by Company X. As the potential rider opens the mobile application they will see a map on their screen that shows them nearby vehicles that are operated by Company X. Once they reach the vehicle that they wish to rent, they have to use the application to scan the QR code on the scooter/bike. This will unlock the vehicle. This marks the beginning of a trip. The rider will use the vehicle to arrive at their preferred destination. Once the destination is reached, the rider has to use the mobile application again to end the trip. The cost of a trip depends on the duration of the trip (rather than the distance) which will be calculated at the end of the trip.

Micromobility markets in the USA are subject to varying degrees of regulation by local transportation authorities. In Washington, DC the regulating authority is the District Department of Transportation (DDOT). The DDOT determines various aspects of operations of micromobility service providers. The DDOT determines which companies get to provide services in DC. Since the inception of the pilot program in 2018, the DDOT has been awarding permits to scooter operators every year. In 2019, the DDOT granted eight permits to shared scooter service providers. These operators and the number of vehicles authorized for the permit holders are as follows: Bird(600), Bolt(600), Jump(600), Lime(675), Lyft(720), Razor(600) Skip(720), Spin(720). Each operator has its own fee schedule. Fees for some of the operators take the form of a two-part tariff. A flat fee is paid for unlocking the vehicle and on top of this, the rider pays a per minute charge. Table 1.1 describes the price schedule in effect as of September 2019. Operators are required to charge uniform prices across the city and at all times.

Table 1.1: Fee Structure

Operator	Unlocking fee	Per minute charge	Total cost of 10 minute ride
Bird	$1	$0.29	$3.90
Bolt	none	$0.30	$3.00
Jump	none	$0.25	$2.50
Lime	$1	$0.24	$3.40
Lyft	$1	$0.24	$3.40
Skip	$1	$0.25	$3.50
Spin	none	$0.29	$2.90
Razor	$1	$0.24	$3.40

In addition to offering permits to operate, determining the fleet sizes, and regulating pricing, the DDOT also takes measures to promote equal access. The DDOT also requires operators to offer a low-income customer plan to any customer with an income level at or below 200% of the federal poverty guidelines. It also encourages operators to keep a steady supply at equity emphasis areas designated by the city by collecting data on the number of trips initiated in these areas. These numbers are then factored in the DDOT's decision to renew permits for the next year.

1.3.2 Data collection

In addition to those mentioned in the previous section, there is one other requirement for permit holders in DC, to which I owe the data set used here. Permit holders are required to provide a publicly accessible application program interface (API) that shows the current locations of dockless vehicles available for rental, at all times. This information is publicly available in real-time through the DDOT website, although past data are not available.[1] Bulk of the data used in this chapter comes from the public API. I also use data from a mobile application developed by a third party aggregator, called Scooter Map. The data provided in this mobile application is essentially the same as that provided in DDOT Dockless Vehicles API, with a single exception. Some scooter operators choose to mask unique vehicle identifiers when sharing their data through the public API. This makes it impossible for me to track a vehicle over time. On the other hand, vehicle identifiers are visible in the information shared on Scooter Map. Hence, I can complement data from the public API with data from Scooter Map. I collect data from these two sources for a period covering October 2019-November 2019.

The data are in the form of two-minute interval snapshots for vacant vehicles all around the city. For each vehicle, I observe the operator that the vehicle belongs to, a unique vehicle identity, exact latitude, and longitude of the vehicle. In addition to these, some of the operators also publish the battery level of their vehicles. Using the availability snapshots, I infer trips in

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[1] For real-time available dockless vehicle information: `https://ddot.dc.gov/page/dockless-api`

the following fashion: Imagine a unique vehicle ID appearing at location (38.9213, -77.0437) in a snapshot. Say, then this particular vehicle does not appear in the data for the upcoming five snapshots. In the sixth snapshot, it appears back, but this time at the location (38.9152, -77.0314). Then, I infer that a trip has happened during those 12 minutes over a distance of roughly around 1 mile. Tracking all vehicles in this fashion, I can infer all scooter trips in the city for each day. Table 1.2 summarizes the distance and duration of these inferred trips. Trips taken with scooters tend to be short in distance and duration, supporting the idea of first/last mile usage of micromobility alternatives.

	Mean	SD	25%	75%
Trip Duration(mins)	12	8	8	22
Trip Distance(km)	0.7	0.52	0.28	1.1

Table 1.2: Trips summary

Along with the trips, there is also another kind of movement of vehicles that are crucial for my purposes. From the data set, I can infer rebalancing activities that the operators perform throughout the day. The kinds of fleet rebalancing activities by a firm happen in a number of ways. The most common way in which an operator rebalances its fleet is to drop off more vehicles and pick up vehicles from locations around the city. I can observe this kind of activity in the data I collected. If a unique vehicle ID was not present in the data since the beginning of the day and appears at a later period, I can infer that the operator has dropped off new vehicles. Similarly, if a unique vehicle ID disappears from the data before the end of the day, then I can infer that the operator has chosen to pick up the vehicle. I mark these types of activities as rebalancing unless they occur at the beginning or end of the day to avoid picking up the recharging activities as much as possible. Data also reveals occasional long term disappearances of vehicles. Whenever a vehicle disappears for longer than an hour and appears at a different location, I classify this movement to be a rebalancing activity as well. The average trip length is about 12 minutes, which means an hour as a cut-off is a conservative choice. In Table 1.3, I report the daily average number of drop-offs and pick-ups I infer from the data. Figure 1.1 describes the spatial distribution of these activities for a given day.

	Drop-off	Pick-Up
Bolt	42	45
Jump	151	137
Lime	145	170
Skip	113	123
Spin	89	95
Razor	56	62

Table 1.3: Average daily rebalancing activities per operator

Even though the data covers the entire Washington, DC area, due to the sparse presence of scooters in certain parts of the city, I restrict attention to 215 block groups which correspond to roughly one-third of the city's area. This leaves me with 152,137 unique trips and 38,473 unique rebalancing activities I categorize 50 block groups as downtown and the rest as non-downtown locations. The map of the area of study can be found in Figure 1.2.

For the differentiated products demand system that I will be setting up in the next section, I let rider preferences depend on product characteristics. To create variables that describe product characteristics, I use the DDOT's evaluations for each operator's performance on various dimensions of operations. DDOT uses this scoring scheme for the purpose of granting permits

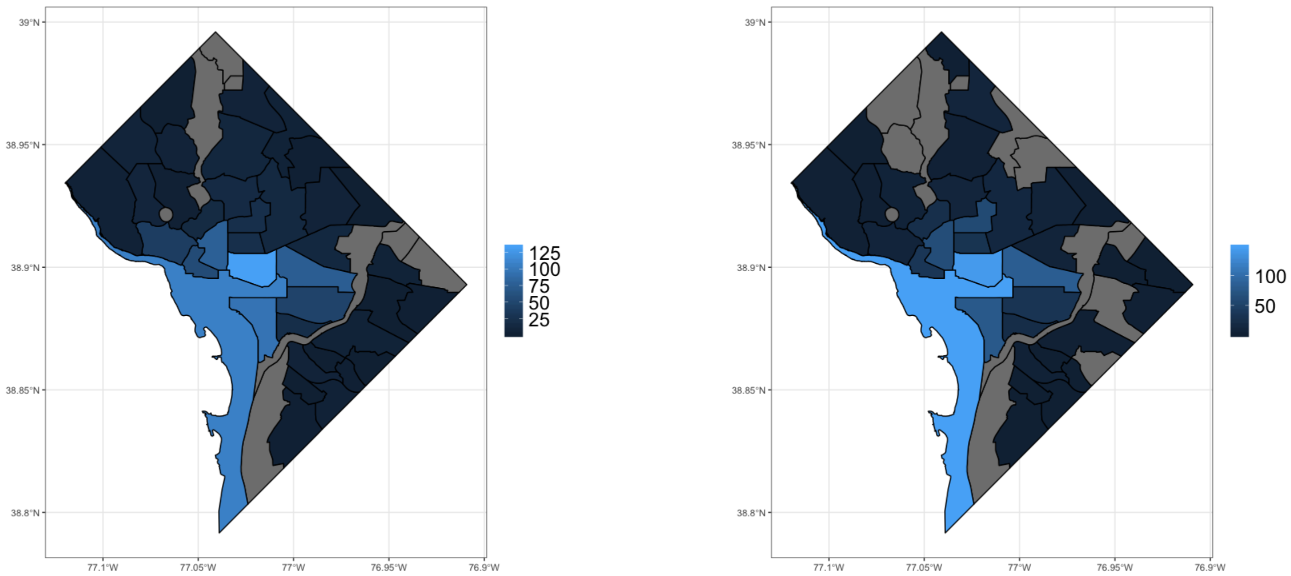

Figure 1.1: Rebalancing activities across neighborhoods

Note: Left panel shows pick-ups and right panel shows drop offs

for the upcoming year and evaluating requests to increase fleet sizes. DDOT scores operators on accountability, sound equipment design, sustainability, and safety. These scores are publicly available at the DDOT website.

1.4 Model

In this section, I present: (1) a discrete choice demand model for differentiated products; (2) a supply model that captures the key features of the operation of scooter operators; (3)

1.4.1 Demand

I use a standard nested logit model to describe demand by riders. I define a market as a location l-time t pair. A potential rider in a given market can either choose to ride a vehicle operated by one of the scooter firms in the market, depending on availability, or may choose the outside

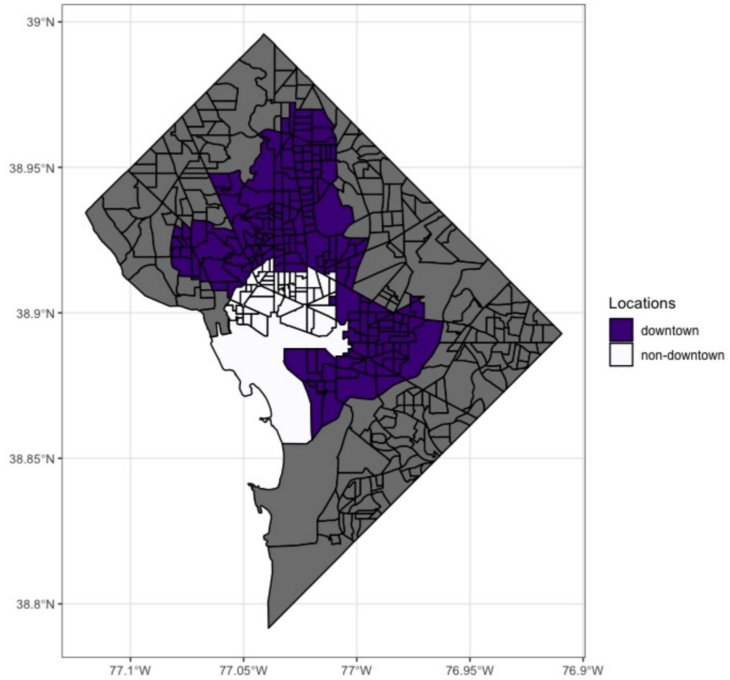

Figure 1.2: Area of study

option (walking, public transportation, on-demand ride services, etc.) to complete the desired trip. All scooter options are nested in one group and the outside option is nested in a separate group. The indirect utility of potential rider i in market lt, from riding a scooter by operator f is given by:

$$\begin{aligned} U_{iflt} =& x_{flt}\beta + \alpha ln(y_l - p_{flt}) + \xi_{flt} + \zeta_{i,g(j)lt} + (1-\sigma)\varepsilon_{iflt} \\ &= \delta_{flt} + \zeta_{ig(j)lt} + (1-\sigma)\varepsilon_{iflt} \end{aligned} \tag{1.1}$$

where x_{flt} is observed product characteristics, p_{flt} is the price of riding a scooter by company f and y_l is the daily median household income in location l. ξ_{flt} is product-specific unobservable, ε_{iflt} is i.i.d Type I Extreme Value, $\zeta_{i,g(j)lt}$ is the group specific taste of the consumer. The parameter σ, known as the nesting parameter, governs the degree of substitution between the two groups, scooters versus the outside option. As σ approaches 1, within group substitution becomes stronger; and as σ approaches 0, substitution within nest becomes weaker and the model reverts back to standard multinomial logit. Mean utility of outside option, δ_{0lt} is normalized to 0, so that:

$$U_{i0lt} = \alpha ln(y_l) + \zeta_{i0lt} + (1-\sigma)\varepsilon_{i0lt} \tag{1.2}$$

The implied market shares for some firm f in market l, t can be written as:

$$s_f = s_{f|g}s_g = \frac{e^{\frac{\delta_f}{1-\sigma}} I_g^{-\sigma}}{1 + I_g^{1-\sigma}} \tag{1.3}$$

where $I_g = \sum\limits_{f \in g} e^{\frac{\delta_f}{(1-\sigma)}}$.

1.4.2 Supply

I describe a dynamic discrete game with incomplete information to capture the defining features of the supply side of the market. Model scooter operators will maximize expected discounted profits by choosing optimal rebalancing activities.

1.4.2.1 Environment

There are F operators, indexed by $f \in \{1, \ldots, F\}$, that are permitted to operate in the market. Each operator delegates rebalancing decisions to a set of local managers, each of which oversees a smaller region within the city. The city is divided into R regions and a local manager is therefore indexed by a region r and operator f. Each region r consists of M locations, indexed by m. The city consists of $R \times M = L$ locations. Each period t, local managers decide simultaneously on how to rebalance locations, i.e. manage the supply within their own region. A local manager's set of rebalancing choice alternatives in a location is $\{-a, \ldots, 0, \ldots, a\}$ which is finite and discrete. Negative values in this set represent a local manager taking a scooters off (rebalancing down) the street while positive values represent dropping off a additional vehicles (rebalancing up). Hence, the rebalancing decision is how a local manager controls the supply of vehicles in the locations they oversee.

In practice, my data contains 6 scooter operators. I use Washington, DC block groups as locations and I form regions by grouping 5 adjacent locations together. A map of the area of study can be found in Figure 1.2. Excluding locations without consistent scooter presence, my sample will consist of 215 block groups which are then divided into 43 regions. The concept of local managers should be considered as a modeling assumption rather than an actual description of operator behavior. In reality, how the operators make the rebalancing decisions varies from operator to operator. Anecdotes from employees suggest that while some operators rely on complicated algorithms to direct their employees in real-time on the ground, other operators follow less sophisticated methods. Even in face of these nonuniform approaches adopted by the operators, the natural way to model rebalancing decisions would be to centralize the decision making at the operator level. However, due to the fact that the size of the state space implied by such an approach is enormous, it is unfeasible. Therefore, local managers assumption is used to facilitate estimation and equilibrium calculations.

The decision of local manager r of operator f in location m at time t is denoted by a_{mt}^{fr}. At the beginning of period t, a local manager's problem is characterized by two state variables that determines profits: (1) A collection of vectors that describe the states of all local managers, $x_t \equiv \{x_t^{1,1}, \ldots, x_t^{f,r}, \ldots, x_t^{F,R}\}$, which denote the supply of vehicles by each operator at every location (2) ε_t^{fr}, private information for local manager f, r. These shocks represent factors that affect local managers' rebalancing decisions that are not captured by revenues and costs.

Local manager chooses rebalancing action a_{mt}^{fr} each period to maximize expected discounted intertemporal profits,

$$E\left\{\sum_{t=s}^{\infty}\beta^{t-s}\sum_{m=1}^{M}\Pi^{fr}(a_{ms}^{fr},x_s,\epsilon_{ms}^{fr})\mid x_t,\epsilon_t^{fr}\right\}, \tag{1.4}$$

where Π is the per period profit function in location m and β is a discount factor.

In the data set, I observe that a location can have 0 to 50 vehicles at a given moment although over 95.5% of observations fall within 0 to 10 vehicles and 93.1% of observations fall within 0 to 5 vehicles. When constructing the state space, I take 10 to be the maximum number of vehicles that can be available at a location. With 5 locations to be overseen by a given local manager, and restricting the total number of vehicles over a region to 13, I get 8,463 states per local manager. I restrict the action space to be $-1, 0, 1$ with no ability to rebalance down when a location has no vehicles and no ability to rebalance up when a location has 10 vehicles.

The assumptions on model primitives Π, x, and ϵ are as follows:

- *Assumption 1*— Additive separability: Private information of the operator enters additively in the profit function

- *Assumption 2*— Conditional independence: Private information variables do not affect the transition of common knowledge state variables given local manager's decision and private information variables are identically and independently distributed over time.

- *Assumption 3*— Independent private information: Private information is independently distributed across players.

- *Assumption 4*— Discrete common knowledge variables: Common knowledge variables are discrete and have a finite support.

These are common assumptions in the literature for dynamic discrete choice settings. Assumption 1-3 is crucial to make estimation tractable (Rust, 1987). Assumption 4 is crucial to follow the estimation method presented in Aguirregabiria and Mira (2007) and the assumption doesn't impose any restrictions in the context of scooters.

1.4.2.2 Per period profit functions

In this section, I present the per period payoff functions for local managers. Current profits for a local manager in location m is given by:

$$\begin{aligned}&\Pi_m^{fr}(a_{mt}^{fr}, x_t) + \theta^{\epsilon}\epsilon_{mt}^{fr}(a_{mt}^{fr})\\ &= \left[\sum_{l}^{L} p^f \tau_{ml} \min\{d_m s_{mt}^{fr}, x_{mt}^{fr}\}\right] - w^{fr}(a_{mt}^{fr}, x_{mt}^{fr})\theta^{reb,fr} - c(x_t^{fr})\theta^{main} - h(x_t^{-f,r})\theta^{vis.} + \theta^{\epsilon}\epsilon(a_{mt}^{fr}).\end{aligned} \tag{1.5}$$

Revenues: First term in the brackets represents revenues to the local manager from trips that originate in location m. Since fees are based on trip durations, trip destinations matter for revenue calculation purposes. Accordingly, revenues from a given origin location will be given by summation over revenues from all possible destination locations l. p^f represents the price. τ_{ml} is the entry ml of the adjacency matrix T that summarizes trip origin-destination preferences weighed with trip durations. Therefore, τ_{ml} is the proportion of trips that originate from m towards some destination location l times the duration of a trip between m and l. The term in the minimum operator represents number of trips initiated at location m. d_m is the market size for location m and s_{mt}^f is the market share of operator f in location m. The total number of trips that originate from location m is the minimum of trips demanded and supply of vehicles at location m. So the number of trips that originate at location m cannot exceed the supply of vehicles.

In practice, I calculate the adjacency matrix T based on inferred trips data. For each origin-destination pair, the relevant matrix entry is calculated as the multiplication of the following: (1) trip duration averaged over all trips from origin location to destination location (2) proportion that indicates destination popularity given an origin location averaged over all trips taken from the origin location. Market share s^{f}_{mt} are predicted by the demand model presented in section 1.4.1. Shares are calculated according to equation 1.3.

Rebalancing costs: $w^{fr}(a^{fr}_{mt})\theta^{reb.,fr}$ stands for the rebalancing costs that the local manager incurs in location m. These may include expenses for trucks and employees necessary to undertake the rebalancing activities. Rebalancing costs depend on the operator, the state in location m, the type of rebalancing choice, and characteristics of location m. In practice, I will estimate 24 parameters for $\theta^{reb.}$ for 6 operators, for rebalancing up and down in downtown and non-downtown locations.

Maintanence cost: $c(x^{fr}_{t})\theta^{main.}$ represents maintenance costs incurred by the local manager. It captures the expenses incurred to keep the vehicles on the street in operating condition. I allow maintenance costs to depend on the local manager's state in location m. In practice, I will estimate 1 parameter $\theta^{main.}$.

Visibility cost: $h(x^{-f,r}_{t})\theta^{vis.}$ captures the effect of visibility on local manager's profits. Visibility indicates a local manager's vehicle stock at a location in proportion to competitors' stock. It is reasonable to expect that local manager's supply decisions are to some extent shaped by building a presence in order to attract more riders. Increased presence may also help operators to build their brand in the long run. The natural way to build the effect of visibility into the model would be to incorporate it in the demand side. Without a term to explicitly account for visibility in the demand model, the effect of visibility on competition cannot be fully captured by the market shares. However, allowing for a visibility term in the nested logit demand system causes the demand estimates to be inelastic. Therefore, I add a term in the payoff function to take care of the effect of visibility on local competition. Visibility cost is a function of the proportion of a local manager's supply of vehicles in the total vehicle supply in a location. I assume that the parameter on visibility cost is the same across all operators and therefore estimate 1 parameter $\theta^{comp.}$.

Payoff shock: $\theta^{\epsilon}\epsilon(a_{mt}^{fr})$ represents i.i.d payoff shocks from each possible rebalancing action. These shocks are drawn from Type 1 extreme value distribution. θ^{ϵ} is the scale of the payoff shock. The shocks are private information and they capture all unobservable factors that affect local managers' rebalancing decisions. These could include factors such as rebalancing team's distance to the location, traffic conditions to get to the desired location, potential parking violations that need to be addressed, etc.

1.4.2.3 Timing of events

Within each period t, the timing of events are as follows:

1. Local manager observes their state, i.e. the beginning of period supply of vehicles within their respective regions.

2. Local manager pays maintenance and visibility costs.

3. New trips depart their origin locations. Realized trips are determined by the predicted shares, origin-destination preferences, and availability of vehicles.

4. Local managers observe their private information payoff shocks. Rebalancing decisions are made and rebalancing activities are finalized. Rebalancing costs are paid accordingly.

5. Trips that started within the period reach their destination. The period ends.

1.4.3 Value functions and equilibrium concept

Before laying out the dynamic model further, I have to make it clear that in order to model interactions between local managers, I rely on the concept of oblivious equilibrium introduced by Weintraub et al. (2008). The dimensions of the problem make it near impossible for a given local manager to follow the full industry state as a Markov perfect approach would require. In contrast, the oblivious equilibrium allows each local manager to make their decisions based on long run stationary states of other local managers. I assume that each local manager is oblivious to both the competitor operators' local managers' and own operator's local managers' (coworkers) states. This choice of equilibrium concept has important implications on the per-period profit functions and the state transitions.

A local manager's state in region r is the number of vehicles in each location m in region r at the beginning of period t. The next period state in r is determined by the following: (1) the current state; (2) the inflow of vehicles into each location m (trips that originated elsewhere in the city that arrive in m); (3) the outflow of vehicles (trips that originate from each location m); (4) the rebalancing decisions. Inflows and outflows in turn are determined by the adjacency matrix (τ), state of all local managers affiliated with firm f (denoted x_t^f), and the market shares of firm f in all locations m predicted by the demand model.

It is easy to calculate the outflows for a local manager since outflows only depend on the beginning of state supply of vehicles within the region and demand. However, in order to calculate the actual inflows, each local manager would have to fully observe coworkers' states, x_t^f. Given the infeasibility of this task, I allow each local manager to form expectations on inflows into their own region based on the long run average states of their coworkers. Following an oblivious approach, given an arbitrary set of strategies (choice probabilities conditional on state) for local managers and a guess on coworkers' states, I can calculate a state transition matrix for a local manager that governs probability of reaching a future own state given current own state $f(x_{t+1}^{fr} \mid x_t^{fr}, \tilde{x}_t^{f,-r})$ where $\tilde{x}_t^{f,-r}$ is the long run expected state of all other coworkers. I do this following an iterative approach. For every local manager, I do the following to calculate transitions: Given a current state, I can calculate expected departures using predicted shares from the demand model. Given a guess on coworkers' state, I can calculate arrivals using predicted shares in coworkers' locations and the origin destination preferences matrix. These outflows and expected inflows determine local manager's supply next period before she undertakes any rebalancing activity in her region. Using the guess on conditional choice probabilities for rebalancing actions, I can now calculate the probability with which a local manager will find herself in a particular state in the upcoming period. Doing this for all possible current states for the local manager yields a transition matrix for the local manager. Next, I calculate the stationary distribution implied by the transition probabilities matrix. Using the stationary distribution, I can now calculate the expected long run state for the local manager. Then, I update guesses on coworkers' states based on the the expectations from the previous calculations. I follow these steps until the updated guesses on long run states match the long run states implied by the flow of vehicles and transition matrices.

Note that visibility cost of a local manager is a function of other operators' long run average state. Expectations for the competitors' local managers' states will be formed in the same fashion as explained above. This iterative approach is embedded in the equilibrium calculation. In each iteration to calculate equilibrium conditional choice probabilities, new expected long run states for local managers are calculated.

Let μ^{fr} be a stationary oblivious strategy for a local manager that maps a state (x^{fr}, ϵ^{fr}) to an action a^{fr} regardless of period t. Let μ describe oblivious strategies for all local managers. Then, for local manager with a particular state who uses her optimal strategy while other local managers play according to μ, I can write oblivious value function $V^{\mu}_{f,r,m}(x^{fr}_t, \tilde{x}_t(\mu), \epsilon^{fr}_{mt})$ as:

$$\begin{aligned} V^{\mu}_{f,r,m}(x^{fr}_t, \epsilon^{fr}_{mt}) = \\ & \max_{a\in A}\Big[\Pi_m(a, x^{fr}_t, \tilde{x}(\mu)) + \theta^{\epsilon}\epsilon^{fr}_{mt}(a) \\ & + \beta \sum_{x^{fr}_{t+1}\in X}\Big[\int V^{\mu}_{f,r,m}(x^{fr}_{t+1}, \epsilon^{fr}_{m,t+1})g(\epsilon)d\epsilon\Big] f(x^{fr}_{t+1} \mid a, x^{fr}_t, \tilde{x}^{f,-r}_t(\mu)\Big] \end{aligned} \tag{1.6}$$

by Bellman's optimality principle. Define the integrated value function as:

$$\bar{V}_{f,r,m}(x^{fr}_t) = \int V(x^{fr}_t, \epsilon^{fr}_{mt})g(\epsilon)d\epsilon \tag{1.7}$$

Then, choice specific oblivious value function for local manager f, r at location m net of current payoff shock can be written as:

$$v^{\mu}_{f,r,m}(a, x^{fr}_t) =$$

$$\Pi_m(a, x^{fr}_t, \tilde{x}(\mu)) + \beta \sum_{x^{fr}_{t+1} \in X} \bar{V}^{\mu}_{f,r,m}(x^{fr}_{t+1}) f(x^{fr}_{t+1} \mid a, x^{fr}_t, \tilde{x}^{f,-r}_t(\mu)). \tag{1.8}$$

Finally, given the distribution of payoff shocks, the conditional choice probabilities (CCPs) can be written as:

$$P^{\mu}_{f,r,m}(a, x^{fr}) = \frac{exp\left(\frac{v^{\mu}_{f,r,m}(a, x^{fr}_t)}{\theta^{\epsilon}}\right)}{\sum_{\bar{a} \in A} exp\left(\frac{v^{\mu}_{f,r,m}(\bar{a}, x^{fr}_t)}{\theta^{\epsilon}}\right)} \tag{1.9}$$

1.4.3.1 Solving for the equilibrium:

In order to solve for the oblivious strategies that constitute an equilibrium of this game, I do the following:

1. Set model demand and supply parameters obtained from the estimation. Calculate origin-destination preferences matrix T. Set the discount parameter (0.99).
2. Set an initial guess for conditional choice probabilities μ^0.
3. For every local manager, set an initial guess on long run expected state of coworkers and competitors' local managers $\tilde{x}^{0,0,\mu}$.
4. Given the guesses for conditional choice probabilities and long run states, calculate state transition densities for each local manager.

5. Use transition densities to calculate long run distribution of states and calculate long-run expected states for each local manager.

6. Update the expectations of coworkers' and competitors' states until the long-run expectations match each local managers' guess $\tilde{x}^{0^*,\mu}$.

7. Given the updated expectations $\tilde{x}^{0^*,\mu}$, calculate profit functions given a set of demand and supply parameters (α, β, θ).

8. Construct value functions using state transitions and use value function iteration to calculate values.

9. Using value functions calculate new conditional choice probabilities μ^1 according to 1.9.

10. Repeat steps 3-8 until conditional choice probabilities $abs(max\{\mu^k - \mu^{k-1}\})$ is within tolerance (1e-6) to obtain equilibrium choice probabilities μ^*.

1.5 Estimation and results

Estimation of the model presented above consists of two main stages. In the first stage: (i) I estimate demand side parameters (β, α, σ) using an instrumental variables generalized method of moments approach; (ii) using demand side data and parameters estimated, I calculate origin-destination preferences, the average trip duration for origin-destination pairs, and using these, I calculate revenues; (iii) I estimate initial conditional choice probabilities that are necessary to initiate the nested pseudo likelihood procedure. In the second stage, I estimate ($\theta^{reb.}, \theta^{main.}, \theta^{vis.}, \theta^{\epsilon}$) using nested pseudo likelihood procedure.

1.5.1 Nested logit demand

To understand riders' preferences, I estimate the discrete choice differentiated products demand model based on the nested logit model explained in section 1.4.1.

I aggregate the trips inferred from the vehicle availability data at block group-hour level. This aggregation allows me to calculate market level product shares for each operator. Following Berry (1994), I rewrite demand equations:

$$log(s_{flt}) - log(s_{0lt}) = x_{flt}\beta - \alpha\frac{p_{flt}}{y_l} + \xi_{flt} + \sigma log(s_{glt}) \tag{1.10}$$

where s_{flt} is the market share of operator f in market lt, s_{0lt} is the market share of the outside option, and s_{glt} is the market share of the nest g (market share of scooters in this case). The market size is defined as 10% of the block group population plus 10% of number of jobs per block group. Note that in the above specification I make use of $ln(y_l - p_{fl}) \approx ln(y_l) - \alpha\frac{p_{fl}}{y_l}$. The term $ln(y_l)$ drops out from 1.10 since it is common to all choices. x includes product characteristics for the operators defined as the DDOT assessments on safety, accountability, sound equipment. The values for these product characteristics are weighed by availability of vehicles to add variation. The regression specification includes operator, location, day fixed effects.

Parameters on price α and within-group share σ are prone to endogeneity problem since unobserved characteristics may be correlated with price and group share variables. Even though operators are required to use uniform pricing for all locations throughout the city, the price they set is at their discretion. At the time of setting prices, operators are likely to take the unobserved product characteristics into account. Therefore I use an instrumental variables (IV) approach to deal with the problem of endogeneity. Price and within-group share variables will be instrumented by sums of product characteristics by other operators. Instrumental variables of this sort are common in the literature. The identification relies on the assumption of orthogonality of these observed characteristics with the unobserved characteristics. Since product characteristics in my setting come from the evaluations by the regulating authority, it is plausible to argue their exogeneity. Instruments defined in this way are appropriate for my setting since operators' vehicle availability varies across markets, hence also the choice sets of consumers. This introduces some variation in the instruments across markets.

Before presenting the estimation results for demand parameters, I have to address one salient feature of the data. I encounter a significant amount of zero market shares for the scooter operators. The next section describes the method used to deal with zero market shares.

1.5.2 Zero market shares

I encounter a significant amount of zero market shares for the scooter operators. Zero market shares emerge when a particular operator's vehicles remain idle at a particular location throughout a given day-hour period. For the 6 operators in my sample, zero market shares emerge in 15-40% of time.

Standard estimation procedures for demand estimation with aggregate data such as the Berry (1994) cannot be used in the presence of zero empirical market shares because logarithms of zero market shares are not well defined. Therefore, most applications of discrete choice demand models with aggregate data resort to ad hoc fixes when faced with the zero market share problem. Aggregating data over larger areas or longer time period could be an alternative but this would result in losing richness of the data. Dropping alternatives with zero market shares is one of the fixes, which would mean those alternatives are combined with the outside option. When zero market shares are prevalent in the data, dropping observations can lead to large biases. Another way in which zero market shares are often treated is to add a small number to them. This method cures the symptom but the underlying problem remains undealt with, as Gandhi et al.(2020) discuss. Ultimately, these ad hoc fixes produce biased estimates.

Gandhi et al.(2020) develop asymptotically consistent point estimators using moment inequalities to handle presence of zero market shares. They first identify the source of bias created by the presence of zero market shares as the wedge between choice probabilities which are derived from the theoretical model of demand and market shares which are interpreted as the empirical counterparts of those choice probabilities obtained from the data. When the choice probabilities are small, this is often manifested as zero market shares in the data. Methods that rely on constructing moment conditions based on substitution of empirical market shares for theoretical choice probabilities are therefore subject to bias. The method that Gandhi et al. (2020) proposes bounding the mean utilities from above and below and constructing moment inequalities based on these bounds. Even though the demand estimates are obtained through moment inequalities, the method yields point estimates. The point estimates are given by a GMM type estimation that minimizes deviations from moment inequalities. Gandhi et al. (2020) proves that these estimates are consistent under plausible assumptions. The important assumption is the existence of some product with market share bounded away from zero. The identification comes from these *safe* products. As long as there is an instrumental variable that can identify observations of safe products, consistency of the estimator is achieved. This assumption is easily satisfied in most settings because the share of outside good usually tends to be sufficiently away from zero.

In my setting, the lowest value the outside good's share attains is 0.83.

Moment inequalities are based on bounds constructed for mean utility δ_{ft} (Here I suppress the subscript for location l to simplify notation and let t represent a market a market-location pair). Mean utility will be bounded from below and above by δ_{ft}^{ℓ} and δ_{ft}^{u} with $\delta_{ft}^{u} > \delta_{ft}^{\ell}$. For nested logit, these bounds will be defined as:

$$\delta_{ft}^{u} = (1-\sigma)\text{log}((n_t s_{ft} + \iota_u)/n_t) - \text{log}(s_{0t}) + \sigma\text{log}(s_{gt}) \tag{1.11}$$

$$\delta_{ft}^{\ell} = (1-\sigma)\text{log}((n_t s_{ft} + \iota_{\ell})/n_t) - \text{log}(s_{0t}) + \sigma\text{log}(s_{gt}) \tag{1.12}$$

where n_t is the market size. ι_u and ι_l are positive constants.[2] The identification comes from the fact that bounds will be tight for safe products with market shares away from zero whereas for risky products with zero market shares, bounds will be large but will still hold. Even though risky products won't contribute, they don't impair the identification.

Let $\lambda = (\beta, \sigma)$. Based on (1.11) and (1.12), moment conditions are written:

$$m_T^{u}(\lambda, g) = T^{-1}\sum_{t=1}^{T}\sum_{f=1}^{F_t}(\delta_{ft}^{u} - x'_{ft}\beta)g(z_{ft}) \tag{1.13}$$

$$m_T^{\ell}(\lambda, g) = T^{-1}\sum_{t=1}^{T}\sum_{f=1}^{F_t}(\delta_{ft}^{\ell} - x'_{ft}\beta)g(z_{ft}) \tag{1.14}$$

where θ is the parameter vector and $g(z) \in \mathbb{G}$ denotes instrumental indicator functions, which will be detailed later. The objective function based on these moments is written as:

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[2] In practice as Gandhi et al. (2020) suggest, I use $\iota_u = 2$ and $\iota_\ell = 2^{-12}$. For more detail on derivation of these values, refer to Gandhi et al. (2020).

$$\begin{aligned} Q_T(\lambda) =& \sum_{g \in \mathbb{G}} \mu(g) \left([m_T^u(\lambda, g)]_-^2 + [m_T^\ell(\lambda, g)]_+^2 \right) \text{ and} \\ \hat{\lambda} =& \arg\min_{\lambda \in \Lambda} Q_T(\lambda) \end{aligned} \tag{1.15}$$

where $\mu(g) : \mathbb{G} \to [0,1]$ is a probability mass function over collection of instruments $\mathbb{G}$.[3] This GMM-like procedure will yield θ such that the distance between upper and lower bounds are minimized. The implementation of the method requires the instrument space to be discretized. I follow Andrews and Shi (2013) to create indicator functions of hypercubes, that are rich enough to preserve the information provided by the instruments. To do this, I first normalize all continuous instruments to be in $[0,1]$ interval. I denote set of continuous instruments as Z_c with dimension d_{z_c} and the set discrete instruments as Z_d. $g(z)$ are created according to:

$$\mathbb{G} = \{g_{a,r,\zeta}(z_d, z_c) = \mathbb{1}((z_c', z_d')' \in C_{a,r,\zeta}) : C_{a,r,\zeta} \in \mathbb{C}\} \tag{1.16}$$

where

$$\begin{aligned} \mathbb{C} =& \{(\times_{u=1}^{d_{z_c}} [(a_u - 1)/(2r), a_u/(2r)]) \times \{\zeta\} : a_u \in \{1, 2, ..., 2r\}, \\ & \text{for } u = 1, ...d_{z_c}, r = r_0, r_0 + 1, ... \text{ and } \zeta \in Z_d\} \end{aligned} \tag{1.17}$$

In practice, as the number of instruments used grows, this procedure suffers from curse of dimensionality. As explained before, here I use a rich model with fixed effects, therefore dimensions of g quickly expand. Specifications with fewer instruments verified that the estimates

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[3] Following Gandhi et al.(2020) and Andrews and Shi (2013), I use $\mu(g) \propto (100 + r)^{-2}(2r)^{-d_{z_c}} K_d^{-1}$ where d_{z_c} is the dimension of continuous instruments and K_d is the number of elements in discrete instruments. For more details refer to Andrews and Shi (2013).

obtained under continuous and discrete instruments are very close to each other. Therefore I will proceed with continuous instruments in order to preserve the richness of the specification.

In order to allow rider tastes to vary across downtown and non-downtown locations, I will estimate the nested logit model separately for these two types of locations. It is reasonable to expect that especially nesting and price coefficients to differ across downtown and non-downtown locations due to the differences in the availability of different travel modes, income of potential riders etc. Result are reported in Table 1.4. I estimate demand parameters using OLS in (1) and (2), IV-GMM in (3) and (4), and IV-GSL in (5) and (6). For OLS and IV-GMM columns, I add 10^{-8} to all zero market shares. Preferred estimates that will be used in the rest of Chapter 1 and the counterfactual analyses in Chapter 2 will come from IV-GSL columns (5) and (6). Standard errors reported in columns (5) and (6) are obtained through 100 bootstrap replications .

The signs of coefficients on product characteristics (defined as scores from DDOT evaluation on safety, accountability and, sound equipment) are positive for most specifications as expected. OLS estimates for both downtown and non-downtown locations point out inelastic demand (with mean price elasticities -0.196 and -0.017 for downtown and non-downtown respectively). IV-GMM specification with within-group share and price instrumented with competitors' product characteristics yield mean price elasticity of -4.22 for downtown and -3.2 for non-downtown locations. As expected accounting for endogeneity of prices and within-group market shares, demand becomes more elastic. As pointed out in Gandhi et al. (2020), these figures become even more elastic, -5.65 and -3.98 respectively, when I employ GSL method to account for zero market shares. The nesting parameter σ is smaller for downtown across all specifications. This is interpreted as stronger within-nest substitution or stronger correlation of within-nest alternatives in non-downtown locations compared to downtown locations. To illustrate the substitutability of scooters with the outside good given a price increase, I calculate the percentage of riders who substitute to the outside good as a percentage of all who substitute away. The estimates from (5) and (6) imply that on average $\%61.2$ of all those who substitute away will choose the outside good in downtown locations. In contrast in non-downtown locations, this figure becomes $\%56.1$.

Table 1.4: Demand Parameter Estimation Results

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	IV-GMM	IV-GMM	IV-GSL	IV-GSL
	Downtown	Non-downtown	Downtown	Non-downtown	Downtown	Non-downtown
Nesting σ	0.649***	0.669***	0.585***	0.655***	0.478	0.59
	(0.000)	(0.000)	(0.009)	(0.004)	(0.202)	(0.191)
Price α ($\frac{p}{y}$)	-1.532***	-0.127	-47.46***	-28.59***	-59.965	-34.976
	(0.182)	(0.0740)	(4.619)	(3.180)	(5.126)	(3.283)
Safety	-0.169	-0.153***	1.093***	0.112	1.258	1.172
	(0.153)	(0.011)	(0.118)	(0.059)	(0.238)	(0.259)
Accountability	1.258***	0.182*	7.670***	3.161***	6.512	4.393
	(0.150)	(0.079)	(0.687)	(0.363)	(2.349)	(1.924)
Sound Equipment	-0.259*	0.159*	0.781***	0.468***	5.874	3.221
	(0.118)	(0.068)	(0.217)	(0.125)	(1.132)	(1.373)
Constant	-6.043***	-5.466***	-7.547***	-5.414***	-4.551	-4.218
	(0.062)	(0.034)	(0.261)	(0.111)	(0.743)	(0.657)
Operator F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Location F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Mean Elasticity	-0.196	-0.017	-4.220	-3.163	-5.652	-3.984
No. of obs.	32502	49012	32502	49012	32502	49012

1.5.3 Initial CCPs

To initialize the NPL procedure, I need to have a set of conditional choice probabilities. In the absence of data limitations, non-parametric frequency estimators can be used to calculate initial CCPs. However in my case with a large state space, following a parametric approach makes more sense. I derive initial CCPs for all operators and local managers through estimating a multinomial logit model. The dependent variable of this specification is the rebalancing decision. The independent variables are the number of vehicles a local operator has in a location (Own), the number of vehicles a local manager has in other locations within the region ($OwnRegion$), number of vehicles by the competitor within the location ($Competition$), interactions of these variables with a dummy variable indicating whether a location is in downtown and a categorical variable for each operator, fixed effects for location and time. For ease of exposition, in Table 1.5 I report results for a specification without the interactions with operators.

The results of this first stage CCPs reveal that all else equal, local managers are more likely to undertake rebalancing activities in downtown locations. A local manager is more likely to rebalance up and down as their supply at a location is greater. As the supply of competitor operators increases, operators tend to engage in more rebalancing activities. Intuitively it may make sense that a local manager would like to increase supply at a location as competitors' supply increases, however justifying the same for rebalancing down is trickier. The relative sizes of the coefficient on $Competition$ suggest that as the supply of competitors rises, local manager's incentive to rebalance up is stronger than rebalancing down.

Table 1.5: First stage multinomial logit model for rebalancing choice

	Rebalance Down	Rebalance Up
Own	0.168***	0.012***
	(0.003)	(0.004)
OwnRegion	0.0102***	0.00536***
	(0.002)	(0.002)
Competition	0.142***	0.550***
	(0.021)	(0.027)
Downtown=1	2.447***	4.445***
	(0.219)	(0.709)
Downtown*Own	-0.0662***	0.0877***
	(0.004)	(0.004)
Downtown*OwnRegion	-0.00455**	-0.00525**
	(0.002)	(0.003)
Downtown*Competition	-0.0245	0.171**
	(0.021)	(0.054)
Constant	-5.057***	-6.412***
	(0.218)	(0.710)
Operator F.E.	Yes	
Location F.E.	Yes	
Time F.E.	Yes	
No. of obs.	322,500	

*** $p < 0.001$, ** $p < 0.05$, * $p < 0.10$

Standard errors in parentheses.

Base outcome is the choice of not rebalancing.

1.5.4 Nested pseudo likelihood estimation

For the estimation of the dynamic supply side model, I use the nested pseudo-likelihood procedure by Aguirregabiria and Mira (2010). The procedure relies on Hotz and Miller (1993)'s work exploiting the mappings from value functions to probabilities of making a particular choice. The representation of the dynamic programming problem in the conditional choice probability space rather than the value function space leads to the ability to estimate parameters with considerably less computational burden.

For what follows, it is useful to rewrite the value functions as functions of CCPs. Let μ^* be an equilibrium. Then, the per period profit function before the payoff shock can be written as:

$$\begin{aligned}\tilde{\Pi}^{\mu^*}_{f,r,m}(x^{f,r}_t) &= \left[\sum_{l}^{L} p^f \tau_{ml} \min\{d_m s^f_{mt}, x^{fr}_{mt}\}\right] \\ &- \sum_{a\in A} \mu^*_{f,r,m}(a \mid x^{fr}_t)\left(w^{fr}(a, x^{fr}_{mt})\theta^{reb,fr} - c(x^{fr}_t)\theta^{main} - h(\tilde{x}^{-f,r}_t)\theta^{vis.} + \theta^{\epsilon}(\gamma - log(\mu^*_{f,r,m}(a \mid x^{fr}_t))\right)\end{aligned} \tag{1.18}$$

where the last term comes from the fact that under extreme value distribution the expectation of the payoff shock conditional on a state and alternative has a closed form expression, where γ is the Euler constant. Using this, I can rewrite the integrated value function as:

$$\bar{V}^{\mu^*}_{f,r,m}(x^{f,r}_t) = \tilde{\Pi}^{\mu^*}_{f,r,m}(x^{f,r}_t) + \beta \sum_{x^{fr}_{t+1}\in X} \bar{V}^{\mu^*}_{f,r,m}(x^{f,r}_{t+1}) f(x^{fr}_{t+1} \mid x^{fr}_t, \tilde{x}^{f,-r}_t, \mu^*). \tag{1.19}$$

Now stacking equations together for all possible states x for a local manager, I can write:

$$\bar{V}_{f,r,m} = \tilde{\Pi}_{f,r,m} + \beta \bar{V}_{f,r,m} F^{\mu^*} \tag{1.20}$$

where F is the transition matrix that summarizes transition probabilities f for any given state given μ^*. Then, I can calculate $\bar{V} = (I - \beta F^{\mu^*})^{-1}\tilde{\Pi}$. Now, let $\Gamma_{f,r,m}(\mu) \equiv \{\Gamma(x, \mu) : x \in X\}$. Γ can be interpreted as a valuation operator for some strategy profile μ. At an equilibrium μ^*, we have $\bar{V}^{\mu^*}_{f,r,m}(x) \equiv \Gamma_{f,r,m}(x, \mu^*)$. Then, I can characterize an equilibrium as a fixed point of the mapping $\Psi(\mu) \equiv \{\Psi_{f,r,m}(a_{f,r,m} \mid x, \mu)\}$ where:

$$\Psi_{f,r,m}(a^{f,r}_m \mid x, \mu) = \int \mathbb{1}\left(a^{fr}_m = \arg\max_{a \in A}\left\{\Pi^{\mu}_{f,r,m}(a, x) + \epsilon(a) + \beta \sum_{x' \in X} \Gamma(x', \mu) f^{\mu}(x' \mid x)\right\}\right) g(\epsilon) d\epsilon \tag{1.21}$$

Note that Ψ takes local managers' future values as given, as the solution of the linear equation in (1.20). Therefore solving for the fixed point of Ψ doesn't require the solution of the dynamic programming problem. To estimate the supply parameters θ, now I can write a pseudo likelihood function that describes the joint probability of observed choice data as a function of θ for a given set of conditional choice probabilities. Then I can use the NPL following the steps below:

1. Calculate an initial set of CCPs μ^0 using estimates from 1.5.3.
2. Given μ^0 calculate oblivious transition matrices for local managers.
3. Calculate current profits for all states.
4. Using the system of linear equations in (1.20) calculate values.
5. Set up the pseudo likelihood functions and estimate θ^0 using conditional logit.
6. Calculate μ^1 implied by θ^0 and equation (1.9).

7. Update the initial CCPs and repeat steps 2-6 until to obtain a fixed point for θ^{NPL}. Here, I set the tolerance as 10^{-4}.

Following these steps, I estimate θ. I allow rebalancing costs to depend on the operator, whether a location is downtown or not, and the type of rebalancing activity. Maintenance costs depend on the number of vehicles that a local manager oversees in a location. Competition costs depend on the number of vehicles operated by the competitor local managers. In total, 27 parameters are estimated. Results are presented in Table 1.6.

The estimates suggest that costs of rebalancing, both up and down, are slightly higher in non-downtown locations as opposed to downtown counterparts. The cost of rebalancing up seems to be higher than the cost of rebalancing down. A reason why this is the case could be that rebalancing up requires the local managers to position a vehicle strategically and in accordance with parking regulations whereas for rebalancing down there less diligence to be exercised. Maintenance and visibility costs are smaller in size compared to rebalancing costs. Finally, the scale parameter θ^{ϵ} is estimated as 0.51. In discrete choice games, the data alone isn't usually enough for the scale parameter to be identified however in my setting since the timing of the game is such that revenues are revealed before the choice, I can estimate the scale parameter together with cost parameters. Due to the scaling, operator profits can be interpreted in dollar terms.

With θ in hand, I can follow the procedure in section 1.4.3.1 to calculate the implied equilibrium choice probabilities and compare them with their counterparts in data. In Table 1.7, I present the results. I calculate the average choice probability of a given rebalancing action in downtown and non-downtown. Both the model and the data point out that: (1) More rebalancing activities are undertaken in downtown compared to non-downtown locations. According to data,

$\theta^{reb.}$	Rebalance up	Rebalance down
Downtown		
Operator 1	2.525	2.461
	(0.113)	(0.097)
Operator 2	1.403	1.201
	(0.027)	(0.058)
Operator 3	1.633	1.104
	(0.040)	(0.071)
Operator 4	2.186	1.065
	(0.245)	(0.059)
Operator 5	1.542	0.753
	(0.062)	(0.051)
Operator 6	1.834	0.741
	(0.98)	(0.128)
Non-downtown		
Operator 1	2.731	1.765
	(0.087)	(0.043)
Operator 2	1.625	1.213
	(0.051)	(0.063)
Operator 3	1.951	1.378
	(0.047)	(0.172)
Operator 4	2.311	1.570
	(0.045)	(0.096)
Operator 5	1.842	1.479
	(0.074)	(0.089)
Operator 6	2.385	1.332
	(0.173)	(0.100)
$\theta^{main.}$	0.412	
	(0.150)	
$\theta^{vis.}$	0.151	
	(0.082)	

Table 1.6: Supply model parameters θ^{NPL}

no rebalancing action is undertaken 93.2% of the time in non-downtown locations and 82.7% of the time in downtown locations. The model predictions for these figures are 96.6% and 88.9% respectively. (2) Rebalancing down happens more often than rebalancing up. Over all locations in the city, operators rebalance down in 5.4% of the time in data whereas model predicts that they rebalance down 3.7% of the time. In contrast, rebalancing up happens 3.9% of the time in the data and 1.5% of the time according to the model.

Table 1.7: Data vs Predicted choice probabilities

Data			Model		
Non-downtown	Down	0.0388	Non-downtown	Down	0.0287
	None	0.9316		None	0.9657
	Up	0.0296		Up	0.0066
Downtown	Down	0.1030	Downtown	Down	0.0654
	None	0.8266		None	0.8891
	Up	0.0704		Up	0.0455
Overall	Down	0.0537	Overall	Down	0.0370
	None	0.9073		None	0.9479
	Up	0.0390		Up	0.0151

Next, I discuss long run average number of vehicles implied by the model. To do this, I calculate state transition probabilities based on equilibrium conditional choice probabilities. Then, I calculate the limiting distribution of these transition probabilities and finally obtain the long run expected number of vehicles at each location. In Table 1.8, I report a break down of the percentage of locations by long run average supply implied by the model versus data. In the data, it can be seen that most locations fall into the 0 to 2 vehicles category. The same pattern can be observed in the model prediction. One important observation is that the model predicts that firms would have on average less vehicles on the street than what the data suggests. For example, the data suggests that 1-5 locations would have more than 8 vehicles per operator however no locations are predicted to have more than 8 vehicles according to the model prediction.

Table 1.8: Data vs Predicted supply

		Number of vehicles				
		0-2	**2-4**	**4-6**	**6-8**	**8-10**
Data	Operator 1	89.30%	4.65%	2.33%	3.26%	0.47%
	Operator 2	83.72%	9.77%	3.26%	2.33%	0.93%
	Operator 3	72.09%	17.21%	5.12%	3.72%	1.86%
	Operator 4	88.37%	5.12%	2.33%	2.79%	1.40%
	Operator 5	79.53%	9.77%	4.19%	5.12%	1.40%
	Operator 6	78.14%	11.63%	3.26%	4.65%	2.33%
		0-2	**2-4**	**4-6**	**6-8**	**8-10**
Model	Operator 1	91.61%	7.92%	0.47%	0.00%	0.00%
	Operator 2	88.82%	9.31%	1.87%	0.00%	0.00%
	Operator 3	86.05%	13.02%	0.93%	0.00%	0.00%
	Operator 4	89.76%	7.91%	2.33%	0.00%	0.00%
	Operator 5	85.58%	10.23%	4.18%	0.00%	0.00%
	Operator 6	83.72%	13.02%	3.26%	0.00%	0.00%

Lastly, I would like to consider an alternative version of the supply model as a robustness check. In the model presented above, the local manager incurs costs for both rebalancing up and down. In the alternative version, I reconsider this approach and replace it with the following: The local manager incurs costs when they rebalance, and this cost does not depend on the specific rebalancing act. And moreover, I add a term that captures the value of shifting the location of scooters around the city. In this setting, every local manager will be able to take the opportunity cost of rebalancing into account in terms of lost expected net revenues for the city as a whole. This term will account for the future revenues lost all over the city whenever a local manager decides to rebalance down. Similarly, when the local manager rebalances up, futures revenues that will be earned from that extra vehicle will be factored in the profit function. The calculation of this term will rely on the rebalancing action chosen, origin destination preferences and market shares informed by the demand model. The profit function under this new setting can be written as (1.22) with the new term represented with $r(.)$.

$$\begin{gathered}\tilde{\Pi}^{\mu^*}_{f,r,m}(x_t^{f,r}) = \left[\sum_{l}^{L} p^f \tau_{ml} \min\{d_m s^f_{mt}, x^{fr}_{mt}\}\right] \\ w^{fr}(a, x^{fr}_{mt})\theta^{reb,fr} + r(a, s^f, T) - c(x_t^{fr})\theta^{main} - h(\tilde{x}_t^{-f,r})\theta^{vis.}\end{gathered} \tag{1.22}$$

Estimation of the structural parameters under the alternative profit function yields smaller $\theta^{reb.}$ with around 0.4 when averaged across operators. This yields conditional choice probabilities for rebalancing activity to be very small overall. So the preferred specification for the per period profit functions will still comes from equation (1.5). However, this alternative approach can be explored further.

1.6 Conclusion

In this chapter, I set up and estimated a demand and supply model of a shared mobility market. The model captures salient features of both sides of the market. On the demand side, I model consumer choice using a nested logit model. For the estimation of this model, I rely on a novel method by Gandhi et al. (2020) to account for the zero market shares observed in the data. On the supply side, I model operator behavior as a dynamic oligopoly game where operators maximize profits by choosing optimal rebalancing activity every period. Ideally, I would like to keep state and action spaces for scooter operators larger and adopt Markov perfect equilibrium as the working equilibrium concept when solving for the equilibrium of the model. However, due to the large memory requirements accompanied by that approach, I rely on the concept of oblivious equilibrium. Moreover, I allow operators to coordinate decisions through a group of local managers. The oblivious approach adopted here for local managers limit interactions between local managers of the same operator as well as strategic interactions with competitors' local managers.

It is also important to mention that the dynamic model presented in this chapter is very likely to have multiple equilibria. NPL algorithm relies on the assumption that even if the game has multiple equilibria, the data are generated by a single equilibrium. However, with a collection of local markets, this assumption is very likely to hold. Moreover, as Pesendorfer and Schmidt-Dengler (2010) illustrates if certain stability conditions on best response mappings don't apply, the NPL algorithm is prone to either non-convergence or converging to the wrong equilibrium. One of the weaknesses of the estimation here is that I will not address problems associated with multiple equilibria.

With parameter estimates from demand and consumer sides, in the next chapter, I employ several counterfactual scenarios and report comparisons of welfare outcomes induced by those scenarios.

Chapter 2: Regulation in Micromobility Markets: Counterfactual Analyses

2.1 Introduction

In this chapter, I evaluate two counterfactual scenarios based on the model and estimation results from Chapter 1. I start by describing the regulatory environment around micromobility markets.

Many cities around the world have opened their streets to dockless bicycles and scooters in hopes to provide an environmentally friendly alternative to the first/last mile problem in local transportation. Yet, anecdotal evidence suggests there are shared concerns among the cities that welcomed these dockless vehicles. The main points of skepticism focus on safety issues and parking violations (Sun, 2018). Faced with these concerns, municipal transportation authorities have responded in a multitude of ways. These responses range from limiting number of operators, putting restrictions on fleet size, increasing penalties for parking violations to charging higher operation fees for companies to imposing speed limits on vehicles. Another tool of regulation some cities make use of is geofencing technology to restrict scooter pick up and drop off areas and therefore ensure fewer parking violations and safety hazards. There are many instances of cities such as San Francisco, Nashville, and Atlanta, that attempted to put a ban (successfully and unsuccessfully) on scooters altogether or temporarily due to increasing public pressure.

On the other side of the story, many scooter companies have walked out of cities that they deemed unprofitable due to regulatory burden. The industry has also seen mergers and acquisitions. To name a few prominent of these, ride-hail company Uber has acquired Jump in 2018, Ojo announced that it will be acquiring Gotcha in 2019. Reportedly, for many of the dockless vehicles firms, revenues are falling steadily as of 2018.[1] These developments in the industry makes it relevant to talk about implications of competition.

Scooter operator entry to a new city is at the disposal of local authorities. Some cities such as Chicago grant licenses to as many as 10 operators while others limit the number of operators to only two. Washington, DC launched its dockless vehicles pilot program in September 2017. Since then, each year the city accepted applications for permits from up to 19 companies and granted access to a number of these applicants. For 2019, the city had granted eight permits. These companies and the number of vehicles authorized for the permit holders are as follows: Bird(600), Bolt(600), Jump(600), Lime(675), Lyft(720), Razor(600) Skip(720), Spin(720). Companies can make quarterly fleet expansion requests. DDOT grants permissions for expansions based on performance evaluation.[2] In 2020, permits were granted to a total of four companies with 2,500 vehicle fleets allowed for each.

The DDOT also outlines specifics for the distribution of vehicles. 2019 permit holders were required to deploy at least 6 vehicles at each of eight wards of the city by 6 am each day. In 2019, the DDOT encouraged operators to offer their services in lower income areas by keeping track of the number of trips initiated from the equity emphasis areas designated by the city. These numbers would then be factored in a scoring scheme for determining permit holders in 2020. In 2020, permit holders will be held up to more restrictive standards. According to 2020 terms and

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[1] Source https://news.crunchbase.com/news/birds-leaked-numbers-detail-the-high-price-of-scooter-growth/

[2] Details of terms and regulations that apply to permit holders as outlined by the District Department of Transportation(DDOT) can be found in their website: https://ddot.dc.gov/page/dockless-vehicles-district

conditions, each operator has to deploy 400 vehicles in equity emphasis areas by 7 am each day.

In this chapter, using the theoretical model and estimation results presented in the previous chapter, I set up and present results from two counterfactual scenarios. First, I evaluate the welfare impacts of a subsidy introduced for low income neighborhoods in order to address the issue of equity in micromobility markets. Ideally, I would like to address the welfare impact of supply restrictions in a counterfactual in the spirit of the 2020 requirements. But since in the demand model the utility functions for potential riders don't respond to changes in vehicle availability, the effect of a supply restrictions on consumer welfare cannot be identified. Second, I will consider the welfare effects of removing operators from the market. The vehicle availability data reveals that vehicles remain idle roughly around $85 - 95\%$ of their time on the street depending on the operator. Motivated by that observation, I set up a scenario where the DDOT grants fewer permits.

2.2 Equity in micromobility

In this counterfactual, I address the issue of equity in micromobility markets. Since the inception of the pilot program for dockless scooters, one of the objectives of the DDOT has been to promote equitable access to this new form of mobility. There are three main challenges to access to micromobility alternatives. The first one is that the potential riders need to have access to a smart phone, internet access and, an online payment method. The DDOT requires the scooter companies to offer an option to use SMS to unlock vehicles and offer cash payment options for rides. The second challenge is the affordability of rides. Riders who are below 200% of the federal poverty guidelines can enroll in low-income customer plans. The third challenge is to guarantee a steady supply of vehicles in low income neighborhoods. In 2019, the DDOT did not require strict supply restrictions in equity emphasis areas but it encouraged rides originating from these areas by assigning a score to each operator based on their performance in the equity emphasis areas. However, in 2020, each operator was required to deploy 400 vehicles in total in the equity emphasis areas at the beginning of the day with no other requirements for the rest of the day.

Here I consider an alternative policy to promote equity by introducing a 20% subsidy for trips originated in equity emphasis areas. First, I describe the equity emphasis area designated by the city. The map of the equity emphasis area can be seen in Figure 2.1. In Figure 2.2, I map the intersection of the area of this study in this chapter and the equity emphasis area. Unfortunately bulk of the equity emphasis area falls in the southeast quadrant of the city which is not covered by the area of study. The observations on the southeast quadrant were excluded from the area of study because of the patchy and infrequent presence of scooters in these areas. The intersection includes 46 block groups in total with 17 of them falling in the downtown area (highlighted in light blue in Figure 2.2) and 29 of them falling in the non-downtown area (highlighted in dark blue in Figure 2.2). Average daily per capita income in the equity emphasis areas in the intersection with the area of study is \$135 whereas average daily per capita income in the area of study is \$193. As a reference, mean per capita daily income in Washington, DC is \$159 (around \$58,500 yearly).

I will consider implementing a %20 subsidy to rides originating from equity emphasis areas. Results are reported in Table 2.1. I breakdown results for 4 main regions in the city: Downtown-equity emphasis areas, rest of downtown, non-downtown-equity emphasis areas, rest of non-downtown. The baseline scenario will take October 15, 2019 data for observations of ve-

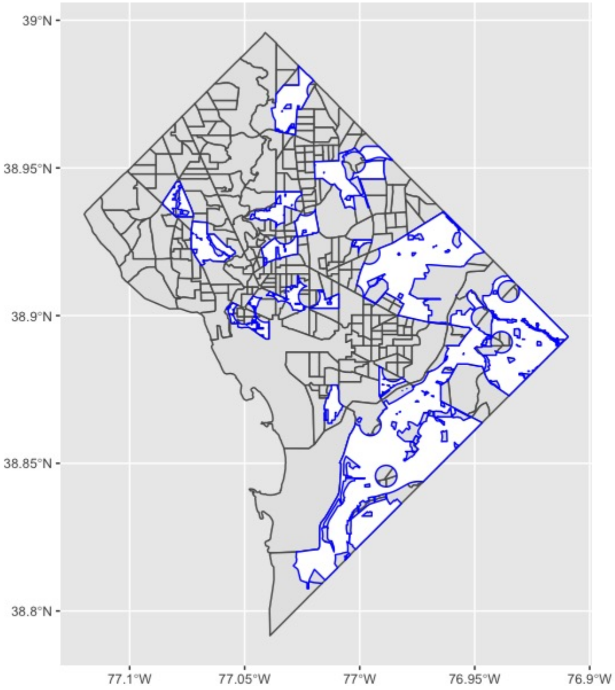

Figure 2.1: Equity emphasis area

Note: Equity emphasis areas are highlighted in white.

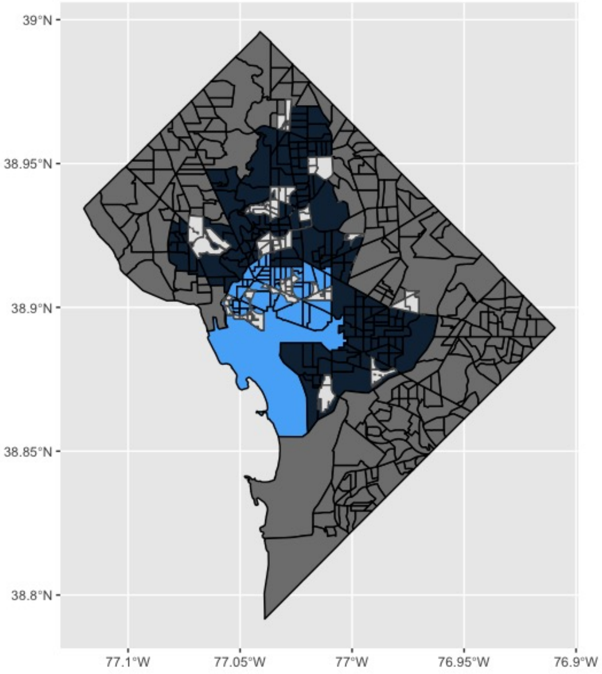

Figure 2.2: Intersection of area of study and equity emphasis areas

Note: Equity emphasis areas are highlighted in white.

Table 2.1: Subsidies in the equity emphasis areas

	Baseline	**20% Subsidy in EEA**
Consumer surplus		
Total	1195.23	1230.83
Downtown-EEA	180.34	203.5
Downtown-rest	567.01	567.01
Non-downtown-EEA	71.80	84.24
Non-downtown-rest	376.08	376.08
Profits		
Total	8633.38	9107.11
Downtown-EEA	913.23	1047.5
Downtown-NEEA	3679.10	3790.83
Non-downtown-EEA	756.54	820.9
Non-downtown-NEEA	3284.51	3447.88

Note: Units are in dollars.

hicle availability. First thing to notice in Table 2.1 is that since the demand model doesn't respond to vehicle availability, calculated consumer surplus does not take the network effects induced by the implementation of the subsidy. The subsidy will induce a different supply distribution in the non-subsidized locations than the baseline scenario. The change will come from both the change in trips induced by the subsidy and the change in rebalancing activities. As mentioned before, the demand model presented in section 1.4.1 does explicitly take the supply of vehicles in the utility function. That's why the consumer surplus in non-subsidized locations remain unchanged under the subsidy. On the other hand, consumer surplus increases in equity emphasis areas. However, the supply side of the model can respond to the network effects because the change in predicted market shares in the subsidized locations will induce new transitions and therefore new conditional choice probabilities all over the city.

On the operators side, profits increase in both equity emphasis areas and the rest of the locations in the area of study. The subsidy induces more trips in equity emphasis areas, which in turn increases supply in both downtown and non-downtown regions. Table 2.2 shows that overall less rebalancing activities are undertaken (i.e. the probability of taking no rebalancing action increases) throughout the city. Under the subsidy, local managers would like to rebalance both downtown and non-downtown equity emphasis areas more, whereas they want to rebalance up in the rest of downtown less. Since now more vehicles come into the rest of the downtown regions, there is less need to increase supply.

Table 2.2: Rebalancing choice probabilities under %20 subsidy in equity emphasis areas

	Baseline				20% Subsidy in EEA		
	Up	None	Down		Up	None	Down
Downtown-EEA	3.10%	90.34%	6.56%	Downtown-EEA	4.53%	90.46%	5.01%
Downtown-Rest	4.99%	88.03%	6.98%	Downtown-Rest	4.39%	89.33%	6.28%
Non-downtown-EEA	0.71%	95.54%	3.75%	Non-downtown-EEA	1.88%	95.17%	2.95%
Non-downtown-Rest	0.73%	95.89%	3.38%	Non-downtown-Rest	0.89%	96.22%	2.89%

Table 2.3: Average supply of vehicles per location and operator-Subsidy

	Baseline	20% Subsidy
Downtown-EEA	2.58	2.71
Downtown-Rest	3.48	3.56
Non-downtown-EEA	1.1	1.26
Non-downtown-Rest	1.32	1.37

Table 2.4: Total Trips-Subsidy

	Baseline	20% Subsidy
Downtown-EEA	520	563
Downtown-Rest	1103	1137
Non-downtown-EEA	438	458
Non-downtown-Rest	1002	1019

Under the subsidy, local managers keep more vehicles on the street. It can be seen in Table 2.3 that long-run number of vehicles per location and operator increases in both equity emphasis areas and the rest of the city. Even though the demand model doesn't take the network effects into account, based on the changes in long run vehicle supply and rebalancing probabilities, my prediction would be that the change in consumer surplus reported in Table 2.1 is a lower bound on the increase in consumer surplus. Since operators deploy more vehicles under the subsidy, it is reasonable to expect that consumer surplus would increase further when the network effects are accounted for.

2.3 Fewer permits granted

In this counterfactual scenario, I investigate what happens when the DDOT grants fewer permits. DDOT as the regulating authority in the market grants 6-8 permits every year since the inception of the pilot program for dockless vehicles. In the data, I observe many vehicles remaining inactive for extended periods of time throughout the day. I also observe that in particular, some operators tend to perform significantly worse than others. Motivated by this observation, I will remove two of the operators from the picture and investigate the welfare effects on both sides of the market induced by that event. The operators of choice here are Operator 1 and Operator 4. It is worth noting that since 2021 these two operators are out of the DC market.

My baseline scenario will still be based on October 15, 2019 observation and estimates from Table 1.4 columns (5) and (6) and Table 1.6. I solve the model under baseline and under fewer permits assumptions. Removing two of the alternatives from the choice set is expected to result in decreased consumer surplus overall. Since the operators that will be removed from the choice set had sparse presence in a considerable amount of locations, especially in the non-downtown locations, and were prone to low market shares, I expect the decrease in consumer surplus to be low. In Table 2.4, I report welfare outcomes for consumers and operators. I again breakdown results for 4 main regions in the city: Downtown-equity emphasis areas, rest of downtown, non-downtown-equity emphasis areas, rest of non-downtown.

When Operator 1 and 4 are removed, as expected, consumer surplus decreases with a larger impact on downtown locations. Looking at the breakdown among firms, I see that the profits for the remaining operators increase. To investigate the reasons for this, I provide Table 2.5 and Table 2.6.

Table 2.6: Rebalancing choice probabilities-Fewer permits granted

	Baseline				Operators 1+4 removed		
	Up	None	Down		Up	None	Down
Downtown-EEA	3.10%	90.34%	6.56%	Downtown-EEA	3.53%	90.74%	5.73%
Downtown-Rest	4.99%	88.03%	6.98%	Downtown-Rest	5.54%	88.77%	5.69%
Non-downtown-EEA	0.71%	95.54%	3.75%	Non-downtown-EEA	0.67%	95.94%	3.4%
Non-downtown-Rest	0.73%	95.89%	3.38%	Non-downtown-Rest	0.64%	96.14%	3.22%

For the remaining operators, profits increase due to 2 factors: When two operators are removed, the remaining firms enjoy less intense competition, especially in downtown locations.

Table 2.5: Fewer permits granted

	Baseline	**Operators 1+4 removed**
Consumer surplus		
Total	1195.23	1112.22
Downtown-EEA	180.34	170.98
Downtown-rest	567.01	520.90
Non-downtown-EEA	71.80	66.21
Non-downtown-rest	376.08	354.13
Profits		
Total	8633.38	7284.23
Downtown-EEA	913.23	669.81
Downtown-rest	3679.10	2992.28
Non-downtown-EEA	765.54	690.75
Non-downtown-rest	3284.51	2931.39
Operator 1	481.32	—
Operator 2	1205.49	1221.81
Operator 3	1582.61	1614.19
Operator 4	980.9	—
Operator 5	2137.42	2172.05
Operator 6	2245.64	2276.18

Units are in dollars.

Visibility costs will therefore decrease. Moreover, operators rebalance slightly less compared to the baseline. Probability of rebalancing down decreases in all 4 main regions. The probability of rebalancing up increases in downtown locations (both equity emphasis and the rest), however, decreases slightly in non-downtown locations. Overall the implied number of vehicles averaged over locations and operators increases slightly in all 4 main regions with a higher increase in downtown locations.

Table 2.7: Average supply of vehicles per location and operator-Less permits granted

	Baseline	Operators 1+4 removed
Downtown-EEA	2.58	2.68
Downtown-Rest	3.48	3.63
Non-downtown-EEA	1.1	1.12
Non-downtown-Rest	1.32	1. 33

2.4 Conclusion

Micromobility alternatives have undoubtedly become a part of the urban landscape for the past few years. The need for environmentally friendly modes of local transportation, and the expected shifts in consumer preferences over travel modes in the post-pandemic world towards forms of transportation that allow limited social interaction [3] call for mindful policy making for micromobility. It is no secret that scooter companies are running significant losses over the past few years and subsequently there is a trend of concentration in the industry [4]. In face of a potential surge in demand and environmental concerns, it is of general public interest to regulate shared micromobility providers without disrupting the possibility of sustainable business. However, equity concerns in access to alternative forms of micromobility should also be addressed along the way.

The ultimate goal of the chapter is to look at the welfare implications of implementing

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[3] Source: https://www.washingtonpost.com/local/trafficandcommuting/why-bike-and-e-scooter-companies-hit-hard-by-the-pandemic-may-come-back-stronger/2020/05/16/076e2900-95d5-11ea-91d7-cf4423d47683˙story.html

[4] Source: https://www.bloomberg.com/news/articles/2020-01-27/where-the-electric-scooter-industry-will-go-next

subsidizing low-income riders and limiting the number of operating firms through counterfactual scenarios. Currently, all of these aspects are shaped by the local transportation authorities, not just in Washington, DC but also in cities such as Chicago, Baltimore, and Los Angeles. I find that subsidizing scooter rides from low income neighborhoods benefits both the consumers and the operators. The findings of this project could potentially provide insights into the ongoing policy making efforts.

Chapter 3: Entry Threat and Strategic Investment in the US Fixed Broadband Industry

3.1 Introduction

In the face of potential entry, incumbent firms typically react in a number of ways. These reactions could either be targeted at deterring entry if possible or ensuring the continuation of profitable business in the post-entry competitive environment. Theoretical and empirical literature has studied various strategies employed by incumbents. These include altering pricing, introducing high switching costs to lock in the existing demand, investing in capacity or advertisement, etc. This chapter will discuss strategic investment in quality improvement as a potential preemptive measure taken by the incumbent in the presence of entry threat.

The fixed broadband industry in the United States provides an example of a competitive environment where the incumbent internet service providers (ISPs hereafter) face potential entry by firms that are capable of providing customers with a higher quality service. In the last two decades, the industry is characterized by an ever-increasing demand for fast and reliable services. In line with this surge in demand, the technologies with which ISPs deliver broadband access have transformed and proliferated. Until recently, the industry was led by incumbent ISPs that use various digital subscriber line (DSL) and cable modem technologies. With the recent flourishing of fiber-to-the-premises technologies, the market composition has started to change. The most intriguing aspect of this new competitive environment is due to the fact that fiber-optic technology is inherently capable of delivering faster and more reliable internet access compared to DSL and cable modem. While both DSL and cable modem technologies had been subject to frequent quality improvements, as it stands, only cable modem is capable of potentially catching up with what fiber-optic technology has to offer for its customers.

Good examples of this new competition faced by incumbent DSL and cable modem ISPs are demonstrated in the cities where Google Fiber announced its plans to roll out services. After Google Fiber selected Kansas City as the first city in the US to receive its fiber-optic network, the major incumbents AT&T and Time Warner have both promised to increase speed rates at current prices. In addition to this, many incumbents started adding new and free products to their bundled offers, such as free access to HBO.

Another example is Nashville, where in 2017 AT&T and Comcast have sued the metropolitan government over a rule that facilitated Google Fiber's easy access to the city's utility poles.[1] AT&T and Comcast's victory in this court battle led Google to look for alternatives to utility poles that were necessary for the deployment of wires. Finally, Google Fiber resorted to using micro-trenching to bury their wires underground. It is also worth noting that, Google Fiber has since pulled out of several cities including parts of Kansas.[2]

There is also anecdotal evidence on how small fiber ISPs struggle to find patient investors since the entry costs are high and the investment pays off over five to ten years in most cases. In addition to this, small fiber ISPs face other major challenges when it comes to providing bundled

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[1] Source: https://arstechnica.com/tech-policy/2017/11/att-and-comcast-win-lawsuit-they-filed-to-stall-google-fiber-in-nashville/

[2] https://hbr.org/2018/09/why-google-fiber-is-high-speed-internets-most-successful-failure

services such as TV programming as their competitors do. Small fiber ISPs and major incumbents do not compete on equal ground when it comes to content buying power.[3]

On the other hand, fiber ISPs enter new markets with aggressive strategies to claim their shares in local markets. They often offer services at cheaper rates than their competitors as well as additional promotional offers. For example, AT&T Fios (AT&T's fiber-optic internet services) offered 500$ in credit to cover early termination fees for new customers who switch from another ISP.

Here, I will abstract from various forms of incumbent behavior such as strategies that involve limit pricing, foreclosures, term contracts as well as institutional barriers to entry. Instead, the main focus will be on the implications of network upgrade investments by the incumbents in a local market when faced with the threat of entry by high-speed fiber ISPs. More specifically, I will use data from Wisconsin for a period spanning 2011-2016 to do so. First, I find evidence that incumbent cable modem ISPs behave differently in markets that are threatened by fiber ISP entry as opposed to unthreatened markets. Furthermore, the nature of this difference points out a particular pattern. I find evidence of relatively higher investment in medium-sized threatened markets. This finding suggests that incumbents consider medium-sized markets as a battlefield where they stand a chance for deterring entry. In contrast, in larger markets, entry deterring efforts might not prove useful or in smaller markets, it might not be necessary at all. This is a familiar result in the empirical entry deterrence literature.

In section 2, I will give a review of existing literature on the broadband industry, entry threat, and preemptive behavior. In section 3, I will give an overview of the fixed broadband in-

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[3] Source: https://arstechnica.com/information-technology/2014/04/one-big-reason-we-lack-internet-competition- starting-an-isp-is-really-hard

dustry. I will talk about the relevant legislation that outlines the rules of operating in the industry. I will present the data that will be used in the empirical analysis. In section 4, I will provide evidence on preemptive behavior by incumbent ISPs. I will try to discuss the motivation behind the observed preemptive behavior. I will also look at the behavior of potential entrants and try to understand the determinants of entry decision in general. Finally, I will lay out a discussion of my findings and conclude.

3.2 Related literature

The broadband industry and more broadly, various forms of telecommunications, had been under the spotlight from many different angles. Notably, the relationship between the availability of quality broadband services and various development indicators, income inequality, educational attainment, labor market outcomes have been a largely explored topic. Here, I contribute to the existing literature of competition in the broadband industry while making connections to the broader empirical literature that has dealt with strategic investment, entry threat, and entry deterrence.

The theoretical work on strategic investment goes back to Stackelberg (1934) and is extended by many others. Tirole (1988) gives an overview of different arguments made in this line of literature as well as laying out a taxonomy of optimal investment strategies in face of entry threat. Although the theoretical literature has explored strategic investment in many contexts, empirical work seems to have stayed more limited. As pointed out in Dafny (2005), the empirical literature on strategic investment has faced two challenges. The first one is finding appropriate measures of ex-ante entry threat. The second one is having an empirical strategy that would allow one to distinguish the level of investment that is undertaken as a reaction to entry threat from the level of investment that would have been realized in the absence of any entry threat. Once a preemptive response by the incumbent is established, then the next question is to identify the underlying motives as either entry deterring or entry accommodating.

To address the first challenge mentioned above, I will make use of a regulation that is currently in effect in the industry. My ex-ante measure of threat will be due to this regulation that requires broadband providers to hold licenses in local markets that they wish to operate. I will talk about these licenses in the next section in detail. Coming to the second issue raised previously, I largely follow Ellison and Ellison's (2011) and Goolsbee and Syverson's (2008) framework to provide evidence of preemptive behavior. Moreover, to the best of my ability, I will address the distinction between deterring and accommodating behavior using a similar line of arguments provided in these aforementioned papers.

Ellison and Ellison (2011) investigate a cross-section of pharmaceutical markets where branded drugs are approaching the end of their patent protections. The expiration of patent protections would mean that pharmaceutical incumbent faces entry threat by generics. The empirical framework that they develop to test the presence of entry deterring motives relies on inferences from theory. They develop two alternative models in the paper: One where the potential entrant observes the level of investment chosen by the incumbent in the previous period before making the entry decision and one where the entrant learns the level of investment by the incumbent after the entry decision. In the latter model, the incumbent's investment decision cannot have a causal effect on the potential entrant's entry decision. Then, under certain conditions, the differences in the equilibrium investment levels chosen by the incumbent under these two models can be attributed entirely to entry deterring motives. They suggest that, if the attractiveness of the market under question and the investment levels chosen by the incumbent exhibit a monotonic relation in the latter model, absent the entry deterrence motive, the observation of non-monotonicity when the incumbent can affect the entry decision is an indication of entry deterring motives. This idea relies on the intuition that deterring entry might be a pointless endeavor in larger markets and an unnecessary effort in smaller markets. Yet, medium-sized markets are the battlegrounds for the incumbent to over or underinvest to deter entry. Within this framework, Ellison and Ellison (2011) do not completely address the issue of empirically distinguishing between accommodative and deterring investment. The argument provided is again a theoretical one. Timings in both models allow the incumbent to recognize and react to incentives to accommodate.

Dafny (2005) follows Ellison and Ellison (2011) methodology to look for entry deterring investment in inpatient procedure markets. In a setting where identifying potential entrants is easier relative to most industries, the paper finds evidence for strategic entry deterring investment.

Goolsbee and Syverson (2008) examine the competitive responses by passenger airlines when they perceive entry threat by Southwest in a given market. The first set of findings establishes that there is a preemptive response by the threatened incumbent airlines. Specifically, the incumbents seem to cut their prices in threatened markets prior to Southwest entry. A further investigation into the nature of this preemptive response suggests some evidence of entry deterrence. In markets where entry is likely to be inevitable, there seems to be a less aggressive price cut response relative to those markets where Southwest has not committed to entry. The authors draw attention to the limitations of this interpretation. One would have to have a clear idea of the ways in which accommodation and deterrence would be undertaken to be able to address the issue. Theoretically, as discussed in Tirole (1988), it has been shown that under some circumstances deterring and accommodating strategies do not necessarily work in opposite directions.

There is a considerable body of work on competition in the fixed broadband industry. Notably, Prieger and Connolly (2013) provide a descriptive analysis of characteristics of entry and exit in the fixed broadband industry in 2005-2008. The industry is more or less stabilized in this period since a lot of local markets have received their first ISPs. An interesting finding from this paper is the existence of high rates of simultaneous entry and exit, despite the fact that the industry is characterized by high entry costs. Furthermore, most of the entry is in the form of existing providers expanding their service area or diversifying their service offerings. They also illustrate differences in practices by ISPs of different technologies and provide a critique of theoretical models where broadband services and firms have been treated as homogenous.

Xiao and Orazem (2011) expand the Bresnahan and Reiss (1991, 1994) entry threshold models into a dynamic setting and they allow for differences in sunk costs between entrants and incumbents. They use data from the early years of the industry, 1999-2003, where they observe the number of ISPs operating in each zip-code tabulation area level market. Contrasting a model that accounts for sunk costs to one where sunk costs are ignored, they report differences in entry thresholds over time. While the model with sunk costs predicts stable entry thresholds over time, absent these sunk costs authors find a large and unrealistic variation. More specifically, the model without sunk costs predicts increasingly unfavorable entry conditions for the fourth firm. Xiao and Orazem's framework has a number of shortcomings since the data they use does not allow them to see the exact number of firms operating in a market if that number is smaller than four. This means that they fail to capture the entry dynamics within those less competitive markets. It is also worth noting that firms that deliver broadband using different technologies are treated homogeneously.

Xiao et al. (2018) study decision-making by potential entrants instead of focusing on incumbents in the broadband industry. They aim to test two competing theories: One that suggests delayed entry due to entry threat from other entrants, against another one that suggests accelerated entry if incentives to preempt are strong enough. Empirical work on entry threat often struggles to find ways to distinguish threat of entry from actual entry. Xiao et al. (2018) use a measure of entry threat that is constructed based on the market conditions in the neighboring markets. A market is identified as threatened if a firm is absent in that market while operating in a neighboring market. Accounting for the endogeneity of entry threat in this setting, they find that threatened markets, on average, have delayed first time entry compared to unthreatened markets. Additionally, they argue that delayed entry translates into lower quality broadband services in the long term. One of the insights that I obtain from the data is that the neighborhood approach to entry threat does not necessarily reflect how entry into new markets unfolds, at least looking at the fiber-optic ISPs. Here, I will follow Skiti (2020)'s novel method to define entry threat. This will be explained further in the following section.

A study that is closely related to this paper is Seamans (2012). Using the same quality investment strategy as I consider here, this paper discusses whether these investments are undertaken with an underlying entry deterring motive. Their measure of entry threat by a municipal provider is based on the presence of a municipal electric utility. Municipal electric utilities own the infrastructure that can easily be repurposed to serve cable TV. The findings of their empirical analyses are consistent with the entry deterrence motive. The private incumbent cable firms upgrade their systems earlier in markets where municipal entry exists compared to those without municipal entry threat. Further evidence is provided for the strategic entry deterrence motive by looking at incumbent actions after the network upgrade takes place.

In the next section, I will give some background information about the US fixed broadband industry and provide an overview of the data that will be used.

3.3 US boadband industry and data

3.3.1 US broadband industry background

The competitive landscape in the telecommunications industry as a whole was shaped by 1996 Telecommunications Act to a great extent. The act was primarily aimed at fostering more competition in the industry. The change in the regulatory environment with the 1996 Telecommunications Act and the improved spectrum use coincided with developments in fiber-optic technologies that innovate data transmission. During the telecom bubble of the end of 1990s to mid-2000s, especially telephone companies have invested heavily in laying fiber-optic cables. Couper et al. (2003) state that these investments are estimated to amount to over 100 billion dollars. The fiber-optic cables that were laid underground during this period largely stood as redundant capacity to this day.

As the demand for increasingly faster and more reliable internet access soared, telephone and cable TV companies were the first ones to respond. Telephone companies altered their existing copper cable networks to accommodate upstream and downstream data transmission using Digital Subscriber Line (DSL) technologies. Most recent DSL technologies typically allow for data transmission at 5-35 Mpbs downstream and 1-10 Mpbs upstream speeds. The reliability of services delivered by DSL depends on the distance from the provider facilities and the bandwidth sharing property leads to decreased speeds in heavy traffic hours.

On the other hand, cable TV companies use a combination of fiber and coaxial copper cables to deliver internet services to end-users. cable modem technologies typically have 10-500 Mbps downstream and 5-50 Mbps upstream speeds. Bandwidth sharing is still an issue for cable modem as it is for DSL technologies, yet reliability is higher than DSL. To explain the large range of service speeds available by cable modem calls for a more detailed explanation of the technology. The protocol that allows television cables to transmit data is called DOCSIS (Data Over Cable Service Interface Specification) protocol. DOCSIS protocol is developed in 1997 and since then there had been many iterations of it. The ones that are predominantly used today are DOCSIS 2.0 and DOCSIS 3.0 with the latter being superior to the former.

The third and final major category with which internet services are provided to end-users is fiber-optic technologies. As the name suggests, internet services are delivered through fiber cables which enable 250-1000 Mbps speeds at both upstream and downstream. Fiber-to-the-Premises techniques used today eliminate problems associated with bandwidth sharing. Overall, fiber-optic connection is considered to be superior to DSL and cable modem. Yet, cable modem connections are capable of delivering comparable quality to fiber-optics.

My focus in this chapter will be on the incumbent cable modem firms' investment decisions in network upgrades. The investment to upgrade services from DOCSIS 2.0 to DOCSIS 3.0 is an irreversible one. It requires alterations to the existing infrastructure and replacement of the modems installed in end-user locations with DOCSIS 3.0 compatible devices. A medium-sized ISP, Cablevision, with estimated $3.1M customers around the US is reported to spend $60 per home passed during its upgrade to DOCSIS 3.0.[4] I will consider fiber-optic ISPs as potential entrants in my setting. To give an idea about the entry costs for fiber-optic firms, I go back to the Google Fiber example mentioned earlier. Bernstein Analysis estimates Google Fiber's capital

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[4] Source: https://www.tvtechnology.com/news/cablevision-seeks-top-speed-for-us-broadband

expenditure in Kansas City as $563 per household.[5]

Prior to 2005, firms interested in offering cable services to consumers in the US were required to negotiate separate agreements with each local authority before they could lay cable in the ground or place cable along utility poles. This meant that in some cases, ISPs had to negotiate up to 2500 different agreements in a single state. In 2005, Texas became the first state to switch to a ”statewide franchise agreement”. This legislation means ISPs that wish to operate within the boundaries of a state are required to apply for a single statewide franchise agreement. This statewide agreement streamlines certain aspects that were previously subject to negotiation with local authorities such as franchise fees and pole access. Currently, 20 states in the US have adopted statewide franchise agreement legislation similar to Texas.

Among the states where similar legislation is in place is Wisconsin. Upon passing 2007 Act 42 State Franchise Legislation, local regulation of cable services was replaced with statewide regulation. For the purposes of this study, the fact that Wisconsin has adopted statewide cable franchise regulation is important. The statewide regulation ensures that institutional barriers faced by an ISP who wishes to provide services in a certain area are more or less uniform across localities.

3.3.2 Data

This chapter makes use of two major sources to construct the data set to be used in the following sections. The first one is Wisconsin’s comprehensive directory of issued statewide franchise agreements.[6] Any ISP wishing to operate in a new local market is obligated to add the

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[5] Source: https://www.businessinsider.com/the-cost-of-building-google-fiber-2013-4

[6] Directory of Wisconsin State - Issued Certificates of Franchise Authority, Source: https://web.archive.org/web/20180430193853/https://www.wdfi.org/˙resources/indexed/site/corporations/SICFA-

corresponding market into their service area outlined in the statewide agreement. The records include the date of the original franchise agreement with each ISP as well as the original service area footprint at the city/town/village level. Moreover, any amendments to original applications are dated and the expansion or withdrawal of service area is recorded. The records in this directory will be used to flag entry threat in a local market. The directory of licenses is of particular importance since much of the empirical literature struggles to find exogenous measures of entry threat. Relying on this directory, I construct the variable $Threat_{mt}$ for local market m at time t:

$$Threat_{mt} = \begin{cases} 0 & \text{if no ISP holds a license in market m at } t \\ 1 & \text{if some ISP holds a license in market m at } t \end{cases}$$

One important aspect of these agreements that needs to be noted here is that, the fact that a town/city/village is added to the scope of the agreement does not mean that all census blocks in the area will be served by the ISP. Although in most cases, I observe simultaneous fiber entry in all census blocks in a city, partial coverage is also a common practice. Moreover, it isn't a definitive measure of fiber entry since the majority of the fiber ISPs also happen to provide internet service using other technologies. In particular, Form 477 data suggests that the bulk of fiber entry is due to former DSL ISPs. In the next section, I will provide ex-post and ex-ante probabilities of entry to further justify this point.

The second major source is Fixed Broadband Deployment Data from FCC Form 477.[7] As a part of Connect America: National Broadband Plan, FCC requires all facilities-based broadband connection providers to end-users to file data twice a year. The data includes a list of census

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Log.pdf

[7] Source: https://www.fcc.gov/general/broadband-deployment-data-fcc-form-477

blocks where each provider offers services to at least one end-user.[8] The details of each connection such as the provider name, holding company, the technology used to deliver the service, the advertised download and upload speed rates are also included.

As mentioned earlier, Form 477 Data are reported at Census block level. I choose to define markets at block group level. Census block groups are fairly small geographic areas with typically 600-3000 population. The choice of aggregation to block group is justified since the variation across blocks in a block group is negligible. This leaves us with 4466 local markets per year. For demographic variables such as income and population in Census block groups, I use American Community Survey (ACS).

I summarize the availability of at least one ISP of each technology in Wisconsin in Table 3.1. The data suggest widespread availability of cable modem and DSL technologies in Wisconsin over the time period observed. I also see that fiber-optic presence is around 10% in 2011 and reaches up to around 57% by 2017 with the bulk of the entry happening at and after 2014. I believe that this pattern of fiber-optic ISP is informative on different choices of entry threat variable. Using a neighborhood approach as Xiao et al. (2018) explained earlier wouldn't reflect the entry patterns I observe. The data suggests simultaneous entry in neighboring markets as opposed to a spread-out to nearby locations over time. Figure 3.1 provides two maps of Wisconsin, one that corresponds to fiber presence in 2011 and another one in 2016.

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[8] It is useful to give some formal definitions provided by FCC's Form 477 glossary. FCC defines broadband connection as lines (or wireless channels) that terminate at an end-user location and enable the end-user to receive information from and/or send information to the Internet at information transfer rates exceeding 200 kilobits per second (kbps) in at least one direction. A facilities-based provider is a provider of broadband connections to end-user locations that: (1) owns the portion of the physical facility that terminates at the end-user premises or obtains the right to use dark fiber or satellite transponder capacity as part of its own network to complete such terminations; (2) obtains unbundled network element (UNE) loops, special access lines, or other leased facilities that terminate at the end-user premises and provisions/equips them as broadband. Finally, an end-user is a residential, business, institutional, or government entity that uses services for its own purposes and does not resell such services to other entities. Source: https://transition.fcc.gov/form477/477glossary.pdf

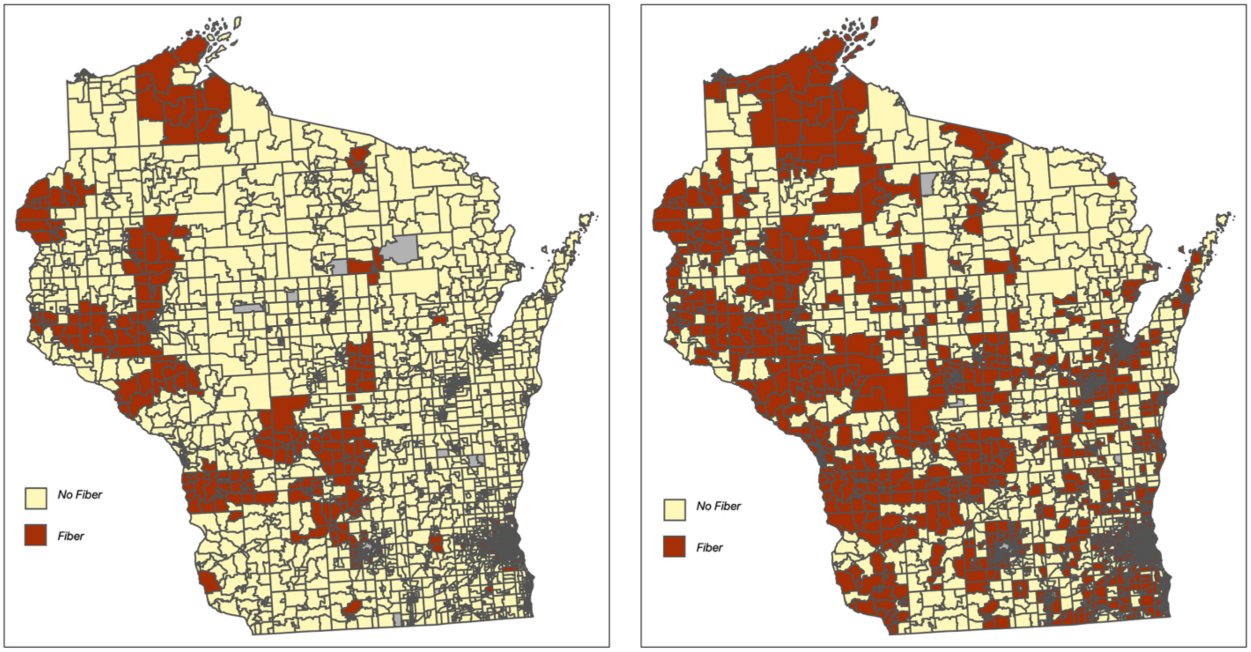

Figure 3.1: Fiber rollout 2011 vs 2016

Table 3.1: ISP presence by technology

	2011	2012	2013	2014	2015	2016
DSL	4334	4372	4368	4347	4335	4387
Cable Modem	4145	4124	4127	4145	4142	4130
Fiber	406	471	601	1793	2337	2587
Number of Markets	4462	4466	4467	4466	4467	4468

In Table 3.2, I give an overview of the number of providers operating fusing each technology and report the average number ISPs operating in a market. I again see that for cable modem and DSL, these figures are stable over time. My understanding is that change in the competitive environment over the observed period in a block group is due to fiber entry rather than other forms of technologies. Table 3.2 also reports the total number of ISPs of each technology operating throughout Wisconsin. The numbers may strike one as being too large however it is worth noting that there are many ISPs reported in FCC Form 477 with a very small service area footprint, in some cases limited to a single city.

Next, I define a variable to capture the network upgrade investment by cable modem ISPs. I do not have a continuous measure of investment such as capital expenditures to do so. Yet, Form 477 Data informs us about whether a Cable ISP employs services using DOCSIS 2.0 or DOCSIS 3.0 protocol. Accordingly, I define variable $Upgrade_{mt}$ as follows:

$$Upgrade_{mt} = \begin{cases} 0 & \text{If no Cable ISP offers DOCSIS 3.0 in market } m \text{ at time } t \\ 1 & \text{if some Cable ISP offers DOCSIS 3.0 in market } m \text{ at } t \end{cases}$$

Figure 3.2 illustrates the evolution of $Upgrade_{mt}$ from 2011 to 2016. As can be seen, a considerable amount of local markets have received DOCSIS 3.0 upgrade by 2011. The fact that

Table 3.2: Number of providers by technology

		2011	2012	2013	2014	2015	2016
DSL	Average	1.35	1.36	1.35	1.37	1.43	1.50
	Max	5	5	5	5	5	6
	Total	39	38	46	48	49	49
Cable Modem	Average	0.96	0.97	0.98	0.97	0.97	0.96
	Max	3	3	3	3	3	3
	Total	16	16	17	20	21	21
Fiber	Average	0.1	0.11	0.15	0.57	0.79	0.82
	Max	2	3	3	7	9	8
	Total	25	27	29	46	51	57

I am not able to observe the evolution of the network upgrade decisions prior to 2011 will bring some limitations to the kinds of questions this study will be able to answer. This will be made clear in the empirical analysis section.

While creating the variable $Upgrade_{mt}$, I make the following assumption: If there are more than one cable modem ISPs that provide services in a local market and some of them implemented DOCSIS 3.0 while others did not, I consider the market as an upgraded market. Since the block groups where there are more than one ISPs that operate amount to 6% of all markets, this assumption is expected to have a negligible effect on my results. In Table 3.3, I provide a joint summary of the two variables, $Threat$ and $Upgrade$ for 2011 and 2016. The breakdown of network upgrades at threatened and unthreatened markets is reported for markets where fiber entry has not occurred.

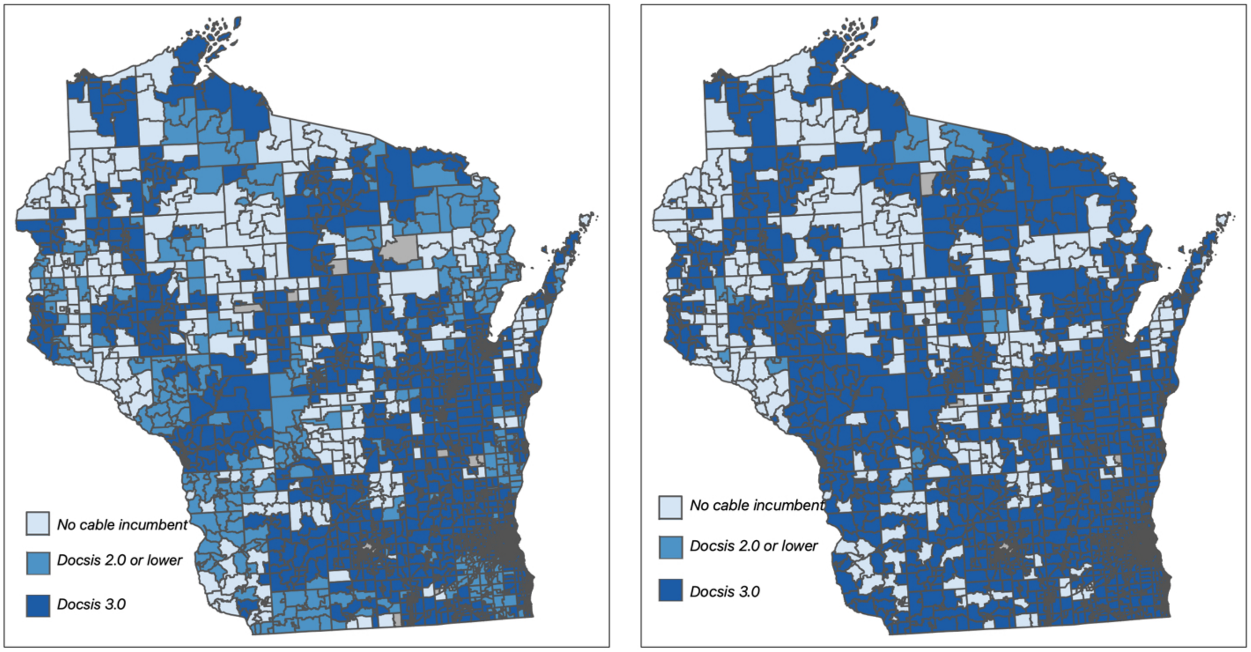

Figure 3.2: DOCSIS 3.0 Implementation 2011 vs 2016

There are some shortcomings of the Fixed Broadband Deployment data from FCC Form 477. First of all, I do not observe the number of connections served by each ISP. This means I can't talk about market shares for any ISP in the local markets I examine. Second, I do not know whether the internet connection service is bundled with other types of services such as video programming, telephony services, cloud access, and home security. Likewise, I do not observe the nature of contractual practices and prices adopted by individual ISPs. Lack of information about these limits my ability to speak about the post-entry competitive environment. As later will be discussed, not having a prediction of post-entry competition, in turn, blurs the line between deterrence and accommodation.

Table 3.3: DOCSIS 3.0 upgrade in threatened vs unthreatened markets

		Threatened	Unthreatened
2011	DOCSIS 3.0	2491	785
	DOCSIS 2.0	334	190
2016	DOCSIS 3.0	1037	496
	DOCSIS 2.0	5	12

* Markets without Fiber ISP

3.4 Empirical evidence

In this section, I will try to provide empirical evidence on strategic entry deterrence incentive by incumbent cable providers. To do so I will make use of Ellison and Ellison (2011) framework. To come up with a testable empirical hypothesis on strategic investment with entry deterrence motive, they argue the following: If in the absence of entry threat, we observe a monotonic relation between a measure of market attractiveness and the amount of the investment undertaken, then establishing a non-monotonic relationship between market attractiveness and investment would point out to entry deterring motives.

The reasoning behind this is as follows: In the least and most attractive markets, following Bain's terminology, entry is effectively blockaded, meaning that in the least attractive markets, potential entrant sees no opportunity for profitable business hence any entry deterring action is unnecessary. Meanwhile in the largest markets entry is perhaps inevitable, hence undertaking costly deterring action is useless. In contrast, medium-sized markets can be considered as battlegrounds for the incumbent. The potential entrant may be on the fringe while deciding whether they should enter or not. Hence, the incumbent can have greater returns to deterring action.

With this idea in mind, they develop two competing models: One where the potential entrant does not observe the incumbent's investment decision at the time they decide whether to enter or not. And in the next period conditional on entry decision, the incumbent earns either monopoly profits or duopoly profits. This model they call, model without entry deterrence motive. This is due to the timing of the game. In this setting, incumbent's investment decision cannot have a causal effect on the potential entrant's decision. Then a second model is proposed where the potential entrant observes the previous investment by the incumbent, and again due to the timing of events, the incumbent now has a motive to deter entry.

Using the model where there are no deterrence motives, they derive a set of conditions under which incumbents' investment decision will be monotonic in market attractiveness. So that any deviations from those monotonic investment decisions in the model with deterring motive could be attributed to entry deterring motive. They also note that equilibrium investment decisions in both of their models account for any incentive to accommodate, so the differences observed are due to deterring motives only.

As explained in the previous sections, the investment decision of DOCSIS 3.0 upgrade to be considered here as a tool of entry deterrence, has been rolled out since 2007. However, observations of these upgrades go back as far as 2011 and by 2011 majority of census block groups have received DOCSIS 3.0. This limits our ability to exploit the panel nature of my data set. Therefore, the empirical tests in this section will be limited to an investigation of the relationship between network upgrade decisions *by 2011* and entry threat. If I were to have data covering 2007-2010, the argument could be modified to address the dynamic nature of these decisions.

With that idea in mind, I intend to show some evidence for how the setting under question here is in line with Ellison and Ellison's framework. First of all, I need a measure of market attractiveness. My choice here will be the population of a local market, being the population of census block group. Choice of population as a measure of market attractiveness in the specific context of the broadband industry makes sense since it is a good proxy for demand for broadband services in a local market. In the literature most notably Bresnahan Reiss (1991, 1994) point out population as a proxy of the market size in their entry threshold models.

To justify that that choice further, I group markets into population quintiles and look at ex-post and ex-ante probabilities of entry by a fiber ISP. My measure of ex-ante probability of entry is based on the threat variable, $Threat_{mt}$, that was introduced earlier. First row of Table 3.4 reports the average of $Threat_{m,2011}$ for block groups of each population quintile. And we see that this ex-ante measure of entry probability is indeed increasing in population. Ex-post fiber entry probability on the other hand is calculated using actual fiber entry during 2011-2016 observed from Form 477 data. Ex-post entry probability is also higher for more crowded local markets.

Table 3.4: Ex-post and ex-ante measures of entry by market attractiveness

Population Quartile	Q1	Q2	Q3	Q4	Q5
Ex-post Fiber Entry Probability	0.53	0.54	0.60	0.68	0.75
Ex-ante Fiber Entry Probability	0.74	0.73	0.75	0.77	0.81

With observations for both threatened and unthreatened markets, one other helpful exercise is to look at network upgrade behavior in markets of different sizes. In Figure 3.3, I restrict attention to markets with at least one incumbent cable modem ISP and plot DOCSIS 3.0 upgrade against local market population quintiles. A first observation looking at Figure 3.3 suggests that threatened markets are more likely to receive DOCSIS 3.0 investment compared to unthreatened markets. The fact that investment is on average higher in threatened markets suggests the presence of preemptive behavior. In Bain's taxonomy of the incumbent's behavior in face of entry threat, blockaded entry is defined as a situation in which the incumbent operates as if there were no entry threat. Figure 3.3 refutes the presence of such a scenario. The shift in average investment rates in the threatened and unthreatened markets also rejects the theories in the literature that argue that costly competitive actions should be delayed until after the entry occurs or that preemptive response is not sequentially rational.

Having established the presence of preemptive behavior by incumbents, a more important observation here is the following: In unthreatened markets, it can be seen that proportion of markets that receive the DOCSIS 3.0 implementation by 2011 is monotonically increasing in market size measured as population quintile. In threatened markets however, we see a rather different picture: Smaller markets are still the most unlikely to have the network upgrade yet medium-sized markets in the second, third, and fourth quintiles have higher DOCSIS 3.0 implementation rates compared to large markets. The hike at medium quintiles provides a first direct evidence for non-monotonicity of investment argument. Next, I employ formal tests to establish the presence of preemptive behavior and the non-monotonic investment.

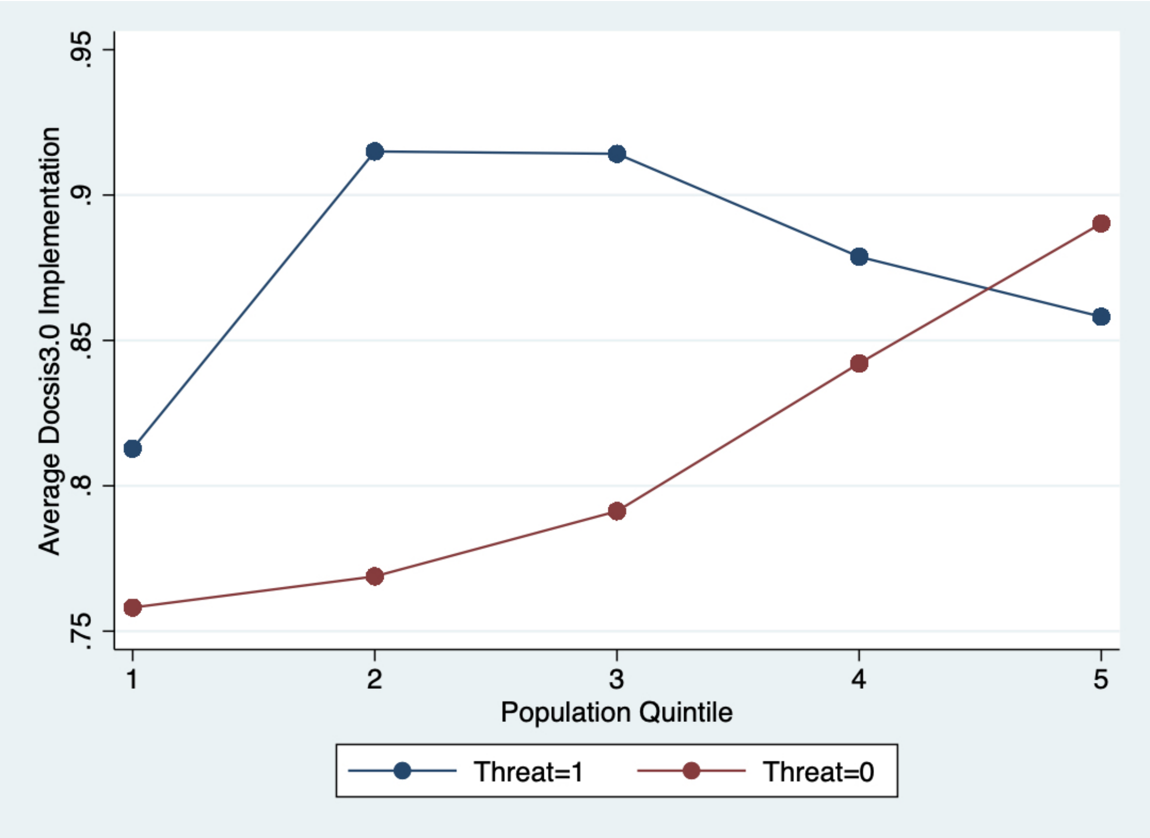

Figure 3.3: Average DOCSIS 3.0 investment and market attractiveness for threatened vs unthreatened markets

3.4.1 DOCSIS 3.0 upgrade as a preemptive action

In this section, I explore the nature of investment undertaken by incumbent cable modem ISPs. I quantify the raw findings from Figure 3.3. I start by formalizing the argument of the existence of preemptive action. The dependent variable is DOCSIS 3.0 implementation in the cross-section of markets in 2011, provided that there is at least one cable incumbent operating in 2011 and fiber entry has not occurred. I use the following logit specification:

$$Pr(Upgrade_m = 1 | X_m, Z_m, Theat_m) = \Lambda(\alpha X_m + \beta Z_m + \gamma_{county} + \delta Threat_m)$$

where X_m contains controls for market characteristics such as median income, population, median age at block group level, a categorical variable that indicates whether the local market is part of a metropolitan, rural, or nonmetropolitan area adjacent to a metropolitan area. Z_m contains variables that control for the existing competitive environment such as the number of DSL firms operating and the existence of a major cable modem incumbent. In light of Form 477, I establish that Time Warner and Charter are the two major incumbents in Wisconsin. I also include county-specific dummies in my regressions. Summary statistics for these variables are presented in Table 3.5.

Table 3.5: Summary Statistics

	Mean	Std. Dev.	Min	Max
Upgrade	0.85	0.34	0	1
log(Population)	7.05	0.42	5.50	8.76
(log(Pop.)-$\bar{P})^2$	0.18	0.26	0.00	2.93
Metro	0.74	0.43	0	1
Metro /Rural	0.23	0.42	0	1
Rural	0.02	0 .13	0	1
log(Housing Units)	6.14	0.430	1.79	7.88
(log(Housing Units)-$\bar{H})^2$	0.18	0.40	0.00	18.97
log(Median Age)	3.63	0 .22	2.70	4.32
log(Median Income)	10.81	0 .43	8.55	12.31
Cableno	1.04	0.22	1	3
DSLno	1.34	0.56	0	4
Threat=1	0.64	0.47	0	1
Threat=2	0.07	0.26	0	1
Threat=3	0.04	0 .20	0	1
Observations*	4143	4143	4143	4143

Markets with at least one Cable Incumbent

The main variable of interest here is $Threat_m$. The finding of a positive and significant coefficient on this variable would suggest the existence of preemptive behavior in threatened markets. The intuition for this expectation is due to incumbents' incentives to lock in the existing demand for high-speed reliable broadband services before the entrant arrives hence increasing chances for deterring entry. This incentive must be best demonstrated in the threatened markets. Results are reported in Table 3.6. The first column is a logit specification without any control variables. The second and third columns differ only in terms of the inclusion of county-specific dummies. Overall, the results in Table 3.6 are an indication of preemptive action taken by the incumbent cable modem ISPs. In addition, we see that metropolitan markets, markets with more DSL incumbents, markets with a major incumbent Cable ISP are more likely to receive the network upgrade.

Next, I want to test the non-monotonicity hypothesis using a similar framework to Ellison and Ellison (2011). As Dafny (2005) argues if the underlying monotonic relationship between market attractiveness and the amount of investment undertaken in the absence of entry threat is too steep or convex, then empirically establishing non-monotonicity in the threatened markets may not be possible. Hence, the finding of non-monotonicity should suggest a strong entry deterring action if that is the case. Having this in mind, I intend to capture any non-monotonicity by introducing quadratic variables. In addition to the demographic and market condition variables used in the last section, I create a new variable: $(log(Population) - \bar{P})^2$ where $\bar{P}$ is the mean of log population. By defining this new variable that captures the deviation of log(Population) from its mean, I intend to pin down the extent to which this non-monotonic behavior occurs. I estimate the following logit specification to this end:

Table 3.6: Effect of entry threat on DOCSIS 3.0 implementation

	DOCSIS 3.0 Upgrade		
	(1)	(2)	(3)
Threat	0.0696***	0.00870	0.0158
	(5.93)	(0.76)	(0.90)
log(Median Income)		-0.0679***	-0.0533***
		(-4.71)	(-3.81)
log(Median Age)		-0.0524	-0.00982
		(-1.91)	(-0.37)
log(Population)		0.0240	0.0262*
		(1.94)	(2.13)
DSLno		0.0355***	0.0403***
		(4.07)	(4.49)
Metro/Rural		-0.0158	-0.0918
		(-1.19)	(-1.29)
Rural		-0.108*	-0.0810
		(-2.03)	(-0.31)
Major ISP		0.595***	0.739***
		(18.63)	(18.09)
County			Yes
Observations	3800	3800	3532

Threatened and unthreatened markets with at least one incumbent Cable ISP and without fiber entry.

Test statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

$$Pr(Upgrade_m = 1 | X_m, Z_m, log(Population_m), \left(log(Population_m) - \bar{P}\right)^2) =$$

$$\Lambda(\alpha X_m + \beta Z_m + \gamma_{county} + \delta log(Population_m) + \theta \left(log(Population_m) - \bar{P}\right)^2)$$

The main variables of interest here are $log(Population)$ and $(log(Population) - \bar{P})^2$. A positive coefficient on the former and a negative coefficient on the latter variable would suggest an inverted-U shaped marginal effect on network upgrade. The results are reported in Table 3.7 for threatened markets and Table 3.8 for unthreatened markets. For threatened markets, the coefficients on $log(Population)$ and $(log(Population) - \bar{P})^2$ turn out to be in line with expectations in favor of strong entry deterrence incentive in medium-sized markets. In the unthreatened markets, both coefficients are positive. Overall the findings are in line with the theory.

3.4.2 Robustness check for entry deterrence evidence

In this section, I consider two alternative measure of market attractiveness to check robustness of the non-monotonicity results in the previous section. The first market attractiveness measure to be considered here is the number of housing units in a local market. One would expect this measure to be an acceptable proxy to potential demand for fixed broadband since service units are based on residences. It is also reasonable to expect results under population and number of housing units as a measure of market attractiveness will yield fairly similar results since the two measures are highly correlated. I first provide evidence from raw data in a similar fashion to Figure 3.3. In Figure 3.4, I report the average investment in threatened and unthreatened markets for each quintile for number of housing units. The results are similar to the case of population as a measure of market attractiveness. While the relationship is close to monotonic in unthreatened markets, there is a non-monotonic pattern in threatened markets.

Similarly, the same arguments for non-monotonicity can be made by using a variable that captures the deviation of logged housing units from its mean, $\big(log(\text{Housing Units}_m) - \bar{H})\big)^2$. The following specification is estimated:

Table 3.7: Population as a measure of market attractiveness (threatened markets)

	DOCSIS 3.0 Implementation		
	(1)	(2)	(3)
log(Population)	0.00464	0.0223	0.0365**
	(0.35)	(1.64)	(2.69)
(log(Pop.)-$\bar{P})^2$	-0.0361	-0.0493*	-0.0604**
	(-1.71)	(-2.48)	(-3.12)
log(Median Income)		-0.0665***	-0.0517**
		(-4.17)	(-3.28)
log(Median Age)		-0.0525	0.000835
		(-1.65)	(0.03)
DSLno		0.0411***	0.0537***
		(4.10)	(5.18)
Metro /Rural		-0.00610	-0.247*
		(-0.36)	(-2.35)
Rural		-0.0863	-0.0899
		(-0.80)	(-0.50)
Major Cable ISP		0.424***	0.487***
		(8.74)	(5.36)
County			Yes
Threatened markets			
Observations	2825	2825	2807

Threatened markets with no fiber entry and at least one incumbent cable modem ISP.

Test statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

$$Pr(Upgrade_m = 1 | X_m, Z_m, log(\text{Housing Units}_m), \left(log(\text{Housing Units}_m) - \bar{H}\right)^2) =$$

$$\Lambda(\alpha X_m + \beta Z_m + \gamma_{county} + \delta log(\text{Housing Units}_m) + \theta \left(log(\text{Housing Units}_m) - \bar{H}\right)^2)$$

Table 3.8: Population as measure of market attractiveness (unthreatened markets)

	DOCSIS 3.0 Implementation		
	(1)	(2)	(3)
log(Population)	0.0312***	0.0651*	0.0529*
	(19.31)	(3.19)	(2.27)
(log(Pop.)-$\bar{P})^2$	0.036**	0.002	0.012*
	(2.94)	(1.89)	(1.63)
log(Median Income)		-0.0278	-0.0361
		(1.78)	(-1.91)
log(Median Age)		0.032	-0.0296
		(0.87)	(-0.70)
DSLno		0.0286	0.0181
		(1.35)	(1.07)
Metro/Rural		-1.138***	-0.0733***
		(-4.5)	(-3.99)
Rural		-0.128	-0.0713
		(-1.84)	(-1.40)
Major Cable ISP		0.912***	0.840***
		(19.32)	(27.31)
County			Yes
Unthreatened Markets			
Observations	987	987	987

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results in Table 3.9 indicate that the analysis of non-monotonicity between market attractiveness and network upgrade investment in threatened markets is robust to the housing units definition. The results for unthreatened markets also follow a similar pattern as those in Table 3.8.

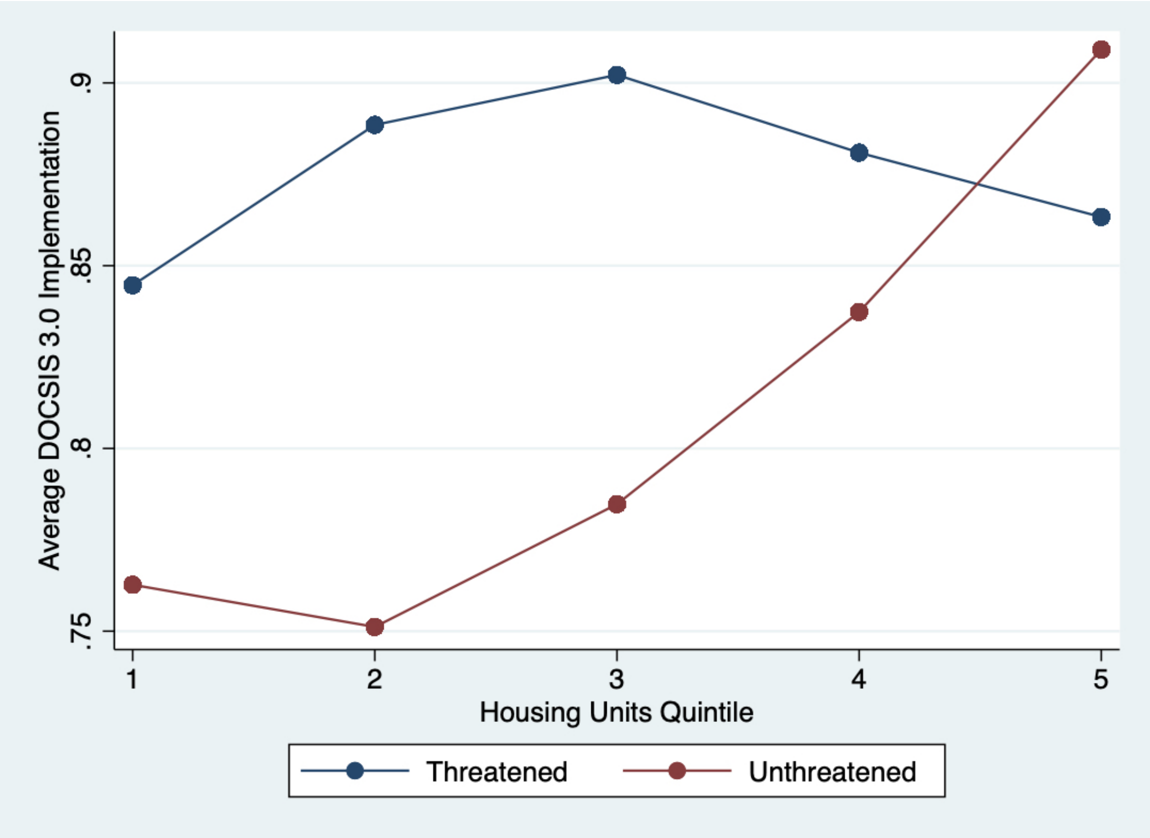

Figure 3.4: Average DOCSIS 3.0 investment and market attractiveness for threatened vs unthreatened markets

As a second check on robustness, I use Dafny's (2005) framework. An alternative approach developed by Dafny (2005) is to use the number of potential entrants as a measure of market attractiveness instead of a more straightforward measure such as market population. The intuition is similar to Ellison and Ellison (2011). In markets where the number of potential entrants is smaller, the return on entry deterring must be higher in comparison to markets threatened by multiple entrants. Hence, entry deterring investment must be heavier in markets with a single potential entrant. Using Wisconsin's directory of state-issued licenses, in Table 3.10, I summarize markets by the number of potential entrants and report ex-post entry probability for each category.

Table 3.9: Housing units as a measure of market attractiveness

	DOCSIS 3.0 Upgrade	
	(1)	(2)
log(Housing Units)	0.0388	0.0275^{*}
	(1.57)	(2.04)
(log(Housing Units)-$\bar{H})^2$	0.009^{***}	-0.0374^{*}
	(3.04)	(-2.01)
log(Median Income)	-0.148^{**}	-0.0443^{**}
	(-2.11)	(-2.91)
log(Median Age)	0.0101	-0.0231
	(1.14)	(-0.77)
DSLno	0.0015^{*}	0.0528^{***}
	(2.1)	(5.09)
Metro/Rural	-0.018	-0.244^{*}
	(-1.88)	(-2.31)
Rural	-0.055 **	-0.101
	(-2.71)	(-0.56)
Major Cable ISP	0.684^{***}	0.482^{***}
	(7.83)	(5.25)
County	Yes	Yes
	Unhreatened markets	Threatened markets
Observations	981	2822

Test statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In my sample, the maximum number of potential entrants is equal to 3 and the majority of markets are threatened only by 1 entrant. Notice that markets where the number of potential entrants is equal to 0 have 0.46 ex-post entry threat. This is due to some of these markets being unthreatened in 2011 but becoming threatened at a later point in the sample period.

In order to test for non-monotonicity between the number of potential entrants and network upgrade decisions, I group markets into three categories: unthreatened, threatened by one potential entrant, and threatened by more than one potential entrant. An observation of a greater coefficient on the second category would be an indication of greater entry deterring action in moderately threatened markets. The incumbent would put less effort into network upgrades in markets where they are facing multiple threats since the chances of successful deterrence are lower when the battle is fought on multiple fronts. Table 3.11 reports the results for the following specification:

$$Pr(Upgrade_m = 1 | X_m, Z_m, \mathbb{1}(\text{Potential entrant}_m = 1), \mathbb{1}(\text{Potential entrant}_m > 1)) =$$

$$\Lambda(\alpha X_m + \beta Z_m + \gamma_{county} + \delta \mathbb{1}(\text{Potential entrant}_m\text{=1}) + \theta \mathbb{1}(\text{Potential entrant}_m > 1))$$

Table 3.10: Ex-post entry probability by Number of Potential Entrants

Number of potential entrants	Number of markets	Ex-Post entry probability
N=3	166	0.96
N=2	284	0.72
N=1	2375	0.59
N=0	975	0.46

Markets with at least one Cable Incumbent and no fiber ISP

The findings from Table 3.11 suggest that the marginal effect of $\mathbb{1}(\text{Potential entrant}_m = 1)$ is greater than $\mathbb{1}(\text{Potential entrant}_m > 1)$. The first column with no control suggests that implementation is more likely in markets where there are multiple potential entrants as opposed to unthreatened markets however this relation flips when we add demographic and competition controls. Yet, relative magnitudes of $\mathbb{1}(\text{Potential entrant}_m = 1)$ and $\mathbb{1}(\text{Potential entrant}_m > 1)$ stay the same across specifications. This could be considered as further evidence of entry deterrence incentive where the returns to investment are expected to be the most.

In the following section, I will look at this potential entrant versus incumbent story from the perspective of the potential entrant in hopes to have a more complete understanding of the competitive environment.

3.4.3 First fiber entry into a local market

In this section, I analyze factors that contribute to the first fiber entry into a local market. I begin the analysis by estimating the following latent variable model:

$$y_{mt} = \gamma \mathit{Upgrade}_{mt} + X_{mt}\beta + Z_{mt}\theta + \alpha_{county} + \varepsilon_{mt}$$

where y_{mt}=1 denotes local market *m* has received its first fiber ISP at time *t*. *Upgrade* is the binary indicator that takes on the value 1 if the cable incumbent has invested in the network upgrade and 0 otherwise. *X* is a matrix of demand determinants in a local market such as population density and median household income *Z* is a matrix of market characteristics such as the number of cable and DSL ISPs operating at the market. Here, I focus only on the subset markets that had a cable ISP operating during the period 2011-2016. This leaves us with 4145 markets per year in total. The data used here is right-censored since I do not observe the first fiber entry into a local market beyond 2016.

Table 3.11: Number of Potential Entrants

	Docsis3.0 Upgrade by 2011		
	(1)	(2)	(3)
Threat=1	0.0837***	0.0183	0.0268
	(5.88)	(1.55)	(1.43)
Threat>1	0.0393	-0.0571**	-0.120***
	(1.85)	(-2.78)	(-3.45)
log(Median Income)		-0.0673***	-0.0507***
		(-4.69)	(-3.69)
log(Population)		0.0300*	0.0385**
		(2.42)	(3.13)
log(Median Age)		-0.0513	-0.00575
		(-1.88)	(-0.22)
DSLno		0.0308***	0.0340***
		(3.50)	(3.83)
Metro/Rural		-0.0228	-0.274**
		(-1.66)	(-2.69)
Rural		-0.112*	-0.261
		(-2.09)	(-0.66)
Major ISP		0.596***	0.731***
		(18.85)	(17.17)
County Dummies			Y
Observations	3800	3800	3532

Threat=0 as omitted category.

Test statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

First fiber entry is an absorbing state, so I model y_{mt} as a discrete hazard probability that a local market will receive the first fiber entrant at time *t* provided that entry has not occurred up until *t*. I use two alternative link functions that are commonly used in discrete hazard settings, complementary log-log and logit. For the non-parametric specifications, I create a dummy for each duration interval in my sample period. For the data that I am working with, this would be equivalent to creating year dummies. For parametric specifications, I use a logarithmic functional form for the baseline hazard function. Estimation results are reported in Table 3.12.

The results indicate that local markets that have received network upgrades are more likely to receive their first fiber entry. This suggests an accelerated pattern of fiber entry as a response to network upgrades. The intuition for this pattern can be explained by fiber firms' incentive to enter into upgraded markets before incumbent cable modem ISP can absorb the demand for high-speed internet. Since contracts for fixed broadband services often include restrictions for early termination fees, the timing for potential fiber entrants can be crucial.

3.5 Discussion and concluding remarks

The results presented in the previous sections indicate two important findings on competition between fiber and cable modem ISPs. The first one is cable modem ISPs engage in preemptive action when faced with fiber entry threat. I examine network upgrade decisions by cable modem ISPs and conclude that threatened markets are more likely to receive upgrades that enable cable modem providers to deliver services that are comparable to fiber ISPs. The second finding is on the underlying motive behind this preemptive investment decision. Based on the patterns of

Table 3.12: First Fiber Entry

	(1) Cloglog Nonparametric	(2) Cloglog Parametric	(3) Logit Parametric	(4) Logit Nonparametric
First Fiber Entry				
DOCSIS 3.0	0.119^{**}	0.140^{***}	0.128^{***}	0.111^{**}
	(3.17)	(4.62)	(4.53)	(3.19)
Cableno	0.00557	0.00667	0.00667	0.00455
	(0.43)	(0.62)	(0.62)	(0.35)
DSLno	0.0330^{***}	-0.00564	-0.00576	0.0325^{***}
	(9.60)	(-1.46)	(-1.51)	(8.86)
log(Median Income)	0.0236^{***}	0.0207^{***}	0.0208^{***}	0.0238^{***}
	(3.38)	(3.48)	(3.46)	(3.43)
log(Pop)	0.00936^{***}	0.00639^{***}	0.00640^{***}	0.00922^{***}
	(5.74)	(4.56)	(4.44)	(5.54)
Metro/Rural	-0.00741	-0.00973	-0.00988	-0.00493
	(-1.00)	(-1.56)	(-1.55)	(-0.66)
Rural	-0.0771^{***}	-0.0632^{***}	-0.0647^{***}	-0.0736^{***}
	(-4.44)	(-4.49)	(-4.53)	(-4.07)
Year (2011-2016)	Yes	No	No	Yes
County Dummies	Yes	Yes	Yes	Yes
Observations	15253	19023	19023	15253

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

investment observed in threatened and unthreatened markets, an argument can be made in favor of entry deterrence. I observe that investment decisions are monotonically increasing in market attractiveness in the absence of entry threat. In contrast, the same relationship is characterized by an inverted-U shape in the threatened markets. I argue that moderately attractive markets receive more investment under entry threat because the incumbent sees higher chances of successful deterrence in these markets. The incumbent may not undertake costly deterring projects in the least attractive markets since they anticipate that the potential entrant may not consider those markets as a target and in the most attractive markets deterring entry may be a useless effort. The empirical analysis supports this line of reasoning.

I check the robustness of these results using population and housing units in a local market as measures of market attractiveness. I also consider deterring incentives in face of one or multiple potential entrants. Although the results are not included here, one more robustness check for market attractiveness decision is conducted using population density. This exercise refuted the existence of non-monotonicity between investment and market attractiveness. This is a striking result since population density could be an even better measure of attractiveness compared to the population. Population density is a better proxy since more dense markets would not only mean more potential demand for a fixed broadband provider, but it also potentially means less costly investment due to the ability to pass more houses using less input.

A final issue to be raised about the findings is the limited ability of Ellison and Ellison's (2011) framework to address the accommodation versus deterrence incentive behind preemptive action. The theory developed in this paper assumes firms are expected to react to accommodating incentives under two competing models. Hence any difference in equilibrium investment levels observed under the model with and without deterring incentives is purely attributed to deterrence. The lack of data on measures such as post and pre-entry market shares, prices, contractual practices limits my ability to empirically distinguish between accommodation and deterrence. Data suggests the investment decisions in the least and most attractive markets to be different under threatened and unthreatened cases. This could point out to an accommodation incentive. The findings on determinants of first fiber entry are also important to address this issue. If potential fiber entrants are responding to network upgrades by accelerated entry, would this mean an unsuccessful attempt at entry deterrence or accommodation by the incumbents? To answer this question, more information on the post-entry competition is required.

I intend to check the robustness of the results under alternative market definitions. Since franchise agreements between state and ISPs are made at the city/town/village level, it is important to review the results by using a larger geographical choice. I also intend to give a more detailed analysis of the potential entrant side of the story to have a more complete understanding of both sides of the story.

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