HANGCHENG ZHAO

The Wharton School, University of Pennsylvania

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EDUCATION

The Wharton School, University of Pennsylvania *2020 – 2025 (Expected)*
Ph.D. in Quantitative Marketing
Dissertation Committee: Ron Berman (Chair), Eric Bradlow, Pinar Yildirim

University of Chicago *2018 – 2019*
Master in Economics
Thesis Advisor: Philip Reny

Tsinghua University, Beijing, China *2014 – 2018*
Bachelor in Economics

RESEARCH INTERESTS

Pricing, Algorithmic Decision-Making, Reinforcement Learning, Recommendation Algorithms, Platforms, Online Marketing, Empirical IO

WORKING PAPERS

Algorithmic Collusion of Pricing and Advertising on E-commerce Platforms *(Job Market Paper)*

With Ron Berman (University of Pennsylvania)

Ridge Distributions and Information Design in Simultaneous All-Pay Auction Contests [SSRN]

With Zhonghong Kuang (Remin University of China) and Jie Zheng (Shandong University)

- Minor Revision at ***Games and Economic Behavior***

Strategic Design of Recommendation Algorithms [SSRN]

With Ron Berman (University of Pennsylvania) and Yi Zhu (University of Minnesota)

- Under Review at ***Management Science***

Analyzing Healthcare Price Transparency: Will Patients Shop for Services More Effectively? [SSRN]

With Ron Berman (University of Pennsylvania)

- Under Revision

CONFERENCE PRESENTATIONS

Algorithmic Collusion of Pricing and Advertising on E-commerce Platforms

- 2024 INFORMS Marketing Science Conference *Sydney, Australia, June 2024*
- 14^{th} Annual Theory + Practice of Marketing Conference *Austin, TX, May 2024*
- 4^{th} Annual AI in Management (AIM) Conference *Los Angeles, CA, March 2024*

Analyzing Healthcare Price Transparency: Will Patients Shop for Services More Effectively?

- 2023 INFORMS Marketing Science Conference — *Miami, FL, June 2023*

Ridge Distributions and Information Design in Simultaneous All-Pay Auction Contests

- ASSA 2020 Annual Meeting — *San Diego, CA, January 2020*
- 30$^{\text{th}}$ International Conference on Game Theory — *Stony Brook, NY, July 2019*

RESEARCH AND PROFESSIONAL EXPERIENCE

Ph.D. Economist Intern — *July 2023 - September 2023*
HP, Inc., Pricing Analytics Group

Research Assistant to Prof. Pinar Yildirim and Prof. Ron Berman — *July 2019 - June 2020*
The Wharton School, University of Pennsylvania

Research Assistant to Prof. Richard Hornbeck — *October 2018 - June 2019*
Booth School of Business, University of Chicago

TEACHING EXPERIENCE

The Wharton School, University of Pennsylvania, Philadelphia, PA

Teaching Assistant to Prof. Jagmohan Raju — *Summer 2022, Spring 2023, Spring 2024*

- MKTG 7540 Pricing Policy (MBA, WEMBA)

HONORS AND AWARDS

ISMS Marketing Science Doctoral Consortium Fellow	*2024*
Mack Institute Research Fellowship	*2023*
Analytics at Wharton Research Funding	*2023*
George James Travel Award for the Wharton Doctoral Program	*2023*
Wharton INSEAD Alliance Doctoral Student Short - Term Visit Award	*2023*
Ph.D. Program Fellowship, the Wharton School, University of Pennsylvania	*2020-Present*
University of Chicago Scholarship for Master of Arts Social Sciences Program	*2018-2019*
“Top Open” Student Overseas Research Grant, Tsinghua University	*2017*
Undergraduate Student Academic Research Grant, Tsinghua University	*2017-2018*

TECHNICAL SKILLS

Programming Languages — Stata, C++/C, R, Python, Matlab, Mathematica, SQL, Amazon AWS

REFERENCES

Ron Berman
Associate Professor of Marketing
The Wharton School
University of Pennsylvania
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Eric Bradlow
K.P. Chao Professor
Professor of Marketing, Statistics, Economics and Education
The Wharton School
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Email: ebradlow@wharton.upenn.edu

Pinar Yildirim
Associate Professor of Marketing and Economics
The Wharton School
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Email: pyild@wharton.upenn.edu

ABSTRACTS

Algorithmic Collusion of Pricing and Advertising on E-commerce Platforms *(Job Market Paper)*

With Ron Berman (University of Pennsylvania)

Firms have been adopting learning algorithms to drive automatic decision making such as setting product prices and setting bids in online ad auctions. One concern that arises when firms compete using such algorithms is that of tacit collusion—the algorithms learn to settle on higher than competitive prices which increase firm profits, but hurt consumers. We investigate the impact of such learning algorithms to determine if they are always harmful to consumers, but in a setting with two-dimensional decisions, because many firms need to decide on pricing and bidding together. Our analysis uses a multi-agent reinforcement learning simulation of the Q-learning algorithm that is compared to analytical results from a game theoretical model. Our main findings are that algorithms can facilitate outcomes that are beneficial for both consumers, sellers, and even the platform when consumers have heterogeneous search costs. The intuition is that algorithms learn to coordinate on lower bids, which lowers advertising costs, leading to lower prices for consumers and enlarging the demand on the platform. We also analyze a large-scale product dataset from Amazon.com and find robust evidence of substantial consumer search costs, suggesting that the beneficial outcomes of algorithmic pricing can hold for most, if not all product markets we analyze. We show that even if the platform responds strategically by adjusting the ad auction reserve price or the sales commission rate, the beneficial outcomes for both sellers and consumers are likely to persist.

Strategic Design of Recommendation Algorithms [SSRN]

With Ron Berman (University of Pennsylvania) and Yi Zhu (University of Minnesota)

We analyze recommendation algorithms that firms can engineer to strategically provide information to consumers about products with uncertain matches to their tastes. Monopolists who cannot alter prices can design recommendation algorithms to oversell, i.e., that recommend products even if they are not a perfect fit, instead of algorithmically recommending perfectly matching products. However, when prices are endogenous or when competition is rampant, firms opt to reduce their overselling efforts and instead choose to fully reveal the product's match (i.e., maximize recall and

precision). As competition strengthens, the algorithms will shift to demarket their products, i.e., under-recommend highly fitting products, in order to soften price competition. When a platform designs a recommendation algorithm for products sold by third-party sellers, we find that demarketing might be a more prevalent strategy of the platform. Additionally, we find that platforms bound by fairness constraints may gain lower profits compared to letting sellers compete, while discriminatory designs do not necessarily result in preferential outcomes for a specific seller.

Ridge Distributions and Information Design in Simultaneous All-Pay Auction Contests [SSRN]

With Zhonghong Kuang (Remin University of China) and Jie Zheng (Shandong University)

Two privately informed contestants compete in a contest, and the organizer ex-ante designs a public anonymous disclosure policy to maximize contestants' total effort. We fully characterize ridge distributions, under which the organizer achieves the first best outcome in equilibrium: the allocation is efficient, and the entire surplus goes to the organizer. When the prior is a mixture of a ridge distribution and a perfectly correlated distribution, the first-best outcome is achievable by the signal that solely generates ridge distributions as posteriors.

Analyzing Healthcare Price Transparency: Will Patients Shop for Services More Effectively? [SSRN]

With Ron Berman (University of Pennsylvania)

Recently, the US mandated healthcare price transparency to facilitate easier comparison of healthcare prices. However, the potential effectiveness of this policy is an open question. We use a large-scale health insurance claims dataset to estimate the potential maximum savings from price transparency. We focus on short-term, demand-side estimates, where patients can shop around and switch to cheaper providers. We analyze the set "shoppable" services whose price information must be reported online. Initially, our data points to a large potential for savings due to a large degree of price dispersion. However, when viewed from the consumer shopping perspective, even the most optimistic estimates of potential savings become limited. The reasons are that the location and insurance network of the patient, the structure of healthcare insurance payments, and the information made available by the transparency rule lower patients' incentive to save. We find that the best-case scenario for patients' out-of-pocket savings from price - shopping is 3% of the total cost on average. Our analysis suggests that the existing estimates in the literature might be overestimated, as they overlook the consumer shopping perspective. Hence, patients' potential savings and the demand-side impact of the transparency rule might not be as impactful as initially hoped for.

Last Updated: July 2024