ECONOMICS WORKING PAPER

Dynamics of Ride Sharing Competition

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Abstract

This paper studies the dynamics of ride-sharing competition. Ride-sharing is modelled as a spatial two-sided market with heterogeneous passengers and drivers, both located on a Salop (1979) circle. The model is simulated to study four aspects of ride-sharing competition:(i) price distribution and dynamics, (ii) strategic pricing, (iii) fixed pricing vs. surge pricing, and (iv) information-sharing. Dynamic platform competition in a spatial setting can generate distinct and persistent bands of fluctuating prices. Space and stochastic luck can mitigate winner-take-all effects in price competition. Platforms adopting fixed pricing can compete with platform with surge pricing provided the former are not set too high. However, space and stochastic luck can also render the outcomes of such competition uncertain. Information sharing eliminates price fluctuations by pooling information on demand. The complexity of ride-sharing implies that the impact of policy interventions cannot be known in advance in some cases.

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"We are not setting the price. The market is setting the price. We have algorithms to determine what that market is."

Travis Kalanick, Former CEO, Uber[1]

1 Introduction

Ride-sharing services has had significant and disruptive impact on public transport in many countries in recent years. Even though ride-sharing services per-se are not new, having existed intermittently in the US during the 1940s and 1970s, the advent and confluence of new technologies has led to a rapid and sustained growth of such services in many countries since late 2000s.[2] Today, the ride-sharing services market is still evolving. Platforms such as Uber, Didi Chuxing, Grab and Lyft continue to fine-tune their business model and pricing practices as well as cope with new regulations. Often, these new regulations have varied across countries. In some countries, such as Japan, ride-sharing services have been outright prohibited. In other countries, such as Singapore, regulators have embraced ride-sharing markets but have gradually increased regulatory oversight. The varied responses observed across many countries clearly suggest that transport regulators are still struggling to make sense of the ride-sharing market. The regulatory challenges have been compounded by the nascent nature of the research literature on ride-sharing.

The goal of this study is to provide insights into the nature and dynamics of competition in the ride-sharing market.[3]. The importance of such an endeavour cannot be underestimated as policymakers and regulators have expressed difficulties in applying insights from the research literature to their work (Auer and Petit, 2015).

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[1] "Uber boss says surging prices rescue people from the snow", WIRED, 17 December 2013.

[2] See Hahn and Metcalfe (2017) for a brief discussion of the historical evolution of ride-sharing services.

[3] Rysman (2009, p.125) defines a two-sided market as a market in which: "(1) two sets of agents interact through an intermediary or platform, and (2) the decisions of each set of agents affects the outcomes of the other set of agents, typically through an externality."

In this study, a series of computer simulations are undertaken using a stochastic ride-sharing model in a spatial setting. The distributions of market prices are examined within the context of a decentralized market in spatial setting. The effects of pricing strategies adopted by competing platforms will be compared. This include competition between platforms using fixed and surge pricing. As information on demand and supply conditions is a key issue, this study will also explore the impact of rival platforms sharing information on demand conditions.

The outline of this paper is as follows. Section 2 will provide a brief description of the ride-sharing. Section 3 will discuss the theoretical and empirical literature relevant to ride-sharing. This leads to a discussion of the specific topics to be investigated in Section 4. The structure of the model and simulation implementation are described in Section 5. Section 6 discusses the simulation results. Section 7 concludes.

2 Ride-Sharing

Ride-sharing is essentially a 'match-making' service implemented using a digital platform (such as Uber, Didi Chuxing, Grab and Lyft) that matches independent drivers with passengers. This matching enables drivers to provide rides (taxing services) to passengers for a fee (**Figure 1**).[4] This is made possible by the use of mobile applications (apps) created by the platforms that can geographically locate both passengers and independent drivers.

The process of ride-sharing can be described as follows:

- Step 1: A passenger use his/her ride-sharing mobile app to request for a ride by inputting and sending a signal to a platform (Grab/Uber) which contains information on the trip's origin and destination.

- Step 2: The platform's mobile app instantaneously computes a fare and sends the offer fare to the passenger. This fare is computed based the demand (number of ride requests) and supply (number of drivers) around the passenger's location.

- Step 3: The passenger has the option of accepting or rejecting the fare. If he or she accepts the proposed fare, this decision is conveyed to the platform.

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[4]Ride-sharing is also part of the "sharing economy". See Sundararajan (2016).

- Step 4: The accepted proposed set of trip and fare is then transmitted to the nearest driver (also identified and computed algorithmically).

- Step 5: The driver has the option of accepting or declining the proposed set of trip-fare. If the driver accepts the offer, he/she will then receive instruction on how to reach and pickup the passenger.[5]

- Step 6: The transaction ends when the destination is reached. Both the passenger and driver are given the opportunity to rate the quality of their experiences.
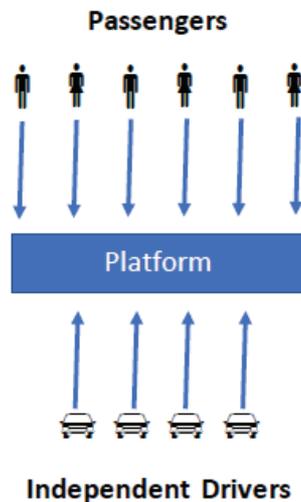

Figure 1: Match Making in Ride-Sharing

A key element in ride-sharing is the dynamic pricing of fares that are implemented using a "surge pricing" algorithm that reduces the gap between demand and supply. This algorithm has been described by Uber's consultants and researchers as one that "assigns a simple multiplier that multiplies the standard fare in order to derive the surged fare" (Hall *et al.*, 2015, p.1). The surge algorithm kicks in when there is a significant amount of demand for rides compared to supply (available drivers within a location). The rationale underlying the surge algorithm is two-fold. First, on the demand-side, when there is excessive demand - higher prices will ensure that only passengers with a high valuation of a ride (hence, a higher willingness to pay)

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[5]If he/she declines the offer, the platform will send the offer to another driver. This process will loop for a fixed number. If no driver accepts, the passenger will be informed that no drivers are available and is advised to wait/re-book.

will obtain a ride. This brings about, it is argued, an efficient allocation of resources as such resources go to its highest valued use. Second, the higher price will attract more drivers to (i) start driving (propensity) and (ii) drive to location with high-demand (intensity). The result is an increase in the supply of drivers in the location with high demand. The demand and supply responses to surge pricing act to reduce the gap between demand and supply.

The size of the multiplier in surge pricing has been reported to exceed two (2x) and even reach 9.9x in some cases.[6] The surge pricing algorithm can be suspended by platforms in situations when its implementation could provoke public anger such as in the cases of terror attack or rail breakdown. More recently, Uber has re-designed its apps by removing the display of multiplier factor (which has irritated riders). In its place, the estimated fare is calculated and offered (though this is still be based on surge pricing).

Another important aspect of ride-sharing is its two-sided nature - passengers (buyers) on the one side and drivers (sellers) on the others. The ride-sharing platform is a two-sided platform in which network effects at both end are important. For passengers, the greater availability of cars at a given platform would attract them to use the platform due to lower prices (smaller excess demand gap) and shorter waiting time. Similarly, the greater the number of passengers that have signed up to a given platform, the more attractive the platform will be to drivers due to greater probability of picking up passengers (lower idle time).

Finally, ride-sharing is a two-sided market with "multi-homing" on the demand and supply sides. On the demand side, passengers can download more than one car-hailing apps (e.g. Grab and Uber) and use them to compare prices (arbitrage)and availability. Similarly, drivers can sign-up to more than one platform, choosing which platform to use depending on various factors - financial incentives offered as well as network effects (probability of picking up passengers).

In response to these factors, platforms have strategically implemented programs aimed at increasing the cost of passengers and drivers from switching from one platform to another. For passengers, platform have offered discounted fares and loyalty programs (accumulated points that can redeemed

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[6]In the aftermath of the terror attack in London in June 2017, Uber's surge price in the vicinity was reported to be around 2.1x. See "Uber criticized for surge pricing after London terror attack", CNN Tech, 4 June 2017. The 9.9x surge occurred at Miami Beach during the 2016 New Year celebrations. See "Uber Users Are Complaining About Pricey New Year's Eve Rides", TIME, 2 January 2016.

for free rides). More recently, the introduction of post-paid programs (credit card top up, often with the chance of getting a quota of free rides) has the potential of encouraging loyalty to a platform because consumers have already paid ex-ante for rides. For drivers, incentive programs based on the number of passengers served (trips) during a given time window (peak hours during weekdays and/or weekends) make it difficult for drivers to use more than one platform (which will incure the risk of not achieving the targets in these incentive programs).

Finally, ride sharing is a complex market. Even though the mechanisms used in matching passengers with riders can be simple, the decentralized and spatial nature of the interactions between riders and passengers can produce unexpected outcomes. This dimension has not been fully explored yet - a task this study aims to undertake by modelling ride sharing as a complex system with heterogeneous agents interacting in a decentralized manner.

3 Related Literature

The research literature on ride-sharing is at a nascent stage even though the recent re-emergence of ride-sharing has been around for more than five years. The pace of research on this topic has been constrained both by data availability and theoretical developments. Both empirical and theoretical literature are reviewed in this section. This then provides the opportunity to discuss how the present study contributes to the literature.

3.1 Empirical Literature

In the domain of empirical research, most of the few studies that have emerged involved participation by researchers from ride-sharing companies - primarily, Uber (e.g. Hall *et al.* (2015), Cohen *et al.* (2016) and Castillo *et al.* (2017)). The empirical literature on ride-sharing has primarily focused on a few key topics such as surge pricing, consumer surplus, capacity utilization, and traffic congestion.

One of the earliest study on Uber's surge pricing was Hall *et al.* (2015). The study, which involved researchers from Uber, primarily focused on explaining the impact of Uber's surge pricing on reducing the gap between supply and demand (see earlier discussions). High-frequency data on demand (ride requests and users opening Uber's app) and supply (number of drivers in the

area experiencing surge in demand) from Uber were used in the study. The study provided evidence on the impact of surge pricing on allocating rides to those who value them more during the surge period. However, the authors were more reluctant to claim that surge pricing had a strong positive impact on the supply of drivers because the change in supply could itself be induced by drivers' expectation/knowledge of increase in demand (thus resulting in double counting or over estimation of the causal effects).

The earlier findings on surge pricing by Hall *et al.* (2015) were somewhat supported by the study by Chen *et al.* (2015) which did not use data from Uber directly. Chen *et al.* (2015) found that surge pricing did have a strong and negative effect on passenger demand but a weaker and positive effect on car supply. Furthermore, even though there is some regularity in the occurrence of price surge (e.g. during rush hours on weekdays), the surge multipliers could not be forecasted. The study also found that the spatial dynamics of ride-sharing is complex - whilst the spatial concentration of drivers can be predicted (around CBDs and tourist attractions), the relationship between car density and estimated waiting time is not straight forward.

A more recent study that used data from Uber is Castillo *et al.* (2017). The study argued that surge pricing can help prevent a "wild goose chase" - an equilibrium outcome that has a low number of idle drivers resulting in deficient matching and long pickup lines. In the absence of surge pricing, a high uniform would be needed to reduce demand - one that is even more harmful to consumers than surge pricing.

There are a number of other empirical studies on ride-sharing that do not focus directly on surge pricing. One such study is that of Cramer and Krueger (2016) which compared capacity utilization by taxi drivers and Uber drivers. The authors found that, on average, UberX drivers has 30 percent higher capacity utilization (measured in time) compared to taxi drivers. This gap is even larger - at 50 percent - if capacity utilization is measured in terms of mileage. Several explanations were offered to explain these findings: (i)more efficient driver-passenger matching technology, (ii) higher number of ride-sharing drivers than taxi drivers, (iii) inefficient taxi licensing regulations that restricts taxi operations geographically, and (iv) flexible labour supply model in ride-sharing services. The authors also highlight two additional implications of the differences in capacity utilization between ride-sharing drivers and taxi drivers: (i) ride-sharing drivers can charge lower fares than taxis and earn the same amount of revenue, and (ii) ride-sharing can lower traffic congestion and fuel consumption.

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More recent studies have begun the examine the impact of ride-sharing on social welfare. One aspect of social welfare is consumer surplus. Using data from Uber, the study by Cohen *et al.* (2016) estimated consumer surplus to be around USD2.88 billion in 2015 for four major cities in the US. Another aspect of social welfare is traffic congestion. Using a natural experiment approach, Li *et al.* (2017) found evidence of ride-sharing reducing traffic congestion. This was done by comparing the level of traffic congestion in 101 urban areas in the US namely before and after the entry of Uber.

3.2   Theoretical Literature

On the theoretical front, at least two strands of literature are relevant to the analysis of ride-sharing markets. The first strand is the literature on two-sided markets or platforms.[7] The early literature on two-sided markets dates back to the seminal contributions of Caillaud and Jullien (2003), Rochet and Tirole (2003) and Armstrong (2006). The early works have primarily focused on the actions of the platform (market intermediary). These actions pertain to price level and price structure. The latter refers to the setting of prices at both ends of a two-sided market in such a way as to maximize output (efficiency) by charging more on one side compared to the other side. This is determined by a number of factors, namely: (1) the relative size of cross-group elasticities, (2) fixed fees or royalties, and (3) presence of single or multi-homing. The more recent literature has focused on a number of topics such as platform ownership structure, asymmetric networks on both sides of the market, and cross-subsidization on both sides. Even though the empirical literature on ride-sharing has not drawn explicitly from the theoretical literature, the latter remain useful. Collectively, this body of literature can be used to provide a more formal approach to characterizing ride-sharing and for analyzing factors that affect the pricing strategies adopted by platforms in ride-sharing. These include ride-sharing incentives on both the demand side (discounted fairs and loyalty membership) and supply side (trip-based bonus incentives) that are clearly related to network effects. Similarly, switching cost can be interpreted as an important strategic variable to enhance network effects.

Beyond the above insights from the two-sided market literature, more recent theories could provide further insights into ride-sharing. These are theories of dynamic platform competition and theories of spatial platform competition.

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[7]For a general treatment, see Rysman (2009), Evans (2011), Evans and Schmalensee (2016) and Einav *et al.* (2016)

In an early work by Chen and Tse (2008), dynamic platform competition is modelled as a differential game involving the growth of platform users. They find that a two-sided market is likely to be dominated by a single platform (winner take all) when multi-homing tendency is high and in the absence of market segmentation. In Dou and Wu (2016), dynamic platform competition is studied using a multi-period symmetric duopoly platform model. In their study, platforms subsidize buyers and sellers in the initial period but the subsidies are reduced on one-side in subsequent stages. Platforms can also gain competitive advantage at the early stage by importing external users (piggybacking) and subsidizing them. The importance of platforms taking an early market lead in dynamic competition (network effects) is also examined by Halaburda *et al.* (2016). An interesting result from the paper is the presence of multiple equilibria in infinite time horizon models in which either low or high quality platforms can dominate. The authors also extended their model to incorporate stochastic change in qualities. In such models, higher quality platforms will only prevail when platforms are more forward looking (less myopic). Another study that looks at dynamic and stochastic price competition with network effects is Cabral (2011). Even though the study does not focus on platform competition per se, findings from the study is useful to understand network effects in dynamic competition. One interesting result from the study is that when network effects are sufficiently strong, the stationary distribution of market shares is typically bimodal in which the system is mostly in a state where the large network has a high market share.

Finally, another group of theoretical work that is relevant to this study is that which attempts to model platform competition spatially. One of the first paper to do this is Raalte and Webers (1998) which studied competition between two platforms (intermediaries) using commission fee in a one-stage (static) spatial setting. In their model, the two platforms are located diametrically opposed to each other along a Salop (1979) circle. Two types of agents with different densities are distributed uniformly along the circle. The equilibrium outcome is one in which: (i) each platform has an equal share of the two types of agents, and (ii) one type of agent is charge zero fee. The Salop (1979) circle is also used in the study by Kodera (2010) which studied how the equilibrium price is affected by cross-group network effects. If such effects are larger on the sellers' side, competition amongst platforms for buyers will be more intense (hence lower prices on the buyers' side). In the presence of free market entry, network effects will result in a sub-optimal number of platforms.

3.3 Lessons and Guidance from the Literature

There are clearly some differences between the empirical and theoretical literature. In the empirical literature on ride-sharing, the main focus has clearly been on the nature and impact of surge pricing. The empirical studies have also mostly examined the impact from the operation of one platform, namely Uber. This is due to market structure and data constraints.

In the case of the theoretical literature, the seminal works on two-side platforms pre-dates the entry of Uber (2009). These and subsequent works focus on two-sided platforms in general and especially on pricing strategies (level and structure) in the presence of network effects. Network effects are clearly important in ride-sharing but this does not appear to be a key issue in the empirical literature. This is because it has focused primarily on one platform (Uber) rather than two platform competition (Grab vs. Uber). This raises the interesting question of how network effects are related to surge pricing. A platform may lower prices/fares (subsidize) to enhance market share and in the process increase the more demand for riders.

The literature survey also indicates that most of the models in the literature are static and non-spatial in nature (**Table 1**). There are a few dynamic models of platform competition but these are primarily non-spatial in nature. Thus, more research is needed on dynamic and spatial models of two-sided platform competition.

Table 1: Types of Two-Platform Models
(Example of Studies)

	Static	Dynamic
Non-Spatial	Rochet and Tirole (2003)	Chen and Tse (2008)
Spatial	Raalte and Webers (1998)	?

What is to be gained by studying two platform models that are both dynamic and spatial? There are some clues from the literature on dynamic game-theoretic spatial models (Lindgren, 1997). Complete dominance of a strategy (winner take all scenario) may not take place in dynamic spatial models. This could be particularly true for models with stochastic elements (as hinted in the study by Cabral (2011)). These could explain the empirical findings on the complex nature of the relationship between driver/car density and waiting time.

Finally, one important aspect that is not discussed much in the literature is the distribution of prices.[8] This is important in a spatial competition setting where prices vary over time and space due to changes in demand-supply conditions. By incorporating these elements, this study hopes to contribute towards extending the research literature on the dynamics of spatial two-platform competition in general, and on ride-sharing more specifically.

4 Dynamics of Competition in Ride-Sharing

The general goal of this study is to examine the dynamics of competition in ride-sharing in a spatial setting. This section explicates which aspects of ride-sharing competition will be examined and why.

4.1 Price Distribution and Dynamics

Price is a key variable in the study of markets. In ride-sharing, demand and supply conditions change continuously over time and across space (locations). Even though prices are set in a centralized manner by each platform using a specific algorithm or formula, there is no single price at each moment in period. Rather, what is observed is a distribution of prices across time and different locations. Is the distribution of prices Gaussian (normal - a in **Figure 2**), heavy-tailed (b), lepto-kurtic (c) or bi-modal (c)? An understanding of the distribution of these prices is important for any assessment of the distribution of welfare effects. The impact of surge pricing will depend on what the distribution of prices look like. An examination of the dynamics of price change in a spatial setting might also reveal interesting features. Do prices at different locations vary randomly or do they tend to converge?

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[8]There is now an emerging interests in micro pricing data e.g. Cavallo and Rigobon (2011), Cavallo (2015), and Rigobon (2015)

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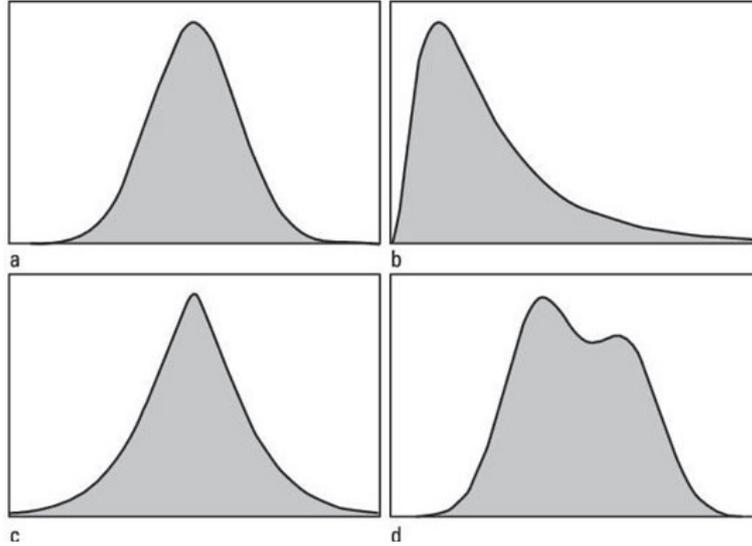
Figure 2: Statistical Distributions
Source: http://www.dummies.com/education/science/biology/
the-symmetry-and-shape-of-data-distributions-often-seen-in-biostatistics/

4.2   Strategic Pricing

Pricing strategies is a key feature in the theoretical literature. This can take the form of setting lower prices (subsidize) to take advantage of network effects. This strategy is often observed in ride-sharing when there is intense competition between two or more platforms.[9] For example, in a market with two platforms $i = (A, B)$, what would be the effects of adopting the following surge pricing strategies with different discount factor δ at location j?:

$$p_{i,j} = f(\text{Demand}_j - \text{Supply}_{i,j}) \tag{1}$$

At what discount level would a platform completely dominates the market (winner take all scenario)?

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[9]"Fare cuts by Uber, Grab will hurt sector: Taxi body", Straits Times, 24 April 2016; "Price War Sees Uber Lose \$2.7m A Day In China", Sky News, 18 February 2016.

4.3 Fixed Pricing vs. Surge Pricing

One market competition scenario that is not often discussed in the research literature is one in which a platform uses surge pricing while its rival uses a fixed price (or metered fare). Surge pricing is a form of dynamic pricing that takes into account current demand and supply conditions at a given location. For fixed pricing, prices are fixed and do not vary over time as demand and supply conditions change. The co-existence of fixed and surge pricing is not only a theoretical possibility. In many markets, both pricing approaches co-exists with ride-sharing adopting surge pricing whilst taxis adopting fixed (metered) pricing. How will the two platforms with different pricing approaches fare in such situations? This, of course, depend on the level of price at which the fixed prices are levied. This raises the issue of the possibility and usefulness of conceptualizing an "sustainable price" that can be used for fixed pricing that will ensure taxis' survivability.

To study this problem, two types of simulations are carried out:

- Pure Fixed Pricing - in which both platforms adopt fixed pricing

- Fixed Pricing and Surge Pricing - in which one platform adopts fixed pricing while the other adopts surge pricing.

4.4 Information Sharing

Another topic that will be examined is the impact of information sharing between rival platforms. This is related to (but is not identical) to the issue of monopoly and mergers that recur in the research literature. In a competitive setting, rival platforms set prices based on the demand at a given location and its own supply condition (number of its drivers). This is expressed earlier, for platform i at location j as:

$$p_{i,j} = f(\text{Demand}_j - \text{Supply}_{i,j}) \tag{2}$$

When information is shared, prices at location j are set based on the collective demand and supply at the location:

$$p_{i,j} = f(\text{Demand}_j - \text{Supply}_j) \tag{3}$$

The result would be as if both platform offering identical prices with consumer choosing randomly between the two. The two platforms may still have different market shares due to the different locational distributions of their drivers.

5   Ride-Sharing Model

5.1   Description of Model

This section provides a description of the ride-sharing model that will be simulated in this study. The ride-sharing market is modelled as a two-sided market that comprises three types of agents, namely, (i) drivers that use the platforms to provide taxing services; and (ii) passengers that use the services provided by the drivers through the platforms; and (iii) platforms that match drivers with passengers.

Assume that there are two platforms ($i = 1, 2$) in the market providing platforms for ride-sharing. These platforms serve to match drivers with passengers. The two platforms can set the price p that drivers can charge their passengers.

It is assumed that the total number of drivers in the market is fixed at N. A driver can only sign-up with one platforms (**single homing**).[10] The number of cars using platform i is given by n_i. Thus, at any one time, the following constraint is met:

$$n_1 + n_2 = N \tag{4}$$

The Salop (1979) circle is used to model space in the model with a total of y locations. In the first period, the N drivers from both platforms are randomly distributed across the y locations. It is further assumed that there are C passengers in the market which are also randomly distributed across the y locations along the circle.

For simplicity, it is assumed that a driver can only travel if they can pick up a passenger. Otherwise the driver will remain stationary in that period. Thus, the number of passengers can be - (i) less than, (ii) equal to, or (ii) more than - the number of drivers at each location. The number of passengers that can actually travel at a given location is constrained by the number of available cars at that location. Similarly, the number of drivers that can travel from a given location will depend on the number of passengers at that location.

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[10]In reality, drivers can sometimes sign-up with two platforms even though this is often discouraged contractually and via incentive mechanisms (e.g. drivers can only accumulate enough rides if the trips they make are allocated to one platform).

During each period (an iteration in the simulations), a passenger j plans to travel distance x_j in a one-way (single direction) along the circle. The minimum distance is zero (not travelling) and the maximum distance of travel is assumed to be half of the locational circumference of the circle (y). Thus,

$$\text{Max } x_j = \frac{y}{2} \tag{5}$$

The planned distance of travel by each passenger x_j (trip distance) is generated via a uniform random draw from a set comprising zero and positive integer numbers:

$$x_j = \text{Rand}\,(X) \tag{6}$$

where $X = [0, 1, 2, ..., y/2]$ with $x_j = 0$ indicating that passenger j will not travel.

In order to travel, a passenger has to use the service of a driver from one of the two platforms. Passengers are assumed to **multi-home** - they can choose either one of the platform in each period. Let c_j be the number of passenger choosing to use the service of cars under platform i. Thus,

$$c_1 + c_2 = C \tag{7}$$

In this model, it is assumed that a passenger will choose to use the platform offering the lowest price i.e. $\text{Min}(p_1, p_2)$.[11]

It is assumed that each platform is only aware of its own distribution of cars at each location and not those under the other platform. Platform i will set its price based on the market demand and its own supply conditions at each location. To approximate surge pricing, the pricing formula used by platform i at a given location s depends on excess demand for platform i at that location:

$$p_{i,s} = 1 + \frac{c_s - n_{i,s}}{C/2} \tag{8}$$

where c_s is the number of passengers at location s, $n_{i,s}$ is the number of drivers under platform i at location s and C total number of passengers.

The intuition behind the above equation is that when there are more drivers than passengers at a given location, higher prices are offered. Each platform will allocate one driver to each passenger. If both platform offer the same

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[11]In this model, the reservation price of consumers are not modelled explicitly. We can assume that underlying the passenger's decision-making is a reservation price (v_j). For consumers that choose to travel (i.e. $x_j > 0$), $\text{Min }[p_1, p_2] \leq v_j$.

price - a consumer will randomly choose one of them. For simplicity, it is assumed that the surge pricing at a given location that comes about from high excess demand do not increase the supply of drivers at that location. This could be a reasonable simplification as existing empirical studies tend to find a relatively weak supply response to surge pricing (see earlier discussions).

5.2   Implementation of Simulations

The following is the sequence of the algorithm for the simulations:

- Step 1: Distributions are generated for the locations of of drivers (n_1, n_2) and passengers (c_j).

- Step 2: Distributions are generated for the travel destination for each passenger (x_j).

- Step 3: The prices for each platform at each location $(p_{i,s})$ are computed using the price formula (equation 8).

- Step 4: The set of passengers that can travel is generated based on the availability of passengers and drivers at each location.

- Step 5: Each passenger that can travel is assigned a driver from one of the platform based on which platform's price is lower. In cases where both platforms' prices are identical (due to equal number of drivers), the passenger's choice is randomized.

- Step 6: The locations of passengers and drivers are updated (completion of trips).

- Step 7: The sequences of Step 2 to Step 6 is iterated in a loop to generate a sequence of movements by passengers and drivers.

The base-line simulations were implemented using *Mathematica* using the following parameters:

- Number of total drivers for the two platforms: 40 (or 20 each)

- Number of passengers: 60

- Number of location: 10

- Number of iterations (period): 100

6 Simulation Results

Four classes of simulations were carried out corresponding to the four topics discussed in the earlier section. The results from the simulations are reported and discussed below.

6.1 Price Distribution and Dynamics

The price algorithm used in this study's simulations is based on an excess demand function (see equation 8). When supply matches demand, the price is equal to one (1). The model is simulated with two identical platforms - they have the same number of drivers and price-setting function. However, the distribution of cars under each platform across the locations are different.

In the simulations, prices do fluctuate at the various locations due to mismatches between demand and supply. Interestingly, whilst there may be cases where prices do fluctuate around a single band (**Figure 3**), there are cases when prices can bifurcate into two (**Figure 4**) or three (**Figure 5**) distinct bands. This takes place while the market shares of the two platform fluctuates in every period (panel c in Figures 3-5) and despite both having a cumulatively equal market share (due to the identical/symmetric platforms). Thus, in a fully competitive two-platform market, prices can bifurcate and persist - the latter exhibiting path-dependence.

Another take-away from these simulations is the need to re-evaluate the notion of a single equilibrium price or a single equilibrium price distribution. Even though prices are set in a centralized manner by each platform, the effective price - defined as prices that are accepted by passengers - are decentralized at each location.
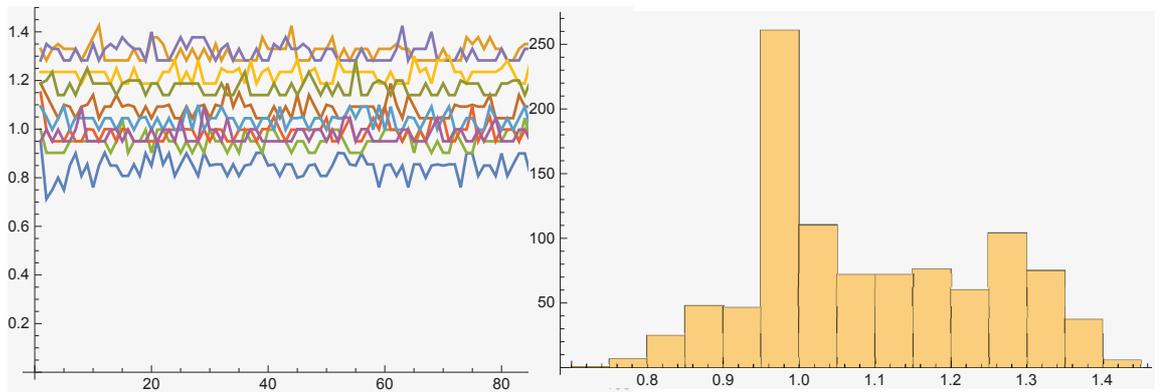
(a) Price by Location

(b) Distribution of Prices
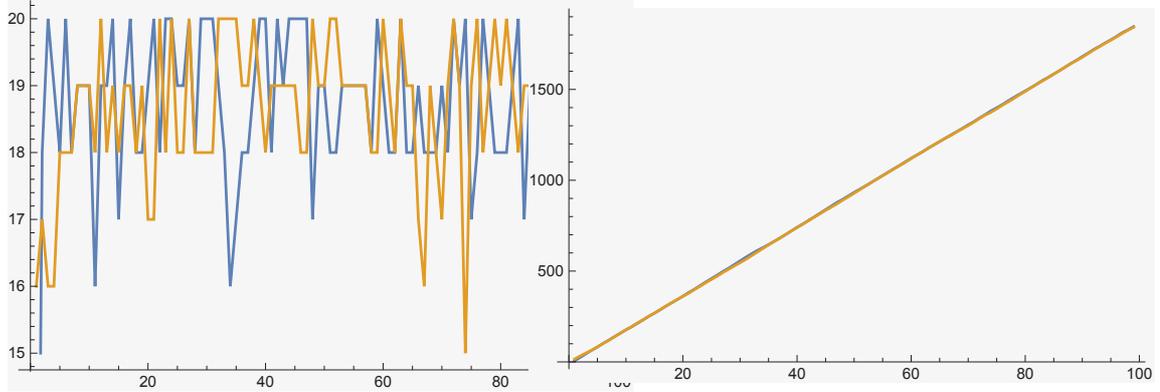
(c) Number of Trips by Platform

(d) Cumulative Trips by Platform

Figure 3: Simulation Results: Baseline 1
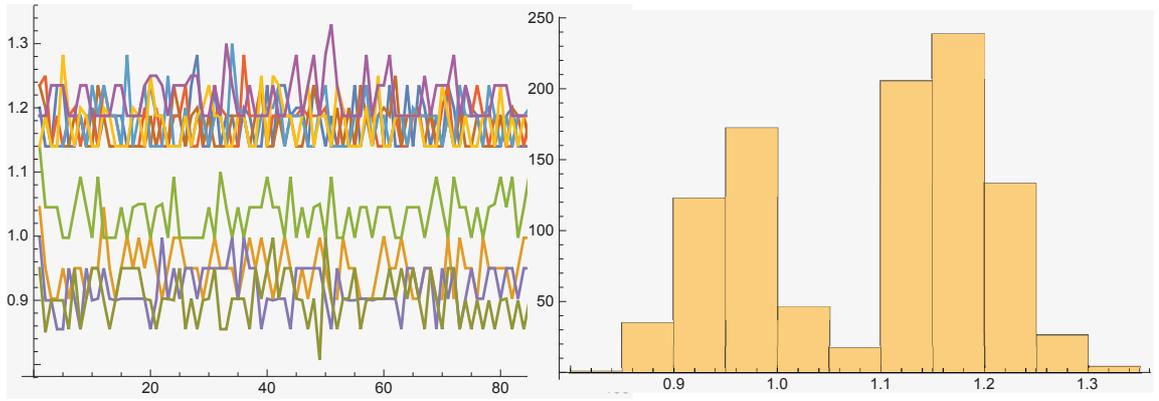
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(a) Price by Location

(b) Distribution of Prices
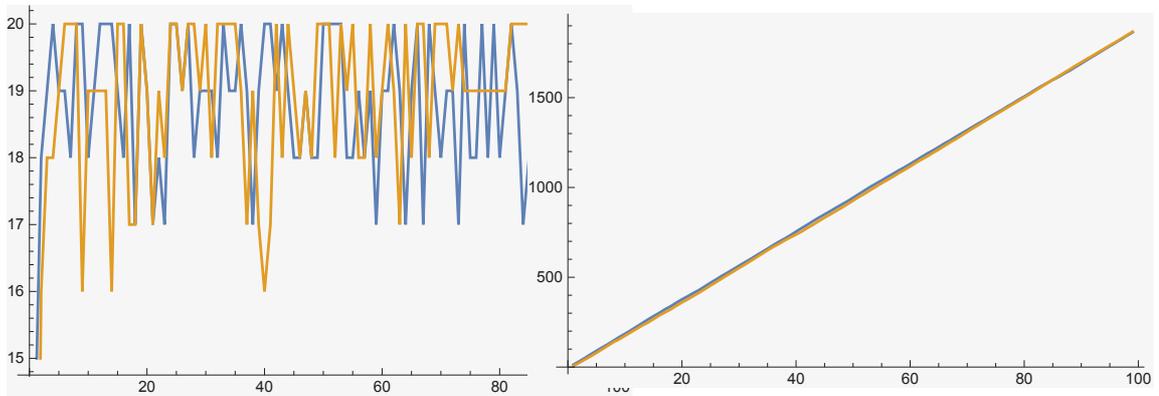
(c) Number of Trips by Platform

(d) Cumulative Trips by Platform

Figure 4: Simulation Results: Baseline 2
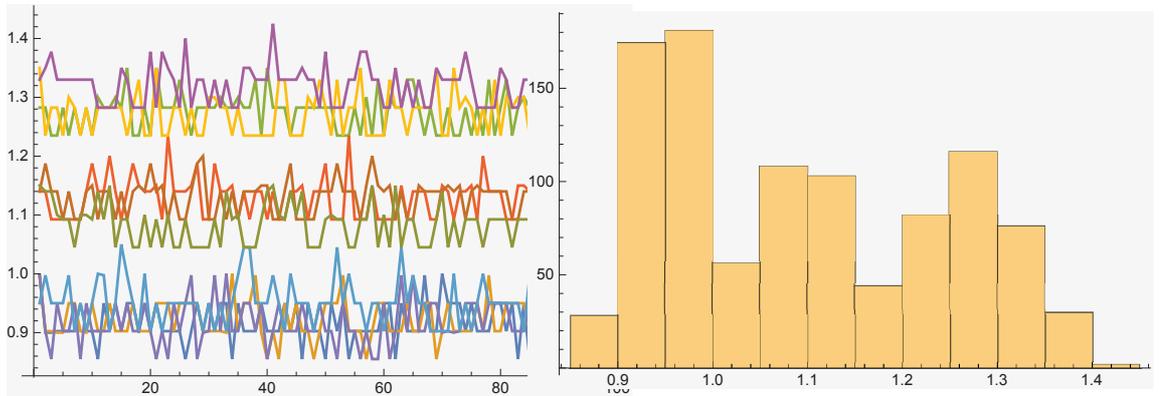
(a) Price by Location

(b) Distribution of Prices
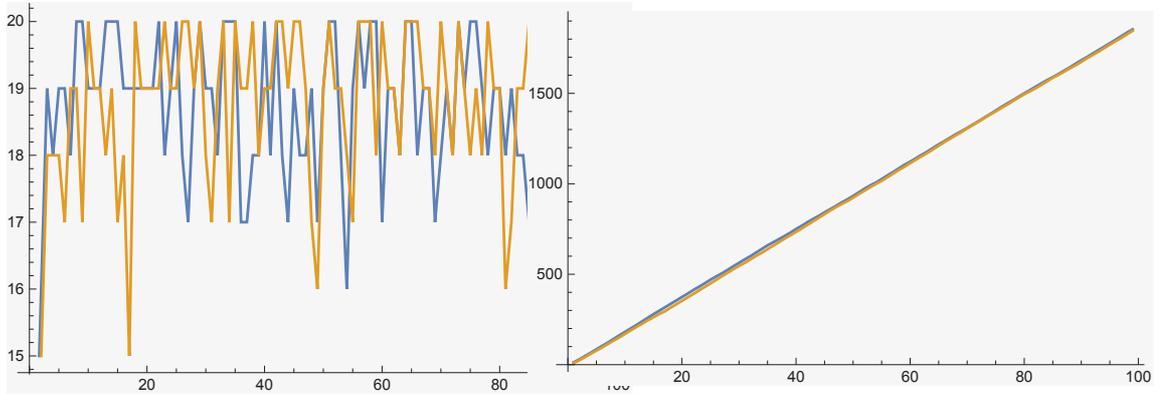
(c) Number of Trips by Platform

(d) Cumulative Trips by Platform

Figure 5: Simulation Results: Baseline 3

6.2 Strategic Pricing

The literature on platform competition often discusses the use of price reduction (subsidy) as a strategy to increase market share which potentially leads to a complete dominance situation (winner take all). As the passengers in the model base their decisions on price alone, the winner take all is an obvious outcome. What is less certain, however, is the extent of price reduction by one platform that is needed to achieve compete dominance. Furthermore, the spatial distribution of drivers also implies that even when the prices of a platform is lower than another, the former may not have available cars or have very few cars at a given location compared to the demand level.

Simulations are undertaken for a few scenarios in which one of the platform reduces its price by applying a discount factor on the pricing formula. Different sizes of discount (5%, 10%, 20%) are applied. The results are as follows.

(a) 5% Price Discount

From the simulations, a price reduction of 5% by one of the platform is clearly insufficient to completely dominate the market. Thus, space does mitigate the effects of price competition to some extent. However, the platform with lower prices does have a distinct but small advantage over its rival. This can be seen in panel (d) in **Figure 6** - the blue line (platform with lower price) is above the orange line.

(b) 10% Price Discount

When a platform offers an even higher discount - 10% in this case - the market share of the firm increases in a more stark manner. The market shares of both platforms continue to fluctuate in each period but the platform with the lower price has a higher market share in most periods (panel (c) in **Figure 7**). The longer-run advantage of the firm with lower prices is even more clear (panel (d) in **Figure 7**).

(c) 20% Price Discount

With an extreme level of discount, the winner take all scenario materializes (**Figure 8**). The platform with lower prices (by 20%) completely dominates the market. Prices at the different location become fixed at different levels. Note that in this scenario, only drivers that are under the platform with lower price is picking up passengers and moving. This fixed price level out-

come could be due to a significant number of passengers (almost half) are no longer served by the market (see panels (c) and (d) in **Figure 8**). However, the winner take all scenario is not a given. In some simulations, the platform with lower prices can survive, though with a significantly lower market share (**Figure 9**). In other words, "luck matters" in a stochastic world.


(a) Price by Location

(b) Distribution of Prices

(c) Number of Trips by Platform

(d) Cumulative Trips by Platform
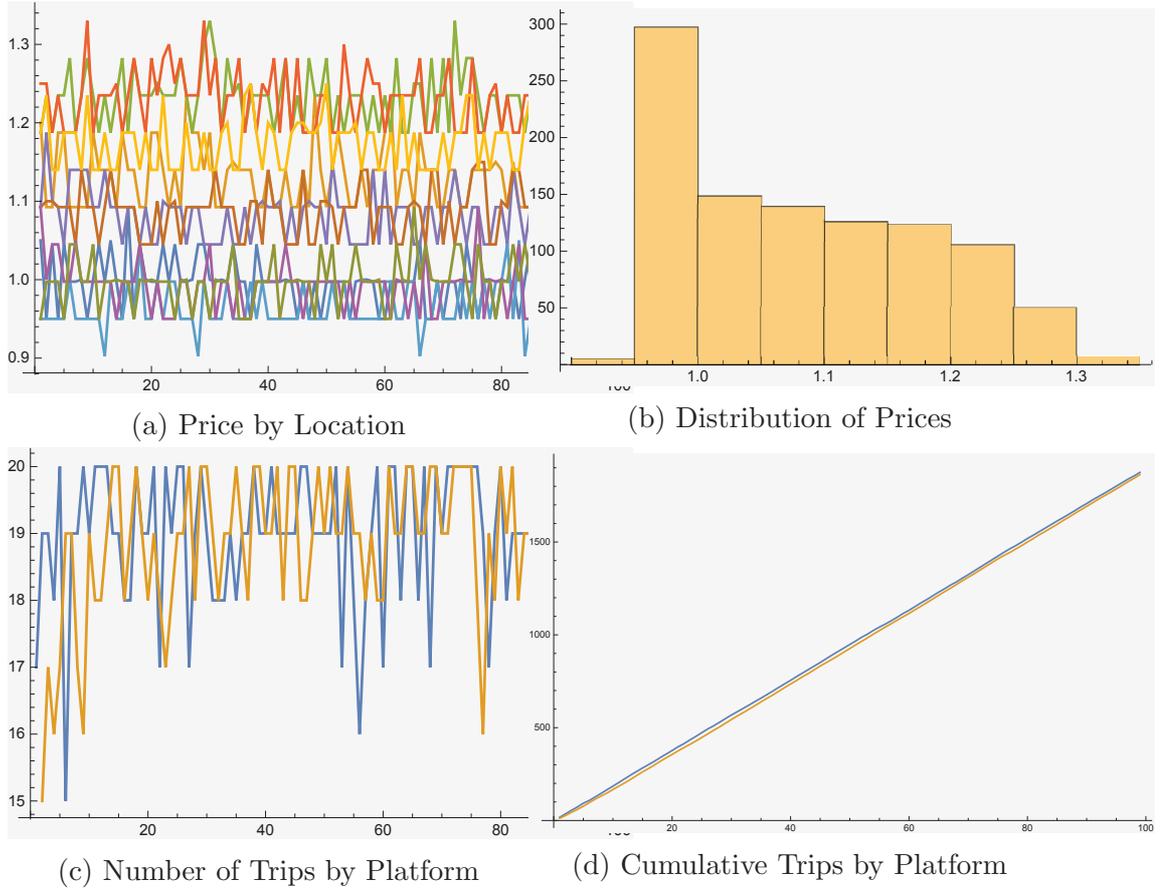
Figure 6: Simulation Results: 5% Price Discount
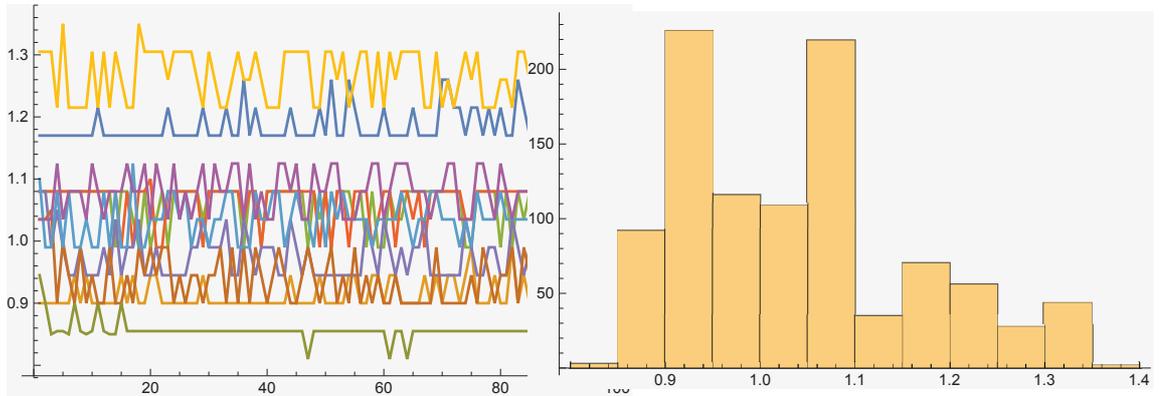
(a) Price by Location

(b) Distribution of Prices
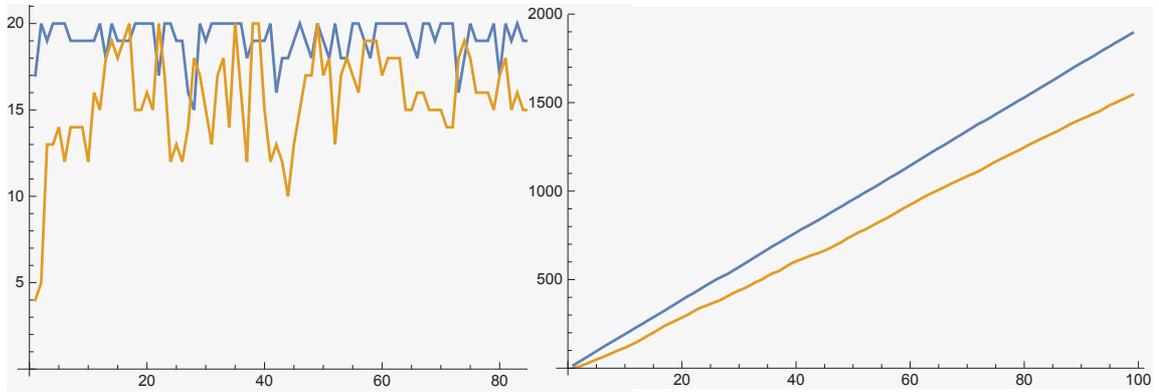
(c) Number of Trips by Platform

(d) Cumulative Trips by Platform

Figure 7: Simulation Results: 10% Price Discount
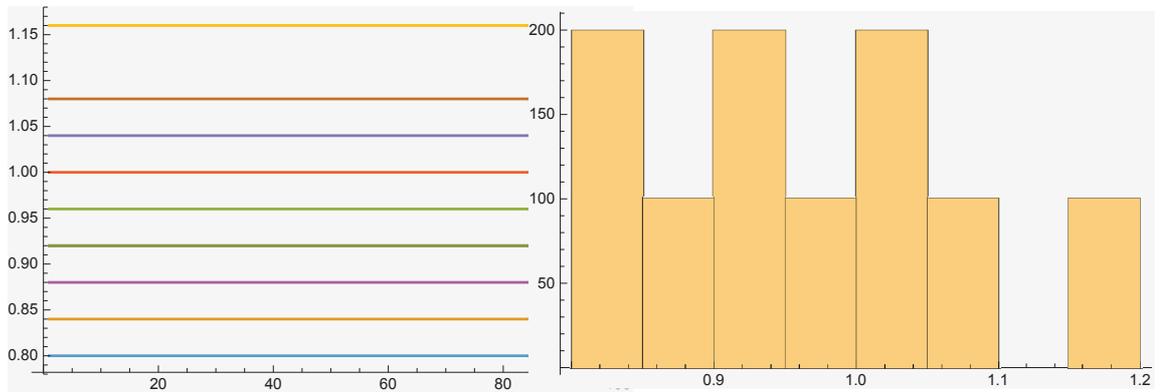
(a) Price by Location

(b) Distribution of Prices
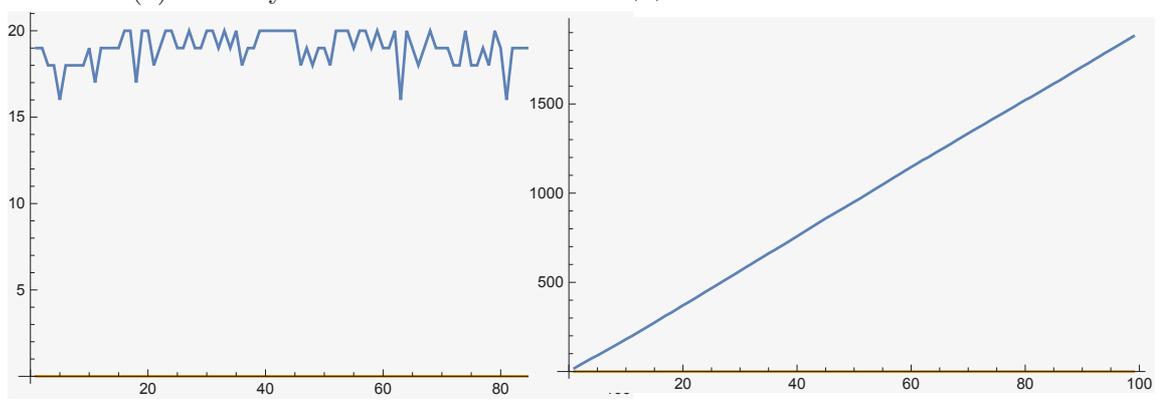
(c) Number of Trips by Platform

(d) Cumulative Trips by Platform

Figure 8: Simulation Results: 20% Price Discount - Winner Take All
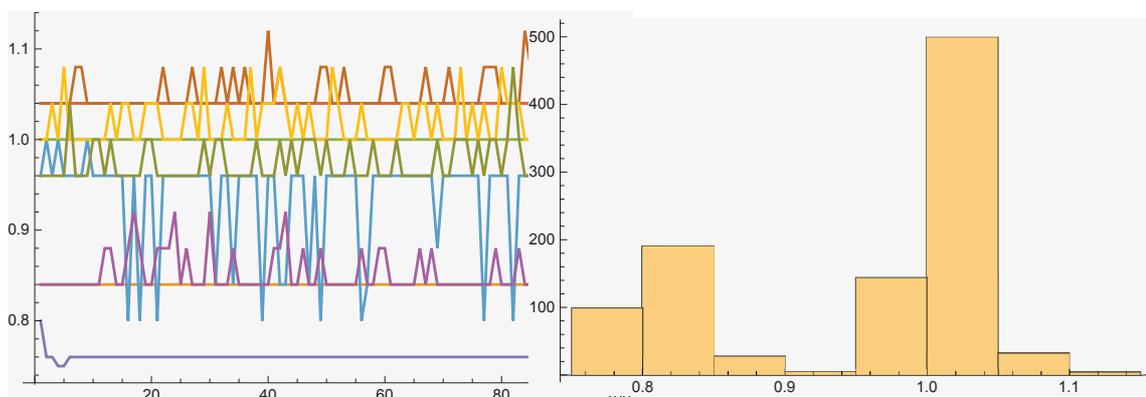
(a) Price by Location

(b) Distribution of Prices
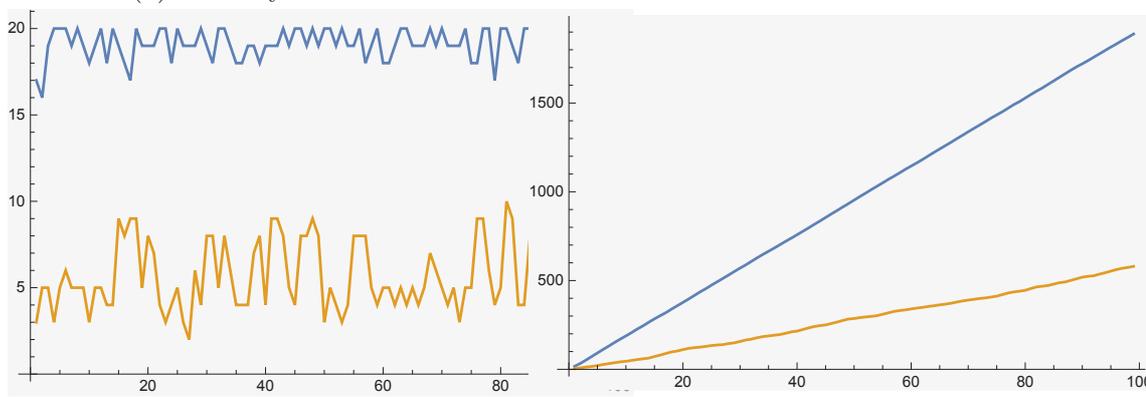
(c) Number of Trips by Platform

(d) Cumulative Trips by Platform

Figure 9: Simulation Results: 20% Price Discount - Luck Matters

6.3　Fixed Pricing vs. Surge Pricing

Taxi platforms and ride-sharing platforms often co-exist and compete in ride-hailing markets. In these markets, taxi and ride-sharing platforms often adopt different pricing approaches. As discussed earlier, two scenarios are simulated: (i) pure fixed pricing - when all firms adopt fixed pricing, (ii) mixed market where one platform adopts fixed pricing while the other adopts surge pricing.

(i) Pure Fixed Pricing

When prices are fixed at zero excess demand, the outcome is predictable. One single price prevail ($p = 1$) with fluctuating market share and both firms having equal cumulative market share over time (**Figure 10**).


(a) Price by Location

(b) Distribution of Prices

(c) Number of Trips by Platform

(d) Cumulative Trips by Platform
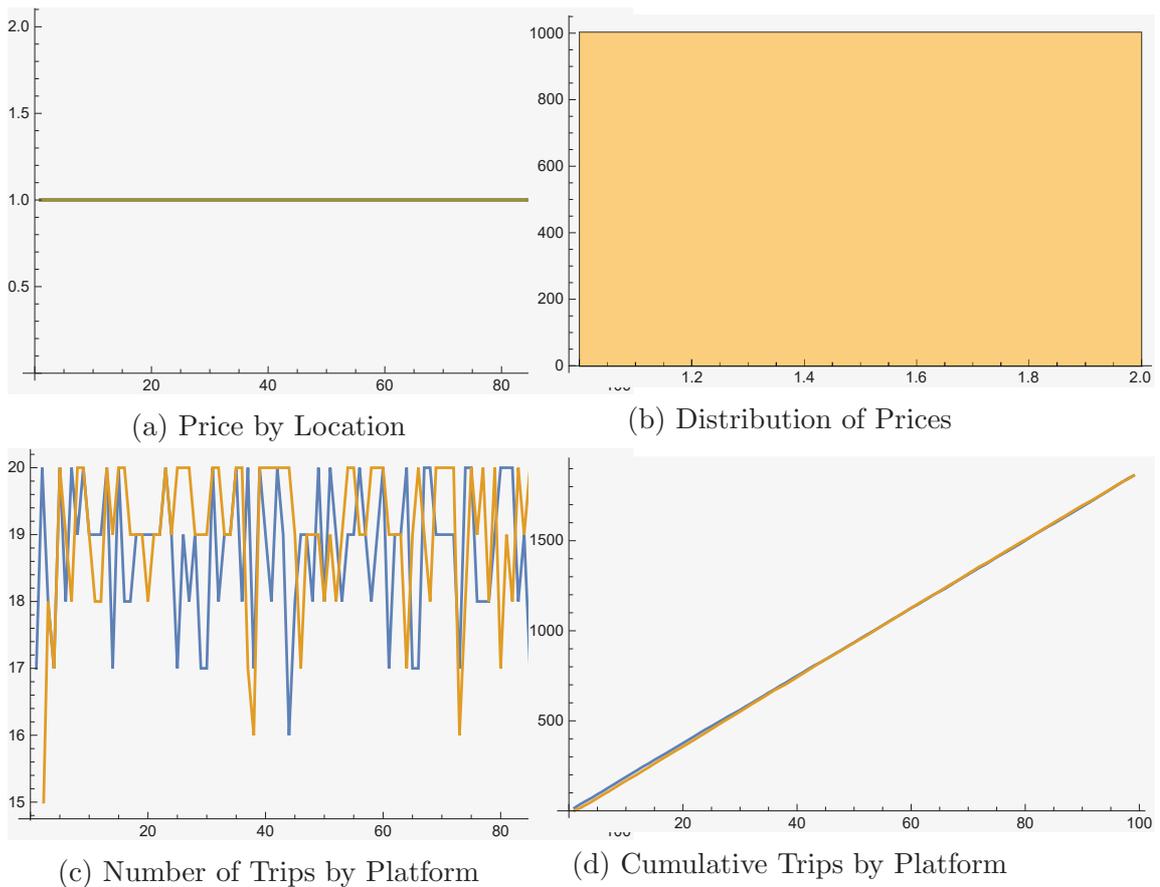
Figure 10: Simulation Results: Pure Fixed Pricing

(i) Mixed Pricing

The more interesting case is the one with mixed market pricing. It is obvious that it matters at what level is the price fixed. In the first simulation, the fixed price is set at $p = 1$. The simulation results clearly indicate that the fixed price at $p = 1$ is lower than the prices set via surge pricing. This is evidence by the higher market share of the platform using fixed pricing (blue line in **Figure 11**).


(a) Price by Location

(b) Distribution of Prices

(c) Number of Trips by Platform

(d) Cumulative Trips by Platform
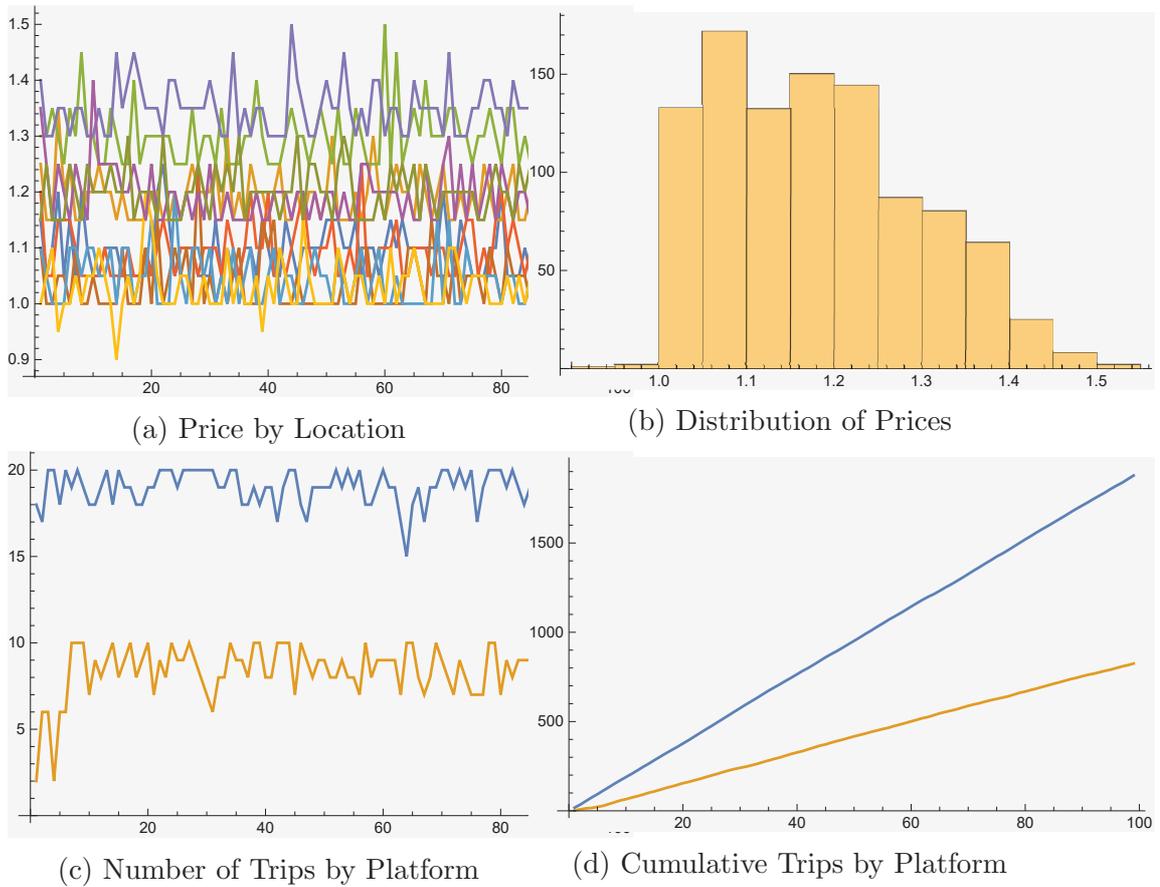
Figure 11: Simulation Results: Mixed Pricing I

(Fixed Price, $p = 1.00$)

When the fixed price is set at a higher level ($p = 1.25$), there seems to be two classes of market outcomes.[12] In the first case, the market share of the platform using surge pricing (orange line) is higher than the platform using fixed pricing (blue line) (**Figure 12**).

(a) Price by Location

(b) Distribution of Prices

(c) Number of Trips by Platform

(d) Cumulative Trips by Platform
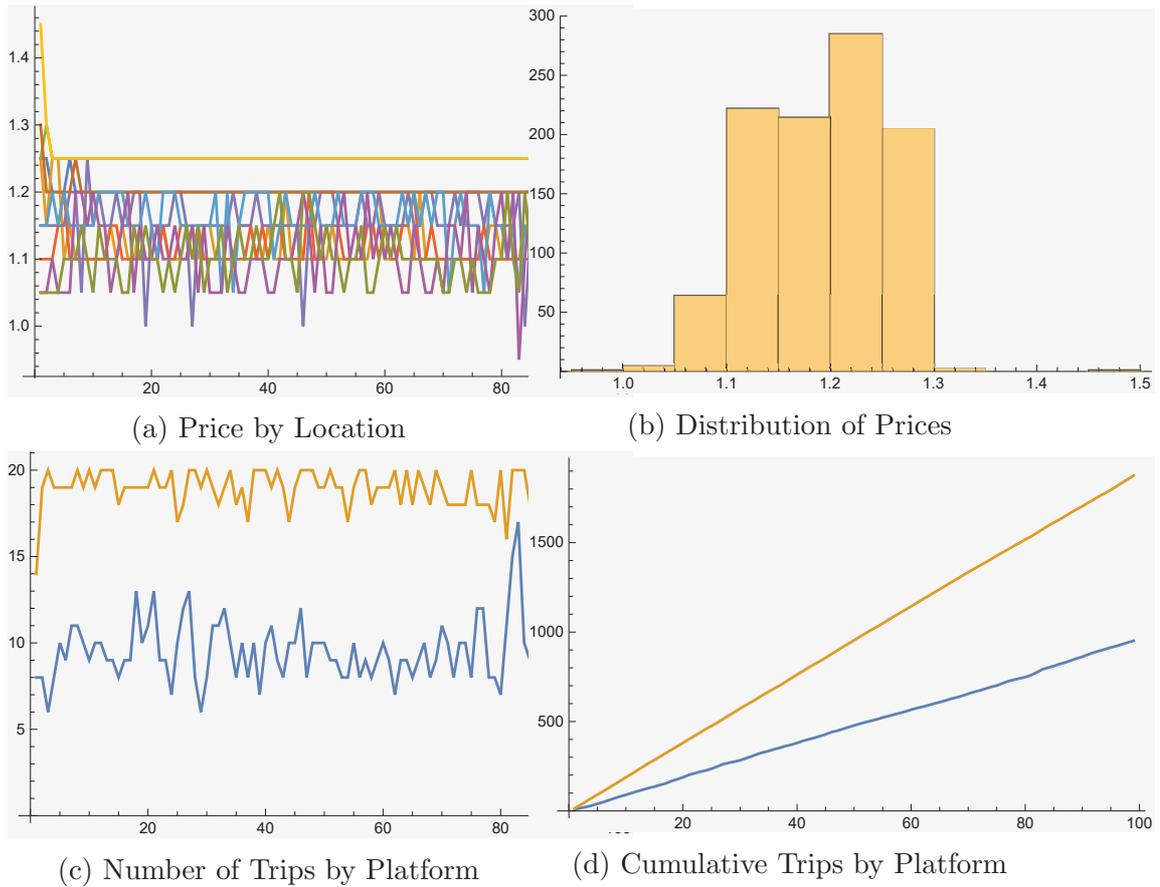
Figure 12: Simulation Results: Mixed Pricing II

(Fixed Price, $p = 1.25$)

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[12]We are reluctant to use the term equilibria.

However, in the second case, some simulations show that the advantages of using surge pricing do not always persist over time. The platform using surge pricing can lose market share over time, eventually losing its lead to the platform using fixed pricing (orange line in panel (c) and (d) in **Figure 13**).


(a) Price by Location

(b) Distribution of Prices

(c) Number of Trips by Platform

(d) Cumulative Trips by Platform
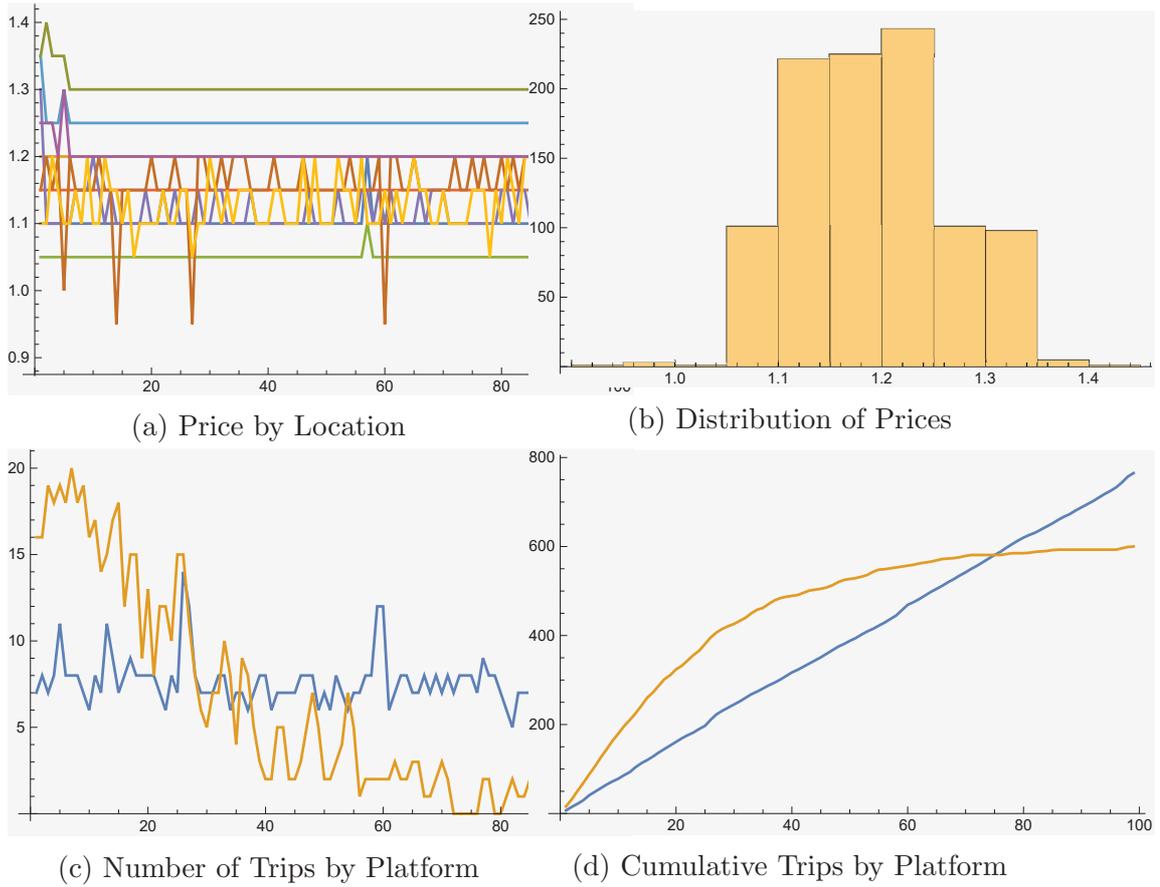
Figure 13: Simulation Results: Mixed Pricing III

(Fixed Price, $p = 1.25$)

What if the fixed price is set significantly higher (e.g. at $p = 1.5$)? We would expect that the platform setting a high fixed price will become completely uncompetitive. This is indeed the case in some simulations (**Figure 14**).


(a) Price by Location

(b) Distribution of Prices

(c) Number of Trips by Platform

(d) Cumulative Trips by Platform
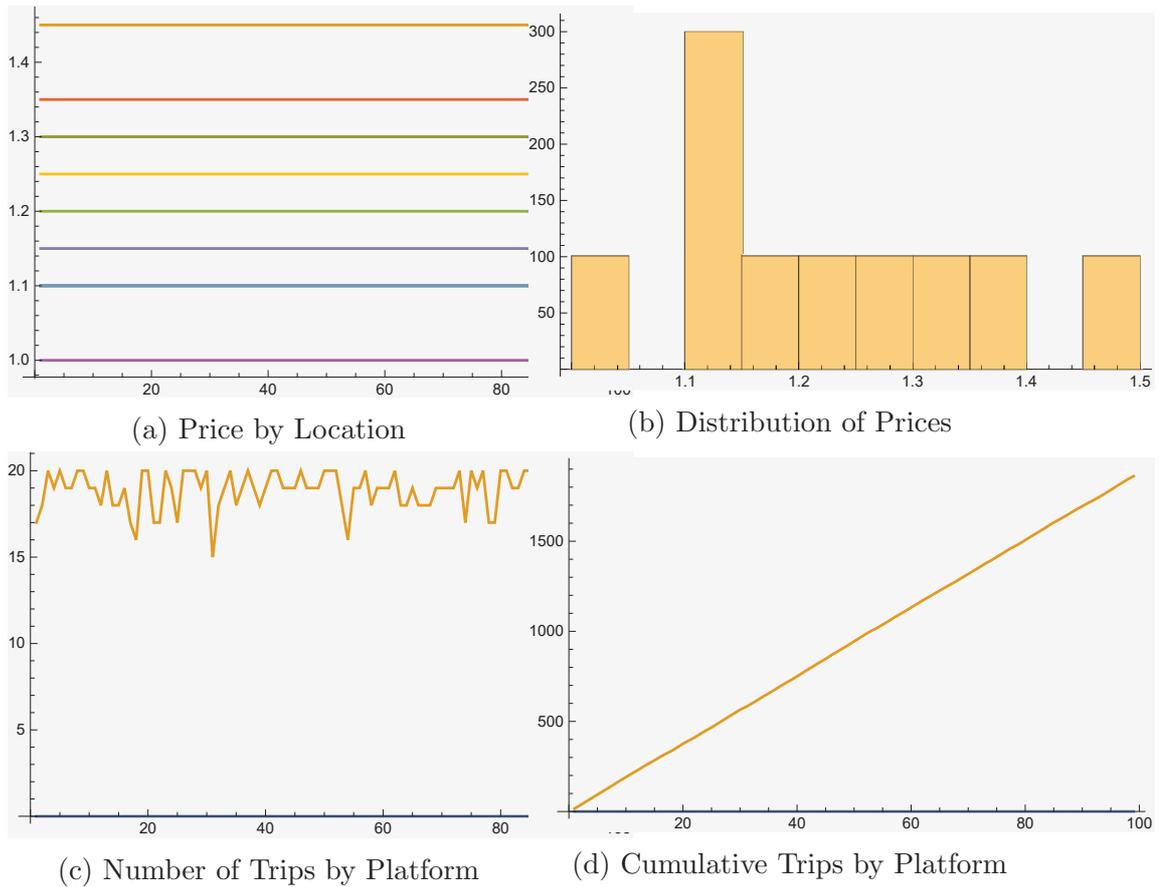
Figure 14: Simulation Results: Mixed Pricing IV

(Fixed Price, $p = 1.30$)

However, though not as frequent, there are simulations that indicate that the competitive gap between the two platforms may decline over time (**Figure 15**). This can be attributed to what we term earlier as stochastic luck. However, the market share of the platform with high fixed price is relatively low. Over time, even the market share of the platform using surge pricing declines to a low level. These two trends in market share seem to suggest that the market could converge over time to a situation where the market only serves a small number of passengers.

(a) Price by Location

(b) Distribution of Prices

(c) Number of Trips by Platform

(d) Cumulative Trips by Platform
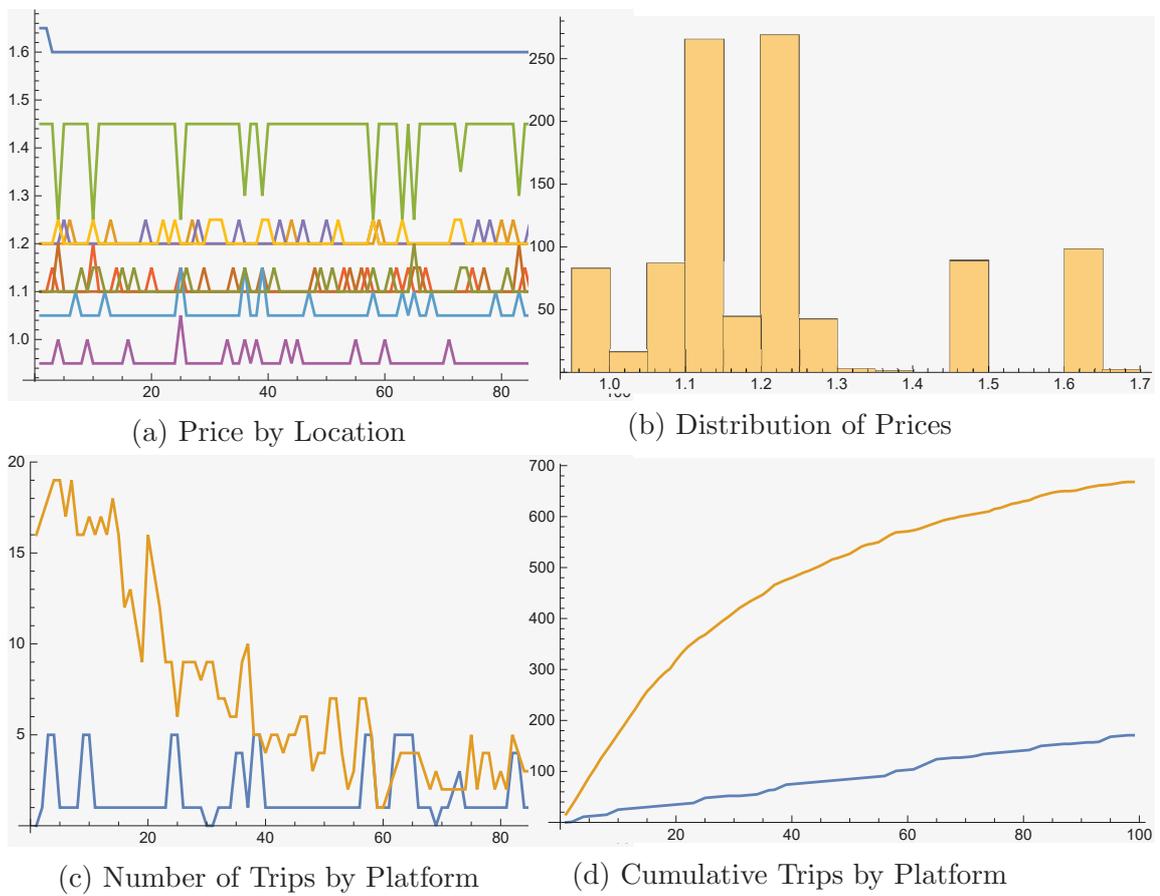
Figure 15: Simulation Results: Mixed Pricing V

(Fixed Price, $p = 1.30$)

To sum up, the mixed pricing simulations indicate that in spatial markets with stochastic elements, there are a number of potential outcomes - each occurring with different probabilities. Whilst we eschew the term "multiple equilibria", but there is some parallel here between this concept and what is observed from the simulations. Perhaps, a more appropriate characterization is that of a complex system that can move along a number of several possible trajectories depending on various factors such as initial conditions, stochastic shocks and parameters of the system (in this case, the price level fixed).

6.4   Information Sharing

In the literature on two-sided markets, comparisons are sometime made between two-sided platform competition and a monopoly. One possible approach to mimicking the monopoly platform model is for rival platforms to agree on sharing information on the total cars available (under both platforms) at each location and use that as a basis for setting prices. Results from the simulations on information sharing suggests that whilst the market share of platform fluctuate over time, prices become stationary at the different locations. However unlike other situations where the outcome is also stationary prices, the number of total trips are much higher on average.

(a) Price by Location

(b) Distribution of Prices

(c) Number of Trips by Platform

(d) Cumulative Trips by Platform
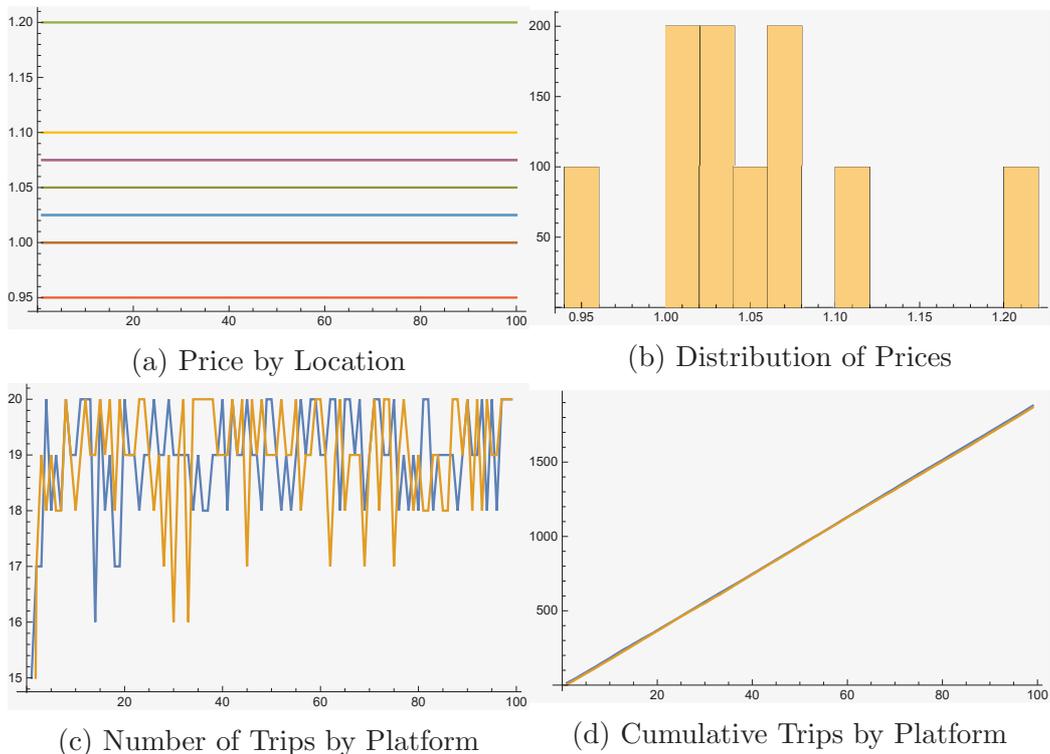
Figure 16: Simulation Results: Information Sharing

(Under Surge Pricing)

7   Conclusion

Ride-sharing has disrupted the public transportation system in many countries. The research literature on ride-sharing per se is still at a nascent stage. The recent empirical literature on ride-sharing has mostly focused on surge pricing in a single platform (Uber) setting. In the theoretical literature on two-sided platforms, there is an absence of studies that are both dynamic and spatial. This study attempts to fill the existing empirical and theoretical research gap by implementing simulations of competition in ride-sharing. By doing so, it is hoped this study will provide some useful insights for policy-makers and regulators dealing with new and disruptive services such as ride-sharing.

To understand competition in ride-sharing, four classes of simulations were carried out focusing on:(i) price distribution and dynamics, (ii) strategic pric-

ing, (iii) fixed pricing vs. surge pricing, and (iv) information-sharing. The simulations on price distributions and dynamics indicate that even when a market is competitive in the symmetric sense (identical platforms), prices can bifurcate into two or more distinct bands of prices for different locations. The decentralized determination of prices (by location) also imply that it might be more useful to study the distribution of prices rather that focusing on an "equilibrium price". In the simulations on strategic pricing, the setting of lower prices can lead to a complete dominance by the platform with lower prices. However, the spatial and stochastic nature of the model can mitigate this "winner take all" effect. This can be due to "stochastic luck" - random shocks that produces spatial distributions that favour a disadvantaged platform. The competitive dynamics of markets with ride-sharing (surge pricing) co-existing with taxi services (fixed price) can be complex. The market outcomes depend on the level of the fixed prices. In some cases, the advantages of surge pricing can be eroded over time. Platforms with extremely high fixed prices may continue to get passengers (due to stochastic luck) but their volume of trips are very small. Finally, information sharing reduces price fluctuations as information on market demand is pooled.

Overall, spatial and stochastic elements in two-sided markets such as ride-sharing make such markets complex. These markets can have a number of possible dynamic trajectories each with different outcome probabilities. This implies that the impact of policy interventions cannot be known in advance in some cases.

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