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Essays on Two-sided Platforms: Market Entry Strategy and Dynamic Pricing

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Abstract

This dissertation consists of two chapters: In the first chapter, we build a theoretical framework to study the dynamic entry interactions between two platforms with homogeneous products into city-based markets. This research is applicable for studying the entry strategies between, for example, Uber and Lyft; Groupon and Living Social, and other business models with the attributes of switching cost, network effect, and segregated markets. We address three questions in this paper: 1) What determines the expansion path of city-based platforms?; 2) What factors are affecting the market concentration structures; and 3) Under what conditions can a second mover become the market leader (with more than 50% of the market share)? We find that a significant degree of the network effect and large switching cost will build a natural barrier for the late entrant; Transaction-efficient markets with larger transaction volume are less likely to be concentrated than transaction-inefficient markets. We take consideration of entry cost and initial fund in our dynamic settings, and find that the uncertainty in market return will make the platforms' expansion path and the final outcome less predictable. However, on average, the capability of capturing the largest market first is crucial for both players; if a platform loses the opportunity of being the first to capture the largest market, it may have to raise a considerable amount of money to overcome its disadvantages in the following competitions.

In the second chapter, we empirically investigate the effect of the dynamic pricing system on ride-sharing platform drivers' labor supply. Rather than working-hour and wage-rate relation explored by previous and current literature, we examine the instantaneous response of drivers to price surges. Using data from New York City, we estimate the structural model through a constrained non-parametric instrumental variable (NPIV) approach. We find that the emergence of a price surge is a strong incentive for drivers, and the dynamic pricing scheme of ride-sharing platforms effectively solves the geographical disparity problem of uncoordinated taxi systems. Consequently, the overall accessibility and quantity of pickup service in the entire city will increase. In the absence of dynamic pricing, we show in a counterfactual analysis that platform drivers will be clumped in the Manhattan area and airports, a dilemma shared by the taxi drivers. The counterfactual context implies that 27 % of the total supply will be lost, including a significantly large 59% reduction in the non-Manhattan area.

Dedication

To my grandma.

Acknowledgments

I am greatly indebted to my advisor, Tom Chungsang Lam for his advice and encouragement. I give special thanks to James Brannan as well as to F. Andrew Hanssen, Matthew Lewis, and Scott Baier for being my committee members. I also thank Patrick Warren, Charles Thomas, Babur De los Santos, and all other participants in the Clemson IO workshop for their valuable comments. All errors are mine.

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Contents

List of Tables

List of Figures

Chapter 1

Market Entry Strategies for City-Based Platforms

1.1 Introduction

Today, increasing numbers of businesses are organized around platforms, via which multiple sides interact to conduct transactions. These companies are involved in areas such as social media (Facebook), online trading platform (eBay), and search engine (Google). The majority of these platforms compete in one aggregate market, and therefore their entry decision has broader boundaries — once an entry decision is made, soon it will open access to users on all sides; in this way, we will only observe one entry movement at one specific time. In contrast, some platforms have narrower market boundaries, such as Groupon, Airbnb, and Uber. These platforms need to make contracts with customers and suppliers from a local base (Table 1.1 lists several examples of city-based platforms); hence, their expansion paths are quite different from the previously mentioned platforms, their entry decisions could be more discrete and dynamic, and we may observe several entries with different timings. In this way, markets' characteristics and timing of decisions will have a significant influence on a platform's final performance.

Table 1.1: Examples of local-based platforms

Platform(s)	Market	Side 1	Side 2
Uber, Lyft, Juno, Via, Didichuxing	Ride-sharing	Drivers	Riders
UberEats, Yelp Eat 24, Seamless, Meituan	Food Delivery	Restaurants	Diners
Groupon, Living Social, Yipit, CoolSavings	Online Deal & Promotion	Merchants	Deal-Shoppers
OfO, Mobike, CitiBike	Bike-sharing		Riders
Airbnb	Room-sharing	Room-owners	Tenants

In this paper, we study the entry decision of homogeneous city-based plat- forms. We attempt to address the following questions: 1) What determines the expansion path of city-based platforms? 2) What kind of markets are capable of holding more entrants? And 3) How can a late entrant take over market leadership? To answer these questions, we build a theoretical framework for market entry strategies for city-based platforms. We also extend the framework to two-player games. In these games, we test the relative importance of multiple factors related to the platform economy:

Network effect and switching cost

Network effect and switching cost are two important research streams studying business operations via platforms. (e.g., Klemperer (1987), Katz and Shapiro (1994), Anderson (1998), and Lam (2017)). In multi-sided platforms, we have indirect network effects: such as the case of Uber: as more riders join the platform, the more attractive it is to drivers; and direct network effects: such as social media (Facebook and Twitter). For these platforms, network effects act as the "Matthew effect" — "to those who has will more be given", a large degree of network effect will make the market highly concentrated.

Further, switching cost determines how difficult it is for a late entrant's products to be accepted by customers. For platforms with lower switching costs, customers can easily home in on multiple platforms, such as Amazon and eBay; for platforms with higher switching cost, it is difficult for users to practice multi-homing,(e.g., cellphone users — once a cellphone is purchased, it can only support apps from one operating system; or video game players — games are incompatible between different consoles). In this paper, network effect and switching cost mutually control the market share function of platforms. We find that a large network effect and large switching cost will result in market concentration, and make the second mover disadvantaged in the later competitions.

Transaction efficiency and market uncertainty

We also test the player's equilibrium behavior under different setups of transaction efficiency. We find that higher transaction efficiency will make large cities more attractive to the second mover, and markets with higher transaction volume are less likely to be concentrated. In this way, occupying the largest market becomes crucial. For a second mover to take over market leadership, they either needs sufficient initial funds to capture the largest market before the first mover does, or the market is particularly open for a second mover with low network effect and adept at multi-homing.

We also take into consideration market uncertainty in our model—before one market is being explored, its actual return rate or participation rate is unknown to all. In this way, the first entrant of the market will have to face the risk of possible low return. The numerical experiments demonstrate that uncertainty in market return will give the second mover more opportunities to catch up with the first mover in the dynamic game.

Entry cost and initial fund

In a similar manner as for a regular start-up company, in our model, before players start to explore the markets, they will raise an initial fund. We simplified the fund-raising process to be only one round for both players. Because we don't allow for negative market return in our simulations, the players will spend the initial fund on entry cost. Hence, in each period, a player will make entry decisions by solving a BLP (binary linear programming) problem. We find that a second mover with a higher initial fund is more likely to take over market leadership.

1.1.1 Related Literature and Contributions

This paper contributes to the current literature by being the first to construct a theoretical framework to model the real-world entry dynamics between platforms. The research applies to businesses with the attributes of network effect, switching cost, market return uncertainty, and limited market boundaries. We provide adjustable parameters to fit in different types of platforms.

This work mainly complements the literature studying the order-of-entry problem (e.g., Lambkin 1988; Mitchell 1989; Lilien and Yoon 1990; Mitchell 1991; Golder and Tellis 1993; Lee 2008; Wu 2013, etc.). Lieberman has a series of research works on the first mover advantages, such as Lieberman and Montgomery (1988, 1998) and Lieberman (2005), Lieberman and Montgomery (1988) survey the theoretical model and empirical evidence that confer the first mover advantages; they also examine the possible source of first mover disadvantages. Lieberman (2005) assesses the magnitude and sources of first-mover advantages in 46 Internet markets; he finds that network effect and patented innovations are related to higher market valuation for pioneer movers. and Lambkin (1988) find that pioneer incumbents on average outperform late entrants. Previous works mostly focus on empirically and theoretically identifying the sources of first mover advantages, whereas in this paper, we apply the concept of first mover advantages in our model, and ask under what condition can a second mover be able to overcome the first mover advantages.

Some of the related works on platform entry problems are concluded as follows: Zhu and Iansiti (2012) build a theoretical model and find that an entrant's success depends on the strength of indirect network effects and on the consumer expectation of future applications. They find that under certain conditions, a small quality advantage can help the entrant compete against install-based advantaged incumbent. They empirically examine the model applicability by investigating the video game industry. Dewenter, Rösch, et al. (2012) analyze the impact of indirect network effects in emerging two-sided markets on price, quantities, profits, and market entry, and find that, when network effect is strong, market entry will no longer occur, thus leading to a natural monopoly. Seamans and Zhu (2013) empirically investigate the impact of Craigslist's entry on local newspapers; and Kim, Lee, and Park (2013) empirically study the two-sided market entry strategies in the online daily deals promotion industry. Our paper is different from the above works in two ways: first, we do not focus on post-entry firm interactions such as pricing strategies or quality competition, but rather we focus on the decision of entering the market; second, their analyses are mostly within one market, whereas we are examining the entry decisions into multiple markets.

Although, there have been substantial increases in the literature studying multi-sided markets (e.g., Armstrong 2006; Rochet and Tirole 2003, 2006; Rysman 2009; Jullien 2011.), most of the theoretical work focuses on optimal pricing strategies and interactions between sides. This work complements this theoretical stream by offering a dynamic approach to study the interaction between firms.

1.1.2 Motivation

Although the model in this research applies to many local-based platforms, the motivation of starting this research comes from several interesting unexplained observations of the leading ride-sharing platforms, Uber and Lyft. First, both Uber and Lyft have a strong preference for large cities. Uber made its first entry into San Francisco in 2010; then New York, Seattle, and Chicago in 2011; and San Diego, Los Angeles, Philadelphia, Atlanta, and so on, in 2012. Two years later, Lyft also launched its first ride in San Francisco, then Los Angeles, Seattle, Chicago, and so on. If we examine the first several entries of both platforms (Table 1.2), we can find that both of them have a strong preference for large cities.

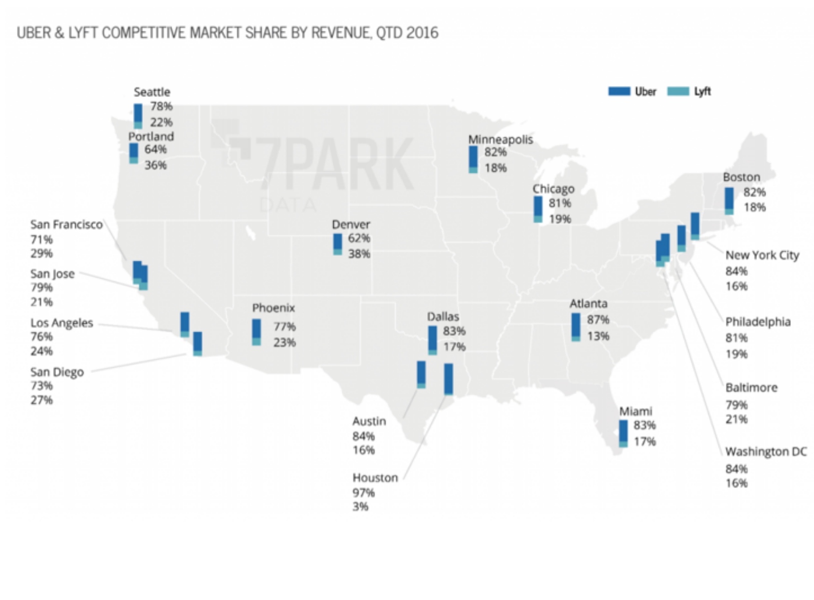
Table 1.2: First 13 city launches of Uber & Lyft

Uber Cities	Uber Launch Date	Lyft Cities	Lyft Launch Date
San Francisco	7/10/2010	San Francisco	6/1/2012
New York	5/3/2011	Los Angeles	1/31/2013
Seattle	7/25/2011	Seattle	4/1/2013
Chicago	9/22/2011	Chicago	5/9/2013
San Diego	1/6/2012	Boston	5/31/2013
Los Angeles	3/8/2012	San Diego	7/2/2013
Philadelphia	6/6/2012	Washington	8/9/2013
Atlanta	8/24/2012	Atlanta	8/29/2013
Denver	9/5/2012	Minneapolis/St.Paul	8/29/2013
Dallas	9/14/2012	Indianapolis	8/29/2013
Boston	9/19/2012	Phoenix	9/5/2013
Minneapolis/St.Paul	10/25/2012	Charlotte	9/12/2013
Phoenix	11/15/2012	Denver	9/19/2013

Things can be easily understood for Uber because a large city means a large market. But if we look at Lyft's entry path, we notice that Lyft seems to follow the same entry path as Uber: in the beginning, Lyft always chose to enter the markets already being occupied by Uber, rather than exploring a new but smaller market. More evidence can be found from the launch choices of other ride-sharing platforms, such as Juno and Via, who both started in New York; similarly, SitBaq and Summon both started in San Francisco and the Bay area. Thus the following question arises: Why do second mover ride-sharing platforms always choose to enter these large cities to face intensive competition, rather than exploring a new but smaller market?

Second, no matter the entry order and initial funds, Uber always tends to dominate the market. Before Uber started its first launch in San Francisco in 2010, it raised \$1.3M in the angel round. Almost two years later, June 1st, 2012, Lyft, a ride-sharing platform providing almost an identical service, announced its first launch in the same city, San Francisco; and this time, with Uber already proving the potential of ride-sharing business, Lyft raised \$7.3M for its debut launch. However, a more successful initial fund-raising round did not help Lyft become the market leader. Figure 1.1 is a report of Uber and Lyft's market share in major cities in 2016 (Peltier 2016).

Figure 1.1: Uber & Lyft competitive market share by revenue QTD 2016



We can see from the figure that market shares of both firms are around the ratio of 20:80, although most of the cites where Uber makes the first entry, there are also several special cases (Table 1.3).

Table 1.3: Cities entry time of Uber & Lyft

Cities	Uber Launch Date	Lyft Launch Date
Washington D.C	8/8/2013	8/8/2013
Houston	2/21/2014	2/19/2014
Miami	6/4/2014	5/23/2014
Austin	6/3/2014	5/29/2014

For these four cities, Uber and Lyft entered at almost the same time; for Miami and Austin, Lyft even entered several days ahead. But we can see from Figure 1.1 that, Lyft only owned around 16% to 17% of the market; for Houston, it was exceptionally low, only 3%. Why is the market share ratio so constant across the country, and why does Uber always dominate the market even when Lyft was the first mover?

This research could also join the recent emerging studies on ride-sharing platforms (e.g. Li, Hong, and Zhang 2016; Hall, Horton, and Knoepfle 2017; Hall and Krueger 2018; Cramer and Krueger 2016; Greenwood and Wattal 2015; Chen, Mislove, and Wilson 2015).

The rest of the paper is arranged as follows: In section 2, we will propose the fundamental model setups applied in later chapters; then, in section 3, we solve for Nash-equilibriums in static games under different market conditions. In section 4, we extend the static game to a dynamic game and provide numerical experiments in section 5. Finally, in section 6, we will state our conclusions and discuss future research potentials.

1.2 The General Rules

Before exploring the static game, we will go through three fundamental rules, which will be applied in the static game and dynamic game, taking account of market size, pre-entry uncertainty, and the market-splitting rule. These rules will build a general model framework for the city-based platform entry problem.

Transaction Volume

Suppose each city is a market, and platforms face a line of potential cities ranked by population size. As in Table 1.4, the largest city in the U.S is New York City; its population is approximate twice the population of the second largest city, Los Angeles; and the third largest city Chicago, is nearly one-third the population of NYC, and so on. This phenomenon (rule) is called "Zipf's Law for Cities" (Zipf et al. 1949; Xavier 1999).

Table 1.4: U.S Top cities by population 2016 (in millions)

Rank	1	2	3	4	5	6
City	New York	Los Angeles	Chicago	Houston	Phoenix	Philadelphia
Population	8.538	3.976	2.705	2.33	1.615	1.568
Ratio to NYC	100.0%	46.6%	31.7%	27.3%	18.9%	18.4%
	1	$\approx \frac{1}{2}$	$\approx \frac{1}{3}$	$\approx \frac{1}{4}$	$\approx \frac{1}{5}$	$\approx \frac{1}{6}$

Data Source: US Census Bureau

Also, suppose platforms compete over a fixed size of the population in each city, the market rank K has $\frac{N}{K}$ service consumer and $\frac{M}{K}$ service provider on each side. Consider a transaction efficient setup, that every service provider is capable of interacting with every service consumer. The potential transaction volume of such platforms will be similar to the setup in traditional two-sided market literature (Rochet and Tirole 2003): simply multiply both supply and demand sides together, which is equal to $\frac{NM}{K^2}$. From this setup, the market potential transaction volume is substantially enlarged in large cities. For instance, the first largest market is 4 times the second largest market and 9 times the third ($\frac{NM}{1}$ compares with $\frac{NM}{4}$ and $\frac{NM}{9}$).

Pre-entry Market Uncertainty

Before being explored, the average benefit α_k of each potential transaction in the Kth market is unobservable to both platforms. However, platforms know the distribution of the benefit $\alpha_K \sim F(\alpha_K)$. Once market K is being explored, α_K would reveal to all. One can consider this α_K as a platform-specific city (exogenous) characteristic; because, for different types of businesses such as Groupon for deals, Airbnb for room-sharing, and Uber for ride-sharing, α_K should have different values. Here, α_K has two meanings: first, it is the platforms' average profit per potential transaction, which means it takes into account the revenue and cost at the same time. Second, it also represents the utilization rate of a platform in the Kth market, because $\frac{NM}{K^2}$ is the ideal transaction volume, in reality, based on city culture and city characteristics, some cities may use the platform more frequently, and other cities may not use the platform much at all. Hence, α_K also measures each city's preference.

Market Share

Suppose users in one representative market i are facing a nested choice problem, and there is no outside option available within this choice set. Before the second mover enters the market, the incumbent gains all the market share, because no other choice is available. And after the entry of the second mover, the utility of an average user choosing platform n in one transaction will be:

$$U_{nit} = \begin{cases} V_{nit} + \gamma x_{nt} & \text{, if platform n is the incumbent} \\ V_{nit} + \gamma x_{nt} - h_n & \text{, if platform n is the entrant} \end{cases} \tag{1.1}$$

$$x_{nt} = \frac{m_{nt}}{m_{nt} + m_{-nt}} \tag{1.2}$$

Where $\gamma \in [0, \infty)$ represents the parameter of network effect larger γ means larger network effect, m_{nt}, m_{-nt} are platform sizes of the player and it's opponent, calculated by the numbers of users already captured by a platform; x_{nt} is the relative firm size; V_{nit} is the average user utility gains from service provided by platform n; it is related to service price, service quality and other platform characteristics. Finally, parameter h_n represents the dis-utility of switching from incumbent platform $-n$ to entrant platform n, if n is a second mover.

The market share of each platform based on nested logit choice model is:

$$S_{nit} = \begin{cases} \dfrac{e^{(V_{nit} + \gamma x_{nt})}}{e^{(V_{nit} + \gamma x_{nt})} + e^{(V_{-nit} + \gamma x_{-nt} - h_{-n})}} & \text{, if platform n is the incumbent} \\ \dfrac{e^{(V_{nit} + \gamma x_{nt} - h_n)}}{e^{(V_{-nit} + \gamma x_{-nt})} + e^{(V_{nit} + \gamma x_{nt} - h_n)}} & \text{, if platform n is the entrant} \end{cases} \tag{1.3}$$

If we consider a homogeneous case, that switching cost and average service utility are the same for both platforms, so that $h_n = h_{-n} = h$ and $V_{nit} = V_{-nit} = V$, the share functions will become:

$$S_{nit} = \begin{cases} \dfrac{(e^{x_{nt}})^\gamma}{(e^{x_{nt}})^\gamma + p(e^{x_{-nt}})^\gamma} & \text{, if platform n is the incumbent} \\ \dfrac{p(e^{x_{nt}})^\gamma}{(e^{x_{-nt}})^\gamma + p(e^{x_{nt}})^\gamma} & \text{, if platform n is the entrant} \end{cases} \tag{1.4}$$

Where $p = e^{-h} \in (0, 1]$[1], when $h = 0$, $p = e^{-h} = 1$, there is no switching cost; when $h \to \infty$, $p = \lim_{h \to \infty} e^{-h} = 0$, the switching cost of a new platform is extremely large, users are fully unacceptable for a second mover.

Therefore, the final rule of market share is concluded as follows: When a platform n decides to enter a new market without any incumbent, it will capture the entire market; when a platform n decides to enter a market already occupied by another incumbent $-n$, they will split the market:

$$S_{nit} = \begin{cases} 1, & \text{if market i has 0 incumbent} \\ \dfrac{p(e^{x_{nt}})^\gamma}{(e^{x_{nt}})^\gamma + p(e^{x_{-nt}})^\gamma}, & \text{if market i has 1 incumbent} \end{cases} \tag{1.5}$$

$$S_{-nit} = 1 - S_{nit} \tag{1.6}$$

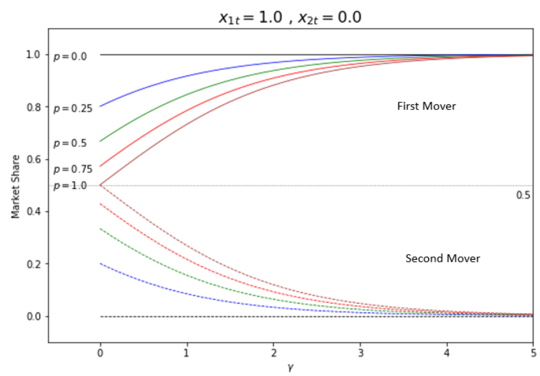
Therefore, if there are two firms in the market, they will split the market based on their current firm sizes, parameter $p \in (0, 1]$, and parameter $\gamma \in [0, \infty]$. Note here, that, we essentially assume that platforms are open to multi-homing, but with some degree of

[1]Note that their could be the case of second mover advantage $p > 1$, but it is beyond the discussion of this paper. In this paper, we regard the second mover advantage as ahead of disclosure of hidden market information, or the chance of avoiding a bad return market

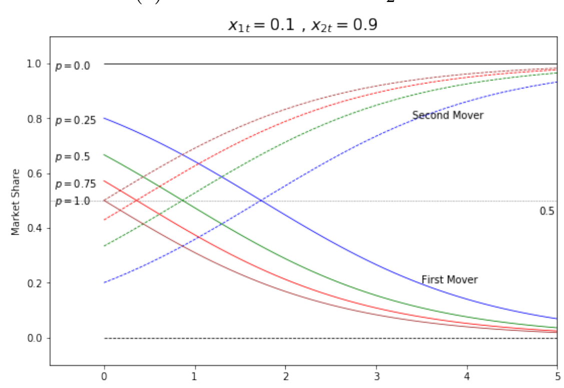
difficulties, parameter p basically is a measurement of second mover disadvantage; but in the utility function, it is the switching cost per transaction from one platform to another. One can consider this switching cost has many sources, for example, the monetary cost induced by the platforms, that users have to pay some amount of money or lose the opportunity of earning some amount of benefit by switching to a new platform. Another example is adaption cost: users who are used to one platform will incur some dis-utility when switching to another one. Typically, researchers mostly consider firms offering heterogeneous products to have larger second mover disadvantages towards each other. However, platforms providing similar goods can also establish a barrier to preventing customers from switching to each other. For example, Lyft and Uber offer power-drive bonuses for drivers in some cities. If a driver completes a certain number of rides within a specific period of time, the platform will pay them an extra bonus as a reward. This method on the one hand keeps the driver active during rush hours; on the other hand, it creates an opportunity cost, which helps to make the drivers stick to the platforms to earn the bonus. Another example is cellular service companies — usually, the customer has to pay a cancellation fee if they want to switch to another service provider, and the service of the two companies could be highly similar.

This market splitting rule ensures that new entrants with zero market size will still gain some market share as a second mover, and provides a testable structure for different types of business models. Both γ and p are treated as exogenous parameters related only to the type of business, which means in this research that, we will mainly discuss the case of homogeneous service platforms.

Consider a special case similar to the situation that the first mover has already been in the market for some time and gained some users, and hence it has some degree of network effect scaled by γ. Then, the second mover just completes its seed round and starts to explore the markets. For the markets already occupied by the first mover, they will split the market following the rule in Equations 1.5 and 1.6. For example, refer to Figure 1.2a when $\gamma = 2$ and $p = 0.25$, the first mover will win 96.7% of the market and the second mover will only receive 3.3%. Another scenario is described as when a small firm occupies a market first, then a big company enters the market as a second mover (refer to Figure 1.2b), where, as long as the network effect γ is not particularly large, an incumbent can still hold most of its current market even if it is facing a market giant.



(a) Second mover with $m_2 = 0$



(b) First mover with small size m_1

Figure 1.2: Market share under different values of γ and p

1.3 Static Game

In this section, we will illustrate the above settings more clearly in a two-player static game, and will also calculate the platforms' Nash-equilibriums under different market conditions.

First, we will make the following basic assumptions to build the static game 1) Firms are risk-neutral[2]; 2) A firm's average benefit from each potential transaction is drawn from one same distribution, i.e., the expectation of profit per potential transaction is the same for all markets: $E(\alpha_i) = \alpha \ \forall i \in F$, F is the set that includes all feasible markets 3) Once a market is being explored by a player, it will generate profits in every subsequent period; 4) $p = 1$ no switching cost[3], and 5) For simplicity, we only consider three available markets in our model that $F := \{K, K+1, K+2\}$

Game Setups 1 (Static Game)

1. **Time 1,** First mover, Player 1 with size $m_{11} = 0$ enters market K reveals market K's profit parameter α_k, and gain a profit $\frac{NM}{K^2}\alpha_k$, update $m_{12} = \frac{NM}{K^2}\alpha_k$;

2. **Time 2,** Second mover. Player 2 with size $m_{22} = 0$ comes into existence and both firms simultaneously decide which market to enter.

   (a) Player 1 gains profits from market K;

   (b) If player 2 decides to enter market K, they will split the market based on their current relative size m_{11}, m_{21}, and γ, refer to Equation 1.7;

[2] This assumption is made to simplify the problem; the firms are not necessarily risk-neutral, but a firm's preference on risks is beyond the discussion of this paper.

[3] The purpose of inducing the measurement of switching cost, is to make both players have some degree of disadvantages when acting as a second mover, because in the static game, only Player 2 has a chance to become second mover; network effect from period 0 will already make them disadvantaged when competing in the same market with Player 1. Thus, here $p = 1$ for simplicity

The payoff matrix of this static game can be seen in Table 1.7, where S_1 means the market share of Player 1 as first mover; $1 - S_1$ means the market share of Player 2 as second mover.

$$S_1 = \frac{(e^1)^\gamma}{(e^1)^\gamma + (e^0)^\gamma} \tag{1.7}$$

1.3.1 Static Equilibriums

Proposition 1 When Player 2 chooses action K, Player 1 will always choose K+1; when Player 2 chooses action K+2, Player 1 will always choose K+1; when Player 2 chooses K+1, if and only if $K < \frac{2\sqrt{S_1}-1}{1-\sqrt{S_1}}$ Player 1 will choose K+1, otherwise Player1 will choose K+2.

Proposition 2 When Player 1 chooses action K+1, Player 2 will choose K, K+1 or K+2; when Player 1 chooses action K+2, Player 2 will choose K, K+1 or K+2.

Proposition 3 Four PSNE (pure strategy Nash equilibrium) and two MSNE (mixed strategy Nash equilibrium) exist in the myopia static game. They are PSNE (K+1,K), (K+1,K+1), (K+1,K+2), (K+2,K+1); and MSNE in anti-coordination game, (K+1,K+2) and (K+2,K+1), (K+1,K) and (K+2,K+1)

From proposition 1,2,3, we can see that for each pair of $\{\alpha_K, \gamma\}$, there exist a threshold $\bar{K}$ for $K \in \mathbf{Z}^+$, below which $\forall K < \bar{K}$, Player 2 will choose to compete; above which $\forall K > \bar{K}$, Player 2 will choose to avoid direct competition. Intuitively, when players discover that market K is good, Player 2 will be more likely to enter a good market in period 1. Similarly, when the market condition is welcoming for a second mover, that both the network effect and switching cost is lower, Player 2 will be more likely to face competition from Player 1. When K increases, the benefit from market size cannot cover the loss in competition; both players will tend to explore a new market, rather than compete in an old one. Hence, in this manner, one can expect the benefit of market size from a transaction-efficient market to be held longer than a transaction-inefficient setup, because the transaction volume is enlarged in the former one.

Figure 1.3 compares the evolution of PSNEs under transaction-efficient setup versus transaction-inefficient setups under different values of γ, K, and α_K. We can see that PSNE (K+1, K+1) rarely occurs — only when α_K is really below expectation ($\alpha_K = 0.1$), and the network effect of existing markets is significantly low ($\gamma < 0.3$), most of the time, a later entrant will either enter and compete in the largest city (K) or explore a much smaller one (K+2).

From Figure 1.3 we can clearly observe the evolution of threshold $\bar{K}$ with α_K and γ: When α_K increases, the margin for Player 1 to deviate to K+2 does not move, because from Proposition 1, we know that this line is only related to the size of market share — or at root related to γ; however, the area of PSNE (K+1,K) becomes larger when α_K increases. If we take one horizontal slice of Figure 1.3 to examine the comparative statics, for example, in the $\alpha_K = 1.0$ high transaction volume scenario, if we hold $\gamma = 2$, and look at the change of different Nash equilibriums under different K, we will be able to gain some insight in the firm's entry path. When markets are large, the second mover will always enter and compete in those larger markets; then, with the decrease of market size, both firm will finally deviate to a non-aggressive strategy to avoid competition.

The same idea applies if we take a vertical slice from the figure, so that to hold market size constant and analyze how network effect affects a firm's entry behavior; clearly, larger network effect will make second mover more disadvantaged when competing with the first mover.

Next, in Table 1.8 and Table 1.9, we list several specific numerical experiments under transaction-efficient markets versus transaction-inefficient markets respectively, with $E(\alpha_i) = 0.5$ and NM equals some arbitrary positive [4] , to further illustrate the firm's behavior.

D_1, D_2 here represent Player 1 and Player 2's entry decisions, respectively. Market share of each firm is controlled by γ. From Tables 1.8 and 1.9 we can see how much the second mover favors the largest city in transaction-efficient market — when $K = 1$, as long as the market yield is average level or above, the second mover in a platform-based market will always choose to enter the largest city (see cases 1 to 6). When conditions in the first market K are not good, $\alpha_k = 0.1$ is quite below the expectation value; player 2 has the advantage of information disclosure, it has the opportunity to avoid the bad ones, therefore, it will enter market K+1, and K+2, and skip market K. In other scenarios, when K is larger, and city size is smaller, good profit and welcoming market environment can still be a strong incentive for Player 2 to enter a competitive market. However, in most of the cases when the benefit from a large market cannot cover players' loss from competition, player 2 will skip the second largest market and jump to the third to avoid direct competition with Player 1, because even without second mover disadvantages, the lack in existing network effect will still put it in an unfavorable competing position.

In contrast, the situation for Player 1 will be more favorable — holding the largest market K in hand, the network effect will give the player many advantages in the further competitions. Thus, when the market size is large enough, the dominant strategy for the first mover will always be continuing the previous exploration step to the next largest city, no matter the strategy of Player 2; when market size is not large enough (e.g. $K = 10$) or the market does not have large network effects (e.g. $\gamma = 0$, $p = 1$), there will be two MSNEs: two platforms will play anti-coordination games to avoid face-to-face competition.

[4] In static game, the value of NM does not matter to the final Nash-equilibrium, because (refer to Table 1.7) NM will be cancelled from the nominators due to it appearing in all equations

An interesting scenario is described in cases 4 to 6, when $\alpha_k = E(\alpha) = 0.5$; one can regard these cases as: how would a risk-neutral second mover behave if the former incumbent does not reveal the market information.

1.3.2 Sequential Equilibriums

So far, we have discussed the static equilibriums under one-period static game, and the static game is based on the assumption that Player 1 does not foresee the advent of another competitor (or the discount rate is very large). In this subsection, we will briefly discuss the sequential game under the assumption that Player 1 does foresee the advent of Player 2's entry (or there is no discount rate). The game setup is similar:

Game Setups 2 (Sequential Game)

1. **Time 1,** Player 1 with size $m_{11} = 0$, chooses one among market K, K+1 and K+2 to enter, reveal the market information, gain a profit, and update m_{12}
2. **Time 2,** Second mover. Player 2 with size $m_{22} = 0$ comes into existence and both firms simultaneously decide which market to enter.

The extensive game tree and payoff matrix of each node can be seen in Table 1.6, because before the first player enters the first market, no market information is known by either player, Player 1 will guess the state in the second period through expectation return $E(\alpha)$, and hence $E(\alpha)$ will be cancelled from the payoff matrix. The subgame perfect Nash equilibrium is solved through backward induction in Figure 1.4, α_i here is the revealed market return after Player 1's first entry, i here could be K, K+1 or K+2.

In most of the cases, in the beginning period, Player 1 will choose the largest market K, under several scenarios, Player 1 will choose market K+1 or K+2; note here, if Player 1 does not enter market K in the beginning, market K will be a dominant strategy in the second period for Player 1 in the subgame, indicating that in the real world, if the degree of network effect γ is uniformly distributed, most of the time, we will observe entries into the largest market. Or, in another perspective, if the degree of network effect is uncertain but follows a uniform distribution, for a start-up platform, entering the largest market is the safest strategy, because it has the highest probability to be the best choice. In Table 1.5, we summarize the average return of all tested numerical experiments of different values of K. Clearly, on average, entering the larger market will generate better returns.

Table 1.5: Average returns of sequential equilibriums under different values of K

	K	**1**		**2**		**3**		**5**		**10**	
		P1	P2	P1	P2	P1	P2	P1	P2	P1	P2
t_1	K	0.917	0.142	0.263	0.042	0.122	0.025	0.049	0.011	0.012	0.004
	K+1	0.679	0.128	0.221	0.059	0.111	0.037	0.044	0.019	0.012	0.006
	K+2	0.600	0.125	0.181	0.056	0.086	0.032				

The static game gives us good insights to explain the following phenomenon: Why in the beginning do second movers such as Lyft, Juno and Gett, always prefer to be a follower, entering large cities and facing intense competition rather than exploring a new but smaller market. The nature of platform-based multi-sided interactions significantly enlarges the amount of transactions in large cities, offsetting the disadvantage as a second mover and small network effect. On the contrary, the market structure in a non-platform-based or lower transaction efficiency market would be more concentrated, and we would expect to see more natural monopolies in such markets.

Static game plots general equilibrium in a simple scenario; there are some caveats to serve the purpose of mimicking the real world, for example, firms can only enter one market at a time, the interactions take only one period, and they do not take entry cost into consideration. In this way, the static setup could not provide answers when the firms' interactions are more dynamic or when there are more markets available.

Thus, next, we will present a model of a dynamic sequential game to solve the above problems and answer the remaining questions.

1.4 Dynamic Game

The fundamental assumptions of the dynamic game are inherited from the previous static game: 1) Firms are risk-neutral; 2) All markets' average transaction profits are drawn from one same distribution: $E(\alpha_i) = \alpha$, $\forall i \in F$, F is the set that includes all feasible markets. 3) Once a market is being explored by a player, it will generate profits in every period. Besides the assumptions from the static game, in the dynamic game we add two more assumptions: 4) The one-time fixed entry cost is diminishing in market size: $\frac{c}{K}$, for the Kth market, and for both players. Finally, without loss of generality 5)

Players move in turn: player 1 moves the even turn, player 2 moves the odd turn;

The structure of entry cost plays a crucial role in designing the algorithm that solves the firm's best behavior. Note that, K to the power 1 in the denominator :$\frac{C}{K}$, guarantees that the size of the feasible markets set F converges to an upper limit $\bar{K}$[5]:

$$\bar{K} = \frac{NM}{rc} E(\alpha_{\bar{k}}) \tag{1.8}$$

Where the expected present discount value $\frac{NM}{r\bar{K}^2} E(\alpha_K)$ of the last market $\bar{K}$ will just cover the one-time entry cost for the last market $\frac{c}{\bar{K}}$.

Inducing the entry cost term in the dynamic game is important because, in the model, it adds a budget constraint for every decision; hence we have a constrained optimization problem[6] to solve; And in reality, a firm's expansion is closely related to its money stock; it is rare that a city-based platform would enter all the markets at one time. As in the ride-sharing case, a platform's expansion decision is closely related to its funding rounds. Part of the expansion cost is reflected here as a one-time fixed cost, and part of the expansion cost is reflected in the post-entry realization of α_K as average cost per potential transaction.

Game Setups 3 (Dynamic Game)

1. Before the game begins, p, γ, r[7], are predetermined parameters for both players;

2. Game starts at time 0, $t \in [0, T]$, $X_{n0} = \emptyset$ for $n = 1, 2$, $I_0 = \emptyset$, $J_0 = F$[8];

3. Player 1 starts at time 0 with initial fund u_{10}; Player 2 starts at time 1 with initial

[5]Note that here $\bar{K}$ is different from what it is in static games.
[6]In each period the problem can be simplified to a 0-1 package problem
[7]Parameter r is the discount rate.
[8]I_t, J_t represent the sets of markets with 1 player, and markets with 0 players respectively. X_{nt} is the set of current markets entered by player n at time t

fund u_{21}; u_{nt} here represents how much money the player n owns at time t;

4. Within each turn, one player will first load the status of its current state.

   (a) Load the current states: u_{nt}, u_{-nt}, m_{nt}[9], m_{-nt}, I_t, J_t ,X_{nt}, X_{-nt};

   (b) Calculate S_{nit} and $1 - S_{nit}$ for $i \in I_t \cup J_t$ (Equation 1.5 and 1.6) for both players;

5. Second, a player solves the following binary linear programming (BLP) problem to find the optimal market entry strategy set $(\boldsymbol{z_t^*}, \boldsymbol{y_t^*})$:

$$
\begin{aligned}
\max_{y_{it}, z_{jt}} \quad & \sum_i y_{it} \tfrac{NM}{(K_i)^2} S_{nit} \alpha_{Ki} + \sum_j z_{jt} \tfrac{NM}{(K_j)^2} E(\alpha) \\
\text{s.t.} \quad & C_{nt} = \sum_i y_{it} \tfrac{c}{K_i} + \sum_j z_{jt} \tfrac{c}{K_j} \leq u_{nt}, \\
& y_{it} \tfrac{c}{K_i} \leq \tfrac{NM}{r(K_i)^2} S_{nit} \alpha_{Ki}, \forall\ i \in I_t, \\
& z_{it} \tfrac{c}{K_j} \leq \tfrac{NM}{r(K_j)^2} E(\alpha), \forall\ j \in J_t, \\
& y_{it} \in \{0, 1\}, \forall\ i \in I_t, \\
& z_{jt} \in \{0, 1\}, \forall\ j \in J_t.
\end{aligned}
$$

   (a) I_t represents the set of markets already being explored by the other player at time t, therefore, α_{Ki} is revealed to all; J_t represents the set of undeveloped markets at time t, and hence α_{Kj} is not revealed, and players can only make decisions through expected profit $E(\alpha)$;

   (b) Total cost of the entry has to be no larger than a player's current money stock;

[9] In this game it equals the amount of revenue one platform generated from the previous $t-1$ period: R_{nt-1}.

(c) The real present discounted value of a market must cover the entry cost for markets in I_t; the expected present discounted value of a market must cover the entry cost for markets in J_t;

(d) y_{it} and z_{jt} are decision variables of market entry; it is either 1 or 0 (enter or not);

(e) S_{nit} represents the player n's market share in market i at time t, when player n is a first mover $S_{nit} = 1$

6. Third, update the status for the next period and next player;

(a)

$$\begin{aligned} m_{nt+1} = R_{nt} = \sum_{i} \tfrac{NM}{(K_i)^2} S_{nit} \alpha_{Ki}, \forall i \in X_{nt+1} \\ m_{-nt+1} = R_{-nt} = \sum_{j} \tfrac{NM}{(K_j)^2} S_{-njt} \alpha_{Kj}, \forall j \in X_{-nt+1} \end{aligned} \tag{1.9}$$

(b)

$$\begin{aligned} u_{nt+1} = u_{nt} + R_{nt} - C_{nt} \\ u_{-nt+1} = u_{-nt} + R_{-nt} - 0 \end{aligned} \tag{1.10}$$

(c)

$$\begin{aligned} X_{nt+1} = X_{nt} \cup \boldsymbol{y_t^*} \cup \boldsymbol{z_t^*} \\ X_{-nt+1} = X_{-nt} \\ I_{t+1} = I_t \setminus \boldsymbol{y_t^*} \cup \boldsymbol{z_t^*}, \\ J_{t+1} = J_t \setminus \boldsymbol{z_t^*} \end{aligned} \tag{1.11}$$

7. Repeat Step 4,5,6;

8. If $t = T$ end the game.

The basic idea behind this setup is that in a dynamic sequential game, each player's action will change the future states for both players, thus, in each period, players are making decisions upon changing states.

First, note here that m_{nt} and u_{nt} are two completely different things. Only by occupying (some of) the markets can one player make changes in its firm size; m_{nt} here, is in control of the player's market share when it has to split the market with the other one. u_{nt} is the platform's current cash flow, and can be regarded as the aggregation of that platform's revenues and costs from time 0 to time t; u_{nt}, here, is in control of the player's budget constraint of new entries.

Second, we can see from the above game setups that, a player's market share is not related to the current market's characteristics, but is only related to the players' current state.

Third, once a game is initiated, no intervention is required in the process of playing. The source of randomness comes from the realization of α_K, once the α is known to all, the "optimal solution" is somehow destined, for one bundle of parameters; as long as α_K are generated for each city, there will only exist one entry path for both players, although, from the firms' perspective, they are facing many uncertainties. While, in this research, we only discuss the situation when α_K is positive, with all markets generating positive returns in each period, and hence there is no need for exit after entry. While if we allow for negative market return, the post-entry market information disclosure, will add more randomness to players' market positions — the late entrant has the chance to avoid the harmful markets, and therefore could have more opportunity to take the leadership. Moreover, if both platforms can gradually learn the properties of α_K during the entry process, they may have more chance to survive.

Finally in Step 8, we can see that, the game does not stop at the exact time when $I_t = J_t = \emptyset$ such that no further empty markets are available. This is because, even after all the feasible markets have been explored, the firms will continue operating. One can see from the simulation results that, the status of two players will tend to a steady state after they complete the entry process.

The complexity of the dynamic model makes it difficult to solve for the analytical solution, hence, in the next section, we will present the results of several numerical experiments with different initial parameters to gain insights into city-based platforms' behavior patterns in the market entry problem.

1.5 Numerical Results

In this section, we will describe the numerical experiments, which focus on two parts: First, we investigate the joint effect of switching cost and network effect on platforms' market entry decisions. Second, we test the results under different initial funds[10].

1.5.1 Network Effect and Switching Cost

From previous setups, we know that, γ and p jointly determine how players split the market — in homogeneous cases, these two are exogenous parameters related only to the type of platform's business model. From static games we know that γ and p eventually affect the platforms' willingness to compete. However, one has to note that, although γ and p control the market share together, p has a more sophisticated effect, because in a segregate markets setup, if the second player takes the advantage of entering first, it will be difficult for the first player to enter the market either. The initiation of

[10]The code for the games and simulations applied in this paper can be found in https://github.com/QingWei2018/two_sided_market_entry_simulation, we use Pyomo to solve for the BLP problems in each period (Hart, Watson, and Woodruff 2011; Hart et al. 2017).

dynamic games in this section will be set as follows:

1. Game starts with K=1, t=0;
2. $u_{10} = 20$, $u_{21} = 20$, $c = 20$, NM = 20 , $r = 0.01$;
3. $\alpha_{Ki}\ for\ i = 1, 2, 3...$ are generated from uniform distribution $U(0, 1)$, $E(\alpha_{Ki}) = 0.5$;
4. The maximum number of periods is 50, T=50.

Several things should be noted from the above initiation: 1) In this case, the start funds for both players will just cover the entry cost of the first market. 2) Refer to Equation 1.8, $\bar{K} = 50$.

The numerical results shown in this part will be arranged as follows: 1) For each scenario, we will present an averaging result of 1000 simulations, and in each simulation, the program will re-generate a new series of $\alpha_{Ki}\ for\ i = 1, 2, 3....$ 2) Then, we will present a special case, in which, series $\alpha_{Ki}\ for\ i = 1, 2, 3...$ are fixed to illustrate the differences in players' choices (such as Figures 1.6 and 1.8). Moreover, in Table 1.10, we summarize the aggregate simulation results to provide a detailed view. Where "player order" represents the player's entry order, either as a first mover: "1", or as a second mover: "2", or no entry: "0". And "average market revenue", is the average total market revenue in the final period, and it reflects the market size under each sub-category when the game ends (at time T=50). The last column represents the percentage of total markets (50 in total) that are under each sub-category at the time when the game ends.

Switching Cost

When a second mover attempts to enter a market with an incumbent, it is often in a disadvantaged position. In this paper, this disadvantage is captured by switching cost. Intuitively, the larger the switching cost, the more difficult it is for the market to accept a late entrant; in this way, the market tends to be more concentrated.

This situation is exemplified well in cases 1 and 2 — case 1 is a special setup where a late entrant is fully disadvantaged: users in case 1 totally reject to accept another platform at all. Hence, the markets are extremely concentrated — in Table 1.10, case 1, we can see that none of the markets are entered by two firms, with player 1 capturing most of the markets, and most of the revenues. Even if the market has some degree of network effect $\gamma = 1$, it will not affect firms' strategies at all. The reason player 1 is able to gain more revenue, is because it took the exclusive occupation of the largest market first. In case 2, we slightly decrease the difficulty for multi-homing; let $p = 0.1$, we can see from Table 1.10, case 2, that some fraction of the markets are entered by both firms, and they are all large markets, with average total revenue 9.25 and 3.99. Compare cases 1 and 2 in Figure 9: in case 2, on average player 2 is catching up with player 1. Also, in Figure 1.6, we can observe that, the first 4 movements in both cases are exactly the same; however, in period 4 case 2, player 1 turns to explore some of the territories of player 2. And player 2 with bad luck entered a bad market number 2 in its first period, so that later on it can only explore some small markets because of insufficient cash flow, and finally after several periods of accumulation, player 2 gathered sufficient money and picked up the two best markets of player 1 to enter: market 1 with large transaction volume and market 4 with large return.

Network Effect

Similarly, we can also expect that a larger network effect makes the market more concentrated. Users would be more likely to gather around larger platforms under the effect of networking, as in cases 3 and 4, and here we test the effect of network effect.

Case 3 is another special scenario where both network effect and switching cost equal zero. In this case, all markets will be split in half if entered by both players. Without the disadvantages of being a second mover, from Figure 1.7 case 3 we can see that both players will eventually have the same money stock and the same market size. However, in case 4 if the network effect increases only slightly ($\gamma = 1$), we can see a big gap between the two players: Player 2 is in an unfavorable situation, from Figure 1.8 case 4, player 1 is able to have massive expansions in almost every period, and even when it is acting as a second mover, player 1 will still gain most of the market share because of large network effect and player 2 can only make scattered entries after player 1.

From case 1 to 4 we can see that, network effect and switching cost mutually determine the market structure: either of these two parameters being high will finally lead to monopoly in most of the markets. Network effect and switching cost also provide a natural barrier for the late entrant; even if both players offer the same quality product and start with the same amount of funding, lack of user base would make player 2 significantly disadvantaged. This situation corresponds to the Uber and Lyft case, and the following question arises: Why did Uber always dominate the market leadership irrespective of the entry order in a city? This research provides a possible explanation: because Uber had already taken a large amount of the market in other cities, the nation-wide network effect gives it a built-in advantage when conquering a new market. Also we can expect Lyft to charge a lower price on the platform, in order to compensate for the utility loss in network effect. When two platforms offer homogeneous services in the same market, a late entrant might have to lower its price to attract more users; however, this strategy will lead to shortages in money stock, and make it difficult for the small platform to expand in the future. Thus, that late entrant either needs to raise more money or limit the amount of expansion. Next, we will discuss the influence of initial fund in the dynamic games.

1.5.2 Initial Fund

From case 1 to 4 we can see that, part of the success of player 1 results from its prior occupation of the largest city. Therefore, we can presume that whether a player has sufficient funds to enter the largest city is important in the dynamic of the two-player entry game. In this section, we will test the numerical experiments under different starting funds.

The initiation of dynamic games in this part will be set as follows:

1. Game starts with K=1, t=0;
2. $\gamma = 1$, $p = 0.8$, $c = 20$, NM = 20 , $r = 0.01$;
3. $\alpha_{Ki}\ for\ i = 1, 2, 3...$ are generated from uniform distribution $U(0, 1)$, $E(\alpha_{Ki}) = 0.5$;
4. The maximum number of periods is 50, T=50.

Again, the arrangement of numerical results present in this part will be: 1) For each scenario, we will present an averaging result of 1000 simulations, and in each simulation, the programming will re-generate a series of $\alpha_{Ki}\ for\ i = 1, 2, 3....$ 2). Then, 2) we will present a special case, in which series $\alpha_{Ki}\ for\ i = 1, 2, 3...$ are fixed to illustrate the differences in players' choices.

The market environment in this part is fixed, with some level of network effect and some degree of switching cost. From Figure 1.2a we know that when $\gamma = 1$, $p = 0.8$, the first mover at most will receive around 70% of the market when facing a second mover.

First Mover without Sufficient Fund

In case 5, both firms do not have sufficient funds to enter the first market in the beginning, but player 1 obtains advantages from the first move. But without sufficient funds, the entry path for player 1 moves in zigzags; then at around period 15, there is a leap in player 1 's firm size or total revenue per period; we can treat this leap as on average when player 1 finishes its accumulation of entry funds, and finally enters market 1. In contrast, the situation for player 2 is not so optimistic, it is at the edge of surviving; although it is still expanding, a lack of network effect will put it in a disadvantageous position when competing with player 1. However, in case 6, the situation is totally different; here player 2's starting fund is just enough to cover the entry cost of the largest market, and player 1 stays the same. With occupation of the largest market, large amounts of revenue are generated in each period, offering sufficient funds for player 2 to explore the world. It will soon occupy all cities, such as in Figure 1.10 case 6 player 2 has a highly aggressive expansion, within 3 periods, it will expand to all the markets, and player 1 this time will be at the edge of barely surviving, even if its initial fund is the same as in case 5. Facing a strong component, a first mover start-up company such as player 1 in case 6, could die soon, if it fail to seize the opportunity to attract the most majority target group (the largest city) at first. This is the real story for some of the start-up companies; according to a report by venture capital database *CB Insights* (Insights 2014), 9% of the start-ups' failure results from failed geographical expansion; and 13% of the start-ups' failure results from product mistiming.

First Mover with Sufficient Fund

However, things will change again, in platform-based markets; a large amount of money raising does not necessarily lead to market success, as in Figure 1.11, when player 1 raises sufficient funds to enter the largest market in the beginning. We can see that player 1 will dominate the market again, even if in case 8 player 2 raises double the amount of funds to start. Player 1 will still hold the market leadership. For example, in Figure 1.12, player 1 enters the largest one in the beginning, then player 2 with a higher amount of initial funds, attempts to compete in market 1, it will only receive about 30% of the market. For player 2 to best allocate its 40 at the beginning, player 2 will enter Market 1, 2, 3, and spend 36.66 out of 40, while the remaining 3.33 is not sufficient to cover markets 4 and 5, and thus it will enter market 6 and spend the 3.33. In this special case, player 2 has really bad luck; the second largest market is a bad one with only 0.061 average return, whereas for player 1 after accumulating revenues from the largest market for 2 periods, starting from time 2, player 1 will begin its massive expansion, and player 2 with a larger initial fund will only catch up slightly in this case.

Therefore, from the above cases we know that, in platform-based markets the entry timing is highly important — if we treat cities as different groups of users, a majority of the transactions and revenue are generated by the largest group. Whoever capture this largest group of users, will be more likely to succeed in the following expansions, because benefits from these users secures the entry expense in other markets. Also, the network effect and switching cost of platform-based markets will create a built-in barrier to prevent the entry of other competitors; in this way, first mover small start-ups may have a way to defend themselves from the impact of market giants.

Above all, the condition for a homogeneous service provider second mover to take market leadership in a platform-based market is highly stringent. Not only does it require sufficient funds, but it also have to enter the market at the right time plus have a little bit of good luck.

1.5.3 Other Implications

Besides the factors mentioned above, the dynamic model also has explanatory power for some other phenomena in the real world.

First, for example, in all 8 cases above, at some point of time during the game, the model predicts a massive expansion (refer to the 4th graph “Market entries per period” in the aggregation figures). In the beginning, both players will enter a small number of markets due to the limitation of budget constraints and high entry cost, then with the decrease of entry cost and accumulation of money stock, players at some point in time will make a massive expansion. This result can correspond to the expansion path of ride-sharing platforms in the real-world, as when, in 2010, Uber started with only one city, San Francisco. Not until almost a year later, did it make its next expansion in another 3 cities: New York, Seattle, and Chicago. Then, in 2012, Lyft announced its first launch in San Francisco, and not until 6 months later did Lyft announce its second move, into Los Angeles, followed by several scatter entries in 2013. Based on their official launch record, both firms are expanding at an increasing rate, particularly Lyft. Lyft had only 20 cities in the beginning of 2014, yet in April 2014 Lyft suddenly announced a massive 24-city expansion in 24 hours, and in Jan 2017 it announced a 40-city expansion, followed by a 50-city substantial launch only one month later. For Uber, in April 2014, it only occupied 47 cities, and Lyft had 60. Right now, they are both in more than 300 U.S. cities, occupying almost all the cities available in the U.S.

Second. from the second graph "Firm size" in the above figures, we can see that, after some point in time, the relative firm size between two firms will converge to a constant. That is because, after exploring the largest several cities, small expansion cannot have much influential power on the firm size any more. Recall that firm size eventually determines the market share of two platforms when entering the same market, and therefore the market share of two firms will converge to a constant ratio. This can provide an explanation for Figure 1.1 with respect to why the market share in most of the cities across the U.S tends to be a constant 20:80.

Third, post-entry market information revelation gives the game many uncertainties; it actually gives the second mover some source of advantages. As shown in the interesting case in Figure 1.10, case 5; when both firms start with the same amount of money, only sufficient to cover the second largest market, and it happens to be a really bad market, with $\alpha_2 = 0.061$ that is far lower than players' pre-entry expectation $E(\alpha) = 0.5$. Player 1, in this time, had a really bad luck, such that its first entry is poor; not only will this market give its low return, but also it fails to establish a sizable network effect for player 1 to defend the competition from late entrants. Because of this mistake, player 1 loses the opportunity to explore the other large cities; the trivial return generated from the first period only made affordable some small markets in its next turn and, unfortunately, without proper market information, the next two entries for player 1 are even worse, with $\alpha_{33} = 0.157$ and $\alpha_{34} = 0.085$. In contrast, player 2 is relatively lucky this time: as second mover, it has the chance to avoid the market 2, and explore other markets; this time, it is much luckier: although the market size is relatively smaller, the markets' returns are much better, and the good start gives player 2 the chance to overcome the disadvantages as a second mover. We can see that, finally, player 2 will enter market 1 after it accumulate sufficient funds. And in reality there are many examples of a first mover losing its market advantage because of expanding into the wrong market or at the wrong time.

Finally, from Figure 1.6, for some type of businesses without network effect, we will still observe a concentrated market structure in some small local market; because the market size is too small for both players to be profitable. We suggest that this situation may provides an explanation regarding why it is generally possible to only find one super mall in one suburban area.

1.6 Conclusion

In this paper, we study the relative importance of multiple factors on entry decision of city-based platforms with homogeneous products.

We build a theoretical framework that incorporates the idea of city size and pre-entry uncertainties, and find that, besides the strength of network effect, high switching cost, low market size, and low realized market return can also lead to market concentration.

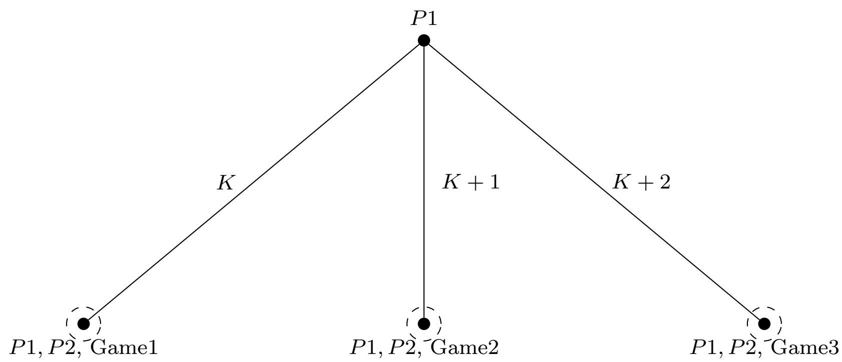
The static equilibrium in the two-player static game shows that, for each pair of market return and network effect, there is a threshold market size for the second mover; when the market size is larger than the threshold, the second mover will always choose to compete in the largest market with the first mover. Further, for the first mover, the network effect generated from the first entry secures its advantageous position in the later movement, in that exploring the next largest market will always be a dominant strategy for the first mover.

Then, taking into account the effect of entry cost and budget constraint, we extend the two-player static game to a multi-period-two-player dynamic game. Consistent with the static-game prediction, the results of numerical experiments in the dynamic game also demonstrate the importance of network effect, switching cost, market size, and realization of market return on players' entry decision and the market structure. Including entry cost and budget constraint into the model adds more uncertainty into the final results; the expansion path plot in our special cases show that, the late entrant has an advantage of information disclosure, in that they can avoid spending money on the bad return markets. In general, from the accumulated results of our numerical experiments, capability of capturing the majority of the service target group or, say, the largest city before a rival competitor, is crucial in winning the market for both first and second movers. If a second mover lost the opportunity of capturing the largest market, it may have to raise a significant amount of money to overcome its disadvantage in the later competitions.

The content discussed in this paper can be applied to explain the expansion interactions between emerging city-based service platforms, such as Uber and Lyft, and Groupon and LivingSocial. This paper plots a scenario of homogeneous platform entry dynamics, where copy-and-paste is easy between digital platforms, and quality difference is difficult to achieve.

However, according to Equation 1.1 and 1.3 in Section 3, the utility function in fact allows for heterogeneous services. Intuitively in such scenarios, in addition to the conditions that are discussed in this paper, a second mover can also take the market leadership by lowering the service price or providing higher quality products. But the heterogeneous case is beyond the scope of this paper. This could be a good point for future study regarding city-based platform entry problems.

1.7 Tables and Figures



		P2		
		K	$K+1$	$K+2$
P1	$K+1$	$S_1\frac{1}{K^2}+\frac{1}{(K+1)^2}$, $(1-S_1)\frac{1}{K^2}$	$\frac{1}{K^2}+S_1\frac{1}{(K+1)^2}$, $(1-S_1)\frac{1}{(K+1)^2}$	$\frac{1}{K^2}+\frac{1}{(K+1)^2}$, $\frac{1}{(K+2)^2}$
	$K+2$	$\frac{1}{(K+2)^2}+S_1\frac{1}{K^2}$, $(1-S_1)\frac{1}{K^2}$	$\frac{1}{(k+2)^2}+\frac{1}{K^2}$, $\frac{1}{(K+1)^2}$	$S_1\frac{1}{(k+2)^2}+\frac{1}{(K)^2}$, $(1-S_1)\frac{1}{(K+2)^2}$

(a) Game 1

		P2		
		K	$K+1$	$K+2$
P1	K	$S_1\frac{1}{K^2}+\frac{1}{(K+1)^2}$, $(1-S_1)\frac{1}{K^2}$	$\frac{1}{K^2}+S_1\frac{1}{(K+1)^2}$, $(1-S_1)\frac{1}{(K+1)^2}$	$\frac{1}{K^2}+\frac{1}{(K+1)^2}$, $\frac{1}{(K+2)^2}$
	$K+2$	$\frac{1}{(K+2)^2}+\frac{1}{(K+2)^2}$, $\frac{1}{K^2}$	$\frac{1}{(k+2)^2}+S_1\frac{1}{(K+1)^2}$, $(1-S_1)\frac{1}{(K+1)^2}$	$S_1\frac{1}{(k+2)^2}+\frac{1}{(K+1)^2}$, $(1-S_1)\frac{1}{(K+2)^2}$

(b) Game 2

		P2		
		K	$K+1$	$K+2$
P1	K	$S_1\frac{1}{K^2}+\frac{1}{(K+2)^2}$, $(1-S_1)\frac{1}{K^2}$	$\frac{1}{K^2}+S_1\frac{1}{(K+2)^2}$, $\frac{1}{(K+1)^2}$	$\frac{1}{K^2}+S_1\frac{1}{(K+1)^2}$, $(1-S_1)\frac{1}{(K+2)^2}$
	$K+1$	$\frac{1}{(K+2)^2}+\frac{1}{(K+2)^2}$, $\frac{1}{K^2}$	$\frac{1}{(k+2)^2}+S_1\frac{1}{(K+1)^2}$, $(1-S_1)\frac{1}{(K+1)^2}$	$S_1\frac{1}{(k+2)^2}+\frac{1}{(K+1)^2}$, $(1-S_1)\frac{1}{(K+2)^2}$

(c) Game 3

Table 1.6: Sequential game with imperfect information.

Table 1.7: Static game payoff matrix.

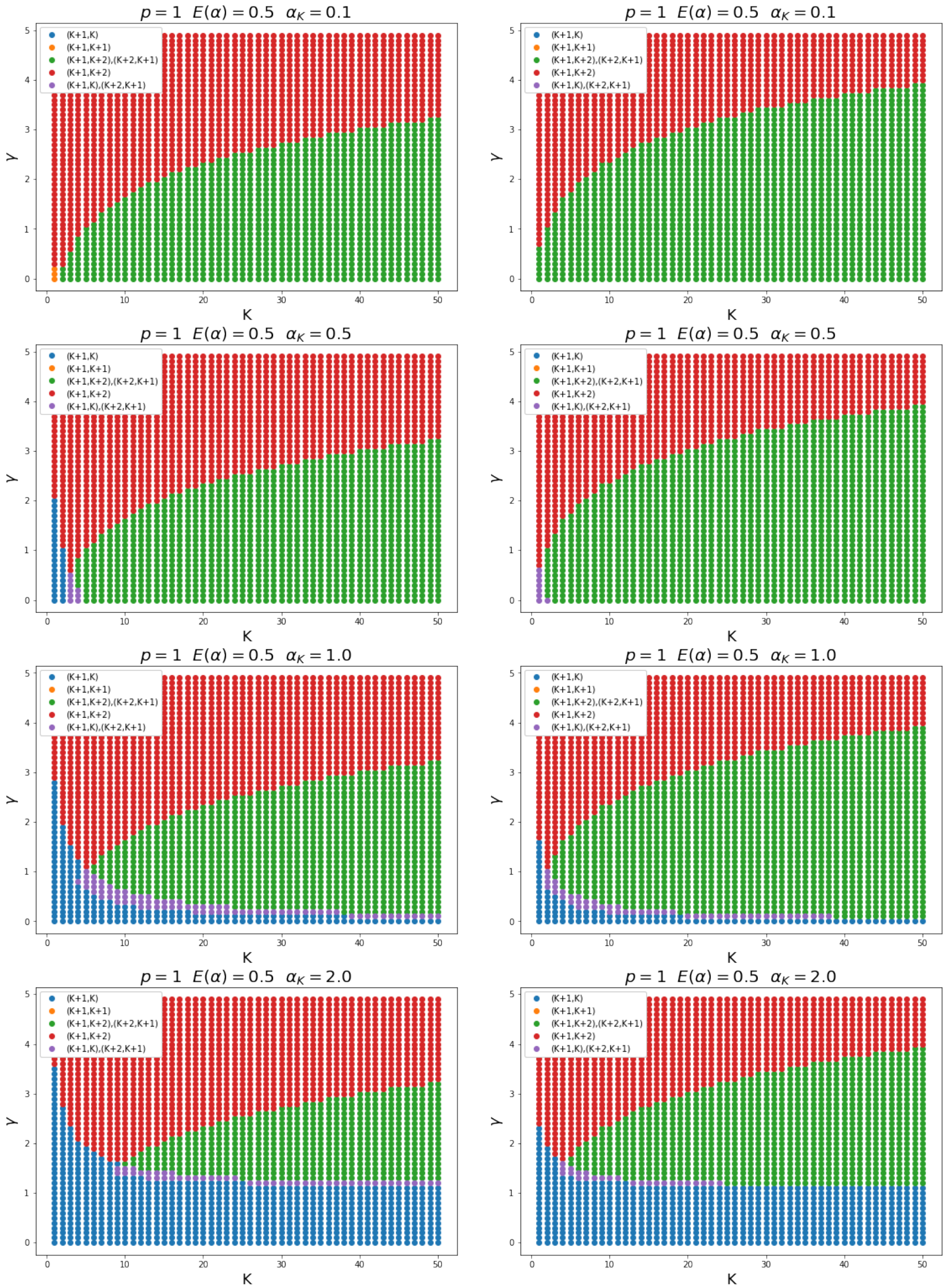
		P2		
		K	$K+1$	$K+2$
P1	$K+1$	$\frac{NM}{(K+1)^2}E(\alpha) + S_1\frac{NM}{K^2}\alpha_k$, $(1-S_1)\frac{NM}{K^2}\alpha_k$	$S_1\frac{NM}{(K+1)^2}E(\alpha) + \frac{NM}{K^2}\alpha_k$, $(1-S_1)\frac{NM}{(K+1)^2}E(\alpha)$	$\frac{NM}{(K+1)^2}E(\alpha) + \frac{NM}{K^2}\alpha_k$, $\frac{NM}{(K+2)^2}E(\alpha)$
	$K+2$	$\frac{NM}{(K+2)^2}E(\alpha) + S_1\frac{NM}{K^2}\alpha_k$, $(1-S_1)\frac{NM}{K^2}\alpha_k$	$\frac{NM}{(k+2)^2}E(\alpha) + \frac{NM}{K^2}\alpha_k$, $\frac{NM}{(K+1)^2}E(\alpha)$	$S_1\frac{NM}{(k+2)^2}E(\alpha) + \frac{NM}{K^2}\alpha_k$, $(1-S_1)\frac{NM}{(K+2)^2}E(\alpha)$

Table 1.8: PSNEs under different values of K, α, γ, p of transaction-efficient markets.

K		**1**	**2**	**3**	**5**	**10**
$\alpha_k = 1.0$			(Case 1: $\gamma = 0$, $p = 1$, $S_1 = 0.5$, $1 - S_1 = 0.5$)			
	D1	K+1	K+1	K+1	K+1	K+1
	D2	K	K	K	K	K
			(Case 2: $\gamma = 1$, $p = 1$, $S_1 = 0.73$, $1 - S_1 = 0.27$)			
	D1	K+1	K+1	K+1	K+1, K+2	K+1, K+2
	D2	K	K	K	K, K+1	K+2, K+1
			(Case 3: $\gamma = 2$, $p = 1$, $S_1 = 0.88$, $1 - S_1 = 0.12$)			
	D1	K+1	K+1	K+1	K+1	K+1
	D2	K	K+2	K+2	K+2	K+2
$\alpha_k = 0.5$			(Case 4: $\gamma = 0$, $p = 1$, $S_1 = 0.5$, $1 - S_1 = 0.5$)			
	D1	K+1	K+1	K+1, K+2	K+1, K+2	K+1, K+2
	D2	K	K	K, K+1	K+2, K+1	K+2, K+1
			(Case 5: $\gamma = 1$, $p = 1$, $S_1 = 0.73$, $1 - S_1 = 0.27$)			
	D1	K+1	K+1	K+1	K+1, K+2	K+1 , K+2
	D2	K	K	K+2	K+2, K+1	K+2 , K+1
			(Case 6: $\gamma = 2$, $p = 1$, $S_1 = 0.88$, $1 - S_1 = 0.12$)			
	D1	K+1	K+1	K+1	K+1	K+1
	D2	K	K+2	K+2	K+2	K+2
$\alpha_k = 0.1$			(Case 7: $\gamma = 0$, $p = 1$, $S_1 = 0.5$, $1 - S_1 = 0.5$)			
	D1	K+1	K+1, K+2	K+1, K+2	K+1, K+2	K+1, K+2
	D2	K+1	K+2, K+1	K+2, K+1	K+2, K+1	K+2, K+1
			(Case 8: $\gamma = 1$, $p = 1$, $S_1 = 0.73$, $1 - S_1 = 0.27$)			
	D1	K+1	K+1	K+1	K+1, K+2	K+1, K+2
	D2	K+2	K+2	K+2	K+2, K+1	K+2, K+1
			(Case 9: $\gamma = 2$, $p = 1$, $S_1 = 0.88$, $1 - S_1 = 0.12$)			
	D1	K+1	K+1	K+1	K+1	K+1
	D2	K+2	K+2	K+2	K+2	K+2

Table 1.9: PSNEs under different values of K, α, γ, p, of transaction-inefficient markets.

K		**1**	**2**	**3**	**5**	**10**
		(Case 1: $\gamma = 0$, $p = 1$, $S_1 = 0.5$, $1 - S_1 = 0.5$)				
	D1	K+1	K+1	K+1	K+1	K+1
	D2	K+2	K+2	K+2	K+2	K+2
		(Case 2: $\gamma = 1$, $p = 1$, $S_1 = 0.73$, $1 - S_1 = 0.27$)				
$\alpha_k = 1.0$	D1	K+1	K+1,K+2	K+1,K+2	K+1, K+2	K+1, K+2
	D2	K	K,K+1	K+2,K+1	K+2, K+1	K+2, K+1
		(Case 3: $\gamma = 2$, $p = 1$, $S_1 = 0.88$, $1 - S_1 = 0.12$)				
	D1	K+1	K+1	K+1	K+1	K+1,K+2
	D2	K+2	K+2	K+2	K+2	K+2,K+1
		(Case 4: $\gamma = 0$, $p = 1$, $S_1 = 0.5$, $1 - S_1 = 0.5$)				
	D1	K+1,K+2	K+1,K+2	K+1, K+2	K+1, K+2	K+1, K+2
	D2	K,K+1	K,K+1	K+2, K+1	K+2, K+1	K+2, K+1
		(Case 5: $\gamma = 1$, $p = 1$, $S_1 = 0.73$, $1 - S_1 = 0.27$)				
$\alpha_k = 0.5$	D1	K+1	K+1,K+2	K+1,K+2	K+1, K+2	K+1 , K+2
	D2	K+2	K+2,K+1	K+2,K+1	K+2, K+1	K+2 , K+1
		(Case 6: $\gamma = 2$, $p = 1$, $S_1 = 0.88$, $1 - S_1 = 0.12$)				
	D1	K+1	K+1	K+1	K+1	K+1,K+2
	D2	K+2	K+2	K+2	K+2	K+2,K+1
		(Case 7: $\gamma = 0$, $p = 1$, $S_1 = 0.5$, $1 - S_1 = 0.5$)				
	D1	K+1,K+2	K+1, K+2	K+1, K+2	K+1, K+2	K+1, K+2
	D2	K+2,K+1	K+2, K+1	K+2, K+1	K+2, K+1	K+2, K+1
		(Case 8: $\gamma = 1$, $p = 1$, $S_1 = 0.73$, $1 - S_1 = 0.27$)				
$\alpha_k = 0.1$	D1	K+1	K+1	K+1,K+2	K+1, K+2	K+1, K+2
	D2	K+2	K+2	K+2,K+2	K+2, K+1	K+2, K+1
		(Case 9: $\gamma = 2$, $p = 1$, $S_1 = 0.88$, $1 - S_1 = 0.12$)				
	D1	K+1	K+1	K+1	K+1	K+1,K+2
	D2	K+2	K+2	K+2	K+2	K+2,K+1



(a) Transaction efficient market

(b) Transaction in-efficient market

Figure 1.3: PSNEs under different values of α_K, γ and K.

Table 1.10: Simulation results of dynamic games.

Case	p	γ	u_{10}	u_{21}	Player 1 Order	Player 2 Order	Average Mkt. Revenue	% of Total Mkts
1	0	1	20	20	0	1	4.51	36.12%
					1	0	11.86	63.88%
					1	2	0	0.00%
					2	1	0	0.00%
2	0.1	1	20	20	0	1	0.92	40.12%
					1	0	1.35	52.00%
					1	2	9.25	2.84%
					2	1	3.99	5.04%
3	1	0	20	20	0	1	0.18	11.06%
					1	0	0.15	41.33%
					1	2	15.05	35.10%
					2	1	2.05	12.51%
4	1	1	20	20	0	1	0.12	11.76%
					1	0	0.42	46.24%
					1	2	13.13	27.16%
					2	1	3.27	14.84%
5	0.8	1	10	10	0	0	0.56	0.70%
					0	1	1.59	18.70%
					1	0	5.53	46.16%
					1	2	6.28	16.33%
					2	1	2.61	15.11%
6	0.8	1	10	20	0	1	3.29	56.08%
					1	0	0.26	11.21%
					1	2	3.59	12.45%
					2	1	9.14	20.23%
7	0.8	1	20	20	0	1	0.23	12.75%
					1	0	0.68	50.52%
					1	2	11.71	22.02%
					2	1	3.78	14.71%
8	0.8	1	20	40	0	1	0.15	20.20%
					1	0	0.19	40.00%
					1	2	11.73	15.39%
					2	1	4.70	24.41%

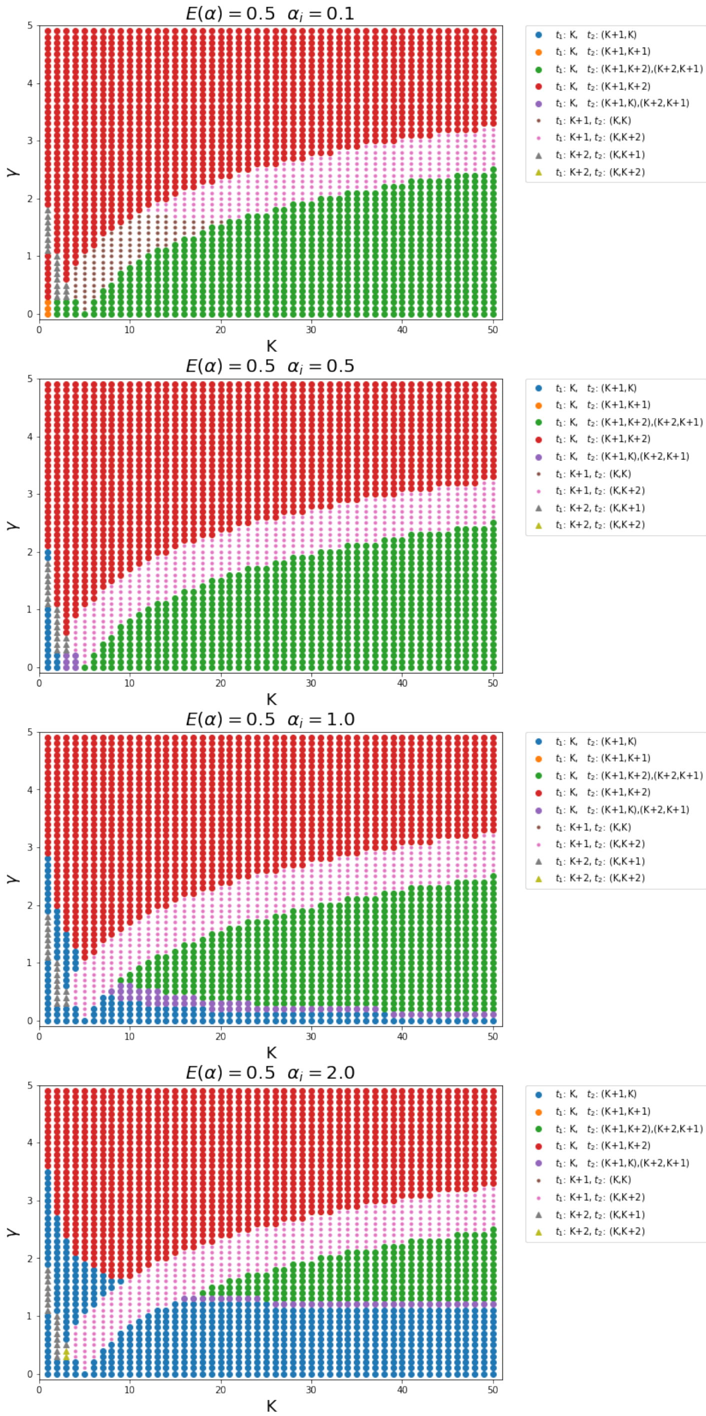
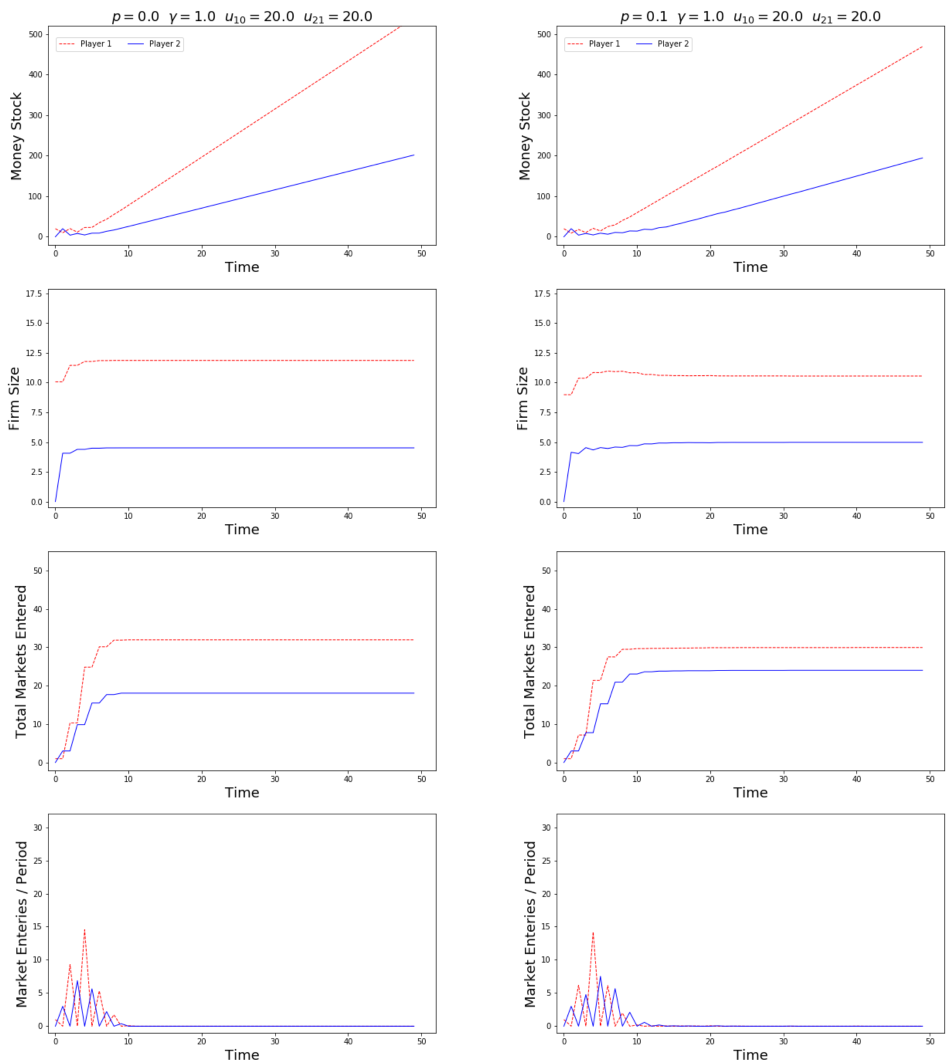
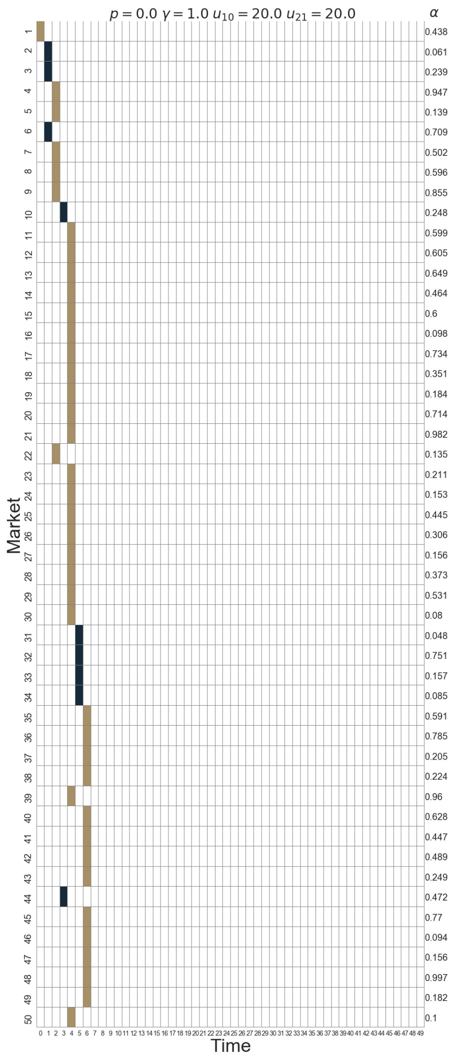


Figure 1.4: SPNEs under different values of α_K, γ and K.

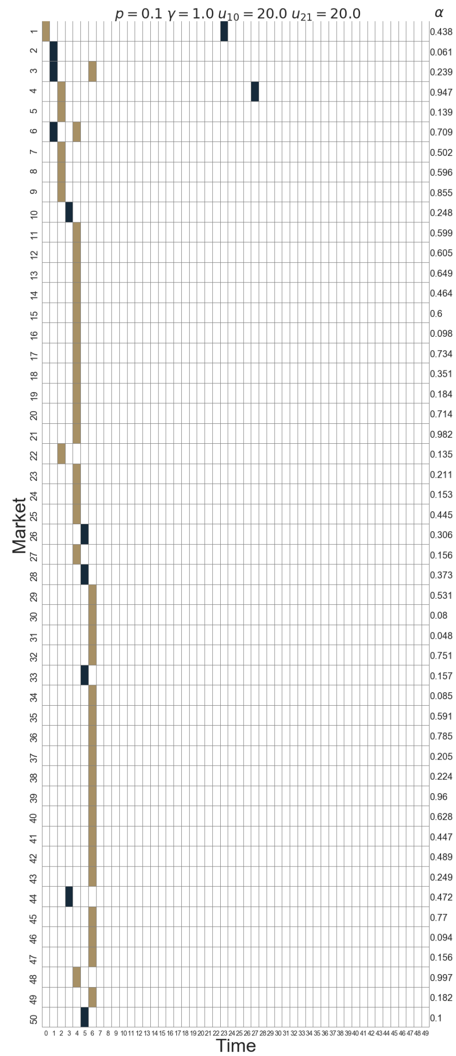


Case 1: $p = 0$, $\gamma = 1.0$, $u_{10} = 20$, $u_{21} = 20$ Case 2: $p = 0.1$, $\gamma = 1.0$, $u_{10} = 20$, $u_{21} = 20$

Figure 1.5: Simulation results under different values of p, (aggregation result of 1000 simulations).

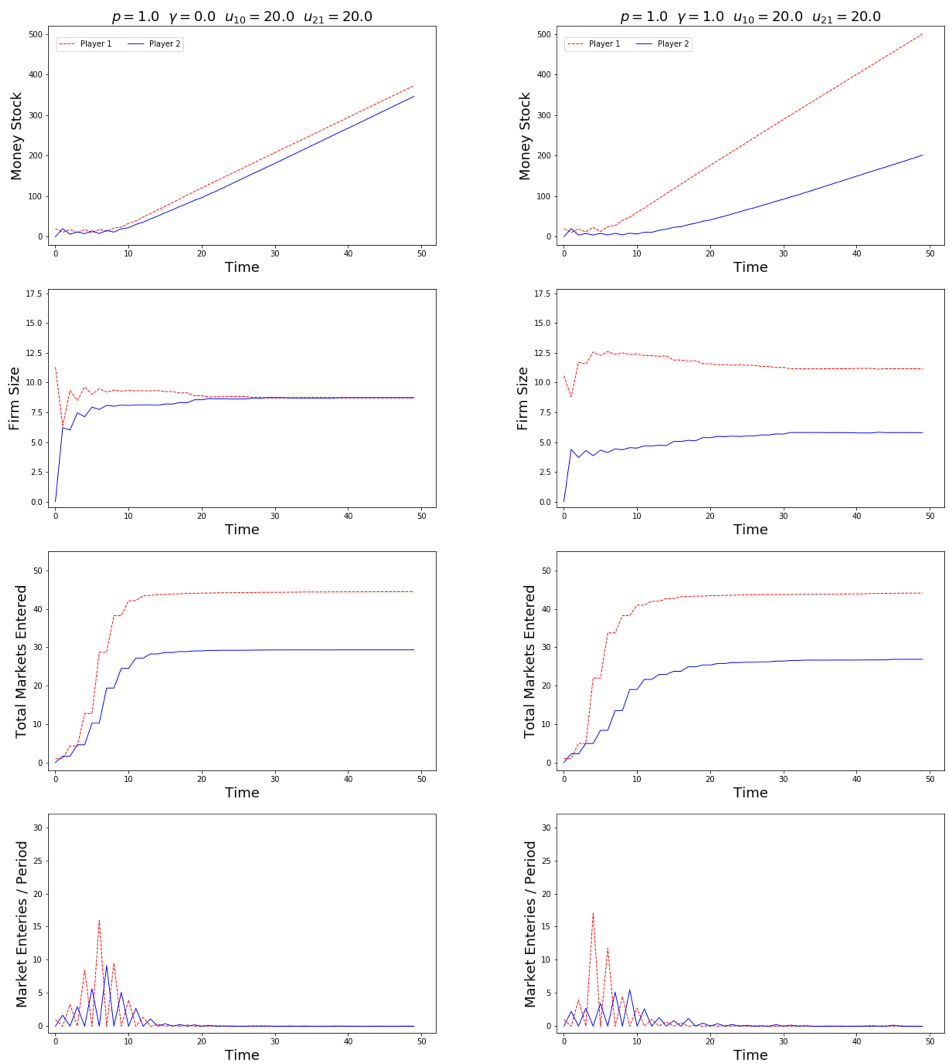


Case 1: $p = 0$, $\gamma = 1.0$, $u_{10} = 20$, $u_{21} = 20$



Case 2: $p = 0.1$, $\gamma = 1.0$, $u_{10} = 20$, $u_{21} = 20$

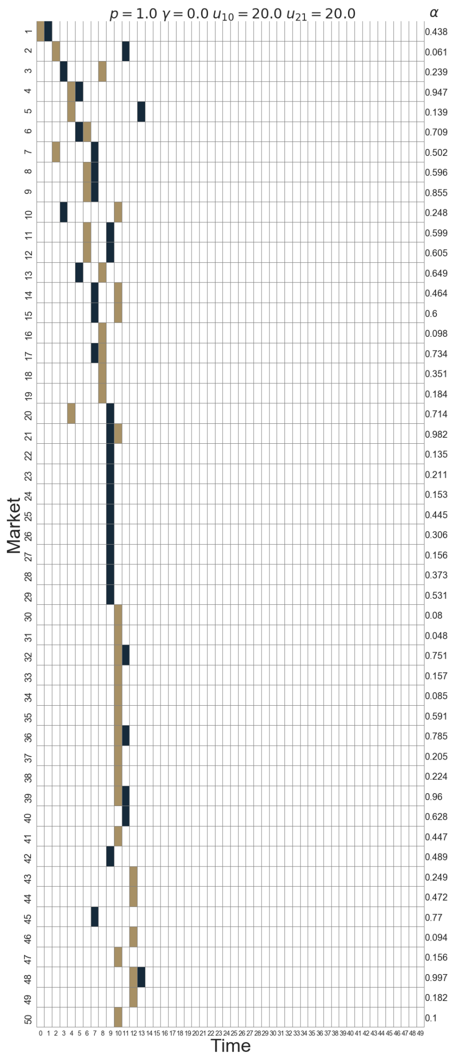
Figure 1.6: Simulation results under different values of p, (one special case).



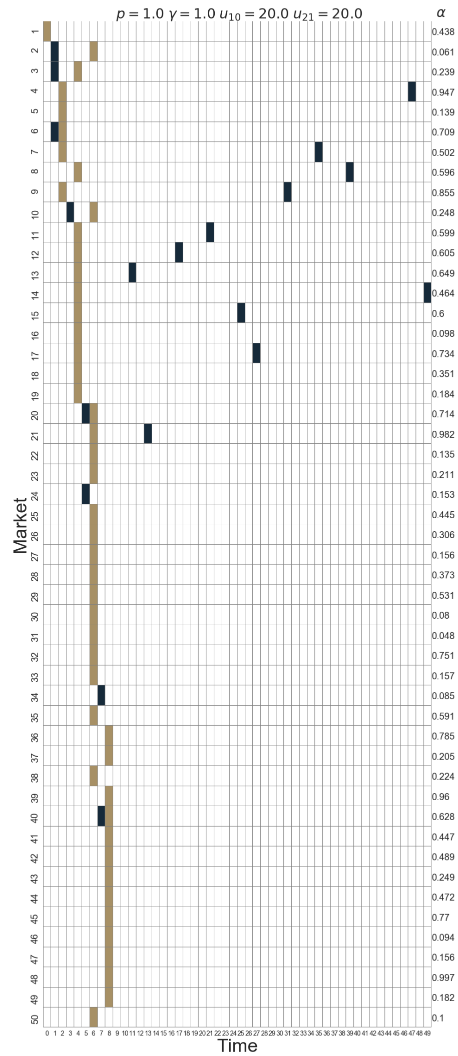
Case 3: $p = 1.0$, $\gamma = 0$, $u_{10} = 20$, $u_{21} = 20$

Case 4: $p = 1.0$, $\gamma = 1.0$, $u_{10} = 20$, $u_{21} = 20$

Figure 1.7: Simulation results under different values of γ, (aggregation result of 1000 simulations).

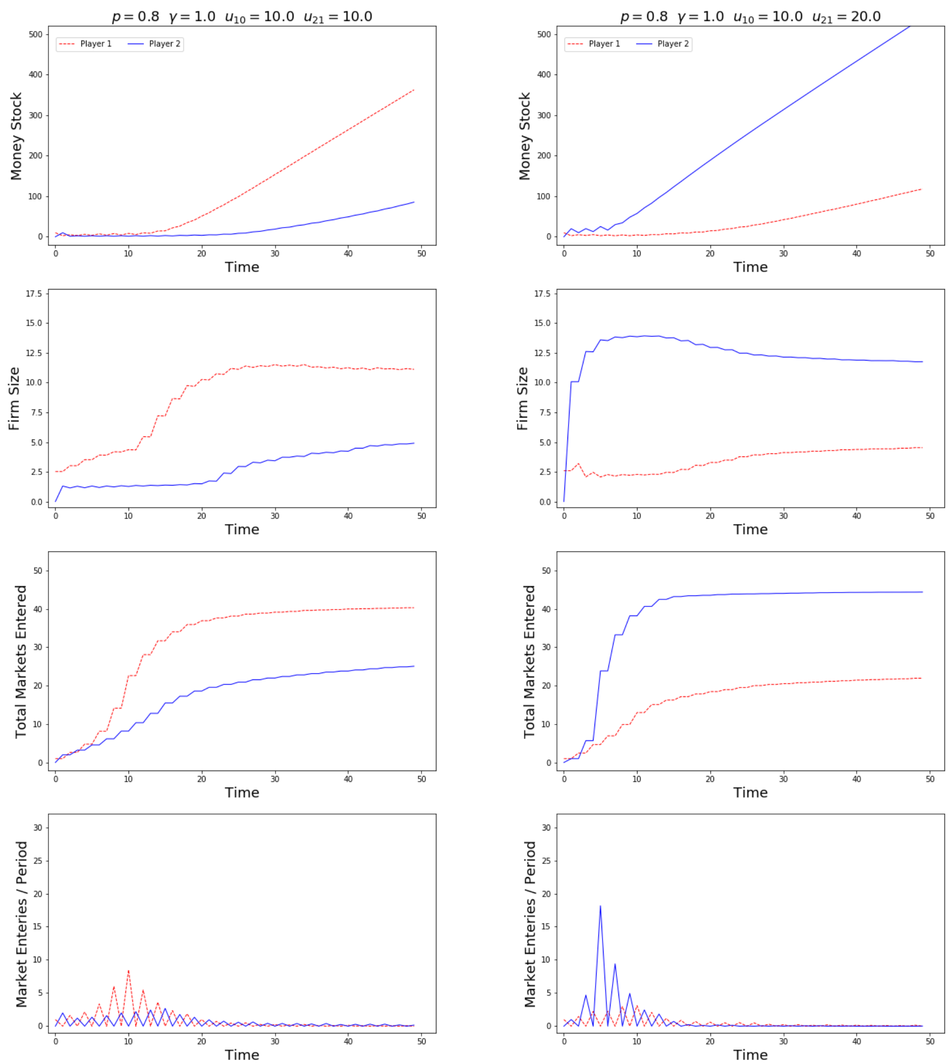


Case 3: $p = 1.0$, $\gamma = 0$, $u_{10} = 20$, $u_{21} = 20$



Case 4: $p = 1.0$, $\gamma = 1.0$, $u_{10} = 20$, $u_{21} = 20$

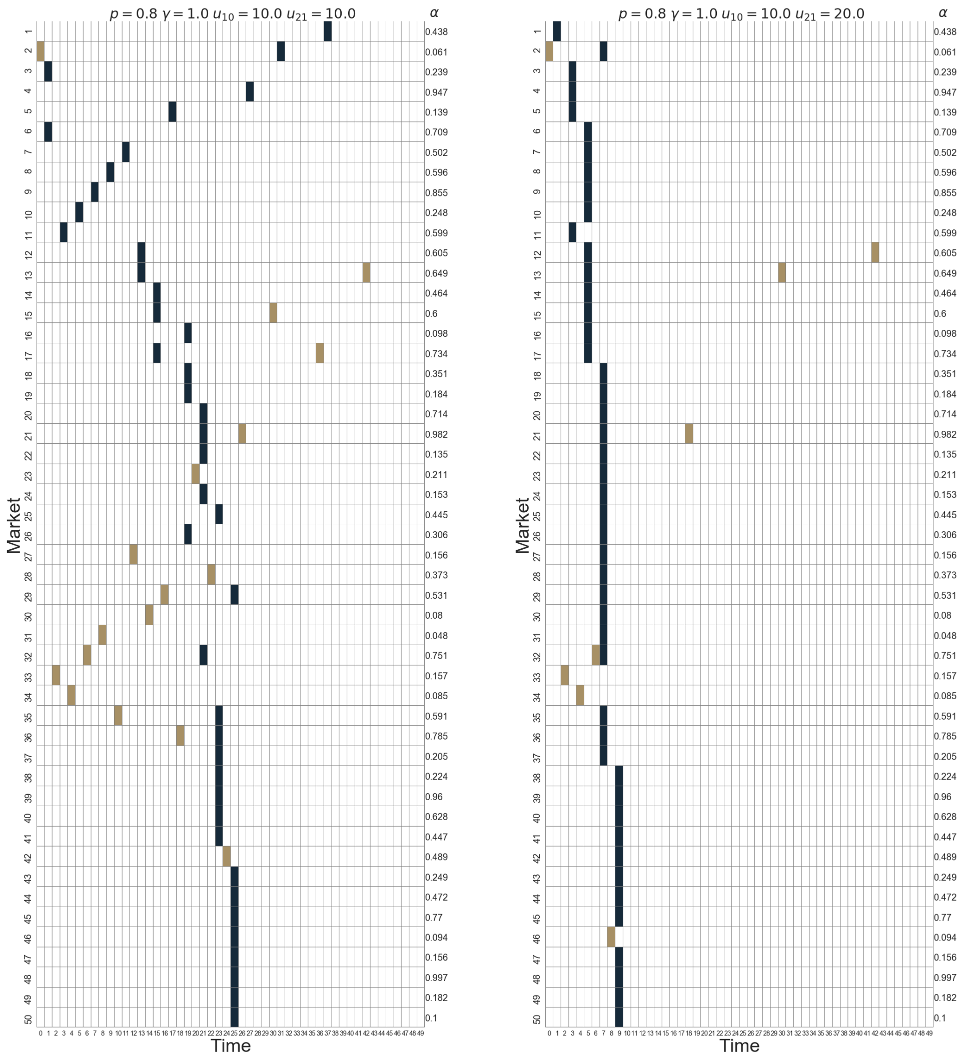
Figure 1.8: Simulation results under different values of γ, (one special case).



Case 5: $p = 0.8$, $\gamma = 1.0$, $u_{10} = 10$, $u_{21} = 10$

Case 6: $p = 0.8$, $\gamma = 1.0$, $u_{10} = 10$, $u_{21} = 20$

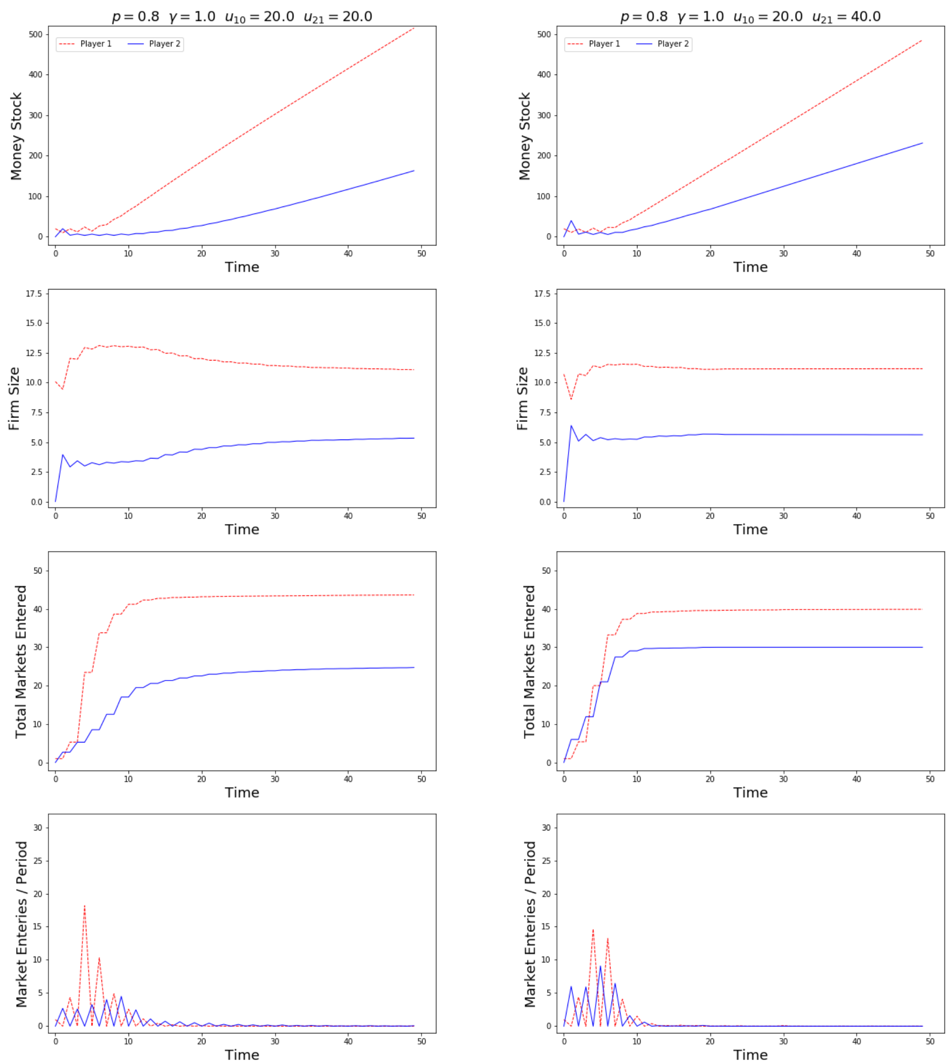
Figure 1.9: Simulation results under different initial funds, (aggregation result of 1000 simulations).



Case 5: $p = 0.8$, $\gamma = 1.0$, $u_{10} = 10$, $u_{21} = 10$

Case 6: $p = 0.8$, $\gamma = 1.0$, $u_{10} = 10$, $u_{21} = 20$

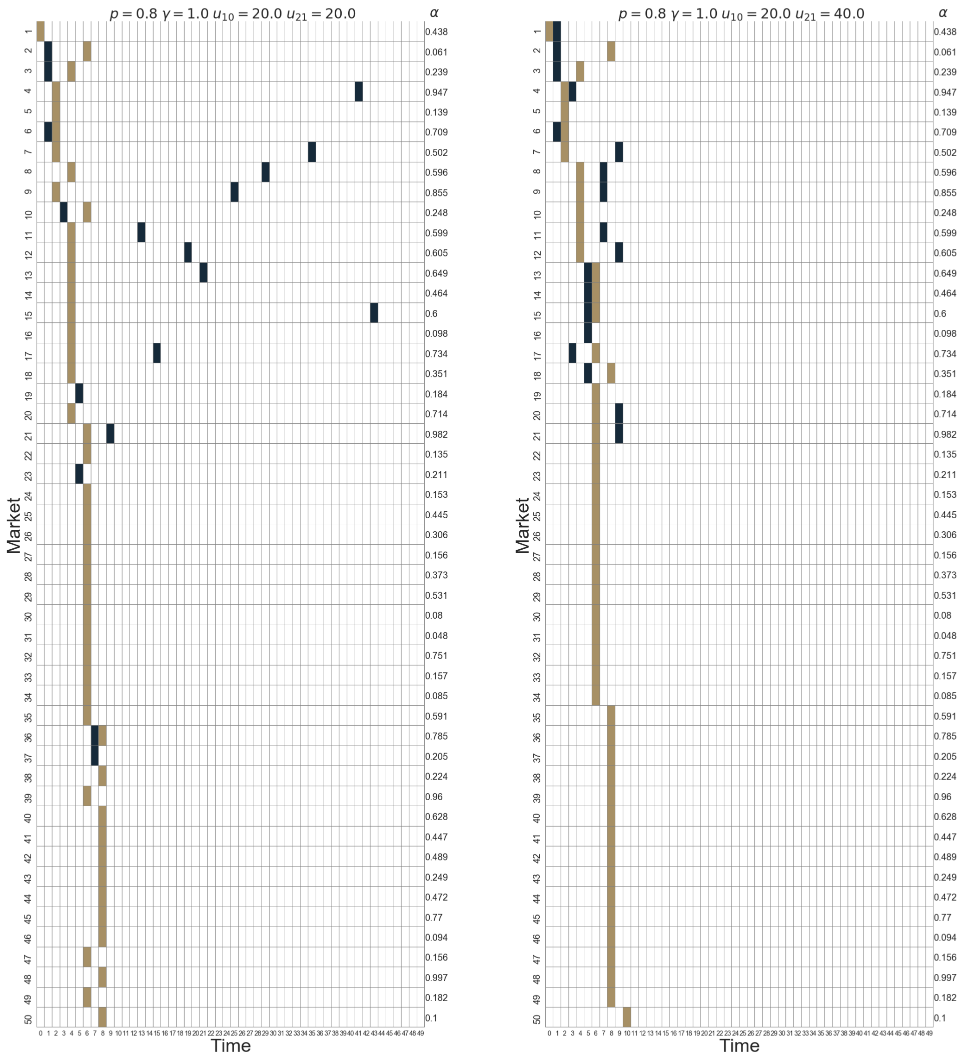
Figure 1.10: Simulation results under different initial funds, (one special case).



Case 7: $p = 0.8$, $\gamma = 1.0$, $u_{10} = 20$, $u_{21} = 20$

Case 8: $p = 0.8$, $\gamma = 1.0$, $u_{10} = 20$, $u_{21} = 40$

Figure 1.11: Simulation results under different initial funds, (aggregation result of 1000 simulations)



Case 7: $p = 0.8$, $\gamma = 1.0$, $u_{10} = 20$, $u_{21} = 20$ Case 8: $p = 0.8$, $\gamma = 1.0$, $u_{10} = 20$, $u_{21} = 40$

Figure 1.12: Simulation results under different initial funds, (one special case).

Chapter 2

Dynamic pricing solves the urban transportation disparity - Evidence from NYC on-demand ride-sharing drivers

2.1 Introduction

Ride-sharing platforms have introduced a more efficient matching technology than traditional taxis. The core of this matching scheme is the dynamic pricing system, based on Uber's official blog (Uber 2018): surge pricing is base fare multipliers generated automatically from the platform's back-end algorithms; it is a real-time location-based pricing scheme, with the dual purpose of suffocating demand, boosting supply, and then maximizing the number of completed rides. Because both the riders and drivers of ride-sharing platforms are highly elastic (Uber 2014), we can observe the market equilibrium change rapidly with respect to price changes.

Current and previous economic research on ride-sharing services focus more on drivers' behavior changes in working hours brought by the so-called "gig economy" (for example, Chen and Sheldon (2016) and Hall, Horton, and Knoepfle (2017)), researchers rarely investigate the real-time response of drivers to surge pricing, and how such pricing scheme will affect the geographical disparity of pickups.

Hence, the purpose of this paper is two-fold: first, we aim to investigate how drivers respond to price changes. To serve this purpose, we collect a significantly large real-time dataset from the ride-sharing market-leading companies Uber and Lyft, for a one-month period from New York City. We use the data to construct and estimate the structural model of the drivers' labor supply. Second, we aim to determine how the dynamic pricing system makes a difference. To answer this question, we compute the counterfactual case: what will happen to the city's overall ride-sharing pickups if the surge pricing is banned.

To more accurately capture the curvature of drivers' supply, we use a non-parametric instrumental variable estimation method (Horowitz 2011; Chetverikov, Kim, and Wilhelm 2017; Chetverikov and Wilhelm 2017; Compiani 2018) to estimate the transformed utility function, and we add a model constraint to the least square residual minimization function to solve the ill-posed inverse problem that usually comes with the non-parametric estimations. We find our final estimation results reasonable, significant, and consistent.

We find that drivers' labor supply are more elastic in non-Manhattan than Manhattan regions; and for both areas, drivers' labor supply are more elastic when surge pricing is equal to 1, implying that the emergence of price surges is a strong positive incentive for drivers, (i.e., that a slight increase in price will cause drivers to work more).

We also find that the dynamic pricing system of ride-sharing platforms effectively solves the geographical disparity problem of the taxi, and increases the overall accessibility and pickups in the entire city. As calculated in our counterfactual case, if there is no dynamic pricing, platform drivers will be crowded in the Manhattan area as taxi drivers. Further, 27% of the total supply will be lost, including a significantly large 59% reduction in the non-Manhattan area, and, due to an in-flow of drivers from other areas, Manhattan's supply will only fall by 3%.

2.1.1 Literature and contribution

First, this paper contributes to the growing literature on supply-side analysis of ride-sharing services. Camerer et al. (1997) find the estimated wage elasticity of taxi drivers to be significantly negative and conclude that taxi drivers' supply behavior is consistent with target-earning. Farber (2015) replicate and extend the analysis in Camerer et al. (1997) using data from taxi trip records in NYC for the five years from 2009 to 2013. His results negate previous the "weather shock – demand increase – hourly wage increase – drivers fulfill income target – work less" explanation for less taxi supply during rainy days in NYC; instead, he reports a positive estimated labor supply elasticity and concludes that taxi drivers work less on rainy days possibly because it is unpleasant to drive in the rain, and that "there is no additional benefit in continuing to drive". In contrast, in this paper, from our estimation results, ride-sharing drivers in fact eager to drive on rainy days, with the coefficient of "rain" in our structural utility function being positive and significant. Chen and Sheldon (2016) conduct a similar approach to study the working hour decision of Uber drivers using UberX partners' data from multiple cities, and they also report a positive labor supply elasticity: in response to surge pricing, drivers choose to extend their sessions and provide more rides on the Uber platform. Hall, Horton, and Knoepfle (2017) examine the long-run labor market outcomes when facing a change in the "base fare", they find that increase in base fare causes no detectable increase in drivers' long-run hourly wage, because drivers' utilization rate will also decrease, and the total trip quantity will fall.

Castillo, Knoepfle, and Weyl (2017) use theoretical and empirical evidence to demonstrate that dynamic surge pricing can help avoid the so-called "wild goose chase" problem while maintaining system functioning when demand is high. Cramer and Krueger (2016) compare the efficiency of ride-sharing services with traditional taxis, and find that UberX drivers work more hours and drive more miles, partially due to Uber's surge pricing system matching supply with demand more closely.

In this paper, we have a similar conclusion regarding drivers' positive labor supply, but use a different structure of data. Rather than working schedule flexibility, we focus on the effect of dynamic pricing on spatial mobility. In contrast to the traditional labor economic hourly-wage and working-hour model applied in previous literature, our structural model is more of a choice model approach, as adopted by McFadden et al. (1973) and Berry (1994). We do not consider the drivers' working choice in the perspective of "One day at a time"; instead, we segment the drivers' pickup decision processes into 10-minute time intervals and estimate drivers' instantaneous responses to price changes.

This paper also contributes to the research on geographical transportation disparities.(for example, Tomer et al. (2011) and Kaufman et al. (2014)). These authors are in agreement that great economic and employment opportunities exist in the improvement of mobility inequity. Lam and Liu (2019) apply a similar approach but study the consumer choice model and find that ride-sharing mitigates geographical disparity in transportation by providing accessible ride-hailing service to low-accessibility neighborhoods. In this paper, we focus on the effect of dynamic pricing on the supply side and find a similar result that without surge pricing, ride-sharing drivers will primarily concentrated in the airports and the Manhattan area, as do taxi drivers.

This paper can also be added to the emerging empirical applications of The constrained non-parametric instrumental variable estimation (NPIV) method. For example, Chetverikov and Wilhelm (2017) estimate the gasoline demand from U.S. data; Compiani (2018) estimates the structural demand function of strawberries using California grocery store data. Both papers use a fully non-parametric approach in their empirical practices; however, in this paper we add a parametric logit frame work to the non-parametric utility function prior to conducting the estimation. This approach is adopted because, in contrast to one or zero substitutes for target products in their cases, in the ride-sharing case, for one single choice (one zone) defined in our model, there are too many substitutes (253 zones) and we will have an excessive number of endogenous variables in one equation if we use a fully non-parametric estimation method, a structural logit function can help solve this problem.

The rest of the paper is organized as follows: In section 2, we introduce the structural model that describes the behavior of drivers; In section 3, we explain the data and data sources; In section 4, we explain the framework for empirical estimation; Then, in section 5, we will introduce the constrained NPIV model used for estimation. We calculate the counterfactual to test the influence of the dynamic pricing system in section 6. Finally a conclusion is provided in section 7.

2.2 Structural Model

2.2.1 Setup

Consider a decision process described by the following decision tree in Figure 2.1: A driver i at the beginning of his workday makes decisions on the following: 1) whether to drive or not; 2) whether to drive for Uber or Lyft; 3) (at each time t) which zone to offer service. And these decisions don't need to occur at the same time.

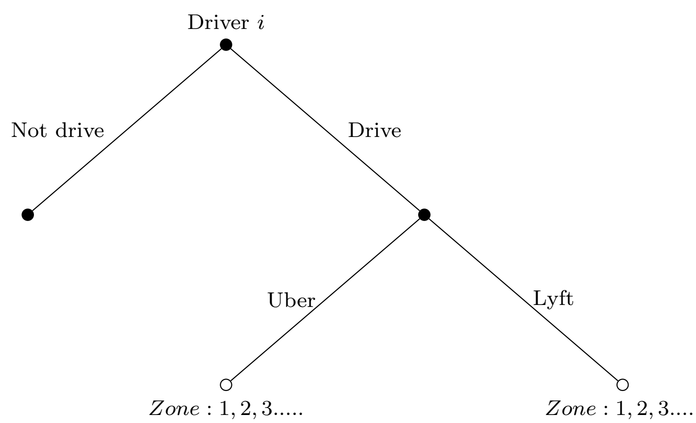


Figure 2.1: Decision tree of representative driver i

Drivers use time and effort to exchange for service payment. In 2016, Uber and Lyft only allowed drivers to see the pickup locations of the riders; no information of the destinations were available when they made the pickup decision. Therefore, drivers were not aware of the actual price of each trip, and, they could only see the Surge Multiplier of each pricing zone.

The indirect utility of a driver i at time t to do a pickup in location j from platform s is specified as:

$$U_{isjt} = f(SurgeMultiplier_{sjt}, X^1_{sjt}) + X^2_{sjt}{}'\beta - \gamma Distance_{ijt} + \xi_{sjt} + \epsilon_{isjt} \tag{2.1}$$

Where $X = \{X^1_{sjt}, X^2_{sjt}\}$ represents a vector of location-time-platform, specified exogenous characteristics that affect utility. $Distance_{ijt}$ is the travel distance for driver i to zone j from his current location at time t. ξ_{sjt} is the unobserved (to researchers) location-time-platform-specified utility component common to all drivers, ϵ_{isjt} is an i.i.d. driver's idiosyncratic utility term. Although drivers do not directly observe the actual service price, they do know the surge pricing, the structural form of how the Surge Multiplier entering the utility function is unclear, and we thus assume that it enters the utility function in a non-parametric manner: $f(.)$. Due to revealed preference, drivers are going to make one pickup choice that gives the highest utility each time. Assuming that ϵ_{isjt} are distributed in Type I extreme-value distributions, the discrete choice model is a nested logit. Let δ_{sjt} represent the average utility of doing the pickup through platform s in location j at time t:

$$\delta_{sjt} = f(p_{sjt}, X^1_{sjt}) + X^2_{sjt}{}'\beta - \gamma Distance_{jt} + \xi_{sjt} \tag{2.2}$$

Where p_{sjt} is short hand for $SurgeMultiplier_{sjt}$. Note, here ξ_{sjt} is the structural error; according to Berry (1994), it is not the difference between the predicted value and the actual value. Also, we expect ξ_{sjt} to be correlated with p_{sjt}, particularly in a high trading frequency two-sided market setup, where the market equilibrium depends greatly on both supply and demand sides. The number of pickups in location j from platform s as a proportion of the potential market at time t is:

$$S_{sjt} = \frac{e^{\delta_{sjt}}}{1 + \sum_s \sum_j e^{\delta_{sjt}}} \tag{2.3}$$

Where we assume that the utility of outside option is 0, so that $e^{\delta_0} = 1$.

2.3 Data

We collect a substantial amount of data from different sources, for a one-month period from June 1st 2016 to June 30th 2016, for New York City. Because the main data source New York City TLC (Taxi Limousine Commission) divides the city into 263 zones (we have data for 253 out of 263 of these zones), and reports their data accordingly, in this paper, I will follow the same spatial segmentation rules for all location-based data. Also we aggregate and average the data into 10-minute time intervals. For June 2016, the total number of time intervals will be $30 \times 24 \times 6 = 4320$, and the full-balanced panel dataset will have $4320 \times 253 \times 2 = 2194560$ observations. Further, all data listed below are collected and processed accordingly, and the summary statistics can be found in Table 2.1. In our research we will focus on service type "UberX" and "Lyft" because they are viewed as close substitutes to taxi.

Table 2.1: Summary Statistics

Variable	Mean	Std. Dev.	Min	5%	25%	50%	75%	95%	Max
Surge multiplier	1.077	0.204	1	1	1	1	1	1.525	5
Rain	0.025	0.156	0	0	0	0	0	0	1
Aver. trip distance	3.999	2.658	0.267	2.089	2.720	3.386	4.308	8.635	21
Aver. tips	1.988	2.013	0.023	0.425	1.071	1.602	2.071	5.437	26
Pickups	3.074	6.491	0	0	0	1	3	15	151
EWT	279.156	158.192	78	120	180	240	330	540	3750

1. **Real time Uber and Lyft data**

   First, we request a significant amount of real-time API data from Uber and Lyft for every 2 to 3 minutes, including surge multiplier and expected waiting time (EWT) for all service types available at the geographical central point of each zone. Uber changes its price more smoothly, for a rate of 0.1 each time; in contrast, most likely due to an unstable market condition caused by fewer users, Lyft changes its price more aggressively and more frequently for a rate of 0.25 each time.

2. **New York City TLC Uber and Lyft trip records**

   New York City TLC provides For-Hire-Vehicle ("FHV") trip records, which capture pick-up date, time, and taxi zone Location ID. We identify "UberX" and "Lyft" from the trip records by maintaining the base category "community car".

3. **New York City TLC Taxi records**

   Although little information was given from the FHV trip records, New York City TLC provides highly detailed data of taxi trip records. For each trip, it records: pick-up and drop-off coordinates, number of passengers, trip distance, trip duration, trip fare, tips received, method of payment, etc.

4. **Central Park Weather**

   Wunderground.com reports detailed New York Central Park weather conditions on an hourly basis, in order to capture the most important features; as well as considering the computation difficulty, we only include the dummy for "rain" at the current hour.

5. **Subway Status**

   Subway status is acquired from the website Subwaystats.com, which updates the status information of every NYC subway line every 5 minutes, and report the subway status in 5 categories :"Good service", "Delay", "Planned Work", "Service Change", and "Suspended". In my data, when a certain zone has several subway line across it, we will only record the most severe case within this 10-minute time interval. For example, if "Good service" and "Service Change" occur for two subway lines in the same zone at the same time, we will record "Service Change", this rule also applies if there is a status transition within the 10-minute time interval.

2.4 Empirical Framework

2.4.1 Setups

Definition of Markets

We define the market t, based on the level of 10-minute time interval, and the choice set (products) is defined as zones and platforms to provide services, as in Figure 2.1.

Utility Transformation

We use the maximum total pickups of all zones in a 10-minute time interval as our size of potential market, which is 3,107 in our data.

We use this number to calculate the market shares, then, use the inversion method to calculate the average utility values:

$$\delta_{sjt} = logS_{sjt} - logS_0 \tag{2.4}$$

Where S_0 is the market share of the outside option.

Ones and Zeros

One problem with the data is that, referring to Table 2.1, almost 75% of the time, there is no surge pricing at all. Further, platforms do not allow for the surge multiplier to be less than 1, hence there are excessive number of ones in the data. Thus, we could face two problems: first, we cannot identify the true equilibrium price, when surge multiplier equals 1, because there might be the case of supply access, the actual equilibrium surge price might be less than 1, and we have no track of it. Second, when we average the coefficients when surge price equals to 1, because of the price floor, the actual supply conditional on price could be more than the recorded pickups; therefore, we are under estimating the driver's utility.

We attempt to solve this problem by identifying the case when surge pricing is at the right tail of being 1: we maintain the data for the surge multiplier to be equal to 1 ($p_{sjt} = 1$) at time t, iff at time $t + 1$, at the same location, a surge multiplier larger than 1 ($p_{sjt+1} > 1$) occurs.

We also drop all $S_{sjt} = 0$ in our data set, because in the above utility transformation process, $ln(0)$ does not exist.

Supply Shifters

We divide the daily 24 hours into 8 time blocks as Lam and Liu (2019), including: Morning rush (weekdays 7a.m. - 9 a.m.), evening rush (weekdays 4 p.m. - 7 p.m.), weekday day time (weekdays 10 a.m. - 3 p.m.), weekday night (weekdays 8 p.m. - 11 p.m.), weekday late night (0 a.m. - 6 a.m.), weekend day time (weekends 5 a.m. - 5 p.m.), weekend night (weekends 8 p.m. - 11 p.m.), and weekend late night (weekends 0 a.m. - 4 a.m.). We also separate the regression into Manhattan and non-Manhattan areas.

Besides surge multiplier, we include the following variables as exogenous supply shifters: 1) The average tips paid by taxi passengers within each time block of each zone; 2) whether it is raining in the current 10-minute time interval; 3) the average taxi trip distance of passengers within each time block of each zone; 4) dummies for Uber and airports.

By setting these supply shifters, we assume that 1) although the drivers could not have specific knowledge on each trip, he/she at least has some expectation related with time and location; 2) taxi and ride-sharing platforms are sharing a similar distribution of customers, therefore, their behavior patterns are similar for us to use as proxies for ride-sharing platforms.

Independence of Irrelevant Alternatives(IIA)

We choose to use the nested logit framework in this paper, and since Uber and Lyft are providing almost identical services, we assume the nest dissimilarity factor to be 1 for both Uber and Lyft, mathematically indicating that the products are equally similar within and across platforms. This setup will reduce our estimation framework to a simple multinomial logit. Instead, we add a dummy variable for $Uber = 1$ to capture the difference between platforms. Moreover, because we do not have the data regarding driver's demographic information, we cannot take into account the random utilities in our regression; However, this approach is sensible, because we are looking at the overall effect of the dynamic pricing system, and thus, estimating the average effect could sufficiently serve our research purposes.

2.4.2 Identification

Because of the high trading frequency in the two-sided platforms, the supply and demand could be highly volatile, thus our estimation is subject to the price endogeneity problem. We construct the instrumental variable for the surge multiplier using the average local expected waiting time and the local subway status within the 10-minute time interval. Where the expected waiting time was also acquired from Uber and Lyft's API, it is a variable in the unit of seconds measuring the estimated waiting time for a pickup prior to a rider sending out the request. This one can only be observed by the riders; therefore, no drivers have any prior knowledge regarding where the request is sent from or if the driver is being matched for this request. Another advantage of using expected waiting time as the instrumental variable is that this one has a lot of variations (refer to table 2.1). However, one problem with this instrumental variable is that, it is related to overall demand access of all riders and drivers in the nearby zones, thus, although an individual driver cannot observe it, it is still in some degree reflecting some general information regarding changes in the preferences of surrounding drivers.

Another potential instrument is the subway status, which is supposed to be a valid instrumental variable because subway status is proposed as being independent of ride-sharing supplies. However, there are two problems with these variables as instruments: first, not all zones have subway lines running across them, (refer to Figure 2.4) only 185 out of 253 zones have at least one subway station inside. The second problem is that they are lack of variation.

Due to the fact that there will be transformations of our variables into B-spline bases in the estimation process, the instrumental variables are required to have at least one continuous variable, and the current expected waiting time data from the API has some endogeneity issue. We address this problem by fitting the expected waiting time with subway status, and other location, time and platform characteristics. And use the fitted expected waiting time ($\widehat{EWT}$) as our final instrumental variable. The purpose of this approach is to capture the parts in the expected waiting time that are due to the changes in subway status; for example, a delayed train in the nearby subway station, could lead to a positive demand shock at the current location, hence increasing the local expect waiting time for ride-sharing requests.

Table 2.2: First-stage Linear Regression

Surge Multiplier	Manhattan Coefficient	Non-Manhattan Coefficient
$\widehat{EWT}$	-0.000215***	-0.000190***
	(-51.50)	(-115.36)
Rain	0.0163***	0.0349***
	(6.42)	(24.17)
Average local trip distance	-0.00897***	0.00035***
	(-20.92)	(4.92)
Average local tips	0.00223***	-0.000403***
	(4.48)	(-6.45)
Uber	-0.114***	0.0111***
	(-176.14)	(-36.29
Airport	-	-0.000579
	-	(-0.26)
Constant	1.239***	1.126***
	(892.42)	(1980.43)
R^2	0.0672	0.0109
$F-statistic$	8770.77	3246.47

*** denotes p -value$<$ 1% significance level based on robust standard error

The BLP type instruments (Berry 1994; Berry, Levinsohn, and Pakes 1995), such as sum of surge prices of UberX and Lyft in the surrounding zones, or sum of surge prices of other types of services in the surrounding zones, is not applicable here, probably due to several reasons: 1) surge prices are generated from the same platform algorithm, there could be a problem of tautology; 2) there is a lack of variation in the BLP type instruments, because the values of surges are equal to 1 for most of the time; and 3) there is a spatial correlation among zones, one regional shock may alter the supplies and prices of several adjacent zones together, such as traffic jams, and hence the surge prices of surrounding zones are also correlated to the local supply. Because of the problems listed above, we cannot use these variables as instruments.

We report the linear first-stage regression coefficients in Table 2.2.

2.4.3 Spatial Disparity

Another problem with estimating the structural model is that: drivers' pickup decision at time t are in fact depends on their previous drop-off location, which means that the distribution of drivers at the beginning of time t, affects the market share of each zone at time t, but we do not have the trip-level drop-off coordinates in our data, and hence cannot estimate the $\gamma Distance_{jt}$ term in our structural model. To solve this problem, we assume that the average distance for drivers to all jt is a constant ($Distance_{jt}$ is a constant). This assumption requires drivers to be equally distributed for all markets $\forall t \in T$. Hence, we do not consider the spatial disparity in our estimation, and the distance term enters the structural model as a constant α:

$$\delta_{sjt} = f(p_{sjt}, X^1_{sjt}) + X^2_{sjt}{}'\beta - \alpha + \xi_{jt} \tag{2.5}$$

Where $\alpha = \gamma Distance_{jt}$.

We also assume that at each time t, drivers are making decisions among all zones in the New York City area, an assumption which may actually not be the case, referring to Uber and Lyft, their algorithms automatically match up drivers with nearby riders, and typically the decisions drivers can make is whether to accept a job or not. But according to surveys by Lee et al. (2015): "...drivers strategically controlled when and where to work and when to turn on the driver mode of an app to get the types of requests and clienteles that they preferred: limiting the area that they worked in by turning off the driver mode...", the authors also find that drivers do not chase surge if the surging area is too far away, because the surge pricing changes too rapidly, and may therefore disappear by the time they arrive.

Thus, we consider that the spatial disparity problem for one time t, should not make our final estimation results invalid, because we are examining the average results over many time periods (4320); although the distributions of drivers is not even at one time t, the overall aggregate distribution should be, for 4320 time periods (markets). If we look at the taxi drop-off map in June 2016, Figure 2.6, the drop-off locations are more evenly distributed than the pickup locations, also, there is a clear difference between Manhattan and non-Manhattan areas, and we already capture the difference in our estimation. Hence, our final estimation result for an average influence of distance should be valid.

2.5 Estimation

2.5.1 Constrained NPIV estimator

Objective Function and Constraint

We use the constrained NPIV(non-parametric instrumental variable) method introduced by Chetverikov and Wilhelm (2017), to estimate our structural model. In this structural model we assume that all the exogenous parts enter the model in a separable linear way such that:

$$\delta_{jt} = f(p_{jt}) + X'\beta - \alpha + \xi_{sjt}, \qquad E(\xi_{sjt}|Z, X) = 0 \tag{2.6}$$

$$\xi_{sjt} = \delta_{jt} - f(p_{jt}) - X'\beta + \alpha \tag{2.7}$$

Where Z is a vector of instrumental variables. In this paper, Z is the parts of a consumer's expected waiting time explained by current subway operation status. We want to estimate the function $f(.)$ based on random samples generated from $\{\delta, P, X, Z\}$. Consider a series estimator, let $\{g_k(p), k \geq 1\}$, $\{q_k(z), k \geq 1\}$ be two orthonormal bases in $L^2[0, 1]$ space, let $g(p) := (g_1(p), ..., g_K(p))'$ and $q(z) := (q_1(z), ..., q_J(z))'$ for $J \geq K \geq 1$, be two vectors of basis functions. Define $\mathbf{G} := [g(p), X]$, $\mathbf{Q} := [q(z), q(z) \times X]$. Where $q(z) \times X$ is the tensor product of $q(z)$ and X , that, it is the intersections of $q(z)$ with exogenous variables X.

Consider the general "law of supply"; we are expecting the driver's utility to be positively correlated with the price, and therefore the first order of $f(p)$ should be positive such that: $\frac{df(p)}{dp} > 0$. The constrained estimator from moment condition is:

$$\min_{\theta} \qquad (\delta - \mathbf{G}\theta)'\mathbf{Q}(\mathbf{Q}'\mathbf{Q})^{-1}\mathbf{Q}'(\delta - \mathbf{G}\theta) \tag{2.8}$$

$$\text{subject to} \qquad \frac{df(p)}{dp} > 0 \tag{2.9}$$

Where $\theta = [\theta_p, \beta, \alpha]$, θ_p $(K \times 1)$ is the coefficient vector of non-parametric basis functions of p. Note here, that we construct an estimator of $f(p)$ as a linear combination of basis functions that: $f(\hat{p}) = g(p)'\theta_p$. Because X is a vector of exogenous variables, $\frac{dX}{dp} = 0$, the constraint can also be written as $\frac{dg(p)}{dp}\theta_p > 0$.

Regression Parameters

To estimate the utility function, we use a power 2 B-spline basis for both endogenous and instrumental variables, as in Chetverikov and Wilhelm (2017), and the number of knots on both splines are chosen by cross validation based on the criteria of minimizing MSE; the computation complexity is also taken into consideration that the maximum knots test by cross validation is 7. Finally we choose the number of knots to be 6 for both instrumental and endogenous variables.

Robustness Check

In order to exclude the outliers in our data, in our regression, we keep $1 - 99\%$ percentile of the surge multipliers, such that the surge multipliers in our estimation data falls into the range of $[1, 3]$.

Moreover, to test the robustness of the non-parametric estimation, we evenly divide the surge multiplier into 0.1-length intervals, and within each surge pricing interval, we randomly draw 1,000 observations; then we repeatedly (100 times) estimate the model on these random subsets.

We compare among the estimation methods - constrained NPIV, unconstrained NPIV and linear regression, using regression results from the 100 subsets (refer to Appendix C for comparison), and find that the performance of the constrained NPIV is the best among the three, with the lowest coefficients standard errors (consistent), and the highest probability of significance.

Estimation Method

We use a two-step estimation method to capture the non-parametric and parametric parts in the structural model separately:

In the first step, we estimate the entire model as in Equation 2.9, to get $\hat{\theta} = [\hat{\theta_p}, \hat{\beta}, \hat{\alpha}]$; In the second step, we extract the non-parametric part from δ_{sjt}, and use OLS to regress the residuals on the other supply shifters:

$$\hat{Residual} = \delta_{sjt} - g(p)'\hat{\theta_p} \tag{2.10}$$

For unknown reason, in practice, we find that if we reverse the order in step 2, as Chetverikov and Wilhelm (2017) do in their working paper: extract the linear part $X'\beta - \alpha$ first, then re-estimate the non-parametric part $f(p)$ using NPIV, we tend to under estimate the utility.

2.5.2 Estimation Results

The estimated non-parametric B-spline coefficients are reported in Table 2.3.

Table 2.3: Estimation Results of Non-parametric B-spline Knots

N=100	Knot 1	Knot 2	Knot 3	Knot 4	Knot 5	Knot 6
			Manhattan			
Average	-6.91935	-6.61819	-6.61637	-6.61637	-5.82712	7.438699
Std. Err.	0.693959	0.145532	0.14491	0.14491	0.922791	4.525964
95% Conf. Interval	-6.8496	-6.60356	-6.6018	-6.6018	-5.73437	7.893575
	-6.98909	-6.63281	-6.63093	-6.63093	-5.91986	6.983822
			Non-Manhattan			
Average	-9.36882	-6.79264	-6.38106	-5.34883	-5.30653	-5.24012
Std. Err.	2.152473	0.713096	0.602384	0.489985	0.516812	0.815026
95% Conf. Interval	-9.15248	-6.72097	-6.32052	-5.29959	-5.25459	-5.15821
	-9.58515	-6.86431	-6.4416	-5.39808	-5.35848	-5.32203

Due to the fact that the coefficients of non-parametric part $f(p)$ is complicated and also difficult to explain, we also report the curves of fitted $f(p)$ for Manhattan and non-Manhattan areas in Figure 2.2. Recall that we assume drivers to have the same price sensitivity for both platforms.

We can see that holding other things constant, when surge pricing is low, the Manhattan area is more attractive for drivers, but the drivers are less sensitive to price here than they are in the non-Manhattan area.

The coefficients of the linear supply shifters are concluded in Table 2.4, we report the one with the highest R^2 from 100 estimations. As expected, the constant term α for the average effect of pickup distance is negative, that drivers do not like to do pickups far from their current location, it is also reasonable that $\hat{\alpha}^{Manhattan} > \hat{\alpha}^{non-Manhattan}$, because it is clear that geographical zones in Manhattan area are closer to each other than zones in other areas, and there are in general more pickups in Manhattan than in other areas that: $\overline{Distance_{jt}}^{Manhattan} < \overline{Distance_{jt}}^{non-Manhattan}$, so holding parameter $-\gamma$ constant for Manhattan and non-Manhattan areas, it is reasonable to see that the average effect of distance in the non-Manhattan areas to be relatively larger.

In general, drivers do not like the zones with higher average trip distance, and prefer the zones with higher average tips; also, drivers favor Uber more than Lyft. Surprisingly, different from what Camerer et al. (1997) and Farber (2015) find in their papers for taxi drivers, "Rain" is in fact an incentive for platform drivers — they are more willing to offer rides on rainy days.

All coefficients are significant at the 1% significance level.

2.5.3 Elasticity of Supply

We calculate the average supply elasticity use equation:

$$Elasticity = \frac{df(p)}{dp} p(1 - \bar{S}_s) \tag{2.11}$$

Table 2.4: OLS Estimation Results of Linear Part

	Manhattan	Non-Manhattan
Variable	Coefficient	Coefficient
Rain	0.642***	0.390***
	(6.33)	(6.18)
Mean local trip distance	-0.467***	-0.0782***
	(-17.30)	(-10.56)
Mean local tips	0.722***	0.0474***
	(12.51)	(4.91)
Uber	1.822***	0.965***
	(48.22)	(41.46)
Airport	-	2.191***
	-	(17.01)
Constant	-0.218***	-0.312***
	(-2.81)	(-11.04)
R^2	0.3039	0.1928
$F - statistic$	710.65	484.25

*** denotes p -value< 1% significance level based on robust standard error

Where $\bar{S}_s$ is the average share of platform s for all zones and all markets. However, because both Uber and Lyft's average market share are particularly small compared to 1, which makes little difference when doing $(1 - \bar{S}_s)$, the actual elasticity difference between the two platforms are extremely trivial, so we consider drivers' average supply elasticity to be the same for both platforms.

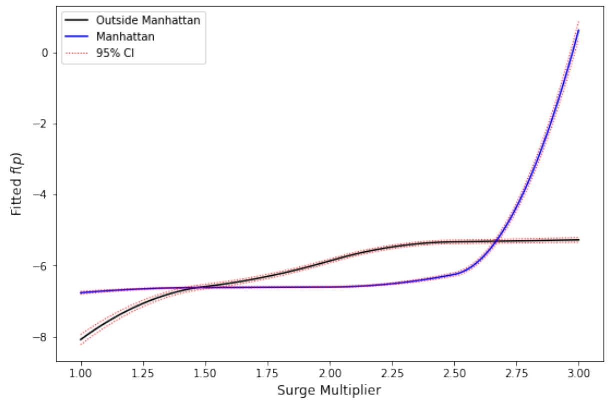


Figure 2.2: Fitted Nonlinear part: $f(p)$

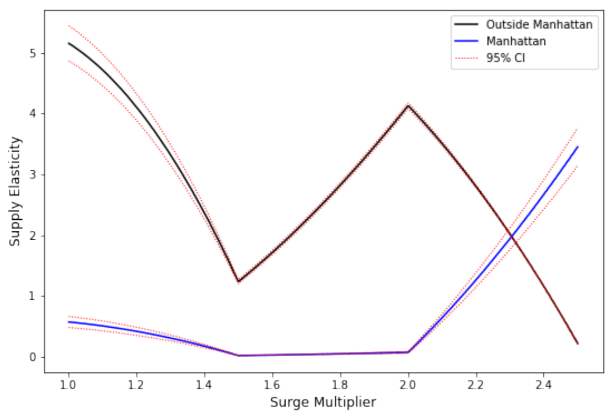


Figure 2.3: Estimated Supply Elasticity

The estimated supply elasticity is reported in Figure 2.3. We can see that for both Manhattan and non-Manhattan areas, the supply is more elastic at the point where surge equals 1, which imply that the emerging of price surging is a strong incentive for drivers to offer more rides, especially for drivers in the non-Manhattan area. We can also observe that on average drivers' supply in the non-Manhattan area is more elastic than it is in the Manhattan area.

One problem with the estimated elasticity is that there are many "kink" points; this issue is due to unsmooth derivatives of B-spline specified $g(p)'$, clearly, each "kink" point corresponds to one B-spline "knot" in Figure 2.3, this problem can be regarded as an ill-posed inverse problem caused by specific functional form. But the general trend and range of drivers' labor supply elasticity should be in good shape.

Another issue is the fitted $f(p)$ and supply elasticity for Manhattan area significantly increasing after $SurgeMultiplier > 2.5$. It is potentially due to two reasons: first, we have few (only 1.5K) observations after this point, and hence the sampling process cannot mitigate the errors in different estimations, a small fluctuation in the spline will cause the estimated elasticity to deviate from the truth. Second, this issue may also due to that the variation in our instruments fails to control for the endogeneity when $SurgeMultiplier > 2.5$.

2.6 Counterfactual

In this section, we use the previous estimation results to test the influence of Uber and Lyft's dynamic pricing system, and ask: what if surge pricing is banned?

The counterfactual results are summarized in Table 2.5, we can observe that if there is no surge pricing, in June 2016 NYC, the total supply of ride-sharing platforms will decrease by more than 27%. Uber would lose almost 27% of the supply, compared with 25% for Lyft.

Also, supply in the non-Manhattan areas would be damaged more by losing more than 59% , and the Manhattan area will only lose approximately 4%, because without surge pricing, most of the drivers would prefer to work in the Manhattan area, drivers

Table 2.5: Counterfactual: What if surge pricing is banned?

	Real Pickups	Counterfactual	Δ	$\Delta\%$
Uber	5346025	3863178	-1482847	-27.74%
Lyft	1073680	799757	-273923	-25.51%
Manhattan	3699627	3558715	-140912	-3.81%
Non-Manhattan	2720078	1104220	-1615858	-59.41%
Total	6419705	4662935	1756770	-27.37%

from the non-Manhattan area will flood into Manhattan, and offset previous losses. The result of forbidding surge pricing will be more clear if we compare the two figures in Figure 2.7: Most of the previous non-Manhattan rides would flood into Manhattan borough, and the dark purple zone with most pickups in the corner of Manhattan borough is the Randalls Island, it is the famous recreation center in Manhattan area, as seen in Figure 2.4 and Figure 2.5, there is no subway line across this island, with people visiting there on average being willing to pay more tips. Thus, in our counterfactual case, Randalls Island will be the most attractive place for drivers.

Moreover, if we compare the counterfactual map with the aggregate taxi pick-ups in Figure 2.6, they are highly similar, with most of the pickups concentrating in lower Manhattan, and the lights being relatively dim in other boroughs, except for the airports. This result implies that the dynamic pricing system is the key reason explaining why ride-sharing drivers distribute more evenly in the urban area than taxi drivers, increasing overall accessibility of the entire city and effectively re-distributing the drivers.

2.7 Conclusion

In this paper, we investigate the effect of the dynamic pricing system on ride-sharing platform drivers' labor supply decisions. Rather than working-hour and wage-rate relations explored by previous literature, we examine the instantaneous response of drivers to price surges. Using data from New York City, we estimate the structural choice model through a constrained non-parametric instrumental variable (NPIV) approach. We use the estimated coefficients to calculate the drivers' supply elasticity and compute the counterfactual case involving the following question: What will happen to drivers if the surge pricing system is banned?

We find that:

1. Drivers prefer Uber to Lyft;
2. Drivers like to do pickups in areas that pay more tips;
3. The emergence of a price surge is a highly strong incentive for drivers, such that the supply is more elastic at the point $SurgeMultiplier = 1$;
4. Different from what Camerer et al. (1997) and Farber (2015) find in their papers, drivers are more willing to serve during rainy days;
5. The dynamic pricing system effectively solves the geographical disparity problem faced by the taxi industry, helping to re-distribute the drivers and increasing the overall accessibility of the entire New York City area: without dynamic pricing, platform drivers would be crowded in the Manhattan area;
6. Without dynamic pricing, the total supply in June 2016 NYC would decrease by 27%, among which, more than 59% of the non-Manhattan supply would be lost;
7. Due to an in-flow of drivers from other areas, supply in Manhattan will only reduce by 3%.

Finally, I would like to mention one limitation of this paper: we did not consider the long-term endogenous behavioral changes of drivers, and it is possible that the actual impact of forbidding dynamic pricing would be more severe; when drivers know that there is no dynamic pricing, their expected hourly income would decrease, and they would choose to leave the market, and hence the overall potential market size would shrink. And for those who stay in the industry, they will have to increase their utilization rate to meet their previous wage level, causing a further decrease in drivers' welfare.

2.8 Tables and Figures

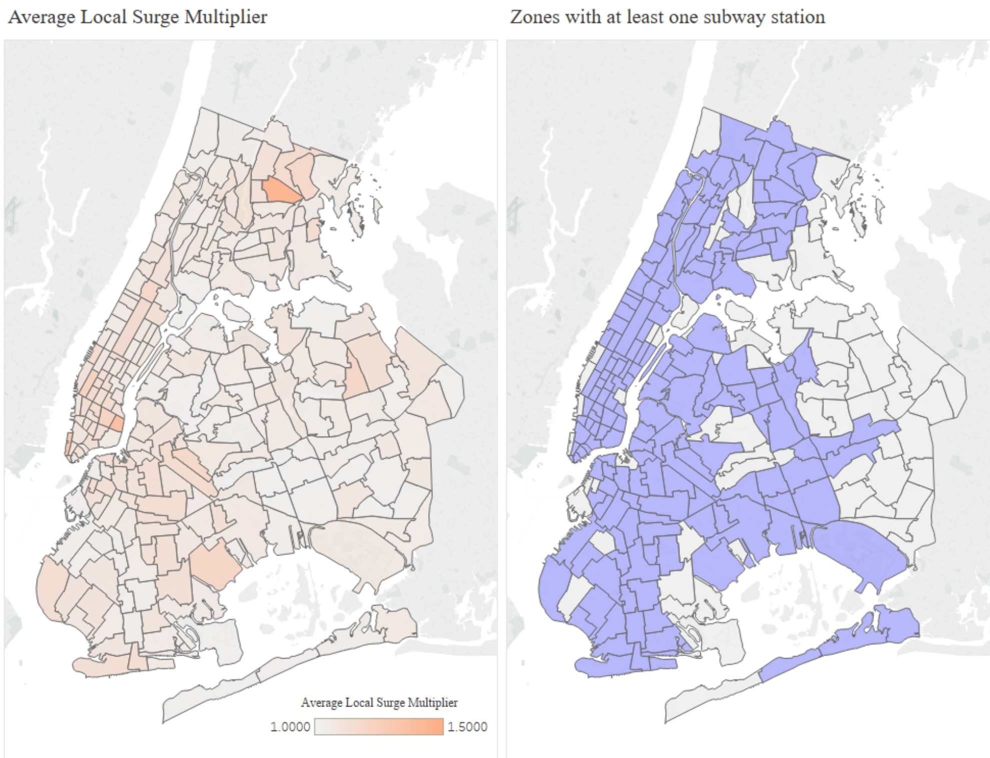


Figure 2.4: Average Local Surge Multiplier & Subway Maps.

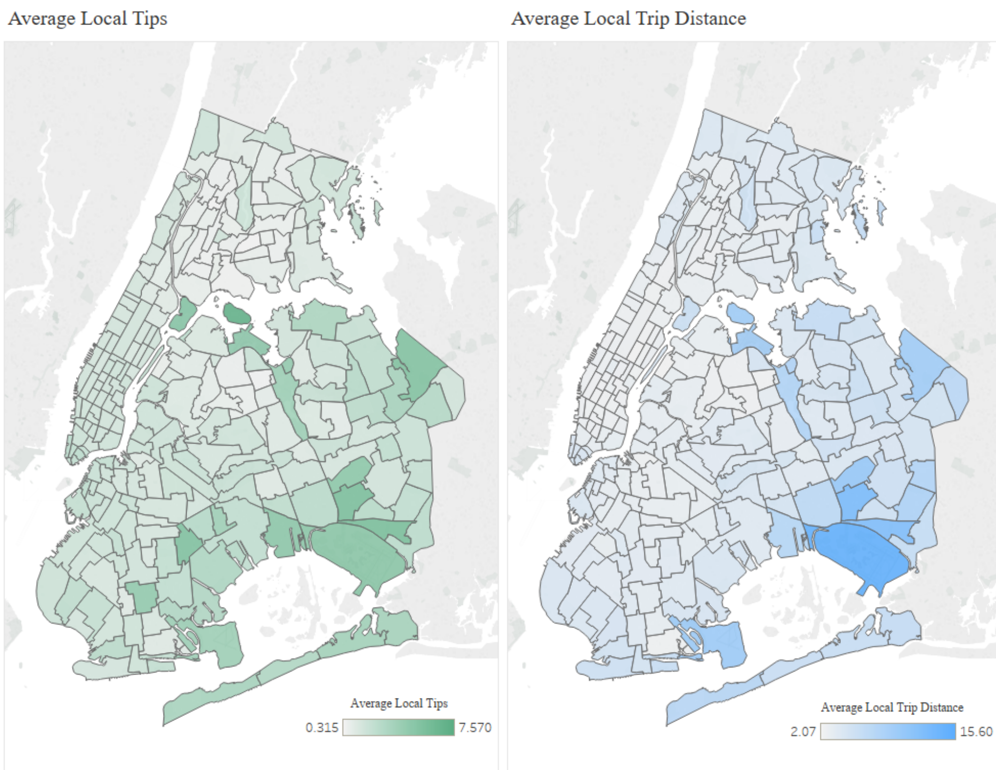


Figure 2.5: Average Local Tips & Average Local Trip Distance.

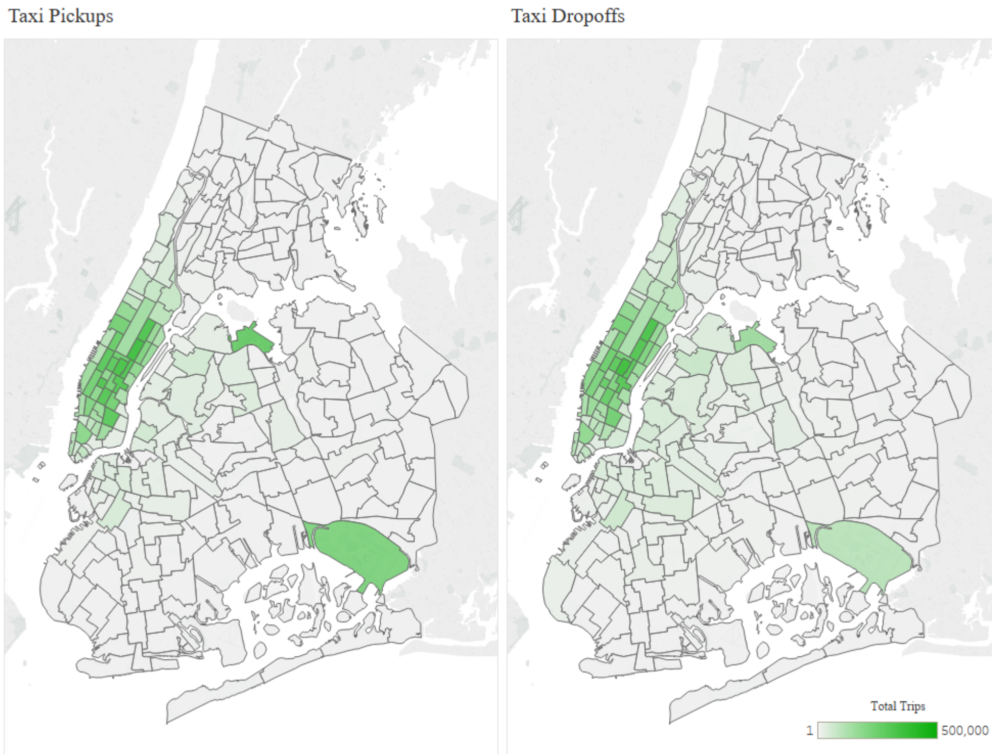


Figure 2.6: Aggregate taxi pickups and drop-offs in June 2016, NYC.

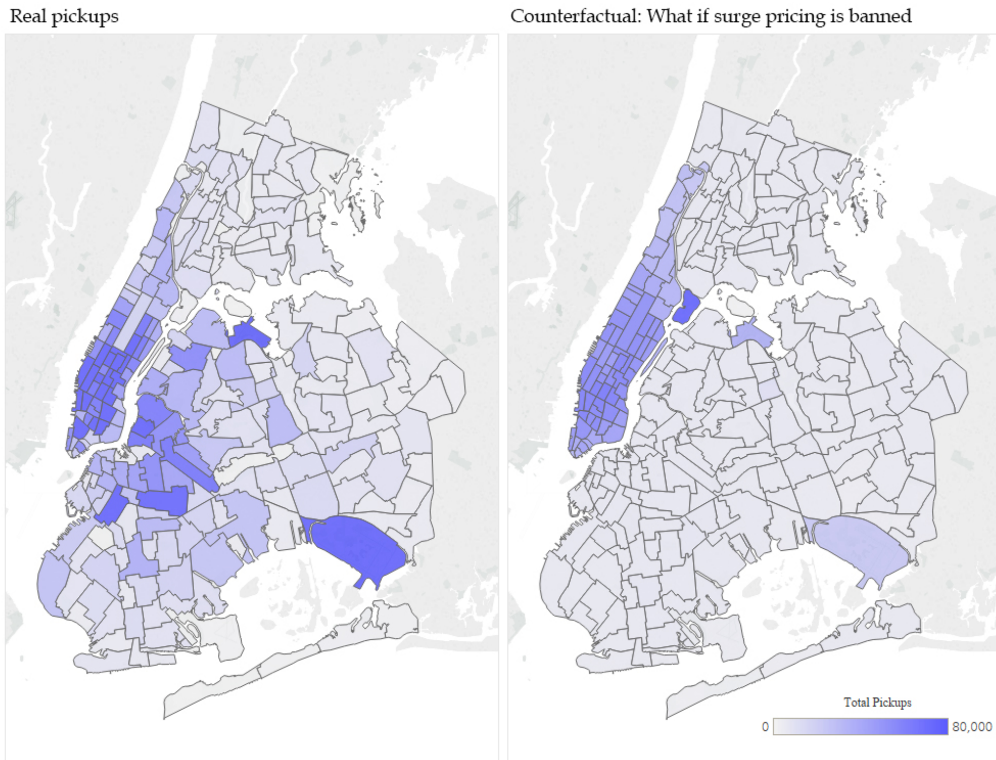


Figure 2.7: Real ride-sharing pickups and the counterfactual pickups in June 2016, NYC.

Appendices

Appendix A Notations for Chapter 1

Table 6: Notations

Notation	Definition
i, j	index for markets
n, -n	index for players
N, M	Base amount of demands and supplies in one city
t	index for time/period
K	Cities' rank on population
α_K	Average return per transaction in the Kth market
γ	Degree of network effect
$-h$	Switching cost
V	Average utility per transaction
p	Degree of second mover disadvantage
r	Depreciation rate
c	Cost constant
F	Set for all feasible markets
X_{nt}	Set for occupied markets for player n at time t
I_t	Set for markets with 1 player at time t
J_t	Set for markets with 0 player at time t
y_{it}	Decision variables for market i $\forall$ $i \in I_t$ at time t
z_{jt}	Decision variables for market j $\forall$ $j \in J_t$ at time t
$\boldsymbol{z_t^*}, \boldsymbol{y_t^*}$	Player n's optimal choice set at time t
u_{nt}	Player n's money stock at time t
m_{nt}	Player n's total market size at time t
x_{nt}	Player n's size ratio at time t
S_{nt}	Player n's market share at time t
R_{nt}	Player n's total revenue from all occupied markets at time t
C_{nt}	Player n's total entry cost at time t

Appendix B Proofs for Chapter 1

Proof of Proposition 1

$\frac{NM}{(K+1)^2}E(\alpha)+S_{11}\frac{NM}{K^2}\alpha_k > \frac{NM}{(K+2)^2}E(\alpha)+S_{11}\frac{NM}{K^2}\alpha_k$, so, Player 1 will choose K+1 when Player 2 chooses K. And $\frac{NM}{(K+1)^2}E(\alpha)+\frac{NM}{K^2}\alpha_k > S_{10}\frac{NM}{(K+2)^2}E(\alpha)+\frac{NM}{K^2}\alpha_k$ so Player 1 will choose K+1 when Player 2 chooses K+2.

When Player 2 chooses K+1, Player 1 also chooses K+1, iff $S_{10}\frac{NM}{(K+1)^2}E(\alpha)+\frac{NM}{K^2}\alpha_k > \frac{NM}{(k+2)^2}E(\alpha)+\frac{NM}{K^2}\alpha_k$, so $S_{10}\frac{1}{(K+1)^2} > \frac{1}{(K+2)^2}$, $(\frac{K+2}{K+1})^2 > \frac{1}{S_{10}}$, since $S_{10} \in [0.5, 1]$, $K < \frac{2\sqrt{S_{10}}-1}{1-\sqrt{S_{10}}}$, $\frac{2\sqrt{S_{10}}-1}{1-\sqrt{S_{10}}}$ is monotonically increasing in $S_{10} \in [0.5, 1]$, the threshold $\bar{K}$ for Player 1 chooses K+1 is increasing with S_{10}

Proof of Proposition 2

When Player 1 chooses K+1, the size of $(1-s_1)\frac{NM}{K^2}\alpha_k$, $(1-s_1)\frac{NM}{(K+1)^2}E(\alpha)$ and $\frac{NM}{(K+2)^2}E(\alpha)$ is changing with K, γ and α_K, $E(\alpha_K)$, So all three actions are possible best responses. When Player 1 chooses K+2, same as above.

Proof of Proposition 3

From Proposition 1 and 2, when K+1 is the dominant strategy for Player 1, there are three PSNEs. When Player1 has the incentive to deviate to K+2, there will be 2 anti-coordinates PSNEs and 2 MSNEs.

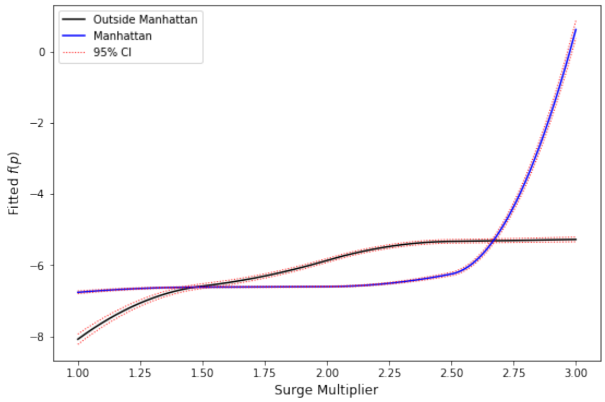
Appendix C Estimation methods comparison for Chapter 2

Table 7: Summary statistics of coefficients under different estimation methods

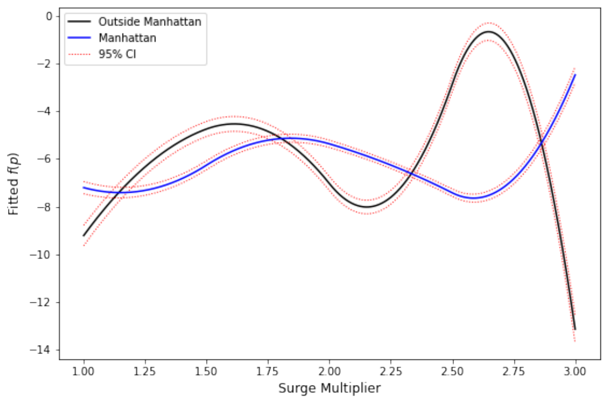
(based on estimation results from regressions on 100 sub-samples)									
			Surge	Rain	Distance	Tips	Uber	Airport	Constant
Constrained	non-Manhattan	Mean	-	0.597	-0.077	0.050	0.936	2.030	-0.525
		SD	-	0.062	0.006	0.008	0.024	0.144	0.148
		Min	-	0.432	-0.094	0.029	0.876	1.751	-0.927
		Max	-	0.803	-0.062	0.067	0.999	2.440	-0.165
NPIV	Manhattan	Mean	-	0.493	-0.459	0.722	1.821	-	-0.110
		SD	-	0.076	0.025	0.042	0.030	-	0.068
		Min	-	0.351	-0.529	0.637	1.759	-	-0.330
		Max	-	0.674	-0.408	0.810	1.930	-	0.000
NPIV	non-Manhattan	Mean	-	0.639	-0.090	0.036	0.921	1.985	-0.906
		SD	-	0.131	0.016	0.020	0.059	0.280	0.297
		Min	-	0.276	-0.127	-0.022	0.812	1.277	-1.665
		Max	-	0.965	-0.041	0.085	1.088	2.944	-0.286
	Manhattan	Mean	-	0.496	-0.463	0.719	1.824	-	-0.145
		SD	-	0.110	0.038	0.064	0.041	-	0.148
		Min	-	0.208	-0.535	0.505	1.740	-	-0.524
		Max	-	0.722	-0.340	0.904	1.970	-	0.186
Linear	non-Manhattan	Mean	19.628	-6.370	-0.172	-0.262	-0.817	4.694	-38.681
		SD	118.042	41.206	0.571	1.351	10.415	16.421	194.478
		Min	-510.278	-310.226	-4.798	-8.387	-79.575	-60.217	-1421.660
		Max	861.414	175.624	1.924	5.872	40.062	130.538	839.827
Regression	Manhattan	Mean	-2.460	1.041	-0.762	1.197	1.898	-	-1.927
		SD	1.059	0.260	0.139	0.209	0.049	-	1.961
		Min	-6.686	0.659	-1.261	0.839	1.772	-	-4.965
		Max	-0.785	2.140	-0.529	1.881	2.041	-	5.956

Table 8: Percentage of significant coefficients under different estimation methods

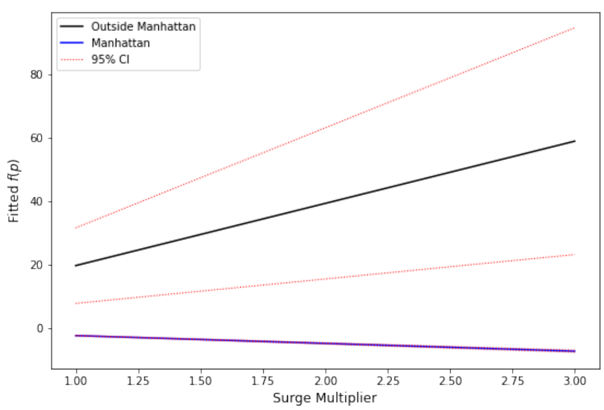
(based on estimation results from regressions on 100 sub-samples)									
			Surge	Rain	Distance	Tips	Uber	Airport	Constant
Constrained NPIV	non-Manhattan	10% level	-	100%	100%	100%	100%	100%	100%
		5% level	-	100%	100%	100%	100%	100%	100%
		1% level	-	100%	100%	100%	100%	100%	100%
	Manhattan	10% level	-	100%	100%	100%	100%	-	42.42%
		5% level	-	100%	100%	100%	100%	-	31.31%
		1% level	-	100%	100%	100%	100%	-	14.14%
NPIV	non-Manhattan	10% level	-	100%	100%	55.10%	100%	100%	100%
		5% level	-	100%	100%	48.98%	100%	100%	100%
		1% level	-	98.98%	98.98%	22.45%	100%	100%	100%
	Manhattan	10% level	-	98.95%	100%	100%	100%	-	46.32%
		5% level	-	97.89%	100%	100%	100%	-	37.89%
		1% level	-	94.74%	100%	100%	100%	-	28.42%
Linear Regression	non-Manhattan	10% level	18.56%	7.22%	53.61%	0.00%	3.09%	50.52%	34.02%
		5% level	7.22%	3.09%	46.39%	0.00%	3.09%	44.33%	24.74%
		1% level	2.06%	0.00%	30.93%	0.00%	0.00%	32.99%	7.22%
	Manhattan	10% level	62.11%	94.74%	96.84%	96.84%	100%	-	30.53%
		5% level	38.95%	89.47%	96.84%	95.79%	100%	-	18.95%
		1% level	7.37%	75.79%	89.47%	90.53%	100%	-	14.74%



Constrained NPIV

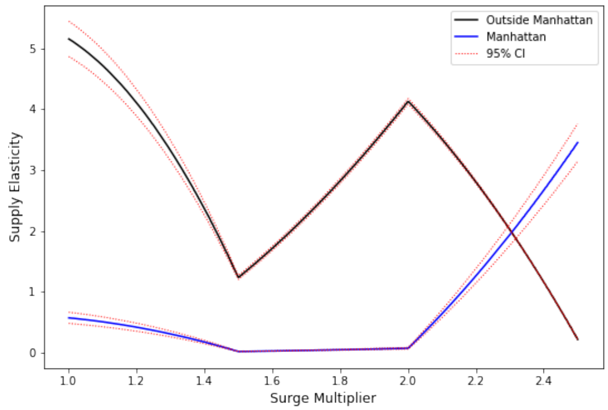


NPIV

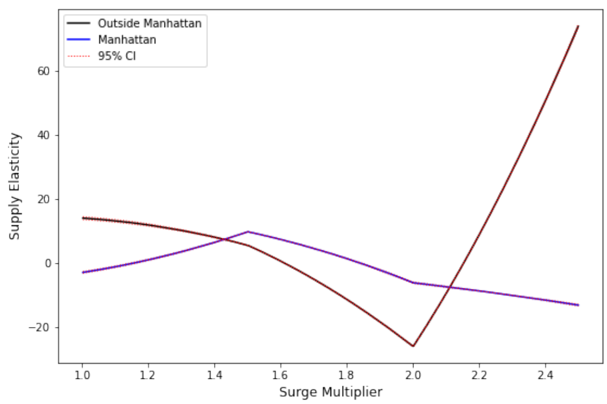


Linear Regression

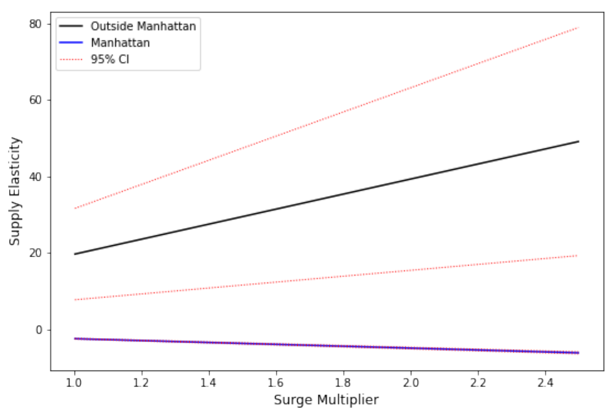
Figure 8: Fitted $f(p)$ under different estimation methods



Constrained NPIV



NPIV



Linear Regression

Figure 9: Estimated supply elasticity under different estimation methods

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