A Discriminatory Mechanism for Real-time Pricing and Matching in On-demand Platforms

Introduction

The rise and growth of on-demand platforms, which operate by leveraging independent sellers to serve requests from potential buyers through dynamic matching, have enabled new types of transactions that provide important opportunities to enhance the economic and operational performance of underlying markets. Three critical features that distinguish on-demand platforms from traditional markets are real-time management of demand and supply, matching capabilities, and flexible payment schemes. First, on-demand platforms face opportunities to use real-time demand information when managing imbalances between demand and supply, which provides additional flexibility as compared to the traditional approaches to job scheduling and revenue management. Second, the management of demand and supply can be achieved through personalized matching between buyers and sellers, in contrast with most markets relying on first-come first-served operating procedures. For instance, a labor provider such as TaskRabbit can determine which seller to allocate to each request to satisfy objectives such as minimizing wait times, meeting individual requirements, or rewarding highly rated agents. Third, online payment capabilities permit the implementation of personalized pricing and revenue management schemes, in contrast with most markets relying on posted prices. For instance, surge pricing in transportation platforms provides capabilities to apply differentiated prices based on spatial-temporal characteristics of ride requests and driver supply.

These platform characteristics enable the design and implementation of novel solutions to the long-standing economic and operational issues associated with the dynamic management of demand and supply imbalances in the presence of customer heterogeneity and information asymmetries. As most traditional markets, platforms face variable demand over time and capacity limitations that constrain their ability to serve buyer demand. Efficient platform management therefore involves demand-side pricing mechanisms (i.e., determining price levels for every buyer request with such objectives as maximizing revenues or market share) and supply-side allocation mechanisms (i.e., assigning sellers to buyer requests with such objectives as maximizing service levels and minimizing wait times). These problems can be significantly complicated by the heterogeneity of buyer preferences. Indeed, buyers typically exhibit differentiated willingness to pay for a good or a service, as well as differentiated willingness to wait if immediate service cannot be provided. However, this information is private to each individual buyer and unknown to the platform. Existing approaches to managing demand and supply typically rely on dynamic spatial-temporal pricing and revenue management [1, 2, 3]. However, these two paradigms rely exclusively on public information, and do not enable the buyers to reveal their preferences to the system, thus maintaining information asymmetries between the platform and the buyer pool. Ultimately, these asymmetries may result in lost revenue opportunities and mismatches between service offers and customers’ expectations.

This paper proposes an original dynamic pricing and allocation mechanism in online platform systems that relies on the elicitation of buyer preferences in order to provide personalized pricing and service levels, while, at the same time, smoothing out the imbalances between demand and
supply. We consider a setting with stochastic demand and a heterogeneous set of buyers that includes time-sensitive agents, characterized by a high willingness to pay and a low willingness to wait, and price-sensitive agents, characterized by a low willingness to pay and a high willingness to wait. For instance, in the transportation context, this heterogeneity captures the variance between riders who are in a hurry and place a premium on fast pickup, and other riders with a higher tolerance for waiting, but higher price sensitivity. The proposed mechanism enables the buyers to reveal these preferences to the platform, and then leverages this information to set price levels and to allocate sellers to buyer demand accordingly. This elicited information provides benefits for price discrimination over heterogenous buyers, as well as for the dynamic management of imbalances between demand and supply over time in the face of demand stochasticity.

Model Overview

We develop a theoretical model to study the design of the platform’s pricing and allocation mechanism. We formalize this problem in a dynamic setting with discrete time and infinite horizon. At each time period, a stochastic number of agents arrive into platform, and request service. The platform faces excess supply in periods with low incoming demand, and excess demand in periods with high demand realizations. We model buyer heterogeneity with a subset of time-sensitive buyers, who have a high willingness to pay but leave the platform if they are not served immediately, and a subset of price-sensitive buyers, who have a lower willingness to pay but are willing to accept a delay up to one period.

We formulate a dynamic programming model that optimizes, in every single period, the price of service and the (probabilistic) allocation of sellers to (i) the time-sensitive buyers, (ii) the price-sensitive buyers who just placed a request, and (iii) the price-sensitive buyers who are waiting for requests placed in the previous time period. The state variable at any given time period includes (i) the realized demand in the period considered, and (ii) the number of time-sensitive buyers who are transferred from the previous period and waiting for late service. We formulate the problem with a single decision variable: the number of time-sensitive buyers to transfer to the next period. The model maximizes the platform’s expected profit, subject to buyer incentive compatibility (IC) and individual rationality (IR) constraints, as well as the overall capacity constraints. We derive a closed-form characterization of the optimal policy, as a function of the relative valuations across time-sensitive and price-sensitive buyers and the demand characteristics.

There are several important trade-offs that govern the platform’s optimal pricing and allocation mechanism. First, it is of the interest of the platform to prioritize the allocation of its sellers to time-sensitive buyers, at a price premium. Second, the platform wants to maximize the numbers of requests from price-sensitive agents served with no delay on the one hand; but this has a negative effect on the price that it can charge to the time-sensitive agents due to the incentive compatibility constraints. In consequence, the platform may instead prefer to transfer some of the price-sensitive agents to a late service in the next period for discriminatory purposes. At the same time, transferring excessive numbers of (price-sensitive) agents to the next period may lead to suboptimal dynamics and lost revenue opportunities. In particular, if the incoming demand in the next period turns out to be high, providing late service to all these agents may not be feasible. This induces a risk associated with the platform’s decision that influences the optimal pricing and allocation policy, due to the stochastic and inter-temporal effects of demand accrual in the system and the effects of buyer heterogeneity.
Overview of Results and Insights

The model’s results fall into three main categories. First, we show that, over the range of parameter space, the optimal mechanism exhibits different dynamic structures. In some cases, the optimal policy is associated with history-independent components in that the allocation and the pricing rules just depend on the realized demand in the current period. In contrast, in some other cases, the optimal policy depends crucially on the history. This dependence, demonstrates different patterns over the time periods with high and low demand realizations. We show that, when the gap between the valuations of time-sensitive and price-sensitive agents is sufficiently large, time becomes a significant tool to discriminate over the agents. In this case, the platform extracts all the surplus without leaving any information rent to agents. In order for being able to do this, it has to give up from some of the potential social welfare that it could generate, hence there is a loss of efficiency from a system-wide standpoint. As valuation heterogeneity becomes weaker, time becomes less important for discrimination, and the platform uses the allocation mechanism primarily to manage the dynamic imbalance between supply and demand. In this case, the platform has to leave some of the surplus to the time-sensitive agents as information rent, but the overall system efficiency is maximized. Second, we show that, in contrast to conventional wisdom, the price does not necessarily increase with the realized demand. More precisely, under some certain circumstances, the price that the time-sensitive agents are charged for service is higher when the incoming demand in that period is lower. Third, comparisons with baseline policies based on non-discriminatory dynamic pricing suggest that the elicitation of buyer preferences in the proposed mechanism can enhance the platform’s revenues, and result in matching policies that are more consistent with buyers’ preferences.

These results suggest potential opportunities to enhance the economic and operational performance of sharing platforms by eliciting buyer preferences and adjusting prices and service levels accordingly. First, this shows that current practices based on dynamic pricing (such as surge pricing practices from on-demand transportation providers, for instance) can be significant enhanced by leveraging buyer heterogeneity. Second, the insights from this paper follow recent developments of new policies and products that partially account for some consumer heterogeneity, such as Uber Pool and Amazon Prime, which provide cheaper service to price-sensitive riders and faster service to time-sensitive buyers, respectively. This paper suggests that this approach can be applied in a wide range of on-demand platforms without creating separate products or policies, but by eliciting buyer preferences upon arrival into the platform.

References

