MANUFACTURING & SERVICE OPERATIONS MANAGEMENT
Vol. 24, No. 1, January–February 2022, pp. 91–109
ISSN 1523-4614 (print), ISSN 1526-5498 (online)
http://pubsonline.informs.org/journal/msom

Surge Pricing and Two-Sided Temporal Responses in Ride Hailing

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Received: February 6, 2020
Revised: August 11, 2020
Accepted: September 20, 2020
Published Online in Articles in Advance: February 3, 2021

https://doi.org/10.1287/msom.2020.0960

Abstract. ***Problem definition*:** We investigate surge pricing in ride-hailing platforms from a temporal perspective, highlighting strategic behavior by riders and drivers and that drivers respond to surge pricing much more slowly than riders do. ***Academic/practical relevance*:** Surge pricing in ride-hailing platforms is a pivotal and controversial subject. Despite abundant anecdotal evidence, strategic behavior by riders and drivers has not been formally studied in the literature. ***Methodology*:** We adopt and analyze a classic two-period, game-theoretical model as in the strategic consumer literature. ***Results*:** We identify two types of equilibrium pricing strategies. The first consists of a short-lived, sharp price surge followed by a lower price, which we refer to as *skimming surge pricing* (SSP). The second consists of a low initial price followed by a higher price, which we refer to as *penetration surge pricing* (PSP). We find that PSP equilibria are generally superior to SSP equilibria when both exist but require platforms to share demand–supply information with drivers. ***Managerial implications*:** The SSP equilibrium rationalizes the controversial sharp surge-pricing practice: the short-lived sharp price surge causes many high-value riders to voluntarily wait out the initial surge period, which attracts additional drivers to the region to serve riders at a much lower price than the initial surge price. The theoretically superior PSP equilibrium suggests that a vastly different approach may improve surge pricing and highlights the potential value and importance for platforms to share demand–supply information with drivers.

Funding: This work was supported by the National Natural Science Foundation of China [Grants 71902018 and 71831003] and the Canadian Network for Research and Innovation in Machining Technology, Natural Sciences and Engineering Research Council of Canada [Grant RGPIN-2015-06757].
Supplemental Material: The online appendix is available at https://doi.org/10.1287/msom.2020.0960.

Keywords: surge pricing • temporal response • ride hailing • strategic consumer behavior

1. Introduction

One of the most prominent marketplace innovations in the past decade has been the advent of sharing (or gig) economies, defined by online platforms helping match individual service providers to individual customers. Some sharing economy platforms, such as TaskRabbit and Airbnb, serve as online marketplaces on which service providers and customers engage in their own matching processes. Other platforms, most notably ride-hailing platforms, such as Uber and Lyft, completely control the matching process, dictating in real time which driver serves which rider and how much the rider is charged while keeping a percentage of the rider's payment (e.g., roughly one quarter for both Uber and Lyft according to Krisher and Sell 2017) and transferring the rest to the driver. For these ride-hailing platforms, pricing is their primary lever to manage demand and supply and is, thus, of utmost importance.

Dynamic demand and supply on ride-hailing platforms necessitate dynamic pricing. To this end, Uber implements an instrument called surge pricing, and Lyft implements a similar instrument called prime time pricing. In this paper, we generally refer to such instruments as surge pricing. The basic principle of surge pricing is that a platform sets a regular price and dynamically adjusts the price by a multiplier based on the current demand and supply, effectively adjusting the price in real time. Although the platforms claim that surge pricing is designed to improve experience (Uber 2018), it has been one of the most controversial aspects of ride hailing. Riders have accused Uber of price gouging (Lowrey 2014). Drivers complain that surge pricing is too unpredictable and short lived (Kerr 2015, Rosenblatt 2018). Proponents, on the other hand, claim that surge pricing is consistent with basic economic principles of supply and demand

(*Economist* 2016). Despite the controversies, Uber and Lyft appear to be committed to this instrument.

Surge pricing, as such a pivotal and controversial subject, deserves careful inspection. The developing literature on surge pricing primarily takes a *spatial* perspective and investigates how prices at different locations influence driver distributions; see Bimpikis et al. (2019) and Besbes et al. (2021). However, we are primarily drawn to an important *temporal* characteristic unique to ride hailing: namely that riders and drivers on a ride-hailing platform respond to surge pricing on different timescales. A rider seeing a price surge can decide to leave the platform by putting away their phone in mere seconds. By contrast, when a driver wants to take advantage of surge pricing in a particular region, the driver may need to finish the current ride, leave home, or travel from a different region, which can take 10 minutes or more. More crucially, drivers' and riders' different response timescales lead to strategic behavior that is supported by abundant anecdotes. For example, Kerr (2015) suggests that drivers are well aware of the time it takes them to drive to a surge region and take this into consideration in their decisions. Rosenblatt (2018) states, "Some Uber drivers say they feel misled when they travel to a surge area in high demand only to find that it has disappeared. The consensus in driver forums is, 'Don't chase the surge.'" On the other hand, Diakopoulos (2015) suggests riders can anticipate that a surge may not last and wait out the surge in just a few minutes. The different response timescales and strategic rider and driver behavior can have profound implications on the design and effectiveness of surge pricing.

In this paper, we emphasize the temporal perspective and adopt a two-period model that captures riders' and drivers' different response timescales to pricing and their corresponding strategic behavior. We also test the model's robustness when incorporating spatial elements. We use this model to attempt to answer the following questions: Accounting for salient temporal elements of ride hailing, what is a platform's optimal/equilibrium surge-pricing policy? Can the ride-hailing platforms' current pricing practices be explained? How may such platforms improve their surge-pricing policies? And what impact would there be if a platform neglects riders' and drivers' strategic behavior in their surge-pricing practice?

To answer these questions, we adopt the following two-period model. At the beginning of period 1, a total volume of one (continuous, normalized) driver is available in a small region, and a total volume of $r > 1$ riders with heterogeneous valuations appear in the same region, constituting a demand surge. The platform sets price p_1 for period 1. Given the initial price p_1, some riders request rides in this period, some strategically wait out period 1 at a cost and request rides only in period 2, and the rest do not request rides in either period. Currently unavailable drivers may decide to "chase the surge" and make themselves available in the region (i.e., drive toward the region) at a cost, but they only become available in period 2. The riders requesting rides in period 1 and currently available drivers are randomly matched. If drivers outnumber riders, all rider requests are satisfied. If riders outnumber drivers, unserved riders may wait at a cost. In period 2, new drivers who decided in period 1 to chase the surge become available and join any remaining drivers, and the platform sets the second-period price p_2. Given the price p_2, the remaining riders from period 1 decide whether to request rides, and those who do are again randomly matched with available drivers.

We adopt the notion of rational expectations to characterize the equilibrium behavior over the two periods. Through various analyses, we recover the commonly seen surge-pricing pattern of a short-lived sharp price surge followed by a lower price as an equilibrium, which we refer to as *skimming surge pricing* (SSP) for its resemblance to price skimming. The SSP equilibrium matches current pricing practices and reveals a more nuanced mechanism of surge pricing beyond simply setting prices to make supply meet demand as the platform may strategically inflate the price above the level that micromatches supply and demand in the surge region. The short-lived sharp price surge causes many high-value riders to voluntarily wait out the initial price surge, which serves to attract additional drivers to the region despite their slow responses. After the initial period, new drivers arrive, and the market clears at a price point lower than the initial surge price. In practice, SSP's sharp price surge can robustly signal that a region has many unserved riders when drivers have no other information. Additional drivers may then make themselves available in the surge region—not to chase the surge but to pursue riders.

Interestingly, another distinct and somewhat counterintuitive equilibrium can also occur in which, upon observing a demand surge, the platform sets a low price followed by a higher price, which we refer to as *penetration surge pricing* (PSP) for its resemblance to penetration pricing. The rationale behind the PSP equilibrium is that the platform sets a low price to entice many riders into requesting rides. This, alongside random matching, forces many high-value (as well as low-value) riders to wait out the initial surge period, which serves to attract additional drivers to the region. After the initial period, new drivers arrive, and the market clears at a price point higher than the initial price. We find that when PSP and SSP equilibria coexist, PSP can be superior to SSP in generating a higher platform profit and matching volume and reducing price variability in addition to avoiding the initial sharp price surge. Both PSP and SSP operate on the fundamental principle of keeping high-value riders around to attract drivers to the current region. The difference is that PSP does so with lower prices, which increases the matching volume and platform profit. One possible reason the PSP strategy is not widely observed is that it requires the platform to share demand–supply information with drivers, which is not yet common practice. To this end, our findings suggest that platforms may consider strategies, such as sharing demand–supply information with drivers or committing to future price surges to enable PSP policies to improve profit and efficiency and mitigate controversies surrounding sharp price surges.

We study several extensions. First, we confirm the preceding insights by accounting for the spatial perspective that additional drivers may come to the surge region with different costs by traveling different distances. We find that, given the same total amount of drivers in a disc with the surge spot in the center, a more clustered distribution of drivers generally leads to larger matching volumes and higher platform profits than a uniform driver distribution. Second, we show that, if the platform fails to account for riders' and drivers' different response timescales and strategic behavior and instead sets prices myopically to match demand and supply, all parties may be worse off, which speaks to the importance of the temporal perspective in ride-hailing pricing. Finally, we show that our key insights remain valid when not all riders are strategic and when there are incoming riders in period 2 to confirm the robustness of these insights.

In the rest of this paper, we survey the related literature in Section 2 and introduce our model in Section 3. The main analysis is conducted in Section 4. We then analyze four model extensions in Section 5 before concluding the paper in Section 6. The appendix contains additional technical results. All proofs are relegated to the online appendix.

2. Literature Review

As sharing economies become more prevalent and prominent, a growing body of literature has provide insights into various aspects of two-sided market platforms. Examples of issues investigated include how platforms influence potential customers' purchase decisions (Jiang and Tian 2016, Benjaafar et al. 2018, Chen et al. 2019, Feng et al. 2020), how platforms manage self-scheduling service providers (Gurvich et al. 2019) and incentivize them (Sun et al. 2019), how platform operations are affected by online reviews (Yang and Zhang 2018) and information provision (Chu et al. 2018), how ride-hailing platforms route drivers (Su 2018) and compete/cooperate with each other (Cohen and Zhang 2019), and how supply and demand are matched on platforms (Allon et al. 2012, Özkan and Ward 2020, Hu and Zhou 2021). Narasimhan et al. (2018) provide a review of the sharing economy literature from the marketing perspective, and Hu (2018) considers the operations perspective.

Our paper fits in the literature examining pricing strategies on ride-hailing platforms, especially the surge-pricing strategy (see Banerjee and Johari 2018 for a framework of modeling, optimizing, and reasoning about ride-hailing platforms). In the domain of empirical and experimental studies, Chen (2016) empirically finds that Uber drivers adjust their schedule to work more during surge times. Cohen et al. (2018) use field experiments to investigate how different subsidy schemes affect the engagement of riders who experience the frustration of long waiting or travel times. Jiang et al. (2021) conduct laboratory experiments to study drivers' relocation decisions with financial incentives, such as surge pricing and subsidy. The authors observe that financial incentives must be combined with demand information sharing to be the most effective in incentivizing drivers to relocate to a demand surge region.

In the sphere of analytical works on pricing decisions for ride-hailing markets, there are at least three research streams. The first stream includes *stationary* single-location models that capture the first-order effects of ride-hailing markets. The platform, as an intermediary, optimizes the price offered to riders and the wage paid to drivers. Unlike a traditional supply chain, the platform indirectly manages independent self-scheduling contractors through wages. Taylor (2018) studies an on-demand service platform and shows that uncertainty in delay-sensitive customers' valuations or the agents' opportunity costs can lead to counterintuitive insights; delay sensitivity can increase the optimal price or lower the optimal wage. Complementing Taylor's (2018) work, Bai et al. (2019) focus on the impact of the demand rate, sensitivity to waiting time, service rate, and the number of available providers on the optimal price, wage, and payout ratio. The authors show that the optimal price, wage, and payout ratio increase in the potential customer demand rate. These two papers use a queueing model that takes into account the interaction of drivers and delay-sensitive riders. More recently, Benjaafar et al. (2021) and Nikzad (2019) focus on labor welfare in on-demand service platforms with two-sided pricing decisions by showing that, in equilibrium, labor supply may have a nonmonotonic effect on labor welfare. In all these papers, pricing decisions, such as price and wage, are determined and committed to for a relatively long term.

Among this stream of single-location models with stationary system parameters but demand uncertainty, there is a set of papers focusing on the debate about whether the platform should adopt short-run surge pricing (i.e., dynamic pricing based on realized demand) or static pricing. Cachon et al. (2017) show that drivers and riders are generally better off with different prices contingent on varying supply and demand conditions. Banerjee et al. (2016) adopt a queueing approach to show, on one hand, static pricing can be nearly optimal when the market is thick with large volumes of supply and demand. Chen and Hu (2020) further confirm the asymptotic optimality of static pricing in a thick market even when buyers and sellers exhibit forward-looking behavior. On the other hand, Banerjee et al. (2016) show that dynamic pricing is much more robust than static pricing to variations or information in system parameters. When the time a driver takes to pick up a rider is considered (which is ignored in most models), Castillo et al. (2018) show that there could be multiple equilibria for a given price, and surge pricing can help the system adjust itself based on market conditions to avoid the less efficient wild-goose-chase equilibrium. Hu and Zhou (2020) show that, in a market with demand and supply uncertainty, a fixed payout ratio can be optimal or near optimal for the platform though the price and wage would change depending on the market conditions.

The second stream of developing literature on the ride-hailing market involves *static* models with spatial considerations. Bimpikis et al. (2019) explore the equilibrium spatial price distribution when allowing drivers to decide whether to work and where to position themselves in a network of interconnected locations. Under the assumption that potential supply is infinite, their findings highlight the impact of the demand balancedness across locations on the platform's prices, profits, and consumer surpluses. Afèche et al. (2018a) consider a queueing network model and focus on the performance impact of operational controls, demand-side admission control, and supply-side repositioning from the perspectives of the platform, drivers, and riders. They show under what conditions it is optimal to strategically reject demand at a low-demand location to induce drivers to reposition themselves to a high-demand location. Besbes et al. (2021) consider a linear city in which the drivers can reposition themselves. The platform sets location-specific prices along the linear city, and then riders' requests along the city are realized. The drivers then relocate themselves with zero travel time in a simultaneous-move game based on prices, demands, and driving costs.

In all the aforementioned papers, either drivers and riders make decisions within the same timescale (see, e.g., Cachon et al. 2017, Hu and Zhou 2020) or drivers decide on whether to join the platform in the long run based on the expected payoffs over a set of short-run demand scenarios with prices for riders committed or determined contingently (see, e.g., Banerjee et al. 2016). By contrast, we are among the first to focus on the unique temporal characteristics of the ride-hailing market and consider riders' and drivers' different decision-making timescales and resulting strategic reactions to short-run contingent surge pricing.

Our paper and two other closely related papers belong to a third research stream that considers *nonstationary* models. Guda and Subramanian (2019) show that surge pricing can be used strategically to move drivers from a price-surge area into a neighboring area where higher demand is predicted, which is the exact opposite of what is commonly perceived as the effect of surge pricing. Similar to our model, they also consider consecutive periods and strategic driver behavior. The most important distinction is that they consider *predictable* demand surges in the future and show how surge pricing can be used in a counterintuitive way to manage anticipated demand surges. By contrast, we consider *unpredictable* demand surges and study optimal/equilibrium pricing strategies after the surges have already occurred. Their main finding is that surge pricing can be used in a region with *excess* supply to throttle demand and force drivers to move to another region with less supply. By contrast, in our paper, we show that surge pricing can be used in a region with *insufficient* supply to attract drivers from neighboring regions.

Afèche et al. (2018b) consider the transient behavior of a ride-hailing network after an unexpected demand shock of uncertain duration occurs at a hot-spot location. Drivers are geographically dispersed and forward-looking in deciding whether to reposition toward the hot spot given their location-dependent repositioning delay and payoff risk. Their paper compares the performance of various dynamic platform policies for setting rider prices and driver wages, considering the interplay of three timescales, rider patience, demand shock duration, and drivers' repositioning delays. Whereas we focus on the interplay of forward-looking riders and strategic drivers in one location, Afèche et al. (2018b) focus on geographically dispersed, myopic riders and strategic drivers. Therefore, their model of surge pricing lacks the intertemporal demand response to surge pricing, which is a pivotal element in our model.

One critical difference between our paper and these two papers is that we model *forward-looking riders* and investigate the interplay of strategic riders and drivers. Specifically, we focus on the intertemporal effects of surge pricing; that is, pricing in one period can affect the supply of drivers as well as the demand of riders in the next period. The adopted two-period model is commonly seen in the literature of strategic (forward-looking) customer behavior; see, for example, Shen and Su (2007), Cachon and Swinney (2009), Cachon and Feldman (2015), and Papanastasiou and Savva (2016). In summary, our paper complements the growing literature on ride-hailing markets by taking a temporal perspective and makes the unique contribution of capturing riders' and drivers' two-sided strategic responses to surge pricing on different timescales.

3. Model

We adopt a two-period model to capture riders' and drivers' different response timescales to surge pricing and their resulting strategic behavior with each period representing roughly 5–10 minutes of real time. At the beginning of period 1, a total volume of one (continuous, normalized) driver is available in a small region, and a total volume of $r > 1$ (continuous) riders appear in the same region, constituting a demand surge. Hence, we model unpredictable demand surges for which surge pricing is implemented reactively. The riders' incremental valuations of getting rides from the platform, net of their next best options (taking a bus, asking a friend for a ride, forgoing the trip, etc.), are assumed to be distributed uniformly between zero and one. Each unit of riders requires one unit of drivers to provide service. For simplicity, we assume that the destinations are outside of the demand-surge region; thus, once matched, both rider and driver leave the region permanently. For tractability and following conventions of the strategic behavior literature, we assume all information to be public. Although this is clearly a simplification of reality, throughout the paper, we show that, in some cases, the full-information assumption is a reasonable approximation, and in other cases, it has meaningful managerial implications.

In period 1, the platform sets price p_1 for the period. Given the price p_1, some riders request rides in this period, some strategically wait out period 1 and request rides only in period 2, and the rest never request rides. The riders requesting rides in period 1 and currently available drivers are randomly matched. (Random matching is a direct consequence of the fact that the platform does not know each individual rider's exact valuation.) Based on prevalent ride-hailing pricing practices, we assume that, out of each matched rider's paid price p_1, γp_1 goes to the driver and $(1-\gamma)p_1$ goes to the platform, where $\gamma \in (0,1)$ is an exogenous payout rate. We do not model drivers strategically turning down matched riders because ride-hailing platforms generally strongly discourage drivers from rejecting matched rides. For example, Uber drivers who reject requests risk being locked out of the system for up to 15 minutes (McFarland 2016); hence, it is extremely unlikely for drivers to strategically decline matched rides.

If riders who request rides outnumber currently available drivers, each rider, regardless of valuation, has the same likelihood of not getting a ride. This mechanism is the so-called "proportional rationing" (see, e.g., Tirole 1988, pp. 213–214). If drivers outnumber riders, all riders receive rides, and excess drivers remain in the surge region for the next period. We denote by ρ_i^r, $i = 1, 2$ the likelihood that a rider in period i is matched with a driver in the current period. On the other hand, drivers currently not in the region or in the region but unavailable to provide service in period 1, can decide to chase the surge and make themselves available at cost c with a key assumption that *they only become available in period 2*. This assumption captures drivers' relatively slower responses to surge pricing. We denote by d the volume of incoming drivers in period 2 and by ρ_2^d the resulting likelihood that a driver in period 2 is matched with a rider. (The drivers' likelihood of being matched in period 1 is easy to express with other parameters; thus, we do not dedicate a symbol to it.) We focus the base model on the temporal perspective and ignore the spatial perspective by assuming a fixed c for all drivers. In Section 5.1, we incorporate spatial elements into the model by allowing c to depend on the distance a driver must travel to the surge region, which, in turn, depends on the driver distribution around the surge region.

In period 2, new drivers who decided in period 1 to react to the initial price p_1 arrive in the surge region to join any remaining drivers, and the platform sets the second-period price p_2. The remaining riders from period 1 then decide whether to request rides, and those who do are again randomly matched with available drivers. (In the base model, we assume that no new riders other than those who arrived in period 1 but decided to wait out the surge appear in period 2. This assumption is relaxed in Section 5.4.) Riders' valuations of getting rides in period 2 are discounted by a factor of $\alpha \in (0,1)$ to capture the disutility of waiting. However, riders, drivers, and the platform do not discount payments made in period 2 because 5–10 minutes is too short to generate any meaningful financial discounting. Riders failing to receive rides in period 2 take their next best options and gain zero utility.

All decision makers are assumed to be risk-neutral, expected-profit/utility maximizers. Consistent with the strategic behavior literature, we adopt the concept of rational expectation equilibria; that is, we assume a period 1 outcome, solve for the subsequent period 2 outcome and, in turn, require the assumed period 1 outcome to be optimal given the subsequent period 2 outcome. The exact definition is as follows.

Definition 1 (Rational Expectation Equilibria). A subgame perfect Nash equilibrium with rational expectations $(p_1^*, p_2^*, d, \rho_1^r, \rho_2^r, \rho_2^d)$ to the game among the firm, riders, and drivers satisfies

1. The firm in period 1 sets the price p_1^* to maximize the expected total profits over two periods subject to its belief about the number of new drivers arriving at period 2, $\hat{d}$. That is, $p_1^* = \arg\max_{p_1}[\min\{(1-\underline{v})r, 1\}p_1 + \pi_2^*(\underline{v}, \hat{d})]$, where $\underline{v}$ is the valuation of those customers who would be indifferent between making a request in period 1 or not, $\pi_2^*(\underline{v}, \hat{d})$ is the optimal profit of period 2 (see Equation (2)), and p_2^* is the optimal price of period 2 that achieves the optimal profit.
2. Riders in period 1 make their request decision given the observed price p_1^* and subject to their beliefs about the price of period 2, $\tilde{p}_2$, and their matching probabilities in periods 1 and 2, $\tilde{\rho}_1^r$ and $\tilde{\rho}_2^r$. Specifically, a rider with valuation v makes a request if $\tilde{\rho}_1^r(v - p_1^*) + (1-\tilde{\rho}_1^r)\tilde{\rho}_2^r(\alpha v - \tilde{p}_2) \ge \tilde{\rho}_2^r(\alpha v - \tilde{p}_2)$ in the scenario $\alpha v \ge \tilde{p}_2$ or $v \ge p_1^*$ in the scenario $\alpha v \le \tilde{p}_2$.
3. Drivers who may be available in period 2 make their joining decisions subject to their beliefs about the price of period 2, $\breve{p}_2$, and their matching probability in period 2, $\breve{\rho}_2^d$. Specifically, they make themselves available in the surge region if $\gamma \breve{p}_2 \breve{\rho}_2^d \ge c$.
4. Beliefs are consistent with equilibrium outcomes, that is, $\tilde{p}_2 = \breve{p}_2 = p_2^*$, $\hat{d} = d$, $\tilde{\rho}_1^r = \rho_1^r$, $\tilde{\rho}_2^r = \rho_2^r$, and $\breve{\rho}_2^d = \rho_2^d$.

4. Surge-Pricing Equilibria

To solve the model, we first take the riders' perspective. In an equilibrium, riders form rational expectations about ρ_1^r and ρ_2^r—matching probabilities in periods 1 and 2 for all riders requesting rides ($\rho_i^r = 1$ if available drivers outnumber riders requesting rides in period i, $i = 1, 2$, otherwise, $\rho_i^r < 1$)—and about p_2 in period 2. Given the expectations, the following lemma characterizes riders' requesting decisions based on their valuations and is illustrated in Figure 1. Recall that α is the valuation discount factor for riders taking rides in period 2.

Lemma 1. *Suppose the platform sets prices p_1 and p_2 in periods 1 and 2, respectively, and riders form rational expectations ρ_1^r and ρ_2^r about their matching probabilities in periods 1 and 2, respectively.*

a. *Suppose $p_1 \ge p_2/\alpha$. Riders with high valuations $v \ge \underline{v} \doteq (p_1 - \rho_2^r p_2)/(1 - \alpha\rho_2^r)$ request rides in period 1 and, if not matched, wait and continue to request rides in period 2. Riders with medium valuations $v \in [p_2/\alpha, \underline{v})$ wait through period 1 and only request rides in period 2. The remaining low-valuation riders never request rides and leave the platform immediately.*

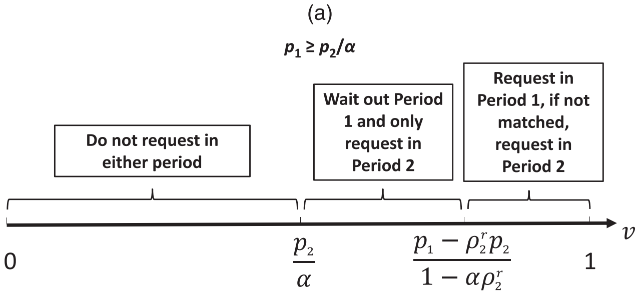
b. *Suppose $p_1 < p_2/\alpha$. Riders with high valuations $v \ge \underline{v} \doteq p_1$ request rides in period 1. Of riders requesting rides but not matched in period 1, those with valuations $v \ge p_2/\alpha$ remain on the platform and continue to request rides in period 2, and those with valuations $v \in [\underline{v}, p_2/\alpha)$ leave the platform and do not request rides in period 2. Riders with low valuations $v < \underline{v}$ never request rides and leave the platform immediately.*

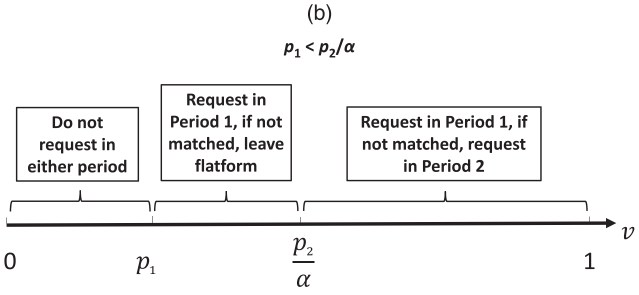
Based on the lemma, we next consider the platform's pricing strategies and identify equilibria of the model. A simple case is when incoming drivers' cost c is sufficiently high. In this case, the platform sets a "greedy" optimal price in period 1, disregarding period 2, and any remaining riders and drivers leave the platform after period 1. The following proposition describes this case.

Proposition 1 (Greedy Surge Pricing (GSP)). *In the equilibrium characterized in Table A.1, riders and drivers not matched in period 1 leave the platform, matching does not occur in period 2, and the platform sets the optimal price myopically for period 1.*

The greedy surge pricing equilibrium is intuitive: when drivers' outside opportunities are sufficiently appealing (i.e., c is sufficiently high), the platform gives up attracting drivers in period 2 and focuses on maximizing the profit in period 1 only. Such an equilibrium captures the scenarios of extreme and large-scale demand surges, in which attracting new drivers is infeasible although this scenario is neither highly representative nor very interesting.

Figure 1. Riders' Requesting Decisions Based on Their Valuations





Next, we consider cases in which c is not excessively high and matching may occur in period 2. Recall from Lemma 1 that only riders with valuations above a threshold $\underline{v}$ request rides in period 1. Therefore, two types of riders may request rides in period 2: those with valuations above $\underline{v}$ who requested but did not get rides in period 1 and those with valuations below $\underline{v}$ who did not request rides in period 1. The latter type exists only when the second-period price is sufficiently attractive. Recall that ρ_1^r is the riders' matching probability in period 1. Given the second-period price p_2, the total volume of riders requesting rides in period 2 is given by

$$q(p_2) \doteq \begin{cases} \left(1 - \dfrac{p_2}{\alpha}\right)(1-\rho_1^r)r, & \text{if } p_2 \geq \alpha\underline{v}, \\ (1-\underline{v})(1-\rho_1^r)r + \left(\underline{v} - \dfrac{p_2}{\alpha}\right)r, & \text{if } p_2 \leq \alpha\underline{v}. \end{cases} \tag{1}$$

We denote the volume of remaining drivers at the end of period 1 by $y \doteq [1-(1-\underline{v})r]^+$ and the volume of drivers arriving in the surge region in period 2 by d. Given $\underline{v}$, y, and d, the platform sets the optimal period 2 price to maximize the second-period profit; that is,

$$\pi_2^* \doteq \max_{p_2}[(1-\gamma)\min\{q(p_2), y+d\}p_2]. \tag{2}$$

As previously mentioned, p_2^* denotes the optimal solution to (2). The resulting riders' and drivers' matching probabilities in period 2, respectively, denoted by ρ_2^r and ρ_2^d, are given by

$$\rho_2^r = \min\left\{\frac{y+d}{q(p_2^*)}, 1\right\}, \quad \rho_2^d = \min\left\{\frac{q(p_2^*)}{y+d}, 1\right\}.$$

The following lemmas characterize the equilibrium in period 2.

Lemma 2. *Assume c is sufficiently low such that there is matching in period 2: (i) $q(p_2)$ is decreasing in p_2; (ii) $\rho_2^r = 1$ in any equilibrium.*

Lemma 2(i) is intuitive. Lemma 2(ii) states that, in any equilibrium, when there is matching in period 2, because everything can be correctly anticipated, additional drivers arrive such that all those riders who want to make a request in period 2 can be served.

Lemma 3. *The conditions and equilibrium outcomes in period 2 are provided in Table A.2.*

Based on period 2's equilibrium outcomes, we characterize two types of equilibrium in the next two propositions, in addition to GSP, which is presented in Proposition 1.

Proposition 2 (SSP)**.** *In the equilibrium characterized in Table A.3, matching occurs in both periods, and the platform's prices are such that $p_1^* > p_2^*/\alpha(> p_2^*)$, namely a high price followed by a (waiting-adjusted) low price.*

The SSP equilibrium is named for its resemblance to the *price skimming* strategy in marketing, in which the price of a product or a service is initially set high and lowered over time to maximize revenue. The SSP equilibrium is consistent with ride-hailing platforms' current surge-pricing practices, which often exhibit a short-lived sharp price surge followed by lower prices. The fundamental logic of the SSP equilibrium is that the platform sets a high price in period 1 and lowers it in period 2 so that a group of relatively high-value riders are willing to forgo immediately requesting rides and wait until period 2 in anticipation of the arrival of additional drivers. The presence of these riders in period 2, in turn, attracts drivers to come to the surge region in period 2, thus completing the circle and forming a rational expectations equilibrium. Because this equilibrium is simply meant to attract incoming drivers, it occurs when incoming drivers' opportunity cost c is small.

The SSP equilibrium matches very well the observation that ride-hailing platforms frequently set short-lived sharp surge prices followed by lower prices. This surge-pricing practice often draws public outcry that the platform gouges riders during demand surges. The classic economic explanation argues that, because of the mismatch in demand and supply, the platform should charge a higher price to direct the limited supply to those who are willing to pay more, resulting in more efficient resource allocation (measured in terms of total social welfare). By contrast, we identify a more nuanced mechanism of surge pricing and show that the platform may want to set an initial surge price much higher than what is justified to make supply meet demand. The initial sharp surge price causes many high-value riders to voluntarily wait out the initial surge period, which serves to attract additional drivers to come to the region despite their slow responses. In addition, recall that we adopt a full-information model and assume that drivers are aware of the demand surge. In practice, drivers do not directly observe the demand surge. However, the sharp surge price sends a strong signal about the surge region having many riders awaiting drivers. Therefore, even though the SSP equilibrium is derived from a full-information model, it still helps us understand the platform's pricing strategies and the riders' and drivers' responses in practice.

To summarize, despite the controversies surrounding sharp surge prices, our analysis justifies such practices by revealing the nuanced mechanism pertaining to temporal structures of surge pricing and strategic behavior of riders and drivers. We recommend that platforms more explicitly explain the nuance behind surge pricing to ease public concerns over sharp surge prices. To their credit, platforms are already doing so to some extent; for example, Uber advises riders to "wait a few minutes to see if the rates go back down to normal" (Uber 2018). Such arguments may be much more convincing if supported by an in-depth explanation of the mechanism as revealed earlier.

Interestingly, our analysis also uncovers another surge-pricing strategy that attracts drivers through a completely different mechanism.

Proposition 3 (PSP). *In the equilibrium characterized in Table A.4, matching occurs in both periods, and the platform's prices are such that $p_1^* < p_2^*/\alpha$, namely a low price followed by a high (waiting-adjusted) price.*

The PSP equilibrium is named for its resemblance to the *penetration pricing* strategy in marketing, in which the price of a product or a service is initially set low to quickly grow its market share and later increased to a normal level. A PSP equilibrium presents a drastically different approach to surge pricing with a moderate and delayed price increase. Notably, the initial period 1 price is below the minimum price to attract drivers, c/γ (which turns out to be the period 2 price in PSP); in other words, the platform *strategically deflates* the period 1 price despite the driver shortage. This observation is in stark contrast with the SSP equilibrium, in which the platform strategically inflates the period 1 price beyond the level that micromatches supply and demand. The fundamental logic of the PSP equilibrium is that the platform sets a low price in period 1 to entice many riders into requesting rides. This leads to random matching, and consequently, many high-value (alongside low-value) riders are forced to wait out the initial surge period; they do not leave the platform in anticipation of additional drivers arriving soon. The presence of these riders in period 2, in turn, attracts drivers to come to the surge region in period 2, thus completing the circle and forming a rational expectations equilibrium. Unlike the SSP policy, the PSP policy maximizes period 1 rider–driver matching and is more efficient. The downside is that there may not be sufficient riders left to attract drivers in period 2. Therefore, the policy is most suitable for heavy demand surges with high values of r.

Notably, the PSP equilibrium may coexist with the GSP or SSP equilibria in certain parameter regions, providing an opportunity to compare these different approaches to surge pricing. We use the superscript to indicate the equilibrium type.

Proposition 4 (PSP versus GSP/SSP). *In parameter regions where PSP equilibrium coexists with GSP or SSP equilibria,*

i. *The platform profit is always higher under PSP than GSP and can be higher than SSP: $\pi^{PSP} \geq \pi^{GSP}$ and π^{PSP} can be higher than π^{SSP}.*

ii. *The matching volume is always higher under PSP than GSP or SSP: $V^{PSP} \geq V^{GSP}$ or V^{SSP}.*

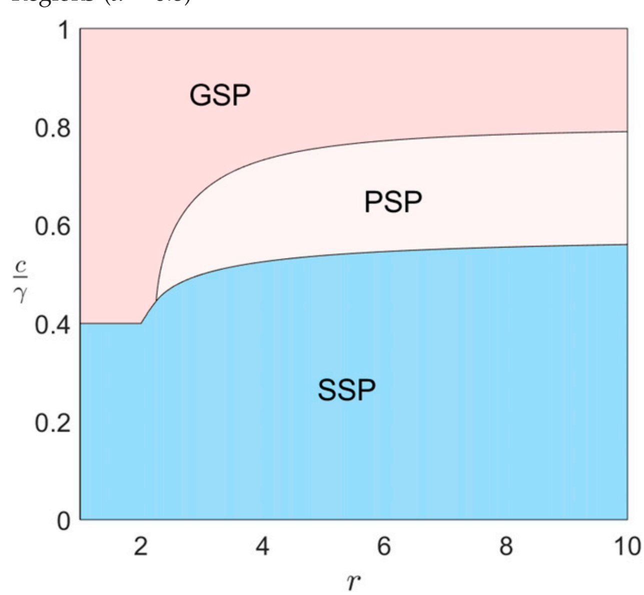
iii. *The period 2 price is always lower under PSP than SSP (which implies the same for the period 1 price): $(p_1^{PSP} <)p_2^{PSP} \leq p_2^{SSP}(< p_1^{SSP})$; the period 1 price is always lower under PSP than GSP: $p_1^{PSP} \leq p_1^{GSP}$.*

iv. *The price gap between the two periods is always lower under PSP than SSP: $0 \leq p_2^{PSP} - p_1^{PSP} \leq p_1^{SSP} - p_2^{SSP}$.*

Proposition 4 shows that PSP is superior in several ways to GSP or SSP whenever these equilibria coexist. Parts (i) and (ii) state that PSP policies are preferable in terms of matching volumes and, hence, social efficiency, and can often be superior in terms of platform profitability (see Figure A.1 for a numerical comparison of GSP, SSP, and PSP). Note that, although we model a profit-maximizing platform, in practice, a platform may also consider other objectives, such as user experience and the platform's growth. The matching volume is a useful performance metric related to such nonprofit objectives, and it is notable that PSP policies outperform GSP or SSP policies in terms of the matching volume.

Although both PSP and SSP operate on the fundamental principle of keeping high-value riders around to attract drivers to the current region, PSP does so with lower prices, which increases the matching volume and often boosts the platform profit as well. Part (iii) states that PSP policies lead to lower prices than SSP across both periods. In the meantime, PSP policies incorporate gradual price increases in lieu of the short-lived sharp price surges under SSP, which have caused controversies. Part (iv) complements part (iii) and shows that, not only do prices under PSP move in the opposite

Figure 2. (Color online) GSP, SSP, and PSP Equilibrium Regions ($\alpha = 0.8$)



direction of those under SSP, but the price variability is also lower under PSP than SSP. These advantages speak volumes to the potential advantages of adopting PSP to replace the current SSP policies. However, unlike under the SSP policy, in which some riders in period 1 voluntarily choose to wait for the price to go down, under the PSP policy, riders not matched in period 1 are forced to wait while the price goes up. Psychologically speaking, the same amount of wait under PSP may feel longer for riders than that under SSP. Although we make such an informal observation, we do not model this aspect and leave it to future potential behavioral studies.

Despite the theoretical advantages, PSP is not commonly observed in practice. We believe that a key factor may be the information structure. Recall that we adopt a full-information model, which assumes drivers are aware of the demand surge even without a sharp price surge. Currently, drivers on most ride-hailing platforms have no access to such information. This discrepancy may explain why the PSP equilibrium is not common. It, however, does not mean that our discovery has no practical value. On the contrary, our findings suggest that the theoretical advantages of PSP policies may be unleashed if platforms inform drivers of demand–supply information. One approach is to display a real-time map of request-to-driver ratios. Incidentally, the Land Transport Authority of Singapore implements such a system, called the Driver Guidance System, for local GrabTaxi drivers to highlight regions of adjacent demand surges on a map (Driver Guidance System 2018). An alternative approach is to commit to future (i.e., period 2 in our model) price surges. For example, if a platform commits to a driver that, in 15 minutes, the price in an adjacent region will surge to a certain level for at least 10 minutes (while keeping the current price at a normal level), it is a clear signal that the platform is experiencing a demand surge in that region and intends to adopt a PSP policy. Therefore, our findings from the full-information model provide meaningful managerial implications. At a high level, informing drivers of demand–supply information would mark a departure from the prevalent ride-hailing practice of managing demand and supply with the sole lever of pricing. Incidentally, practitioners have also argued that ride-hailing platforms should utilize additional tools to manage demand surges rather than depending solely on pricing (*Economist* 2016). Adopting such strategies requires fundamental changes to current practices and will inevitably meet hurdles. Our theoretically predicted improvements in efficiency and mitigation of controversies surrounding sharp price surges may provide a justification for overcoming these hurdles.

Suppose the platform informs drivers of demand–supply information, and thus, the PSP equilibrium exists. In cases of multiple equilibria of different types, we assume that the platform selects the one that maximizes its expected profit. The resulting equilibrium regions are illustrated in Figure 2. To understand the intuitions behind the regions, note that, when incoming drivers' costs are sufficiently high, the platform cannot attract drivers to the surge region and has to resort to GSP. With moderate incoming drivers' costs, the platform can attract drivers to the surge region using two drastically different approaches. SSP uses a short-lived, sharp price surge to strategically keep high-value riders waiting to attract drivers, which is a targeted approach and works with any level of demand surge; however, because of the high initial price, it is less efficient, and the inefficiency rises with incoming drivers' costs. Therefore, SSP is suitable for relatively low incoming drivers' costs. By comparison, PSP uses a low initial price to keep riders waiting to attract drivers, which is more efficient, especially with high incoming drivers' costs, but works only for heavy demand surges.

Next, we consider the impact of α, which measures the riders' patience. Intuitively, when riders are more patient, they are more likely to wait until period 2; therefore, the GSP region should shrink. Furthermore, we know that the PSP policy is more suitable for heavier demand surges, and we may expect that, for larger values of r, the PSP region grows and that, for smaller values of r, the SSP region grows when riders are more patient. These intuitions are confirmed in the following proposition and illustrated in Figure 3.

Proposition 5. *As α increases, the GSP region defined for Figure 2 shrinks. Furthermore, for $r \le 2/\sqrt{\alpha}$, the SSP region grows; otherwise, the PSP region grows.*

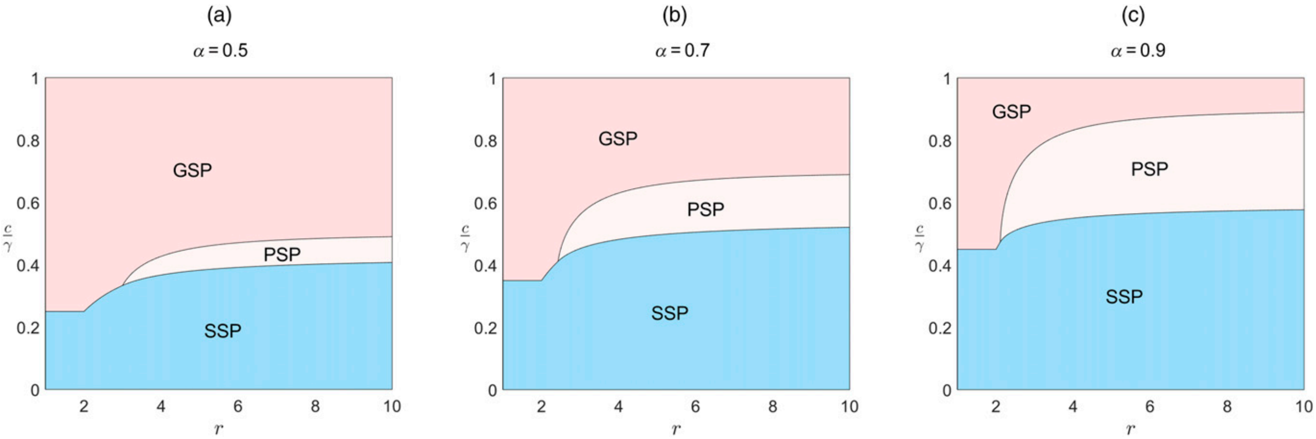
To summarize, we fully characterize the equilibria of the game and identify three types of equilibrium. The SSP equilibrium matches the observed practices of platforms setting sharp and short-lived surge prices and reveals a nuanced mechanism behind such practices. The PSP equilibrium, characterized by gradual and moderate price increases, is superior to the SSP equilibrium in efficiency when they coexist but requires platforms to share demand–supply information with drivers. The GSP is a less interesting extreme case that completes the analysis.

5. Extensions

5.1. Temporal–Spatial Model

Our base model focuses on the temporal dimension although spatial aspects of surge pricing are ignored for clean insights. The lack of spatial consideration is captured by the assumption that all incoming drivers incur the same cost c. In this extension, we consider

Figure 3. (Color online) Equilibrium Regions Under Various α



that additional drivers are distributed around the surge region; as such, when more drivers come to the surge region, they need to travel longer distances at higher costs.

Specifically, we assume that by attracting a total of d drivers in period 2, the cost of the marginal (last increment of) incoming driver is $c_0 + c_1 f(d)$. The term c_0 represents fixed costs, such as getting off the couch. The term c_1 represents per-travel-distance costs, such as the fuel cost. The increasing function $f(d)$ represents the marginal incoming driver's travel distance as a function of d and is determined by the driver distribution around the surge region. Our general observation is that the same types of equilibria still exist. Therefore, the structural insights derived from our base model continue to hold when accounting for spatial aspects of surge pricing.

Proposition 6. *When incoming drivers' costs are in the form of $c_0 + c_1 f(d)$, the equilibrium can only be in the form of the GSP, SSP, and PSP equilibria. In particular, for $f(d) = d$, all equilibria are fully characterized in Tables A.5–A.7.*

We next investigate the quantitative impacts of different driver distributions. In particular, we consider two specific scenarios with equal total numbers of drivers in the same region with the surge point in the center. In the first scenario, we suppose drivers are uniformly distributed around the point of a demand surge at unit density; the uniformly distributed drivers are representative of large metropolitan areas. It would be reasonable to assume that surge pricing always attracts drivers from a disc of a particular radius l. It, thus, follows that $d = \pi l^2 \Rightarrow l = \sqrt{d/\pi}$. Therefore, the cost of the marginal incoming driver is $c_0 + c_1\sqrt{d/\pi}$. We assume that there are a total of $\bar{d}$ drivers distributed in a disc of a radius $\bar{l} = \sqrt{\bar{d}/\pi}$ with the surge point in the center.

In the second scenario, we suppose the driver distribution to be denser closer to the surge region, which is typical for smaller towns. In particular, we assume that the driver density at distance l from the demand surge point is $\bar{l}/(2l)$. The scale factor $\bar{l}/2$ is chosen such that a total of $\bar{d}$ drivers are located within a radius of $\bar{l}$, identical to the first scenario. One can derive that, when attracting d drivers, the marginal driver travels $d/\sqrt{\pi\bar{d}}$, and the cost of the marginal incoming driver is $c_0 + c_1 d/\sqrt{\pi\bar{d}}$, which increases faster in d than that in the first scenario.

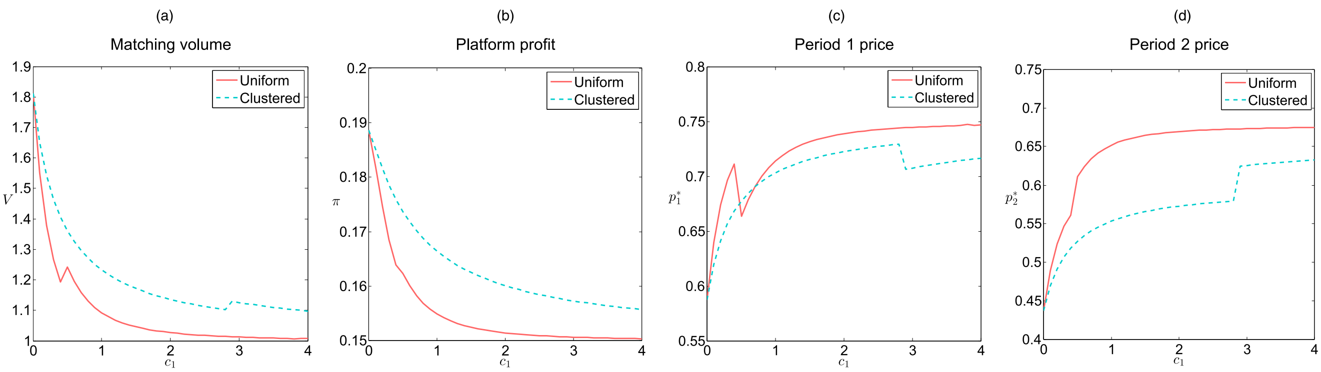
Figure 4 compares the platform profit π, matching volume V, and both periods' prices p_1^* and p_2^* against varying per-travel-distance costs c_1 for the aforementioned uniform and concentrated driver distribution scenarios. It can be observed that the clustered driver distribution generally yields lower equilibrium prices (except at jumps between equilibria) and higher platform profits π and matching volumes V than the uniform driver distribution. This observation is intuitive given that it is easier to attract drivers when they are concentrated around the surge area, improving system efficiency and platform profitability.

5.2. Myopic Surge Pricing

Thus far, we have assumed that the platform is aware of and accounts for drivers' and riders' strategic behavior in setting surge prices. What would be the impact if the platform neglects such strategic behavior? In this extension, we consider a myopic platform that sets prices to maximize its profit in each period, assuming all riders with values above the prices request rides, whereas the riders and drivers actually still behave strategically (i.e., anticipating future outcomes and making current decisions accordingly). We refer to such a policy as *myopic surge pricing* (MSP). The following proposition presents the MSP policy.

Proposition 7 (MSP). *The MSP policy is fully characterized in Table A.8. Under such a policy, matching can occur only in period 1, only in period 2, or in both periods. When the matching occurs in period 2, the platform's prices are such that $p_1 > p_2/\alpha$, namely a high price followed by a low (waiting-adjusted) price.*

Figure 4. (Color online) Equilibrium Outcomes Under Different Incoming Drivers' Costs ($\bar{l} = 4$, $\alpha = 0.8$, $\gamma = 0.8$ $c_0 = 0.35$, $\bar{d} = 2$)



Given that the platform neglects riders' and drivers' strategic behavior, the pricing may be unbalanced, leading to no matching in either period. One may expect that, in all important metrics, MSP policy should be mostly worse than the strategic equilibria in Section 4, in which the platform accounts for drivers' and riders' strategic behavior. Analytically, we can only partially characterize the comparison because of the complexity (see Proposition A.1), and we focus on numerically comparing strategic and myopic policies in Figure 5. The myopic policies are indeed largely outperformed or at least matched by strategic equilibria in terms of the platform profit, matching volume, and driver/rider surplus. These findings point to potentially dire consequences of a platform's myopic pricing aimed at micromatching currently available riders and drivers. Therefore, it is important for ride-hailing platforms to recognize and account for riders' and drivers' different response timescales and corresponding strategic behavior when setting prices.

5.3. Mixed Strategic and Myopic Riders

Although the base model assumes that all riders are strategic for simplicity, in reality, only a proportion of consumers may be strategic (Li et al. 2014). In fact, mixed strategic and myopic customers may even be an endogenized outcome (Aflaki et al. 2020). In this extension, we assume only a θ proportion of riders are strategic. The remaining $1 - \theta$ proportion of myopic riders always request rides in period 1 as long as the price is below their valuation and leave if they are not matched.

Proposition 8. *When a θ proportion of all r riders are strategic and the remaining $1 - \theta$ proportion are myopic, the GSP equilibria remain the same as in Table A.1, and the SSP and PSP equilibria are fully characterized in Table A.9. In addition, Proposition 4 continues to hold.*

Proposition 8 shows that PSP policies are still superior to SSP and GSP policies even in the presence of myopic riders. The next proposition introduces how mixed strategic and myopic riders impact the equilibrium structure.

Proposition 9. *As more riders are strategic (i.e., θ increases), the PSP region grows and the SSP and GSP regions (including that overlapped with PSP) remain unchanged as with all strategic customers. In addition, as θ increases, p_1^* under the PSP equilibrium decreases, p_2^* remains unchanged, and V^{PSP} and π^{PSP} increase.*

When more riders are strategic, there are generally more available riders in period 2 because strategic riders may wait out period 1. Therefore, the PSP policy is more likely to arise to capitalize on period 2 riders and lead to higher matching volume and profit for the platform. For the same reason, as shown in Proposition 9, with more strategic riders, the platform sets a lower price in period 1 to force more riders into period 2 and improve its profit. Notably, when $\theta = 1$, the model is reduced to the base model without myopic riders. When $\theta = 0$, that is, all riders are myopic, no matching occurs in period 2; thus, only GSP equilibria can arise.

Finally, we note that, although Section 5.2 addresses the impact of a myopic platform and Section 5.3 addresses the impact of myopic riders, we have not addressed the impact of myopic drivers. In fact, when some drivers are myopic, the impact is similar to all drivers being strategic but having a higher cost c to come to the surge region (because, in both cases, fewer drivers in the neighboring region respond to the anticipated price in period 2). Therefore, the impact of myopic drivers would be similar to having an increased cost c, which is thoroughly studied in Section 4.

5.4. Incoming Riders in Period 2

Our base model assumes that all riders arrive in period 1 and no riders arrive in period 2. In this extension, we assume an additional r_n riders with the same valuation distribution $U[0,1]$ arrive at the beginning of period 2. Note that, with the incoming riders in period 2, the GSP policy, under which matching occurs only in period 1, becomes irrelevant. With a given r_n, Equation (1) becomes

$$q(p_2) \doteq \begin{cases} \left(1-\frac{p_2}{\alpha}\right)(1-\rho_1^r)r + (1-p_2)r_n, & \text{if } p_2 \geq \alpha\underline{v}, \\ (1-\underline{v})(1-\rho_1^r)r + \left(\underline{v}-\frac{p_2}{\alpha}\right)r + (1-p_2)r_n, & \text{if } p_2 \leq \alpha\underline{v}. \end{cases} \tag{3}$$

Similar to Lemma 2 in the base model analysis, the following lemma characterizes the platform's optimal pricing decision in period 2 with incoming riders.

Lemma 4. *The conditions and equilibrium outcomes with the incoming riders in period* 2 *are provided in Table* A.10.

Lemma 4 allows us to derive the following proposition.

Proposition 10. *With incoming riders in period* 2, *GSP equilibria do not exist. SSP and PSP equilibria are, respectively, characterized in Tables* A.11 *and* A.12.

In Figure 6, we plot the equilibrium outcomes with incoming riders in period 2. Compared with Figure 2, the most prominent difference is the lack of the GSP region: as we noted earlier, the GSP policy is irrelevant in this case. The original GSP region with large values of c is absorbed by the PSP region. The intuition is that, when there are guaranteed period 2 riders, drivers are willing to come to the region even if their costs of doing so are high.

Finally, we note that this model can be extended to allow random incoming riders in period 2; that is, r_n is a random variable. Certain results that depend on the realized r_n remain unchanged, such as those in Table A.10. Other results that require taking expectations with respect to r_n, unfortunately, cannot be analytically obtained. Nevertheless, because our key intuitions are not affected by a random r_n, we expect the observations about Figure 6 to generally hold.

6. Concluding Remarks

Ride hailing is a vital and fast-growing industry in the sharing economy. The business model pioneered by Uber and adopted by most players in the industry is one in which the platform almost entirely dictates the matching process. Surge pricing is the primary lever to manage demand and supply in this scenario. Furthermore, surge pricing is one of the most controversial aspects of ride hailing and has been described as price gouging although major platforms remain committed to the practice. Most of the

Figure 5. (Color online) Differences Between Strategic and Myopic Policies (Strategic − Myopic; $\alpha = 0.8$ and $\gamma = 0.72$)

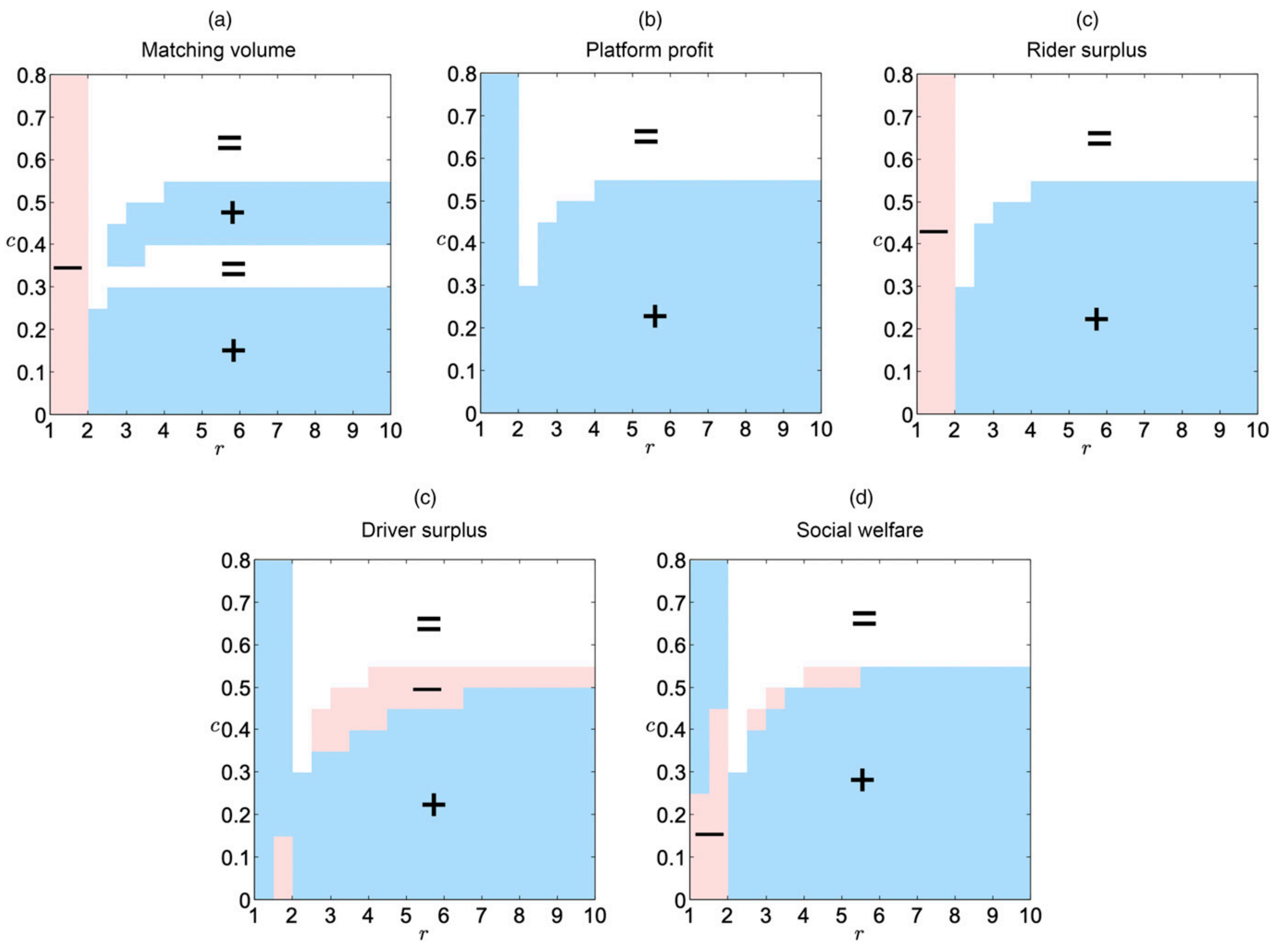
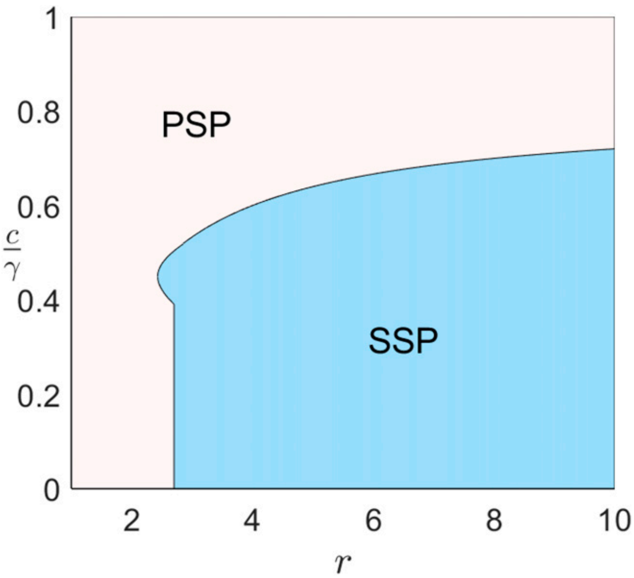


Figure 6. (Color online) Equilibrium Regions with New Arrivals in Period 2 ($\alpha = 0.8$, $r_n = 3$)



literature takes the spatial perspective and treats surge pricing at a location as a simple tool for rebalancing demand and supply, not unlike the methods used in other marketplaces. In this paper, we investigate surge pricing with an emphasis on its temporal characteristics unique to ride hailing. That is, drivers respond to surge pricing more slowly than riders, which results in strategic driver and rider behavior.

We find that the commonly observed pattern of a short-lived, sharp price surge followed by a lower price occurs in an equilibrium, which we refer to as SSP. This finding, to some extent, justifies the controversial sharp price surges by establishing a more nuanced mechanism of how surge pricing works beyond simply setting prices to make supply meet demand. We recommend that platforms more explicitly explain the nuance behind surge pricing to ease public concerns over sharp surge prices.

Interestingly, we also identify another equilibrium surge-pricing strategy, in which the platform sets a low initial price followed by a higher price. We refer to this strategy as PSP. We find that, when coexisting, the PSP equilibrium is superior to the SSP equilibrium in several essential metrics. Although theoretically attractive, practical uses of such a pricing strategy are hindered by drivers' lack of demand–supply information (because it is not signaled by a sharp price surge). We recommend that platforms either directly communicate demand–supply information to drivers or commit to future price surges to be able to adopt the PSP strategy to potentially improve profit and efficiency and mitigate controversies surrounding sharp price surges.

In terms of potential future research directions, we note that our work (as well as most existing literature on ride hailing) models a single platform. Generally, competition to a platform leads to increased costs to attract drivers and reduced rider valuation (relative to alternative options) on the platform. Insights obtained from this work (e.g., Figure 2) suggest that, in these cases, the PSP policy is more likely to outperform the currently prevalent SSP policy. Therefore, our recommendation for adopting the PSP policy is even more relevant when the platform faces competition. A competing platform may further employ sophisticated pricing strategies to counter strategies studied in this paper; see, for example, a recent paper by Bernstein et al. (2021). On the other hand, we note that forced waiting under the PSP policy may feel longer for riders than voluntary waiting under the SSP policy. Similarly, price changes over time may induce behavioral responses from riders; see, for example, a survey by Zheng and Özer (2012). Our study of a single platform with rational players can potentially serve as a basis for future studies of platform competition and the behavioral aspects of ride hailing.

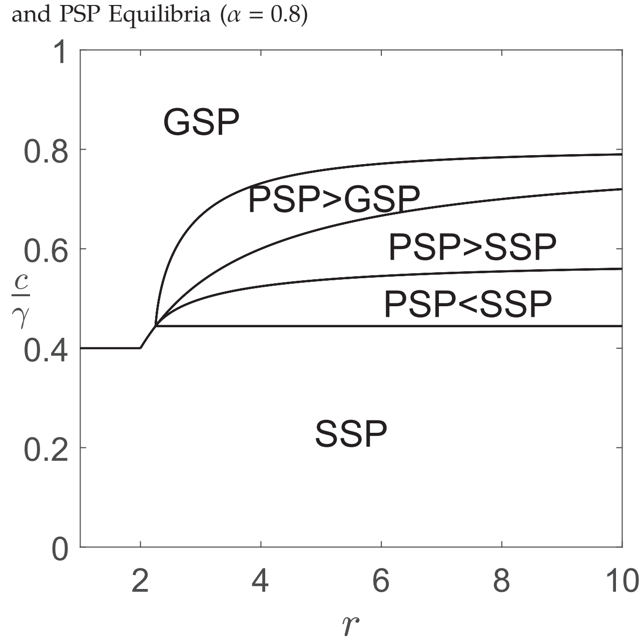
Acknowledgments

The authors gratefully acknowledge Hau Lee (the department editor), the associate editor, and two anonymous referees for their valuable comments, which helped significantly improve this paper.

Appendix

Proposition A.1 (MSP vs. SSP)**.** With sufficiently large r and small $\frac{c}{\gamma}$ (see the proof for specific conditions), comparing the MSP and SSP equilibria, the prices of both periods under

Figure A.1. Comparison of Platform Profit Under GSP, SSP, and PSP Equilibria ($\alpha = 0.8$)



the MSP equilibrium are, respectively, higher than those under the SSP equilibrium, and the social welfare under the SSP equilibrium is also larger than that under the MSP equilibrium.

Table A.1. GSP Equilibria

Equilibrium	GSP1	GSP2
Condition	$\frac{c}{\gamma} \geq \frac{\alpha}{2},\ r \leq 2$	$\frac{c}{\gamma} \geq \alpha\left(1-\frac{1}{r}\right),\ r > 2$
Period 1 price p_1^*	$\frac{1}{2}$	$1-\frac{1}{r}$

Table A.2. Conditions and Outcomes in Period 2

Condition					Solution
$(1-\underline{v})(1-\rho_1^r)r \geq d+y$	$\frac{1}{2}(1-\rho_1^r)r \geq d+y$	—	—	—	1
	$\frac{1}{2}(1-\rho_1^r)r \leq d+y$	—	—	—	2
$(1-\underline{v})(1-\rho_1^r)r \leq d+y$	$\underline{v} \geq \frac{1}{2}$	—	$d+y \geq \frac{1}{2}\cdot[(1-\underline{v})(1-\rho_1^r)+\underline{v}]r$	—	3
		—	$d+y \leq \frac{1}{2}\cdot[(1-\underline{v})(1-\rho_1^r)+\underline{v}]r$	—	4
	$\underline{v} \leq \frac{1}{2}$	$(1-\underline{v})(1-\rho_1^r) \geq \underline{v}$	—	—	2
		$(1-\underline{v})(1-\rho_1^r) \leq \underline{v}$	$d+y \geq \frac{1}{2}\cdot[(1-\underline{v})(1-\rho_1^r)+\underline{v}]r$	$\left[(1-\underline{v})(1-\rho_1^r)+\underline{v}\right]^2 \geq \left(1-\rho_1^r\right)$	3
				$[(1-\underline{v})(1-\rho_1^r)+\underline{v}]^2 \leq (1-\rho_1^r)$	2
			$d+y \leq \frac{1}{2}\cdot[(1-\underline{v})(1-\rho_1^r)+\underline{v}]r$	$(d+y)[(1-\underline{v})(1-\rho_1^r) - \frac{d+y}{r}+\underline{v}] \geq \frac{1}{4}(1-\rho_1^r)r$	4
				$(d+y)[(1-\underline{v})(1-\rho_1^r) - \frac{d+y}{r}+\underline{v}] \leq \frac{1}{4}(1-\rho_1^r)r$	2

Solution	Price p_2^*	Platform profit π_2	Percentage driver matched ρ_2^d
1	$[1-\frac{d+y}{(1-\rho_1^r)r}]\alpha$	$(1-\gamma)(d+y)[1-\frac{d+y}{(1-\rho_1^r)r}]\alpha$	1
2	$\frac{\alpha}{2}$	$\frac{1}{4}(1-\gamma)(1-\rho_1^r)\alpha r$	$\frac{(1-\rho_1^r)r}{2(d+y)}$
3	$\frac{1}{2}[(1-\underline{v})\left(1-\rho_1^r\right)+\underline{v}]\alpha$	$\frac{1}{4}(1-\gamma)\cdot\ [(1-\underline{v})(1-\rho_1^r)+\underline{v}]^2\alpha r$	$\frac{[(1-\underline{v})(1-\rho_1^r)+\underline{v}]r}{2(d+y)}$
4	$\left[(1-\underline{v})(1-\rho_1^r)+\underline{v}-\frac{d+y}{r}\right]\alpha$	$(1-\gamma)(d+y)\cdot\ \left[(1-\underline{v})(1-\rho_1^r)+\underline{v}-\frac{d+y}{r}\right]\alpha$	1

Table A.3. SSP Equilibria

Equilibrium	SSP1	SSP2
Condition	$\frac{c}{\gamma} \leq \frac{\alpha(2-\alpha)}{2(4-3\alpha)}$ $r \leq \frac{4-3\alpha}{2(1-\alpha)}$	$\frac{c}{\gamma} \leq \frac{\alpha}{2}(1-\frac{1}{r})$ $r \geq \frac{4-3\alpha}{2(1-\alpha)}$
Period 1 price p_1^*	$\frac{(2-\alpha)^2}{2(4-3\alpha)}$	$(1-\frac{1}{r})(1-\frac{\alpha}{2})$
Period 2 price p_2^*	$\frac{\alpha(2-\alpha)}{2(4-3\alpha)}$	$\frac{\alpha}{2}(1-\frac{1}{r})$
Equilibrium	**SSP3**	**SSP4**
Condition	$\frac{\alpha}{4} \leq \frac{c}{\gamma} \leq \frac{\alpha}{2}$ $r \leq 2$	$\frac{\alpha}{2}(1-\frac{1}{r}) \leq \frac{c}{\gamma} \leq \alpha(1-\frac{1}{r})$ $r \geq 2$
Period 1 price p_1^*	$\frac{1-\alpha}{2}+\frac{c}{\gamma}$	$(1-\frac{1}{r})(1-\alpha)+\frac{c}{\gamma}$
Period 2 price p_2^*	$\frac{c}{\gamma}$	$\frac{c}{\gamma}$

Table A.4. PSP Equilibrium

Equilibrium	PSP
Condition	$\frac{\alpha}{1+\alpha} \le \frac{c}{\gamma} \le \frac{\alpha}{2} + \sqrt{\frac{\alpha^2}{4} - \frac{\alpha}{r^2}},\ r \ge \frac{2}{\sqrt{\alpha}}$
Period 1 price p_1^*	$1 - \sqrt{\frac{c}{\gamma}(1 - \frac{c}{\alpha\gamma})}$
Period 2 price p_2^*	$\frac{c}{\gamma}$

Table A.5. GSP Equilibria in the Temporal-Spatial Model

Equilibrium	GSP1	GSP2
Condition	$\frac{c_0}{\gamma} \ge \frac{\alpha}{2},\ r \le 2$	$\frac{c_0}{\gamma} \ge \alpha(1 - \frac{1}{r}),\ r > 2$
Period 1 price p_1^*	$\frac{1}{2}$	$1 - \frac{1}{r}$

Table A.6. SSP Equilibria in the Temporal-Spatial Model

Equilibrium	SSP1	SSP2
Condition	$c_0 + c_1[\frac{(6-5\alpha)r}{2(4-3\alpha)} - 1] \le \frac{(2-\alpha)\alpha\gamma}{2(4-3\alpha)}$ $r \le \frac{4-3\alpha}{2(1-\alpha)}$	$\frac{r-1}{2}c_1 + c_0 \le \frac{1}{2}\left(1 - \frac{1}{r}\right)\alpha\gamma$ $r \ge \frac{4-3\alpha}{2(1-\alpha)}$
Period 1 price p_1^*	$\frac{(2-\alpha)^2}{2(4-3\alpha)}$	$\left(1 - \frac{1}{r}\right)\left(1 - \frac{\alpha}{2}\right)$
Period 2 price p_2^*	$\frac{\alpha(2-\alpha)}{2(4-3\alpha)}$	$\frac{\alpha}{2}\left(1 - \frac{1}{r}\right)$
Equilibrium	**SSP3**	**SSP4**
Condition	$\alpha\gamma \le (3r-4)c_1 + 4c_0,\ r \le 2$ $\alpha\gamma \ge (r-2)c_1 + 2c_0$	$c_0 \le (1 - \frac{1}{r})\alpha\gamma,\ r \ge 2$ $\frac{r-1}{2}c_1 + c_0 \ge \frac{1}{2}\left(1 - \frac{1}{r}\right)\alpha\gamma$
Period 1 price p_1^*	$\frac{1-\alpha}{2} + p_2^*$	$(1 - \frac{1}{r})(1 - \alpha) + p_2^*$
Period 2 price p_2^*	$(1 - \frac{\alpha\gamma + c_1 - c_0}{\alpha\gamma + c_1 r})\alpha$	$(1 - \frac{\alpha\gamma + c_1 - c_0}{\alpha\gamma + c_1 r})\alpha$

Note. Here, $\rho_2^{d,SSP1} = \frac{2(c_0 + c_1 d)}{\alpha\gamma\underline{v}}$, $d^{SSP1} = \frac{-(c_0 + c_1 y) + \sqrt{(c_0 + c_1 y)^2 - 4c_1[c_0 y - (\frac{1}{2}\underline{v})^2\alpha\gamma r]}}{2c_1}$, where $y = 1 - (1 - \underline{v})r$.

Table A.7. PSP Equilibria in the Temporal-Spatial Model

Equilibrium	PSP
Condition	$(1 - \underline{v})(r - \frac{1}{1 - p_1^{PSP}}) > d,\ \frac{1}{2}(r - \frac{1}{1 - p_1^{PSP}}) > d,\ p_1^{PSP} < 1 - \frac{1}{r}$
Period-1 price p_1^*	p_1^{PSP}
Period-2 price p_2^*	$\frac{c_0 + c_1 d}{\gamma}$

Table A.8. MSP Equilibria

Equilibrium	MSP1	MSP2	MSP3 (GSP2)
Condition	$\frac{c}{\gamma} \le \frac{\alpha}{2-\alpha}(1-\frac{1}{r})$ $\alpha \le \frac{2}{r}$	$\frac{\alpha}{2-\alpha}(1-\frac{1}{r}) \le \frac{c}{\gamma} \le \alpha(1-\frac{1}{r})$ $\alpha \le \frac{1}{r}+\frac{c}{\gamma}$	$\frac{c}{\gamma} \ge \alpha(1-\frac{1}{r})$
Period 1 price p_1^*	$1-\frac{1}{r}$	$1-\frac{1}{r}$	$1-\frac{1}{r}$
Period 2 price p_2^*	$\frac{\alpha}{2-\alpha}(1-\frac{1}{r})$	$\frac{c}{\gamma}$	—

Equilibrium	MSP4	MSP5
Condition	$\frac{c}{\gamma} \le \frac{\alpha}{2}$ $\{\frac{c}{\gamma} \le \frac{\alpha}{2-\alpha}(1-\frac{1}{r}), \alpha \ge \frac{2}{r}\}$ or $\{\frac{\alpha}{2-\alpha}(1-\frac{1}{r}) \le \frac{c}{\gamma} \le \alpha(1-\frac{1}{r}), \alpha \ge \frac{1}{r}+\frac{c}{\gamma}\}$	$\frac{c}{\gamma} \ge \frac{\alpha}{2}$
Period 1 price p_1^*	$1-\frac{1}{r}$	$1-\frac{1}{r}$
Period 2 price p_2^*	$\frac{\alpha}{2}$	$\frac{c}{\gamma}$

Table A.9. SSP/PSP Equilibria with Mixed Strategic and Myopic Riders

Equilibrium	SSP1	SSP2
Condition	$\frac{c}{\gamma} \le \frac{\alpha(2-\alpha)}{2[(2-\alpha)^2+\alpha\theta(1-\alpha)]}$ $r \le \frac{2[(2-\alpha)^2+\alpha\theta(1-\alpha)]}{(2-\alpha)^2-\theta\alpha^2}$	$\frac{c}{\gamma} \le \frac{\alpha(r-1)}{2r-(1-\theta)\alpha r}$ $r \ge \frac{2[(2-\alpha)^2+\alpha\theta(1-\alpha)]}{(2-\alpha)^2-\theta\alpha^2}$
Period 1 price p_1^*	$\frac{(2-\alpha)^2}{2[4\theta-3\alpha\theta+(1-\theta)(2-\alpha)^2]}$	$\frac{(r-1)(2-\alpha)}{r[2-\alpha(1-\theta)]}$
Period 2 price p_2^*	$\frac{\alpha(2-\alpha)}{2[(2-\alpha)^2+\alpha\theta(1-\alpha)]}$	$\frac{\alpha(r-1)}{2r-(1-\theta)\alpha r}$
Equilibrium	**SSP3**	**SSP4**
Condition	$\frac{\alpha}{2[2-(1-\theta)\alpha]} \le \frac{c}{\gamma} \le \frac{\alpha}{2}, r \le 2$	$\frac{\alpha(1-\frac{1}{r})}{2-\alpha(1-\theta)} \le \frac{c}{\gamma} \le \alpha(1-\frac{1}{r}), r \ge 2$
Period 1 price p_1^*	$\frac{1-\alpha+2\theta\frac{c}{\gamma}}{2[1-(1-\theta)\alpha]}$	$\frac{(1-\frac{1}{r})(1-\alpha)+\theta\frac{c}{\gamma}}{1-\alpha(1-\theta)}$
Period 2 price p_2^*	$\frac{c}{\gamma}$	$\frac{c}{\gamma}$
Equilibrium	**PSP**	
Condition	$\frac{\alpha}{1+\alpha\theta} \le \frac{c}{\gamma} \le \frac{\alpha}{2} + \sqrt{\frac{\alpha^2}{4} - \frac{\alpha}{\theta r^2}}, r \ge \frac{2}{\sqrt{\alpha\theta}}$	
Period 1, 2 prices p_1^*, p_2^*	$1 - \sqrt{\theta\frac{c}{\gamma}(1-\frac{c}{\alpha\gamma})}, \frac{c}{\gamma}$	

Table A.10. Conditions and Outcomes with Incoming Riders in Period 2

Condition					Solution
$(1-\underline{v})(1-\rho_1^r)r + (1-\alpha\underline{v})r_n \geq d+y$	$(1-\rho_1^r)r + r_n \geq 2(d+y)$	—	—	—	1
	$(1-\rho_1^r)r + r_n \leq 2(d+y)$	—	—	—	2
$(1-\underline{v})(1-\rho_1^r)r + (1-\alpha\underline{v})r_n \leq d+y$	$(1-2\underline{v})(1-\rho_1^r)r \leq (2\alpha\underline{v}-1)r_n$	—	$d+y \geq \frac{1}{2}[(1-\underline{v})(1-\rho_1^r)r + \underline{v}r + r_n]$	—	3
		—	$d+y \leq \frac{1}{2}[(1-\underline{v})(1-\rho_1^r)r + \underline{v}r + r_n]$	—	4
	$(1-2\underline{v})(1-\rho_1^r)r \geq (2\alpha\underline{v}-1)r_n$	$[(1-\underline{v})(1-\rho_1^r) - \underline{v}]r \geq (2\alpha-1)r_n$	—	—	2
		$[(1-\underline{v})(1-\rho_1^r) - \underline{v}]r \leq (2\alpha-1)r_n$	$d+y \geq \frac{1}{2}[(1-\underline{v})(1-\rho_1^r)r + \underline{v}r + r_n]$	$\pi_2^{1,1} \geq \pi_2^{2,1}$	3
				$\pi_2^{1,1} \leq \pi_2^{2,1}$	2
			$d+y \leq \frac{1}{2}[(1-\underline{v})(1-\rho_1^r)r + \underline{v}r + r_n]$	$\pi_2^{1,2} \geq \pi_2^{2,1}$	4
				$\pi_2^{1,2} \leq \pi_2^{2,1}$	2

$\pi_2^{1,1} = \frac{[(1-\underline{v})(1-\rho_1^r)r+\underline{v}r+r_n]^2}{4(\frac{r}{\alpha}+r_n)}$, $\pi_2^{1,2} = (d+y)\frac{(1-\underline{v})(1-\rho_1^r)r+\underline{v}r+r_n-(d+y)}{\frac{r}{\alpha}+r_n}$, $\pi_2^{2,1} = \frac{[(1-\rho_1^r)r+r_n]^2}{4(\frac{(1-\rho_1^r)r}{\alpha}+r_n)}$,

Solution	Price p_2^*	Platform profit π_2	Percentage driver matched ρ_2^d
1	$\frac{(1-\rho_1^r)r+r_n-(d+y)}{\frac{(1-\rho_1^r)r}{\alpha}+r_n}$	$(1-\gamma)\pi_2^{2,2}$	1
2	$\frac{(1-\rho_1^r)r+r_n}{2[\frac{(1-\rho_1^r)r}{\alpha}+r_n]}$	$(1-\gamma)\pi_2^{2,1}$	$\frac{(1-\rho_1^r)r+r_n}{2(d+y)}$
3	$\frac{(1-\underline{v})(1-\rho_1^r)r+\underline{v}r+r_n}{2(\frac{r}{\alpha}+r_n)}$	$(1-\gamma)\pi_2^{1,1}$	$\frac{(1-\underline{v})(1-\rho_1^r)r+\underline{v}r+r_n}{2(d+y)}$
4	$\frac{(1-\underline{v})(1-\rho_1^r)r+\underline{v}r+r_n-(d+y)}{\frac{r}{\alpha}+r_n}$	$(1-\gamma)\pi_2^{1,2}$	1

$\pi_2^{2,2} = (d+y)\frac{(1-\rho_1^r)r+r_n-(d+y)}{\frac{(1-\rho_1^r)r}{\alpha}+r_n}$

Table A.11. SSP Equilibria with Incoming Riders in Period 2

Equilibrium	SSP1	SSP2
Condition	$\frac{c}{\gamma} \le \frac{\underline{v}r+r_n}{2(\frac{r}{\alpha}+r_n)}$ $r \le 2 + \frac{r}{2(\frac{r}{\alpha}+r_n)(1-\alpha)}$	$\frac{c}{\gamma} \le \frac{\underline{v}r+r_n}{2(\frac{r}{\alpha}+r_n)}$ $r \ge 2 + \frac{r}{2(\frac{r}{\alpha}+r_n)(1-\alpha)}$
Period 1 price p_1^*	$[1-\alpha+\frac{r}{2(\frac{r}{\alpha}+r_n)}]\underline{v}+\frac{r_n}{2(\frac{r}{\alpha}+r_n)}$	
Period 2 price p_2^*	$\frac{\underline{v}r+r_n}{2(\frac{r}{\alpha}+r_n)}$	
Equilibrium	**SSP3**	**SSP4**
Condition	$\frac{\underline{v}r+r_n}{2(\frac{r}{\alpha}+r_n)} \le \frac{c}{\gamma} \le \frac{\alpha}{2}$ $r \le 2$	$\frac{\underline{v}r+r_n}{2(\frac{r}{\alpha}+r_n)} \le \frac{c}{\gamma} \le \alpha(1-\frac{1}{r})$ $r \ge 2$
Period 1 price p_1^*	$\frac{1-\alpha}{2}+\frac{c}{\gamma}$	$(1-\frac{1}{r})(1-\alpha)+\frac{c}{\gamma}$
Period 2 price p_2^*	$\frac{c}{\gamma}$	$\frac{c}{\gamma}$

Table A.12. PSP Equilibria with Incoming Riders in Period 2

Equilibrium	PSP1	PSP2	PSP3	PSP4
Condition	$\frac{c}{\gamma} \ge \frac{1}{2}$ $r \le 2$	$\frac{c}{\gamma} \ge \alpha(1-\frac{1}{r})$ $r > 2, \frac{c}{\gamma} \ge \frac{1}{2}$	$\frac{c}{\gamma} \le \frac{1}{2}$ $r \le 2$	$\frac{c}{\gamma} \le \frac{1}{2}, r > 2$ $\alpha(1-\frac{1}{r}) \le \frac{1}{2}$
Period 1 price p_1^*	$\frac{1}{2}$	$1-\frac{1}{r}$	$\frac{1}{2}$	$1-\frac{1}{r}$
Period 2 price p_2^*	$\frac{c}{\gamma}$	$\frac{c}{\gamma}$	$\frac{1}{2}$	$\frac{1}{2}$

Equilibrium	PSP5
Condition	$\frac{\alpha}{1+\alpha} \le \frac{c}{\gamma} \le \frac{\alpha}{2}+\sqrt{\frac{\alpha^2}{4}-\frac{\alpha}{r^2}}, r \ge \frac{2}{\sqrt{\alpha}}, (\frac{2c}{\alpha\gamma}-1)(r-\frac{1}{\sqrt{\frac{c}{\gamma}(1-\frac{c}{\alpha\gamma})}}) \ge (1-\frac{2c}{\gamma})r_n$
Period 1 price p_1^*	$1-\sqrt{\frac{c}{\gamma}(1-\frac{c}{\alpha\gamma})}$
Period 2 price p_2^*	$\frac{c}{\gamma}$
Equilibrium	**PSP6**
Condition	$2\frac{c}{\gamma}(\frac{r-\frac{1}{1-\underline{v}}}{\alpha}+r_n) \le r-\frac{1}{1-\underline{v}}+r_n, (2\underline{v}-1)(r-\frac{1}{1-\underline{v}}) \le (1-2\alpha\underline{v})r_n$
Period 1 price p_1^*	$\underline{v}_0$
Period 2 price p_2^*	$\frac{(1-\underline{v})r-1+(1-\underline{v})r_n}{2[\frac{(1-\underline{v})r-1}{\alpha}+r_n]}$

Note. Here, $\underline{v}_0$ is the solution to $(r-\frac{1}{1-x}+r_n)(\frac{r-\frac{1}{1-x}}{\alpha}+(2-\frac{1}{\alpha})r_n) = 4(\frac{(1-x)r-1}{\alpha}+(1-x)r_n)^2$.

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