Hangcheng Zhao
Marketing Doctoral Candidate
The Wharton School, University of Pennsylvania

September 4, 2024
Where: 741 JMHH
When: 12:00 PM to 1:20 PM

ALGORITHMIC COLLUSION OF PRICING AND ADVERTISING ON E-COMMERCE PLATFORMS

ABSTRACT:

Online sellers have been adopting AI learning algorithms to automatically make product pricing and advertising decisions on e-commerce platforms. When sellers compete using such algorithms, one concern is that of tacit collusion—the algorithms learn to coordinate on higher than competitive prices which increase sellers' profits but hurt consumers. This concern, however, was raised primarily when sellers use algorithms to decide on prices. We empirically investigate whether these concerns are valid when sellers make pricing and advertising decisions together, i.e., two-dimensional decisions. Our empirical strategy is to analyze competition with multi-agent reinforcement learning, which we calibrate to a large-scale dataset collected from Amazon.com products.

Our first contribution is to find conditions under which learning algorithms can facilitate win-win-win outcomes that are beneficial for consumers, sellers, and even the platform, when consumers have high search costs. In these cases, the algorithms learn to coordinate prices that are lower than competitive prices. The intuition is that the algorithms learn to coordinate on lower advertising bids, which lower advertising costs, leading to lower prices for consumers and enlarging the demand on the platform.

Our second contribution is an analysis of a large-scale, high-frequency keyword-product dataset for more than 2 million products on Amazon.com. Our estimates of consumer search costs show a wide range of costs for different product keywords. Among these products, more than 50% show evidence that prices are lower when more sellers adopt algorithms to choose their prices and bids. In these product markets, consumers benefit from tacit collusion facilitated by algorithms.

We also provide proof that our results do not depend on the specific reinforcement-learning algorithm that we analyzed. They would generalize to any learning algorithm that uses price and advertising bid exploration.

Finally, we analyze the platform's strategic response through adjusting the ad auction reserve price or the sales commission rate. We find that reserve price adjustments will not increase profits for the platform, but commission adjustments will, while maintaining the beneficial outcomes for both sellers and consumers.

Our analyses help alleviate some worries about the potentially harmful effects of competing learning algorithms, and can help sellers, platforms and policymakers to decide on whether to adopt or regulate such algorithms.