Managing Market Mechanism Transitions: Evidence from a Field Experiment*

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Abstract

Online platform design entails deciding on a set of fundamental market mechanisms. As design decisions are often made early in the life of the platform, executives must regularly implement market mechanism changes, while managing the fallout of such transitions. We report on a field experiment conducted during a market design transition on a sharing economy platform, where providers who formerly set rental prices for their assets were randomly assigned to groups with varying levels of pricing control. Even when faced with the prospect of significantly higher revenues, providers retaliate against the centralization of pricing by exiting the platform, reducing asset availability and cancelling transactions. Allowing providers to retain partial control lowers retaliation substantially even though providers do not frequently utilize this additional flexibility. We discuss information asymmetry and divergent incentives as alternative explanations for our results. Our work also highlights the challenges in implementing dynamic pricing in sharing economy platforms and argues that providing partial control is a way to mitigate these challenges.

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1 Introduction

Early online markets, such as eBay and Amazon, have deepened our understanding of the principles underlying the design, operations, and management of online platforms. Today, “sharing economy” and other peer-to-peer (P2P) markets have transcended retail and operate across a range of industries. These platforms aggregate demand, match customers with goods and services, and provide digitized forms of trust. Unlike previous online platforms, these sharing economy markets rely on decentralized and heterogeneous crowds of providers—individuals and small businesses who vary in their size, expertise, and objectives—for their supply of capital and labor (Sundararajan, 2016; Filippas et al., forthcoming).

The greater degree of decentralization frees sharing economy markets from the need to make large asset investments, and allows them to scale more seamlessly. However, absent the typical directive authority and culture-building capabilities that traditional firms use to manage their employees, sharing economy platforms must constantly fine-tune market design in order to maintain some uniformity across what is offered, and to deliver a branded service experience that is of consistent high quality (Sundararajan, 2014). As a result, these platforms represent instances of a new, digitally-enabled firm-market hybrids that span the spectrum between traditional firms and decentralized markets.¹

The mechanisms that comprise a platform’s market design include how prices are set, how reputation systems work, and how market participants search and match. Of course, which mechanism is best—or even possible—can change over time. For example, an effective centralized pricing mechanism, hard to implement in a nascent market, can lead to large efficiency and revenue gains as the platform grows, accumulates transaction data, and conducts experiments. However, transitioning is challenging: the motivation for and consequences of a new mechanism can result in unanticipated market outcomes, may be misunderstood by market participants, and might even induce adverse participant reactions that can negate the anticipated efficiency or revenue gains.

Our study is situated in one such market mechanism transition undertaken by a peer-to-peer car rental platform we partnered with. Prior to the summer of July 2017, the platform delegated all of its pricing and rental availability decisions to the providers (owners) who listed their cars for rent. Over a 2-month period (August 1st to September 26th, 2017), the platform conducted a randomized trial that involved its San Francisco bay area providers.

¹For example, Didi Chuxing, Lyft, and Uber, operate matching markets between drivers and passengers, but also feature characteristics one typically associates with a hierarchical organization as they set prices, provide customer support, and manage operations. On the other hand, Airbnb more closely resembles a light-touch market, providing customer support, but delegating pricing, merchandising, inventory, and customer relationship decisions to the providers—individuals who share their homes on the platform.
Providers retained control over rental availability decisions, but the level of control over pricing varied, with each provider assigned to one of three treatment groups:

- For the first treatment group (T1), the platform assumed complete control over pricing the providers’ cars, using an internally developed algorithm aimed at increasing revenue.

- For the second treatment group (T2), the platform assumed partial control over pricing the providers’ cars: while prices and inter-temporal price variation were determined and implemented centrally by the platform by using the same algorithm, an owner could raise or lower the price level by up to 30 percent.

- Providers in the control group (T0) maintained complete control over pricing.

Our primary experimental finding is that providers in treatment cell T1 retaliated against the pricing mechanism change via three channels: (i) exiting the market, (ii) reducing asset availability (defined as the percentage of time the asset is made available on the platform), and (iii) canceling booked transactions. When compared to the providers in the control cell T0, we find that providers in treatment cell T1, on average exit at a 29.4% higher rate, reduce the availability of their cars by 19.3%, and cancel 19.9% more transactions. These effects are statistically significant, indicating that providers retaliate in response to loss of pricing control.

Providers in treatment cell T2—who retained partial pricing control—also retaliated, but the magnitude of their responses was significantly lower across the three channels. When compared to the providers in treatment cell T1, we find the providers in treatment cell T2 on average exited at a 48.4% lower rate, increased car availability by 51.4%, and canceled 34.9% fewer transactions. All three effects are statistically significant, indicating that some degree of control on pricing can mitigate retaliation.

We next examine the reasons behind provider retaliation. We first focus on provider revenue per available hour, which we define as the ratio of provider average weekly revenue during the experimental period over the number of hours the provider’s car is made available. We find that, compared to the providers in the control cell T0, providers in treatment cells T1 and T2 enjoyed 21.3% and 19.2% higher revenues per available hour, respectively. Therefore, providers are retaliating despite revenue increases from the pricing mechanism change.

We then turn to exploring an alternative explanation for our findings: the higher revenues for providers might be coming at the expense of higher costs. We posit that centralized revenue optimization is not accounting for some of these costs, especially a range of bring-to-market (BTM) costs (Filippas et al., forthcoming) that the providers are better informed
Filippas et al. decompose the BTM costs into (i) usage-based BTM costs, which scale with the rental duration, and (ii) transaction-based BTM costs, which are incurred for each rental transaction. In our application context, usage-based costs comprise depreciation and regular wear and tear (the fuel costs are borne by the renter), and the transaction-based BTM costs include screening the renter, answering questions, and inspecting and cleaning the car after each rental.

We find evidence that the new pricing mechanism increased provider’s BTM costs. Specifically, the providers in treatment cells T1 and T2 saw their revenue per mile drop by about 27.8% and 20.5%, respectively, when compared to the providers in the control cell T0. In addition, the revenue per transaction dropped by 14.7% and 4% for the providers in T1 and T2, respectively, when compared to the providers in T0. The increased BTM costs imply that, while provider revenue increased, the true utility from rentals may have decreased, at least for some providers, resulting in retaliation. The lower costs experienced by the providers in T2 might explain the lower retaliation from them.

Overall, our results suggest that providing partial control to providers is highly effective. In a post-experiment survey administered by the platform, the providers in treatment cell T2 expressed 30% greater satisfaction with the centralized pricing tool when compared to the providers in treatment cell T1. Based on the experimental and the survey findings, the platform decided to roll out treatment cell T2 to its entire San Francisco provider population.

More broadly, we argue that provider input can help address the two key challenges of implementing dynamic pricing in sharing economy platforms: (i) mismatched platform and provider objectives and (ii) lack of individual provider cost information. In sharing economy platforms, the objective of the platform is to maximize overall revenue, but the objective of the providers is to maximize their own individual profits. Increasing platform profits at the expense of individual provider profits can result in provider retaliation. To account for this mismatch, the pricing algorithm must incorporate individual provider costs. But these cost structures generally vary significantly across providers and with time, are unknown to the platform and also hard to estimate. Provider input can mitigate this issue by making available to the platform valuable cost and provider reservation price information, which the platform can use to optimize prices.

Our findings are, of course, subject to some limitations. The most important limitation is that our experiment is conducted on a single sharing economy market. Future research could attempt to replicate similar experiments in sharing economy or P2P markets where different goods and services are transacted. Our experiment also leverages on a change in the pricing mechanism of the platform: follow-up research could verify that providers retaliate in similar ways against changes in different market mechanisms. It is important to also note
that the primary focus of this paper is not on the question of centralized versus decentralized pricing in online markets, but rather focuses on how providers react to changes in online market design.\textsuperscript{2} Despite these limitations, this paper presents—to our knowledge—the first systematic study of the trade-offs faced by sharing economy companies when implementing platform design changes, which recognizes the new design challenges faced by platforms that do not have the same level of control over providers that firms enjoy over employees.

The rest of the paper is organized as follows. Section 2 surveys the related literature, and presents the empirical context for our study. Section 3 describes the conceptual framework underlying the pricing change, and the experimental design. Section 4 examines how providers responded to the change, and Section 5 examines the reasons behind these responses. Section 6 discusses the implications of our study for implementing changes in online markets, and Section 7 concludes with thoughts on directions for future research.

\section{Empirical context}

The empirical context for our study is a large sharing economy marketplace for car rentals. Sharing economy markets are online P2P platforms, where providers (owners) rent out their assets to renters (buyers). These platforms extensively use technology to improve market design, thereby allowing providers and consumers to find, assess, and transact with one other more efficiently than what is possible in many physical markets (Cramer and Krueger, 2016; Einav et al., 2016; Sundararajan, 2016; Horton, 2017; Filippas et al., 2018; Liu et al., 2018; Athey and Luca, 2019; Filippas et al., forthcoming).

There has been great interest on the economic implications of the sharing economy. On the supply side, sharing economy platforms lower the costs to entry for smaller providers, enabling them to reach buyers more easily (Einav et al., 2016), while providing them with substantial flexibility (Chevalier et al., 2018). On the demand side, product variety is expanded, and benefits disproportionately accrue to previous non-owners who gain access to the asset or service (Fraiberger and Sundararajan, 2015; Filippas et al., forthcoming). Sharing economy platforms also have important implications for actors outside the marketplace. Recent work has documented how sharing economy platforms have disrupted the competitive landscape across several industries (Zervas et al., 2017; Farronato and Fradkin, 2018; Hall and Krueger, 2018), but also that these platforms bring about new social costs and benefits, even for non-participating consumers (Cui et al., 2016; Coles et al., 2017; Davidson and Infranca, 2018; Filippas and Horton, 2018).

\textsuperscript{2}Nevertheless, Section 5 presents evidence that centralized pricing can have a market-expanding effect, and that providers are sensitive to BTM costs which can be hard to estimate for the platform.
A crucial market design decision in sharing economy and other peer-to-peer platforms is how prices should be set. Platforms can choose between a multiplicity decentralized pricing mechanisms such as haggling, auctions, and posted prices (Einav et al., 2015; Farronato, 2017). However, decentralized pricing decisions could lead to an inefficient high price/low quantity equilibrium (Diamond, 1971; Li et al., 2016; Castillo et al., 2017), and many sharing economy platforms hence choose to centralize pricing decisions. Much of the recent literature has focused on how centralized pricing mechanisms should be implemented, as well as on their welfare effects (Cachon et al., 2017; Ma et al., 2018; Taylor, 2018; Bimpikis et al., 2019; Gurvich et al., 2019). However, there is little evidence on the market effects of centralized pricing mechanisms in practice. Hall et al. (2018) find that centralized pricing affects the market equilibrium, but does not affect provider earnings in the long-run. Our work adds to this literature stream by providing empirical evidence of market outcomes under centralized pricing, as well as how centralized pricing mechanisms affect the costs that these providers face when bringing their underutilized capacity to the market.

Whether centralized or decentralized, the optimality of a given market mechanism changes over time, depending on factors including market conditions, platform experience, shifts on the competitive landscape, and technological innovation. Platforms then need to transition to new mechanisms, but such transitions can be met with substantial provider retaliation. Resistance to change has been a key topic of study for organization science scholars (Hannan and Freeman, 1984; Orlikowski, 1996; Greenwood and Hinings, 1996; Tsoukas and Chia, 2002; Jones et al., 2005; Buchanan and Dawson, 2007). Most closely related to our paper is the concept of introducing new technologies in firms. Employees may subsequently embrace the new technology and use it as developers intended, but may ignore this technology (Sobrepenguez, 2008; Satchell and Dourish, 2009; Kane and Labianca, 2011), or use only some of the provided features (Stein et al., 2015). These responses could also be interpreted as different manifestations of exit and voice (Hirschman, 1970).

In the context of sharing economy platforms—and, more broadly, P2P markets—there is little empirical evidence on (i) how providers retaliate against mechanism changes, and (ii) how platforms can successfully transition to new market mechanisms. Most relevant to our paper is research focusing on shifts in the relationship of buyers and sellers in online markets (Pavlou and Gefen, 2005), and on the reactions of external contractors when firms implement changes (Levina and Ross, 2003). To our knowledge, our paper reports on the first experiment aiming to provide additional empirical insight to this important managerial problem, by reporting empirical evidence on how sharing economy providers respond to changes, what the reasons are behind these responses, and how market changes can be successfully implemented.
Online platforms increasingly employ experiments to gain insights that can help improve their operations (Kohavi and Thomke, 2017). Several researchers in the operations management and information systems community have recently used field experiments to address research questions (Cui et al., 2018; Fisher et al., 2017; Horton, 2017; Singh et al., 2017; Zhang et al., 2017; Cohen et al., 2018; Horton and Johari, 2018; Gallino and Moreno, 2018; Barach et al., 2019; Jung et al., 2019; Sun and Taylor, 2019). Our paper adds to this budding literature.

2.1 The focal platform: descriptive statistics

In the focal platform, providers-owners rent out their cars, choosing when their cars will be available, and at what rental rate. Renters-buyers perform a standard, map-based search. Providers cannot reject a transaction, but may subsequently cancel the transaction; while a monetary penalty for cancelling transactions exists, the platform has never exacted that penalty. The platform offers typical online market services: building and maintaining search and reputation systems, curating the matching process, handling payments, and providing insurance and customer support. The main novelty of the platform is the provision of proprietary hardware and software for the mobile phone-based, keyless unlocking of rented cars, which greatly reduces transaction costs (Filippas et al., forthcoming).

For the purposes of our study, we focus on the San Francisco market. Figure 1a depicts the spatial density of the cars made available on the platform in the city of San Francisco, from January 1, 2017 to August 1, 2017. The heat map suggests that the density of rentals mirrors the population density of the city.

We now present some descriptive statistics to reveal the underlying characteristics of the platform. Most of the rental activity on the platform is short-term, despite the flexibility that the platform offers allowing the providers to rent out their cars for as short as half an hour or as long as a month. Among all the rentals that took place between January 1, 2017, and August 1, 2017, about 89 percent of the rentals were for less than one day and only 1.6 percent were for more than three days. Figure 1b depicts the histogram of all rental durations during this period, binned into six duration categories: 1 to 4 hours, 4 to 8 hours, 8 hours to a day, 1 to 3 days, 3 days to a week, and more than a week.

The car availability on the platform varies widely across the providers. Figure 1c plots the histogram of monthly car availabilities of different providers between January 1, 2017, and August 1, 2017, where the monthly car availability of a provider is defined as the percentage of time the car is made available for rentals on the platform. The wide variation of the car availabilities across the providers indicates a great degree of heterogeneity in platform
Figure 1: Some descriptive statistics of rental activity in the focal platform

(a) Heatmap of the spatial density of available cars in San Francisco.

(b) Distribution of the duration of rentals.

(c) Distribution of car availability.

Notes: This figure reports descriptive statistics on the rental activity taking place in the focal platform. The top panel plots the spatial density of rental activity in San Francisco. Red colors indicate high rental activity, and green colors indicate low rental activity. The middle panel plots the distribution of rental durations, discretized into 6 categories. The bottom panel plots the distribution of monthly car availability, defined as the percentage of time that a car was made available on the platform, discretized into 10 categories. For each panel, the value of each bin is shown above it, and the red line depicts the corresponding cumulative distribution function. All panels use data from January 1, 2017 to August 1, 2017, for providers located in San Francisco. Using other samples yields qualitatively similar results.
usage among the providers. Presumably, some providers are “casual” platform users who are making their cars available when they are at work, when they are traveling for leisure or business, or when demand for rentals is high. Other providers may be more “serious” users, who lease or buy cars to make them available on the platform at all times, as a means of earning supplemental income. In addition, we note that about 70 percent of the providers make their cars available on the platform more than half of the time. This finding is consistent with existing empirical evidence that car owners user their cars less than 4 percent of the time.³

Asset utilization on the platform is quite low. Over the period from January 1, 2017, to August 1, 2017, about 63 percent of cars had less than 30 percent utilization, defined as the percentage of time the car was rented of the time it was available for rent. Figure 2a plots the histogram of monthly car utilization between January 1, 2017 and August 1, 2017. The distribution of car utilizations approximates a Pareto distribution. Low utilization indicates forgone opportunities for revenue generation. While the underlying cause for low utilization cannot be known from this descriptive analysis, one potential explanation is the existence of market inefficiencies caused because of sub-optimal rental pricing by providers. Indeed, providers substantially differ in their pricing decisions: some providers may be experienced or sophisticated agents who constantly monitor the state of the market, responding to demand and the shifting competitive landscape; others may be less experienced, less sophisticated, and less closely resemble a professional, opting for suboptimal car pricing but a more seamless experience (Al-Ubaydli and List, 2017).

Finally, once set, providers rarely or never change the rental prices of their cars. Figure 2b plots the histogram of monthly number of price changes for San Francisco providers, for the period between January 1, 2017 and August 1, 2017. About 70 percent of the providers changed their price at most one time per month. Fewer than 4 percent of the providers changed price of their cars at least one every two days. The low frequency of price changes might be resulting in market inefficiencies and subsequent low asset utilization (seen in Figure 2a) because the price changes are not keeping up with changes in market conditions. As the focal platform employed an ad-valorem business model, the executives believed that this inefficiency likely reduced platform revenue, and decided to transition to a different pricing mechanism.

Figure 2: Car utilization and provider pricing decisions

(a) Distribution of car utilization.

(b) Distribution of provider price changes per month.

Notes: This figure reports descriptive statistics on the rental activity taking place in the focal platform. The top panel plots the distribution of monthly car utilization, defined as the percentage of time that a car was rented out over the percentage of time that the car was made available, discretized into 10 categories. The bottom panel plots the distribution of provider changes per month, discretized into 11 categories. For each panel, the value of each bin is shown above it, and the red line depicts the corresponding cumulative distribution function. All panels use data from January 1, 2017 to August 1, 2017, for providers located in San Francisco. Using other samples yields qualitatively similar results.

3 Experimental change in the pricing mechanism

3.1 Transitioning to centralized pricing

Motivated by the likely link between provider-led pricing and low car utilization, the platform set out to develop a new, centralized pricing system. In addition to increasing revenues, the platform expected that centralized pricing would lead to a better customer experience, as prices for similar cars could vary wildly when prices were set by the providers. The platform developed a centralized pricing system in-house, which was found to outperform provider pricing across a variety of measures on both historical and out-of-sample data.

Despite the potential revenue gains, the platform operators were cognizant that removing the providers’ ability to price their cars could be met with strong retaliation. For example,
centralized pricing mechanisms may fail to take into account the providers’ transaction and reservation costs, which are generally private, idiosyncratic, and time-varying. Similar to firm employees, dissatisfied providers could react by reaching out to the platform operators to voice their concerns, or exiting the platform in search of better alternatives (Hirschman, 1970). Unlike firm employees, sharing economy providers could also employ different methods to retaliate against unwanted changes, such as decreasing the availability of their assets, or cancelling a larger fraction of transactions.

Toward that end, the platform decided to introduce two versions of the centralized pricing mechanism experimentally, for providers located in San Francisco. In the first version of the centralized pricing feature, the platform assumed complete pricing control over the providers’ cars. In the second version, the platform assumed partial control over pricing the providers’ cars: while prices and inter-temporal price variation were determined and implemented by the pricing algorithm, providers were able to control a price slider through which they could raise or lower the centrally-set prices by up to 30 percent. The rationale behind a pricing mechanism that allows providers to retain some pricing control was that providers could use that control to indirectly reveal their idiosyncratic preferences. A control group remained at the status-quo pricing system.

3.2 Sample definition and internal validity

Eligible providers were those who had made their car available for at least 24 hours during the month prior to start of the experiment, amongst whom the platform selected a random subset to be included in the experiment. Providers were the unit of randomization, and will be the primary unit of analysis throughout this paper. The final sample for the experiment is composed of 1,218 providers in the platform, who rented out their cars 17,729 times to 9,749 renters. The experiment began on August 1, 2017 and ended on September 26, 2017. The length of the experiment was determined by an ex ante power calculation conducted by the platform.

Providers were randomly assigned to one of the two treatment groups, with probability 13.5% each, or to the control group, with probability 73%. The first treatment group (T1) was assigned to the first version of the pricing centralized pricing feature, losing all control

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4For confidentiality reasons, we do not report this fraction.
5The intent was to have an experiment large enough to have sufficient power to detect a 5 percentage point change in the probability of a user dropout, at 90% power. The experiment ran longer than required for this level of power, as making the correct business decision was crucial for the platform operators; as we show in what follows, the “realized” power for the main experimental outcomes was vanishingly close to 100% for a 5 percentage point effect.
6The relatively small fraction of providers that as assigned to the two experimental treatments helped ensure that financial risk to the platform would be mitigated.
over pricing; the second treatment group (T2) was assigned to the second version of the centralized pricing feature, maintaining partial control through the use of the price slider; the control group (T0) remained in the status-quo pricing feature, maintaining complete pricing control. The pricing interfaces for the three groups are shown in Appendix A.

To verify whether the assignment to the experimental groups was correctly performed, we perform a typical balance test. In Table 1, we present a series of pairwise mean comparison statistical tests. The randomization was effective, with the control and treatment groups being well balanced.

Table 1: Summary statistics and mean comparison for providers in the experimental groups for pre-experimental observable variables.

<table>
<thead>
<tr>
<th>Provider attributes</th>
<th>T0 mean (s.e.)</th>
<th>T1 mean (se)</th>
<th>T2 mean (se)</th>
<th>T0-T1 p-value</th>
<th>T0-T2 p-value</th>
<th>T1-T2 p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>35.21 (0.29)</td>
<td>35.13 (0.7)</td>
<td>35.22 (0.6)</td>
<td>0.92</td>
<td>0.99</td>
<td>0.93</td>
</tr>
<tr>
<td>Tenure</td>
<td>1.11 (0.02)</td>
<td>1.12 (0.06)</td>
<td>1.11 (0.06)</td>
<td>0.96</td>
<td>1</td>
<td>0.97</td>
</tr>
<tr>
<td>Cars</td>
<td>1.14 (0.02)</td>
<td>1.13 (0.05)</td>
<td>1.23 (0.07)</td>
<td>0.9</td>
<td>0.25</td>
<td>0.28</td>
</tr>
<tr>
<td>Revenue</td>
<td>3.79 (17.92)</td>
<td>-12.31 (30.96)</td>
<td>-3.35 (41.17)</td>
<td>0.65</td>
<td>0.87</td>
<td>0.86</td>
</tr>
<tr>
<td>Cancellations</td>
<td>1.39 (0.05)</td>
<td>1.46 (0.11)</td>
<td>1.47 (0.12)</td>
<td>0.57</td>
<td>0.55</td>
<td>0.96</td>
</tr>
<tr>
<td>Availability</td>
<td>0.63 (0.01)</td>
<td>0.65 (0.02)</td>
<td>0.63 (0.02)</td>
<td>0.58</td>
<td>0.91</td>
<td>0.71</td>
</tr>
<tr>
<td>Utilization</td>
<td>0.2 (0.01)</td>
<td>0.21 (0.01)</td>
<td>0.19 (0.01)</td>
<td>0.43</td>
<td>0.48</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Notes: This table reports means and standard errors of various owner attributes across the three experimental groups, at the time that providers were allocated to treatment groups. These attributes are (i) provider age, (ii) provider tenure on the platform, (iii) number of cars each provider has made available on the platform, (iv) provider revenue (demeaned), (v) number of transactions each provider has cancelled post completion, (vi) percentage of time each provider made their car available on the platform, (vii) percentage of time each providers car was rented out when it was made available on the platform. Attributes (iii) to (vii) are measured between July 1st, 2017 and July 31st, 2017, and choosing other sample periods yields similar results. The reported p-values are the for two-sided t-tests of the null hypothesis of no difference in means across groups.
3.3 Subpopulations of providers

In addition to reporting the results of our analyses for the entire population sample, hereafter referred to as ALL, we also report results for the following two subpopulations: (1) NEW, consisting of all workers with less-than-median tenure on the platform by the time that the experiment started, and (2) LOW, consisting of all workers with less-than-median car availability in the year prior to the commencement of the experiment.

We report results across these subpopulations to detect heterogeneous effects, if any, in subpopulations of interest. We choose these subpopulations to understand how providers who are new or “casual” users of the platform (with low availability of cars on the platform) potentially differ in their reactions to platform changes when compared to the overall population. Presumably, providers who are new or casual users of the platform react less strongly to platform changes when compared to the more “serious” and long-time platform users. Our analysis should reveal such differences, if present.

4 Provider responses to the market mechanism change

In this section, we examine how treated providers responded to the pricing mechanism change. We find that providers retaliated through three distinct channels: exiting the platform, reducing the availability of their assets, and cancelling transactions. We also find that non-treated providers did not change their pricing strategy.

4.1 Exit from the platform

Our first outcome of interest—which was also the primary outcome of interest for the platform operators—is whether the assignment of the treatment resulted in providers exiting the platform. Consider a regression of provider exit on the treatment indicators, that is,

\[ \text{EXIT}_j = \beta_0 + \beta_1 T_{1j} + \beta_2 T_{2j} + \epsilon, \]

where \( \text{EXIT}_j \) is an indicator variable for whether owner \( j \) dropped out of the platform by the end of the experimental period, and \( T_{ij} \) is an indicator variable for whether owner \( j \) was assigned to Treatment \( i \). The ordinary least squares estimates \( \hat{\beta}_i \) for each of the two active treatment cells are reported in Figure 3a. Around each point estimate, a 95% confidence interval is shown, calculated with robust standard errors. All regression results are additionally presented as tables in Appendix B.

The imposition of the centralized pricing mechanism had a substantial effect on the exit
decisions of the treated providers. Starting with ALL, we can see that providers in both treatment groups exited at a higher rate compared to the control group. This increase in exit rates was statistically significant for both treatment groups. In the T1 cell, which had the larger increase in exit rates, the increase is 29.4 percentage points. This increase is from a baseline exit rate of 8.8% for cell T0.

Allowing providers to retain some pricing control substantially ameliorated the exit response effect. In the T2 cell, the exit rate rose by 15.1 percentage points, compared to the control group. While the increase in the exit rates of providers in the T2 cell was still substantial, the exit rate was about 48.4% lower than that of providers in the T1 cell. The difference in exit rates amongst the two treatment groups is also statistically significant.

In the subpopulations, the effects of the treatments are similar, but smaller in size compared to ALL. Most notably, in the T2 cell, the increase from the baseline exit rates is about 9 percentage points for both NEW and LOW, and hence about 40.5% lower than the corresponding increase in ALL. This suggests that providers with less experience, and with lower availability react less strongly to the pricing mechanism change. This can be bad news for the platform, as providers who make their cars available to be rented more often, and providers with long tenure on the platform are likely the more valuable ones.

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Note that here—and throughout the paper—for differences in levels where the outcome is naturally discussed as a fraction, we label level differences as “percentage points.” For percentage changes with respect to the outcome of the control, or another treatment cell, we use the “%” symbol.
Figure 3: Providers responses to the pricing mechanism change

(a) Effect of the pricing mechanism change on provider exit from the platform

(b) Effect of the pricing mechanism change on car availability decisions.

(c) Effect of the pricing mechanism change on transaction cancellations.

Notes: This figure shows the treatment effects for each of the active treatment cells. In the top panel, the dependent variable is the change in provider exit rate. In the middle panel, the dependent variable is the change in provider car availability. In the bottom panel, the dependent variable is the change in provider transaction cancellation rate. All changes are compared to the corresponding dependent variable for the control group. A 95% confidence interval is plotted around each estimate. Each panel shows results in three facets, labeled ALL, NEW, and HIGH, corresponding to the sample used in that regression. For details on the definition of these samples, see Section 3.3. For details on the regression results, see Appendix B.
Figure 4: Provider responses to the pricing mechanism change over time

(a) Weekly average car availability.

(b) Weekly average transaction cancellation rate.

(c) Weekly average number of price changes.

Notes: This figure shows the responses of providers to the pricing mechanism change. The top panel plots the weekly average car availability, the middle panel plots providers’ cancellation rate, and the bottom panel plots the number of price changes. In all panels, the orange line indicates the responses of control group providers, and the blue line indicates the responses of providers pooled from the two treatment cells. A 95 percent confidence interval is shown around each mean. The vertical dashed lines indicate the beginning and end of the experimental period.
4.2 Asset availability

Providers responded to the price mechanism change by exiting the platform, similarly to dissatisfied employees quitting their jobs. However, providers on sharing economy markets, as well as in other P2P markets, may also respond to changes they perceive as negative by employing alternative channels of retaliation. One such channel is asset availability. In the focal market, providers may choose to make their cars less available for rentals. It is worthwhile noting that employees have no such power in the traditional firm setting: asset availability is a channel of retaliation unique to P2P markets.

Figure 3b reports regressions of provider car availabilities on the treatment indicators. Availability is defined as the percentage of time each provider makes their car available on the platform, ranging from 0, for cars that are never made available, to 1, for cars that are always available. We report an estimate of the treatment effect on availability that includes providers who exited during the experimental period. For providers who exited, we set the corresponding car availabilities to zero for all periods after their time of exit. 

In the full population ALL, providers in the T1 and T2 cells reduced their car’s availability by about 19.3 and 12.7 percentage points respectively, from an average of 61.8% availability for providers in the control group. Both effects are statistically significant, and so is the difference between the availability responses of the two treatment cells: the availability reduction for providers in T1 was 51.4% higher than that of providers in T2. The story does not dramatically change in the subpopulations, with only the magnitude of the effect being larger in size for the NEW subpopulation, and smaller for the LOW subpopulation: the latter is somewhat expected, as the LOW subpopulation is defined to include providers with lower-than-median car availabilities.

To put emphasis on the longitudinal aspect of the data, we report providers’ availability decisions over time in Figure 4a. We plot the average weekly availability for providers in the control group, and for providers pooled from the two treatment groups. The responses of the treated providers illustrate the role of availability as an important lever that sharing economy providers can use to retaliate against changes that leave them dissatisfied. Furthermore, Figure 4a allows us to verify that the observed effect is not due to increased availability of control group providers, but rather due availability decreases by the treated providers.

In Appendix B, we report an alternative estimate that restricts our sample to providers who did not exit the platform throughout the experiment (Gerber and Green, 2012), and find a similar pattern of results. In the context of availability decisions, estimates that only include providers who did not exit the platform may be interpreted as a lower bound on the availability responses: providers who exited the platform would presumably exhibit large car availability reductions had they remained on the platform.
4.3 Transaction cancellations

Another lever that dissatisfied providers may employ to retaliate against unwanted change is transaction cancellations. In the focal market, providers could cancel transactions without incurring any costs: while a fee for cancelling transactions existed, the platform never extracted that fee from any provider. This situation is common when market power resides with the supply side, as is the case in the focal market—the entire capacity comes from providers renting out their cars.

Figure 3c reports the results of regressions of the provider cancellation rate on the treatment cell indicators. Cancellation rate is defined as the percentage of transactions cancelled by each provider, ranging from 0, for providers who never cancel any transaction, to 1, for providers who cancel every transaction. The estimate presented includes providers who exited during the experimental period, setting these providers’ cancellation rate to one for all periods after their time of exit.9

In the full sample, providers in treatment group T1 increased their cancellation rate by about 19.9 percentage points, and providers in treatment group T2 increased their cancellation rate by about 12.9 percentage points, from an average of 17% cancellation rate for providers in the control group. Both effects are statistically significant. The difference between the cancellation responses between the two treatment cells is both statistically significant and substantial: the cancellation rate of providers in T2 was 34.9% lower than that of providers in T1. The results are similar across provider subpopulations.

A graphical representation of the cancellation rates of providers is shown in Figure 4b, which plots the average weekly cancellation rate for providers in the control group, and providers pooled from the two treatment groups. The responses of the providers indicate that transaction cancellations is an additional lever that sharing economy providers can use to retaliate against unwanted changes, and that allowing these providers some control may help ameliorate this problem.

4.4 Price changes

Providers who were assigned to the two versions of the decentralized pricing mechanism presumably obtained a competitive advantage over providers who remained at the status-quo pricing mode. It is then plausible that providers in the control group could respond by changing their pricing behavior.

---

9In Appendix B, we report an alternative estimate that restricts our sample to providers who did not exit the platform, and find a similar pattern of results. This estimate may be interpreted as a lower bound on the cancellation responses: providers who exited the platform would presumably exhibit large transaction cancellation rates had they remained on the platform.
Figure 4c plots the average weekly price changes for providers in the control group, before and after the experiment. We do not observe any shift in the pricing behavior of these providers; on the contrary, our data suggests that there is a downward trend in the frequency with which providers in the control group updated the prices of their cars. We interpret this as an absence of evidence in our data in support of the hypothesis that providers in the focal platform responded to the shift in competition by changing their pricing behavior. Furthermore, this finding broadly supports the platform’s claim that centralized pricing may increase transaction efficiency—sharing economy providers do not seem to be responsive to market shocks, at least in the short-run.

5 Reasons for the provider responses

We next examine the reasons behind provider responses. We first analyze the potential costs and benefits to the providers because of the platform change. We find that when compared to the control group, providers in the treatment groups experienced large increases in average revenue for every hour they made their cars available on the platform. But they also experienced higher usage- and transaction-based BTM costs. Therefore, the increase in provider costs are potentially not compensated by the corresponding increase in revenues, leading to provider retaliation. We also find that providing partial control reduces transaction-based BTM costs, while keeping revenues and usage-based BTM costs about the same, when compared to providing no control. This finding potentially explains the stronger reactions we observed for providers with no control.

5.1 Effects on provider revenue per available hour

A plausible explanation for the providers’ responses is that the centralized pricing mechanism decreased providers’ revenue. If providers saw their revenues decrease after losing control over pricing their vehicles, then their retaliation against the pricing mechanism change would simply be a response to suboptimal platform pricing.

Figure 5a reports the results of regressions of provider revenue per available hour on the treatment cell indicators. Provider revenue per available hour is defined as the ratio of providers’ total revenue over the number of hours providers’ cars were made available during the experimental period. This metric measures the platform’s ability to monetize providers assets. We report a population-level estimate that includes providers who exited the platform, using all weekly observations before their time of exit.\footnote{We also report an estimate that restricts the sample to providers who did not exit the platform during the}
The decentralized pricing system had a substantial positive effect on provider revenue per available hour. In the entire population ALL, providers saw their revenue per available hour increase by 21.3% for the cell T1, and by 19.2% for the cell T2, when compared to the revenue per available hour for providers in the control group. Both effects are statistically significant, but the difference between the revenue of the two groups is statistically indistinguishable. The pattern of the effects is similar in the subpopulations NEW and LOW, where T1 more clearly outperforms T2, but the effects of the two treatments remain statistically indistinguishable.

To further support our findings, we report in Figure 6a the average weekly revenue per available hour for providers in the control group, and for providers pooled from the two treatment groups. Each point estimate includes providers who had not exited the platform during the corresponding week. Treated providers saw increases in the revenue per available hour during every week of the experiment. A plausible explanation for the increase in revenues per available hour is that revenues did not increase, but, instead, providers made their cars less available on the platform. Figure 6b shows that this is not the case: treated providers’ revenue increased for every week during the experimental period.¹¹

Together, these results imply that the platform’s version of the decentralized pricing algorithm was successful—insofar that the objective of the platform was to increase provider revenues. Furthermore, allowing providers to retain some control over the pricing of their cars did not lead to a substantial decrease in revenue per available hour, compared to completely decentralizing pricing. It is worth noting that we cannot extrapolate these findings—and the findings presented in the rest of this section—to the case where the platform rolled out its decentralized pricing mechanism to the entire market. While such an extrapolation would be tempting, making valid inferences would require us to take into account the equilibrium effects of a market-wide change, and is not the focus of this paper.

¹¹See Appendix C for estimates of the effect of the pricing mechanism on provider revenues.
Figure 5: Economics outcomes following the pricing mechanism change

(a) Effect of the pricing mechanism change on revenue per available hour

(b) Effects of the pricing mechanism change on revenue per mile

(c) Effect of the pricing mechanism change on revenue per transaction.

Notes: This figure shows the treatment effects for each of the active treatment cells. In the top panel, the dependent variable is the change in revenue per available hour. In the middle panel, the dependent variable is the change in revenue per mile. In the bottom panel, the dependent variable is the change in revenue per transaction. All changes are compared to the corresponding dependent variable for the control group. A 95% confidence interval is plotted around each estimate. Each panel shows results in three facets, labeled ALL, NEW, and LOW, corresponding to the sample used in that regression. For details on the definition of these samples, see Section 3.3. For details on the regression results, see Appendix B.
Figure 6: Economic outcomes following the pricing mechanism change

(a) Weekly average provider revenue per available hour.

(b) Weekly average provider revenue.

(c) Weekly average provider revenue per mile.

(d) Weekly average provider revenue per transaction.

Notes: This figure shows the economic outcomes for providers before and during the experimental period. Panel (a) shows the weekly average revenue per available hour, panel (b) shows the weekly average revenue, panel (c) shows the weekly average revenue per mile, and Panel (d) shows the weekly provider revenue per transaction. In all panels, the orange line indicates the economic outcomes of control group providers, and the blue line indicates the economic outcomes of providers pooled from the two treatment cells. A 95 percent confidence interval is shown around each mean. The vertical dashed lines indicate the beginning and start of the experimental period.
5.2 Effects on usage-based BTM costs

The revenue increases noted above were achieved by increasing the how often providers’ cars were rented out.\textsuperscript{12} As such, the higher revenues providers experienced need not necessarily imply higher provider utilities. The reason is that providers incur “bring-to-market” (BTM) costs when renting goods on sharing economy platforms (Filippas et al., forthcoming).

Filippas et al. decompose BTM costs into (i) usage-based BTM costs, that is, costs that are analogous to the rental duration, and (ii) transaction-based BTM costs, that is, costs that providers incur for each rental. Usage-based BTM costs include the labor costs, asset depreciation, and complementary consumables. Transaction-based BTM costs include the costs inherent in finding trading partners, coming to terms, executing payments, and handing off and “resetting” the good.\textsuperscript{13}

In the focal platform, providers incur both types of BTM costs. The main component of usage-based BTM costs is car mileage increases, whereas transaction-based costs include screening the renter, answering questions, and inspecting and cleaning the car after each rental. While the pricing mechanism change does not affect BTM costs directly, it could affect them indirectly, by changing the type of demand faced by treated providers. Although we cannot observe these costs directly, we can examine how the pricing mechanism change affected meaningful proxies for the two types of BTM costs.

We first examine the effect of the centralized pricing mechanism on revenue per mile that rented cars were driven during the experiment. If renters drive cars more at a fixed rental rate, then the utility of providers decreases: both car mileage and the risk of asset damage increase, but this increased cost is not priced in. As such, providers find renting out their cars less profitable—or even loss-making.

Figure 5b reports the results of regressions of revenue per mile on the treatment cell indicators. Revenue per mile is defined as the ratio of the total provider revenue over the total number of miles a car was driven during the experimental period. Similarly to our estimation strategy in the previous sections, we report a population-level effect estimate.\textsuperscript{14}

The pricing mechanism change substantially decreased providers’ revenue per mile. In the entire population, ALL, providers saw their revenue per mile decrease by about 27.8% for the cell T1, and by 20.5% for the cell T2, compared to the revenue per mile for providers

\textsuperscript{12}In Appendix C, we report evidence that the new pricing mechanism substantially increased the number of hours that available cars were rented out.

\textsuperscript{13}For example, the usage-based BTM costs of driving with Uber include labor, increases in the car’s mileage, and gas. The transaction-based BTM costs include the costs of drivers and passengers finding and screening each other’s identity before each transaction.

\textsuperscript{14}We report an estimate that restricts our sample to providers who did not exit the platform in Appendix B. The pattern of results is similar across the two estimation strategies.
in the control group. Both effects are statistically significant, and similar across the true treatment cells, as well as across the different subpopulations. To put emphasis on the longitudinal data, we also show the weekly revenue per mile in Figure 6c, for providers in the control group, and for providers pooled from the two treatment groups.

5.3 Effects on transaction-based BTM costs

We next turn to provider revenue per transaction for a measure of the effect of the pricing change on the transaction-based BTM costs. Transaction-based costs imply that if a provider has to complete more transactions to earn the same revenue, then, all other factors equal, the provider obtains lower utility from renting.

Figure 5c reports the results of regressions of revenue per transaction on the treatment cell indicators. Revenue per transaction is defined as the ratio of the total provider earnings over the total number of transactions for a car during the experimental period. Following the same estimation strategy as in the previous sections, we report a population-level effect. The pricing mechanism change decreased providers’ revenue per transaction. In the entire population, ALL, providers saw their revenue per mile decrease by about 14.7% for the cell T1, and by 4% for the cell T2, compared to the revenue per mile for providers in the control group. In our sample, only the effect for T1 is statistically significant, with the effect for T2 being statistically indistinguishable from zero for conventional significance levels. The pattern persists across the different subpopulations, with differences being more pronounced in NEW, and less pronounced in LOW. This result implies that providers in T1 had to make more transactions to earn the same revenue, but the effect for providers in T2—who had access to the pricing slider—is substantially smaller. We also plot the effects over-time in Figure 6d, finding further support for this result.

6 Discussion

Changes in the market design of online markets need to be implemented often: no platform is perfectly designed at its conception, and shifts in the competitive and innovation landscape necessitate further redesign. However, changes can be met with strong user retaliation, and methods that reduce the magnitude of this retaliation can be of substantial practical importance to both platform designers and managers. Our findings suggest that one such method is allowing providers to retain some control, which attenuated provider retaliation.

15We report an estimate that restricts our sample to providers who did not exit the platform in Appendix B. The pattern of results is similar across the two estimation strategies.
through all channels we measured.

To elicit additional feedback, the platform administered a survey after the end of the experiment. Treated providers were asked whether they preferred setting their own prices or the new pricing mechanism. In addition, providers were also asked to provide textual feedback regarding the new feature, and were asked some other demographic questions. Figure 7 shows a bar plot for the responses across the two treatment groups, ordered in increasing positivity of sentiment from left to right. While respondents reacted fairly negatively to the new feature in aggregate, providers who were allowed to retain some pricing control reported substantially more positive attitudes towards the new pricing mechanism.

Figure 7: Answers to the satisfaction question “Which of the following best describes your experience with our new pricing feature?”.

![Bar Chart](image)

Notes: This figure plots the responses to the survey question “Which of the following best describes your experience with our new pricing feature?”. The survey was administered to all treated providers after the experimental period, and the response rate was 31 percent for both treatment groups.

### 6.1 Short- and long-run use of the price slider

Providers in the treatment cell T2 were given partial control over setting prices for their cars, but only 47.8% of these providers moved the price slider at least once by the end of the experiment. Figure 8a plots the distribution of price slider levels for providers in the experimental group T2 at the end of the experimental period. While some providers chose to change the centrally-set prices using the slider, we see that about 55% of the providers chose to not change the centrally-set prices. Amongst those providers who chose to use the price slider, the vast majority increased the rental rates for their vehicles. The cars of providers
who did not use the slider were effectively priced identically to what would have been the case had they been assigned to the experimental group T1, and hence the platform doubled the “enrollment” to the intended feature—fully decentralized pricing—at no extra cost.

After the end of the experimental period, the platform decided to roll out treatment cell T2 to its entire San Francisco provider population. Figure 8b plots the providers’ average price slider level over time. The average slider level is close to 100%, which is the platform-set price level. This implies that providers generally do not utilize the slider to a large extent, similarly to what we found for the experimental period. However, we see an increasing trend during the summer months, and a decreasing trends during the fall months: providers presumably utilize the slider when car rental demand increases.

Figure 8: Short- and long-run use of the price slider.

(a) Distribution of price slider levels at the end of the experimental period

(b) Price slider levels over time

Notes: This figure shows how providers use the slider, in the short- and in the long-run. The top panel plots the distribution of price slider choices for providers in the experimental group T2, with the choices discretized into 5 categories. The value of each bin is shown above it, and the red line depicts the cumulative distribution function. The bottom panel shows the mean slider level over time, after the end of the experimental period. The average slider levels are computed for every month. A 95% confidence interval is shown for each mean.
6.2 The economic value of pricing control

Allowing providers to retain some pricing control can have many advantages from an economics standpoint. Provider input creates a channel through which the platform can track implementation errors. Such a feature can be of substantial importance for new features, as the platform can trace problems that might be otherwise hard to detect. In our context for example, if providers in the universally set the price slider to its maximum value, this could signal that prices were incorrectly set too low, and vice versa.

Another benefit of provider input is that it can create a channel through which the platform operators can obtain information about economically relevant events that would otherwise be hard to obtain. To wit, providers often have highly localized or temporal information about certain events that the platform does not. For example, higher prices may need to be set in the case of an unexpected event that has created a surge in demand or a drop in supply, for which the platform operators may have no information.

Platforms generally in possess high-quality, system-wide, and historical information that far exceeds individual provider’s capabilities. However, an important component that the platforms do not have access to can be found with idiosyncratic and time-varying private information, such as providers’ reservation prices. Reservation prices can be hard to estimate, especially for new providers, and can also be time-varying and subject to exogenous events. For example, a provider whose parents are visiting for the weekend may experience a positive shock in her reservation price, as her utility from using her car increases. Allowing providers a degree of control amounts to essentially providers revealing their private information, which can help bypass the estimation problem.

7 Conclusion

This paper documents an experiment leveraging the pricing mechanism change in a large sharing economy market, where providers were assigned varying degrees of pricing control over their assets. We find that sharing economy providers employ three main channels of retaliation: exiting the platform, reducing the availability of their assets, and cancelling transactions. This retaliation is despite providers seeing a large increase in their revenues, and can be partially explained by an increase in providers’ BTM costs. The new pricing mechanism increased BTM costs because it increased providers’ asset depreciation, and decreased their revenue per rental.

Allowing providers to retain some pricing control substantially ameliorated provider retaliation across all channels, partially because providers were able to raise prices and decrease
their BTM costs. Strikingly, the majority of providers retained partial pricing control did not utilize it, pointing to biases towards owned goods (Pavlou and Gefen, 2005). As such, for would-be market designers and managers, we propose a method to implement changes in the design of an online platform. Our proposed method consists of implementing the intended change as a subset of continuum that affords a degree of control to the providers.

To the best of our knowledge, this is the first paper that provides experimental, micro-level data, as well as proposing a partial control solution to the fundamental problem of implementing changes in the design of online markets. Implementing design changes is a common managerial challenge for sharing economy platforms that aim to improve their operations or simply respond to the ever-changing competitive landscape. Furthermore, though the context of our study is a sharing economy platform, our findings can be generalized to online peer-to-peer markets, as well as in other settings where the platform does not employ workers, but rather acts as a mediator between consumers and providers.

Implementing changes in online markets is a fundamental problem, that is only made more important by the advent of businesses that are based on operating online markets. We provide a first attempt at addressing this question, but examining other ways through which design changes can be implemented is a promising research direction. Future research could center on whether providers learn to relinquish more control to the platform, their rate of learning, as well as how they use this control to respond to temporal variations in their utility function. Shedding light on the role that conflicting objectives play in shaping provider responses to platform control is likely an interesting next step for future research. Examining the provider- and platform-level benefits of centralized and decentralized pricing remains an open problem.
References


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_ , Jun Li, and Dennis Zhang, “Discrimination with incomplete information in the sharing economy: Evidence from field experiments on Airbnb,” available on SSRN, 2016.


—, The sharing economy: The end of employment and the rise of crowd-based capitalism, MIT Press, 2016.


A Pricing Interfaces

Figure 9 shows the pricing interfaces for the two treatment groups. The pricing interface for the version of the pricing feature where providers lost all pricing control is shown in Figure 9a. The centrally-set price is shown through a graph that depicts the hourly rate fluctuations. The minimum and maximum hourly prices, along with the daily rental rate are also shown for the next seven days. The platform utilized tooltips that provide more information about how the prices are set and what each piece of information in the new interface represented, in order to minimize provider confusion over the change. Figure 9b shows the interface for the version of the pricing feature were providers retained some control through the use of the slider. The price slider and the associated tool tip, explaining how the slider works, is the only difference of this version with the fully centralized variant of the feature. The status-quo pricing page which the control group carried on seeing during the experiment is shown in Figure 10.
Figure 9: Pricing interfaces for the two treatment groups.

(a) Treatment group T1.

Notes: This figure shows the pricing interface for providers in the two treatment groups. The curves show the centrally-set hourly prices for the next 7 days, and the minimum and maximum daily price and the daily price are presented in text. Providers in the treatment group T2 have access to a price slider that they can use to increase or decrease the centrally-set price by up to 30 percent.
Notes: This figure shows the pricing interface for providers in the control groups. Providers could set the pricing for their cars through the use of sliders.
B Regression tables

B.1 Tables for Section 4

Table 2: Effects of the experimental treatment on provider exit

<table>
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Notes: This table reports regressions where the dependent variable is provider exit from the platform. The independent variables are indicators for each experimental group, with the control group excluded. The subpopulation samples are defined as follows: ALL includes all workers, NEW includes workers with less-than-median tenure on the platform by the time that the experiment started, and LOW includes workers with lower-than-median car availability. For more details on the samples, see Section 3.3. Figure 3a plots the treatment effects for the two treatment cells. Significance indicators: $p \leq 0.1 : \dagger$, $p \leq 0.05 : \ast$, $p \leq 0.01 : **$, and $p \leq .001 : ***$. 
Table 3: Effects of the experimental treatment on provider availability

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Observations 1,032 511 516 1,218 615 609

R² 0.008 0.019 0.002 0.044 0.060 0.011

Notes: This table reports regressions where the dependent variable is provider car availability. The independent variables are indicators for each experimental group, with the control group excluded. Columns (1)-(3) compute the effects for providers who did not exit the platform, and Columns (4)-(6) compute the effects for all providers. The subpopulation samples are defined as follows: ALL includes all workers, NEW includes workers with less-than-median tenure on the platform by the time that the experiment started, and LOW includes workers with lower-than-median car availability. For more details on the samples, see Section 3.3. Figure 3b plots the treatment effects for the two treatment cells, for the estimation strategy of Columns (4)-(6). Significance indicators: p ≤ 0.1 : †, p ≤ 0.05 : *, p ≤ 0.01 : **, and p ≤ .001 : ***.
Table 4: Effects of the experimental treatment on provider transaction cancellations

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</tbody>
</table>

**Notes:** This table reports regressions where the dependent variable is provider booked transaction cancellation rate. The independent variables are indicators for each experimental group, with the control group excluded. Columns (1)-(3) compute the effects for providers who did not exit the platform, and Columns (4)-(6) compute the effects for all providers. The subpopulation samples are defined as follows: ALL includes all workers, NEW includes workers with less-than-median tenure on the platform by the time that the experiment started, and LOW includes workers with lower-than-median car availability. For more details on the samples, see Section 3.3. Figure 3c plots the treatment effects for the two treatment cells, for the estimation strategy of Columns (4)-(6). Significance indicators: $p \leq 0.1: \dagger$, $p \leq 0.05: *, p \leq 0.01: **$, and $p \leq .001: ***$. 
### B.2 Tables for Section 5

Table 5: Effects of the experimental treatment on provider revenue per available hour

<table>
<thead>
<tr>
<th></th>
<th>Provider revenue per available hour</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ALL (c)</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td><strong>T1</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.376***</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
</tr>
<tr>
<td><strong>T2</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.277***</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.298***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>1,032</td>
</tr>
<tr>
<td><strong>R²</strong></td>
<td>0.048</td>
</tr>
</tbody>
</table>

**Notes:** This table reports regressions where the dependent variable is total provider revenue earned during the experimental period over the number of hours the provider’s car was made available. The independent variables are indicators for each experimental group, with the control group excluded. Columns (1)-(3) compute the effects for providers who did not exit the platform, and Columns (4)-(6) compute the effects for all providers. The subpopulation samples are defined as follows: ALL includes all workers, NEW includes workers with less-than-median tenure on the platform by the time that the experiment started, and LOW includes workers with lower-than-median car availability. A plot of the data in this table can be found in Figure 5a. Significance indicators: $p \leq 0.1: \dagger$, $p \leq 0.05: \ast$, $p \leq 0.01: \ast\ast$, and $p \leq .001: \ast\ast\ast$. 
Table 6: Effects of the experimental treatment on revenue per mile

<table>
<thead>
<tr>
<th></th>
<th>ALL (c)</th>
<th>NEW (c)</th>
<th>LOW (c)</th>
<th>ALL</th>
<th>NEW</th>
<th>LOW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td><strong>T1</strong></td>
<td>−0.295***</td>
<td>−0.263**</td>
<td>−0.296***</td>
<td>−0.357***</td>
<td>−0.330***</td>
<td>−0.333***</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.082)</td>
<td>(0.070)</td>
<td>(0.062)</td>
<td>(0.083)</td>
<td>(0.090)</td>
</tr>
<tr>
<td><strong>T2</strong></td>
<td>−0.283***</td>
<td>−0.267***</td>
<td>−0.280***</td>
<td>−0.263***</td>
<td>−0.230**</td>
<td>−0.224*</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.067)</td>
<td>(0.065)</td>
<td>(0.062)</td>
<td>(0.078)</td>
<td>(0.091)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>0.974***</td>
<td>0.982***</td>
<td>0.990***</td>
<td>1.285***</td>
<td>1.266***</td>
<td>1.306***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.026)</td>
<td>(0.024)</td>
<td>(0.025)</td>
<td>(0.031)</td>
<td>(0.036)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>1,032</td>
<td>511</td>
<td>516</td>
<td>1,218</td>
<td>615</td>
<td>609</td>
</tr>
<tr>
<td><strong>R^2</strong></td>
<td>0.060</td>
<td>0.044</td>
<td>0.059</td>
<td>0.035</td>
<td>0.034</td>
<td>0.028</td>
</tr>
</tbody>
</table>

**Notes:** This table reports regressions where the dependent variable is revenue per mile that providers’ cars were driven during the experimental period. The independent variables are indicators for each experimental group, with the control group excluded. Columns (1)-(3) compute the effects for providers who did not exit the platform, and Columns (4)-(6) compute the effects for all providers. The subpopulation samples are defined as follows: ALL includes all workers, NEW includes workers with less-than-median tenure on the platform by the time that the experiment started, and LOW includes workers with lower-than-median car availability. A plot of the data in this table can be found in Figure 5b. Significance indicators: \( p \leq 0.1 : \dagger, \) \( p \leq 0.05 : *, \) \( p \leq 0.01 : **, \) and \( p \leq 0.001 : ***. \)
Table 7: Effects of the experimental treatment on revenue per transaction

<table>
<thead>
<tr>
<th></th>
<th>ALL (c)</th>
<th>NEW (c)</th>
<th>LOW (c)</th>
<th>ALL</th>
<th>NEW</th>
<th>LOW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>T1</td>
<td>−12.553**</td>
<td>−18.395**</td>
<td>−12.030*</td>
<td>−11.143***</td>
<td>−13.046*</td>
<td>−10.739*</td>
</tr>
<tr>
<td></td>
<td>(4.072)</td>
<td>(6.558)</td>
<td>(5.361)</td>
<td>(3.270)</td>
<td>(5.240)</td>
<td>(4.581)</td>
</tr>
<tr>
<td>T2</td>
<td>−5.005</td>
<td>−1.564</td>
<td>−8.552‡</td>
<td>−3.048</td>
<td>−1.526</td>
<td>−6.284</td>
</tr>
<tr>
<td></td>
<td>(3.699)</td>
<td>(5.327)</td>
<td>(5.019)</td>
<td>(3.254)</td>
<td>(4.892)</td>
<td>(4.630)</td>
</tr>
<tr>
<td>Constant</td>
<td>76.967***</td>
<td>76.639***</td>
<td>79.172***</td>
<td>75.844***</td>
<td>76.499***</td>
<td>76.928***</td>
</tr>
<tr>
<td></td>
<td>(1.367)</td>
<td>(2.045)</td>
<td>(1.870)</td>
<td>(1.296)</td>
<td>(1.962)</td>
<td>(1.804)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,032</td>
<td>511</td>
<td>516</td>
<td>1,218</td>
<td>615</td>
<td>609</td>
</tr>
<tr>
<td>R²</td>
<td>0.010</td>
<td>0.015</td>
<td>0.014</td>
<td>0.010</td>
<td>0.010</td>
<td>0.011</td>
</tr>
</tbody>
</table>

Notes: This table reports regressions where the dependent variable is the revenue per transaction during the experimental period. The independent variables are indicators for each experimental group, with the control group excluded. Columns (1)-(3) compute the effects for providers who did not exit the platform, and Columns (4)-(6) compute the effects for all providers. The subpopulation samples are defined as follows: ALL includes all workers, NEW includes workers with less-than-median tenure on the platform by the time that the experiment started, and LOW includes workers with lower-than-median car availability. A plot of the data in this table can be found in Figure 5c. Significance indicators: \( p \leq 0.1 : \dagger \), \( p \leq 0.05 : * \), \( p \leq 0.01 : ** \), and \( p \leq .001 : *** \).
### B.3 Tables for Appendix C

Table 8: Effects of the experimental treatment on provider revenue

<table>
<thead>
<tr>
<th>Provider revenue</th>
<th>ALL (c)</th>
<th>NEW (c)</th>
<th>LOW (c)</th>
<th>ALL</th>
<th>NEW</th>
<th>LOW</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>452.509</td>
<td>353.073</td>
<td>408.678</td>
<td>444.222</td>
<td>385.416</td>
<td>429.871</td>
</tr>
<tr>
<td>(2)</td>
<td>452.509</td>
<td>353.073</td>
<td>408.678</td>
<td>444.222</td>
<td>385.416</td>
<td>429.871</td>
</tr>
<tr>
<td>(3)</td>
<td>452.509</td>
<td>353.073</td>
<td>408.678</td>
<td>444.222</td>
<td>385.416</td>
<td>429.871</td>
</tr>
<tr>
<td>(4)</td>
<td>452.509</td>
<td>353.073</td>
<td>408.678</td>
<td>444.222</td>
<td>385.416</td>
<td>429.871</td>
</tr>
<tr>
<td>(5)</td>
<td>452.509</td>
<td>353.073</td>
<td>408.678</td>
<td>444.222</td>
<td>385.416</td>
<td>429.871</td>
</tr>
<tr>
<td>(6)</td>
<td>452.509</td>
<td>353.073</td>
<td>408.678</td>
<td>444.222</td>
<td>385.416</td>
<td>429.871</td>
</tr>
</tbody>
</table>

Constant: 840.628
(29.145)
852.448
(41.386)
511.946
(36.108)
786.122
(27.343)
775.404
(38.321)
476.564
(33.148)

Observations: 1,032
511
516
1,218
615
609

R²: 0.047
0.039
0.061
0.055
0.045
0.072

Notes: This table reports regressions where the dependent variable is total provider revenue earned during the experimental period. The independent variables are indicators for each experimental group, with the control group excluded. Columns (1)-(3) compute the effects for providers who did not exit the platform, and Columns (4)-(6) compute the effects for all providers. The subpopulation samples are defined as follows: ALL includes all workers, NEW includes workers with less-than-median tenure on the platform by the time that the experiment started, and LOW includes workers with lower-than-median car availability. A plot of the data in this table can be found in Figure 11a. Significance indicators: $p \leq 0.1 : \dagger$, $p \leq 0.05 : \ast$, $p \leq 0.01 : \ast\ast$, and $p \leq .001 : \ast\ast\ast$. 
Table 9: Effects of the experimental treatment on number of hours rented

<table>
<thead>
<tr>
<th></th>
<th>ALL (c)</th>
<th>NEW (c)</th>
<th>LOW (c)</th>
<th>ALL</th>
<th>NEW</th>
<th>LOW</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>T1</td>
<td>190.539***</td>
<td>153.001***</td>
<td>158.491***</td>
<td>197.400***</td>
<td>179.113***</td>
<td>172.159***</td>
</tr>
<tr>
<td>T2</td>
<td>139.281***</td>
<td>120.852***</td>
<td>131.345***</td>
<td>143.073***</td>
<td>127.282***</td>
<td>138.255***</td>
</tr>
<tr>
<td>Constant</td>
<td>138.110***</td>
<td>140.940***</td>
<td>83.216***</td>
<td>132.428***</td>
<td>132.983***</td>
<td>82.019***</td>
</tr>
<tr>
<td></td>
<td>(5.914)</td>
<td>(8.224)</td>
<td>(7.535)</td>
<td>(5.391)</td>
<td>(7.357)</td>
<td>(6.829)</td>
</tr>
</tbody>
</table>

Notes: This table reports regressions where the dependent variable is the number of hours providers’ cars were rented during the experimental period. The independent variables are indicators for each experimental group, with the control group excluded. Columns (1)-(3) compute the effects for providers who did not exit the platform, and Columns (4)-(6) compute the effects for all providers, by imputing the values of providers in the period following their exit from the platform with the mean revenue of providers in the same cell. The subpopulation samples are defined as follows: ALL includes all workers, NEW includes workers with less-than-median tenure on the platform by the time that the experiment started, and LOW includes workers with lower-than-median car availability. A plot of the data in this table can be found in Figure 11b. Significance indicators: \( p \leq 0.1 : \dagger \), \( p \leq 0.05 : * \), \( p \leq 0.01 : ** \), and \( p \leq 0.001 : *** \).
C Additional effects of the pricing mechanism change

C.1 Figures

Figure 11: Additional economic outcomes following the pricing mechanism change

(a) Effect of the pricing mechanism change on provider revenue

(b) Effect of the pricing mechanism change on hours rented.

Notes: This figure shows the treatment effects for each of the active treatment cells. In the top panel, the dependent variable is the change in provider revenue. In the bottom panel, the dependent variable is the change in the number of hours cars were rented. All changes are compared to the corresponding dependent variable for the control group. A 95% confidence interval is plotted around each estimate. Each panel shows results in three facets, labeled ALL, NEW, and HIGH, corresponding to the sample used in that regression. For details on the definition of these samples, see Section 3.3. For details on the regression results, see Appendix B.
Figure 12: Additional economic outcomes following the pricing mechanism change

(a) Weekly average hours rented.

Notes: This figure shows additional market outcomes for providers before and during the experimental period. Panel (a) plots the weekly average number of rented hours for cars of providers in the control group and for providers pooled from the two treatment cells. A 95 percent confidence interval is shown around each mean. The vertical dashed lines indicate the beginning and start of the experimental period.