Research Statement

Hongfan Chen
University of Chicago

My research mainly focuses on the interface of revenue management, platform economy, and optimization under uncertainty. My goal is to provide insight into the fundamental structures of revenue decision problems by formulating tractable models and developing policies with proven performance guarantees in complex environments. As the fast-growing field of sharing economy reforms companies’ business models and changes customers’ engagement patterns, previously centralized systems gradually become decentralized. Coupled with challenges of demand uncertainty and agents’ strategic behavior, complex revenue management problems emerge simultaneously. To take the first step in making contributions to such an area, I leverage a broad class of methodologies in optimization, game theory, and probability. My job market paper "Optimal Commissions and Subscriptions in Networked Markets" has been accepted for publication at Manufacturing & Service Operations Management, and another paper "Markdown Markdown Policies for Demand Learning with Forward-looking Customers" is under review at Operations Research.

My enthusiasm has been largely driven by strong curiosity to uncover insight into how companies could improve their revenue performance when interacting with different parties in marketplaces. Such enthusiasm has been further reinforced by my industry experience as researchers at well-known platform marketplace companies like Amazon and Airbnb where I obtained valuable opportunities to observe platforms’ operations and their engagement with different sides of the market. In the following section, I will provide an overview of my research.

Revenue Management in Platform Economy. My job market paper "Optimal Commissions and Subscriptions in Networked Markets" is mostly inspired by the popularity of platform marketplaces that facilitate the transactions of the sellers and buyers. Notable examples include Amazon’s marketplace, the accommodation platform Airbnb, and the freelancing platform Upwork. One common feature for these platforms is that they do not directly dictate the price-setting process. Instead, these platforms charge commission rates and subscription fees that impact the trading in the marketplace. The paper investigates how the platform should optimally choose the commission rates and the subscription fees to maximize the platform’s revenue. Under the key challenge that the revenue optimization problem in the space of commission rates and subscription fees is a nonconvex problem, the paper has established a convex-cost flow problem formulation whose optimal solutions coincide with the optimal equilibrium flows. Based on the tractable for-
mulation, there are two fundamental observations regarding the network structures in the paper. For example, one notable insight about the network structure is that the surplus of the sellers and buyers can be ranked according to the lexicographically optimal base of a polymatroid induced by the network. Another key insight in the network structure is that the platform's optimal revenue depends on a variant of the Hall's marriage condition. Besides the results about the network structures, the paper has also characterized the performance of some widely-applied practice in industry. For example, there is a trend that companies like Airbnb and Upwork charge to both sides of markets with heterogeneous commission rates. To explain these trends from a revenue maximization perspective, this paper has identified that (i) charging to one side of the market is sub-optimal, but it guarantees 50% of the optimal revenue; (ii) charging homogeneous commissions and subscriptions can be arbitrary bad in general. However, with some assumptions on agents' value distribution and network structures, the revenue loss can be bounded. In the end, this paper has also established several social welfare bounds for the platform to implement the revenue-optimal equilibrium. In summary of this paper, we have provided a nice contribution to the interface of revenue management and platform economy by providing a thorough analysis of how a platform should design commission rates and subscription fees for maximization purposes.

Demand Learning and Price-Setting Incentives in Online Marketplaces. Following my job market paper, a natural question about how a platform without price controls should address the challenges of demand model uncertainty emerges naturally. In my working paper "To Interfere or Not To Interfere: Information Revelation and Price-Setting Incentives in a Multiagent Learning Environment", my coauthors and I consider a problem in which the platform has to strategically design information revelation and price coordination policy under demand model uncertainty. Since the platform does not dictate the price-setting process and the decentralized sellers do not have sufficient information to make price decisions, it is ex-ante unclear whether the sellers’ pricing strategies hurt the platform, and whether the platform should reveal its private information with the sellers. In our setting, we assume that the platform has full information about the function form of the demand model, and is capable of observing the features related to the customers. Meanwhile, the only uncertainty the platform faces is the demand model parameter. In contrast, the decentralized sellers have no information about the demand model or the features. Extending the discussions of the past literature by considering a generalized demand model, we identify in our paper that if the platform chooses not to intervene the sellers’ price-setting process, the outcome could either favors or hurts the platform i.e., the regret either grows linearly or decreases linearly in time horizons. If the platform reveals its information and actively engages in providing incentives for the sellers to choose the recommended prices, then the platform can achieve a regret that grows in the order of the square root of the time horizons. The most important result suggests that by strategically revealing the platform’s information to the sellers, the platform can either achieve linearly decreasing regret in good cases and simultaneously limit the regret to the square root of
the time horizons in bad cases. This observation stands in stark contrast to past literature which works on incentivizing decentralized agents.

**Demand Learning under Forward-looking Customer Behavior.** One notable feature that was not captured in the previous two papers is that sellers and customers tend to be forward-looking or strategic. Past literature either characterized the impact of strategic customer behavior in a full-information setting or investigated the profit regret incurred by the demand model uncertainty under the assumption the demand functions are induced only by myopic customers. Due to the notable theoretical challenge, there has been little research into how a seller should design dynamic learning policies under demand model uncertainty when there exists forward-looking customers.

As a first step in understanding how demand learning policies should be designed under forward-looking agents, in my paper "Markdown Markdown Policies for Demand Learning with Forward-looking Customers", my coauthors and I consider a problem where a monopoly seller chooses a dynamic markdown policy facing the challenges of demand model uncertainty and forward-looking customers. In the paper, we have identified that adding forward-looking customers to the dynamic learning setting would fundamentally change the problem structure. In one of our key results, we show that when the customers are forward-looking, the regret can grow in the same order as the worst-case scenario. Coupled with the result, we have also identified the key conditions under which a forced-exploration policy is asymptotically optimal. Perhaps more surprisingly, we show that when the forward-looking customers are endogenous i.e., they have knowledge about the seller’s policy, the seller can regulate the customers' forward-looking behavior and effectively achieves asymptotic optimality by announcing and committing to the forced exploration policy. In the paper, in contrast to the insight about the potential high learning cost incurred by forward-looking customers, we have also established that the patience property of these forward-looking customers can potentially benefit the seller by granting her/him more exploration opportunities before incurring large loss. In summary of the key insights above, we summarize that forward-looking customers introduce some fundamental challenges into the classical learning-and-earning problem, and we have provided insight into how the seller should design asymptotically optimal policies.

**Future Directions.** For future directions, I am broadly interested in (1) how platforms should consider the tradeoff between revenue maximization and welfare maximization in networked markets, (2) how platforms should incentivize sellers and buyers for revenue maximization purpose under the market information uncertainty, and (3) when participants of platforms are strategic, how the platforms should leverage tools to maximize revenue under information uncertainty. In general, I would continue working on research questions related to revenue management, platform economy, and optimization under uncertainty.