Pre-Analysis Plan: Price Information and Competitive Spillovers in an Online Platform in Pakistan

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Abstract

In developing markets facing information and search frictions, how do agents access price information, update their beliefs about market conditions, and make pricing and other strategic choices? Also in such environments, what are the extent to which individual agents' access to information and their choices generate spillovers to other market participants? We explore these questions via a randomized control trial on a major online listing platform for used vehicles in Pakistan, where, along with other developing economies, increasing shares of transactions are shifting to online and mobile platforms. In our intervention we will provide estimates of transaction prices to sellers on a listing platform for used vehicles in Pakistan from February to April, 2022. We vary treatment saturation at the market-segment level by a two-stage randomization design so as to capture both direct and spillover effects. We measure the effect of providing private price information to sellers on their choices and outcomes, and capture spillover effects on competing sellers. In our primary analysis, we will detect direct and spillover effects on a) changes to the listing price, b) occurrence of transaction, c) transaction price, d) usage of advertising tools, and e) index of buyer attention. In our secondary analysis, we will identify ways in which the intervention interacts with, or in turn affects, market efficiency and structure.

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1 Introduction

Information and search frictions may hinder development of emerging markets, which often see high price levels and dispersion (e.g. Allen 2014; Andrabi et al. 2017). Interventions that leverage on information communications technology (ICT) are shown to reduce such frictions (e.g. Aker 2010; Aker and Mbiti 2010; Jensen 2007), yet the mechanisms through which such interventions trigger strategic responses, spillovers, and adjustments to market structure remain underexplored. On one hand, it may be possible that large enough exogenous shocks in information friction may induce general equilibrium shifts, for instance by improving efficiency of the supply channel (e.g. Jensen and Miller 2018). On the other hand, the market structure may determine how participants internalize information friction, and limit the extent to which interventions could shift market equilibria (Mitra et al. 2018).

Our aim is to improve our understanding on links between information friction, individual choices, and spillovers in a developing-market setting. We study the mechanisms by which novel price information may alter agents' strategic behaviors in the market, generate spillover effects onto their competitors, and affect the competitive landscape. We will run a randomized controlled trials (RCTs) in which we provide transaction-price estimates—called the Price Calculator—privately to sellers on a listing platform for used vehicles in Pakistan, PakWheels.com. We generate variation in treatment saturation at the market sub-section level via a two-stage randomization design. This partial identification strategy allows us to estimate not only the direct treatment effect, but also spillover and saturation effects.

It is generally challenging to measure spillovers and strategic responses in large-scale offline markets in developing economies, due to logistical constraints and the lack of data. The increasing popularity of online platforms and marketplaces in developing countries, however, presents us with an opportunity to study market behaviors more extensively and comprehensively than before. Unique data captured by our implementation partner, PakWheels.com, allow us to measure changes in sellers' strategic choices and buyer-side responses. We are also able to identify spillover effects and other market-level consequences, as we capture data from all sellers on this dominant online platform. Furthermore, by providing the Price Calculator estimate privately we can rule out direct information spillovers and instead focusing on knock-on effects of *choices* that treated sellers make.

With this project, we hope to highlight the potential of online platforms in emerging markets to address economically important questions and help reduce frictions and constraints. Our partner, PakWheels.com, is the leading and nationally recognized online classified advertisement platform for used vehicles Pakistan, allowing us to make a stronger claim to external validity than other interventions with smaller and selected subsamples. We conduct our intervention at low cost and within the framework of existing online platform. Our findings may therefore provide insights into the potential efficacy of online platform-based interventions to improve market efficiency in developing countries. As e-commerce in emerging markets grows in importance, so too could the body of evidence on how online markets help improve access to markets for those who were traditionally excluded (e.g. Couture et al.

2018). Our findings may also be relevant to the literature on small-to-medium enterprises in developing economies and business training interventions, which have had relatively low cost-effectiveness (McKenzie and Woodruff 2014; Blattman and Ralston 2015). A platform-based services to improve SME performance could be a low-cost alternative.

The remainder of this pre-analysis plan is organized as follows; Section 2 highlights the primary and secondary research questions we intend to answer with our intervention. Section 3 provides a summary of existing empirical evidence on search and information frictions in developing economies, insights from research on digital platforms, and the emergence of new literature on platform experiments in such contexts. Section 4 presents a summary of the theoretical framework and predictions, and highlights connections to the research questions in Section 2. Section 5 describes the research design and results of power analysis. Sections 6 and 7 discuss data sources and outcomes, respectively. Section 8 pre-specifies the analysis we intend to run, and draws connections with the theoretical framework and the research questions. We provide details of the theoretical framework in Appendix Section A.

2 Research questions

Our empirical objective is to understand how a price-information intervention induces changes in pricing, affects sellers' market outcomes, and generates spillovers that may have implications on the market structure. We divide our research questions into the following two sets.

The first set of questions pertains to direct treatment effects of price information on listing prices, transaction outcomes, and mechanisms at the individual level. Our hypothesis is that the information intervention reduces noise in sellers' beliefs about the distribution of demand, affects their pricing decisions, and improves their market outcomes. We also posit that sellers not make strategic choices beyond pricing, such as advertising, and those choices are contingent upon their pricing decisions and beliefs. We therefore hypothesize that contingent strategic choices like advertising could be affected by the price information intervention.

The second set of questions concerns spillovers and other market-level impact of the information intervention. Possible channels include: a) diffusion of information itself via shifts in the distribution of listing prices, b) competing sellers' pricing and advertising choices to treated individuals' strategic choices, and c) reduction in search friction and congestion in the market. Our empirical objectives, therefore, are to identify spillover effects on our primary outcome variables, and narrow down on channels of such spillovers.

Following is the list of primary (in bold) and secondary questions, with links to the theoretical predictions in Section 4.

1. Does the price information intervention induce direct effects on pricing, advertising, and transaction outcomes?

1.1. **Do sellers adjust their listing prices toward the price signal they receive?** (Prediction 1.)

1.1.1. Does the intervention affect sellers' stated beliefs about the distribution of transaction prices?

1.2. **Does the price information intervention improve sellers' returns from the platform?** (Prediction 2.)

1.2.1. **Does it increase page views?**

1.2.2. **Does it increase the transaction probability?**

1.2.3. **Does it affect the transaction price?**

1.3. **Do sellers respond to the intervention by making strategic adjustments in advertising?** (Prediction 3.)

1.4. Across what characteristics do we observe heterogeneous treatment effects?

- sellers' experience
- product heterogeneity in market clusters
- availability and variation of price information at baseline

2. Does the price information intervention create spillovers and other knock-on effects?

2.1. **Does the intervention induce spillovers in terms of listing prices, transaction outcomes, and the use of advertising?**

2.1.1. Are these spillovers induced by changes in listing prices and advertising by competing, treated sellers? (Prediction 4.)

2.1.1.1. Are there spillover effects on the stated belief about the distribution of transaction prices?

2.1.2. Do spillovers occur through a zero-sum shift in buyer attention toward treated sellers?

2.1.3. Do spillovers occur through changes in congestion? (Prediction 5.)

3 Literature Review

In this literature review, we discuss the empirical background to our research questions and provide our motivation to conduct a study of price information on an online platforms in a developing economy. We first present the main issues our study hopes to address: information and search frictions in developing markets. We then discuss some of the recent studies aimed at reducing search and information frictions in developed economies' online platforms and draw inferences about potential benefits and limits of information interventions in a developing-economy context. We conclude by highlighting an emerging body of evidence from online-platform interventions in developing countries and discussing our potential contributions.

3.1 Search and information frictions in developing markets

High price levels and dispersion have often been cited as a result of search friction, trade costs, and market power in developing markets and supply chains (e.g. Allen 2014; Atkin and Donaldson 2015). It seems straightforward that improved access to information communications technology (ICT) could reduce such friction at the individual level (e.g. Aker 2010; Aker and Mbiti 2010;Andrabi et al. 2017; Jensen 2007). Yet, due in part to the dearth of experiments with variations at the market-segment level, we know relatively little about market-level implications of such interventions. Jensen (2007) and Aker (2010), for instance, are primarily focused on showing convergence in commodity prices in market-wide interventions, making it difficult to capture individual mechanisms or spillover effects. Studies on price information and ICT often focus on small selected subsample and lack the sample or the design to speak to spillovers and market-wide effects.

Previous work has suggested that a large shock to information friction induce knock-on effects up through supply channels or in other general-equilibrium sense (e.g. Jensen and Miller 2018, Hasanain et al. 2019). On the other hand, market structure and form of negotiation may determine how agents respond to information and search frictions. Mitra et al. (2018), for instance, shows that market provision of price information to potato farmers does not affect farm-gate prices and revenue on average, but increases pass-through from middlemen to farmers. This implies that information affects the bargaining power of farmers, but overall effects on price is contingent upon the market structure in which they operate. Further empirical evidence is needed to determine what types of externalities may be generated *within markets* by information interventions, particularly on how they affect strategic choices of individuals and their competitors alike, and implications on market efficiency.

3.2 Roles of online platforms

High levels of information and search frictions make markets in developing economies a particularly appropriate context to conduct interventions on online platforms, especially as policymakers begin to think beyond access *per se* to ICT. A premise of many online platforms is to reduce search costs by making it easier to acquire information about competing products. Yet, evidence of persistent price dispersion in **developed** economies' online markets suggests that platforms will not completely eliminate information and search frictions in developing economies either (Einav et al. 2015; Horton 2019; Fradkin 2015). The question is why search and information frictions persists in a world with plausibly low search and information costs.

One view is that price dispersion and friction on online platforms are in part endogenous choices that platform operators make relative to other objectives, such as the extent of competitive pressure they want to induce. The following tension is at play; on one hand, platforms may want to reduce search friction and guide buyers to small sets of products that match their preferences. On the other hand, platforms also wish to induce price competition between sellers, which becomes more challenging when markets become highly segmented by specific search criteria. This idea is explored by Dinerstein et al. (2018), who evaluate the impact of a redesign by eBay that directed consumers towards products they prefer while inducing stronger price competition among sellers. Estimated search friction and online retail margins suggest that this particular redesign in the search process reduced price levels and variation, suggesting that balance between low information friction and competitive pressure is key to efficient online markets. This trade-off may be even more salient in developing economies with higher existing frictions and other market failures.

3.3 Platform interventions in developing markets

Given the potential trade-off between search friction and competitive pressure, what happens when online platforms in developing economies are introduced or redesigned to reduce search and information frictions? An emerging body of evidence from the literature on online platforms in developing countries provides some insights into this question, albeit with limitations. We summarize this evidence and highlight our potential contributions.

First, it seems that online platforms can reduce information and search frictions and improve welfare, although their successes may be varied. Couture et al. (2018), for example, show that while the benefits of access to e-commerce for rural markets in China are sizable, most of the gains accrue to the consumption side and to a minority of younger and richer users. The findings suggest that simply increasing access does not induce investments required to drive adaptation to e-commerce. In online labor market platforms, studies like Fernando et al. (2020) and Jeong (2020) found positive employment gains for disadvantaged groups, and reductions in wage price dispersion by reallocation of labor. The existence of heterogeneous effects therefore suggests the importance of understanding the mechanisms at play.

Second, existing studies suggest that search and information frictions still plays a major source of inefficiency on online platforms in developing countries. Bai et al. (2020) describe the existence of such friction on a Chinese platform AliExpress, and shows that positive shocks to demand and information improve firms' performance in the long run, independent of productivity or quality. This suggests that market dynamics may generate inefficient firms and low-quality goods to persist in markets with information and search frictions, based on luck of having received positive initial demand shocks.

These strands of work point to potential benefits and limitations of online platforms in reducing information friction, with welfare implications. Gaps in the literature still remain on a) how market participants internalize, and compensate for information friction and other related barriers, and b) spillovers and systematic implications of externally adjusted information environment. We hope to contribute on these points by i) evaluating sellers' responses on a wide range of behaviors on the platform, and ii) systematically measuring spillovers by conducting a platform intervention that induces a shift in the information set at the market segment level.

4 Theoretical Framework

We present a simple conceptual framework describing a search process in which sellers set listing prices and place advertisements under noisy beliefs about demand. We derive predictions on how a price-information intervention may reduces noise in sellers' beliefs and affect list pricing, advertising, and market outcomes. The model is a simple static search framework based on Stigler (1961) and Diamond (1982). Most canonical models that focus on information assume that agents have full knowledge of factors like market friction and demand distributions (as summarized in Baye et al. 2007 and used in papers like Allen 2014). We depart from this standard setup in the following ways:

- Sellers have biased or noisy beliefs about the distribution of buyer willingness-to-pay (WTP), which may lead to biased or noisy beliefs about the probability of sale and to suboptimal list-pricing.
- Sellers can influence the match rate with potential buyers by engaging in costly actions, i.e. advertising.

We set up a model in which a seller i is endowed with an asset and certain unobservable characteristics s_i, as well as information set I_i. The search process is composed of the following steps:

1. Seller i forms beliefs about the distribution of buyers' WTP, based on information I_i.
2. Seller i chooses a listing price p_i^l and amount of advertisements a to optimize expected returns from participating in the marketplace.
3. Seller i matches with a potential buyer via a Poisson process.
4. Once matched, seller i makes a take-it-or-leave-it (TIOLI) offer p_i^t below p_i^l to the potential buyer.
5. Transaction occurs if the matched buyer's WTP is higher than p_i^t.

We provide further detail on the set-up and derive the model in Appendix A.

4.1 Theoretical predictions

We derive the following predictions from the theoretical framework, and connect them to our main research questions in Section 2:

1. The price information intervention brings the listing price p_i^l closer to what it would be under no noise in beliefs about demand. (Research question 1.1.)

2. The information intervention increases expected returns from the search process. (Research question 1.2.)

3. The information intervention increases the consumption of advertising a if sellers' beliefs about expected returns from search are adjusted upward. (Research question 1.3.)

4. Spillover effects could occur through lower noise in publicly available price signals, which could increase returns from the platform and from advertising. (Research questions 2.1.1.)

5. Spillover effects could occur if the intervention affects transaction outcomes and consequently the Poisson match rate in a treated market segment. (Research question 2.1.3.)

5 Research Design

We will conduct a field experiment in which we privately provide Price Calculator estimates to a randomly chosen subset of sellers. The Price Calculator estimates are based on a machine learning model using data on self-reported transaction prices from previous listings collected by PakWheels. The experiment is conducted within PakWheels' web and mobile platforms, when sellers create new listings. We assign treatment via a blocked, two-step randomization procedure with two saturation levels, as described in Section 5.2. This experiment will be conducted over the course of 8 weeks.

5.1 Sample selection

The platform receives upward of 100,000 valid listings per month. Our sample is new posts on the platform during intervention period, except those for which PakWheels do not have sufficient data points to provide a Price Calculator estimate. The exact criteria for inclusion into the sample are masked for confidentiality reasons, but we expect to include approximately 88% of all new posts into the study sample, consisting of approximately 70 distinct make-models.

5.2 Two-step treatment assignment procedure

Our two-stage randomization process is as follows. In step 1, we block-randomize market clusters, defined as the make-model (e.g. Toyota Corolla), into two treatment (high vs. medium saturation) and control groups. In step 2, we randomize posts into treatment based on the last digit of the user ID on PakWheels. The assignment probability is 50 percent for the medium saturation group, and 90 percent for the high group. In order to ensure that treatment and control groups are comparable in the primary outcome variables, we test for balance using listings data from a pre-treatment period with the same sample inclusion criteria and randomization procedure as the experiment. We bootstrap-sample and iterate this randomization procedure over 500 times, and identify seeds for which we fail to reject differences in all primary outcome variables (described in Section 7), adjusted for false discover rate at 5%. We then randomly select one of those qualified seeds.

In step 1 of the two-step process, we run block-randomize make-model clusters into high-treatment, mid-treatment, and control groups. For blocking, we use standardized cluster-level means (except for cluster size) of the following variables:

- log(absolute difference between listing price and Price Calculator estimate)
- 1 if reported as sold
- log(self-reported transaction price)
- advertising index[1]
- buyer-attention index
- cluster size.

The variables above, other than the cluster size, are primary outcome measures defined in Section 7. Blocking is done with R's *blockTools* package (Moore 2012), which uses the optimal-greedy algorithm over the Mahalambois distance. We weight the five main outcome variables twice as heavily as the cluster size variable. Our choice of weights is admittedly arbitrary, but the rationale is that the primary objective is to balance over main outcome variables, and then with cluster size.

Based on these blocks, we assign 50 percent of the clusters to control, and 25 percent each to high- and low-treatment groups. Our choice on shares of clusters to treatment arms is informed by the literature on optimal design of saturation design and our own Monte Carlo simulations using real data from the platform. We provide further detail on this process in Section 5.6.

In step 2, we assign treatment to posts based on the last digit of sellers' user-ID on PakWheels.[2] Treatment digits are chosen by a random number generator in *R*. The choice of digits for treatment is fixed across cluster and time, in order to limit the extent of potential interference and for logistical simplicity. In other words, if a seller with user-ID i is in a treatment group for model m, then all other posts by i in m will be treated, as well as any other model m' that is treated at the same saturation intensity as m. Treatment intensity of 50% or 90% stays constant for the cluster over the course of the experimental period.

[1] There is a minor difference in definitions of constituent variables, due to limitations in the pre-intervention data

[2] The reason for this randomization procedure, as opposed to some other procedures that does not rely on the user-ID, is partly for its simplicity in implementation, but also because we are assigning treatment to a *flow* of new listings (and some new users), meaning that we can cannot pre-assign treatment to posts.

5.2.1 Spillovers between clusters

One potential empirical challenges is interference between assignment clusters at the first stage of the randomization procedure. Our concern is that if we define clusters too narrowly and pricing or advertising choices in one cluster could affect those in another, we would violate the Stable Unit Treatment Value Assumption (SUTVA). We intend to allay this concern by using a relatively broad definition of clusters: the make-model. In this subsection, we discuss our decision based on observations from aggregated search logs data, details on which are given in Section 6.5.1. We also address possible ways in which interference across clusters could still occur as well as their potential magnitudes.

First, we observe that a majority (58%) of specified searches for posts on PakWheels included the make-model, and the majority of those 58% also had additional terms (e.g. model year, city, price ranges). On the other hand, 32 percent of specified searches did not include make-models, but instead included other fairly broad terms such as city name only, vehicle make only, or if the ad was featured or had pictures. We inferred that these broad searches are mostly speculative and unlikely to lead to meaningful price comparisons between posts. We do not have information (due to the capacity constraint at the firm for our data requests) on the remaining 10 percent of less frequent combinations of specified search terms. Overall, the breakdown of specified searches indicates that the make-model is likely a reasonable, and perhaps conservative, level of clustering, and any finer level of grouping could have meaningful interference between clusters.

Second, we believe that any interference across make-model clusters is likely minor given our experimental setup. This is because we provide private information that is specific to treated posts' characteristics, making it unlikely that there would be large direct information spillover effect from one make-model to another. In fact, in our pilot telephone endline survey, almost none of the sellers reported to have looked at listing prices of other models besides the one of their own vehicles.

Yet, the following are some of the ways in which interference *across* make-models could occur, violating SUTVA across treatment clusters:

- Large enough shifts in the distribution of listing prices could eventually induce information spillovers. Such large shifts in list-price distribution could also lead to changes in transaction probability, transaction price, and congestion, which in turn may affect price distributions and market outcomes of similar models.
- Changes to the listing prices or advertising in treated clusters may shift buyers' attention to/from untreated make-models. Changes in buyer attention in untreated make-models may affect sellers' pricing and advertising choices.

We plan on running robustness checks to address these concerns. First, we can include contemporaneous means and standard deviations of comparable models' listing prices as controls in the main estimating equation. Second, we can also include the treatment status of similar make-models to the estimating equation, and interact it with their means and standard deviations of listing prices. Third, we can empirically test if page views shift from comparable untreated to treated make-models.

5.3 Treatment assignment and take-up

The intervention is designed to minimize non-compliance; those randomly assigned treatment are automatically shown the Price Calculator estimate on the interface while they create a post. One exception is if the seller uses an older version of PakWheels' mobile app that does not yet contain the intervention tools. This may generate selection into treatment based on a) users' preference for PakWheels' app (as opposed to the web platform, which does not suffer from this issue) and b) their propensity to update the app. In order to mitigate this issue, PakWheels has launched a new version of the app that contains the intervention tool weeks before the experimental period. Yet it is possible that some non-treatment conditional on assignment could occur. As such, we plan on identifying both intend-to-treat and treatment-on-treated effects, as highlighted in Sections 8.3.2 and 8.3.3.

5.4 Intervention instrument: The Price Calculator

We will provide estimates of the transaction price for used vehicles on PakWheels while sellers are creating their posts. The price information, which PakWheels calls "the Price Calculator", is based on a machine learning model trained to predict self-reported transaction prices using the firm's database on historical listings. The model estimate is conditional on the self-reported occurrence of transaction, and we use observable attributes of the vehicle, but not of sellers' characteristics, as explanatory variables. Our hypothesis is that this information would help sellers identify realistic transaction prices, and set listing prices accordingly.

To identify an error-minimizing forecast model, we take a gradient boosting approach primarily for two reasons. First, gradient boosting—a method of ensemble predictions based on tree-based models—would allow us to construct a predictive model that does not require estimating each of the make-model-modelyear fixed effects. This was beneficial, as it allowed us to predict transaction prices for vehicles that had relatively small number of observations within their own make-model-modelyear, but for which we had sufficient information to provide predictions. Second is that the gradient boosting approach performed best in most measures of error against other approaches in our initial design process. This is consistent with the success of gradient boosting models in recent prediction competitions.

5.4.1 Display of the Price Calculator estimate

On PakWheels' web platform and mobile apps, sellers can create a new post by clicking on "Post an Ad." They are first asked to log in, so that we can identify the user-ID associated with each post. Users would not know their own user-ID (it is internal to PakWheels) or for which last digits we are providing Price Calculator estimates. Once logged in, users are asked to provide information about the vehicle they intend to sell, as shown in Figure 1. They then set the listing price in a box shown in Figure 2. If the seller is assigned to treatment, they are then shown a Price Calculator estimate, i.e. the machine-learning based transaction price forecast, as well as the 10th and 90th percentiles of reported transaction prices for the make-model-model year (or MMMY-version for frequently traded models). These percentile measures would be labeled as "Lower end" and "Upper end" of transaction prices. Figure 3 shows how the Price Calculator estimate is displayed along with a brief description. Treated sellers are then given a chance to update their listing price.

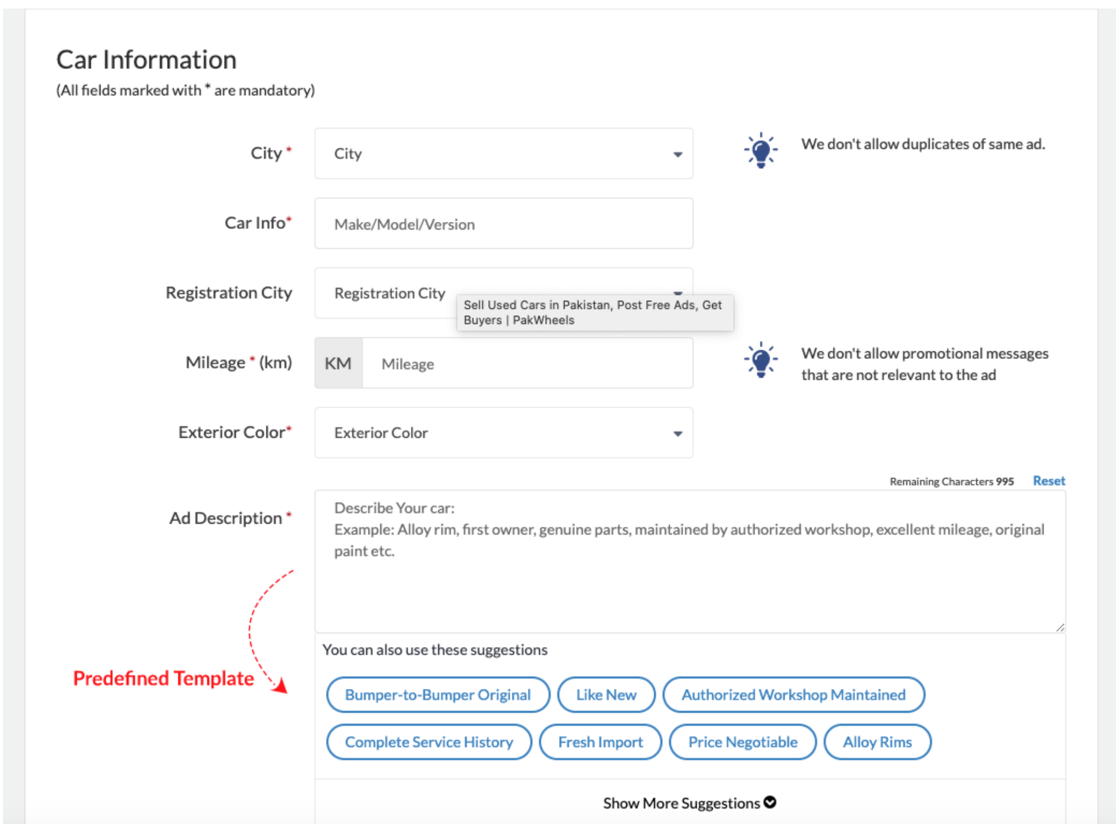

Figure 1: Making of a listing: Vehicle information

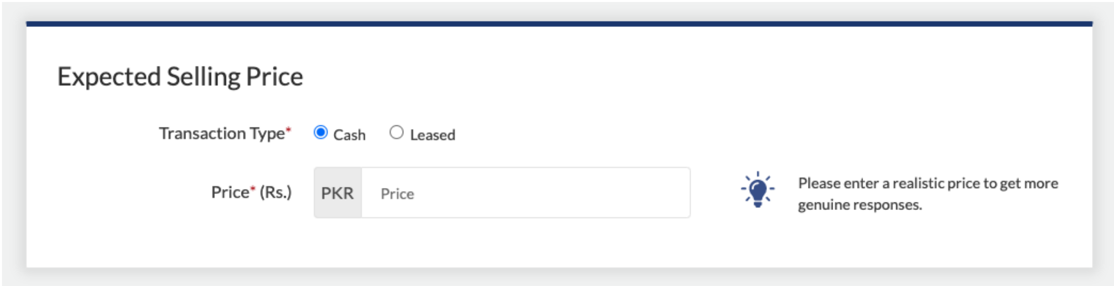

Figure 2: Making of a listing: Vehicle price

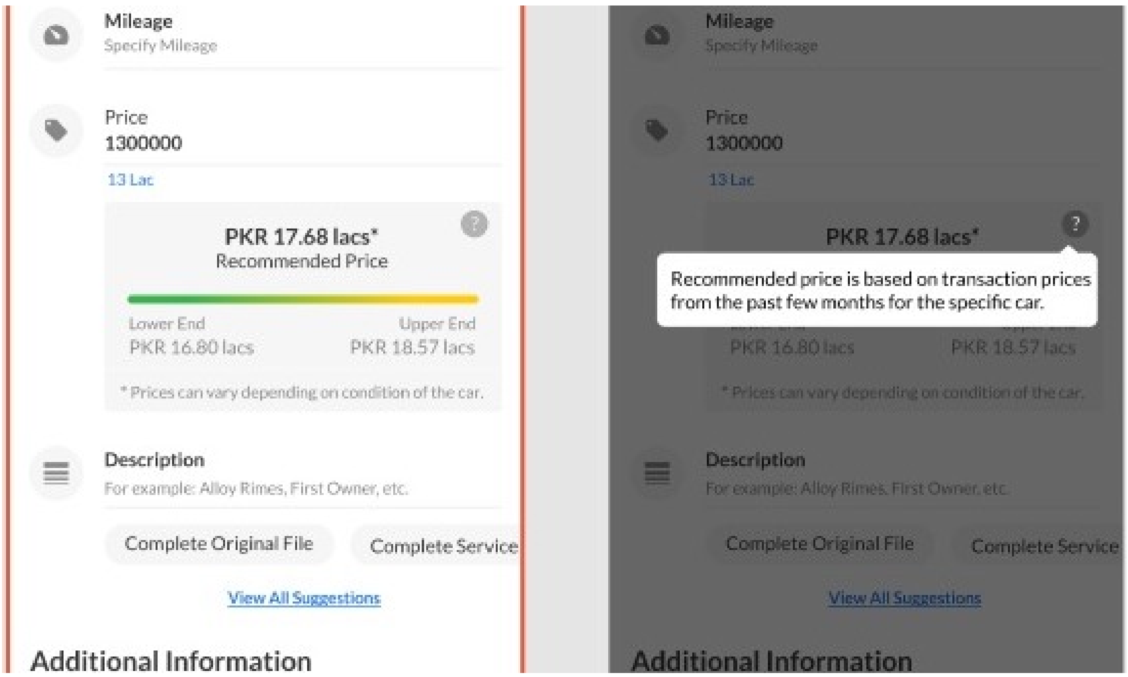

Figure 3: Display of the Price Calculator estimate

5.5 Unit of analysis

We will use the individual post as the unit of analysis for all pre-specified primary outcomes. This is because the treatment is provided at the post level, and we measure the spillover effect across posts. We also plan on conducting analysis at different units for some of the secondary outcomes and robustness checks. For instance, we will run analysis at the seller level to allay a potential concern that within-seller interference across posts would violate SUTVA. We will also run analysis at the model-week level on a range of secondary outcomes, such as the average duration of posts on the platform and higher-order moments of the primary outcome variables. Further details on primary and secondary analyses are provided in Section 8.

5.6 Statistical Power

We make choices on the following dimensions to maximize the statistical power of detecting treatment, spillover, and saturation effects:

- shares of clusters assigned to control, high treatment, and medium treatment groups
- share of posts into treatment assignment for both high- and medium groups.

We take as given the cluster sizes, as it depends on a fixed experimental duration of 8 weeks. We also take as given the number of clusters, as it depends on the number of models PakWheels could offer Price Calculator estimates without risking providing noisy information to infrequently traded vehicle models.

We take a hybrid approach based on theoretical optimal design and Monte Carlo simulations. For the latter, we use real historical data with assumptions about the reduced-form structure and relative effect sizes between direct treatment, spillovers, and saturation. First, we set the share of control clusters to 0.5 and the rest split evenly between high- and medium-treatment groups, based on insight from Baird et al. (2018). Their setup and assumptions are similar to ours, such as that they allow for intracluster correlation and only partial interference (i.e. within clusters but not across). We deviate from the procedure by Baird et al. (2018) on our choices of saturation levels. We assign second-stage randomization based on the last digit of sellers' user-ID, and we expect some level of treatment non-compliance as discussed in Section 5.3. As such, we have chosen the high treatment assignment to be 9 out of 10 digits, and middle treatment 5 out of 10. With a conservative assumption on treatment take-up of about 70 percent, then treatment intensities would be symmetrical around 0.5, as recommended by Baird et al. (2018).

Based on the saturation levels and the range of control group size chosen by the process above, we run Monte Carlo simulations to estimate power under several assumptions. We use actual data from PakWheels and estimate statistical power of detecting a range of effect sizes for direct impact, spillovers, and saturation. We use different data samples and specifications for direct and spillover effects, as described in Section 8.3. We bootstrap-sample the data 100 times, stratified over the make-model. We then assign treatment according to the method described in Section 5.2, and construct outcome variables conditional on cluster and individual assignments into treatment. We assume that direct and spillover treatment effects are linear and additive, except for the transaction outcome. [3] Spillovers are assumed to occur within the make-model cluster evenly for both treated and untreated posts. Using real historical data, we assume that intra-cluster correlation is already built in. We assume no inter-cluster interference.

The outcome variables, which are standardized and identical to the primary outcomes described in Section 7, are the following:

[3] Given that the transaction outcome is binary, we assumed that assignment into treatment would increase the probability of transaction by X%, where X is a standardized effect size based on the standard deviation of the binary variable.

- log(absolute difference between listing price and Price Calculator estimate)
- 1 if reported as sold
- log(self-reported transaction price)
- advertising index[4]
- buyer-attention index.

We estimate power of detecting the intend-to-treat (ITT) effects of direct treatment and spillovers for a range of relatively small effect sizes (0.025 to 0.2 of standard deviation). We explore two scenarios of spillover and saturation effect sizes relative to direct treatment effects:

1. spillover effect in high-saturation is 50% of the direct treatment effect, and in medium saturation 25%.
2. spillover effect in high-saturation is 100% of the direct treatment effect, and in medium saturation 50%.

We identify the optimal division of clusters into treatment arms based on the following proposition by Baird et al. (2018):

$$\psi^* = \frac{-\kappa + \sqrt{\kappa^2 + (1-\rho)\kappa}}{1-\rho} \tag{1}$$

where ψ is share of control clusters, $\kappa \equiv 1 + (n-1)$, ρ the intracluster correlation, and n cluster size. The boundary values of ψ^* are $\sqrt{2}-1$ and 0.5. Plugging in our parameter values to Equation 1 resulted in a control share close to 0.5.

We use the identical estimating equations to estimate intent-to-treat effects as in the main analysis in Section 8.3.2. In other words, we run the *logit* model for the binary outcome, and linear regressions for all other outcomes. These models include the same set of controls as ones used for the primary analysis. We use data from a 8-week period that approximates the actual experimental timing. We also present results that include data from 8 weeks prior in addition to data from the experimental period. This is to gauge how much power gains we could make in detecting spillovers by a larger sample and with cluster fixed effects, as described in Section 8.4.1. In both approaches, we report the false-discovery-rate-adjusted q-values based on 5 p-values corresponding to the main outcomes. These adjustments are made separately for direct treatment, spillover, and high-saturation effects.

[4]There is a minor difference in definitions of constituent variables, due to limitations in the pre-intervention data

5.7 Results of power calculations

The results of power simulations from specifications containing only data from the 8-week experimental period are shown in Figures 4 and 5, corresponding to scenarios 1. and 2., respectively. These figures reveal that the power to detect direct treatment effects of 0.05 SD is 80% or greater for all 5 primary outcomes. The effect size of 0.05 SD translates into 11,594 PKR (65.73 USD at 176.4 PKR to USD) in absolute difference between listing price and Price Calculator estimate (level mean: 305,434 PKR), 2.44 percentage-points in transaction probability (mean: 0.394), and 55,473 PKR (314.47 USD) in transaction price (level mean: 1,893,626 PKR).

Figures 4 and 5 also show that we are able to detect some spillover and saturation effects at 80% power or greater with the specification for primary analysis, depending on the effect sizes and assumptions about their relative sizes to direct effects. Figure 4 suggests that under assumption 1. we would have greater than 80% power to detect a spillover effect of 0.05 SD on advertisement, as well as saturation effects of 0.1 SD on advertisement and demand. Figure 5 suggests that under assumption 2., we would have greater than 80% power to detect spillover effects of 0.1 SD on transaction, demand, and advertisement, and saturation effect of 0.2 SD on all outcomes. Figures 6 and 7 also show that using the two-way fixed-effect specification from secondary analysis in Section 8.4.1 would improve power on some of the spillover outcomes, as compared to Figures 4 and 5, respectively.

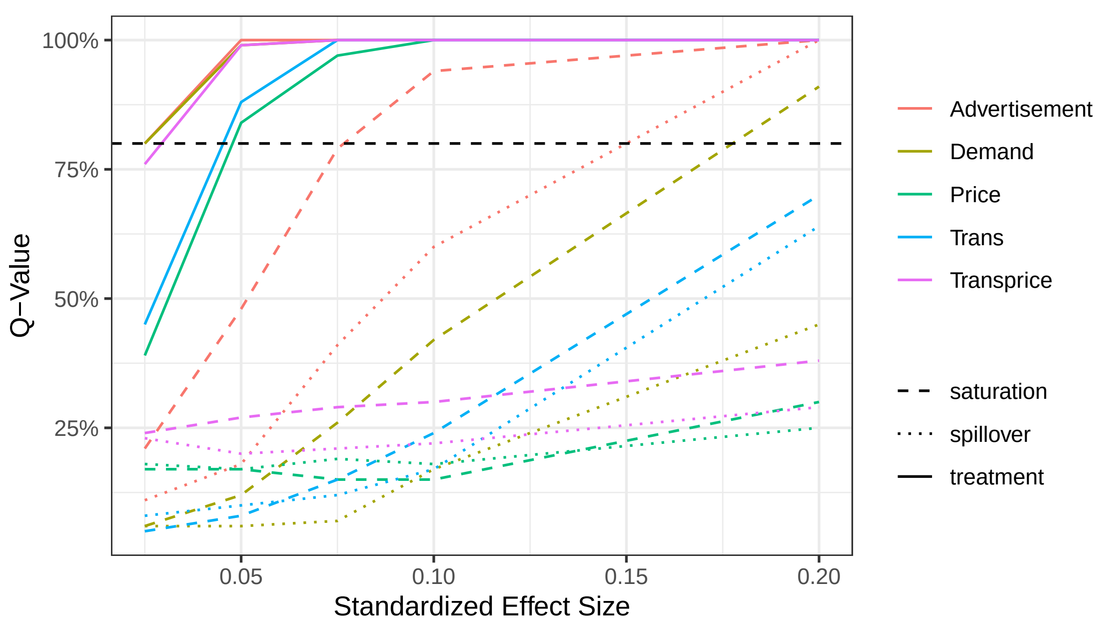

Figure 4: Power estimates: Scenario 1. and data over 8 weeks

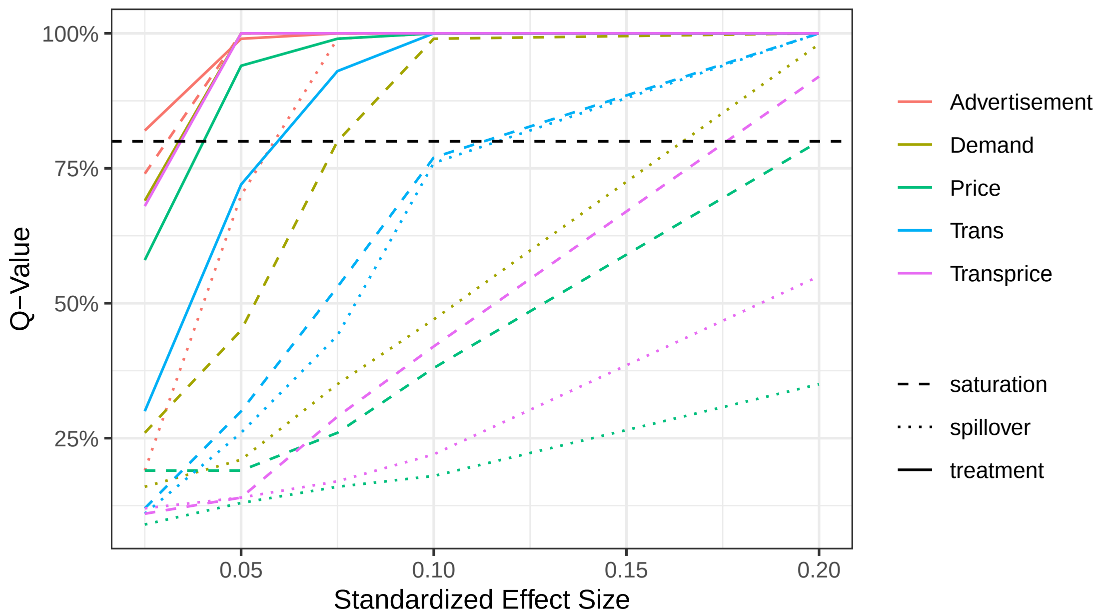

Figure 5: Power estimates: Scenario 2. and data over 8 weeks

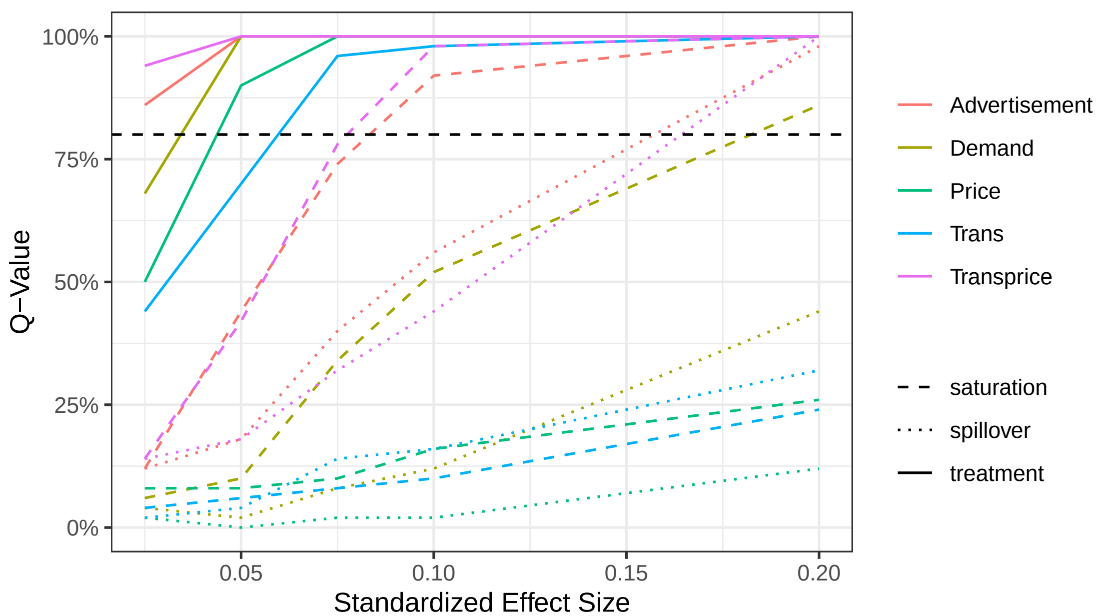

Figure 6: Power estimates: Scenario 1. and data over 16 weeks

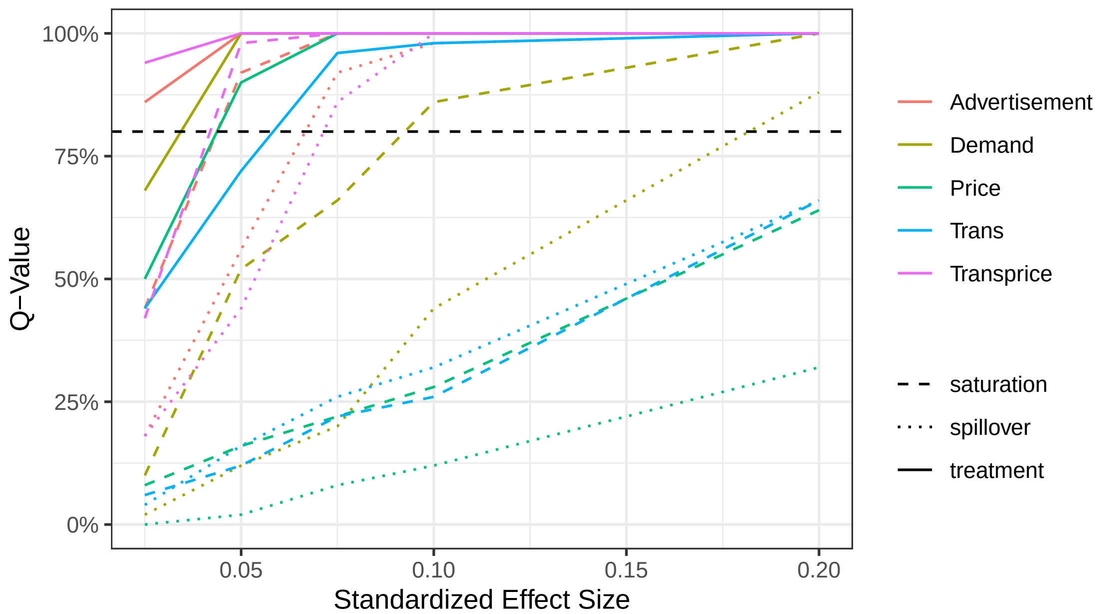

Figure 7: Power estimates: Scenario 2. and data over 16 weeks

6 Data

In this section, we discuss data items used for the design and main analysis. They are:

- vehicle characteristics, listing prices, transaction outcomes, and transaction prices
- usage of advertising tools and other paid services
- views and clicks as a proxy for buyer interest, and
- data from the telephone endline survey on transaction outcomes and their (unincentivized) beliefs about expected transaction prices.

All data, except for the survey, come from PakWheel's near-live database. Other data items we use for design and secondary analysis include i) aggregated search engine results in terms of key words and their combinations, ii) daily search listing orders from PakWheels, and iii) a usage log of a previous iteration of the Price Calculator, which preceded the experiment.

6.1 Posts

PakWheels' database tracks every post on the platform. Once a post is created, it is vetted against spam or fraud, made publicly available on the platform, then removed after 90 days or once the user asks for it to be taken down. We collect the following measures from the database:

- timing of the post's creation, approval, and closure
- vehicle characteristics
  - basic information such as make, model, model-year, mileage, sellers' location, and registration city
  - additional information about vehicle characteristics, such as version, assembly, engine size and capacity
- listing price
- self-reported transaction outcome (e.g. sold to customer on the platform, sold through other means, decided not to sell)
- self-reported transaction price, if sold.

The database also tracks any updates to variables over the course of posts' active status. This allows us to capture sellers' initial choice of listing price before and after exposure to the Price Calculator estimate.

6.2 Advertising tools and vehicle inspection services

PakWheels' database also tracks users' platform-credit purchases and usages, which we consider to be measures of sellers' advertising efforts. Users on PakWheels have two primary tools for advertising: "bump" and "feature" credits. A "bump" credit allows sellers to bring their post to top of the result page in the default, reverse-chronological listing order. This effectively increases the post's visibility, as more people look at first pages of listings. On the other hand, a "feature" credit would put their post in a few reserved spots at the top of the result page and labeled as a "featured ad", in a similar way as promoted ads on Google searches. Posts are otherwise listed in the reversed chronological order within the class of featured ads.

Another way for sellers to attract buyers' attention to their posts is to provide signals of vehicle quality. In order to do so, sellers can request in-person inspections by PakWheels' mechanics, who give scores (out of 100) on 8 dimensions (engine, brakes, suspension, interior, AC, electrical, exterior, and tires) based on a pre-specified rubric. The vehicles would pass the inspection if the unweighted average of scores over these 8 dimensions is above a threshold. They can then be marked as "PakWheels certified" on the platform for an additional fee. Given that certification is endogenous to vehicle quality, we use the data on whether or not the vehicle was ever inspected, as opposed to certified.

6.2.1 Expenditures on advertising tools

Another way of expressing sellers' advertising choices would be to in terms of amount paid to the platform for advertising. This is made difficult, however, by the fact that credits for bumps and features are purchased in bundles, and users can apply them to any posts that they own. We therefore do not plan on using this measure as a primary outcome. Nonetheless, we will collect data on advertising expenditures for robustness checks where the unit of analysis is the user. The data set contains information on purchase timing, descriptions of the bundles or services, quantity, and prices.

6.3 Buyer-attention measures

One of our hypotheses is that the price information intervention and resulting changes to pricing and advertising would affect buyers' attention to certain posts. In order to construct measures of buyer attention, we access PakWheels' data on views and clicks at the post level. We are able to collect cumulative measures of the following:

- page views (i.e. clicks on the post)
- clicks on "Show Phone Number" button within the post to contact the seller.

We also capture the number of times each post appears on search listings. We will run an analysis including this measure in the index as an alternative specification, as well.

6.4 Transaction survey

We use self-reported transaction prices to train and test the Price Calculator estimates. These self-reported data are collected in an online form whenever sellers choose take their posts down. There are concerns about the accuracy of reported transaction prices, particularly for the following reasons:

1. Transaction prices may be selectively reported (e.g. if those who fetched a higher prices are more likely to report).
2. Conditional on reporting, sellers may obfuscate the true value, leading to more noise in the price estimate.
3. Conditional on reporting, sellers may feel that the reported price should be inflated or deflated (because of, for example, their beliefs about a fair transaction price, or the desire to appear successful).
4. Conditional on reporting, sellers may find it easy just to repeat the listing price they have already given for their post.

5. Conditional on reporting, sellers may simply put a random number down to “get it out of the way.”

We can identify the extent of number 4. by comparing transaction prices with listing prices, and address 5. via data cleaning. Concerns like number 2. may introduce noise but should not bias the Price Calculator estimate or our empirical analysis.

We are unable to directly address concerns 1. and 3. from the data, nor is it realistic for us to request sales receipts or access other independent sales records. Instead, we will select a subset of listings (stratified over the vehicle model) and conduct a short phone survey to the owners. We will survey up to 1,000 posts before the experiment as a pilot, then up to 3,000 posts during and after the intervention. The primary objective of the survey is to ask the following questions:

- if they have sold their vehicle
- the transaction price, if they have sold the vehicle
- price at which they expected to sell their vehicle, when they created the post.

Additionally, we will also ask the following questions for further secondary analysis we wish to conduct:

- beliefs about highest possible transaction price, and lowest acceptable price, for their vehicle
- purchase price
- reasons for not selling the vehicle (if not sold)
- relationship with the buyer (if sold)
- recollection of exposure to the Price Calculator, and of the estimates
- beliefs about the accuracy of the Price Calculator estimate
- beliefs about other sellers' access to the Price Calculator
- what information/experience they relied on to set the list price
  - if they searched for listings for other models than your vehicle's
  - other additional terms used in search
  - other information sources offline
- reasons for changing their initial listing price, if at all
- willingness to bargain off the listing price

- beliefs about difficulty of receiving enough inquiries, and/or good price offers
- beliefs about effectiveness of advertising features on PakWheels
- stated willingness-to-pay for Price Calculator estimates.

PakWheels routinely conducts short customer telephone surveys for data quality assurance, and they have conducted some pilot surveys. The main endline survey, however, will be conducted by a Lahore-based economics research organization, the Institute of Development and Economic Alternatives (IDEAS). Survey questions are included in Appendix B.

6.5 Other data sources

Besides the main data items listed above, we collect additional types of data to a) validate our experimental design, b) conduct robustness checks, and c) run exploratory analysis on the structure of spillovers. The following is a list of such data items.

6.5.1 Search engine logs

Aggregated search engine logs tell us which combinations of terms are used most frequently by viewers on PakWheels. We use these aggregate statistics for our justifications for market cluster groupings. Our objective is to minimize concerns about inter-cluster interference, but also retain as many randomization clusters for the step as possible. Our aggregate search logs data are taken from the month of August, 2020. They represent tens of millions of searches over the month, and our data contain numbers of searches per combination of search terms (e.g. make, model, model-years in range, city, range of listing prices). We capture 35,000 most common search combinations, which account for 93% of all searches. We use these data for our definition of clusters in Section 5.2.1.

6.5.2 Listing orders

Beyond the primary analysis, in which we measure the average spillover effects on treated clusters, we plan to assess the extent to which the spillover effects depend on the "proximity" to treated posts, such as how close a given ad is to treated peers in ad listings. For this, we web-scrape listing orders in their default, reverse-chronological order on a daily basis for each make-model cluster in the sample.

6.5.3 Use of an old Price Calculator

We also track usage of a previous version of Price Calculator, which our intervention will replace. The previous iteration of the Price Calculator was designed and implemented prior to the beginning of our research collaboration with PakWheels. It was contained in a separate module in PakWheels' website and mobile apps, unintegrated with the posting process, and was discontinued at the end of December, 2020. The old Price Calculator offered predictions to only a handful of make-model-model years of certain colors, locations, and mileage. PakWheels keeps a log of all price estimates the old Price Calculator provided at each instance. This dataset contains user ID, search inputs (make, model, model year, location, mileage, if seller or buyer), the price estimates, and the time stamp.

7 Outcomes

7.1 Primary outcomes

The primary outcomes for our analysis of direct treatment and spillover effects are the following:

- log(absolute difference between listing price and Price Calculator estimate)
- 1 if reported as sold
- log(self-reported transaction price)
- advertisement index
- buyer-attention index.

We define these outcomes in the subsections below.

7.1.1 log-absolute difference in prices

We consider changes to listing prices as the "first-stage" effect of our intervention, in that impact on other primary outcomes hinge on the changes to listing prices and their distributions. We expect that sellers would adjust their listing price toward the Price Calculator estimate, plus some margin for expected bargaining. In order to capture this type of convergence, we define our primary price outcome to be the natural-log transformation of the absolute difference between the final listing price and the Price Calculator estimate. PakWheels calculates and provides the Price Calculator estimate only to treated posts, so we will estimate the prices that control posts *would have received* using the identical model as the one PakWheels uses for this experiment. If we observe that a larger than ignorable fraction of listing prices are equal to their Price Calculator estimates, we will add 1 to the difference measure then take the natural log.

As discussed in Section 6.1, sellers can update prices and other features as long as their posts are active on the platform. Direct effects of the Price Calculator estimate may happen when the post is created, while indirect effect may occur even after the post is created through feedback from buyers and competition with other posts. We will use the listing price at the end of posts' active status for our primary outcome, so that all changes to the listing prices are factored in. We will also run robustness checks using the listing price from a) when the post is created and b) 7 days after the post's creation.

7.1.2 Transaction outcome and price

Sellers on PakWheels can take down their posts once they no longer wish to receive inquiries, or the post expires after 90 days since the initial posting. When the post is taken down, sellers are asked if they have sold their vehicles. They are required to respond in order to have their ads taken off. They are given options on the form (e.g. sold via PakWheels' website, sold via others, chose not to sell, etc.) and most sellers choose oe of them. However, some respond as "Other" yet report in the comment section that they have sold the vehicle. Our transaction outcome variable accounts for this to the best extent possible by string cleaning responses classified as "Other." The transaction variable is 1 if the seller reported a sale, 0 otherwise.

Sellers are also prompted to report the transaction price on the online form, if they report to have sold their vehicle. The value is missing for those who do not report their transaction outcome. We also remove inputs outside of reasonable price range for their given make-model. We use the natural log of transaction price as the outcome variable.

These self-reported outcome data are likely the best source of information on transactions and prices across a wide range of vehicle characteristics and locations in Pakistan. However, they may be vulnerable to biases and are checked against values collected via a telephone survey described in Section 6.4. We plan on using responses from this survey to construct analogous outcome variables for robustness checks.

7.1.3 Advertisement index

One of our main hypotheses is that, when faced with novel price information, sellers adjust their strategic choices along two margins; list pricing and advertising. We will capture sellers' choices on advertising with data on paid services on PakWheels. As discussed in Section 6.2, sellers can increase visibility of their posts and/or signal quality by "bumping", "featuring," and requesting an inspection for their vehicle. In order to capture both intensive and extensive usage of advertising tools, we construct an index measure consisting of the following variables:

- number of "bumps" the seller applies to the post
- number of weeks the seller "features" the post
- 1 if the seller requests PakWheels to have the vehicle inspected.

7.1.4 Buyer-attention index

We also hypothesize that the price information intervention, and causal effects on pricing and advertising, affects treated posts' visibility on the platform. In order to capture this effect on post's visibility and buyer attention, we construct an indexed measure from data discussed in Section 6.3. The index consists of the following variables:

- page views (i.e. clicks on the post)
- clicks on "Show Phone Number" button within the post to contact the seller.

7.2 Secondary outcomes

7.2.1 Survey data

?? The first-order objectives of the endline phone survey are to confirm reported transaction outcomes on PakWheels' platform and elicit sellers' beliefs about transaction prices. Those outcomes are listed in bold below. We also collect the following measures from survey respondents:

1. validation of self-reported transaction outcome
   - **1 if the vehicle is sold**
   - **transaction price (if sold)**
   - reasons for not selling the vehicle (if not sold)
   - relationship with the buyer (if sold)
2. price elicitation (stated beliefs)
   - **Expected transaction price at the time of initial posting**
   - lower and upper bounds of the expected transaction price
3. purchase price
4. number of vehicles previously traded
5. recall and salience of the Price Calculator instrument
   - 1 if the seller recalls seeing the Price Calculator estimate
   - recall of the Price Calculator estimate
   - beliefs about Price Calculator's accuracy
6. search and information acquisition

- if seller searches for other posts on PakWheels
- terms used for the search
- other sources of information

7. stated beliefs about challenges and frictions on the market
   - if the seller believes it is difficult to receive enough inquiries on PakWheels
   - if the seller believes it is difficult to receive acceptable price offers on PakWheels
8. stated beliefs about the usefulness of the advertising tools offered by PakWheels (i.e. bumps and features)
9. stated willingness to pay for the Price Calculator estimates

7.2.2 Post's duration on the platform

PakWheels' database reports when each post is created and taken down, so we can calculate the duration of post's active status on the platform. One challenge is that posts may be left inactive for a period of time, so this would not be a measure of sellers' active participation in the market. This makes it difficult to interpret meaning of any causal effect on this variable other than in aggregate as a measure of market congestion. For this reason, we consider this as a secondary outcome.

7.2.3 Price changes, and convergence to estimated price

We have chosen the logged absolute difference between the listing price and the Price Calculator estimate as a primary outcome variable. It is possible, however, that the treatment effect on the list price may be better captured if the Price Calculator induces a level shift in price or affected whether sellers ever adjust their initial listing prices. It is also possible that the treatment effect on the listing price is asymmetrical around the Price Calculator estimate. We intend to address these possibility with following alternative outcomes pertaining to the listing price as robustness checks:

- log(list price)
- 1 if the listing price is ever modified
- difference between the initial and final listing prices.

7.2.4 Cluster-level outcomes

Our two-stage randomization procedure allows us estimate impact on cluster-level outcomes because of the two-stage design. Part of our secondary analysis focuses on cluster-level aggregate measures of moments of prices, page views, and post duration. We construct the following variables at the cluster-day level:

- number of new posts
- number of active posts
- standard deviation and kurtosis of the listing price
- standard deviation and kurtosis of page views.

7.2.5 Spillovers based on listing order

As discussed in Section 6.5.2, we also web-scrape the listing order from PakWheels. We will use these data to a) estimate the impact of treatment on sellers' positions on search listings, and b) create a measure of potential spillover intensity based on proximity to treated posts.

We define outcomes from PakWheels' scraped data as follows:

- number of days a post is on the first page of the make-model level search result
- average page number of the search results over the course of its active status.

We also construct the following variables as proxies of exposure to treated posts:

- number of days spent being adjacent to at least one treated post
- average number of treated posts within its listing result page (i.e. if the post resides on page 5 in a given day, then we take the number of treated posts on page 5), over the course of the post's active status.

8 Empirical analysis

8.1 Inclusion criteria

We have access to data from the entire universe of listings on PakWheels going back multiple years, so we could theoretically use all listings that ever existed for analysis. We will, however, impose the following sample restrictions for the analysis.

First, we restrict our sample to listing for which PakWheels would be able to provide Price Calculator estimates. This is limited to listings with large enough comparisons with reported transaction prices. For instance, they do not provide estimates for rare models (e.g. luxury brands or commercial vehicles like trucks). We cannot disclose further details on PakWheels' inclusion criteria into the Price Calculator estimation sample, but the resulting sample constitutes the vast majority of all listings.

Second, we impose restrictions based on when listings are created. For the primary analysis, we restrict the sample to listings created during the 8-week experimental period. For the secondary analysis of spillover effects, on the other hand, we also include listings created 8 weeks prior to the start of the experimental period. This allows us to include model- (and model-version) fixed effects and run two-way fixed effect models, allowing for higher power of detecting treatment effects under an assumption on time trends. We discuss the benefit of these approaches in Section 8.4.1 and implications for power in Section 5.7.

8.2 Balancing checks

We will not be able to observe baseline measures from our sample listings, because the treatment occurs while they are being created. Given this limitation, we test balance over our outcome variables using listings data from a pre-treatment period. We will apply the same sample selection criteria and randomization procedure as the experiment, described in Section 5.2. This ensures that the we have balance over our primary outcome variables on pre-treatment-period data. We can check further balance on a) primary outcomes that were not included in the randomization procedure due to concerns about data quality or availability, b) constituent variables to outcome indices, c) secondary outcome variables, and d) other user-level characteristics.

8.3 Primary analysis

8.3.1 Outcomes of interest

In our primary analysis, we will estimate the intend-to-treat and treatment-on-treatment effects of direct treatment and spillover effects. The following are our primary outcomes and corresponding research questions highlighted in Section 2:

- absolute difference between listing price and Price Calculator estimate (Research question 1.1.)
- binary transaction outcome (Research question 1.2.)
- log(transaction price) (Research question 1.2.)
- indexed measure of advertisement usage (Research question 1.3.)

- buyer-attention index (Research question 1.2.1.)
- spillover effect on all outcomes above (Research question 2.1.1.).

8.3.2 Main specification: Intend-to-treat effects

We will estimate the intent-to-treatment effect of being provided the Price Calculator estimate using Equation 2, where the coefficients of interest are β_1, β_2, and β_3:

$$\begin{aligned} Y_{i,p,m,w} = \beta_0 + \beta_1 * Assign_{i,m} + \beta_2 * Cluster_m + \beta_3 * ClusterHigh_m \\ + \bar{Y}_{m,w\in[-15,-8]} + \psi_w + X'_{i,p}\rho + \epsilon_{i,p} \end{aligned} \tag{2}$$

The subscripts used in the equation above indicate the following:

- i: individual user identifier (defined by PakWheel's user ID)
- p: post (multiple posts could belong to a given i)
- m: vehicle make-model cluster
- w: posting week. $w = 1$ is first week of experimental phase.

This estimating equation will be fitted to data of listings that were created during the 8-week experimental period and for which Price Calculator estimates could be generated, as discussed in Section 8.1.

$\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ capture the ITT effects. $Assign$ is the binary direct treatment variable, $Cluster$ is a dummy variable that equals 1 if the model is selected into first-stage assignment (of either saturation level) and zero otherwise. $ClusterHigh$ is a dummy variable for high-saturation cluster-level treatment. Since we cannot have model fixed effects, we include the pre-experimental, model-level means of the outcome variable from weeks -15 to -8. We select this time period as it would be sufficiently far from the experimental time-frame and the vast majority of posts created in weeks -15 to -8 would already be taken down week 1. ψ_w denotes the week fixed effects, and $X'_{i,p}$ is a vector of controls for vehicle and seller characteristics, as follows:

- Vehicle characteristics:
  - vehicle's age (by model year)
  - log(mileage)
  - engine capacity
  - transmission
  - fuel type (e.g. petrol, CNG)

  - color
  - assembly (domestic or imported)

- Seller's characteristics:
  - Seller's city
  - 1 if professional dealer, as observed through PakWheels' account information
  - log(number of listings ever made on PakWheels)
  - log(months since first listing on PakWheels)

For all dependent variables other than the binary transaction outcome, we will use linear regressions. For the binary outcome variable, we will use the logit model. We will cluster the error at the make-model level, as the first stage of the randomization is conducted at this level. We will also estimate these models using robust standard errors as a robustness check.

An alternative approach to identifying spillover effects may be to focus on the proximity to treated posts within the listing order. For instance, posts that sit next to a higher concentration of treated neighbors in the listing-order space may be subject to more spillover effects than those with fewer treated neighbors. The concentration of treated neighbors would have some natural variation over the listing-order space, which we could exploit. As for the main analysis, we choose to focus on the average spillover effects at low- and high-saturation levels. We will, however, explore the structure of spillovers as secondary analysis, as shown in Section 8.4.2.

8.3.3 Main specification: Treatment-on-the-treated

As discussed in Section 5.3, we may encounter some treatment non-compliance by sellers with old versions of the PakWheels app that does not include the intervention tools. This type of non-compliance will likely be rare but non-random, so we plan to instrument for treatment take-up using the assignment variable.

The treatment-on-the-treated (TOT) effect is estimated via 2SLS, with $Assign$ instrumenting for $Treat$, and $Cluster$ and $ClusterHigh$ included as controls.

$$\begin{aligned} Y_{i,p,m,w} = \theta_0 + \theta_1 * \widehat{Treat}_{i,p} + \theta_2 * Cluster_m + \theta_3 * ClusterHigh_m \\ + \bar{Y}_{m,w\in[-15,-8]} + \psi_w + X'_{i,p}\rho + \epsilon_{i,p} \end{aligned} \tag{3}$$

The first-stage specification for $\widehat{Treat}$ is as follows:

$$Treat_{i,p} = \phi_0 + \phi_1 * Assign_{i,m} + \bar{Y}_{m,w\in[-15,-8]} + \psi_w + X'_{i,p}\tau + \xi_{i,p} \tag{4}$$

$\hat{\theta}_1$ represents the estimated TOT effects. The specifications include controls ψ_w, γ_m , and $X_{i,p}^{'}$ in the first and second stages, as we did for the ITT effect. $\xi_{i,p}$ is error term in the first stage.

8.4 Secondary Analysis

We exclude all tests in the secondary analysis from corrections for multiple hypothesis testing, in order to conserve power for the primary analysis.

8.4.1 TWFE specification to capture spillover and saturation effects

In our default specifications, we measure spillover effects as an average over clusters that are assigned to treatment. We foresee two potential issues with our default approach, which we discuss in this subsection and the following Section 8.4.2. Our first concern is that without cluster fixed-effects, we may not be sufficiently powered to detect spillovers due to relatively small number of clusters.

We address this first concern by adding pre-treatment-period data, which allows us to include model (and even more granular model-version) fixed effects. In other words, we will employ a two-way fixed-effect model, as shown in Equation 5 below:

$$\begin{aligned} Y_{i,p,m,w} = \beta_0 + \beta_1 * Assign_{i,m,w} + \beta_2 * Cluster_{m,w} + \beta_3 * ClusterHigh_{m,w} \\ +\gamma_m + \psi_w + X_{i,p}^{'}\rho + \epsilon_{i,p} \end{aligned} \tag{5}$$

This estimating equation will be fitted to data of listings created during the 8-week experimental period and 8 weeks prior to it. $\hat{\beta}_1$, $\hat{\beta}_2$, and $\hat{\beta}_3$ capture the ITT effects. $Assign_{i,m,w}$ is the binary direct assignment variable, $Cluster_{m,w}$ is the cluster-week level dummy variable that equals 1 if the cluster-week is selected into first-stage assignment (of either saturation level) and zero otherwise. $ClusterHigh_{m,w}$ is a dummy variable for high-saturation cluster-week dummy. ψ_w denotes the week fixed effects, and γ_m the model (i.e. the market cluster) fixed effects. $X_{i,p}^{'}$ is a vector of controls for vehicle and seller characteristics as in the main specifying equation 2, plus the model-version fixed effects[5].

One concern with Equation 5 is that spillovers could happen "back in time," in that posts created right before $w = 1$ would be listed on the platform along with treated posts and could be subject to spillover effects. In order to address this possibility, we will interact the posting-week fixed effect with $Assign$, $Cluster$, and $ClusterHigh$ to estimate treatment effects over posting time.

[5] Versions are proper subsets of models, so in effect they are finer fixed effects than ones at the model level. We include both model and version fixed effects, however, because some listings are missing the version information. We code versions of those listings as "Other" in order not to drop them from analysis

8.4.2 Spillover and saturation effects based on the listing order

Another concern with capturing spillover effects is that they may be localized around treated posts in the listing space, or that there needs to be a high concentration of treated posts in the listing page for spillovers to untreated posts to occur. To capture such effects, we construct variables for potential spillover intensity using data on daily listing orders. We will construct the following variables at the individual post level:

- Share of other posts within the same result page that received the Price Calculator estimates (averaged from daily ad-listing orders)
- Share of days in which posts right above or below are treated.

We will estimate the following equation, where the alternative spillover variables go into $S_{i,p}$

$$\begin{aligned} Y_{i,p,m,w} = \beta_0 + \beta_1 * Assign_{i,m} + \beta_2 * S_{i,p} + \beta_3 * S_{i,p} * Assign_{i,m} \\ + \bar{Y}_{m,w\in[-15,-8]} + \psi_w + X^{'}_{i,p}\rho + \epsilon_{i,p} \end{aligned} \tag{6}$$

β_1 denotes the direct treatment effect, β_2 the spillover based on the intensity measures above, and β_3 additional spillovers on the treated. We no longer include the cluster-level assignment variable.

8.4.3 Level shifts and changes to the listing price

As discussed in Section 7.1.1, we use the deviation of listing prices from Price Calculator recommendations as the primary price outcome. However, we are also interested in any level shifts, or any changes at all, that the Price Calculator intervention might induce on the listing price. We therefore plan on estimating both ITT and TOT effects on the following outcomes using Equations 2 and 3:

- log(final listing price)
- 1 if listing price was ever updated
- absolute difference between the initial and final listing prices.

8.4.4 Heterogeneous treatment effect (Research Question 1.4.)

Similarly, the magnitude of direct treatment effect may vary depending on the salience of information and the extent of search friction and congestion. These hypotheses on mechanisms are framed as Research Question 1.4. in Section 2. We will test them by identifying how the sizes of direct treatment effect and spillovers differ by focusing on the following types of heterogeneity at the cluster (i.e. vehicle model) level:

1. noise in price signals: mean absolute difference in percentages between the listing price and would-be Price Calculator estimates, divided by average transaction price
2. search friction and congestion: indexed measure at the make-model cluster, consisting of:
   - number of posts per month
   - average duration of posts' active status
3. Product heterogeneity: make-model-level index that captures product variation in the following characteristics:
   - model years
   - versions
   - color
4. price information prior to intervention: dummy variable for the previous availability of the old Price Calculator (discontinued in December, 2020)

We modify Equation 2 to get Equation 7. Outcomes of interest are same as those listed in Section 8.3. We interact both the direct treatment and spillover terms with these measures of heterogeneity, denoted as H_m, which varies at the model (i.e. treatment cluster) level. We will code H_m as above/below median at the model level for the main analysis. We plan on estimating heterogeneous saturation effects either by grouping the saturation levels into one, i.e. not including the $ClusterHigh$ term. We do not include the uninteracted H_m term as it would be collinear with $Cluster$.

$$\begin{aligned} Y_{i,p,m,w} = \beta_0 + \beta_1 Assign_{i,m} + \beta_2 Cluster_m \\ + \beta_3 H_m * Assign_{i,m} + \beta_4 H_m * Cluster_m \\ + \bar{Y}_{m,w\in[-15,-8]} + \psi_w + X'_{i,p}\rho + \epsilon_{i,p} \end{aligned} \tag{7}$$

We will also assess heterogeneous treatment effects based on sellers' characteristics, hypothesizing that the impact of our information intervention depends on sellers' access to information and experience. We will use the following variables at the seller-level:

- number of previous posts
- months since first post on PakWheels

- 1 if the seller is a professional dealer
- 1 if they purchased any of PakWheels' advertising services prior to the intervention date

We will use Equation 8 to estimate heterogeneous treatment effects that vary at the individual level. It is identical to Equation 2, except for the subscript on H. These dimensions of heterogeneity are also included in the vector of controls X.

$$
\begin{aligned}
Y_{i,p,m,w} = \beta_0 + \beta_1 Assign_{i,m} + \beta_2 Cluster_m \\
+\beta_3 H_{i,p} * Assign_{i,m} + \beta_4 H_{i,p} * Cluster_m \\
+\bar{Y}_{m,w\in[-15,-8]} + \psi_w + X^{'}_{i,p}\rho + \epsilon_{i,p}
\end{aligned}
\tag{8}
$$

8.5 Other analyses

8.5.1 Changes in beliefs (Research Question 1.1.1.)

Our theoretical framework (see Section 4.1) highlights other potential channels of spillovers beyond what we have listed in secondary analysis in Section 8.4. For example, sellers may adjust their pricing and advertising choices based on changes to their beliefs about market prices as inferred from the distribution of listing prices (theoretical prediction 4.).

We will address this possible mechanism by measuring changes in sellers' beliefs about the demand distribution, i.e. the possibility that tailored price information leads sellers to have less noisy beliefs about the eventual transaction price. We will estimate the treatment effect on sellers' non-incentivized beliefs on their vehicle's expected transaction price. We will collect these beliefs through a phone survey (see 6.4) to a smaller subsample of about 3,000 sellers, balanced across treatment groups. We will test for both for direct treatment and spillover effects on these belief measures, using the specifications listed in Section 8.3.

We will also ask a series of questions pertaining to sellers' beliefs about the market conditions, perceptions of market frictions, and perceptions about the Price Calculator instrument. We intend to use these outcomes to capture a fuller sense of mechanisms at play. This analysis will be secondary and exploratory, in order to conserve power on the main analysis.

8.5.2 Market power

Existing body of evidence suggests (e.g. Mitra et al. (2018)) that the pass-through of price information may be dependent on the extent of market power. We therefore plan on testing how market power drives the effect of price information. We will identify heterogeneous treatment effects based on the following variables:

- the Herfindahl–Hirschman Index (HHI) of sellers' concentration at the make-model level
- the share of professional dealers at the make-model level.

8.6 p-value adjustments

In order to address the issue of multiple hypothesis testing, we follow Romano and Wolf 2005 and correct for the false discovery related to tests on the following primary outcomes:

- log(absolute difference between listing price and Price Calculator estimate)
- binary transaction outcome
- log(transaction price)
- indexed measure of advertisement usage
- buyer-attention index.

Given that we consider direct treatment and spillovers as separate hypotheses, we should adjust their critical values separately.We will therefore report adjusted critical values based on the Romano-Wolf procedure for 3 sets of 5 tests. We will report unadjusted p-values for secondary outcomes.

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A Theoretical Framework

A.1 Introduction

As discussed in the introduction, our research objective is to understand mechanisms through which lack of access to information could generate losses in unrealized transactions, or may induce externalities in terms of search and information frictions. We categorize the potential channels and types of search and information frictions that we focus in this study as follows:

1. lack of access to, or high cost of accessing, price information
    - homogeneous lack of access to information within market
    - heterogeneous lack of access to information (primarily between informed and uninformed sellers)
2. individuals' beliefs about market conditions and in the signal quality
3. spillover effects of individual choices
    - information spillover effects of individual pricing decisions
    - spillover effects of transaction and advertising decisions that affect congestion
    - buyer-side responses to sellers' choices.

In this section, we present a simple search framework that addresses various mechanisms of search and information frictions incurred by agents in a developing market. We demonstrate how sellers facing such frictions set listing prices, promote their posts through advertising, and respond to information about market conditions. Our framework is one of static search, deriving inspiration from canonical models such as Stigler (1961) and Diamond (1982). Most contemporary models that focus on the effect of access to price information and assume full knowledge of parameters on market friction and demand distributions (Baye et al. 2007). We, however, introduce the following deviations from a standard search framework:

- We allow for supply-side heterogeneity of access to information and resulting beliefs about the demand-side distribution. In effect, sellers have biased or noisy beliefs about the distribution of buyers' willingness-to-pay (WTP).
- This, along with (possibly) noisy beliefs about the match rate and efficacy of advertising, would lead to biased or noisy beliefs about the probability of sale and to suboptimal list pricing.
- We allow the match rate with potential buyers to be endogenous with respect to advertising choices sellers make. They can influence the match rate by engaging in costly actions, i.e. advertising.

Our conceptual approach is similar to that of Bai et al. (2020), who model and empirically estimate the search and information frictions buyers experience, and resulting firm and market dynamics. Unlike Bai et al. (2020) who focus on the demand-side, we focus on the role of information friction on the supply-side and search friction they experience. The choices behind our focus on mechanisms are also inspired by previous work such as Bergquist and McIntosh (2021) and Bai et al. (2020), who show that the existence of, or mere access to, online platforms does not resolve issues of search and information frictions, and that frictions that persist on such platforms deserve attention.

The rest of this section is organized as follows; Section A.2 lays out the set-up of our model and provides definitions on terms and parameters. Section A.3 defines the objective function and the maximization problem in terms of the listing price and advertising choices. Section A.4 gives optimality conditions in the case of no information friction. Section A.5 shows how individual choices may be altered when there is noise in beliefs about the demand, and how price information signals would induce updates in beliefs and alter input decisions. Section A.6 concludes by providing predictions on the role of information friction and noisy beliefs on demand, in terms of sellers' choice variables and transaction outcomes.

A.2 Set-up

Suppose that we have a seller i, who is endowed with an asset. The asset- and seller-characteristics are denoted as s_i and information set $\mathcal{I}_i$. The search and transaction process is as follows:

- Seller i forms a prior belief about the demand distribution for their asset based on the information set $\mathcal{I}_i$ and characteristics s_i.
- Some sellers are provided with an information signal, i.e. the Price Calculator estimate denoted as x_i.
- If treated, seller i forms a posterior belief about the demand distribution, based on the information signal x_i, their belief in quality about the signal, and their prior.
- Seller i chooses a listing price p^l and amount of advertisements a, based on their posterior belief about the demand distribution and their characteristics s_i.
- Choices of p^l and a affect the distribution of potential buyers with whom seller i is matched via a Poisson process.
- Once a match occurs, seller i makes a take-it-or-leave-it (TIOLI) offer p^t below p^l to the potential buyer.
- Transaction occurs if matched buyer's WTP is higher than p^t.

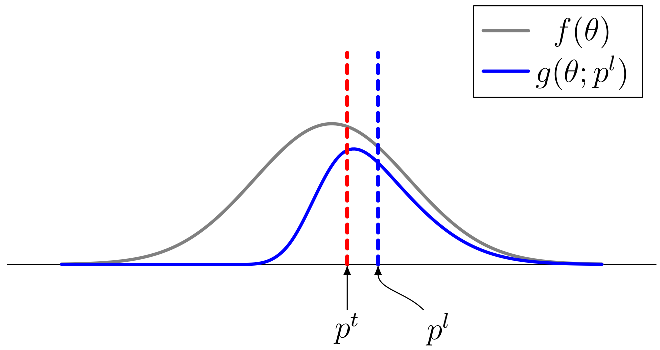

Figure 8: Relationship between list price, the buyer it draws, and the TIOLI price

We denote the probability density function (PDF) of true buyer WTP as $f(\theta)$, and the distribution of potential buyers that get matched to the seller, conditional on p^l, as $g(\theta; p^l)$ and their cumulative equivalents, F and G. The distinction between $F(\theta)$ and $G(\theta; p^l)$ is key, since we assume that the seller's choice of the listing price p^l skews the distribution of potential buyers (who may click on the post depending on the listing price) towards p^l itself. Setting too high of p^l also comes at a cost, as we make the following assumption:

$$\int_{-\infty}^{\infty} g(\theta; p^l) d\theta \leq 1 \tag{9}$$

$$\frac{\delta}{\delta p^l} \int_{0}^{\infty} g(\theta; p^l) d\theta < 0 \tag{10}$$

In other words, the distribution g is a subset of f and does not add up to one. In other words, g does not add up to one, and high values of p^l effectively reduces the pool of buyers to match with. The relationship between p^l and $g(\theta; p^l)$ are also described schematically in Figure 8:

A.3 The objective function

Under no information friction, seller i chooses the listing price and advertisements to maximize the following:

$$V(p^l, a; s_i) = -c - k(a) + \gamma(a) \int \max_{p^t} [\mathbb{E}\pi(p^t; p^l, s_i)] g(\theta; p^l)\, d\theta \tag{11}$$

Sellers incur a constant cost of search, denoted as c. They also incur a variable cost $k()$, based on the amount spent on advertising, a. The term $\gamma(a)$ is a Poisson match rate between the seller and a potential buyer, and it is an increasing function with respect to a. We denote the seller's utility from transaction as $\pi(p^t; s_i)$. This is a function not of the listing price, but of the eventual offer price p^t, which is discussed below. π is also not strictly a profit term, as sellers may also have preferences over how quickly to sell the vehicle, as captured in s_i. We assume the function is a continuously differentiable and concave with respect to its only choice variable p^t, so that there is a single global maximum that is conditional on individual characteristics s_i.

A.3.1 The TIOLI price p^t

Seller i sets the listing price p^l, keeping in mind the distribution of buyers the list price attracts, and the (TIOLI) offer price p^t that seller i would then select. We assume that there is one-to-one correspondence between p^l and p^t conditional on seller i's characteristics. We also assume that potential buyers cannot perfectly infer p^t from p^l, because this depends on the seller's individual characteristics s_i as well as $\mathcal{I}_i$. This allows us to express the seller's problem of maximizing the value function $V()$ as choices of p^l and a.

Based on the mapping we assume between p^l and p^t, we can also express Equation 11 as follows:

$$V(p^l, a; s_i) = -c - k(a) + \gamma(a)\pi(p^t(p^l; s_i))\Omega(p^t(p^l), s_i), \tag{12}$$

$$\text{where } \Omega(p^t(p^l), s_i) = \int_{p^t(p^l)}^{\infty} g(\theta; s_i, p^l)d\theta \tag{13}$$

Ω is a function that represents the probability that a potential buyer's willingness to pay is greater than the TIOLI offer price, given the listing price p^l chosen by the seller. In order to ensure unique and interior solution to the problem, we assume that Ω is decreasing and concave with respect to p^l; As p^l increases, fewer buyers are drawn to the listing and have a WTP greater than the TIOLI price associated with p^l. This ensures that the objective function in Equation 12 is quasiconcave with respect to its argument p^l.

A.4 Identifying optimal p^l and a

Taking the first-order condition of Equation 12 with respect to p^l gives the following expression, where we see that the choice of optimal p^l is independent of a under no information friction.

$$0 = \frac{dV}{dp^l} = \gamma(a)[\pi'(p^t)\frac{dp^t}{dp^l}\Omega(p^t(p^l), s_i) + \pi(p^t(p^l; s_i))\frac{d\Omega(p^t(p^l), s_i)}{dp^l}\frac{dp^t}{dp^l}] \tag{14}$$

Rearranging and simplifying Equation 14, we get:

$$\Omega(p^t(p^l), s_i)\pi'(p^t)\frac{dp^t}{dp^l} = -\frac{d\Omega(p^t(p^l), s_i)}{dp^l}\frac{dp^t}{dp^l}\pi(p^t(p^l; s_i)) \tag{15}$$

The left-hand side of Equation 15 is an expression of "marginal benefit" of price adjustment, i.e. the marginal change in the seller's payoff ($\pi'(p^t)\frac{dp^t}{dp^l}$) times the probability that a matched buyer accepts the TIOLI price ($\Omega(p^t(p^l), s_i)$). The right-hand side is an expression of the "marginal cost" of price adjustment, i.e. the marginal effect of the changes in listing price on the probability of TIOLI price's acceptance ($\frac{d\Omega(p^t(p^l),s_i)}{dp^l}\frac{dp^t}{dp^l} < 0$) times the payoff ($\pi(p^t(p^l; s_i))$). As for the second order conditions, we have made assumptions about the functional forms of $\pi()$ and Ω such that we can show that the "marginal benefit" from Equation 15 is decreasing and "marginal cost" increasing.

Similarly, taking the first-order condition of Equation 12 with respect to a and rearranging give the following expression that identifies the optimal a is conditional on a choice of p^l.

$$\frac{d\gamma}{da}\pi(p^t(p^l; s_i))\Omega(p^t(p^l), s_i) = k'(a) \tag{16}$$

A component of the left hand side of Equation 16 is the marginal gain from advertising, which a product of changes in the Poisson match rate ($\frac{d\gamma}{da}$) and expected payoff ($\pi(p^t(p^l; s_i))\Omega(p^t(p^l), s_i)$). This marginal gain is equal to right-hand side term $k'(a)$, i.e. the marginal cost of advertising. As for the second-order condition, we assume the functional forms of the Poisson matching function $\gamma()$ and the cost function $k()$ such that a unique solution of a exists.[6]

A.5 Information friction and beliefs

The solutions above hinge on the assumption that sellers have accurate beliefs about buyers' WTP, other parameters and functional forms (e.g. Poisson match rate function). However, if there is noise in sellers' beliefs about buyers' WTP, how would it affect sellers' decisions? We explore this possibility, while assuming that beliefs on other parameters and functional forms are accurate.

Suppose that seller i possesses noisy information about the distribution of buyers' WTP. We assume that their beliefs are accurate on average over all sellers, to focus on a point about noise rather than bias. Individual sellers holds beliefs over $f(\theta)$, and the distribution

[6] It is likely reasonable to assume that the Poisson match rate function $\gamma()$ is concave given the diminishing returns to advertising. The potential issues is with the cost function $k()$, including the financial cost of advertising. PakWheels offers quantity discounts of advertising credits, making the per-unit cost of advertisement use cheaper as sellers use more. We will check with data to see if the use of advertising tools in excess (e.g. bumping their ads at a high frequency) is a concern.

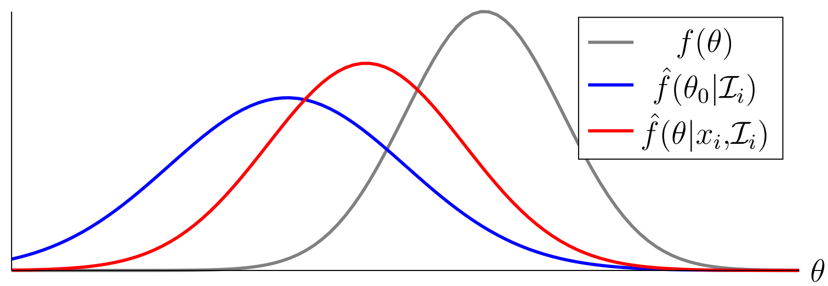

Figure 9: Beliefs about$f$ based on information set $\mathcal{I}_i$ and signal x_i

of buyers they get matched to conditional on p^l(i.e. $g(\theta)$) also depends on their belief over $f(\theta)$. We denote seller i's belief on f as $\hat{f}(\theta|\mathcal{I}_i)$ and their resulting belief over g as $\hat{g}(\theta_0|\mathcal{I}_i)$, where $\mathcal{I}_i$ denotes information quality individuals possess to form a prior belief. The resulting optimality conditions then simply replace f with $\hat{f}(\theta_0|\mathcal{I}_i)$ and g with $\hat{g}(\theta_0|\mathcal{I}_i)$.

The idea behind our intervention is that randomly selected subset of sellers will update their beliefs based on the information signals contained in the Price Calculator estimates. Signal x_i is drawn from the true distribution of the WTP, f. If treated sellers engage in rational Bayesian updating process, their posterior beliefs $\hat{f}(|x_i, \mathcal{I}_i)$ and $\hat{g}(|x_i, \mathcal{I}_i)$ from their equivalents under no information friction. The schematic representation of Bayesian belief updating is shown in Figure 9.

A.5.1 Bayesian belief updating

We assume that sellers engage in a Bayesian belief-updating process when they receive information signals in the form of Price Calculator estimates. We note that in reality some sellers may not be Bayesian and exhibit behavioral deviations (e.g. motivated beliefs). We stay away from such complications and focus on a rational framework, which we believe are more relevant to the main treatment effects we expect to see. Furthermore, we may expect sellers to have heterogeneous strategic responses to the information signal. Formalizing the belief updating process thus allows us to separate the strategic responses (expressed in the functional form of $\pi()$) from the changes in beliefs (parameters of $\hat{f}()$, which we will elicit in the endline survey.

We assume that both buyers' WTP and sellers' prior beliefs about it are normally distributed. We make this assumption to simplify the distributional forms of prior and posterior beliefs, as the normal distribution is its own conjugate prior. We also note that the sellers' prior beliefs are based on information they already have access to, i.e. $\mathcal{I}_i$. We express the prior beliefs and true distributions as follows:

- Prior belief about demand distribution: $\hat{f}(\theta_0|\mathcal{I}_i) \sim\ N(\mu_{i,0}, \sigma_0^2)$
- True demand distribution: $f(x) \sim\ N(\mu, \sigma^2)$

Signals that sellers receive are drawn from the true demand distribution x. If sellers are Bayesian, they would updating θ based on x. Both the prior belief as well as the signals are continuous, so the posterior belief function is as follows:

$$\hat{f}(\theta|x_i, \mathcal{I}_i) \sim \; N(\frac{a\mu_0 + bx}{a+b}, \frac{1}{a+b}), \tag{17}$$

where $a = \frac{1}{\sigma_0^2}$, and $b = \frac{1}{\hat{\sigma}^2}$. We assume that sellers have *perceptions* about the quality of information signals they receive, whether that is the variance of f and/or the standard error of the information signal we deliver in practice. We therefore use $\hat{\sigma}^2$ instead of σ^2 to include individual's perception about the credibility, or variance, of the information signal. Furthermore, we could have specified that $\hat{\sigma}^2$ is a function of some argument (e.g. difference between data and prior mean: $\sigma^2 = \phi(|x - \mu_{i,0}|)$). Instead we stay agnostic about factors that correlate with $\hat{\sigma}^2$ and leave this as an empirical exercise after estimating $\hat{\sigma}^2$.

A.6 Model predictions: direct treatment effects

A.6.1 Information intervention reduces deviation of p^l from p^{l*})

The optimality condition for p^l in Equation 15, under noisy beliefs, can be rearranged as follows.

$$\frac{\pi'(p^t)}{\pi(p^t(p^l; s_i))} = -\frac{\frac{d\Omega(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i)}{dp^l}}{\Omega(p^t(p^l; \hat{f}(\theta_0|\mathcal{I}_i), s_i))} \tag{18}$$

Following the logic from Equation 15, Equation 18 shows that the seller sets their listing price p^l such that their *beliefs* about the expected payoff equals their *beliefs* about the cost. Their choice of p^l based on their belief about $\hat{f}()$, however, does not necessarily equal that based on true $f()$. In other words, it is generally true that given a choice of p^l made under information friction (with access only to $\mathcal{I}_i$) and prior belief $\hat{f}()$:

$$\frac{\frac{d\Omega(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i)}{dp^l}}{\Omega(p^t(p^l; \hat{f}(\theta_0|\mathcal{I}_i), s_i))} \neq \frac{\frac{d\Omega(p^t(p^l;f(\theta),s_i)}{dp^l}}{\Omega(p^t(p^l; f(\theta), s_i))} \tag{19}$$

We make assumptions about the structure of belief-updating process in Section A.5.1 to show how the Price Calculator estimate could help sellers update beliefs about the demand distribution $\hat{f}()$,on average toward the truth $f()$. Given our assumption that the form of the objective function with respect to the choice variable p^l is quasiconcave, we make the following prediction:

- Prediction 1.: Information intervention brings p^l closer to what it would be under no information friction about the demand distribution (call this p^{l*}), if the updated belief brings the posterior distribution $\hat{f}(\theta|x_i, \mathcal{I}_i)$ closer to $f(\theta)$ from $\hat{f}(\theta|\mathcal{I}_i)$. (Research question 1.1.)

A.6.2 Information intervention increases *ex post* payoffs

If information friction results in beliefs about $f()$ and the objective function is quasiconcave with respect to p^l, then the choice of p^l under information friction is *ex post* suboptimal. It follows that the Price Calculator information signal would increase the *ex post* payoff, as posterior beliefs about $f()$ is more accurate and would result in p^l closer to p^{l*} on average. In other words, we can show that:

$$\pi(p^t(p^l; \hat{f}(\theta|x_i, \mathcal{I}_i), s_i))\Omega(p^t(p^l; \hat{f}(\theta|x_i, \mathcal{I}_i), s_i)) \geq \pi(p^t(p^l; \hat{f}(\theta_0|\mathcal{I}_i), s_i))\Omega(p^t(p^l; \hat{f}(\theta_0|\mathcal{I}_i), s_i)) \tag{20}$$

This leads to the next prediction of our theoretical framework that:

- Prediction 2.: Information intervention increases sellers' *ex-post* returns from the platform if the updated belief brings the posterior distribution $\hat{f}(\theta|x_i, \mathcal{I}_i)$ closer to $f(\theta)$ from $\hat{f}(\theta|\mathcal{I}_i)$. (Research question 1.2.)

A.6.3 Information intervention may increase a

We have so far shown that the choice of listing price can be affected by noise in sellers' beliefs about the demand, and that *if* the Price Calculator estimate leads to an updated belief that is closer to the truth, then it would bring the listing price toward the optimum and improve their payoff from engaging with the marketplace. How would their choice of advertising, then be affected by information friction? From Equation 16, we see that under no information friction, sellers use advertising up to the point where the expected marginal benefit of its use equals its marginal cost. Under information friction, however, sellers consume advertising tools to the point where their *beliefs* about the expected marginal benefit equals marginal cost. The following equation makes this point by modifying Equation 16, and putting the term corresponding to beliefs about expected payoffs in a (very) wide hat:

$$\frac{d\gamma(a; s_i, \mathcal{I}_i)}{da} \widehat{\pi(p^t(p^l; \hat{f}(\theta_0|\mathcal{I}_i), s_i))\Omega(p^t(p^l; \hat{f}(\theta_0|\mathcal{I}_i), s_i))} = k'(a; s_i, \mathcal{I}_i) \tag{21}$$

The information intervention improves sellers' *ex-post* payoffs (Equation 20). The Price Calculator intervention may also shift sellers' expectations, i.e. they themselves believe that their *ex-post* payoffs would improve, meaning:

$$\overline{\pi(p^t(p^l;\hat{f}(\theta|x_i,\mathcal{I}_i),s_i))\Omega(p^t(p^l;\hat{f}(\theta|x_i,\mathcal{I}_i),s_i))} \geq \overline{\pi(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i))\Omega(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i))} \tag{22}$$

If Equation 22 is true, then, combined with Equation 21 we see that

$$\frac{d\gamma(a;s_i,\mathcal{I}_i)}{da}\overline{\pi(p^t(p^l;\hat{f}(\theta|x_i,\mathcal{I}_i),s_i))\Omega(p^t(p^l;\hat{f}(\theta|x_i,\mathcal{I}_i),s_i))} \geq k'(a;s_i,\mathcal{I}_i) \tag{23}$$

Then, it follows that $a^*(s_i,x_i,\mathcal{I}_i) \geq a(s_i,\mathcal{I}_i)$. In other words:

- Prediction 3.: Information intervention increases a if sellers' expectations about their *ex-post* returns from the platform are updated upward, when they receive the price information signal.(Research question 1.3.)

A.7 Model predictions: spillovers and their mechanisms

The optimality conditions and predictions above are based on the assumption that exogenous information shocks via the experiment only affect individual choices. We also hypothesize that individual's access to information and their choices may generate spillovers, happening through multiple mechanisms. In this sub-section, we will discuss three possibilities: information spillovers, distribution of buyer attention, and congestion.

A.7.1 Information spillovers

The first possibility is that sellers' choices of p^l may generate changes to the quality of information signals available in the market, therefore affecting $\mathcal{I}_i$ for all seller i in the market segment. This point is captured in research question 2.1.1.. An exogenous shift in the information set available in a market segment would affect sellers' prior beliefs about the distribution of buyers' WTP. The choices of p^l and a made in a treated market segment would therefore be closer to those under no information friction than in an untreated market segment.

In other words, suppose that part of a market segment is exposed to the Price Calculator treatment, and their choices of p^l are closer to the values they would choose under no information friction. Define the resulting information set in this market segment to be a union of the existing information set and information contained in treated p^l's, i.e. $\mathcal{J}_i \equiv \mathcal{I}_i \cup I(\bigcup_{i\in T} p_i^l)$, where I is a function that maps a set of prices and T is a set of treated individuals. Then we get that

$$\pi(p^t(p^l;\hat{f}(\theta|\mathcal{J}_i),s_i))\Omega(p^t(p^l;\hat{f}(\theta|\mathcal{J}_i),s_i)) \geq \pi(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i))\Omega(p^t(p^l;\hat{f}(\theta_0|\mathcal{I}_i),s_i)) \tag{24}$$

- Prediction 4.: Information spillovers from treated individual sellers in a given market segment would weakly improve the information set of all sellers in the market segment, and would bring the prior beliefs about $f()$ and p^l closer to those under no information friction, increase *ex-post* returns, and would increase a if expected returns increase. (Research question 2.1.1.)

A.7.2 Congestion and the match rate

Lastly, the treatment may affect quantities of sellers and buyers actively participating in the market, affecting congestion and the speed at which sellers and buyers are matched. The match rate is expressed via a function $\gamma()$. The spillover effect of changes in congestion levels will depend on what types of sellers and buyers are taken out of the market as a result of the Price Calculator intervention. Complex assumptions about the resulting composition of sellers and buyers are outside the scope of this framework.

One simple scenario we explore is what would happen if the intervention relaxes congestion in the matching process overall and the match rate increases for all sellers. In other words, treated market segments would have $\tilde{\gamma}(a) \geq \gamma(a)$, $\forall a$. Then we get:

$$a^*|_{\tilde{\gamma}} \geq a^*|_{\gamma} \tag{25}$$

This is because the marginal benefit of advertising is now higher in treated market segments for a given a, while the cost function is unchanged. This would lead to further consumption of a to the point where marginal cost equals the benefit. This does not affect the choice of p^l, as it is a separate problem from the chocie of a.

- Prediction 5.: A higher match rate as a result of reduced congestion in treated market segments results in higher consumption of advertising tools than in untreated market segments. (Research question 2.1.3.)

B Endline telephone survey questions

begin group	section_1	Background	
select_one yn_noad	s1_q1	Our records show that you recently listed [make] [model] [model year] in [city location] on PakWheels. Have you already sold this vehicle you posted?	کیا آپ نے اپنی گاڑی بیچی ہے. ہمارے ریکارڈز کے مطابق آپ نے ${make_b}, ماڈل ${model_b} سال ${year_b} شہر ${city_b} کا اشتہار لگایا تھا . کیا آپ نے جس گاڑی کا اشتہار پاک ویلز پر لگایا تھا وہ بیچ دی ہے؟
integer	s1_q2	What was the price you sold this car at? We would like to remind you again that your answers will stay anonymous and be used for research purposes only	اگر گاڑی بیچ دی ہے تو اسکی قیمت کیا تھی. آپ نے کس قیمت پر گاڑی بیچی ؟ ہم آپکو دوبارہ یاد کروا دیں کے آپ کے جوابات کو گم نام رکھا جائے گا اور صرف تحقیقی مقاصد کے لیے استعمال کیا جائے گا.
integer	s1_q3	What was the “expected” price? At what price did you expect to sell this car at, when you initially posted it on PakWheels?	جب اپنے ابتدائی طور پر اِس گاڑی کا اشتہار پاک ویلز پر لگایا تھا تو آپ کو کیا تواقع تھی کے یہ گاڑی کتنے کی بک جائے گی ؟
integer	s1_q4	What is realistically the highest price you could have gotten for your car?	آپ کے خیال میں، آپ کی گاڑی زیادہ سے زیادہ کتنی قیمت پر بیچی جا سکتی تھی؟
integer	s1_q4a	What is realistically the lowest price you could have gotten for your car?	آپ کے خیال میں، آپ کی گاڑی کم سے کم کس قیمت پر بیچی جا سکتی تھی؟
integer	s1_q5	How much did you pay for this vehicle when you first bought it?	آپ نے یہ گاڑی کتنی قیمت پر خریدی تھی؟
select_multiple reason_sell	s1_q6	Why have you not sold the car? (Allow the respondent to elaborate and ask follow-up questions to determine which of the following apply. You can choose more than one options.)	آپ نے گاڑی کیوں نہیں بیچی ؟
text	s1_q6_o	Please specify other	دیگر کی وضاحت کریں
select_one reasons_who	s1_q7	How and to whom did you sell the car? (Allow the respondent to elaborate and ask follow-up questions to determine which of the following apply.)	آپ نے یہ گاڑی کس کو اور کس طرح بیچی؟
integer	s1_q8	In the past 12 months, how many cars did you try to sell in total, not just on PakWheels?	پچھلے 12 مہینوں میں ، آپ نے مجموعی طور پر کتنی گاڑیاں فروخت کرنے کی کوشش کی؟ کل گاڑیاں ,صرف وہ نہیں جن کا اشتیار آپ نے پاک ویلز پہ لگایا ہو
end group	section_1		
begin group	section_2	Price Calculator	
calculate	treat_2nd		کچھ لوگوں کو گاڑی کا اشتہار پاک ویلز کی ویب سائٹ پر بناتے وقت ایک پوپ اپ یا گرافک باکس دکھایا گیا تھا ، جس میں نئے پرائس کیلکو لیٹر کی مدد سے
select_one yesno_dk	s2_q1	When creating the post for a car (in the “Post an Ad” process), a random subset of people were shown a pop-up or graphic box containing price estimate from the new Price Calculator, along with higher and lower end estimates. If you were selected, you would have seen this when you first selected your listing price while creating the post. Do you remember seeing this particular Price Calculator estimate?	کچھ لوگوں کو گاڑی کا اشتہار پاک ویلز کی ویب سائٹ پر بناتے وقت ایک پوپ اپ یا گرافک باکس دکھایا گیا تھا ، جس میں نئے پرائس کیلکو لیٹر کی مدد سے گاڑی کی اندازاً قیمت اور گاڑی کی کم سے کم اور زیادہ سے زیادہ اندازاً قیمت دی گئی تھی۔ اگر آپ ان کچھ لوگوں میں شامل ہیں توآپ نے یہ پرائس کیلکولیٹر سب سے پہلے تب دیکھا ہوگا جب آپ پوسٹ لکھتے وقت لسٹ پرئس سیلیکٹ کر رہے ہوں گے۔ کیا آپ کو یہ پرائس کیلکو لیٹر کی مدد سے لگائی گئی گاڑی کی یہ اندازاً قیمت یاد ہے؟
integer	s2_q2	What was the estimate you were given?	اگر آپکو پرائس کیلکو لیٹر دیکھنا یاد ہے ، آپکو گاڑی کی اندازاً قیمت کیا دی گئی تھی ؟
select_one enum_note	s2_q2_e	Did the respondent give you estimates from the Price Calculator provided to them on the sell-form (the “Post an Ad” process) from the intervention? Or did they give you something else?	کیا جواب دھندہ نے پرائس کیلکو لیٹر پوسٹ این ایڈ پروسیس والے کے مطابق جواب دیا یا کچھ اور جواب دیا ؟
select_one too_hl	s2_q3	Did you think that this Price Calculator box during the "Post an Ad" process gave you a reasonable estimate of transaction price? Or was it too low, or high?	آپ کے خیال سے پرائس کیلکو لیٹر پوسٹ این ایڈ پروسیس والے کے ذریعے جو گاڑی کی قیمت پاک ویلز کی جانب سے بتائی گئی وہ مناسب تھی یا بہت زیادہ تھی یا بہت کم تھی ؟
select_one yesno_dk	s2_q5	Do you know of any other sellers who have gotten the Price Calculator estimates from PakWheels?	کیا آپ کوئی اور گاڑی فروخت کرنے والوں کو جانتے ہیں جن کو پاک ویلز استعمال کرتے وقت پرائس کیلکو لیٹر کی مدد سے لگائی گئی اندازاً قیمت ملی ہو ؟
end group	section_2		
begin group	section3		

select_one yesno_dk	s3_q1	Now I would like to ask you a few questions about searching for similar posts and the choice of listing price. Did you searched for, or looked at other posts that are similar to your vehicle on PakWheels?	اب میں آپ سے کچھ سوال آپ کی گاڑی کی پوسٹ سے ملتی جُلتی پوسٹ اور لسٹ پرائس کے بارے میں پوچھنا چاہتا ہوں. کیا آپ نے اپنی گاڑی سے ملتے جلتے دوسرے اشتہار پاک ویلز پر سرچ کیے ؟
select_one search	s3_q2	Did you search for posts only for ${model_b}, or did you also search for other models?	کیا آپ نے صرف ${model_b} پوسٹس کی تلاش کی یا دوسرے ماڈلوں کی بھی تلاش کی؟
text	s3_q2_o	Please specify which models	آپ نے کون سے ماڈل کی سرچ کی ؟
select_multiple search_m	s3_q3	Did you restrict your search by any other terms? For example, your model year, version, or your city?	آپ نے اپنی سرچ کو درج زیل میں سے کن چیزوں پر محدود کیا ؟ جیسے کے ماڈل کا سال ، ماڈل ورژن یا آپکا شہر وغیرہ
text	s3_q3_o	Please specify other	دیگر کی وضاحت کریں
select_multiple search_op	s3_q4	Besides other listings from PakWheels, what other information or experience did you base your initial listing price on?	پاک ویلز پر دوسری پوسٹس دیکھنے کے علاوہ ، اور کون سی معلومات یا تجربہ کی بنیاد پر آپ نے اپنی گاڑی کی ابتدائی قیمت کو مقرر کیا؟
text	s3_q4_other	Please explain this	پاک ویلز کی دی ہوئی قیمت کے علاوہ کوئی دیگر معلومات کی وضاحت کریں
text	s3_q4_o	Please specify other	دیگر کی وضاحت کریں
select_one yesno_dk	s3_q5	Have you changed your listing price on PakWheels after you have set it initially	کیا آپ نے اپنی گاڑی کی جو شروع میں قیمت پاک ویلز پر مقرر کی تھی اُسے بعد میں تبدیل کیا.
select_multiple price_adj	s3_q6	Could you tell us why you did so?	آپ نے اپنی گاڑی کی ایک قیمت مقرر کی تھی، لیکن بعد میں اِس قیمت کو تبدیل کر دیا۔ کیا آپ ایسا کرنے کی وجہ بیان کر سکتے ہیں؟
text	s3_q6_o	Please specify other	دیگر کی وضاحت کریں
end group	section3		
begin group	section4		
integer	s4_q1	How much (in PKR) were you willing to bargain from the listing price you chose when you created the listing?	آپ اپنے اشتہار میں مقرر کردہ قیمت میں کتنی کم و پیشی کرنے پر رضامند تھے؟
begin group	s4_preamble	Please tell us if you agre with the following statements	مندرجہ ذیل بیانات سے آپ کتنا متفق یا غیرمتفق ہیں؟ بلکل متفق سے بلکل غیر متفق کے پیمانے پر جواب دیں.
select_one likert_agreedk	s4_q2	It was difficult to get enough inquiries for your post on PakWheels	آپنی پوسٹ سے متعلق مطلوبہ انکوائریز پاک ویلز پر حاصل کرنا مشکل تھا
select_one likert_agreedk	s4_q3	It was difficult to get a price offer that you would accept for your car on PakWheels.	آپنی پوسٹ سے متعلق، قابل قبول قیمت پاک ویلز پر حاصل کرنا مشکل تھا
select_one likert_agreedk	s4_q5	Most (around 3 out of 4 or more) of potential buyers of ${make_b} ${model_b} have good information about what are fair used car prices.	گاڑی ${model_b} {make_b} خریدنے والے زیادہ تر (چار میں سے تِین) افراد کو مناسب قیمتوں کا اندازہ ہوتا ہے۔
select_one likert_agreedk	s4_q6	Most (around 3 out of 4 or more) of other sellers of ${make_b} ${model_b} have good information about what are fair used car prices.	گاڑی ${model_b} {make_b} بیچنے والے زیادہ تر (چار میں سے تِین) افراد کو مناسب قیمتوں کا اندازہ ہوتا ہے۔
end group	s4_preamble		
begin group	s4a_preamble	Please tell us if you agre with the following statements	مندرجہ ذیل بیانات سے آپ کتنا متفق یا غیرمتفق ہیں؟ بلکل متفق سے بلکل غیر متفق کے پیمانے پر جواب دیں.
select_one helpful_scale	s4_q7	As you may know, sellers like you can feature your ad, use "bumps" to get your post to be more visible, or requested for vehicle inspections by PakWheels. In a scale of 1 to 5, 5 being the most useful, how useful are these features, bumps, and inspections to get people to buy your car at a higher price?	جیسا کہ آپ جانتے ہیں، جو لوگ آپ کی طرح پاک ویلز کی ویبسائٹ پر اپنی گاڑی کو بیجنے کےلئے اشتہارلگاتے ہیں وہ اپنے اشتہار کو فیچر کر سکتے ہیں یا مشہور بنانے کے لئے "بمپس" کا استعمال کرسکتے ہیں یا پاک ویلز کی طرف سے اپنی گاڑی کی انسپیکشن کرواسکتے ہیں۔ ایک سے پانچ کے پیمانے پر بتایں کے ان سہولیات کا استعمال آپ کو اپنی گاڑی کو زیادہ قیمت پر بیچنے میں کتنا مدد گار ثابت ہو سکتا ہے ؟ ایک کا مطلب ہے بلکل مدد کار نہیں اور پانچ کا مطلب ہے بہت زیادہ مدد کار
select_one helpful_scale	s4_q8	Again in a scale of 1 to 5, how useful are these features, bumps and inspections to increase the chance that it sells, or sells faster?	ایک سے پانچ کے پیمانے پر بتاین کے آپ کی گاڑی کے بکنے کے امکانات میں اضافه کرنے میں بمپز اور فیچر کا استعال کتنا مدد گار ثابت ہو سکتا ہے ؟ ایک کا مطلب ہے بلکل مدد کار نہیں اور پانچ کا مطلب ہے بہت زیادہ مدد کار
select_one yesno_dk	s4_q9	The Price Calculator is currently provided for free. But in the future if it were offered for 100 rupees per post, would you be willing to pay for it?	فل حال پرائس کیلکولیٹر فری ہے، لیکن اگر مستقبل میں اس کی قیمت ایک سو روپے فی پوسٹ مقرر کردی جائے تو کیا آپ اس کے استعمال کے لئے پیسے دیں گیں؟
integer	s4_q10	What is the maximum amount (PKR) that you would be willing to pay for the Price Calculator, per post?	پرائس کیلکولیٹر کے استعال کے لئے آپ زیادہ سے زیادہ کتنی قیمت فی پوسٹ ادا کرنا چاہتے ہیں؟
end group	s4a_preamble		
end group	section4		