Research Statement

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My primary research interest is **behavioral and data-driven operations management** for the future of work, currently focusing on the **gig economy**/flexible workforce. Recent technologies create and accelerate new work arrangements that provide workers with flexibility in their work schedule and choice of service. At the same time, the decisions a worker faces have become more complex. Platforms dynamically offer competing incentives, and the independent nature of gig work means that workers do not experience the benefits of learning from colleagues. While economists and psychologists have long studied workers' labor decisions, less is known about how gig workers respond to flexibility and real-time incentives.

In my work, I combine tools from operations, economics, behavioral science, and machine learning to address operational challenges introduced by the gig economy. Specifically, I study how workers respond to dynamic incentives using econometric analyses and structural estimation. Then, I apply those insights to develop tools to help workers improve performance using interpretable machine learning and randomized experiments. Finally, I use optimization and simulation tools to demonstrate how a deeper understanding of workers' behaviors can help firms better entice and retain their flexible workforce, and also help inform the design of new regulations to protect workers' welfare. This research excites me as it exposes me to emerging business models, the role of human behavior in the future of work, and a versatile research toolkit.

While the focus of my projects is on the gig economy and I believe that this economy is only going to grow in size and complexity, I believe that the questions are broader and pertain to other human-centric systems. More broadly, I am interested in and have conducted research on integrating behavioral insights and data analytics into plausible operational and social problems, including pricing and urban planning.

Current Work: Managing a Flexible Workforce via Behavioral and Operational Lenses

One of the most unique and novel features of the gig economy is the independent nature of employment. Ride-hailing and delivery service workers can work whenever they want and seamlessly switch between different platforms to work for. Moreover, with the current pandemic, traditional companies have started to offer gig jobs and more workers are seeking alternative independent work opportunities. Such flexibility introduces new challenges: on-demand platforms are now competing for not only customers but also a limited pool of workers. Understanding workers' preferences and behaviors is crucial for platforms to manage a flexible workforce successfully.

(i) Gig Workers' Decisions on Flexible Schedules *(Econometrics)*

Without a fixed schedule for workers, gig companies face challenges in planning and committing to their service capacity, both during periods of high and low demand. Various types of strategies to entice workers have been used, but their effectiveness relies on a good understanding of how workers make decisions. While economists have long studied labor decisions of workers who have some discretion over their schedules, it is unclear how workers would make decisions given the full flexibility offered in the gig economy.

In ***"The Impact of Behavioral and Economic Drivers on Gig Economy Workers"*** (with G. Allon and M. Cohen, 1st round Major Revision at *M&SOM*), we empirically investigate how gig workers decide on *when to work* and *for how long* depending on varying financial incentives and personal goals. Using the comprehensive data from a ride-hailing industry partner, we develop an econometric framework that rigorously addresses several empirical challenges, including sample selection bias and endogeneity in the incentives. Our results demonstrate that, while workers exhibit positive income elasticity as predicted by standard income theory, their decisions are significantly influenced by their cumulative earnings (more likely to stop working when reaching their income goal) and recent work duration (tend to stay working after long hours of work or exhibit *"inertia"*), more akin to behavioral theory of labor supply.

An important phenomenon that emerged from this work is the existence of inertia, which captures both the formation of work habits and tendency to stay with the focal platform. Amidst intensifying competition among platforms, inertia is a potential signal of platform loyalty that could be induced through optimal incentive design. Thus, we propose a heuristic to optimize the allocation of incentives and demonstrate through counterfactual simulations the monetary and capacity benefits of accounting for our behavioral insights. Using New York City's *Driver Income Rules* as a case study, we further show how our insights could guide policymakers to quantify the improvement of worker welfare from a new regulation and identify potential further improvement if they integrate gig workers' decision-making into regulatory design. *Ongoing and future directions* include investigating how workers form and adjust income and time goals, refining our theory of inertia, and testing our findings in a controlled field experiment.

(ii) Gig Workers' Behaviors in Presence of Platform Competition *(Structural Estimation)*

With the flexibility in the choice of service, gig workers often exhibit a "multihoming" behavior. The majority of ride-hailing drivers work for more than one platform and many also provide other services such as food delivery. An increase in the number of available options has resulted in increased competition among platforms to win over a limited mutual pool of workers. Such competition has only been further exacerbated in cities like New York and Seattle, which recently passed caps on the number of ride-hailing drivers. How workers respond to platform competition is therefore an important topic to study, but studying multihoming behavior empirically is challenging due to the unobservability of workers' options.

In ***"The Structural Behavioral Model of Gig Economy Workers"*** (with G. Allon, M. Cohen, and K. Moon, work in progress), we leverage proprietary data from our ride-hailing industry partner and the publicly available trip record data to develop and estimate a structural model of gig workers' sequential dynamic decisions in the presence of alternative work opportunities. Our major contributions are in the modeling and estimation of dynamic decisions with temporal and spatial components and dynamic outside options, and the development of an efficient simulation-assisted estimation framework in the presence of analytically or computationally intractable likelihood functions and high-dimensional data.

Our results characterize workers' forward-looking behavior and heterogeneous cost of working. We find that workers are strategic in their choice of initial service location to ensure high utilization and are prone to multihoming behavior when facing longer idle times. The natural follow-up question is how the firm can reduce (or induce in some cases) multihoming behavior. Our counterfactual analyses demonstrate the effectiveness of different strategies commonly used in practice and offer insights that can help the firm retain workers during high demand or nudge them to take a break when demand is low. *Ongoing and future directions* include allowing for additional factors driving multihoming behavior, further improving our simulation-estimation framework, and running field experiments to test our insights.

(iii) Gig Workers' Learning to Improve Performance *(Machine Learning/Experiments)*

Workers spend a significant amount of time learning how to make good decisions. While most traditional workers can learn by sharing best practices with their co-workers, gig workers face challenges in learning due to the independent nature of their work. For example, an Uber driver might have to independently rediscover good strategies to get more trips that might already be known to other drivers. One promising source of best practices is the largely untapped trace data of human decisions accumulated in many domains (e.g., every movement of a driver is recorded on a ride-hailing platform). Such data implicitly encodes the collective knowledge acquired by numerous workers about how to effectively perform their jobs.

My working paper ***"Learning Best Practices: Can Machine Learning Improve Human Decision-Making?"*** (with H. Bastani and O. Bastani, in preparation to submit to *Management Science*) proposes a novel machine learning algorithm to automatically extract best practices from the trace data and infer simple tips that can help workers learn to make better decisions. We use an approach based on imitation learning and interpretable reinforcement learning and consider simple if-then-else rules that modify workers' strategy in a way that most improve their performance, capture useful insights that are challenging for workers to learn by themselves, and are simple enough for workers to understand. To validate our approach and test the performance of our algorithm, we design a virtual kitchen-management game and conduct large-scale pre-registered behavioral studies on Amazon Mechanical Turk.

Our experiments show that rules inferred from our algorithm are effective and significantly outperform rules from other sources at improving performance and speeding up learning among workers. In particular, we help workers identify optimal early actions that help them improve in the long term, un-learn existing strategies to better adapt to disruptions to their work environment, and discover additional optimal strategies beyond what is stated by our algorithm. *Ongoing and future directions* include testing our framework with real data, extending to a team setting, and optimizing the delivery of advice to enhance compliance and reduce algorithm aversion among human workers.

(iv) Behaviors of the Demand Side *(Analytical Modeling/Experiments)*

While most of my recent works have focused on the behaviors of the supply side, I believe there are several exciting research directions regarding consumer behavior in the on-demand economy. In particular, I am interested in how consumers' decisions are influenced by real-time information and dynamic prices offered by competing platforms. On this front, I have another stream of research focusing on incorporating behavioral insights into pricing where classical dynamic pricing models do not account for behavioral factors. In ***"Markdown Pricing with Quality Perception"*** (with R. Hariss, G. Perakis, and Y. Zheng, 2$^{\text{nd}}$ round Major Revision at *M&SOM*), we study how price information affects consumers' perception of product quality and purchase decision and how a retailer should incorporate such behavior into optimizing their pricing strategies. Our randomized controlled experiments reveal consumers' reaction to price markdowns and inventory information and help calibrate our analytical model of their purchase decisions. We offer insights on when the firm should offer a price markdown when consumers associate the firm's pricing decisions with quality. This work provides a first step towards a deeper understanding of complex consumers' perception of service quality in the gig economy where platforms employ even more dynamic pricing strategies and consumers can easily compare across options in real time.

Future Research

I have been actively working on expanding my research in behavioral operations management to several other directions. Below is a brief description of my other research highlights and future research agenda:

<u>Scheduling workers with different skill levels:</u> I am interested in studying the adoption of a flexible

workforce in new sectors. In health care where cost and quality pose serious concerns, an on-demand system could shorten wait times for patients and reduce labor costs. In ***"Scheduling Customers and Resources in the On-Demand Economy"*** (with G. Allon and C. Terwiesch, work in progress), we examine the behaviors of health care providers on an on-demand telehealth platform and how the platform can optimize staffing practitioners of different skill levels. Unlike ride-hailing, medical practices are highly skilled and require traits that are difficult to train. The pool of providers is therefore much smaller and consists of roles with overlapping capabilities (e.g., physicians and nurse practitioners). This work also compares an on-demand system with a scheduling approach via patients' preference functions. We hope to offer an optimal hybrid system design that accounts for both patients' and flexible providers' behaviors.

Impact of flexible staffing: In ***"Signaling Quality and Speed Through Staffing Decisions"*** (with S. Netessine, work in progress), we study the impact of flexible staffing on a physical retail store's success in converting traffic into paying customers. We find the retail industry interesting as it has long seen the employment of temporary/seasonal workers and the staffing level can affect consumers' perceptions of the store's quality and speed of service. Our preliminary results show the positive impact of staff availability on consumers' decision to visit the store and make a purchase, and that sales associates with experiences working for multiple locations through flexible staffing are more effective at driving sales.

Gig workers' behavior change: Inspired by my interactions with gig workers in the field and recent regulations, I am passionate about designing interventions to encourage healthier work behaviors among gig workers. For example, ride-hailing drivers have been reported to work dangerously long hours, causing concerns for the health and safety of the drivers and the public. In 2017, New York City passed the *Fatigued Driving Prevention* rules to limit the number of hours drivers can work consecutively, but drivers could get around working on multiple platforms. The COVID-19 pandemic further raises concerns about their well-being. On this front, I hope to design and test different interventions to induce a positive behavior change in a controlled experimental setting and eventually in the field.

Designing new experimental paradigm: As noted earlier, there are several empirical challenges to study gig workers' behaviors due to limited observability. With experience running experiments and designing a game, I aspire to develop a new experimental paradigm to study gig workers' behaviors in a controlled setting. The study of the multihoming behavior and policy analysis could benefit from this design as researchers can control the market conditions, test interventions, and observe a series of workers' choices.

Behavioral urban planning: I believe that the better we understand human behavior the better we can design the world for the people. Through my Wharton Social Impact Fellowship, I use high-resolution urban data to investigate the relationship between neighborhood safety and aspects of the community and built environment in Philadelphia. My working paper, ***"Community Vibrancy and its Relationship with Crime in Philadelphia"*** (with S. Jensen, under review at *PLOS One*), proposes a novel metric of community vibrancy by leveraging data on permits to host local block parties and studies the impact of such vibrancy on the crime rate. Inspired by my experience transforming a vacant lot in Kensington, a Philadelphia neighborhood suffering from drug and homelessness issues, I am also investigating the impact of vacant lot greening on the surrounding community. In Fall 2019, I was invited to present my work at the City of Philadelphia's Office of Innovation and Technology and discuss with government officials and city planning professionals for potential future collaborations. Finally, growing up and experiencing first-hand social problems in Thailand, I am determined to expand my research to solve issues plaguing developing countries and incorporate insights from operations management to make a positive social impact.