The Impact of Multi-Homing in a Ride-Sharing Market

Oksana Loginova* X. Henry Wang† Qihong Liu‡

October 9, 2020

Abstract

Platforms such as Uber, Lyft and Airbnb serve two-sided markets with drivers (property owners) on one side and riders (renters) on the other side. Some agents multi-home. In the case of ride-sharing, a driver may drive for both Uber and Lyft, and a rider may use both apps and request a ride from the company that has a driver close by. In this paper, we are interested in welfare implications of multi-homing in such a market. Our model abstracts away from entry/exit by drivers and riders as well as pricing by platforms. Both drivers' and riders' surpluses are determined by the average time between a request and the actual pickup. The benchmark setting is a monopoly platform and the direct comparison is a single-homing duopoly. The former is more efficient since it has a thicker market. Next, we consider two multi-homing settings, multi-homing on the rider side and multi-homing on the driver side. Relative to single-homing duopoly, we find that multi-homing on either side improves the overall welfare. However, multi-homing drivers potentially benefit themselves at the cost of single-homing drivers. In contrast, multi-homing riders benefit themselves as well as single-homing riders, representing a more equitable distribution of gains from multi-homing.

Keywords: Ride-sharing platform, two-sided markets, network externalities, multi-homing.

JEL Codes: D85, L12, L13.

*Department of Economics, University of Missouri, 325 Professional Building, Columbia, MO 65211, USA; E-mail: loginovao@missouri.edu (corresponding author).

†Department of Economics, University of Missouri, 333 Professional Building, Columbia, MO 65211, USA; E-mail: wangx@missouri.edu.

‡Department of Economics, University of Oklahoma, 308 Cate Center Drive, Norman, OK 73019, USA; E-mail: qliu@ou.edu.

1 Introduction

A prominent feature of the digital economy is the booming of platforms leveraging previously untapped supplies (e.g., taxi rides, apartments), supported by fast-growing mobile technology (smartphones with GPS capabilities and better/cheaper cellular service). Examples include Uber and Lyft for the ride-sharing market, and Airbnb and HomeAway for the short-term lodging market. These platforms serve two-sided markets with drivers (owners) on one side and riders (renters) on the other side. It is well known that some agents may multi-home in two-sided markets (e.g., a consumer may carry and a merchant may accept multiple credit cards). In the case of ride-sharing, a driver may drive for both Uber and Lyft, and a rider may use both companies' apps and request a ride from the company that has a driver closer by.

In this paper, we construct a simple theoretical model of a ride-sharing market that enables us to examine the welfare implications of multi-homing, in particular, how it affects the average wait/pickup time on both sides of the market. Given our focus on drivers and riders and to keep the model tractable, we abstract away from market dynamics of entry/exit by drivers and riders as well as pricing decisions by the platforms.[1] With a fixed amount of driver hours and a fixed number of rides, both drivers' and riders' surpluses are determined by the average wait time (the time between a request and the actual pickup). We consider several settings and compare them pairwise. The benchmark setting is a monopoly platform and the direct comparison is a single-homing duopoly with two symmetric platforms. The amount of driver hours and the number of rides are the same in the two settings. However, the monopoly platform setting is more efficient since all riders experience less wait time and all drivers benefit from shorter pickup distance. This is quite intuitive. If we view the ride-sharing market as a matching market, the monopoly platform has a thicker market, improving the matching quality (the wait/pickup time).

Next, we allow multi-homing and start with the setting where riders multi-home. Our results show that the more riders multi-home, the better off every agent will be. Multi-homing on the rider side improves the wait/pickup time so all drivers and the multi-homing riders are better off. Moreover, the multi-homing riders have a positive impact on single-homing riders. This is because once a multi-homing rider is served, he/she is out of the system and the freed-up driver time shortens the wait time for all other riders.

We then consider the setting where drivers multi-home. Relative to the single-homing duopoly, we find that multi-homing on the driver side benefits the riders, and the more

[1] See Section 4 for discussions of these assumptions.

drivers multi-home, the better off the riders will be. The impact of multi-homing on the drivers is more complex. The multi-homing drivers are unambiguously better off. They not only spend less time to get to riders, but also "steal" some rides from the single-homing drivers. While the singe-homing drivers enjoy shorter pickup times, they now spend more time idling because some of their rides have been stolen by the multi-homing drivers.

One of the earliest papers in the literature that explicitly considers wait time is Arnott (1996). Like in our model, the expected wait time in Arnott (1996) is inversely proportional to the square root of the density of idle taxis. The paper considers a single platform and focuses on social optimum. More recently, Bryan and Gans (2019) examine competition among ride-sharing platforms. In their paper, wait time is also explicitly modeled. However, they treat wait time as a choice variable by the platforms. Our paper complements Bryan and Gans (2019) by providing a tractable model in which wait time is endogenously determined by interactions between drivers and riders. In Bryan and Gans (2019), wait time affects both the platform's revenue through demand and its costs. In our model, wait time does not affect the platform directly, but it affects the welfare of drivers and riders.[2]

Our theoretical study is tied to the recent empirical works that focus on platforms in the new sharing economy. Cramer and Krueger (2016) investigate the efficiency of Uber by comparing the capacity utilization rates of UberX drivers and taxi drivers in several U.S. cities. Uber drivers do not need to drive around hoping to pick up passengers on the streets. Instead, after dropping off the previous passenger, they can wait for the platform to assign the next passenger. This makes them more efficient (in terms of capacity utilization rate), which Cramer and Krueger (2016) confirm. Several studies (e.g., Hall et al., 2016) have talked about surge pricing and how Uber uses it to adjust demand and supply in real time.[3] Cohen et al. (2016) also use surge pricing and individual level data to estimate demand elasticities at multiple points along the demand curve and then use these elasticities to estimate consumer surplus. Other studies explore the economic impact of the sharing economy on incumbent firms. For example, Berger et al. (2018) examine the impact of Uber on earnings and employment in conventional taxi services. The authors found that total employment expanded in the cities where Uber was introduced, and that declines in hourly earnings among wage-employed drivers were partially offset by increases in hourly earnings among self-employed drivers. Zervas et al.

[2]Bai et al. (2019) and Bernstein (2020) have also considered wait time. However, these studies focus more on pricing rather than operational issues.

[3]Uber's surge pricing has been featured in the popular media such as NPR, "Uber Plans to Kill Surge Pricing, Though Drivers Say It Makes Job Worth It," NPR All Tech Considered, May 3, 2016.

(2017) use the state of Texas data and found that Airbnb has a quantifiable and negative impact on the lodging industry's revenue, especially for low-end hotels. Airbnb also has rich data of listings and researchers have used these data to study racial discrimination (Edelman et al., 2017) and user-generated ratings (Zervas et al., 2015).

Our paper is also related to the general two-sided market literature. The seminal papers include Caillaud and Jullien (2003), Rochet and Tirole (2003), and Armstrong (2006).[4] Some of these studies consider multi-homing and investigate its implications for competition as compared to single-homing. Choi (2010) examines tying in two-sided markets with multi-homing. Jeitschko and Tremblay (2018) endogenize single- vs. multi-homing decisions on both sides. Landsman and Stremersch (2011) empirically analyze the seller-level multi-homing decisions in the video game console market. The first implication of multi-homing concerns the same side agents. Under single-homing, when platform A signs up an extra agent, it means that platform B loses this agent, resulting in head-on competition between the platforms. In contrast, under multi-homing, when an agent joins platform A, it does not prevent the same agent from joining platform B, so each platform is competing with the outside option instead of head-on competition (see Liu and Serfes, 2013). The second implication is that multi-homing also changes competition on the opposite side (Rysman, 2009). To see this, consider agents on one side who single-home and join platform A only. For any agent on the other side who wants to reach these agents, his/her only option is also to join platform A. This gives platform A monopoly power over providing access to its single-homing agents. Considering a different aspect of multi-homing, our paper focuses on how multi-homing affects efficiency rather than competition intensity since we abstract away from price decisions by the platforms.

The rest of the paper is organized as follows. In Section 2 we set up the model and analyze the benchmark setting (monopoly). Section 3 analyzes duopoly, covering single-homing, multi-homing on the rider side, and multi-homing on the driver side. We discuss the results in Section 4.

2 Monopoly

In this section we assume that only one transportation network company (hereafter TNC) operates in a given market. The model focuses on the activities that happen within one day. Suppose there are N_D full-time drivers for the company and N_R cus-

[4] Rysman (2009) provides a summary of the economic issues related to two-sided markets and their policy implications. Hagiu (2014) and McIntyre and Srinivasan (2017) contain overviews of the recent literature on platforms and multi-sided markets.

Table 1: Notation

Exogenous variables	
N_D	number of drivers
N_R	number of riders
τ	length of a trip
w	expected time that would take a driver located in the center of the city to get to a customer who could be anywhere in the city
γ	fraction of multi-homing riders
δ	fraction of multi-homing drivers
Endogenous variables	
x	fraction of a day a driver spends idling
y	average wait/pickup time
x^*	equilibrium level of x in the monopoly setting
$x^\dagger$	equilibrium level of x in the duopoly setting
y^{sh} (y^{mh})	average wait time a single-homing (multi-homing) rider faces in the duopoly setting with multi-homing riders
$x^{\dagger R}$	equilibrium level of x in the duopoly setting with multi-homing riders
N_R^{sh} (N_R^{mh})	number of riders all single-homing (multi-homing) drivers serve in the duopoly setting with multi-homing drivers
x^{sh} (x^{mh})	fraction of a day a single-homing (multi-homing) driver spends idling in the duopoly setting with multi-homing drivers
$y^{\dagger D}$	equilibrium level of y in the duopoly setting with multi-homing drivers

tomers need a ride.[5] Let τ denote the average length of a trip, measured as a fraction of a day.[6] Let ω denote the expected time (also a fraction of a day) that would take a driver located in the center of the city to get to a customer who could be anywhere in the city. All these variables are exogenously given in the model. Table 1 lists the notation that was introduced above and also some of the notation that will be introduced later.

Let x denote the fraction of a day a driver spends idling (waiting for a ping)[7] and y

[5] Subscripts "D" and "R" stand for "drivers" and "riders" respectively.

[6] This may include the time from the dropoff point to a nearby local center, where the driver will wait for the next request.

[7] After a drop off, a driver can drive around or find a free parking spot, while waiting for a ride. See "What Can Uber Drivers Do While Waiting for a Ride? (Other than Scroll Your Facebook Feed)," http://therideshareguy.com/what-can-uber-drivers-do-while-waiting-for-a-ride-other-

denote the average wait time for the riders. Both variables are determined endogenously in the model. They satisfy the following two equilibrium conditions:

$$\underbrace{N_D}_{\substack{\text{total amount of time} \\ \text{all drivers posses}}} = \underbrace{N_R(\tau + y)}_{\substack{\text{total amount of time} \\ \text{all drivers spend driving}}} + \underbrace{N_D x}_{\substack{\text{total amount of time} \\ \text{all drivers spend idling}}} \tag{1}$$

and

$$y = \frac{\omega}{\sqrt{\underbrace{N_D x}_{\substack{\#\text{ of available drivers} \\ \text{at any point in time}}}}}. \tag{2}$$

To see why the average wait time in (2) is proportional to $\left(\sqrt{\#\text{ of available drivers}}\right)^{-1}$, imagine a square city with one driver in the center of it. The wait time is ω in this case. If we divide our city into four squares and imagine four drivers sitting in the centers of these squares (one driver per square), then the wait time will be halved, $\omega/\sqrt{4}$.[8]

A lower y is obviously good for the riders. Each driver gives N_R/N_D rides, thus spending $(\tau + y)N_R/N_D$ amount of time driving. A lower y is therefore beneficial to both the riders and the drivers. An equivalent statement can be made in terms of x. A higher value of x is beneficial to the drivers, since each driver's total amount of driving time is $1 - x$. From (2), a higher x implies a lower y. Therefore, a higher x is beneficial to both the riders and the drivers.

Substituting (2) into (1) and rearranging the terms yield the following equilibrium equation for x:

$$N_D(1 - x) = N_R\left(\tau + \frac{\omega}{\sqrt{N_D x}}\right). \tag{3}$$

The left-hand side of (3) is the total amount of time supplied by the drivers (curve S in Figure 1). The right-hand side of (3) is the total amount of time demanded by the riders (curve D, not to be confused with the "D" for drivers in N_D). Note that curve S is a decreasing straight line, curve D is a strictly convex and decreasing curve. They generally intersect at two points, $\underline{x}$ and $\bar{x}$.[9]

The lower equilibrium point, $\underline{x}$, is unstable. The reason is that when $x < \underline{x}$, curve D is above curve S (more demand for driver time), which pushes x even lower and away from $\underline{x}$; when $x > \underline{x}$ but still less than $\bar{x}$, curve D is below curve S (less demand for

than-scroll-your-facebook-feed/.

[8]All of our results hold if we replace (2) by $y = \omega\phi(N_D x)$, where $\phi(\cdot)$ is a strictly decreasing and strictly convex function. Note that (2) corresponds to $\phi(z) = z^{-1/2}$.

[9]Assuming that N_D is sufficiently large, the equilibrium in which all riders get a ride exists. That is, the two curves do intersect.

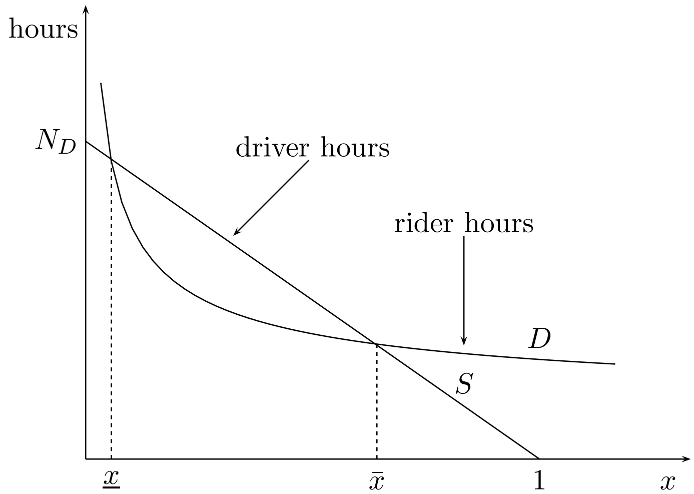

Figure 1: Equilibrium in the monopoly setting

driver time), which pushes x higher and away from $\underline{x}$. Similar argument shows that $\bar{x}$ is a stable equilibrium point. We will only focus on the stable equilibrium and label it x^*.

The equilibrium x^* has the following intuitive comparative statics properties: it decreases in N_R and increases in N_D. That is, the drivers have less idle time when there are more riders and/or less drivers.

3 Duopoly

Suppose two TNCs (A and B) operate in the market. We will start with single-homing and show that it works very similar to the monopoly scenario, only less efficient. We will then move on to multi-homing on the rider and driver sides, respectively.

3.1 Single-Homing

As before, there are N_D drivers and N_R riders. For simplicity, we consider a symmetric duopoly. Specifically, we assume that half of the drivers work for company A and the other half for company B. The riders, too, are divided into two equal groups. The first group is loyal to company A, the second group to company B.

For each company, this setting is equivalent to the monopoly setting with $N_D/2$

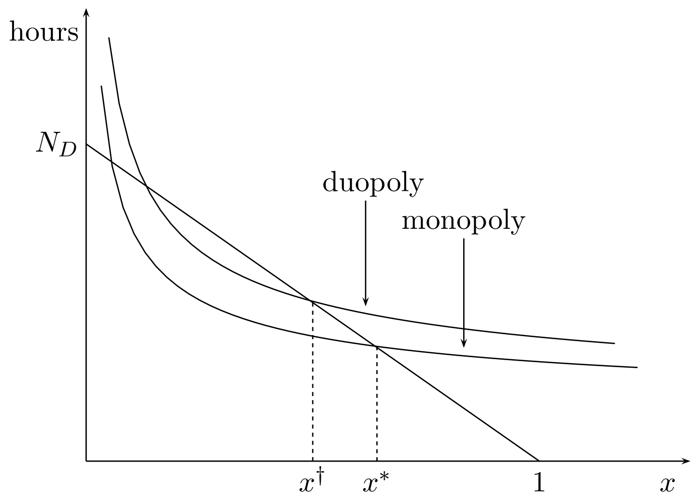

Figure 2: Equilibrium in the duopoly setting

drivers and $N_R/2$ riders. Equation (3) becomes

$$\frac{N_D}{2}(1-x) = \frac{N_R}{2}\left(\tau + \frac{\omega}{\sqrt{\frac{N_D}{2}x}}\right),$$

or equivalently,

$$N_D(1-x) = N_R\left(\tau + \frac{\omega\sqrt{2}}{\sqrt{N_D x}}\right). \tag{4}$$

Let $x^\dagger$ denote the solution to (4). It is the equilibrium level of x for duopoly. Figure 2 illustrates that $x^\dagger$ is lower than x^*, the equilibrium level for monopoly. Obviously, the average wait time under duopoly, $\omega\sqrt{2}/\sqrt{N_D x^\dagger}$, is greater than that under monopoly, $\omega/\sqrt{N_D x^*}$.

Proposition 1. *Relative to monopoly, both drivers and riders are worse off under duopoly.*

While the drivers give the same number of rides in both settings, lower x means they end up burning more gas *getting* to the customers. The riders, too, would rather find themselves in the monopoly setting with a lower average wait time. Since there is no price in our simple model, TNC's welfare remains constant and won't change the calculation of social surplus. Hence, Proposition 1 implies that social surplus goes down under duopoly.

Next, we look into whether multi-homing can alleviate the efficiency loss and if so, how.

3.2 Multi-Homing on the Rider Side

In this subsection we assume that fraction γ of the riders run both company A's and company B's apps on their phones. Thus, γN_R riders multi-home, $(1-\gamma)N_R/2$ riders use only company A's app, and $(1-\gamma)N_R/2$ riders use only company B's. The drivers single-home in this setting: $N_D/2$ work for company A, $N_D/2$ work for company B.

Let x denote the fraction of a day a driver spends idling. Let y^{mh} (y^{sh}) denote the average wait time a multi-homing (single-homing) rider faces. The first equilibrium condition is

$$N_D = (1-\gamma)N_R\left(\tau + y^{sh}\right) + \gamma N_R\left(\tau + y^{mh}\right) + N_D x.$$

Since a single-homing rider has access to $N_D/2$ drivers, while a multi-homing rider has access to all N_D drivers, the other two equilibrium conditions are

$$y^{sh} = \frac{\omega}{\sqrt{\frac{N_D}{2}x}}$$

and

$$y^{mh} = \frac{\omega}{\sqrt{N_D x}}.$$

Substituting for y^{sh} and y^{mh} and rearranging the terms yield

$$N_D(1-x) = N_R\left(\tau + \frac{\omega}{\sqrt{N_D x}}\left((1-\gamma)\sqrt{2} + \gamma\right)\right). \tag{5}$$

Let $x^{\dagger R}$ denote the solution. (The superscript "R" indicates multi-homing on the rider side.)

Note that when $\gamma = 0$, (5) becomes (4), as expected. When $\gamma = 1$, (5) becomes

$$N_D(1-x) = N_R\left(\tau + \frac{\omega}{\sqrt{N_D x}}\right),$$

hence $x^{\dagger R}$ is the same as in the monopoly setting, $x^{\dagger R} = x^*$. That is, the duopoly setting with *all* riders multi-homing leads to the same outcome as the monopoly setting.

In general, the solution to (5), $x^{\dagger R}$, increases in γ, as can be seen graphically from Figure 3. Accordingly, both average wait times, y^{sh} and y^{mh}, decrease in γ.

Proposition 2 (Riders multi-home)**.** *The higher is the fraction of multi-homing riders,*

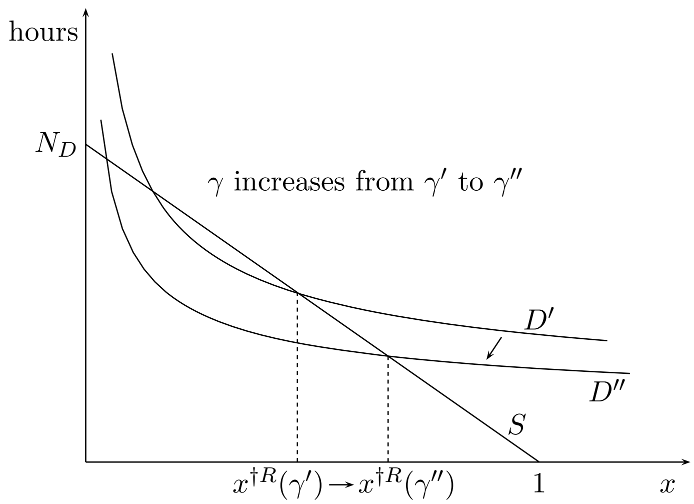

Figure 3: Comparative statics w.r.t. γ in the duopoly setting with multi-homing riders

the better off the drivers and the riders will be. In particular, multi-homing not only improves the multi-homing riders' welfare, but also has a positive impact on the single-homing riders. In the limit when $\gamma = 1$ (all riders multi-home), the duopoly setting leads to the same outcome as the monopoly setting.

This proposition shows a positive externality of multi-homing on the single-homing riders. To provide an intuition for this result, consider a former company A rider who switches to multi-homing. There are three possible scenarios when she calls for a ride. In scenario (i), she gets a company A driver. In scenario (ii), she gets a company B driver who would otherwise be idle. In scenario (iii), she gets a company B driver who would otherwise serve a single-homing company B rider. Scenario (i) means no effect to the system. Scenario (ii) represents an improvement in efficiency for the system since this rider is out of the system once she is served and the freed-up driver time down the line helps to shorten the wait time for all other riders. Scenario (iii) has a positive effect on company A's riders but a negative effect on company B's riders. However, these effects should all cancel out by the switching of a company B's rider to multi-homing.

There is another potential benefit of multi-homing that has not been taken into account. In our model, N_D and N_R are assumed to be fixed. Yet our results above show that multi-homing on the rider side benefits both drivers and riders. This will attract more riders and drivers to the market, leading to larger networks and a more efficient market.

3.3 Multi-Homing on the Driver Side

In this subsection we assume that a fraction of the drivers work for both TNCs. These may be drivers who do not have a strong preference for either company and are sufficiently "tech savvy" to operate on both companies' apps simultaneously. Let δ denote the fraction of multi-homing drivers. Thus, δN_D drivers multi-home, $(1-\delta)N_D/2$ work for company A, and $(1-\delta)N_D/2$ work for company B. We continue to assume that half of the riders are loyal to company A and the other half to company B.

Let N_R^{sh} (N_R^{mh}) denote the number of riders all single-homing (multi-homing) drivers serve, $N_R^{mh} = N_R - N_R^{sh}$. Thus, each single-homing driver gives

$$\frac{N_R^{sh}}{(1-\delta)N_D}$$

rides and each multi-homing driver gives

$$\frac{N_R - N_R^{sh}}{\delta N_D}$$

rides. If we denote by x^{sh} (x^{mh}) the fraction of a day a single-homing (multi-homing) driver spends idling, then

$$x^{sh} = 1 - \frac{N_R^{sh}}{(1-\delta)N_D}(\tau + y) \tag{6}$$

and

$$x^{mh} = 1 - \frac{N_R - N_R^{sh}}{\delta N_D}(\tau + y). \tag{7}$$

A multi-homing driver on average spends *half* the time idling between two consecutive rides as a single-homing driver does. Mathematically,

$$\underbrace{\left(1 - \frac{N_R^{sh}}{(1-\delta)N_D}(\tau + y)\right)}_{x^{sh}} \Bigg/ \underbrace{\frac{N_R^{sh}}{(1-\delta)N_D}}_{\substack{\#\text{ of rides a single-}\\ \text{homing driver gives}}} = 2\underbrace{\left(1 - \frac{N_R - N_R^{sh}}{\delta N_D}(\tau + y)\right)}_{x^{mh}} \Bigg/ \underbrace{\frac{N_R - N_R^{sh}}{\delta N_D}}_{\substack{\#\text{ of rides a multi-}\\ \text{homing driver gives}}}, \tag{8}$$

or equivalently

$$\frac{(1-\delta)N_D}{N_R^{sh}} - (\tau + y) = 2\left(\frac{\delta N_D}{N_R - N_R^{sh}} - (\tau + y)\right). \tag{9}$$

This is a quadratic equation with respect to N_R^{sh}. Once we find N_R^{sh}, we plug it into (6) and (7) to find x^{sh} and x^{mh}. All are functions of y.

It is easy to see that $N_R^{sh} < (1-\delta)N_R$, implying

$$\frac{N_R^{sh}}{(1-\delta)N_D} < \frac{N_R}{N_D} < \frac{N_R - N_R^{sh}}{\delta N_D}.$$

That is, each multi-homing driver serves more riders than each single-homing driver does. From (8),

$$x^{mh} = \alpha x^{sh},$$

where

$$\alpha = \frac{1}{2} \times \frac{(N_R - N_R^{sh})/\delta N_D}{N_R^{sh}/(1-\delta)N_D} \in \left(\frac{1}{2}, 1\right).$$

That α exceeds 1/2 is intuitive. Compared to a single-homing driver, a multi-homing driver spends half the time idling between two consecutive rides, but gives more rides per day.

Finally, we have

$$y = \frac{\omega}{\sqrt{\frac{1-\delta}{2}N_D x^{sh} + \delta N_D x^{mh}}}. \tag{10}$$

As before, under the square root is the number of available drivers at any point in time: each rider has access to $(1-\delta)N_D/2$ single-homing drivers (fraction x^{sh} of them is available) and to δN_D multi-homing drivers (fraction x^{mh} of them is available).

Recall that x^{sh} and x^{mh} are functions of y. Thus, (10) allows us to find the equilibrium value of y, $y^{\dagger D}$. As δ increases from 0 to 1, we move from the single-homing duopoly to the monopoly outcome. In general, the average wait time $y^{\dagger D}$ decreases in δ, as we show in the following proposition.

Proposition 3 (Drivers multi-home)**.** *The higher is the fraction of multi-homing drivers, the better off the riders will be. In the limit when $\delta = 1$ (all drivers multi-home), we recover the monopoly outcome.*

We have already pointed out a business stealing effect between the multi-homing and single-homing drivers. Hence, a driver always has an incentive to multi-home (if he has the capability). As to the single-homing drivers, they give fewer rides, but it now takes them less time to get to each rider (y is smaller). It may be reasonable to expect the negative effect to be dominant, hurting the single-homing drivers. Thus, there is a negative externality of multi-homing on the single-homing drivers.

Before concluding this section, we would like to make the following remark. Propositions 2 and 3 imply that if one side multi-homes completely, it does not matter whether the other side multi-homes, because the monopoly outcome is achieved.

4 Discussions

The present paper shows that multi-homing on either side improves the overall welfare. However, multi-homing drivers potentially benefit themselves at the cost of single-homing drivers. In contrast, multi-homing riders benefit themselves as well as single-homing riders, representing a more equitable distribution of gains from multi-homing.

Our results imply that multi-homing on the rider side should be promoted. To do this, the regulators may adopt different measures. First, the regulators should find ways to reduce the hassle cost of multi-homing for riders. If it is inconvenient for riders to use both platforms so as to look for a better match (e.g., find out which platform has a driver closer to the rider), then few riders will choose to multi-home. Second, riders must be able to multi-home meaningfully. In our model, it is implicitly assumed that the matching between a multi-homing rider and the available drivers is always efficient. For this to happen in practice, accuracy of expected wait times for the closest driver on each platform is important for multi-homing riders to identify the appropriate platform to choose from. As a result, the regulators should study and put in place a mechanism that gives platforms an incentive to report wait times accurately, and more importantly, to improve such accuracy over time.

In this paper, we assume that the market size is fixed. If the numbers of drivers and riders are endogenized, one would expect competition between platforms to attract more drivers and riders to the platforms, leading to a thicker market (and improved efficiency). Multi-homing reduces the efficiency loss relative to a monopoly network, but retains competition among platforms. In fact, competition may be more intense when a rider chooses between two platforms each time a ride is requested rather than choosing a platform and sticking to it for all rides.

For tractability, we only consider symmetric platforms. However, in many markets platforms may be asymmetric. For example, Uber holds a significant advantage over Lyft in size and volume.[10] We conjecture that multi-homing on the rider side is likely to help Lyft better fend off Uber and retain competition in the ride-sharing market. It would be interesting for future research to explore how multi-homing affects competition among asymmetric platforms.

In our model, we abstract away from pricing. We do so because our focus is on the impact of multi-homing on matching efficiency, namely how multi-homing affects

[10] Fortune Magazine reports that in July 2016 Uber completed 62 million U.S. trips relative to Lyft's 13.9 million trips.

the welfare of drivers and riders, taking their participation in the network as given. In reality, pricing policies are very complex.[11] One may instinctively think that moving from monopoly to duopoly, competition necessarily drives prices down. However, we believe this does not have to be the case. Ride-hailing platforms' cost structure includes mostly fixed cost, in the form of R&D, marketing, etc., with negligible marginal cost. Going from monopoly to duopoly, each platform has less business to "tax" from. As a result, they may have to either raise the price/commission rate, or substantially reduce their fixed costs and in turn service quality. The latter would further reduce efficiency beyond what is shown in our model.

Finally, we would like to point out that our model and findings have applications to matching markets, especially one-to-many matching markets. An example is matching between property owners (hosts) and renters (guests) in the short-term lodging market. Our theoretical framework is applicable provided that in a given time period (say, a week) the total capacity on the supply side exceeds total demand, so that on average each property owner has vacancy during the period. Like multi-homing drivers in our model, multi-homing will likely enable property owners to reduce their vacancy rates. This may hurt single-homing owners. On the other hand, multi-homing by some renters should be beneficial to all owners. Overall, multi-homing by either side of the market should improve matching efficiency.

Appendix

Proof of Proposition 3

We want to show that $y^{\dagger D}$ decreases in δ. The first-order effect of an increase in δ on $y^{\dagger D}$ is negative. To see this, we plug $x^{mh} = \alpha x^{sh}$ into (10) to obtain

$$y = \frac{\omega}{\sqrt{\frac{1-\delta}{2} N_D x^{sh} + \delta N_D \alpha x^{sh}}} = \frac{\omega}{\sqrt{\left(\frac{1}{2} + \delta\left(\alpha - \frac{1}{2}\right)\right) N_D x^{sh}}}.$$

Since $\alpha \in (1/2, 1)$, the right hand side is decreasing in δ.

Next, a decrease in y increases both x^{sh} and x^{mh}, as can be seen from (6) and (7). Since the right hand side of (10) is a decreasing function of x^{sh} and x^{mh}, the second-order effect of an increase in δ on $y^{\dagger D}$ (through x^{sh} and x^{mh}) is negative as well. This

[11] Both Uber and Lyft have adopted programs to reward active and high-performing drivers. Launched in June 2016, Uber's Power Driver Plus awards drivers cash bonuses after a set number of trips. Thus, drivers who complete an extra 80-100 trips a week receive 10%-20% extra earnings. Surge pricing is another example of complicated pricing schemes. See Cachon et al. (2017) for a theoretical study of pricing schemes on service platforms, including Uber's surge pricing.

concludes the proof of Proposition 3.

References

[1] Armstrong, Mark, 2006, "Competition in Two-Sided Markets," *Rand Journal of Economics*, 37(3), pp. 668-691.

[2] Arnott, Richard, 1996, "Taxi Travel Should be Subsidized," *Journal of Urban Economics*, 40(3), 316-333.

[3] Bai, Jiaru, Kut C. So, Christopher S. Tang, Xiqun Chen, Hai Wang, 2019, "Coordinating Supply and Demand on a On-Demand Service Platform with Impatient Customers," *Manufacturing & Service Operations Management*, 21(3), 556-570.

[4] Berger, Thor, Chinchih Chen, Carl Benedikt Frey, 2018, "Drivers of Disruption? Estimating the Uber Effect," *European Economic Review*, 110, pp. 197-210.

[5] Bernstein, Fernando, Gregory A. DeCroix, and N. Bora Keskin, 2020 , "Competition Between Two-Sided Platforms Under Demand and Supply Congestion Effects," forthcoming in *Manufacturing & Service Operations Management*.

[6] Bryan, Kevin A., and Joshua S. Gans, 2019, "A Theory of Multihoming in Rideshare Competition," *Journal of Economics and Management Strategy*, 28(1), 89-96.

[7] Cachon, Gérard P., Kaitlin M. Daniels, and Ruben Lobel, 2017, "The Role of Surge Pricing on a Service Platform with Self-Scheduling Capacity," *Manufacturing & Service Operations Management*, 19(3), pp. 268-384.

[8] Cailalud, Bernard, and Bruno Jullien, 2003, "Chicken & Egg: Competition Among Intermediation Service Providers," *Rand Journal of Economics*, 34(2), pp. 309-328.

[9] Choi, Jay Pil, 2010, "Tying in Two-sided Markets with Multi-Homing," *Journal of Industrial Economics*, 58(3), pp. 607-626.

[10] Cohen, Peter, Robert Hahn, Jonathan Hall, Steven Levitt, and Robert Metcalfe, 2016, "Using the Big Data to Estimate Consumer Surplus: The Case of Uber," NBER Working Paper No. 22627.

[11] Cramer, Judd, and Allan B. Krueger, 2016, "Disruptive Change in the Taxi Business: The Case of Uber," *American Economic Review: Papers & Proceedings*, 106(5), pp. 177-182.

[12] Edelman, Benjamin, Michael Luca, and Dan Svirsky, 2017, "Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment," *American Economic Journal: Applied Economics*, 9(2), pp. 1-22.

[13] Hagiu, Andrei, 2014, "Strategic Decisions for Multisided Platforms," *MIT Sloan Management Review*, 55(2), pp. 71-80.

[14] Jeitschko, Thomas D., and Mark J. Tremblay, 2018, "Platform Competition with Endogenous Homing," working paper.

[15] Hall, Jonathan, Cory Kendrick, and Chris Nosko, 2016, "The Effects of Uber Surge Pricing: A Case Study," technical report.

[16] Landsman, Vardit, and Stefan Stremersch, 2011, "Multihoming in Two-Sided Markets: An Empirical Inquiry in the Video Game Console Industry," *Journal of Marketing*, 75(6), pp. 39-54.

[17] Liu, Qihong, and Konstantinos Serfes, 2013, "Price Discrimination in Two-Sided Markets," *Journal of Economics and Management Strategy*, 22(4), pp. 768-786.

[18] McIntyre, David P., and Arati Srinivasan, 2017, "Networks, Platforms, and Strategy: Emerging Views and Next Steps," *Strategic Management Journal*, 38(1), pp. 141-160.

[19] Rochet, Jean-Charles, and Jean Tirole, 2003, "Platform Competition in Two-Sided Markets," *Journal of the European Economic Association*, 1(4), pp. 990-1029.

[20] Rysman, Marc, 2009, "The Economics of Two-Sided Markets," *Journal of Economic Perspectives*, 23(3), pp. 125-143.

[21] Zervas, Georgios, Davide Proserpio, John W. Byers, 2015, "A First Look at Online Reputation on Airbnb, Where Every Stay is Above Average," working paper.

[22] Zervas, Georgios, Davide Proserpio, John W. Byers, 2017, "The Rise of the Sharing Economy: Estimating the Impact of Airbnb on the Hotel Industry," *Journal of Marketing Research*, 54(5), pp. 687-705.