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 pricing mechanism change in a “sharing economy” market, where providers who formerly set rental prices for their assets were randomly assigned to groups with varying levels of pricing control. Providers retaliated against the change through three distinct channels: (i) exiting the platform, (ii) reducing the availability of their assets, and (iii) cancelling transactions. The new pricing mechanism increased providers’ revenues, but it also increased providers’ bring-to-market costs. Allowing providers to retain partial control substantially reduced provider retaliation. We discuss the value of partial control as a managerial practice when implementing changes in online markets.

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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, operating 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, sharing economy markets rely on decentralized and heterogeneous crowds of providers—individuals and small businesses who vary in their scale, 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. On the other hand, absent the typical directive authority and culture-building capabilities that traditional firms use to manage their employees, sharing economy platforms must continuously innovate to maintain uniformity, 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 hybrid, that spans the spectrum between traditional firms and decentralized markets.¹

Operators of these platforms must decide on a number of of fundamental market mechanisms in the early states of the operations of the platform. These mechanisms 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 may be hard to implement in a nascent market. As the platform grows, accumulates transaction data, and experiments, a centralized pricing mechanism may result in large efficiency and revenue gains. As such, platform operators need to continuously to implement changes in the design of the market. These changes affect all market participants, and often lead to unanticipated market outcomes. Furthermore, unlike a traditional firm, sharing economy platform operators lack directive control over providers. As a result, changes that leave providers dissatisfied may be met with strong reactions by these providers, potentially affecting market outcomes. This paper aims to inform this new management challenge faced in sharing economy platforms.

Towards that end, we report on a study that leverages on a pricing mechanism transition

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.
at a large P2P car rental platform. Until July 2017, the platform delegated all of its pricing decisions to its providers, i.e., the car owners. Providers also had complete control over when the cars they listed on the platform were made available for rental. The company developed a centralized pricing algorithm internally, which they believed could raise revenue for providers.

Between August 1st and September 26th, 2017, the platform conducted a randomized trial that involved its San Francisco bay area providers. Providers retained control over availability decisions, but the level of control over pricing varied, with each provider assigned to one of three groups. In the first treatment group (T1), the platform assumed complete control over pricing the providers’ cars. In 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, the owner was able to raise or lower the price level by up to 30 percent. Providers in the control group (T0) maintained complete control over pricing.

Our first question pertains to how providers reacted to the platform change. We focus on three outcomes that are of interest to the platform: (i) the provider exit rate from the market, (ii) the asset availability, and (iii) the booking cancellation rate. In response to the platform change, providers could exit the market by delisting their cars, similar how firm employees could react when dissatisfied. However, the two other channels of retaliation we identify—decreasing car availability, and cancelling future transactions—are unique to sharing economy markets, and more generally, P2P rental markets.

We find that the reactions of providers in treatment cell T1 were substantially higher compared to the corresponding rates for providers in the control group. Treated providers exited the platform at a higher rate, decreased their car availability, and increased their cancellation rates. Our preferred estimates find an exit rate increase of 29.4%, a 19.3% average decrease in car availability, and a 19.9% average increase in cancellation rates, compared to the control group. These effects are statistically significant, indicating that providers retaliate in response to loss of pricing control.

Providers in treatment cell T2—which retained partial pricing control—also retaliated through these three channels. However, these providers’ reactions were substantially lower. Our preferred estimates indicate that, compared to providers in treatment cell T1, providers who retained partial pricing control had 48.4% lower exit rate, 51.4% higher average asset availability, and 34.9% lower transaction cancellation rate. All three effects are statistically significant, indicating that providers retaliate in response to loss of pricing control.

We then turn to examining the reasons behind provider retaliation. Providers could retaliate against the pricing mechanism change if they started making lower revenues as a
result. Compared to control group providers, treated providers had 53.8% higher revenue for treatment cell T1, and 51.6% higher revenue for treatment cell T2. As such, treated providers retaliated despite experiencing a higher revenue stream.

The higher revenues treated providers experienced were made at the expense of a higher utilization of providers’ assets. We find that cars of treated providers were out substantially more than cars of control group providers. By itself, however, a higher utilization rate does not explain the retaliation of treated providers: the pricing mechanism change was made in order to increase asset utilization in the first place, as car capacity was underutilized.

To explain providers’ retaliation against the new pricing mechanism, we then examine its effects on providers’ bring-to-market (BTM) costs (Filippas et al., forthcoming). Making a good available for rentals is costly: providers have to find and evaluate the renters, and rentals often require labor and complementary consumables, and depreciate the rented asset. We find that the new pricing mechanism increased providers’ BTM costs: providers had to engage in more less valuable rentals, increasing their transaction-based BTM costs, and their revenue per mile driven with their cars also decreased. The increased BTM costs imply that, while provider revenue increased, the true utility from rentals may have decreased—at least for some providers. As such, some treated providers retaliated against the new pricing mechanism. Furthermore, providers in treatment cell T2 experienced lower BTM costs than providers in treatment cell T1, offering a potential explanation about the differences in retaliation between the two groups.

Our data suggests that providing partial control is highly effective, increasing provider satisfaction by 30 percent, as measured through a survey conducted after the experimental period. Furthermore, fewer than half of the providers assigned to treatment cell T2 moved the price slider at least once by the end of the experiment. As such, the platform essentially doubled the “enrollment” to the intended feature—fully decentralized pricing—at no extra cost. In addition to managing the pricing mechanism change, we also discuss the economic value of embedding provider input in a platform’s pricing mechanism. Partial provider control provides valuable information to a platform in optimizing the prices. Furthermore, partial pricing control allows providers to reveal their reservation prices, which can be both highly idiosyncratic and time-varying.

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. Despite these limitations,
this paper represents 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.

2 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 span a range of products and services, including short-term accommodation, startup funding, and commuting. There has been great interest on the economic implications of sharing economy platforms. Sharing economy platforms lower the costs to entry for smaller suppliers, enabling them to reach buyers more easily (Einav et al., 2016). Another important source of added surplus is the flexibility afforded to the providers (Chen et al., 2017). On the consumer 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). Furthermore, these platforms extensively use technology that allows providers and renters to find, assess, and transact with one other more efficiently than what is possible in several physical markets (Cramer and Krueger, 2016; Horton, 2017).

Sharing economy platforms also have numerous important implications for actors outside the marketplace. Recent work has documented how the sharing economy has disrupted the competition status quo in many industries (Farronato and Fradkin, 2015; Hall and Krueger, 2016; Zervas et al., 2017). While the waxing and waning of various industries does not constitute market failure, the same cannot be said about the new social costs and benefits brought about by these platforms (Filippas and Horton, 2018; Davidson and Infranca, 2018). Our work adds to a growing stream of literature examining challenges that arise when organizing economic activity in sharing economy markets, and, more generally, in online P2P markets (Sundararajan, 2014, 2016; Edelman et al., 2017; Filippas and Horton, 2018; Filippas et al., 2018).
Sharing economy platforms generally differ in their scope and focus, but the platform commonly assumes the role of a mediating party, providing value-generating services such as search and ranking systems, algorithmic recommendations, reputation systems, dispute arbitration, and insurance (Einav et al., 2016; Sundararajan, 2016). One important design decision is how transaction prices should be set. Platforms can choose between a multiplicity of pricing mechanisms, such as haggling, auctions, and posted prices, as well as whether pricing decisions will be centralized, i.e., made by the platform, or decentralized, i.e., made by the providers (Farronato, 2017). Recent work has examined the relative benefits of different pricing mechanisms (Einav et al., 2015, 2018); the interplay of complementary market design decisions with the outcomes of the pricing mechanism (Dinerstein et al., 2018); the equilibrium effects of price changes (Cullen and Farronato, 2014; Hall et al., 2017; Castillo et al., 2017); and the pricing decisions of providers (Li et al., 2015; Filippas and Gramstad, 2016; Blake et al., 2018).

The optimality of a given market mechanism generally depends on an array of market conditions. For example, a nascent platform may delegate pricing decisions to users. As the platform matures, obtains access to more transaction data, and experiments, implementing a centralized pricing mechanism may result in large efficiency gains. In words, what market mechanism is optimal can change over time, and platforms eventually have to implement market design changes.

There is little empirical evidence on (i) how to transition between different market mechanisms, and (ii) what the market outcomes are following this transition. Previous research has focused either on shifts in the relationship of buyers and sellers (Pavlou and Gefen, 2005), or on the reactions of external contractors/vendors when a firm implements changes (Levina and Ross, 2003). To our knowledge, our paper provides the first experiment aiming to provide additional empirical insight to this literature, 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.

2.1 The focal platform

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 will 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 sharing activity the density of rentals is analogous to the population density of the city.

Providers may choose to rent out their cars for as short as half an hour, and as long as a month. Despite this flexibility, the nature of the rental activity on the platform is mostly short-term. Figure 1b depicts the histogram of rental durations, for all rentals that took place between January 1, 2017 and August 1, 2017. Rental durations are 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. About 89 percent of the rentals last less than one day, and only 1.6 percent last more than three days, indicating that the renters mostly use the platform for short-term car rentals.

Providers presumably differ in their usage of the platform. Some providers may be 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 lease or buy cars that they make available on the platform at all times, as a means of earning supplemental income. Figure 1c plots the histogram of monthly car availabilities between January 1, 2017 and August 1, 2017. We define car availability to be the percentage of time that the car is made available for rentals on the platform. The availability distribution has significant mass across all categories. About 70 percent of the providers make their cars available on the platform more than half of the time. This is, of course, not counter-intuitive: car owners use their cars less than 4 percent of the time. However, a substantial percentage of providers only rarely make their cars available, suggesting the existence of providers who attempt to monetize their cars in periods when demand is at its highest, but are otherwise indifferent between renting out and idling their cars.

If the main advantage of sharing economy markets is that they enable users to put idle assets to use, then highly underutilized cars would imply foregone opportunities for transactions, and lower-than-optimal revenue for the platform. Figure 2a plots the histogram of monthly car utilization between January 1, 2017 and August 1, 2017. Utilization is defined as the amount of time that the car was rented out over the amount of time that the car was made available for rentals in the platform. The distribution of car utilizations approximates

\[ \text{Utilization} = \frac{\text{Rented Out}}{\text{Available}} \]

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.
a Pareto distribution. About 63 percent of the cars are rented out less than 30 percent of the time they are made available for rentals. However, there exists a small percentage of highly utilized cars: about 6 percent of the cars are utilized more than 60 percent of the time that they are available.

The low average utilization of cars indicates the existence of inefficiencies in the market, and more specifically, in how the market clears. Basic economic theory suggests that a likely explanatory factor is suboptimal pricing of the cars, and, more specifically, suboptimal pricing decisions by the 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).

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.
Figure 2b plots the histogram of monthly price changes for San Francisco providers, for the period of January 1, 2017 to August 1, 2017. Strikingly, most providers rarely or never change the price for their cars: about 70 percent of the providers change their price at most one time per month. Fewer than 4 percent of the providers change price of their cars at least one every two days. As such, Figure 2b provides some evidence that prices, as set by providers, were failing to function as a market-clearing mechanism in the focal platform, subsequently causing the low car utilization observed in Figure 2a. As the focal platform employed an ad-valorem business model, the executives believed that this inefficiency likely reduced platform profits, and decided to transition to a different pricing mechanism.

3 Experimental change in the pricing mechanism

3.1 Transitioning to centralized pricing

Motivated by the likely link between provider pricing-led pricing and low car utilization, the platform set out to develop a new, centralized pricing system. In addition to increasing profits, 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 profit 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 similarly 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 owners’ 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 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 seemingly effective, with the control and treatment groups being well balanced.

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3For confidentiality reasons, we do not report this fraction.
4The 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.
5The relatively small fraction of providers that as assigned to the two experimental treatments helped ensure that financial risk to the platform would be mitigated. This relatively small allocation is also a useful design feature, in that it reduces concerns about validity-threatening movements of the market, which constitute a type of SUTVA violation (Blake and Coey, 2014). For example, if a large number of treated providers saw their revenue increase at the expense of the revenues of providers in the control group, then inferences about the causal effect of the treatment on the outcomes of interest would be dubious. As we show later, this did not occur.
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</th>
<th>T1</th>
<th>T2</th>
<th>T0-T1</th>
<th>T0-T2</th>
<th>T1-T2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean (s.e.)</td>
<td>mean (se)</td>
<td>mean (se)</td>
<td>p-value</td>
<td>p-value</td>
<td>p-value</td>
</tr>
<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>Earnings</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 earnings (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 samples: (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. Reporting treatment effect estimates for these two subpopulations allows us to verify that our results are robust across samples, or to detect evidence of heterogeneous effects in subpopulations of interest.
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 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 decentralized 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. 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.

\[^6\text{Note that here—and throughout the paper—for differences in levels where the outcome is naturally discussed as a fraction, we label level differences as "percentage points." For percentage changes with respect to the outcome of the control, or another treatment cell, we use the "%" symbol.}\]
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 over time to the pricing mechanism change

(a) Weekly average car availability.

![Graph showing availability over time with different providers indicated]

(b) Weekly average transaction cancellation rate.

![Graph showing cancellation rates over time with different providers indicated]

(c) Weekly average number of price changes.

![Graph showing price changes over time with different providers indicated]

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.

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.

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. As such, the reported estimate is the “intention-to-treat” effect estimate (Gerber and Green, 2012).

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

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7In addition to the “intention-to-treat” effect estimate, we report the “complier average causal effect” estimate in Appendix B, by restricting our sample to “compliers,” that is, providers who did not exit the platform throughout the experiment (Gerber and Green, 2012). In the context of availability decisions, estimates that only include “compliers” may be interpreted as a lower bound on the availability responses: providers who exited the platform would presumably exhibit the largest car availability reductions.
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.

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. Our preferred estimate is the “intention-to-treat” effect estimate, that includes providers who exited during the experimental period, setting these providers’ cancellation rate to one for all periods after their time of exit.\(^8\)

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.

\(^8\)We also report the “complier average causal effect” estimate in Appendix B, by restricting our sample to providers who did not exit the platform throughout the experiment. This estimate may be interpreted as a lower bound: providers who exited the platform would presumably exhibit the largest transaction cancellation rates.
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.

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 begin by developing a conceptual framework of how mechanism changes affect providers in online markets. We then examine the effects of the pricing change mechanism on provider revenue and car utilization, and decompose the rental costs that providers incurred into (i) usage costs, such as the costs from asset depreciation, and (ii) transaction costs, such as the costs of handing off and “resetting” assets.

5.1 Effects on provider revenue

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

Figure 5a reports the results of regressions of log provider revenue on the treatment cell indicators. Provider revenue is defined as the total revenue providers earned during the experimental period. Our preferred estimate is the “complier average causal effect” estimate, which includes only those providers who did not exit the platform during the experiment.9

The decentralized pricing system had a substantial positive effect on provider revenue. In the entire population ALL, providers saw their income increase by 53.8% for the cell T1, and by 51.6% for the cell T2, when compared to the income of providers in the control group. Both effects are statistically significant, but the difference between the earnings of the two groups is statistically indistinguishable. The pattern of the effects is similar in the subpopulations NEW and LOW, where T2 seems to do slightly better than T1, but the effects of the two treatments are also statistically indistinguishable.

Figure 6a shows the average weekly revenue for providers in the control group, and for providers pooled from the two treatment groups. It is worthwhile noting that treated providers saw revenue increases in every week during the experiment. 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 revenue. Furthermore, allowing providers to retain some control over the pricing of their cars did not lead to a substantial decrease in revenues, compared to completely decentralizing pricing. While it would be tempting to extrapolate these findings to the case where the platform rolled out

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9We report a population-level effect estimate in Appendix B, by including providers who exited during the experimental period, and imputing the revenue of these providers in the periods following their exit from the platform with the corresponding mean for providers assigned to the same cell. The pattern of results is similar across the two estimation strategies.
its decentralized pricing mechanism to the entire market, such an inference would require us to take into account the equilibrium effects of such a change, and is not the focus of this paper.

5.2 Effects on asset utilization

Our next question is how the decentralized pricing system managed to increase the profits of treated providers. Toward that end, we examine the intensive margin of car rentals for cars that were made available on the platform during the experimental period.

Figure 5b reports the results of regressions of the number of hours cars were rented out on the treatment cell indicators. Hours rented are defined as the total number of hours each car was rented during the experimental period. Our preferred estimate is the “complier average causal effect” estimate, which includes only cars of providers who did not exit the platform during the experiment.10

The decentralized pricing system substantially increased the number of hours that available cars were rented out. In the entire population, ALL, providers saw the hours their cars were rented out increase by about 138% for the cell T1, and by 100.8% for the cell T2, when compared to the number of hours cars of providers in the control group were rented out. Both effects are statistically significant. The results vary little for the reported subpopulations, with the percentage increase being similar for providers in LOW, and higher similar for providers in NEW. Across all samples, cell T1 has experienced the larger increase in hours rented, but we cannot statistically distinguish between the two effects with our sample size.

A graphical representation of this result is shown in Figure 6b, which reports the average weekly number of hours rented for cars of providers in the control group, and for providers pooled from the two treatment groups. Clearly, the mechanism through which centralized pricing increased the revenue of providers was by trading off decreases in the intensive margin (revenue per hour rented) for increases in the extensive margin (number of hours rented).

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10We report a population-level effect estimate in Appendix B, by including providers who exited during the experimental period, and imputing the revenue of these providers in the periods following their exit from the platform with the corresponding mean of providers assigned to the same cell. The pattern of results is similar across the two estimation strategies.
Figure 5: Economics outcomes following the pricing mechanism change

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

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

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 car utilization. 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 owner revenue.

(b) Weekly average hours rented.

Notes: This figure shows the market outcomes for providers before and during the experimental period. The top panel shows the weekly average provider revenue for providers in the control group, and for providers pooled from the two treatment cells. The bottom panel 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.
5.3 Effects on BTM costs

The centralized pricing mechanism increased treated providers’ revenue by increasing the utilization of their cars, and hence the platform seemingly achieved its primary objective. However, higher provider revenues do not imply higher provider utilities. The reason is that providers incur “bring-to-market” (BTM) costs when renting out a good on a 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. For example, driving with Uber requires labor, increases the car’s mileage, and consumes gas. Transaction-based BTM costs include the costs inherent in finding trading partners, coming to terms, executing payments, and handing off and “resetting” the good. Back to the Uber example, drivers and passengers have to find each other before each transaction, and screen each other’s identity.

In our 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 earnings 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 7a reports the results of regressions of earnings per mile on the treatment cell indicators. Earnings per mile are defined as the ratio of the total earnings over the total number of miles a car was driven during the experimental period. Similarly to our estimation strategy in the previous sections, our preferred estimate is the “complier average causal effect” estimate, which restricts our sample to providers who did not exit the platform.11

The pricing mechanism change substantially decreased providers’ earnings per mile. In

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11We report a population-level effect estimate in Appendix B, by including providers who exited during the experimental period, and imputing the revenue of these providers in the periods following their exit from the platform with the corresponding mean of providers assigned to the same cell. The pattern of results is similar across the two estimation strategies.
the entire population, ALL, providers saw their earnings per mile decrease by about 30.3% for the cell T1, and by 29.1% for the cell T2, compared to the earnings per mile for providers in the control group. Both effects are statistically significant, and similar across the true treatment cells, as well as across the different subpopulations.

We next turn to provider earnings 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, then that provider obtains lower utility from renting.

Figure 7b reports the results of regressions of earnings per transaction on the treatment cell indicators. Earnings per transaction are defined as the ratio of the total earnings over the total number of transactions for a car during the experimental period. Similarly to our estimation strategy in the previous sections, our preferred estimate is the “complier average causal effect” estimate, which restricts our sample to providers who did not exit the platform.\textsuperscript{12}

The pricing mechanism change decreased providers’ earnings per transaction. In the entire population, ALL, providers saw their earnings per mile decrease by about 16.7% for the cell T1, and by 7.8% for the cell T2, compared to the earnings 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.

\textsuperscript{12}We report a population-level effect estimate in Appendix B, by including providers who exited during the experimental period, and imputing the revenue of these providers in the periods following their exit from the platform with the corresponding mean of providers assigned to the same cell. The pattern of results is similar across the two estimation strategies.
Figure 7: Effects of the pricing mechanism change on BTM costs

(a) Effects of the pricing mechanism change on earnings per mile

(b) Effect of the pricing mechanism change on earnings 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 earnings per mile. In the bottom panel, the dependent variable is the change in earnings 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.
6 Discussion

Changes in the design of online markets need to be implemented often: no platform is perfectly designed at its conception, and shifts in the competitive landscape necessitate further redesign. As such, methods that reduce user retaliation against change 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 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 8 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 8: Answers to the satisfaction question “Which of the following best describes your experience with our new pricing feature?”.

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 9a 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 9b 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.

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 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 too can be found with idiosyncratic and time-varying private
Figure 9: 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.

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 on 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


A Pricing Interfaces

Figure 10 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 10a. 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 10b shows the interface for the version of the pricing feature where 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 11.
Figure 10: 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.
Figure 11: Pricing interface for treatment groups.

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.

Your rates include 200 miles per day. You’ll receive 30¢ for each additional mile. Commission (40%) covers renter insurance, driver screening, and payment processing.
### B Regression tables

#### B.1 Tables for Section 4

Table 2: Effects of the experimental treatment on provider exit

<table>
<thead>
<tr>
<th>Provider Exit</th>
<th>ALL (1)</th>
<th>NEW (2)</th>
<th>LOW (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>0.294***</td>
<td>0.302***</td>
<td>0.222***</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.045)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>T2</td>
<td>0.151***</td>
<td>0.090*</td>
<td>0.093*</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.042)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.088***</td>
<td>0.117***</td>
<td>0.107***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.017)</td>
<td>(0.017)</td>
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</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>1,218</th>
<th>615</th>
<th>609</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.088</td>
<td>0.070</td>
<td>0.047</td>
</tr>
</tbody>
</table>

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: $p \leq 0.1 : \dagger$, $p \leq 0.05 : \ast$, $p \leq 0.01 : \ast\ast$, and $p \leq .001 : \ast\ast\ast$. 
Table 3: Effects of the experimental treatment on provider availability

<table>
<thead>
<tr>
<th></th>
<th>Car availability</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ALL (c)</td>
<td>NEW  (c)</td>
<td>LOW (c)</td>
<td>ALL</td>
<td>NEW</td>
<td>LOW</td>
</tr>
<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>-0.073* (0.035)</td>
<td>-0.104* (0.053)</td>
<td>-0.041 (0.053)</td>
<td>-0.193*** (0.029)</td>
<td>-0.238*** (0.043)</td>
<td>-0.108* (0.043)</td>
</tr>
<tr>
<td>T2</td>
<td>-0.075* (0.032)</td>
<td>-0.115** (0.043)</td>
<td>-0.045 (0.049)</td>
<td>-0.127*** (0.029)</td>
<td>-0.143*** (0.040)</td>
<td>-0.054 (0.044)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.649*** (0.012)</td>
<td>0.661*** (0.017)</td>
<td>0.484*** (0.018)</td>
<td>0.618*** (0.012)</td>
<td>0.620*** (0.016)</td>
<td>0.456*** (0.017)</td>
</tr>
</tbody>
</table>

Observations   1,032  511  516  1,218  615  609
R^2            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, by imputing compliers’ car availability with zero following their exit from the platform. 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: \( p \leq 0.1 : \frac{}{}, p \leq 0.05 : *, p \leq 0.01 : **, \) and \( p \leq .001 : ***. \)
Table 4: Effects of the experimental treatment on provider transaction cancellations

<table>
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<th>Transaction cancellation rate</th>
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</thead>
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<td>NEW (c)</td>
</tr>
<tr>
<td></td>
<td>LOW (c)</td>
</tr>
<tr>
<td></td>
<td>ALL</td>
</tr>
<tr>
<td></td>
<td>NEW</td>
</tr>
<tr>
<td></td>
<td>LOW</td>
</tr>
<tr>
<td>T1</td>
<td>0.066** (0.023)</td>
</tr>
<tr>
<td></td>
<td>0.075* (0.037)</td>
</tr>
<tr>
<td></td>
<td>0.119** (0.037)</td>
</tr>
<tr>
<td></td>
<td>0.199*** (0.022)</td>
</tr>
<tr>
<td></td>
<td>0.227*** (0.034)</td>
</tr>
<tr>
<td></td>
<td>0.204*** (0.034)</td>
</tr>
<tr>
<td>T2</td>
<td>0.015 (0.021)</td>
</tr>
<tr>
<td></td>
<td>0.042 (0.030)</td>
</tr>
<tr>
<td></td>
<td>−0.009 (0.035)</td>
</tr>
<tr>
<td></td>
<td>0.129*** (0.022)</td>
</tr>
<tr>
<td></td>
<td>0.131*** (0.032)</td>
</tr>
<tr>
<td></td>
<td>0.098** (0.034)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.165*** (0.008)</td>
</tr>
<tr>
<td></td>
<td>0.173*** (0.011)</td>
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<tr>
<td></td>
<td>0.165*** (0.013)</td>
</tr>
<tr>
<td></td>
<td>0.170*** (0.009)</td>
</tr>
<tr>
<td></td>
<td>0.181*** (0.013)</td>
</tr>
<tr>
<td></td>
<td>0.164*** (0.013)</td>
</tr>
</tbody>
</table>

| Observations     | 1,032 | 511  | 516  | 1,218 | 615  | 609  |
| R²               | 0.008 | 0.011| 0.021| 0.077 | 0.083| 0.062|

Notes: This table reports regressions where the dependent variable is provider 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, by imputing compliers’ cancellation rate with one following their exit from the platform. 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 $p \leq 0.001 : ***$.  

B.2 Tables for Section 5

Table 5: Effects of the experimental treatment on provider revenue

<table>
<thead>
<tr>
<th></th>
<th>Dependent variable: Provider revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ALL (c)</td>
</tr>
<tr>
<td>T1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>T1</td>
<td>452.509***</td>
</tr>
<tr>
<td></td>
<td>(86.812)</td>
</tr>
<tr>
<td>T2</td>
<td>433.475***</td>
</tr>
<tr>
<td></td>
<td>(78.867)</td>
</tr>
<tr>
<td>Constant</td>
<td>840.628***</td>
</tr>
<tr>
<td></td>
<td>(29.145)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,032</td>
</tr>
<tr>
<td>R²</td>
<td>0.047</td>
</tr>
</tbody>
</table>

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, by imputing the revenue of these 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 5a. Significance indicators: \( p \leq 0.1 : \dagger, p \leq 0.05 : *, p \leq 0.01 : **, \) and \( p \leq .001 : ***. \)
Table 6: Effects of the experimental treatment on number of hours rented

<table>
<thead>
<tr>
<th></th>
<th>Hours rented</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ALL (c)</td>
<td>NEW (c)</td>
<td>LOW (c)</td>
<td>ALL</td>
<td>NEW</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</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>
</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>
</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>
</tr>
<tr>
<td></td>
<td>(5.914)</td>
<td>(8.224)</td>
<td>(7.535)</td>
<td>(5.391)</td>
<td>(7.357)</td>
</tr>
</tbody>
</table>

Observations 1,032 511 516 1,218 615 609

R² 0.143 0.103 0.142 0.188 0.158 0.188

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 5b. 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 7: Effects of the experimental treatment on earnings 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>T1</td>
<td>-0.295***</td>
<td>-0.263**</td>
<td>-0.296***</td>
<td>-0.337***</td>
<td>-0.325***</td>
<td>-0.337***</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.082)</td>
<td>(0.070)</td>
<td>(0.038)</td>
<td>(0.060)</td>
<td>(0.054)</td>
</tr>
<tr>
<td>T2</td>
<td>-0.283***</td>
<td>-0.267***</td>
<td>-0.280***</td>
<td>-0.284***</td>
<td>-0.271***</td>
<td>-0.285***</td>
</tr>
<tr>
<td></td>
<td>(0.045)</td>
<td>(0.067)</td>
<td>(0.065)</td>
<td>(0.038)</td>
<td>(0.056)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.974***</td>
<td>0.982***</td>
<td>0.990***</td>
<td>0.974***</td>
<td>0.982***</td>
<td>0.987***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.026)</td>
<td>(0.024)</td>
<td>(0.015)</td>
<td>(0.022)</td>
<td>(0.021)</td>
</tr>
</tbody>
</table>

Observations 1,032 511 516 1,218 615 609
R² 0.060 0.044 0.059 0.089 0.070 0.086

Notes: This table reports regressions where the dependent variable is the earnings 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, by imputing the values of providers in the period following their exit from the platform with the mean earnings per mile 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 7a. Significance indicators: p ≤ 0.1 : †, p ≤ 0.05 : *, p ≤ 0.01 : **, and p ≤ .001 : ***.
Table 8: Effects of the experimental treatment on earnings 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>−13.203**</td>
<td>−20.716**</td>
<td>−14.524*</td>
<td>−10.951***</td>
<td>−15.307**</td>
<td>−11.106*</td>
</tr>
<tr>
<td></td>
<td>(4.326)</td>
<td>(7.055)</td>
<td>(5.776)</td>
<td>(3.221)</td>
<td>(5.036)</td>
<td>(4.478)</td>
</tr>
<tr>
<td>T2</td>
<td>−6.166</td>
<td>−2.526</td>
<td>−10.978*</td>
<td>−2.437</td>
<td>0.284</td>
<td>−5.413</td>
</tr>
<tr>
<td></td>
<td>(3.930)</td>
<td>(5.731)</td>
<td>(5.408)</td>
<td>(3.205)</td>
<td>(4.702)</td>
<td>(4.526)</td>
</tr>
<tr>
<td>Constant</td>
<td>78.948***</td>
<td>79.067***</td>
<td>81.937***</td>
<td>76.696***</td>
<td>76.756***</td>
<td>77.969***</td>
</tr>
<tr>
<td></td>
<td>(1.452)</td>
<td>(2.201)</td>
<td>(2.015)</td>
<td>(1.276)</td>
<td>(1.885)</td>
<td>(1.763)</td>
</tr>
</tbody>
</table>

Observations | 1,032 | 511 | 516 | 1,218 | 615 | 609
R²            | 0.010 | 0.017 | 0.018 | 0.009 | 0.015 | 0.011

Notes: This table reports regressions where the dependent variable is the earnings per transaction 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, by imputing the values of providers in the period following their exit from the platform with the mean earnings per transaction 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 7b. Significance indicators: $p \leq 0.1 : ‡, p \leq 0.05 : *, p \leq 0.01 : **$, and $p \leq .001 : ***$. 
C Additional results

C.1 Results for expensive cars

AF has done this analysis and has found no difference in retaliation, revenue, and utilization, and BTM costs between owners of expensive and inexpensive cars.