

# HANGCHENG ZHAO

The Wharton School, University of Pennsylvania

**Address:**

3730 Walnut Street  
Philadelphia, PA, 19104

**Email:** [zhaohc@wharton.upenn.edu](mailto:zhaohc@wharton.upenn.edu)**Website:** <https://hangcheng-zhao.github.io>

## 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

---

**Substantive:** Pricing, Algorithmic Decision-Making, Recommendation Algorithms, Advertising, Platforms, Online Marketing

**Methodological:** Reinforcement Learning, Artificial Intelligence, Empirical IO

## PUBLICATIONS

---

**Ridge Distributions and Information Design in Simultaneous All-Pay Auction Contests** [\[SSRN\]](#)

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

- Forthcoming at *Games and Economic Behavior*

## WORKING PAPERS

---

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

With Ron Berman (University of Pennsylvania)

**Analyzing Healthcare Price Transparency: Will Patients Shop for Services More Effectively?** [\[SSRN\]](#)

With Ron Berman (University of Pennsylvania)

- Under Revision

**Strategic Design of Recommendation Algorithms** [\[SSRN\]](#)

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

- Under Review at *Management Science*

## CONFERENCE PRESENTATIONS

---

### Algorithmic Collusion of Pricing and Advertising on E-commerce Platforms

- 2<sup>nd</sup> FTC Conference on Marketing and Public Policy *Washington, D.C, October 2024*
- 2024 INFORMS Marketing Science Conference *Sydney, Australia, June 2024*
- 14<sup>th</sup> Annual TPM Conference *Austin, TX, May 2024*
- 4<sup>th</sup> 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*
- 2018 Society for the Advancement of Economic Theory Conference *Taiwan, June 2018*

## RESEARCH AND PROFESSIONAL EXPERIENCE

---

### Ph.D. Economist Intern

*July 2023 – September 2023*

HP, Inc., Pricing Analytics Group

- Designed and executed multi-armed bandit experiments to optimize pricing strategies for various combinations of computer accessories.

### Research Assistant to Prof. Pinar Yildirim and Prof. Ron Berman

*July 2019 – June 2020*

The Wharton School, University of Pennsylvania

- Conducted reduced form analyses and structural estimations for textual newspaper data, geographical railroad network data, and online experiments.

### Research Assistant to Prof. Richard Hornbeck

*October 2018 – June 2019*

Booth School of Business, University of Chicago

- Constructed and analyzed historical individual manufacturing establishments data.

## TEACHING EXPERIENCE

---

### The Wharton School, University of Pennsylvania, Philadelphia, PA

#### Teaching Assistant to Prof. Jagmohan Raju

*2022 – 2025*

- MKTG 7540 Pricing Policy (MBA, WEMBA)

#### Teaching Assistant to Prof. Ron Berman

*2025*

- MKTG 7270/2270 Digital Marketing, Social Media & E-commerce (MBA, Undergraduate)

## HONORS AND AWARDS

---

ISMS Marketing Science Doctoral Consortium Fellow

*2024*

Wharton Dean's Research Fund

*2024*

Mack Institute Research Fellowship

*2023*

Analytics at Wharton Research Funding

*2023*

George James Travel Award for the Wharton Doctoral Program

*2023 – 2024*

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  
Email: [ronber@wharton.upenn.edu](mailto:ronber@wharton.upenn.edu)

Eric Bradlow  
K.P. Chao Professor  
Professor of Marketing, Statistics, Economics and Education  
The Wharton School  
University of Pennsylvania  
Email: [ebradlow@wharton.upenn.edu](mailto:ebradlow@wharton.upenn.edu)

Pinar Yildirim  
Associate Professor of Marketing and Economics  
The Wharton School  
University of Pennsylvania  
Email: [pyild@wharton.upenn.edu](mailto:pyild@wharton.upenn.edu)

## PAPER ABSTRACTS

---

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

With Ron Berman (University of Pennsylvania)

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 on 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 a 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.

### **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.

### **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.

*Last Updated: September 2024*