THREE ESSAYS ON EMPLOYMENT RELATIONS IN THE RIDESHARE INDUSTRY

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This dissertation examines how the relationship between rideshare drivers and platforms (Uber, Lyft, etc.) is shaped by conflict, such as wage reductions, passenger arguments, or deactivations. Drawing on survey data from more than 488 rideshare drivers and 75 interviews, this dissertation suggests that the relationship between workers in the gig economy and their platforms has manifest impact on their work behaviors. Drivers who reported higher levels of conflict were less likely to spend time on platforms, often recruit passengers (and other drivers) to their preferred services, and "drop" platforms that are unable (or unwilling) to resolve their workplace disputes. This research demonstrates that, while gig work lacks the directive control found in a traditional workplace, the management of conflict and workplace disputes plays a central role in cultivating dense platform network effects. This result blends the theoretical work of platform economics with the organizational dispute resolution literature. In doing so, these findings extend the exit-voice-loyalty framework into the digital 1099 economy and suggests that the interplay between workers and organizations is a central strategic concern for platform managers and developers.

BIOGRAPHICAL SKETCH

Michael Maffie was born on February 14, 1985 in Dayton, Ohio to parents Kirk and MaryJo. After graduating from college, he coached Cornell's policy debate team for two years before attending the ILR School's Masters of Industrial and Labor Relations (MILR) program. After completing the MILR degree, he began the M.S./Ph.D. program in dispute resolution and collective bargaining. Starting Fall 2018, he will be an assistant professor at Pennsylvania State University.

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CHAPTER 1

INTRODUCTION

Over the last decade, the rise of platform production has been one of the most profound shifts in the global distribution of goods and services (David S. Evans & Schamlensee, 2016). Today, the largest news distributor in the world (Facebook) writes no articles. The largest transportation company (Uber) owns no cars. The largest photo publisher (Instagram) takes no pictures. These digital intermediaries, also known as platforms, have inverted the way many people think about value creation because they focus on distributing existing goods more efficiently, not producing durable products (Armstrong, 2006; David S. Evans, 2003; David S. Evans & Schamlensee, 2016; Hagiu & Wright, 2015). In fact their explicit goal is to *not* own the products they distribute because platforms thrive in areas where there is already an abundance of goods waiting to be utilized in a more efficient "network" (B. Stone, 2017). The canonical example is the automobile: for 97% of its life, an automobile will sit parked in a garage on a street. Using a platform, however, it may be possible to decrease an automobile's idle time and effectively de-link the concept of ownership from use (Gansky, 2012).

Early platforms focused on the distribution of products, like books (SharingTree) or unused seats in a car (Zimcar). Yet in the last ten years, new platforms have taken the logic of platform production – that there is an abundance but misuse of existing resources – and applied it to labor markets (Srnicek, 2016; Sundararajan, 2016). Platforms like Upwork, Uber, and TaskRabbit ease the distribution of labor by allowing people to take on work from other members of the platform. Workers are not "employed" by the platform; they are hired by another platform user (Prassl & Risak, 2016). Additionally, platforms allow people to set their own hours, work for a platform's competitors, and "quit" and return to an organization with no consequence. Surveys have found that millions of people have worked on a online platform to earn additional income (Farrell & Greig, 2016a, 2016b), with some predicting that as high as 50% of the United States workforce will have worked on an online platform by 2020. With the global trend toward on-call or temp contracts, platforms can help workers trade excess leisure for additional income.

For conflict scholars, platforms may alleviate many of the traditional flashpoints that underlie workplace conflict: most platforms do not require mandatory hours, workers do not have a supervisor or co-workers, and they are not subject to traditional directive control (Cannon & Summers, 2014). In fact, working outside of directive control is marketed as one of the main selling points of these forms of work. Despite this new economic arrangement, there is significant evidence of workplace conflict on these apps, including worker protests in cities all over the world (Arbruzzese, 2016; Fiegerman, 2016; Lazzaro, 2016; Mirsch, 2014), a near 100% annual turnover rate, the formation of unions or associations in Seattle, San Francisco and New York, and hundreds of drivers have become part of an employment misclassification lawsuit against Uber and Lyft (Mishel, 2015; Scholtz, 2016; Wang, 2016). What are the underlying causes of conflict on gig platforms? Why are platforms unable to resolve these disputes? And how does conflict influence organizations when workers can join, leave, and return at their leisure?

This is an important time to investigate the labor relations process on gig platforms. Over the last ten years, these organizations have grown rapidly, with some projecting that in the next 25 years, 50% of all net income from the S&P 500 will come from platforms (Moazed & Johnson, 2016). Some of the worlds most recognizable companies, like Amazon, Uber, and eBay, are platforms, while others, like Apple, have incorporated the logic of platforms into their products. In the labor space, platforms de-link the concept of income from employment, and in doing so both offer a different combination of risk and autonomy to their workforce. These economic models have supplanted decades-old incumbent organizations in a matter of years, but there is also significant concern about balancing this new labor-management relationship. When work rules are hundreds of lines of code, how can organizations incorporate employee voice? And even though workers are now able to work outside of directive control, why is such widespread conflict in the gig economy?

[Figure 1 Here]

Figure 1 illustrates cross-platform competition in the gig labor space. Both labor (left side) and consumers/buyers (right-side) choose which platform to use, and then the platform creates a match between the parties (see the top platform). Yet is the platform responsible for policing the conduct of passengers or labor on their platform? Additionally, should companies be able to use their matching algorithms in a way that furthers their sole organizational interests, like Uber's "Hell" program that allocated additional labor to Uber drivers who also used Lyft? This dissertation argues that platform conflict is rooted in both work rules (pay, matching criteria, discipline, etc.) and cross-market conflicts with "buyers" on a platform (e.g., interactions with customers). Much like conflict on social media platforms, this shows that both user interaction and the structure of the organization itself can generate conflict. Yet the unique structure of these markets allows workers to respond to unresolved workplace conflict both individually and collectively, on the labor side and consumer side of platforms. Individually, labor can withhold their working time in micro-strikes by staging their sign on and avoiding platforms that have poor labor practices. On the consumer side, workers can withhold their purchases from platforms that they perceive do not support them (boycotts). Collectively, workers are using Social Networking Sites to connect with other drivers and organize their labor actions. Together, these responses demonstrate how the economic and institutional composition of platforms influences the location and dynamics of platform conflict.

These responses, however, may be the harbinger of mass labor strife. It has not escaped the attention of scholars that other platforms like Google, Facebook, and Twitter are all monopolies and adopt aggressive, perhaps unethical, behaviors in order to rapidly scale their products. Much like these social media platforms, Uber has engaged in illegal behavior and adopted a 'grow at all costs' ('toe stepping' was their motto) mentality so they can capture the global transportation market. If workers, as this dissertation argues, achieve bargaining power by being able to withhold their labor from one platform (e.g., Uber) while simultaneously working for a competitor (e.g., Lyft), a market convergence means that current labor conflict is likely to accelerate. In the arc of platform development, this suggests that institutional protections for labor will be essential if labor is to retain its bargaining strength in the future since market-based solutions are likely to be absent. By tying together conflict triggers, behavioral responses, and bargaining power on platforms, this dissertation helps inform scholars and policymakers about the dynamics of these exchanges and how institutional interventions can change the relationship between labor and management.

Existing Conflict Research

For decades, scholars have documented that conflict is a central aspect in the employment relationship (Batt, Colvin, & Keefe, 2002; Colvin, 2003, 2004; Cutcher-Gershenfeld, 1991; T. A. Kochan, Katz, & McKersie, 1993; D. B. Lipsky, Seeber, & Fincher, 2003). From strikes (Godard, 1992) to litigation (Clermont & Schwab, 2004, 2009; M. Schneider, 2001), alternative dispute resolution (Bendersky, 2003, 2007; Farber & Katz, 1979; D. Lipsky & Avgar, 2004) to negotiation (Brett et al., 2007), scholars have examined the pathways and structures that guide and shape workplace disputes (Batt et al., 2002; Olson-Buchanan, 1996; Olson-Buchanan & Boswell, 2008). While conflict at work has been studied in several contexts, from the securities industry (D. Lipsky, Lamare, & Maffie, 2014) to automotive manufacturing (H. C. Katz, Kochan, & Weber, 1985), the employment characteristics of these firms have largely remained constant: employees work for one employer, are under a duty of loyalty, and the employer is in the business of providing a service or creating a product. Accordingly, conflict resolution is largely, although not entirely, a study of how labor and management resolve their different desires, needs, and ideas when each faces transactions costs to break the relationship.

These assumptions form the basis of the exit-voice-loyalty framework. This framework is the dominant paradigm for conflict researchers and is frequently utilized in both industrial relations and organizational behavior (Lewin, 2001). Exit-voice-loyalty, first developed by Albert Hisrchman (1979), argues that employees face a finite set of options in the face of workplace disputes: exit (leaving a firm), voice (taking their concerns to management), or loyalty (stay with a firm and attempt to improve the workplace). Future research would add a neglect option, essentially arguing that employees can slowdown their work or engage in small acts of retribution toward their employer. Relying upon this framework, scholars have examined conflict in the nonunion workplace (Colvin, 2003), individual psychological pathways employees navigate to understand conflict (Olson-Buchanan & Boswell, 2002), collective industrial acts (Godard, 1992), and others (Behrens, 2007; Brett & Goldberg, 1983; Budd, 2004; Peter Cappelli & Chauvin, 1991; Colvin, 2004). Yet what happens when that central theoretical assumption – that employees or employers face transaction costs in substituting their economic partner – disappears?

This dissertation examines conflict triggers and behavioral responses in the gig economy. Specifically, this dissertation focuses on the most developed gig industry, both in terms of finances and labor force, the rideshare industry. Drawing on 75 semi-structured interviews with rideshare drivers from across the United States and a longitudinal survey of 489 Uber and Lyft drivers, this study develops a grounded understanding of conflict in the rideshare space. Using this grounded definition of conflict, this dissertation blends the exit-voice-loyalty framework with the underlying economics of platforms to examine how conflict operates in these organizations. Each chapter examines a different behavioral response to conflict and ties this behavior to the underlying economic principles of platform production. In doing so, these chapters link together unresolved conflict with both existing behavioral responses, like exit (dropping platforms), but also new responses that are derived from platforms' economic and institutional structures: drivers withholding their labor from platforms for short periods of time, engaging in temporary consumer boycotts, and using online social networks to organize collective industrial actions. These new links provide a basis for understanding platform production beyond a profit-maximizing framework and creates space for high-road employer practices, where the relationship between workers and platforms is valued and perhaps even cultivated as a competitive advantage.

Chapter Two: Labor-Side Response – Mirco-Strikes

The first study in this dissertation examines how workers can use their ease of entry and exist on platforms to exercise bargaining power. This study is assembled in three parts. First, it draws on 75 semi-structured interviews with rideshare drivers from across the United States to identify how these workers go about their work, how they identify 'conflict' with passengers and rideshare companies, and what their responses are to those conflicts. These interviews were used to form a conflict scale based on the frequency of conflict events on rideshare platforms. Second, using survey results from 489 rideshare drivers in the United States, this chapter validates the conflict scale and shows that greater conflict is associated with drivers fractionally withholding their labor from platforms for which they have a poor relationship – essentially creating micro-strikes. Finally, the chapter links together the multi-sided markets literature on network effects with the industrial relations literature on conflict resolution to show how a platform labor relationship can be mutually beneficial for platforms and workers.

Platform Conflict

Qualitative interviews reported two distinct categories of platform conflict: (1) conflict *across markets* and (2) conflict with platforms. Much like conflict regarding user interaction on social media platforms (Piskorski, 2014), such as Twitter bots harassing journalists or foreign nations using Facebook to spread fake news, interactions *across* platforms – between users – is a site of conflict on rideshare platforms. In interviews, drivers indicated that passengers would behave in various ways that they considered conflict, such as puking in vehicles, attempting to squeeze too many people into a vehicle (beyond the legal limit), or engaging in verbally abusive behavior. Similar to social media platforms, these conflicts place platforms in the middle of the dispute – these organizations facilitated the connection and now are the only (current) entity that can remedy a transgression by one actor. Early in its development, Uber provided technical support in the form of customer support centers located in the United States, but as the platform grew these centers were outsourced to the Philippians. Subcontractors ran these customer support centers in a Taylorist fashion where customer service agents were required to close a set number of tickets per hour, supervisors were rewarded if their "team" of CSR agents hit a certain number of closed tickets, and each team competed against each other for bonuses with their rankings prominently displayed on a large television screen. Popular press reports claimed high turnover, low morale, and low response quality. Several customers and drivers have posted online non-responsive or tone-deaf emails they received from Uber's CSR agents.

Conflict across markets is largely about mediating the interactions between the two agents within a network. Since the central models of industrial relations focuses on the interplay between labor and management (T. A. Kochan et al., 1993), these types of conflicts are not prominently discussed within the existing literature. Gig work, however, has both expanded the boundaries of the firm and made those boundaries porous; workers are now part of the network but not part of the firm. As platforms break the links between their organization and the people who perform work on their platforms, they are refraining from intervening in these types of conflicts; in their parlance, they are 'just helping two parties engage in an exchange' (J. D. Hall, Hoton, & Knoepfle, 2017). Yet the decision to *not* intervene in cross-market disputes is a choice in itself, and this study suggests it has a direct impact on the way workers relate to rideshare platforms.

These types of conflicts operate below the legal threshold for action, but most platforms have not established internal systems for mediating or resolving them. Absent an adequate dispute resolution vehicle, drivers often find themselves with a nonresponsive CSR service and a larger set of rules that favor customers over drivers. As one driver who was interviewed for this dissertation stated, "Uber is very passenger-centric. The drivers, to them, are just individuals they can find more of…My analogy, my reference is, they [Uber] wants to be the Wal-Mart of rideshare."

Within standard employment, conflict between workers and customers could escalate to a manager, designated customer service representative, and/or human resources. Due to the way rideshare platforms structure their relationship with drivers, cross-market conflicts are often unaddressed or resolved against drivers because platforms largely see drivers as interchangeable parts.

The second category of conflict on platforms revolves around the platform's work rules. Platform operators have long posited they are merely facilitating an exchange between two entities, yet platforms also set the rules of entry, exit, standards of behavior, compensation, and communication channels between users. For example, Uber, Lyft, Via, and Juno do not allow drivers to change their compensation, know the number of passengers they are transporting prior to pickup, or a passenger's destination. In doing so, drivers do not actually know the value of a ride when they hit "accept", but are required to accept a certain percentage of rides (unstated) in order to remain connected to the service. Drivers also do not know when they will receive compensation reductions, if their vehicles will quality for luxury status in the coming months or years, and what 'star rating' they will need to maintain in order to stay connected to their platform. Work rules in the industrial shop are easy to identify – pay, vacation days, holiday pay, progressive discipline, etc., yet the rules of the platform are more difficult to name because they operate within the code of the application. For example, the allocation of work in the industrial shop would operate around explicit norms or rules established within a collective bargaining agreement, yet digital dispatch services use hundreds of lines of code to determine which driver is offered a job. The opacity of the work rules allows platforms to write those rules in a way that favors their own interests over labor, as evidenced by Uber's "Hell" program that was used to identify drivers who also worked for Lyft. Using these data, Uber would allocate a constant stream of work to drivers who worked for both platforms in an attempt to prevent drivers from ever turning on the Lyft application.

While the "Hell" program demonstrated how opaque and unknown work rules could be manipulated to benefit the platform over its workforce, the lack of voice regarding workers' terms and conditions of employment is the second category of platform conflict. Much like research on traditional employment, workers' inability to voice their concerns regarding the essential rules governing the workplace, such as entry conditions (e.g., licensing, insurance requirements), compensation (and wage reductions), reimbursements (for tolls, cleanups, etc.), and performance evaluations (acceptance rates and passenger evaluations) creates conflict between workers and platforms.

Behavioral Responses

How does labor respond to conflict on platforms? Interviews with workers indicated that drivers choose between their available platforms based on their relationship with each platform. For example, drivers who referenced particularly negative interactions with Uber (e.g., being unable to dispute a passenger's report that the driver used 'coarse language') also indicated they would spend less time on Uber and would work more hours on other platforms, usually Lyft. In economic arrangements with seamless entry and exit, workers were acting upon their relative relationship across platforms to determine not only *if* they work, but also *how to allocate* their labor between competing applications. Additionally, drivers realize they have direct access to customers on each application for which they work, allowing them to "poach" customers from other platforms. One driver who had a negative relationship with Uber stated, "I'll encourage Uber passengers to download the app [Lyft]. I'll convert Uber passengers." Drivers also suggested they would try to convert their fellow drivers to their most preferred service.

While some have argued that a work relationship is absent from platform work (Jenk, 2016), this evidence suggests that drivers do not merely have transient and transactional relationships with platforms. The first chapter finds that drivers still desire to have a voice in shaping their workplace policies and have access to a dispute resolution process. Additionally, when drivers are shut out of this process, it appears that they engage in a variety of responses in an attempt to reshape these markets toward the service for which they have the strongest relationship. The first study combines these behaviors with the economic logic that holds these markets together to link together platform conflict with key platform performance indicators – network density (David S Evans & Schmalensee, 2017). Since platforms facilitate transactions between users, the more users a platform has, the better that network can meet the needs of its users (Huotari, Järvi, Kortelainen, & Huhtamäki, 2017). This is the basic theory of network effects, in essence: participation is production. By fractionally withholding their labor (temporary exit) and steering drivers and other passengers away from platforms (encouraging others to exit), drivers are tactically bargaining for better working conditions in the gig economy by undermining platform's network density.

Chapter Three: Consumer-Side Response – Boycotts

In the exit-voice-loyalty theory, organizational loyalty is typically defined as an individual's "special attachment" to an organization (Hirschman, 1979) and helps answer the question, why do some employees stay with an organization in the face of conflict while others leave? In effect, some employees identify with an organization and attempt to remedy the problems they encounter at work. Hirschman, however, extends the concept of loyalty into consumer behavior and uses loyalty to explain why organizations can retain high-value customers even in the presence of a newer, higher quality alternative. The boycott, Hirschman argues, is a way for a loyalist to influence an organization from the outside by withholding their purchases and temporarily buying from a competitor. One peculiar aspect of platforms is how quickly people can move back-and-forth across the platform; the Uber driver now may become the passenger in a few minutes. If workers' have an attachment to an organization, do they attempt to act upon that loyalty when they switch sides of the market and become a consumer? In effect, does the relationship between workers and platforms influence network effects on both sides of the market?

This chapter examines how workers act upon their organizational relationship when they switch sides of the market and become consumers. The informal nature of platform work allows workers to begin working for a platform in a matter of hours, allowing gig workers to sign up for multiple new jobs within a day; for Uber drivers, it takes less than a business day to sign up to work on the platform, while taking a job on Upwork requires less than an hour. Due to this, rideshare's informality and rapid growth also means that many people have experienced these platforms from both a consumer’s and a worker’s perspective. Additionally, rideshare companies are rapidly replacing both private and public transit, meaning that workers are faced with the choice of which platform to use for their transit needs. Do workers who have negative experiences as a worker on a gig platform change their behavior on the consumer side of the market? If so, this would link together working experiences with a key concern for gig platforms – customer acquisition and retention.

Utilizing the survey data collected from 489 rideshare drivers, this study examines how the relationship between workers and their platforms influences which platform workers use when they are purchasing a ride as a consumer. The rideshare market is an ideal space to test this behavior because rideshare platforms offer virtually identical products; in fact, most drivers use multiple (competing) rideshare services. This has the practical effect that consumers can order the same product (even the same car) from two different services. The results of this chapter find that workers who have a more positive relationship with a platform are likely to open that rideshare platform first when looking to order a ride. Previous research in the consumer behavior and multi-sided platform literature find that consumer purchases are serially correlated (David S. Evans & Schamlensee, 2016), resulting in platforms competing over which app is the first a consumer opens. This finding indicates that peoples’ experiences as drivers carryover to the other side of the market when they are acting as consumers. With rapid turnover in the rideshare market (~100% every year), this suggests that between 2-5% of the consumer market has previous experience as a worker on these platforms. This finding combines the literatures on industrial relations, multi-sided markets, and consumer behavior to extend Hirschman's concept of loyalty into the digital exchange space.

Chapter Three: Platform Organizing in the Gig Economy

The third chapter in this dissertation explores how the rise of Social Networking Sites (SNS) is providing a new means of organizing collective worker actions in the gig economy. Technologically, SNS and rideshare platforms are similar: they both rely on network effects and reducing the search and transaction costs associated with interactions. For social media and SNS, these networks emerged out of the same advances in telecommunication and algorithms that fuel the gig economy. Existing research in the field of information science has shown that the rise of SNS, text messages, and new forms of communication have not just networked people together in new ways, it is also changing how people act in the "real world" (Bryson, Gomez, & Willman, 2010; Gil de Zúñiga, Jung, & Valenzuela, 2012; Panagiotopoulos & Barnett, 2015). Several social movements, including the Syrian rebellion, Arab Spring, Occupy Wall-Street, and the West Virginia wildcat teacher's strike, were all coordinated using social media and SNS (O'Donovan, 2018). These networks share the same technological heart as gig platforms -- could they also create the foundation of a digital labor movement?

Rideshare companies classify their drivers as independent contractors in order to avoid paying benefits or overtime, but a byproduct of this strategy is that workers must seek out information about their work from other sources. Although the rideshare industry is less than ten years old, there is already evidence that drivers are seeking out SNS and driver forums for advice with their work (Rosenblat & Stark, 2016). Recent evidence demonstrates that workers have built robust online networks on Facebook, with some driver forums reaching as many as 50,000 users. Other institutional actors, like former rideshare driver Harry Campbell, provide information about the industry in the form of podcasts or informational blogging. Out of this gap, workers have built these online networks, and used them to coordinate multiple strikes in New York, San Francisco, Europe, and India (Goswami, 2017; Lazzaro, 2016; Yeung, 2016). Are these one-off events, or are social networking sites forging collective action in the gig economy?

Qualitative interviews with rideshare drivers indicated four distinct methods by which drivers engage with other drivers: texting, social networking sites, reading websites, and meeting up in person. The survey for this dissertation asked drivers about frequency of their interaction across these four measures and created a validated scale from the results. Using this scale, the third chapter looks at how social interaction (and social media specifically) influences drivers' views on collective organizations. Using linear regression models, this paper tests if more frequent interaction with other drivers over social media increases two measures of workers' views toward collective organizations: union instrumentality and interest in joining a rideshare drivers' association. This chapter finds that workers who more frequently interact with other rideshare drivers on social media platforms have more positive views of union instrumentality and are also more interested in joining a rideshare drivers' association.

This study links together the information science literature on SNS with the industrial relations literature on union organizing and collective voice. The results indicate that, although gig work may be structured in an individual fashion, workers begin to warm to the idea of collective action as they interact with other drivers. Other scholars have found a similar phenomenon when examining Amazon Mechnical Turk (mTurk) workers, suggesting that greater online interaction with other workers may be one way to build solidarity and spread information about the difficultly in handling problems in an individual manner. As one driver interviewed for this project said:

> *"I always felt in my previous employment positions, I always had recourse. I had HR that I could go to. I'm gay, for instance, and the last company I worked for, there was a bit of a problem with things that were being said and all that. I finally just got pissed and filed a complaint, right?… I felt that I had recourse… Uber, there's no recourse. If you have a problem, you don't have anyone to talk to. You don't have anyone to go to."*

Online networks, however, may provide an avenue for workers to communicate and coordinate their actions to influence management. Already, Uber drivers in New York City have used their Facebook group to discover a $70 million miscalculation in their wages. The results of this chapter provide evidence that SNS could create the foundation of future union organizing campaigns, and even in temporary or transient 'gig' work, workers are looking for collective ways to solve their problems at work.

Figure 1:

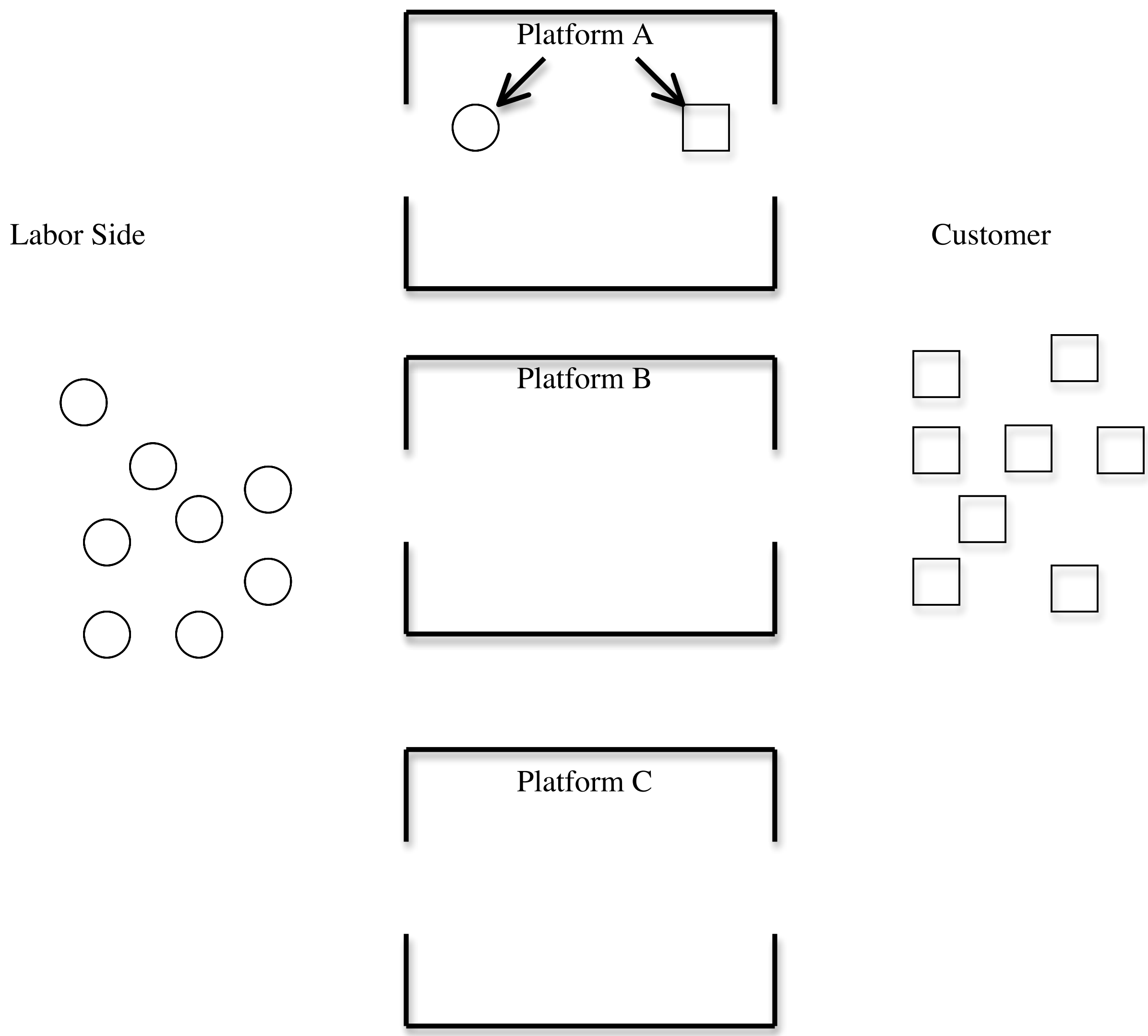

Figure 1: Multi-platform competition in a single space. Three platforms, (A, B, C) compete for the same two sides of the market. These markets are closed (they do not cross-list jobs or opportunities). Each platform must induce both sides to enter the market by setting a price structure that will encourage them to enter the platform space. Platform A has matched two actors in its market space.

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CHAPTER 2: I GOT 1099 PROBLEMS BUT FINDING A CAB AIN'T ONE: CONFLICT AND BEHAVIORAL RESPONSES IN THE RIDESHARE INDUSTRY

Introduction

Following the departure of former CEO Travis Kalanick, Uber Technologies set out to repair its "broken relationship" with drivers (Shahani, 2017). Globally, Uber was facing significant discontent in its workforce: in the United States, workers went on a national "weekend of disruption" and were organizing unions in Seattle, New York City, and Los Angeles (Fiegerman, 2016), in India, hundreds of drivers refused to use the application for three weeks, creating significant delays during rush hour (Goswami, 2017), and across Europe, drivers joined "WhatsApp" groups to coordinate strike activity (Foster, 2017). Uber's attempts at quelling these disputes had largely failed, summed up by one driver in an online question-and-answer session with then-President Jeff Jones:

> "You said you have been talking to drivers over the last five months. You are listening to us. Then you do this hour of Q and A. It looks like the same stuff. We care but nothing announced. I was expecting more. I might go to Lyft."(Parsons, 2017)

During this time, Uber, despite its three-year head start in the rideshare market, faltered from 91% of the United States market share in November 2016 to 74% in summer 2017 (Molla, 2017). This is a remarkable fall for one of the world's largest privately-held companies and one that left experts puzzled: why was Uber's market position not more fortified? Two decades of research had argued that a first mover advantage and significant market share is associated with relatively stable platform growth (David S. Evans, 2003). Yet for Uber, the opposite was happening: Despite more people using smartphone-based transportation apps (A. Smith, 2016), conflict was up and market share was down.

Uber's rise is emblematic of not only the changing nature of national transportation systems, but also presents a sudden shift in the trajectory of working hours in the industrialized world. Since the 1980s, industrial relations scholars have documented the fall of predictable work schedules and the rise of temporary, on-call, or zero-hour contracts across the United States and Europe (Kalleberg, 2000, 2008; K. V. W. Stone, 2004). For manual laborers and some knowledge workers, the industrialized world was returning to the time before the standard forty-hour workweek (L. Katz & Krueger, 2016). Yet around 2010, on-demand labor platforms inverted this equation: workers could now choose their own working hours and assignments (Botsman & Rogers, 2010). Several "cloud" platforms, such as Amazon Mechanical Turk, Upwork, and Fivrr began offering task-work to virtually anyone with an Internet connection. Platforms substituted managers for algorithms as a means of regulating production while outsourcing worker evaluations to other platform participants (Rosenblat & Stark, 2016). While Fivrr, Amazon, and Upwork are the largest online task marketplaces, the spread of smartphones and global positioning systems has fueled the rise of over 13,000 online labor platforms (Future, 2017).

In contrast to traditional production, such as manufacturing or automotive plants, platforms rely on the theory of "network effects" and seek to facilitate transactions between actors who otherwise would have a difficult time entering into an exchange (David S. Evans & Schamlensee, 2016). For Uber, the platform coordinates the closest driver and passenger based on the requirements of the rider. Under this arrangement, a worker must both provide the labor (driving time) and capital (vehicles) to complete an exchange. Shopping malls, credit cards, and online dating services utilize this economic arrangement (Rysman, 2009), but until the rise of a $70 billion transportation company –

Uber – these organizations had only occupied a peripheral space in labor markets. Compared to traditional production, platforms offer an unusual economic bargain for workers: provide both the capital and labor to complete a job and workers can work the hours they desire. Yet why is there so much conflict in an industry where firms have relinquished directive control? Additionally, how does conflict operate when workers trade the stability of traditional workplace protections for greater flexibility and more market risk? Platforms' market and institutional differences provide an opportunity for researchers to re-examine how conflict operates at work and how it might influence larger organizational outcomes.

In traditional production, industrial relations scholars have documented that conflict between management and labor is associated with a number of negative outcomes, including lower productivity and a greater number of product defects (Cutcher-Gershenfeld, 1991; H. C. Katz et al., 1985). In order to understand how conflict operates on labor platforms, I engaged in a yearlong qualitative project interviewing 55 Uber and Lyft drivers. To these workers, unresolved conflict did not result in exit, but instead they would download additional applications and spend more time on these platforms. Drawing on new time-journal and recruitment data from 410 rideshare drivers in the United States, this paper empirically tests those qualitative findings. This paper finds that workers' relationship with platforms is a significant predictor of drivers' time on platforms, allocation of work *across* platforms, and recruitment behavior.

This paper makes two contributions to our knowledge of labor in the digital economy. First, this paper expands the exit-voice-loyalty-neglect framework to reflect the new economic realities of platform labor exchanges. Instead of a binary choice between exit and voice/loyalty/neglect, platform work appears to be a continuum where workers must choose not only *if* they should work but also *their allocation* of labor across several similar options. Conflict, and platforms' current inability to effectively resolve it, appears to guide how drivers allocate their time across platforms. Second, while the current literature assumes workers are passive price takers, this paper provides evidence that workers are more active in steering these markets to reflect their preferences than what is found in the current literature (Rochet & Triole, 2003). In doing so, this paper provides evidence that the relationship between workers and their organizations extends into the digital economy.

Literature Review

A. Multi-Sided Platforms

The study of multi-sided platforms is a rapidly growing area of academic inquiry (Hagiu & Wright, 2015). Unlike the traditional production process, multi-sided platforms are intermediaries that create value by internalizing transaction costs for agents seeking an economic exchange (David S. Evans & Schamlensee, 2016). Rochet and Triole (2003) provide three theoretical conditions for a multi-sided market: (1) there are two (or more) distinct groups of customers (2) members of one group benefit from having his/her demand coordinated with one or more members of another group (3) an intermediary can facilitate that coordination more efficiently than bilateral searching between members of the groups. Airbnb is an example. In this platform, renters and people looking for temporary housing occupy two sides of a market. Seeking out either customers or renters is costly for a single member of the market, yet an intermediary can internalize the search costs for both.

Three aspects of these markets are relevant to this paper: (1) pricing, (2) network effects, and (3) multi-homing. First, theoretical research indicates that prices on one side of the market can be set at or below zero (David S. Evans & Schamlensee, 2016). Shopping malls are an example of zero-cost markets: consumers are free to enter a market while stores are charged to rent space within a mall (David S. Evans, 2003). Credit cards are an example of negative prices. Consumers are frequently given cash-back offers for the use of a card, making the cost of using that card effectively negative (Rysman, 2009). Existing multi-sided market research finds that pricing is not a simple calculation and platforms frequently set prices on one (or both) sides of their market at a socially inefficient point (Boudreau & Hagiu, 2009). One example of this is when a platform seeks to maximize its own gains over growing the size of the market (David S. Evans & Schamlensee, 2016) or improperly estimating the effect of positive or negative network effects when setting their price structure.

Second, much like externalities, agents on either side of the market can exhibit positive or negative network effects (David S. Evans & Schmalensee, 2012). *Positive network effects* occur when an activity on one side of the market indirectly enhances the value of the entire platform to all members on the other side of the market. OpenTable, a multi-sided platform that links together people looking for dinner reservations with restaurants, nearly failed because it could not generate the necessary positive network effects. At first, OpenTable was unable to enlist a sufficient number (the “critical mass”) of restaurants for their service. While nominally these restaurants are competitors, without a diversity of dining options, consumers stopped using the service because it did not sufficiently decrease their search costs (David S. Evans & Schamlensee, 2016). By adding additional restaurants, however, the platform was able to not only increase their profits via online bookings, but also increased the value of the platform itself. *Negative network effects*, in contrast, decrease the value of a network to the other side of the market. For example, newspapers are a two-sided platform that link together advertisers and readers. Yet if a newspaper increases its advertisement to content ratio, some readers will stop reading, decreasing the value of the platform to advertising companies (Rysman, 2009). Balancing these competing effects is an empirically tricky task and researchers are still searching for the best method of estimating the interaction of negative and positive network effects (Rysman, 2009).

Third, some agents can exist in multiple markets simultaneously. This practice is known as "multi-homing" (Armstrong, 2006; Rochet & Triole, 2006). In the example of shopping malls, consumers can travel to different malls while stores rent property in multiple places. Both of these behaviors would constitute "multi-homing". In some markets, it is more difficult for one side of the market to multi-home (e.g., smartphone application developers can build apps for multiple platforms more easily than smartphone owners can switch operating systems), while in other markets, multi-homing is common on both sides (e.g., the newspaper and advertising industry) (David S. Evans & Schamlensee, 2016). Theoretical research suggests that multi-homing is a negative network effect that undermines the value of each additional unit to the other side of the market, but researchers have yet to precisely measure this effect (Armstrong, 2006). For many platforms, developing policies that steer users away from multi-homing is a critical element of their strategy (Rochet & Triole, 2003; Rysman, 2009).

In markets with both multi- and single-homing agents, users who single-home will receive a subsidy from those who multi-home (Armstrong, 2006). This is logical, as single-homing agents do not split their value between competing platforms. The rideshare market is a good example of a market with both single- and multi-homing. Riders can evaluate the prices on Uber and Lyft before booking a ride with either service. Since drivers are (almost uniformly) classified as independent contractors, they are free to work for multiple competing organizations. At the same time, there are some drivers and passengers who only use one platform. This is a market that features both single- and multi-homing.

Existing research has examined the behavior of multi-sided platforms in the areas of Internet commerce, computer operating systems, credit cards, newspapers, shopping malls, and social networking websites (Cusumano & Gawer, 2002; David S. Evans & Schamlensee, 2016). Additional theoretical research has explored how platforms set prices, compete in markets with single- and multi-homing, engage in monopolistic behavior, and shift subsidies from one side of the market to the other (David S. Evans & Schmalensee, 2012; Rochet & Triole, 2003, 2006; Seamans & Zhu, 2014; Weyl, 2010). While multi-sided markets offer several new research questions, academics have yet to examine how conflict may damage the relationship between workers and platforms.

B. Studies of Conflict Resolution

Both industrial relations and organizational psychology inform our thinking about conflict at work. While these two schools part ways in their views on institutions and power in resolving workplace disputes (Lewin, 2001), they generally agree that some types of conflict harm organizational performance (de Wit, Greer, & Jehn, 2012; Thomas A Kochan, Katz, & McKersie, 1994). While organizational psychology focuses on estimating the effect of task, relationship, and process conflicts on workgroups and organizational performance (Jehn, Rispens, & Thatcher, 2010), industrial relations scholars have examined the effects of organization-level conflicts, such as strikes, litigation, and contract arbitration (D. Lipsky & Avgar, 2004). The units of analysis follow each field's view on resolving disputes: industrial relations scholars focus on institutional interventions to ameliorate power differentials between employees and organizations while organizational behavior focuses on how training and progressive management strategies can mitigate or prevent workplace disputes.

Even though these schools differ on the roots of conflict and resolution methods, they both draw upon the exit-voice-loyalty-neglect framework to predict employee behavior in the event of workplace disputes (Bendersky, 2003; Colvin, 2013). This framework argues that, in the face of unresolved workplace conflict, employees must decide to either leave an organization (exit) or attempt to resolve their dispute from within (voice-loyalty) (Olson-Buchanan, 1996). Organizational psychology studies have shown that individual characteristics influence how people react to conflict, such as highly educated employees being less likely to engage in organizational dispute resolution systems (Eigen, 2008b), while older employees are more likely to utilize these procedures (Klaas, 1989; Lewin & Peterson, 1999). At the same time, industrial relations scholars have documented that workplace structures can help surface conflict and remove conflict triggers (Rees, 1991). Colvin (2013) compared these two approaches and found that high performance work systems had both fewer reported conflicts and appeals to advanced steps in the dispute resolution system. This study linked the two by showing that organizational dispute resolution systems that offer non-managerial decision-makers, such as an outside arbitrator, appear to improve employees' willingness to seek internal options to resolve their disputes.

Both perspectives of workplace conflict are relevant to the rideshare industry. In one sense, rideshare drivers act as independent organizations, making decisions about resource allocation, interactions with customers, building business relationships with bars, restaurants, and hotels, and how much, if at all, they work. This independence removes many of the traditional conflict triggers from the workplace, such as mandatory working hours or disputes with supervisors. Due to this, some individual factors appear important in deciphering the relationship between platform workers and workplace disputes. At the same time, however, platforms exert significant control over drivers by setting prices, determining platform rules, dictating acceptable driver behavior, and disciplining or discharging drivers for violating their policies. When platforms allege that drivers violate these rules or change drivers' compensation, drivers indicated that they felt there was no one to go to in the event of a dispute. This type of conflict appears more institutional and is more closely aligned with an industrial relations perspective on conflict.

[Model 1 Here]

Given the ambiguous nature of conflict in the rideshare space, I engaged in a qualitative research project from summer 2016 to summer 2017 to explore how conflict manifests in the rideshare industry. This project involved interviewing 55 rideshare drivers from markets across the United States and was the basis for model 1. There was considerable variance in what drivers considered "conflict" because workers enter the rideshare industry for different purposes; some use it to a new means of bridging unemployment, others are using it to re-enter the workforce after retirement, and others still have turned to this industry for full-time employment. Three larger categories of conflict, disputes over compensation, discipline, and negative interactions with passengers, emerged as the core conceptual areas of conflict in this industry.

Existing studies of workplace conflict suggest that conflict at work degrades workers' quality of their working life. My qualitative interview data was consistent with this finding; these data suggested that workers who experienced a higher incidence of conflict held negative views of their rideshare organizations because these services had poor institutional structures to manage or mitigate workplace disputes. Most rideshare companies only provide a customer service email address with no explicit workplace policies or standards of review. Instead, customer service agents were frequently accused of not reading emails, responding with templates, or providing unhelpful answers. Many experienced drivers recounted that they had stopped contacting customer service because it was of so little help.[1] These data suggest the following relationship between organizational identification and conflict:

H1: Higher levels of conflict will result in lower organizational identification.

If conflict degrades the relationship between drivers and platforms, what is the impact of having a "broken relationship" with platform workers? Drivers who reported low organizational identification indicated they do not "quit" a rideshare platform because there is no benefit to completely leaving a platform. Instead, these drivers would shift their time toward other platforms that they viewed as more driver-friendly. For example, drivers who held a neutral or positive view of Uber said they would log into that platform before other rideshare apps. Yet for drivers who reported a fractured relationship with the company, these drivers were more likely to also drive for Uber's main competitor, Lyft, and spend additional time on that platform.

[1] One driver indicated that the "useless" nature of one company's CSR had led him to purchase and carry a firearm while driving.

Unlike traditional behavioral responses to conflict, my qualitative study suggested that workers in multi-sided markets are not bound by the discrete choice presented by the exit-voice-loyalty framework but instead allocate their labor in accordance with their relative platform preferences. In short, the decision to "exit" does not translate well into this type of work; instead, drivers must decide both *if* to work and *how much* of their labor to allocate to any given platform. This suggests the following hypotheses regarding platform time allocation:

H2: Relationship between platform and driver will predict the total amount of time a driver spends on a platform.

H3: Drivers will spend a greater percentage of their working time on platforms for which they report a stronger relationship.

While driving is the primary working behavior rideshare drivers engage in, they also have the capacity to engage in additional positive platform behaviors, such as passing out passenger referral coupons. Rideshare companies encourage drivers to recruit passengers to their services because it helps grow their market. To facilitate this, platforms provide drivers with referral codes. For each passenger who uses a driver's referral code, the driver is compensated a small sum of money, usually $10-15. Yet drivers reported that they would not refer passengers to all services equally, instead "steering" passengers (and other potential drivers) to use the service that the driver believed supported them best. These claims form the follow hypotheses:

H4: Relationship between platform and driver will predict the likelihood a driver will recruit a passenger to that service.

H5: Relationship between platform and driver will predict the likelihood a driver will recruit a driver to that service.

Methods

A. Instrument: Mobile Questionnaires

This study utilized push questionnaires administrated via a Qualtrics server. Given that every rideshare driver must have a smartphone to work, using online questionnaires does not risk systematically excluding part of the population of interest. Smartphone-delivered questionnaires have been used to research many difficult to reach populations, such as HIV patients (Kirk et al., 2013) and illicit drug users (Freedman, Lester, McNamara, Milby, & Schumacher, 2006). Comparisons between telephone and smartphone administered questionnaires have found smartphone data collection provides virtually identical information to traditional phone administered studies (Johansen & Wedderkopp, 2010).

Mobile data collection is beneficial because it can reduce subjects' recall bias and allows researches to time surveys in a way that minimizes time-based variance across repeated observations (Shiffman, Stone, & Hufford, 2008). These methods also allow researchers to reduce "autobiographical" memory corrections (Bradburn, Rips, & Shevell, 1987) that may change as people make sense of important events – such as conflict (Olson-Buchanan & Boswell, 2008). By offering repeated measurements at different times, mobile surveys are able to "smooth" over variation that may be due to mood or other random events (Shiffman et al., 2008). This also allows researchers to draw on data from multiple points in time, helping address concerns about reverse causality.

Mobile "push" questionnaires also allow researchers to remind participants of incomplete questionnaires, contributing to the high completion rate found in these studies, usually over 85% (Collins, Morsheimer, Shiffman, Paty, & Papandonatos, 1998;

A. A. Stone, Shiffman, Schwartz, Broderick, & Hufford, 2002). Broadly, this research design has been used in a variety of research projects for decades (Shiffman et al., 2008).

B. Participant Recruitment

Rideshare drivers were recruited for this study in three ways. The first set of study participants (N=226) were recruited with the aid of a worker organization in a large northeastern metropolitan area. The worker organization sent out both text messages and emails to its members notifying them of the study. Workers were informed that this study would be about labor conditions in the rideshare industry. At the end of the three-week signup period, 226 drivers had registered to participate.

A second recruitment channel utilized the "popular worker gathering spot" research strategy (Eigen, 2008a; Lind, Greenberg, Scott, & Welchans, 2000; Rosenblat & Stark, 2016). In the world of digital work, this means using online gathering spots to identify and recruit participants. Since Uber (and other gig companies) do not provide onboarding or much other information about how to use the service, drivers frequently turn to online resources in order to troubleshoot problems they experience while working.

Harry Campbell, a former rideshare drive, has one of the most popular online websites for rideshare drivers. Campbell's website is routinely cited by major news outlets, such as the New York Times, Washington Post, and Time Magazine. Campbell posted a call for participants on his website in summer 2017 and sent an email to his mailing list notifying drivers about the study. This recruitment method yielded 234 participants.

Finally, I engaged in targeted Facebook recruitment (Kapp & Oliver, 2013) in an attempt to recruit drivers who had only recently started driving rideshare. Previous research has studied targeted Facebook recruitment and found that it can be appropriate for statistical inference (Fenner Y et al., 2012; Ramo & Prochaksa, 2012). Three closed Facebook groups were identified because they require drivers to send moderators proof of their driver status in order to join the group. Two of the three groups "pinned" the request at the top of their page for 7 days. This recruitment method yielded 26 participants.

Sample Demographics and Comparisons to Existing Research

Three previous studies have attempted to clarify the on-demand rideshare population. Uber Technologies hired Benenson Strategy Group (BSG) to conduct demographic research on their drivers. By virtue of working with Uber, BSG was able to randomly draw a subset of drivers from Uber's 20 largest markets. This work has three important limitations: first, it only surveyed Uber drivers and misses on-demand workers who, either intentionally or incidentally, drive for other platforms. Second, given Uber's poor reputation with its workforce, the survey's low response rate (10%) could indicate a systematic skew in the data. Third, this paper was limited to Uber's 20 largest markets, thereby missing drivers in smaller towns who may systematically differ from those in larger markets.

Second, Harry Campbell conducted an online demographic survey from late 2016 to early 2017. While his site is visited several thousand times a day, this method is likely to miss new rideshare drivers or those who drop out of the labor force in their first few weeks. Campbell's data does have the advantage, however, of being the most recent demographic data that is not confined to a single platform. Finally, Kooti et al. scanned 5 million Yahoo! users' inboxes for Uber activation emails, receipts, and payment information, yielding 220,000 driver accounts. This information was paired with demographic information stored in users' account. Since Yahoo! does not contain user race information, researchers had to backwards derive these characteristics based on the areas where users were driving. This method has the benefit of randomly drawing users from a 300 million-user database, but is limited to Uber users who use Yahoo! as their platform email account. If there were a demographic or platform split regarding email preference, this would skew these data.

[Table 1 Here]

Table 1 compares the demographic characteristics for participants in this study to the demographic findings from these three previous studies. Remarkably, these samples are roughly similar across demographic variables, with the proportion of non-Hispanic Caucasian drivers and those over the age of 65 being the only areas of significant deviation. Since the BGS study was taken in 2014, Uber and Lyft have moved into several new markets, resulting in hundreds of thousands of new drivers working for these services. Given the new geographic areas in which these platforms are operating, it is not clear how these new markets have shaped the overall demographic population of rideshare drivers. Yet the consistency across studies and the demographic makeup of this study suggest the models in this paper are reasonably representative of the rideshare industry.

c. Data and Key Variables of Interest

After completing the informed consent form, participants were sent a link to the first study document. This form contained a set of questions about demographics, time on platform, conflict, and organizational relationship measures. The looping nature of the online questionnaire allowed it to dynamically expand to repeat the same relationship questions for each platform for which a driver worked. Merging the three recruitment methods, 490 participants started the first questionnaire, with 488 providing useable data. A follow-up questionnaire was sent thirty days after the completion of the first questionnaire. This follow-up questionnaire asked drivers about their time on each platform and other work obligations for the past week. A total of 359 drivers completed the follow-up questionnaire (73% retention rate). A second follow-up was sent sixty days after the initial questionnaire. Table 2 breaks down the overall retention rates for time period 2 and 3 by recruitment method.

[Table 2 about here]

This paper proceeds in two phases: First, does greater conflict damage the relationship between drivers and their platforms? Second, if this is the case, what is the impact of having a "broken relationship" with a rideshare company? Drawing on qualitative research, I predict that conflict is associated with lower levels of organizational loyalty because rideshare companies do not provide adequate institutional structures to resolve workplace conflicts. The only vehicle for dispute resolution, customer services lines, are not nearly as sophisticated as traditional human resource departments nor do platforms provide dispute resolution training for CSR agents. Additionally, since drivers are considered independent contractors, many times drivers are told that they must resolve these problems themselves because their rideshare company is merely an intermediary that helps drivers find work. If conflict degrades organizational loyalty because drivers do not feel there are available avenues to resolve their disputes, then reporting a higher level of conflict should be associated with lower levels of organizational loyalty. The first set of models investigates this relationship. The initial questionnaire provided conflict data and organizational loyalty measures for Uber (N=411) and Lyft (N=351).

The second set of models turns to the relationship of low organizational loyalty and rideshare drivers' working behaviors. My qualitative research suggests that, since platforms are largely substitutes in all measures except customer concentration, relationship influences how drivers allocate their labor in these markets. Using data from the initial questionnaire, it is possible to test if drivers report fewer hours on platforms for which she/he reports lower organizational loyalty. This paper uses two measures of time: 1) the total hours a driver spends on Uber and on Lyft and 2) the fraction of time a driver spends on Uber vs. Lyft (e.g., Uber Time / total Uber+Lyft time). The first model estimates the relationship between organizational loyalty and the total amount of time a driver spends on a platform while second tests how drivers split their time when they have the option to work for a competitor. Since drivers must have accounts with both services, these models can only use data for drivers who use both Uber and Lyft (N=291).

The final set of models focus on the relationship between organizational loyalty and recruitment. Participants in my interviews saw customer concentration as the main limitation on their ability to freely choose a platform. In an attempt to reshape these markets, drivers indicated they recruited passengers and other drivers to their preferred service with the hopes that eventually they could drop their least-preferred service. In short, drivers want the market to converge on their preferred platform and encourage other agents in the market to use that service. To test this relationship, the third set of models looks to see if organizational loyalty predicts drivers' reported likelihood to recruit passengers and drivers to Uber over Lyft.

Platform Selection

This study uses Uber and Lyft as the companies of interest for two reasons: First, they are the largest services in terms of drivers and customers. This allows the models to draw upon the largest amount of data when comparing drivers' behaviors across platform. Second, These two companies offer nearly identical rates in all of the markets where they compete head-to-head. A comparison of their rates in fifty large cities across the United States reveals only small economic differences in compensation per mile or per minute. Even where there were differences, they were no more than a $0.05 in either category. This is consistent with qualitative interviews that indicated that Uber and Lyft move their prices in lockstep. This similarity in compensation means the models do not need to account for price per mile or per minute as a relevant factor in drivers' working calculation.

[Table 3 Here]

Key Independent Variables.

This study uses two key independent variables: 1) the frequency of conflict experienced during work and 2) an individual's relationship to a platform. Since the rideshare industry is a new industrial arrangement, scholars lack established measures for both conflict and organizational loyalty for this type of work. To bridge this gap, this paper relies upon both new scales and previously established measures to estimate these concepts.

Conflict Scale. Conflict has long been thought of as an integral part of a worker's relationship to an organization (Lewin, 2001). Yet conflict in the 'gig' economy is a poorly defined construct. In qualitative interviews, drivers identified two categories of conflict: passenger behavior and compensation reductions. These two categories of conflict are areas where the platform establishes and adjudicates work rules associated with passenger-behavior disputes and sets driver compensation. Theoretically, the first area, passenger disputes, is where a platform acts to police the boundaries of its marketplace by determining who was at fault in a cross-market dispute (passengers and drivers). Since passengers can more easily leave platforms than drivers (Kooti et al., 2017), platforms are not neutral actors when adjudicating these disputes. Due to this, platforms have an economic incentive to resolve disputes in favor of customers over drivers. When drivers' and passengers' interests diverge, qualitative research suggests that platforms would side with the passenger. Due to this economic incentive to resolve disputes in favor of passengers, as passenger-driver conflict becomes more frequent, I hypothesize that drivers' will be less loyal to platforms. The full set of questions, means, and standard deviations can be found in the appendix.

Drivers identified four passenger behaviors as 'conflict'. First, drivers identified passenger confrontations as a rare, but important part of their work. Since the most lucrative working times usually occur during times when passengers are intoxicated, drivers may have to engage with aggressive or unruly passengers during these hours. Additionally passengers "squeezing" too many people into a car, a passenger damaging the driver's vehicle (requiring a cleanup fee), and route disputes (usually resulting in drivers losing income) were also reported as conflict. These three categories are areas where the platform protects the passenger's interest over the driver: when passengers "squeeze" too many people into a vehicle, it voids the driver's insurance. Yet if the driver cancels the ride, s/he is not compensated for her/his time driving to the pickup location. Alternatively, drivers reported that platforms would typically resolve route disputes in favor of the passenger.

The other central area of conflict revolves around compensation. This area has two components: wage reductions and incorrect ride compensation. Rideshare platforms set drivers' compensation while using the app (a combination of a base face, per minute pay, and per mile pay). Platforms followed the advice of the platform economics literature and engaged in “penetration pricing”, a practice where platforms aggressively subsidize their platform to gain users and then rapidly cut drivers’ compensation after reaching a “critical mass”. For example, in 2015, Uber drivers in Las Vegas were paid $1.85 per mile and $0.30 per minute. In December of 2016, those numbers has fallen to $0.90 per mile and $0.15 per minute. Rate reductions were often unannounced; drivers would discover the rate changes when they logged into the app after the wage cuts. These reductions were national in scale, such as the January 2015 rate cuts for drivers in over 100 US markets. Finally, drivers reported that they had received incorrect compensation for completing a ride, leaving some feeling like they had been “cheated” by an organization.[2]

Participants were asked to evaluate the frequency of the five events (argument, cleanup fee, routing dispute, squeezing, incorrect compensation). For wage reductions, drivers were asked to quantify the impact, if any, rate reductions had on their income from rideshare (0%, 1-10%, 11-20%, 21-30%, 31-40%, 41-50%, 50+%) These six measures were summed into a scale that returned a 0.78 Cronbach’s alpha.

Organizational Relationship/Loyalty. In industrial relations, the ability to resolve conflict, either formally or informally, is often used as a barometer to measure the overall relationship between employees and employers (Cutcher-Gershenfeld, 1991; H. C. Katz et al., 1985). In this sense, the relationship is a revealed characteristic about the workplace; higher levels of conflict reveal problems in the underlying relationship between management and labor. Yet workers in the rideshare market have the autonomy

[2] One driver emailed researchers after the completion of this project with the following message: “My response is "I hate Uber! They have stolen my income numerous times, and lied like snakes to screw their drivers. That's the end of my commentary.”

to work for several different platforms at once. As demonstrated in my qualitative research, drivers have different relationships with all of the companies for which they work, making a baseline conflict measure an inappropriate choice to estimate the relationship between workers and all their platforms.

Due to this market difference, this study gathered additional data to measure the relationship between drivers and each of her/his rideshare platforms. Individual-level scales suggest organizational identification falls into three general factors, loyalty, obedience, and participation (Dyne, Graham, & Dienesch, 1994). While many of the questions from the obedience scale do not fit the digital workplace because they assume directive control ("I always come to work on time"), or are not applicable to single-person operations, ("I make suggestions to my co-workers"), the loyalty scale includes several useful behaviors for platform workers, like if a worker "represents the organization favorably to outsiders" or defending the organization from criticism. Since reputation is an important aspect of platform competition, platforms would see these as valuable and important actions. Workers were asked to fill out six measures of the "loyalty" scale found in Dyne et al. for each platform for which they drive (the full list of questions can be found in the appendix). For both Uber and Lyft, this scale returned a Cronbach's alpha of 0.78.

Difference in Loyalty Scales. For comparing drivers' preferences for Uber relative to Lyft, a measure was constructed to difference the two scores. Since this was calculated as Uber Loyalty – Lyft Loyalty, a positive coefficient would suggest that a driver prefers Uber relative to Lyft. The mean of this measure (-0.62) suggests that drivers have a relative preference for Lyft over Uber.

Platform Recommendation: When applying these scales to the gig economy, however, loyalty scales crafted with single-employers in mind may include unwanted noise. For example, defending Uber against outside criticism, such as allegations of workplace harassment and illegal compensation prices, may be materially different from the criticisms leveled at Lyft. Additionally, the question about investing in these companies is merely theoretical at this point because they are privately held firms.

Due to these limitations, another more direct measure may prove useful for estimating the relationship between drivers and platforms. In the first questionnaire, drivers were asked, “If a friend was looking to start driving as a rideshare driver, I would recommend s/he use the following services”. Drivers were given the option to rate all of the services for which they had a drivers’ account with. The scale ranged from from 5 (“Highly Recommend”) to 1 (“Strongly Would Not Recommend”). By differencing these two measures, it is possible to get a relative preference for one service over the other. The variable ranged from -4 (would strongly recommend Lyft over Uber) to +4 (would strongly prefer Uber over Lyft). The mean of this measure, -0.64, suggests that the average driver holds a slight preference for Lyft over Uber. This is consistent with the other measures used for this study.

[Tables 4 and 5 Here]

Key Dependent Variables:

Time on platform. Drivers were asked to report all the time they were online over the past seven days even if they were not transporting a passenger. While participants are normally poor estimators of their working time, each service sends workers a time-log of their activity over the previous seven days. Workers are also able to look up their activity, including online time and time with a passenger in the vehicle in their app. While the majority of drivers who completed the introductory survey worked for Uber (N=390), Lyft (N=340), or both (N=287), two drivers reported they drove for other rideshare companies. Combined, Uber and Lyft represent 486 of the 488 drivers who completed the first wave of the study. Despite the loyalty measures suggesting that drivers prefer Lyft to Uber, in each time period drivers reported spending roughly 40% more time on Uber than Lyft.

Drivers who do not log hours on the same platforms consistently across each data collection wave complicated the "total time on platform" variable. For example, some drivers worked for either Uber or Lyft in time period 1 but did not drive for both companies in either time period 2 (or 3, or both). I coded these drivers two different ways. First, models were run using only time reported, so if a driver worked on either Uber or Lyft in time 1 but not in time 2, the follow-up time period was coded as "NA". Alternatively, drivers who reported having a drivers' account in time 1 but not working for a platform in subsequent data collection waves were coded as "0" hours on that platform. Both methods of coding returned similar results, but the coefficients and standard deviations were larger under the "zero hours" coding scheme. Since this research paper asks how loyalty affects drivers' allocation of labor, if drivers who have a weaker relationship with a rideshare platform are more likely to exit the industry, this is an important aspect to how drivers allocate their labor on platforms and how platforms grow their networks. Due to this, the tables and models in this paper reflect the "zero hours" coding scheme.

Fraction of Time on Uber vs. Lyft. Total time may be a noisy way of thinking about the relationship between platform relationships and work. For example, drivers are unlikely to think they must spend additional time on an application because of their feelings of loyalty toward a platform. Instead, it is most likely that drivers will express their relative platform preference by choosing one platform over another *when they do choose to work.* Qualitative interviews suggested that drivers act upon this preference in two ways. First, drivers are able to choose which platform they log into first. Once logged into a platform, drivers are likely to "ride" this platform so long as it provides them work. Once work slows, however, they can turn to a second platform. Second, drivers are able to choose which application to stay on throughout the day. This is to say that, during slow times, drivers are able to choose which combination of apps to keep open while waiting for work.

This variable calculates how drivers divide their time across Uber and Lyft. For each driver who reported driving for Uber and Lyft in time period 1 (N=287), his or her total time on Uber was divided by his or her total time on Uber and Lyft. As this variable approaches 1, it suggests that a driver is spending most of her/his time working on Uber relative to Lyft.

Recruitment Difference. Participants were asked how likely they were to recruit passengers and drivers ("I encourage [passengers/drivers] to join [Platform Name]") for each platform for which they drive. These constituted two separate questions and were on a five point Likert scale (1= "Strongly Disagree", 5= "Strongly Agree"). Recruitment to Uber over Lyft is measured by the difference of these two questions (Uber – Lyft recruitment variable). A positive number suggests a driver is more likely to recruit to Uber relative to Lyft. The mean reported in table 3 suggests that, on average, drivers are more likely to recruit to Lyft over Uber.

Control Variables

The intake questionnaire provides basic demographic information for all participants in this study. The demographic variables in table 1 were crafted to follow Hall and Krueger (2016). [3] Additionally, participants provided information about their vehicle type, educational level, if they had previous transportation industry experience, how many months they were a rideshare driver, and if they were a full-time or part-time rideshare driver. Table 6 provides a report for these variables.

[Table 6 about Here]

Total Platforms. Drivers who work for 4 or 5 platforms are likely to spend less time on any individual platform. When estimating the amount of time (or fraction of time) a driver spends on a platform, it is important to consider how many platforms a driver works for. In the first study questionnaire, each participant was asked for: 1) the number of platforms that operate in their area (from a checklist, but including write-in options), 2) the number of platforms for which they work (a subset of list 1). Ninety-one (18.6%) drivers reported they only drive for Uber while 7.1% of drivers reported they only drive for Lyft. The majority of drivers used Uber (79.9%) and 65.7% of participants used Lyft. The vast majority of respondents drive for multiple services, with the most common combination being Uber and Lyft (57.7%).

Model Specifications

The structure of these data allow for several different estimation methods. The data on conflict and organizational loyalty both come from time period one. Since the response variable is bound at 1, this test uses Tobit models to account for the censored

[3] Models were run weighting demographic variables for Hall and Kreuger's race and education estimates. This did not change the variables of interest.

nature of these data. The relationship between conflict and organizational loyalty was also tested using OLS model and returned similar coefficients and strength of association between the variables of interest. Models testing the relationship between organizational loyalty and time on platform can utilize the longitudinal nature of these data but must address response correlation across time. Random driver effects allow the models to decompose variance both within and across drivers over time (Hausman, 1978). This has an advantage over fixed effects that would discard information across drivers. Random effects models also include time dummies to absorb any exogenous variability associated with the measurement period. Finally, organizational loyalty and passenger steering rely on time period one data and therefore utilize OLS models. This relationship was also tested using Tobit models but did not find any changes in the variables of interest.

[Table 7 about Here]

[Table 8 – Summary of Time Results – About Here]

[Table 9 about here]

Results

Table 6 provides descriptive statistics for categorical variables while tables 4 and 5 provide means and standard deviations for continuous variables. The first question this paper examines is if higher levels of conflict predict lower organizational loyalty. Since the dependent variable is censored at 1, table 9 reports tobit models testing the relationship between the key independent variable, conflict frequency, and the dependent variable, organizational loyalty. These model suggest that each additional point on the conflict frequency scale is associated with a 0.300 decrease in organizational loyalty for Uber (model 1) or a 0.189 decrease in organizational loyalty for Lyft (model 2). For scale, it would require almost a four point shift in the conflict scale to equal a one standard deviation change in either the Lyft (0.75) or Uber (0.80) loyalty scales. Both of these coefficients are significant at the $p<0.001$ level and provide support for hypothesis 1. Consistent with previous work in the area of conflict resolution, these models suggest that more frequent conflict degrades the relationship between workers and their platforms. This also aligns with the qualitative interviews conducted in preparation of this study that suggested drivers would become frustrated with the lack of workplace support provided in the event of an unruly or abusive passenger.

The next set of models test if greater organizational loyalty predicts a greater amount of time working on a platform. Time data was collected in all three time periods while organizational loyalty was collected in time period one. Table 10 displays the results of OLS models with random driver effects and time dummies. In these models, organizational loyalty acts as the key independent variable while the total number hours a worker drives for either Uber (model 1) or Lyft (model 3) act as the dependent variable. Both the Uber ($p<0.05$) and Lyft ($p<0.01$) loyalty scales are positively associated with total working time. A one unit increase in the Uber loyalty scale is associated with 2.56 more hours working on Uber while a one unit increase in the Lyft loyalty scale is associated with 3.29 more hours on Lyft.

Models 2 and 4 in table 10 report the relationship between the recommendation measure (Uber-Lyft) and drivers' time on platform. These models suggest ($p<0.001$) that a one unit increase in relative preference for Uber over Lyft is associated with working an additional 3.078 hours for Uber or -2.894 hours for Lyft . These results imply that drivers who are more loyal to Uber are likely to spend more time working for Uber than those who feel less loyalty toward the platform. Likewise, greater loyalty toward Lyft is associated with working more hours on Lyft. These results support hypothesis 2.

[Table 10 and 11 about here]

In most rideshare markets, drivers can work for multiple platforms. The second set of time models examines how drivers who use both Uber and Lyft allociate their time across the two platforms. Table 11 reports OLS models with random driver effects and time dummies. The key dependent variable is the fraction of time that drivers spend on Uber relative to their total time on Uber and Lyft (e.g., Uber Hours/ (Uber hours + Lyft hours). The key independent variable, preference for Uber over Lyft, is calculated two ways: 1) The difference in platform scales (Uber loyalty – Lyft loyalty, model 1) and 2) the recommendation difference between Uber and Lyft (model 2). The coding for both independent variables is +4 (most loyal/best recommendation to Uber) to -4 (most loyal/best recommendation to Lyft). With this coding, a positive coefficient suggests that as a driver increases her or his loyalty/recommendation to Uber, she/he will spend a greater fraction of her/his working time on Uber relative to Lyft.

The results in table 11 find that that the difference in loyalty scales has a significant association with the fraction of time a driver works on Uber ($p<0.001$). The coefficient indicates that a one-unit increase in loyalty toward Uber would result in a driver spending roughly 8% more working time on Uber. Roughly a four-point change in a driver's loyalty would move the dependent variable by one standard deviation. The second model in table 11 tests if relative preference for recommending Uber over Lyft predicts how a driver will divide her/his working time. This model returned a similarly strong association ($p<0.001$) and coefficient magnitude (0.068) . These results suggest that, when given a choice, drivers' platform preference predicts where they will allocate their labor in the future. These results provide support for hypothesis 3.

[Table 12]

The final question this paper looks at is if a driver's preference for one platform over another influences her/his recruiting behavior. The models look at two types of recruitment: likelihood of recruiting a passenger to Uber over Lyft (model 1) and recruiting a driver to Uber over Lyft (model 2). The key independent variable is a driver's difference in loyalty scales (Uber – Lyft). With this variable coding, a positive coefficient indicates that a greater sense of loyalty to Uber relative to Lyft is associated with a greater probability of recruiting to Uber over Lyft. The models in table 12 are linear probability models.

For both passengers ($p<0.001$) and drivers ($p<0.001$), a driver's relative loyalty was strongly associated with how likely drivers said they would recruit passengers for a particular service. These models suggest that a 1.5 standard deviation shift in the independent variable (0.98) is associated with roughly a 1 standard deviation shift in independent variables (for drivers, 1.58, for passengers, 1.46).[4] These results provide support for hypotheses 4 and 5. Additionally, these models reported an r^2 above 0.50, suggesting the relationship between drivers and platforms plays a significant role in how drivers steer passengers and drivers. The second key independent variable, the platform recommendation difference, also returned a significant association between relative platform preference and recruitment behavior for Uber and Lyft ($p<0.001$).

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[4] Since Uber has the largest customer pool, it could be that this model is actually picking up how likely people are to recruit to Lyft over Uber, but not vice versa, since there are fewer opportunities to recruit people to Uber. In order to test this, models were run using only the Uber Loyalty scale. This scale found a significant association between Uber loyalty and liklihood of recruiting to Uber over Lyft.

Discussion

There are four main takeaways from this study. First, when platforms regulate the interactions between customers and drivers, it can result in conflict. This is similar to studies of social platforms that have found regulating users' status indicators (Twitter) or sorting algorithms (Facebook) have generated conflict between users and platforms. For rideshare companies, the rules that govern the interactions between labor and customers, and labor's compensation, are essentially the rules of the workplace. In the rideshare space, rules that govern drivers' behavior (e.g., not being allowed to smoke in their vehicles), compensation (setting rates and changing them without warning), and controlling the dispute resolution process are all actions where the platform is not acting as a mere matchmaker but instead exerts power over workers' terms and conditions of work. This finding is both a parallel to previous research in the field of industrial relations and also calls into question the central argument that platforms use to decouple themselves from the employer-employee relationship (J. V. Hall, Kendrick, & Nosko, 2016): by exerting control over work rules, platforms appear to have moved beyond simple market clearing devices. This finding suggests that conflict in the digital space is a result of platforms unilaterally promulgating work rules that govern the exchange between labor and customers.

These results, however, cannot speak to how conflict triggers shift drivers between platforms. Due to concerns about recall, conflict data was collected on the aggregate, so the results cannot distinguish how conflict triggers and responses differ from one platform to another. The qualitative research at the foundation of the study indicated that companies offered a variety of driver support mechanisms: Uber offers e-mail, Lyft offers email and phone support, and other services offer walk-in hours in their local offices. Drivers did make distinctions regarding how useful these services were at resolving their disputes, but no service was considered satisfactory. The consistent negative finding for both Uber and Lyft support these anecdotal accounts that conflict resolution options, in their current form, do not appear to be mitigating the effects of conflict at work.

Second, this paper finds a link between organizational loyalty and key platform performance metrics. While previous work in the area of industrial relations has documented several links between the industrial relationship and bottom line organizational outcomes, such as worker productivity and product defects, the economic logic of platforms vary from these linear business models (Srnicek, 2016). Labor platforms are structured in a way that, in theory, makes their production less reliant on internal labor markets or employee engagement. If this is the case, why does a "broken relationship" matter? This study provides a partial answer. Since platforms create value increasing market participation (and therefore network effects), platforms have an interest in maintaining drivers on their network while also attempting to convert drivers who work on competitors' platforms. This means that rideshare companies want to increase both the overall amount of time a driver spends driving on their platform while attempting to minimize the amount of time a driver spends on a competitor's network. This study finds that relationship is a predictor of both behaviors. Since platforms do not offer benefits that could tie workers to their organization nor the capital to complete an exchange, workers are free to move between competitors. This ease of entry and exit allows drivers to act on their relative platform preference and split their labor across competitors according to that preference. This finding is in contrast to existing literature that only uses prices (David S. Evans & Schamlensee, 2016) and customer density

(Rysman, 2009) to explain how workers choose which platforms for which to work. In essence, there is a high road employment strategy in the gig economy: while customer density is one way to "pull" drivers onto a network, cultivating a sense of loyalty or positive relationship can also "pull" drivers onto their market and prevent defection to a competitor.

This study suggests that, once a platform is able to reach a critical mass of customers, drivers can more freely move between competitors based on their preference for one platform over another. Yet how "close" do platforms need to be in customer density before drivers can begin acting on their preference? The data in this study suggest that the critical mass may not be that large. Using publically available data, it is possible to identify the Uber to Lyft bookings ratio for participants who operated in the large northeastern metropolitan area. These data indicated that Uber books 3 rides for every 1 ride booked on Lyft. Yet even confining the above models to this subgroup of the data, the recommendation and loyalty measures still returned a significant effect on how drivers' split their time across Uber and Lyft. For platforms, participation is production, making time shifting a direct negative organizational outcome.

This finding has significant implications for how the relationship between labor and management can influence platform competition. Existing work has argued that rideshare platforms cannot "lock-in" drivers to a single network because they cannot offer unique services or benefits to drivers(Y. Smith, 2016). Without a lock-in, drivers are free to work for multiple competitors and can prevent the market from converging on a single (profitable) platform. Yet if a positive relationship between workers and a platform is able to "pull" drivers onto a network and prevent their defection, then cultivating a relationship between workers and platforms provides a path to resolve this problem. Future research could test this idea by examining if "pro-driver policies", like Uber's new destination selection feature, had an effect on how drivers allocate their labor across Uber and its competitors.

Third, these findings suggest that the existing exit-voice-loyalty-neglect framework may not capture some of the most important responses to conflict found in the 'gig' economy. This study provides evidence that the decision to work on a platform rests on a continuum, where workers must decide how to *allocate* their labor across multiple competing jobs. This is due to the economic structure of 'gig' markets; workers provide both the capital and labor to complete an assignment, resulting in extreme labor mobility. While traditional notions of "exit" assume that workers face costs in finding new employment or leaving an existing job, 'gig' companies like Uber do not even know how many people will login to work each day. The absence of directive control and extreme labor mobility has created new responses for labor, such as recruiting passengers to a rival service or fractionally withholding their labor from a platform.

Finally, for scholars of dispute resolution, this new form of work poses a challenge: what dispute resolution techniques can effectively remedy these types of workplace disputes? With union campaigns in Seattle, Los Angeles, and New York, it appears that workplace due process and fair treatment carry over from the traditional workplace to platform work. Yet existing attempts at providing voice mechanisms to surface and resolve these disputes, such as the American Arbitration Association's driver de-activation panels in New York City, may be too slow to reinstate drivers before they leave for another platform. The results of this study found conflict has a significant impact on driver's organizational loyalty, but this does not answer the question of how to remedy or resolve these disputes. If platform-ADR is too slow to resolve or change worker behavior, then it is unclear why platforms would extend a meaningful investment into a conflict resolution program. In short, the speed with which labor relations play out in the gig economy creates a series of new challenges for practitioners of workplace dispute resolution.

Limitations

This study has several limitations. Platforms have fluid workforces where people are constantly downloading and moving between applications. Empirical work by the JP Morgan Institute (2016b) suggests that half of all gig workers leave the industry within six months. Due to this instability, even a random sample for a single platform's users might not reflect a current or complete picture of the industry. Instead, in order to draw inferences about cross-platform activity, participants must be recruited from multiple different outlets. This study makes an imperfect attempt to recruit drivers at different points in their driving careers by working with labor organizations and popular online resources in order to recruit participants. Yet even this attempt under sampled several populations. While the models in this paper did not find strong demographic differences in driving behaviors, future research will need to find a way to reach early career drivers.

Second, data from time 3 was collected during the removal of Uber's former CEO, Travis Kallanick, and the beginning of Uber's "180 Days of Change". Due to this, it could be possible that our point estimates understate the effect of poor platform relations since workers' views on their platform could have been improving (or, possibly degrading) during the data collection window. Given that it is easy for platforms to update their terms of service and application features (such as notifying drivers where they are dropping off passengers prior to accepting a ride, a policy that was implemented by Lyft during this project's data collection), comparing a static set of policies is difficult.

The number of platforms measured in this study compounds this problem. Since models using both the initial data and follow-up provided consistent results, this helps make the case that app-policy changes did not have substantial effects on these results.

Third, while drivers do have access to their total working time in-app, it is impossible to know if they checked those hours or if they provided estimates. Future research that includes email or app scraping will provide more accurate point estimates for these models. Yet for the purposes of demonstrating if there is a difference between the time drivers spend on their platforms, all that is necessary is drivers' general sense if they spend more, less, or about the same amount of time on each platform. Furthermore, the consistency of results across time calculations and model specifications lends credibility to these estimates even if they are imperfect. Additionally, since we do not have price data for each of these markets, it could be that time decisions were made based on prices (or surge/prime time waves) within markets. Yet previous research finds that Uber and Lyft maintain similar prices in markets where they both compete. Additionally, drivers indicated that these two services pay within a few pennies of each other.

Finally, the drivers in this study are survivors and cannot represent all drivers from the day they sign up for an application or drivers who sign up but decide not to drive. While we attempted to model the linear effects of driving time in these models, it could be there are unexpected effects in the first few months of driving. Researchers did attempt to recruit drivers by handing out fliers outside of Uber's recruitment offices on Long Island, but none of those drivers signed up to participate in the study.

Conclusion

As more people turn to platforms as a means of supplementing or entirely replacing their traditional income sources, industrial relations researchers will need to examine how the relationship between organization and worker has shifted in this space. In these arrangements, workers are asked to bear greater market risk but also possess greater mobility across similar jobs. Strangely, by surrendering directive control, a question from before the age of the standard employment contract has reemerged: how can employers convince workers to show up to work each day? It is not an exaggeration to say that, in a matter of minutes, a driver can download and signup for a new job. The findings of this study suggests that these new organizations must both balance the technological-innovation side of their business and the employment relations side or work, such as managing and resolving conflict between actors on their platform. The results of this study also suggest that workers are not passive price-takers but work to reshape markets to better fit their preferences. While platform work arrangements will continue to change as countries debate how to incorporate these organizations into their existing industrial relations structures, one matter is becoming clear: even for a digital workforce, the relationship between worker and organization is a central concern.

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Table 1: Demographic Breakdown of Samples				
	2014 BSG Survey	Kooit et al., 2017	Campbell, 2017	Maffie, 2017
Age 18-29	19.10%		6.50%	8.64%
30-39	30.10%		16%	21.81%
40-49	26.30%		23.50%	25.99%
50-64	21.80%		29.70%	39.21%
65+	2.70%		24.30%	1.60%
Female	13.80%	24%	19%	17.70%
Less than HS	3.00%		1.70%	1.85%
High School	9.20%		8.50%	9.88%
Some College / Associate's	40.00%		23.60%	29.01%
College Degree	36.90%		33.80%	40.33%
Postgraduate Degree	10.80%		16.40%	18.93%
White Non-Hispanic	40.30%	60%	78.30%	60.29%
Black Non-Hispanic	19.50%	21%	6.80%	10.70%
Asian Non-Hispanic	16.50%	4.70%	4%	12.55%
Other Non-Hispanic	5.90%		3.50%	5.35%
Hispanic	17.70%	13.70%	7.10%	10.49%
Married	50.40%			60.32%
Has Children at Home	46.40%			40.74%
Currently Attending School	6.70%			
Veteran	7.00%			9.47%
Number of Drivers	601	220,000	1150	488

Note: BSG and Kooti are both Uber-only studies, whereas Campbell and Maffie are cross platform surveys. Additionally, since Campbell's 2017 survey, Lyft had entered over 100 smaller markets in the United States.

Table 2: Retention of Participants Across Time Periods			
	Time 1	**Time 2**	**Time 3**
Labor Organization	227	139	126
Harry Campbell	234	190	185
Facebook	26	19	17

Table 3: Description of Key Variables		
Relationship Measures		
	Mean	S.D.
Uber Scale	2.56	0.81
Lyft Scale	3.14	0.75
Scale Difference, Uber-Lyft	-0.62	0.98
Recommendation Difference, Uber-Lyft	-0.64	1.4

Note: The Uber and Lyft scales are 1 (lowest loyalty) to 5 (highest). The scale difference is the sum of these two scales and ranged from -4 (5 loyalty Lyft, 1 Uber) to +4 (5 loyalty Uber, 1 loyalty Lyft).

Table 4: Working Hours Across Time by Platform		
	Mean	**S.d.**
Uber (Time 1)	24.16	20.97
Uber (Time 2)	18.58	18.86
Uber (Time 3)	18.26	19.23
Lyft (Time 1)	17.39	17.55
Lyft (Time 2)	12.79	15.02
Lyft (Time 3)	11.62	13.9
Recruitment Measures		
	Mean	**S.d.**
Driver Recruitment, Uber-Lyft	-0.7	1.46
Passenger Recruitment, Uber-Lyft	-0.86	1.56

Note: adding Uber time/(Uber time+ Lyft time) will not yield the fractions found in Table x because not all drivers drive for both Uber and Lyft.

Table 5: Fraction of Time on Uber vs. Total Time on Uber and Lyft		
Time Period 1		
	Mean	**S.D.**
Uber Fraction	0.54	0.23
Time Period 2		
Uber Fraction	0.46	0.36
Time Period 3		
Uber Fraction	0.59	0.19

Table 6: Demographic Breakdown By Recruitment Source (Percent)					
	Facebook	**Union Email**	**Harry Campbell**	**Union Text**	**Overall Means**
Has a College Degree	50.0	50.4	65.8	56.9	59.2
Female	46.2	7.7	24.9	6.4	17.6
Race					
Black Non-Hispanic	7.7	12.0	8.5	14.7	10.7
Hispanic	3.8	21.4	3.4	15.6	10.49
Caucasian	88.5	30.8	79.9	43.1	60.29
Asian/API	0	27.4	3.0	20.2	12.55
Native American	0	0	1.3	0	0.0
Not specified	0	8.5	3.8	6.4	5.35
Vehicle					
Small Sedan	15.4	4.3	23.5	12.8	15.9
Medium Sedan	42.3	32.5	37.6	33.0	35.6
Large Sedan	3.8	20.5	6.8	12.8	11.2
4 Wheel Drive SUV	15.4	35.9	15.4	25.7	22.7
Minivan	7.7	4.3	6.0	6.4	5.7
Other	15.4	2.6	10.7	9.2	8.6
Age					
18-24	11.5	11.1	3.4	9.2	6.9
25-29	38.5	35.0	10.3	17.4	19.4
30-39	15.4	21.4	23.1	26.6	23.1
40-49	19.2	23.9	40.6	37.6	34.6
50-64	11.5	6.0	22.2	6.4	14.1
65+	3.8	2.6	0.4	2.8	1.6
Has Children	30.8	52.1	32.5	48.6	
Rideshare Insurance					
Yes	42.3	28.0	42.0	38.8	38.4
No	57.7	72.0	56.6	56.3	59.6
Used to	0	0	3	4.9	1.8
Full Time or Part Time					
Full Time	23.1	63.2	24.4	48.6	38.9
Part Time	50.0	17.1	38.0	22.9	30.3
Transitional Job	11.5	12.0	20.9	16.5	17.4
Other	15.4	7.7	16.7	11.9	13.3
Has Transportation Experience	15.4	46.2	17.5	55.0	32.7
Number of participants (total number)	26	117	234	109	486

Table 7: Platform Breakdown By Company and Number	
Company Name	(% of Respondents)
Uber Only	18.64%
Lyft Only	7.17%
Uber and Lyft Only	37.90%
Uses Uber and Lyft	57.7%

Table 8: Summary of Key Results

	Uber Time in Hours	Fraction of Time on Uber	Lyft Time in Hours
Uber Loyalty Models			
Uber Loyalty Scale	**2.56***	**0.0786*****	---
	(1.100)	(0.022)	---
Number of Observations	N=369	N=336	---
AIC	4738.60	42.8	---
Recommendation Difference Models			
Recommendation Difference	**3.076*****	**0.069*****	**-2.894*****
	(0.787)	(0.009)	(0.609)
Number of Observations	N=369	N=336	N=336
AIC	4734	18.65	5100
Lyft Loyalty Model			
Lyft Loyalty Scale	---	---	**3.29****
	---	---	(1.137)
Number of Observations	---	---	N=336
AIC	---	---	5113.17

*Note: *** = p<0.001, ** = p<0.01, * = p<0.05. "—" Each box represents a different regression equation, e.g., column one shows the time 1 regression equations for Uber Time, Lyft Time, and the fraction of time on Uber relative to total time on Uber and Lyft. Error terms are listed under each coefficient. "---" indicates regressions not run.*

Table 9: Tobit Models Regressing Uber and Lyft Loyalty on Frequency of Conflict		
	Uber Loyalty	**Lyft Loyalty**
Conflict Scale	-0.300***	-0.189***
	(0.043)	(0.044)
College [Yes]	**-0.156***	-0.095
	(0.075)	(0.074)
Female	0.011	**0.382*****
	(0.101)	(0.096)
Caucasian	**-0.290***	0.200
	(0.129)	(0.124)
Asian/API	-0.230	0.217
	(0.160)	(0.170)
Native American	-0.469	**1.352****
	(0.472)	(0.511)
Age	**-0.110****	-0.027
	(0.035)	(0.033)
Transition	-0.148	0.090
	(0.109)	(0.111)
Transportation Experience [Yes]	0.122	0.124
	(0.08)	(0.087)
Platform Count	-0.051	-0.116
	(0.040)	(0.044)
	N=409	N=354
-Log-Likelihood	-494.34	-364.48

*Note: ° = <0.10, * = p<0.05, ** p<0.01, ***p<0.001. The number of observations varies across regressions equations due to a different number of Lyft and Uber drives in the sample. Non-significant controls omitted for clarity. Standard Errors listed below regression coefficients*

Table 10: Linear OLS Models with Random Effects Regressing Time on Platform on Organizational Loyalty Measures

	Uber Time in Hours	Uber Time in Hours	Lyft Time in Hours	Lyft Time in Hours
Uber Loyalty	**2.560***	---	---	---
	(1.105)	---	---	---
Lyft Loyalty	---	---	**3.224***	---
	---	---	(1.130)	---
Recommendation Difference	---	**3.349*****	---	**-2.877*****
	---	(0.640)	---	(0.605)
Medium Sedan	**4.542°**	**4.251°**	3.116	1.097
	(2.586)	(2.491)	(2.427)	(2.274)
Large Sedan	**7.364***	**6.213°**	-0.476	0.162
	(3.317)	(3.205)	(3.374)	(3.301)
Four Wheel Drive	**7.230***	**6.541***	0.143	0.786
	(3.317)	(2.751)	(2.677)	(2.618)
Minivan	-0.196	-0.006	**-8.931***	**-8.576***
	(4.621)	(4.446)	(4.008)	(3.907)
Caucasian	-1.334	-0.967	**5.359°**	**5.133°**
	(3.116)	(3.004)	(3.028)	(2.960)
Asian/API	-0.217	-0.359	**9.608***	**9.602***
	(3.920)	(3.769)	(3.989)	(3.900)
Native American	-2.716	0.829	-5.233	-10.116
	(9.984)	(9.645)	(11.120)	(10.934)
Part Time	**-11.92*****	**-10.859*****	**-8.550*****	**-8.538*****
	(2.247)	(2.174)	(2.133)	(2.130)
Transitional Job	**-8.897****	**-9.033****	-1.126	-1.380
	(2.581)	(2.482)	(2.510)	(2.452)
Reason Driving - Other	**-9.478****	**-9.230****	**-5.151°**	**-4.815°**
	(2.984)	(2.870)	(2.819)	(2.744)
Transportation Experience [Yes]	-2.542	-2.818	**-4.322***	**-4.131***
	(2.003)	(1.933)	(1.918)	(1.872)
Number of Observations	701	701	632	632
Number of Groups	363	363	334	334
AIC	5923.285	5903.522	5106.975	5094.954

*Note: ° = <0.10, * = p<0.05, ** p<0.01, ***p<0.001. The number of observations varies across regressions equations due to participants driving for different platforms. Some non-significant controls and time dummies omitted for clarity. "---" is a placeholders for variables not included in regressions.*

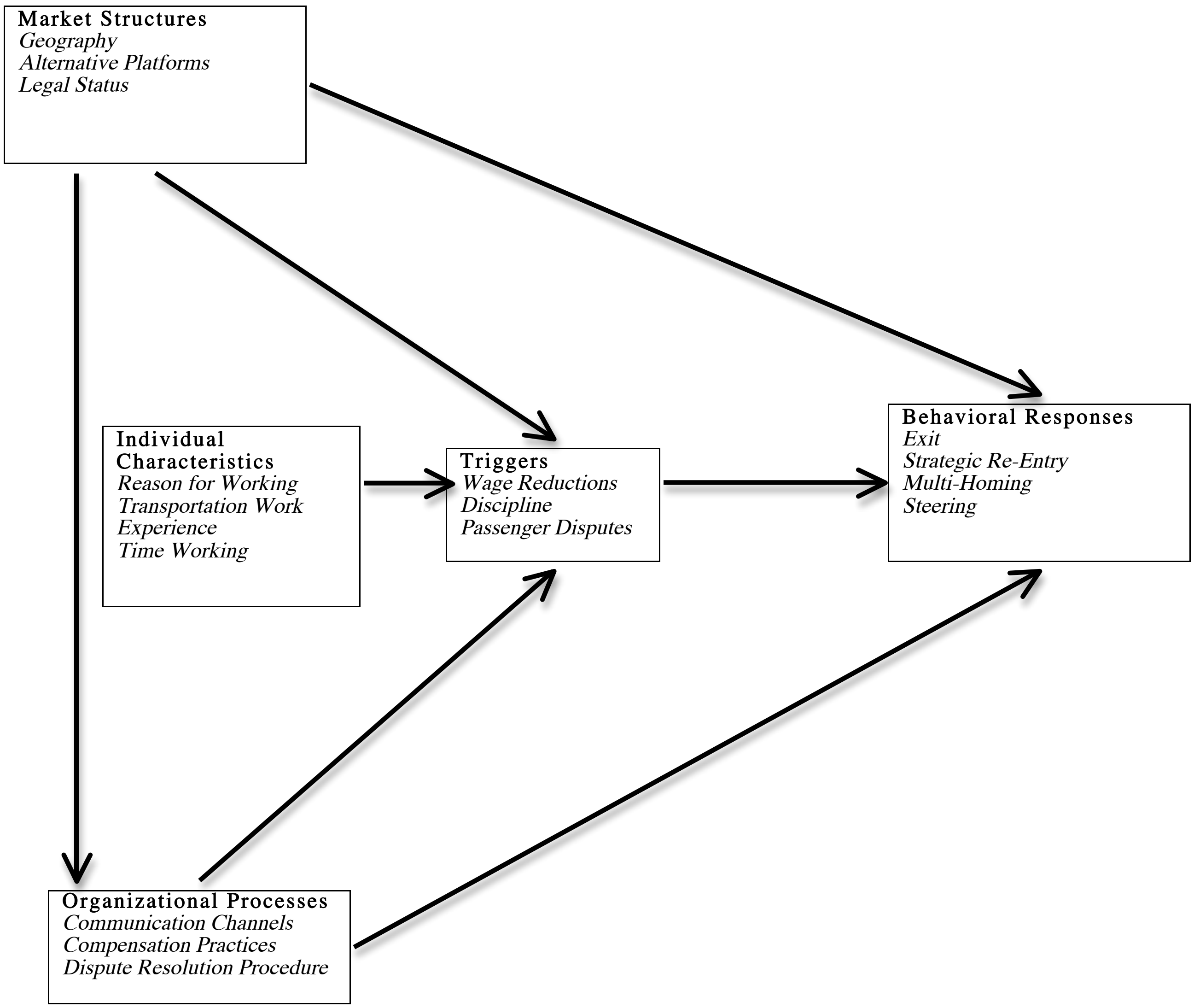
Table 11: Linear OLS Models with Random Effects Regressing Fraction of Time on Uber on Relative Preference for Uber over Lyft		
	Fraction of Time on Uber	Fraction of Time on Uber
Uber Loyalty - Lyft Loyalty	**0.075*** **	---
	(0.013)	---
Recommendation Difference	---	**0.068*** **
	---	(0.009)
Medium Sedan	**0.067°**	**0.067°**
	(0.036)	(0.035)
Large Sedan	**0.097°**	**0.098***
	(0.050)	(0.036)
Four Wheel Drive	0.038	0.036
	(0.040)	(0.038)
Minivan	0.096	0.097
	(0.063)	(0.060)
Vehicle - Other	0.074	0.059
	(0.051)	(0.049)
Hispanic	**-0.154** **	**-0.152** **
	(0.058)	(0.056)
Caucasian	**-0.144** **	**-0.146** **
	(0.047)	(0.045)
Asian/API	**-0.242*** **	**-0.241*** **
	(0.059)	(0.057)
Native American	-0.128	-0.202
	(0.159)	(0.155)
Part Time	0.005	0.0159
	(0.032)	(0.031)
Transitional Job	-0.026	-0.038
	(0.038)	(0.036)
Reason Driving - Other	0.010	0.012
	(0.042)	(0.040)
Number of Observations	503	503
Number of Groups	281	281
AIC	47.959	35.254

*Note: ° = <0.10, * = p<0.05, ** p<0.01, ***p<0.001. Non-significant controls omitted for clarity. "---" act as placeholders for variables not included in regressions. Difference in model sizes within time period are due to incomplete surveys.*

Table 12: Results of Linear OLS Models Regressing Likelihood of Driver and Passenger Recruitment on Platform Relationship				
	Driver Recruitment Difference	**Passenger Recruitment Difference**	**Driver Recruitment Difference**	**Passenger Recruitment Difference**
Uber-Lyft Scale	**1.133*****	**1.086*****	---	---
	0.067	0.065	---	---
Recommendation Difference	---	---	**0.765*****	**0.725*****
	---	---	0.055	0.054
College [Yes]	0.105	-0.106	-0.096	**-0.243***
	0.126	0.121	0.136	0.13
Female	0.134	0.266	-0.005	0.157
	0.171	0.165	0.183	0.175
Hispanic	-0.208	-0.121	-0.321	-0.225
	0.289	0.278	0.306	0.293
Caucasian	-0.125	**-0.386°**	-0.268	**-0.622****
	0.23	0.221	0.249	0.238
Asian/API	0.026	-0.338	-0.191	**-0.564°**
	0.291	0.28	0.316	0.303
Native American	**-1.145°**	1.00	**-1.284°**	0.794
	0.679	0.652	0.752	0.72
Minivan	**0.545°**	0.317	**0.692***	0.44
	0.313	0.301	0.344	0.33
Vehicle - Other	**0.593***	0.241	**0.532°**	0.236
	0.262	0.252	0.288	0.276
Platform Count	**0.152°**	0.105	0.122	0.095
	0.083	0.08	0.088	0.084
Months Driving Rideshare	-0.005	-0.002	0.001	0.002
	0.004	0.004	0.004	0.004
Healthcare [Yes]	-0.013	0.171	-0.007	0.215
	0.164	0.158	0.177	0.17
	N=278	N=272	N=287	N=285
Adjusted r-squared	0.585	0.601	0.488	0.418

*Note: ° = <0.10, * = p<0.05, ** p<0.01, ***p<0.001. The number of observations varies across regressions equations due to participants dropping out of the study. Non-significant controls omitted for clarity. Standard Errors are listed below variable coefficients. . "---" act as placeholders for variables not included in regressions*

Model 1
A Model of Conflict and Behavioral Responses



Model 1: A model of dispute resolution in the rideshare industry. This model is built upon Colvin (2013)'s model of organizational dispute resolution. Since actors in these markets can move between multiple platforms and have varying reasons for engaging in gig work, individual difference and market characteristics were added to this model.

Appendix - Scales

Platform Loyalty Scale

Using the scale below, please indicate the extent to which you agree or disagree with the following statement for $[lm://Field/1]

1. I represent $[lm://Field/1] favorably to outsiders
Uber: Median: 3.0 Mean: 3.23, SD: 1.26
Lyft: Median: 4.0 Mean: 3.91, SD: 1.06

2. I do not go out of my way to defend $[lm://Field/1] from criticism
Uber: Median: 2.0 Mean: 2.23, SD: 1.13
Lyft: Median: 3.0 Mean: 2.87, SD: 1.06

3. I tell others that [lm://Field/1] is a good place to work
Uber: Median: 3.0 Mean: 2.32, SD: 1.16
Lyft: Median: 4.0 Mean: 3.54, SD: 1.07

4. I actively promote $[lm://Field/1]'s service to others
Uber, Median: 3.0 Mean: 2.76, SD: 1.20
Lyft: Median: 4.0 Mean: 3.41, SD: 1.18

5. I would accept a job at a competing rideshare company if they offered me more pay
Uber, Median: 1.0, Mean: 1.58, SD: 0.87
Lyft: Median: 2.0 Mean: 1.87, SD: 0.99

6. I would invest in $[lm://Field/1] if it were a public company
Uber, Median: 3.0, Mean: 2.74, SD: 1.27
Lyft: Median: 3.0, Mean: 3.31, SD: 1.23

Note: lm://Field/1 automatically fills in a rideshare company's name. The questionnaire loops through all the services a driver uses and fills in the name of each service sequentially. Items are coded 5.0 = Strongly Agree, 1.0 = Strongly Disagree. Items 2 and 5 were reverse coded.

Appendix - Scales

Conflict Scale

Using the scale below, please identify the option that best represents your experience with the following statements/events:

1. I interact with an unruly or disruptive passenger [Median: 2.0, Mean: 2.96, SD: 1.48]

2. I file a cleanup fee due to a passenger damaging my vehicle [Median: 1.0, Mean: 2.89, SD: 0.94]

3. Passengers attempt to "squeeze" too many passengers into my vehicle beyond the legal limit [Median: 2.0, Mean: 2.25, SD: 1.41]

4. I receive incorrect compensation from a platform (e.g., you did not receive the full fare for a ride) [Median: 2.0, Mean: 2.89, SD: 1.54]

5. I file a complaint with a rideshare company over passenger behavior [Median: 2.0, Mean: 2.25, SD: 1.22]

Range: “Every time I drive” (6), “Every Week” (5), “Once a Month” (4), “Less than Once a Month” (3), “Almost Never”(2), “Never” (1)

CHAPTER 3: GIVING UBER THE BOOT: HOW CONFLICT AFFECTS NETWORK DENSITY IN PLATFORM PRODUCTION

Introduction

Over the last decade, the emergence of 'platform' work is one of the most significant changes in the industrial economy (Future, 2017; Glöss, McGregor, & Brown, 2016; Kooti et al., 2017; Krueger, 2017; MGI, 2016; Sundararajan, 2016). In only a matter of seconds, people can use their smartphones to accept work as a part-time taxi driver, deliver someone's groceries, walk a dog, or work a shift as a domestic worker. Workers' seamless entry and exit across these jobs is possible because online platforms do not create physical goods but instead manufacture connects between people (Botsman & Rogers, 2010; David S. Evans, 2003; David S. Evans & Schamlensee, 2016; Gansky, 2012). These organizations draw upon advances in information technology, widespread adoption of smartphones with Global Positioning Systems (GPS), and machine learning algorithms to restructure their production process around the concept of *distribution* (O'Reilly, 2017). To avoid a traditional employment relationship, platforms outsource their training, supplies, and worker evaluation to a 'crowd' of users, creating what is sometimes referred to as peer-to-peer production. This firm structure has rapidly expanded, with some of the most valuable companies in the world, such as Uber, Lyft, Handy, Upwork, and others, adopting a peer-production method (Fidler, 2016; Future, 2017). Already, millions of people have engaged in gig work to supplement or entirely replace their "normal" income, and this trend is likely to continue into the future (Bernhart & Thompson, 2017; Li, Hong, & Zhang, 2018).

Despite their popularity, platforms are the site of significant conflict between workers and management (Arbruzzese, 2016; Mishel, 2015; Rosenblat, 2014, 2015, 2018; Scholtz, 2016). Uber drivers have engaged in nation-wide strikes, mass-logoffs, and are organizing informal workers associations in Seattle, New York, and San Francisco. While platforms maintain they are merely 'market clearing mechanisms' where their algorithm adjusts prices and assigns workers jobs based on minimizing labor's downtime (J. D. Hall et al., 2017), the work rules on these platforms have become the site of struggle between workers and platforms. For example, Uber does not provide drivers recourse in the event a passenger assigns them a poor rating, cannot negotiate their fares (and for many years were prohibited from accepting cash tips), are punished for route deviations (even though drivers are told they can use their own judgment), and can be de-activated (fired) from the platform for any reason (Rosenblat, 2015). Much like the conflict around social media platforms regulating users' interactions, disputes between participants (e.g., passengers and drivers) and the structure of network (e.g., prices, surge waves, deactivations, and driver licensing requirements) are largely ignored or poorly handled by online platforms.

Yet how does conflict in this type of work arrangement influence key platforms' outcomes? Traditionally, labor relations scholars conceptualize the behavioral responses to conflict in terms of exit-voice-loyalty (Colvin, 2003, 2013; Hirschman, 1979). This framework links together labor-management relationships and organizational performance (Cutcher-Gershenfeld, 1991; H. C. Katz et al., 1985; T. A. Kochan et al., 1993), through turnover, losing high performing employees, strikes, lockouts, production slowdowns, or grievances, but does not easily translate into platform production. This paper traces the economic logic that holds platforms together and identifies how a platform-labor relationship can influence a key platform performance indicator: network density (Rochet & Triole, 2003, 2006). Specifically, the porous nature of two-sided markets, where labor frequently moves back and forth between producers (e.g., drivers) and buyers (e.g., riders), distinguishes it from a traditional industrial arrangement and opens a new avenue for workers to act upon their unresolved disputes. With frequent movement across the market, this paper finds that workers can whipsaw platforms that have poor labor practices by withholding their purchases from those platforms. Since network density, or the number of participants on either the consumer or producer side of the network is a central performance indicator for this type of production process, selective consumption empowers workers with the ability to punish platforms with poor labor practices and reward those with a positive relationship with its workforce. This finding extends the exit-voice-loyalty framework to capture a key response to unresolved conflict in the 'gig' economy.

The rideshare market is an ideal place to test the relationship between conflict and workers' behavior as consumers because these platforms do not generate unique products. Recent research finds that most rideshare workers use multiple competing platforms (e.g., both Uber and Lyft), allowing people to order a virtually identical product from either service. Additionally, since Uber and Lyft are both debt financed and do not yet need to generate a profit, these platforms engage in a price-matching strategy in virtually all markets. Finally, these two competitors offer the same types of services – standard sedans, SUVs, mini-vans, luxury vehicles, etc. – meaning platforms cannot differentiate by product type. With more than a million drivers working in rideshare, and an average of 100% turnover every year, the number of people who have experience with these platforms as workers is not an insignificant number of market participants.

Drawing on a longitudinal study of 300 rideshare drivers, this study finds that drivers link their workplace experiences to their purchasing behavior. Specifically, drivers who have more negative experiences as a rideshare driver are more likely to say that it influenced their consumption behavior. Second, by looking at drivers' relationships *across* the platforms for which they work, this study finds that drivers reward platforms that they have a better relationship with by opening those applications first. Since open order is a key metric for determining if a user completes a purchase (David S. Evans & Schamlensee, 2016), this links together workplace policies with a key indicator of organizational success in the multi-sided platform literature. In short, drivers are attempting to undermine, or harm, one of their jobs in order to reward another.

As more workers begin supplementing or entirely replacing their existing work with on-demand platform jobs, it is important for industrial relations researchers to investigate how the employment relationship influences workplace outcomes in this production arrangement. The existing multi-sided platform literature largely assumes workers are indifferent across competing platforms and merely respond to changing prices. Yet, this paper finds that users' draw on their experience as workers to whipsaw platforms as consumers, linking together the industrial relations research on conflict management with the platform economics literature on network effects. In doing so, this paper begins to demonstrate how a platform can use a high-road employer strategy to cultivates a sense of loyalty between workers and platforms as a means of maintaining and growing their network.

Literature Review

A) Platform Theory

The study of platforms is the study of intermediaries (Armstrong, 2006; Boudreau & Hagiu, 2009; Rysman, 2009). Theoretically, a platform is a mechanism that eases the connection between people (Gansky, 2012). The connection can take many forms and be unidirectional (one-to-many, e.g., a television broadcast) or multi-directional (many-to-many, e.g., an internet message board) (O'Reilly, 2017). Economically, platforms are the study of how these intermediaries reduce transaction or search costs between two or more actors. While platforms that act as 'matchmakers' have existed throughout human history, the rise of telecommunication and advancement in computer processing power have created the necessary technological base for the emergence of online platforms. Platforms, like Airbnb, Yahoo!, Google, Uber, Lyft, and others use advanced computing power to find the most appropriate match for a user query. In only a decade, these platforms have grown rapidly and become some of the most valuable organizations in the world.

Fundamentally, platforms ask how a large distribution network can generate value by easing the discovery of information, goods, or services (Lin & Wu, 2017). For example, early platforms focused on solving the economic re-use problem, where consumers derive significant value from a single-use of an item (like a DVD or formal attire) but their enjoyment significantly declines after that use (Botsman & Rogers, 2010). Some organizations, like video rental stores, acted as a solution to the re-use problem but faced a distributional problem of their own: maintaining an inventory of high-demand goods. In modern terms, these stores acted as unidirectional platforms where a single institution owned the desired capital goods and would rent or lease them to people for a short period of time. Video rental stores acted as the physical manifestation of a unidirectional platform, while Web 1.0 architecture acted as the ‘online’ version of these unidirectional platforms (O'Reilly, 2017). Some successful platforms, like Rent-the-Runway, still employ a single-to-multi construction, but the development of crowd sourcing, where individuals sell to other individuals, marked an important shift in the trajectory of platform production.

Unlike single-to-multi platform construction, multi-sided platforms focus on facilitating peer transactions (Rysman, 2009; Shekhar, 2017). These platforms ‘crowd source’ goods that already exist but are underutilized due to distribution inefficiencies. Platforms like Airbnb and Sharing Tree built their business model around facilitating the exchange of goods that are owned by other people. Unlike unidirectional platforms, these multi-sided platforms do not need to possess the desired capital good; instead, they focus on discovering underutilized goods and distributing across their user base. A canonical example is the automobile: a high-cost good that, on average, spends 97% of its life on a street or in a garage (David S. Evans & Schamlensee, 2016). Multi-sided platforms grant individual owners the capacity to rent their goods out to other users of the platform for a small fee. Platforms set the rules of the exchange and act as trust mechanisms that filter out participants who abuse the marketplace (Hagiu & Wright, 2015). For example, both the renter and owner of an Airbnb are encouraged to provide public feedback ("rate") each other in order to create trust between participants. Scholars have developed several phrases to describe this method of production, such as crowdsourcing, the "sharing economy", "platform production", "networked firms", and others, but the essential logic remains the same: firms are looking to manufacture connections, not goods or services. In this sense, multi-sided platforms are attempting to solve a distribution problem; in short, how can networks help unlock value in under- or unused goods?

Multi-sided platforms have been studied from several angles. Some scholars have examined the social construction algorithms (M. K. Lee, Kusbit, Metsky, & Dabbish, 2015) to demonstrate how social biases embed themselves within these mechanisms. Others have studied the way social platforms, like Facebook or Twitter, can influence conversations or political realities 'offline' (Bryson et al., 2010). Others still have examined how these platforms are changing the way people assemble their income, with some arguing that online platforms function to offset income volatility (Farrell & Greig, 2016a). Early platform studies, however, focused on the economics of these entities: under what conditions did networked distribution create more efficient outcomes than vertically integrated firms? What are the core economic properties of these technologies? How should organizations structure their prices to 'lock-in' users? Essentially, how can a firm that does not make the primary product it provides become a valuable company?

Network effects are the glue that holds these markets together (Rochet & Triole, 2003, 2006). This theory argues that every market participant indirectly increases the value of the platform to every other user of the network. These are small utility gains, but aggregated over a large population, can provide significant value to a platform. For example, when Uber first launched in 2010, roughly 10 drivers in San Francisco were using the application (and many of them were doing this as a courtesy to their friends, Travis Kalanick and Garret Camp) (B. Stone, 2017). Due to the small number of riders, drivers did not see much value in adding the smartphone application, but without drivers, riders would not benefit from using the app. This is the essential "chicken-and-egg" problem in platform economics: how can platforms attract participants to either side of the market when they are co-dependent (Rysman, 2009)? One solution, used by most modern platforms, is to aggressively subsidize users initial few transactions until the platform reaches a "critical mass". Theory argues that once a (often unclear and undefined) "critical mass" is achieved, participants will naturally join the platform because there are enough people participating on each side that the platform independently generates value. For example, Uber has so many consumers using the app in San Francisco drivers cannot reasonably avoid using the application. This creates a self-reinforcing process, a phenomenon referred to as "positive network effects". Network effect valuation models are why user acquisition and retention is an essential aspect of platform growth.

Virtually all platform theory is based on consumer products, like swapping DVDs or renting out a room in your house to strangers (Gansky, 2012). Yet labor scholars have long found that both economics and institutions influence key organizational outcomes (H. C. Katz et al., 1985; Thomas A Kochan et al., 1994), raising the question of how labor relations influences this new economic and institutional alignment. Specifically, how does the multi-sidedness of these organizations shift the locations, tactics, and outcomes of conflict within organizations? While there is no shortage of evidence that there is conflict in platform work (Arbruzzese, 2016), scholars have yet to map the relationship between conflict triggers and outcomes within the MSP space. This paper examine how the multi-sidedness of these markets, where users frequently 'switch sides', influences worker's behavioral responses to conflict. Specifically, it asks: Do rideshare drivers who have a poor relationship with a rideshare company carry those grievances over to their consumer behaviors? If so, conflicts over work rules may directly influence the key performance metric by which these firms are valued: network density.

B) Linking Industrial Conflict to Platform Theory

Ties between the shop floor and consumer practices have long been acknowledged in the industrial relations literature. Fordism and the rise of mass production saw rising wages and labor peace as a mechanism for growing the number of loyal consumers who could purchase Ford automobiles (Edgell, 2012; Kaufman, 2004; T. A. Kochan et al., 1993). Additionally, scholars argue that labor and management's strategic choices and actions in collective bargaining are constrained by market forces and shifting consumer preferences (T. A. Kochan et al., 1993). Furthermore, prior to the Taft-Hartley amendments, workers at other companies attempted to pressure management through secondary strikes. Consumer boycotts are the most direct link between consumer behavior and labor relations (Crump, 1991; Estey, 1955), although this literature mostly describes non-employee consumers (Harrison & Scorse, 2010).

While existing research sees a relationship between consumers and the labor-management relationship, the vast majority of research focuses on other institutional mechanisms where labor more directly influences organizational performance, such as strikes (Godard, 1992), litigation (Colvin, 2012), workplace slowdowns (H. C. Katz, Kochan, & Colvin, 2015), unionization (Doeringer & Piore, 1970), or filing grievances (Boroff & Lewin, 1997). Given workers' proximity to their production process in traditional firms, these behaviors provide a clearer and more succinct link between the labor-management relationship and organizational outcomes (Thomas A Kochan et al., 1994). Platforms, as detailed above, operate on a slightly different economic logic than the linear production model, opening up new avenues for the labor-management relationship to influence organizational outcomes.

In the multi-sided market space, the distinction between producer and consumer is significantly blurrier than what is found in traditional work arrangements (Sundararajan, 2016). In fact, these categories are sometimes combined into the term *pro-sumer* (Belk, 2013) due to the nearly frictionless entry and exit with which workers can move across the market and become consumers. Unlike traditional work arrangements, platforms have very few barriers to entry: Uber and Lyft drivers are normally activated within 48 hours of submitting their driver's license and insurance information. For workers on other platforms, like Upwork or TaskRabbit, workers are connected after verifying their email address – a trivially easy task. Only in the most restrictive markets, such as San Francisco's rideshare market, do workers need to undergo a lengthy training process or obtain certification prior to working.

Additionally, drivers are increasingly likely to rely on rideshare for their transportation because rideshare is replacing other modes of private and public transit in major American cities: in San Francisco, ridership only covers 75% of the Bay Area Rapid Transit System's costs (Baldassari, 2017), and in New York City, Uber books more rides a day than yellow cabs (T. W. Schneider, 2017). Cities have taken various strategies to incorporate rideshare into their transportation infrastructure, such as allowing residents to pay for rideshare in pre-tax dollars (Hawkins, 2017), subsidizing the cost of rideshare to offset parking shortages, discounting for major events, or using public subsidies in lieu of investing in rail or other public infrastructure (Cmar, 2017).

With a shifting transportation landscape and new institutional incentives, the Uber or Lyft driver now may become the customer a short time later. Due to the informality and low barriers to enter and exit these services, millions of people have already experienced rideshare from the driver-side perspective (Berry, 2017). The informality also means these workers (current or past) represent a larger portion of the rideshare market than what would be found in other industries. Emerging evidence suggests that rideshare platforms lose about 50% of their workers every six months, and one survey found that Uber, on average, loses 96% of its workforce each year (McGee, 2017). With over a million drivers in the United States and 50 million active consumers (Dogtiev, 2018), this suggests that workers represent a nontrivial (and growing) portion of the rideshare market (Efrati, 2017). As more people experience rideshare from a driver's perspective, does this mean that workplace rules may also affect the *consumer* side of the rideshare market? If so, this would link together workplace conflict to platforms key valuation metric.

Testing the relationship between labor-management relations and workers' behavior as consumers has traditionally been complicated because people may choose different products for personal reasons. For example, a Coca-Cola worker may dislike her or his union contract but still prefer Coca-Cola to Pepsi due to the drink's flavor. Three reasons make the rideshare market an ideal place to test the relationship between the employment relationship and customer behavior. First, rideshare companies do not offer economic inducements for workers to use the application as a consumer. Unlike companies that reward their workforce with employee stock options, discounts, or could be disciplined (or terminated) for supporting a competitor, rideshare companies offer no carrots or sticks to encourage workers to purchase their products as riders. Furthermore, many rideshare companies have gone to extravagant lengths to avoid a psychological contract with workers out of fear this may lead a court to deem them an employer. For example, for nearly a decade, Uber would only communicate with drivers through email (Rosenblat, 2014). The lack of any structural incentives to use their work platform as a consumer strongly suggests that drivers will be acting on their experience as drivers.

Second, rideshare companies are primarily debt-financed, allowing them to peg their prices to their competitors without fear of (immediately) going bankrupt. Uber and Lyft, both with billions of dollars of cash on hand, match each other's prices in every major market. For example, as of August 2017, in the fifty largest transportation markets in the United States, Uber and Lyft had identical prices in 49 of them. Finally, most drivers use both Uber and its main competitor, Lyft, simultaneously. These services offer the same types of rides, economy (UberX, Lyft), larger SUV (UberSUV, LyftPlus), carpool (UberPool, LyftLine), and luxury sedan (UberBlack, LyftPremier), among others. Since most workers use both applications and these companies peg prices to each other, drivers will be making choices between nearly perfect substitutes.

There are several ways to measure consumer behavior. Researchers at Yahoo! gathered trip receipts from anonymous user inboxes to develop a trip density distribution curve for Uber users (Kooti et al., 2017). Although this method is useful for gathering mass amounts of transaction data, it is difficult to link these measures to users' experience on apps. Looking at individual transactions, or even recent histories, may not be an ideal way to examine consumer behavior in the rideshare market because of random variation in any individual transaction. Instead, previous work in multi-sided market has identified an important metric when looking at consumer use of these platforms: open order. Across several platforms, researchers have found that consumer purchases are serially correlated with use across time (David S. Evans & Schamlensee, 2016). For example, in the area of credit cards, consumers who pay for a good with one credit card are likely to use that card on the next transaction. Additionally, studies of online storefronts have found that consumers are more likely to purchase a good from the first site they visit (Nair, 2010) and that customer loyalty can be a key strategic advantage for these intermediaries (Cheung, Zheng, & Lee, 2014; Darley & Blankson, 2010; J. Lee, Kim, & Moon, 2000). For drivers who are looking to 'reward' a company for better workplace policies, they may look to that company first when looking for a ride.

This variable is also a generalizable behavior that surveys are likely to be able to capture: are drivers more or less likely to use a rideshare app based on their work experiences? Additionally, when workers are given the choice between multiple competing applications, does their relative preference between two rideshare companies *as a worker* predict which one they are more likely to use *as a consumer*? If so, then workers' relationship with their applications may not only influence how they go about allocating their labor, but would also affect their behavior on the other side of the multi-sided market, their behavior as consumers.

Data and Key Measures

Rideshare drivers were recruited for this study in three ways. The first set of study participants (N=226) were recruited with the aid of a worker organization in a large northeastern metropolitan area. The worker organization sent out both text messages and emails to its members notifying them of the study. Workers were informed that this study would be about labor conditions in the rideshare industry. At the end of the three-week signup period, 226 drivers had registered to participate.

A second recruitment channel utilized the "popular worker gathering spot" research strategy (Eigen, 2008a; Lind et al., 2000; Rosenblat & Stark, 2016). In the world of digital work, this means using online gathering spots to identify and recruit participants. Since Uber (and other gig companies) do not provide onboarding or much other information about how to use the service, drivers frequently turn to online resources in order to troubleshoot problems they experience while working.

Harry Campbell, a former rideshare drive, has one of the most popular online websites for rideshare drivers. Campbell's website is routinely cited by major news outlets, such as the New York Times, Washington Post, and Time Magazine.

Campbell posted a call for participants on his website in summer 2017 and sent an email to his mailing list notifying drivers about the study. This recruitment method yielded 234 participants.

Finally, I engaged in targeted Facebook recruitment (Kapp & Oliver, 2013) in an attempt to recruit drivers who had only recently started driving rideshare. Previous research has studied targeted Facebook recruitment and found that it can be appropriate for statistical inference (Fenner Y et al., 2012; Ramo & Prochaksa, 2012). Three closed Facebook groups were identified because they require drivers to send moderators proof of their driver status in order to join the group. Two of the three groups "pinned" the request at the top of their page for 7 days. This recruitment method yielded 26 participants.

After users signed up to participate in the study, they were sent the study documents via a Qualtrics online server. The study documents were optimized so drivers could respond while waiting for rides. Of the 490 drivers who signed up for the study, 488 provided semi-complete responses. After the first round of data collection, drivers were asked to provide additional information at thirty- and sixty-days following the initial round of data collection. The key independent variables for this study come from time period 1 while the key dependent variables, use of rideshare as a consumer, come from the second and third waves of data collection. Collecting key independent and dependent variables at different times can help address questions of reverse-causality or omitted variables that are temporally bound.

Since this was not a random draw of drivers, drivers' demographic information was checked against three previous demographic studies of rideshare drivers. In comparison to these three benchmarking studies, the participants in this study were slightly older and less racially diverse than previous studies of the rideshare market. Accordingly, models were reweighted to reflect the data found in Hall and Krueger (2015), but this did not change any of the outcomes variable of interest. Given how close the demographics of this study match previously conducted research, this is not unexpected.

Research Question and Key Variables

This paper looks to see if drivers' experience working in the rideshare industry influences their use of rideshare as a consumer. This proceeds in two steps. First, this paper tests if drivers' who have a more negative experience in the rideshare industry are more likely to indicate that their experience influenced their behavior as a consumer. Second, this paper then tests if rideshare company loyalty is associated with application open order as a consumer. The expected relationship is a positive relationship, where drivers reward companies that they feel more loyal toward by opening those applications first. Empirically, since position "1" is the most desirable boot order position, this would present as an inverse relationship where the more loyal a driver is toward a platform, the more likely drivers are use that platform first (as opposed to second, third, etc.).

Although there are many different rideshare applications, this paper focuses on Uber and Lyft. This comparison was selected for three reasons. First, geographically, these two services operate in the largest number of markets, preventing data loss due to geographic discontinuities across platform. Second, these two services are both well funded and peg their prices to one another, meaning their financial position in the rideshare market is unlikely to influence consumer behavior. Importantly, this makes it possible to run the models in this paper without having to control for local prices. Finally, these services focus on human transportation and not the delivery of physical goods, like Postmates, Amazon Flex, or DoorDash.

Key Independent Variables:

Unlike traditional employment, workers frequently move between competing companies when working rideshare. The structure of these markets, where drivers can choose which app to work for and for how long to work for that application, provides workers a significant amount of autonomy when deciding how to allocate their labor. While traditional research on labor-management relationships view the relationship as a revealed phenomenon, usually using conflict, grievances, strikes, or litigation as a barometer for a poor relationship, a worker-level unit of analysis is more appropriate for the rideshare industry. At the worker-level, data will need to be collected for each rideshare company for which a driver works.

Since rideshare is an emerging industry, this study tethers itself to both an established organizational loyalty scale and a new rideshare-specific measure. Empirically, both measures return similar results. These data also allow the models to make comparisons across organizations at the individual-level.

Loyalty Scale: Dyne et al.'s (1994) loyalty scale was selected because its items had logical analogues to the rideshare market (e.g., "I represent [platform] favorably to outsiders") whereas other organizational scales, such as the obedience scale, did not have obvious analogues to the rideshare industry (e.g., “I always come to work on time”). The questionnaire was set up in a looping fashion so as to ask drivers the six-item scale questions for each platform for which a driver worked. The loyalty scale returned a 0.78 Cronbach’s alpha for both Uber and Lyft.

Difference in Loyalty Scales. For comparing drivers’ preferences of Uber relative to Lyft, a measure was constructed to difference the two scores. Since this was calculated as Uber Loyalty – Lyft Loyalty, a positive coefficient suggests that a driver prefers Uber relative to Lyft. The mean of this measure (-0.62) suggests that drivers have a relative preference for Lyft over Uber.

Average Loyalty Scale: This variable assigns drivers’ the *average* of their Uber or Lyft loyalty score. For drivers who only drive for one of these services, they are assigned the value of that service. This variable is used to test if drivers who have, on average, lower evaluations of their platforms are less likely to use rideshare as a consumer.

Platform Recommendation: When applying these scales to the gig economy, however, loyalty scales crafted with single-employers in mind may include unwanted noise. For example, defending Uber against outside criticism, such as allegations of workplace harassment and illegal compensation prices, may be materially different from the criticisms leveled at Lyft. In order to address this possible complication, another measure directly asked drivers how likely they are to recommend each company to a new driver. This question allowed drivers to rate each company for which she/he worked on a 5-point Likert scale from “Highly Recommend” (5) to “Strongly Would Not Recommend” (1). By differencing a driver’s score for Uber and

Lyft, it is possible to get a relative preference for one service over the other. The variable ranged from -4 (would strongly recommend Lyft over Uber) to +4 (would strongly prefer Uber over Lyft). The mean of this measure, -0.64, suggests that the average driver holds a slight preference for Lyft over Uber. This is consistent with the other measures used for this study.

Key Dependent Variable:

There are two key dependent variables in this study. The first is a five-item scale that asks drivers if their experience as a driver has influenced their behavior as a rideshare consumer. The second dependent variable is the order that participants reported they would open rideshare apps as a consumer.

Key Dependent Variable 1: Use of Rideshare As a Consumer

Respondents were asked, "Did your experience as a driver influence which rideshare companies you will use as a consumer". The question was crafted to specifically link drivers' experience *as a driver* with their behavior as a consumer. This was a five point Likert scale from "Definitely Yes" (1) to "Definitely No" (5) with a mean score of 2.17 and standard deviation of 1.26, suggesting that, on average, drivers believe their work as a rideshare driver has changed their use of these companies as a consumer. This question was collected in the first follow-up questionnaire and then re-collected in the final follow-up questionnaire.

Key Dependent Variable 2: Rank-Order Consumer Use

The data collection questionnaire asked respondents to provide a rank-order of the apps they would open first, second, third etc. as a consumer for all the rideshare applications that operated in their geographic area. A previous question asked drivers to provide a list of all the rideshare applications that operated in their geographic area. The rank-order question used those answers to populate the list of possible rideshare applications a driver could open. Lower values are more desirable because it suggests that drivers are more likely to open that application first when looking for a ride. This question was collected in data collection waves 2 and 3. Lyft had a slightly lower ranking in both the first (1.76) and second data collection waves (1.89) compared to Uber (first wave: 1.90, second wave: 1.91). This suggests that the sample, on average, had a preference for Lyft to Uber in both follow-up surveys.

Control Variables

This study uses two types of control variables, demographic controls (age, race, gender, college education) and economic controls (months as a rideshare driver, full time vs. part time, how many more months a driver expects to stay in the industry, what type of vehicle a driver uses, and if the driver has health care). Summary statistics can be found in tables 1 and 2. Demographic variables were selected in order to account for unexplained variation that may be due to social stratification or targeted advertising. Economic variables were selected to control for variation in driver's interactions with and reliance on rideshare companies. Since the data collection tool did not draw a random sample from the rideshare population, regression models were re-weighted using the demographic ratios found in other Hall and Krueger's study of Uber's driver demographic. Demographic comparisons to Hall and Krueger's study, alongside other demographic benchmarks can be found in the Appendix. The demographic differences between this study and Hall and Krueger's study are small, and as expected, reweighting did not change the results of interest.

Methods

Do drivers reward platforms that have better labor practices by being more likely to use those services as a consumer? Or, alternatively: does conflict over workplace policies and experiences market carry over to workers' consumer behavior? The key independent and control variables were collected in the first wave of data collection while the key dependent variables were collected in the second and third data collection waves. Since these data repeatedly measure the same participants over three time periods, a random-effects linear model was used to control for internal driver variation over time (Woltman, Feldstain, MacKay, & Rocchi, 2012).

Results

Table 3 reports the results for OLS models with random driver effects regressing if drivers changed their behavior as consumers on their reported experiences of working for Uber and Lyft. The main independent variable in this model is a driver's average rideshare rating across Uber and Lyft. This model uses drivers' response to the question "Did your experience as a rideshare driver influence your behavior as a consumer?" as the key dependent variable. The returned association between the two, a negative coefficient (-0.251) significant at the $p<0.001$ level, suggests that as drivers have a more negative experience as a rideshare driver, they are more likely to say their experience influenced their consumer behavior. This result suggests that workers are linking their experiences on one side of the market to their behavior on the other side of the market.

Table 4 report OLS models with random driver effects testing the relationship between platform loyalty and rideshare application open order. For these models, Uber's rank order is the dependent variable and each independent variable (Uber loyalty scale, difference in loyalty scales, recommendation difference), with full controls, is tested in an independent model. Model 1 in table 4 shows the results between the Uber loyalty scale and a driver's rank-order preference for Uber as a consumer. The results show a strong ($p<0.01$) relationship between the organizational loyalty scale and a driver's preference to open the Uber app first. Since opening first (rank order 1) is the most desirable position for an application, the negative coefficient (-0.249) suggests that greater organizational loyalty is associated with a driver being more likely to open the app first. The second model in table 4 reports the same model but substitutes the Uber-Lyft loyalty scale in as the key independent variable. Again, this model returns a significant ($p<0.001$) relationship between relative loyalty to Uber vs. Lyft and the rank-order preference for opening the Uber application. The coefficient (-0.289) suggests that drivers who are relatively more loyalty to Uber over Lyft are likely to open Uber before they open the Lyft app. The third model in table 4 uses the same control variables as the first two models but uses the recommendation difference (Uber-Lyft) as the key independent variable. Once again, there is a significant association between if a driver is likely to recommend Uber over Lyft to a new driver ($p<0.001$) and where Uber falls in a driver's open order as a consumer (-0.203). The negative coefficient in this model suggests that as a driver become relatively more likely to recommend Uber to a new driver, that driver is also more likely to open Uber first as a consumer (rank order 1).

Table 5 tests if the same association can be found between platform loyalty and Lyft's open order rank. These models use the same control variables and model specification as the Uber models, but substitute Lyft's rank order preference as the key dependent variable. Model 1 in table 5 uses the Lyft loyalty scale as the key independent variable to test the relationship between loyalty and platform open order. The negative coefficient (-0.506) and significant association ($p<0.001$) suggest that, as a driver becomes more loyal to Lyft, they are also more likely to open Lyft first when acting as a consumer. Model 2 uses the same model construction as model 1 but substitutes the Uber-Lyft loyalty scale as the key independent variable. The positive coefficient (0.246) and significant association ($p<0.005$) suggest that as a driver becomes more loyal to Lyft relative to Uber, they are likely to open Lyft before Uber when acting as a consumer. Model 3 uses the same model construction as models 1 and 2 but uses the recommendation difference (Uber-Lyft) as the key independent variable. Since the independent variable is calculated as Uber minus Lyft, the positive coefficient (0.204) suggests that as a driver becomes more loyal to Lyft compared to Uber, Lyft is more likely to be the first app they open as a consumer ($p<0.001$). These results provide further evidence that drivers' platform preferences spillover in their consumer preferences.

Discussion

What do these results suggest for employment relations in the gig economy? First, these results indicate that an employer's workplace policies may affect workers' behaviors on both sides of a multi-sided market. The first set of models in this study suggest that workers who have more negative experiences as rideshare drivers are likely to carry those negative experiences over with them as consumers. Since platforms see consumer acquisition and retention as two key indicators of success and growth, this creates an association between the employment relationship and a key organizational metric. This is because rideshare companies built their investor base and business models on "network effects", or the theory of self-generating growth. This economic theory has been used by a number of consumer product or social media platforms, like Amazon and Facebook. Under this theory, there is a positive interaction between a platform adding additional drivers and/or consumers, allowing companies to focus on attracting one side of the market so that the other will naturally follow. When people exit their platform, this generates a negative network effect that decreases the value of the network to all users on the other side of the market. Linking together workplace polices and consumer behavior provides an initial association between platforms labor policies and a key performance indicator.

Second, how do workers act upon their preferences when engaging with platforms as consumers? Other platform research has argued that platforms battle to be the default platform for a particular use (e.g., Facebook displaced MySpace as the 'default' social media platform). In many areas, but not all, platforms debt-finance for a number of years in order to gain a near-monopoly position in order to create a natural "lock-in" effect. Network effects, in these markets, create natural barriers to entry for new platforms and raise the costs of entering that industry, allowing platforms to raise prices without jeopardizing their market position. In this light, existing rideshare platform policies, like subsidizing consumers' first three rides, can be seen as behaviorally training consumers to turn to use apps. Consistent with previous research on consumer behavior, this study finds that drivers' relationship and loyalty to a platform is linked to the order in which a driver opens their rideshare apps *as consumers*. Much like the #DeleteUber campaign following Uber's attempt at breaking the New York City JFK airport strike in January 2016, this finding suggests that consumers decide among competing rideshare companies for a variety of reasons, including experience as a driver. For people who have experience behind the wheel working for these companies, this finding suggests that drivers consider their range of experience across platforms and try to "reward" the platform with which they have the best working relationship.

This finding also extends the exit-voice-loyalty model of working conflict beyond the workplace. The economic foundations of platforms, porous entry and exit and informal work arrangements, has brought new people and new types of relationships into the production process. Workers in the 'platform economy' do not face the same transaction and search costs when moving between work nor do they face any labor market repercussions for 'job hopping' too quickly. These low barriers of entry and exit have resulted in million of people experiencing Uber and Lyft "from the other side of the app". In doing so, negative workplace experiences may have the capacity to create a lasting effect on how consumers relate to these highly interchangeable organizations. Aside from exit-voice-loyalty, workers have the capacity to act upon unresolved disputes both in the capacity as workers, but also in their actions as consumers. In short, the informal nature of platform work means that there is a greater overlap between workers and consumers, resulting in conflict having a further reach than in traditional production.

This study provides evidence that conflict in nonstandard working arrangements manifests in nonstandard ways. While some drivers have organized strikes, workers' guilds, publically spoken out against rideshare companies, or quit, the unique structure of these markets appears to provide new methods of driver resistance. With more than 1 million active Uber drivers in the United States, and an estimated 60-94% driver turnover every year, millions of people are experiencing these companies as both a rider and driver. Rideshare companies invest billions of dollars into recruiting and retaining passengers on their service because platform participation is one of the key metrics these companies use to attract investment and drive valuation. Yet this study indicates that the binary view that companies can force drivers to join its network by creating a "critical mass" of customers may not be an accurate representation of these markets in the long run. Instead, poor employment policies may be leading to drivers rewarding rideshare companies that provide supportive work rules or build a psychological commitment with drivers. For platforms, this suggests that finding a way to maintain driver loyalty may also coincide with their interest to attract and retain customers. In essence, there are high road employer policies that will both attract greater participants on the driver side and reward these companies when those drivers act as consumers.

Limitations

One key limitation of this study is that new apps are beginning to cross-list prices across rideshare services. UrbanHail, one of the first cross-platform price comparison tools, had its Application Programming Interface (API) blocked by Uber for obvious strategic reasons. Now, however, Uber routinely cooperates with other applications, like the Atlanta metro app or CityMapper, both apps that list either Uber and/or Lyft's prices in their app. While this may complicate the practical implications of this study, it does not change the underlying finding that consumers link their workplace experiences to their consumer behaviors. In order to predict any given ride, it will be important to test the strength of a driver's loyalty compared to the difference in surge pricing or driver location across competing services. While this may change how consumers act upon their preferences (e.g., boot order), it does not affect the key finding of this study.

Second, the participant recruitment process could present several biases within these data. To check for selection biases, the sample was subdivided into recruitment channels (online vs. offline; union members vs. non-union members). This did not change the variables of interest. This cannot rule out all possible variation, for example, drivers who signed up to participate in the study may have done so in order to voice their objections for either Uber or Lyft. This does not align with the data. Drivers in this study report only a mild preference for Lyft relative to Uber (-0.64 on a 9 point scale), and therefore do not appear to be systematically skewed in favor of one company. The preference for Lyft relative to Uber is consistent with other surveys of rideshare drivers. It is true that drivers in this study represent a more experienced portion of the rideshare driver population. Due to this, these results may only represent consumer behavior after drivers have more than several months experience in the rideshare market. Future research that investigates how soon drivers make distinctions between companies would be fruitful.

Third, OLS models cannot rule out the possibility of reverse causality. This paper attempted to handle this issue by collecting the key independent variables in time period 1 and the key dependent variables in time periods 2 and 3. This provided 30 and 60 days between the collection of the right and left sides of the equation. Furthermore, the variables collected in time period 1 predicted the same outcome in times 2 and 3, independently. While OLS models, as a structure, are vulnerable to a reverse causality problem, it is difficult to construct a logical argument for these two variables. Since the sample frame consisted of rideshare drivers, it is unlikely that drivers' preference for a service as a consumer would influence how that driver views the service as a driver. One other methodological concern is that those who dropped out of the study may differ from those who continued. No significant differences were found in gender, educational level, or other key demographic indicators.

Finally, it is unclear how these results would project outside of Uber and Lyft. These two platforms were selected because they allowed the models to remove price variables, but they are also the largest and most well established platforms in the rideshare market. While these results suggest that either of these two companies receives a consumer bonus from worker loyalty, it is unclear if an emerging company could also capitalize on this same phenomenon because emerging services may not have the necessary critical mass of cars or consumers in their market. Yet interviews with drivers in New York City suggest that drivers will act as ambassadors for whichever service they prefer. For example, in Summer 2016, Juno drivers encouraged me to download the application and use it because drivers preferred it to Uber and Lyft. Despite Juno not having a marketing department, publically available growth data from New York City shows that Juno, in its first six months, was able to attract both passengers and drivers more rapidly than either Uber or Lyft. While this may be due to a maturing rideshare market, it is curious that Juno was able to break into 3-year old market so rapidly.

Conclusion

Existing theories of employment relations have documented that a progressive or peaceful relationships between employees and management can result in greater organizational productivity. This study links together the market structures of the rideshare space with theories of employment relations to demonstrate that the relationship between drivers and platforms have manifest impacts on key metrics within the platform economics space. Cross-platform competition is defined as a battle for recruitment and retention of new market participants, yet the current literature assumes these are distinct and separate groups. The spillover between conflict over workplace policies and consumer behavior was found across multiple applications and measures of employment relationship. Due to the volume of driver churn within these markets, a large number of market participants are experiencing rideshare as a driver. As rideshare companies are looking to find ways to retain participants within their network, it appears that workplace policies may be one way to achieve that goal.

Tables and Figures

Table 1: Means and Standard Deviations of Key Variables		
Key Independent Variables		
	Mean	**S.d.**
Uber Loyalty	2.56	0.81
Lyft Loyalty	3.14	0.75
Scale Difference [Uber-Lyft]	-0.62	0.98
Recommendation Difference [Uber-Lyft]	-0.64	1.4
Key Dependent Variables		
Uber Open Rank (time 2)	1.90	0.96
Uber Open Rank (time 3)	1.91	0.95
Lyft Open Rank (time 2)	1.76	1.05
Lyft Open Rank (time 3)	1.89	0.98

Table 2: Distribution of Categorical Variables	
Age 18-29	8.64%
30-39	21.81%
40-49	25.99%
50-64	39.21%
65+	1.60%
Female	17.70%
Less than HS	1.85%
College Degree [Yes]	59.26%
White Non-Hispanic	60.29%
Black Non-Hispanic	10.70%
Asian Non-Hispanic	12.55%
Other Non-Hispanic	5.35%
Hispanic	10.49%
Married	60.32%
Has Children at Home	40.74%
Full Time	44.91
Part Time	34.9%
Work – Transition	17.34
Work – Other	13.06%
Health Care [Yes]	81.1%
Transportation Experience [Yes]	33%
Drive Future – 0-3 Months	12.0%
4-6 Months	16.8%
6 Months – 1 year	0%
For more than 1 year	71.2%
Small Sedan	15.91%
Medium Sedan	35.7%
Large Sedan	11.22%
Four Wheel Drive	22.8%
Minivan	5.71%
Vehicle – Other	8.5%

Table 3: Reported Likelihood of Using Rideshare as a Consumer Regressed On Average Loyalty Across Platform	
	Will Use Rideshare as a Consumer
Time Dummy	0.139
	0.108
Vehicle - Medium Sedan	0.054
	0.206
Large Sedan	-0.277
	0.288
Four Wheel Drive	-0.199
	0.231
Minivan	**0.781***
	0.395
Race - Hispanic	-0.191
	0.35
Caucasian	-0.462
	0.29
Asian/API	**-0.641***
	0.38
Native American	-1.593
	1.044
Not specified	0.103
	0.439
Part-Time Driver	0.038
	0.192
Transitional Job	-0.011
	0.229
Other Type of Work	0.371
	0.256
Age	0.088
	0.067
Has a College Degree	0.002
	0.155
Healthcare [Yes]	**-0.34***
	0.199
Total Driving Time [Months]	-0.001
	0.005
Transportation Experience [Yes]	-0.299*
	0.168
Average Rideshare Rating	**-0.251****
	0.116
Number of Observations	340

*** = p<0.01, ** = p<0.05, * = p<0.10. "---" indicates variables not used for that regression.

Table 4: Uber Open Order As a Consumer Regressed on Workplace Loyalty and Recommendation Items			
	Uber Open Order	Uber Open Order	Uber Open Order
Time 3 Dummy Variable	-0.001	-0.006	-0.001
	0.076	0.076	0.076
Female	0.291	0.055	0.141
	0.206	0.208	**0.206***
Vehicle - Medium Sedan	**-0.364***	**-0.365****	-0.356
	0.189	0.183	0.186
Large Sedan	**-0.702*****	**-0.571*****	**-0.575****
	0.261	0.253	0.256
Four Wheel Drive	-0.412*	-0.363*	-0.39*
	0.216	0.21	0.212
Minivan	**-0.800****	**-0.775****	**-0.798****
	0.372	0.362	0.366
Other	**-0.796*****	**-0.687*****	**-0.662*****
	0.245	0.24	0.245
Race - Hispanic	0.33	0.402	0.402
	0.315	0.305	0.309
Caucasian	**0.458***	0.34	0.41
	0.26	0.254	0.256
Asian/API	-0.003	-0.046	-0.021
	0.332	0.323	0.327
Native American	0.708	0.108	0.215
	0.826	0.822	0.831
Part-Time Driver	-0.224	**-0.318***	**-0.309***
	0.174	0.169	0.171
Transitional Job	-0.005	-0.081	-0.02
	0.238	0.232	0.234
Other Type of Work	0.1	-0.012	-0.024
	0.23	0.222	0.225
Age	**-0.138****	**-0.132****	**-0.141****
	0.059	0.057	0.058
Has a College Degree	-0.05	0.02	0.048
	0.143	0.136	0.138
Projected Future	0.066	0.033	0.013
	0.078	0.074	0.075
Healthcare [True]	-0.006	0.002	0.024
	0.185	0.18	0.182
Total Months Driving	**0.009***	**0.009****	**0.008***
	0.005	0.005	0.005
Transportation Experience [Yes]	-0.02	-0.015	0.001
	0.153	0.148	0.15
Uber Loyalty Scale	**-0.249*****	---	---
	0.082	---	---
Scale Difference [Uber-Lyft]	---	**-0.289*****	---
	---	**0.068**	---
Recommendation Difference [Uber-Lyft]	---	---	**-0.204*****
	---	---	**0.054**
Number of Observations	223	223	223
AIC	573.0792	580.7091	576.9747

*** = p<0.01, ** = p<0.05, * = p<0.10. "---" indicates variables not used for that regression.

Table 5: Lyft Open Order As a Consumer Regressed on Organizational Loyalty and Recommendation Items			
	Lyft Open Order	Lyft Open Order	Lyft Open Order
(Intercept)	3.614	2.365	2.303
	0.54	0.501	0.497
Time Dummy	0.033	0.03	0.026
	0.112	0.113	0.113
Female	-0.072	-0.281	-0.33
	0.238	0.243	0.237
Vehicle - Medium Sedan	0.151	0.084	0.06
	0.2	0.212	0.211
Large Sedan	0.071	0.267	0.254
	0.28	0.292	0.29
Four Wheel Drive	0.246	0.278	0.295
	0.23	0.244	0.241
Minivan	0.158	0.096	0.098
	0.405	0.426	0.423
Other	0.219	0.244	0.179
	0.264	0.28	0.281
Race - Hispanic	0.077	0.216	0.218
	0.338	0.355	0.353
Caucasian	0.111	0.014	-0.035
	0.282	0.296	0.293
Asian/API	0.132	0.184	0.165
	0.356	0.378	0.374
Native American	-0.135	-0.343	-0.327
	0.855	0.919	0.908
Part-Time Driver	-0.104	-0.228	-0.231
	0.188	0.196	0.194
Transitional Job	0.138	0.093	0.035
	0.266	0.28	0.277
Other Type of Work	-0.061	-0.259	-0.234
	0.246	0.256	0.254
Age	-0.047	-0.01	0.002
	0.064	0.068	0.068
Has a College Degree	-0.2	-0.03	-0.056
	0.152	0.158	0.156
Projected Future	-0.022	-0.103	-0.088
	0.083	0.087	0.086
Healthcare [True]	**-0.364***	-0.344	**-0.362***
	0.202	0.213	0.212
Total Months Driving	0.003	0.004	0.005

	0.005	0.005	0.005
Transportation Experience [Yes]	0.251	0.273	0.26
	0.164	0.173	0.172
Lyft Loyalty Scale	**-0.506*** **	---	---
	0.101	---	---
Scale Difference [Uber-Lyft]	---	**0.247*** **	---
	---	**0.079**	---
Difference In Rating [Uber-Lyft]	---	---	**0.204*** **
	---	---	**0.06**
N	221	221	221
AIC	666.8981	653.2751	665.9749

*** = p<0.01, ** = p<0.05, * = p<0.10. "---" indicates variables not used for that regression.

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CHAPTER 4: WORKER SOCIAL NETWORKS AND UNION ORGANIZING: DO SOCIAL INTERACTIONS IMPOVE WORKERS' VIEWS ON UNIONIZATION?

Introduction

For nearly two decades, scholars have asked how the Internet will change union organizing strategies (Bryson et al., 2010; Osterman, Kochan, Locke, & Piore, 2001). The promise of the Internet is that it connects physically disconnected individuals, eases the distribution of information, and can help expose people to new ideas and debates (Freeman & Rogers, 2002). Moving actions from online to offline can be difficult, and the early 2000s provided little evidence the web was improving labor's long-term trajectory (Nolan, 2017). Yet in March 2018, 30,000 public school teachers in West Virginia engaged in a statewide wildcat strike, demanding higher wages and better healthcare benefits (Bidgood & Robertson, 2018). The teachers' subsequent victory was a dramatic outcome for labor in an otherwise precarious national environment (Zorn, 2018). After the strike, workers pointed to an unusual organizing factor: a Facebook group with 24,000 members started by two teachers in late 2016 called, "West Virginia Public Employees United" (O'Donovan, 2018; Robertson & Bidgood, 2018). After the strike was over, strike supporters commented,

> "This strike wouldn't have happened without the grassroots organization through the private Facebook group… without question, I don't think this would have reached the critical mass that was needed had they not had the platform of the group to communicate" (O'Donovan, 2018).

Organizers for the American Federation of Teachers said that Facebook provided a space where workers, separated by physical proximity, were able to share their collective grievances and develop plans to coordinate their actions. Within a few days of the conclusion of the West Virginia teachers' strike, teachers in Oklahoma formed a 76,000 person Facebook group and also went on strike (Emma, 2018). Teachers in Kentucky, did the same (Goldstein, 2018). Could worker-led Facebook groups become a new tool for organized labor?

Scholars have documented that Computer-Mediated Communication (CMC) and Social Networking Sites (SNS) are a central aspect of modern interaction. Facebook, the world's largest SNS, has more than a billion users; Twitter records more than 500 million tweets per day, while the average American sends between 1,000 and 2,000 text messages a month. Unlike Web 1.0 architecture that was mainly one-to-many communication (e.g., a website where people can read information), Web 2.0 allows people to engage in debates, discuss news articles, and form social bonds with other people in the group (O'Reilly, 2017). These Web 2.0 networks have created new ways for people to communicate both directly (e.g., GroupeMe, WeChat) or anonymously (e.g., on Facebook groups), and have been used by social movements all over the world, from activists in Syria tweeting about the dangers of the Assad regime to the Women's March on Washington. Workers have also used these networks to coordinate collective labor actions, with gig workers in Europe using WhatsApp to coordinate strike activity, and rideshare drivers in New York relying on text messages to coordinate mass "signoffs" (essentially walking off the job). Web 1.0 may have failed to deliver on its promise of a new means of organizing workers, yet these labor actions are worker-driven, reflecting Web 2.0's distributive, collaborative nature, and raises a provocative question: does the new architecture of the Internet offer greater promise for labor organizing?

Anecdotally, researchers have found that increased social media interaction between Amazon Mechanical Turk (mTurk) workers is associated with improved general views on unions (I. Irani, LC & M. Silberman, 2015). Additionally, rideshare drivers have built online networks where workers distribute information about wages, changes in work rules, and how to dispute disciplinary decisions (Rosenblat, 2018). For both Uber drivers and mTurk workers, these worker-built networks resemble the concept of mutual aid and support of fellow workers and may help them bridge the physical distance between themselves and other workers. If social media provides a forum for workers to discover the systematic problems in their industry and begin collectively organizing, this could provide an important new avenue for unions looking to organize these temporary, often precarious, forms of work.

This study empirically tests the relationship between social interaction and rideshare drivers' views on union instrumentality. This paper focuses on the rideshare industry because it is the most developed area of the 'gig' economy and acts as an important reference point for the debate around platform work (Prassl, 2018). Drawing on 75 original interviews with rideshare drivers from across the United States, this study develops a social interaction measure to determine how workers in the rideshare industry interact with one another. This measure identifies four channels by which rideshare drivers build community online and offline: social media, texting, meeting up in-person, and reading websites. Using new survey data from 400 rideshare drivers from across the United States, this study validates these interactions into a scale and tests its relationship to (1) workers' views on union instrumentality and (2) a worker's inclination to join a rideshare drivers' association. Furthermore, this study tests a subset of the scale, using only the social media measure, to see if it is associated with improved views on union instrumentality and interest in joining a rideshare drivers' association. This study finds that drivers who have either greater social media or general social interaction with other rideshare drivers are more inclined to join a drivers' association and have more positive views on union instrumentality. This finding provides empirical support for previous research that suggests online communities have the capacity to influence workers behavior in the "real world" and presents initial evidence of a new organizing tool for labor, the online worker network.

Literature Review

New Forms of Work

Over the last decade, the rise in gig platforms and working arrangements is one of the largest shifts in global industrial systems (Future, 2017; Glöss et al., 2016; Kooti et al., 2017; Krueger, 2017; MGI, 2016; Sundararajan, 2016). In theory, gig platforms attempt to unlock idle resources (P. C. Evans & Gawer, 2016), either unused time when workers would like to earn income or unused capital goods, like renting out an unused bedroom to a weekend traveller (Gansky, 2012). By allowing gig workers to select their own working times, platforms have created a version of informal employment where workers can use the platform to offset unexpected changes in their income, such as losing a shift at work or to help pay off a new expense (Farrell & Greig, 2016b). This flexibility stands in stark contrast to the industrial world's trend toward on-call or zero-hour contracts (P. Cappelli & Keller, 2016; L. Katz & Krueger, 2016).

In lieu of managers scheduling workers' shifts, many platforms retain control over the *price of exchange* between buyer and seller to regulate production (David S. Evans & Schamlensee, 2016). These prices are set by predictive demand algorithms that synthetize both proprietary historical data and current-use trends (J. V. Hall et al., 2016) to adjust prices in order to balance supply and demand on their networks. This model of work shifts the production process from one where managers allocate resources to one where computers adjust market prices to increase or decrease the supply of labor (O'Reilly, 2017). While platforms argue they are merely facilitating a transaction between a buyer (e.g., a rider in the rideshare market) and a seller (e.g., a driver), many retain independent interests, such as increasing their market density, generating a profit for shareholders, obtaining additional capital, and attracting new investors (Hagiu & Wright, 2015).

Gig work in the early 2000s revolved around high skill industries, such as computer programming, but quickly spread into the manual task space (Gansky, 2012). Services like Amazon Mechanical Turk, which has over 1 million "turkers" worldwide, offers human intelligence work for small amounts of compensation, usually between five and ten cents per job (I. Irani, LC & M. Silberman, 2015). mTurker work often involves filling out surveys for researchers, filling in metadata to make photos searchable by web browsers, searching the Internet for coupons, etc. Other services, like Fiverr, Catalant, and Upwork, offer a range of services from financial consulting to home cleaning services. Bolstered by Uber's estimated $48 billion market valuation, investors and software engineers rapidly began looking for the next “Uber for X” and developed thousands of ways people can work through a smartphone, including magicians on demand, “Uber for medical marijuana”, “push for pizza”, and many more. While many of these platforms collapsed shortly after launch, others, like Postmates, have managed to survive the recent downturn in venture capital investment (Srnicek, 2016).

These work arrangements consist of three major shifts in the ways the American industrial system imagines the relationship between workers and employers. First, platforms shift market risk from organizations to workers. In a normal industrial arrangement, firms hold both the burden and benefit of market vacillation; if a product sells well, firms can make high profits, while if there is weak market demand, owners of the firm are responsible for the loss. Alternatively, workers are given basic guarantees about their income (minimum wage) with a soft-cap on working hours (overtime after 40 hours a week) and workplace safety (T. A. Kochan et al., 1993). If the product of workers’ labor is extremely successful, workers are not compensated for that success, but at the same time, workers are somewhat insulated from market risk in the event of a product failure. Gig platforms reverse this equation because *workers* bear the market risk and consequences of weak demand but are given the flexibility to select their own hours (Rochet & Triole, 2006). For many manual tasks markets, this creates a new division of risk that is not present in traditional product markets.

Second, workers provide all the capital and training to complete a job. Unlike firms with internal labor markets, onboarding, or internal workforce development

(Doeringer & Piore, 1970), platforms require workers to provide all the tools to complete a job but do not specify *how* a worker must complete a task (Prassl & Risak, 2016). For Uber drivers, this means that drivers must possess a vehicle, smartphone, and capable data plan to use the service but can also offer other benefits to customers (Rosenblat, 2015). This has unusual implications for workforce quality and standardization within a market. For example, some drivers have extravagant vehicle setups, including mobile wireless hotspots, dedicated Spotify accounts, and mini-fridges, while other drivers attempt to minimize their costs associated with rideshare. To help protect against poorly performing or harmful market participants, many platforms outsource performance evaluations to customers (Rosenblat, 2015). On most rideshare platforms, riders are asked to evaluate their driver on a 1-5 "star" scale. Despite the standardization in the rating representation ("stars"), each rideshare platform handles performance evaluations differently, with some platforms deactivating (firing) drivers for falling below a floating threshold (usually somewhere around an average of 4.7 out of 5).

Finally, these firms have a different organizational shape because they have replaced most managers with an algorithm and share a workforce with their competitors. Much of the research in the gig economy focuses on the de-skilling of workers, such as Uber's algorithm replacing the famous "The Knowledge" test in the UK, a notoriously difficult historical and geographic exam for taxi drivers. Yet that algorithm has entirely replaced managers who would develop and train workers or make branch-level decisions. For example, unlike their brick-and-mortar counterparts, local Airbnb hosts do not have marketing managers, a housekeeping staff, front desk managers, or financial analysts. For workers on rideshare apps, there is no supervisor they can speak with about their performance evaluation or daily pay. Furthermore, since drivers are not bound by a duty of loyalty and platforms do not exercise directive control, rideshare drivers frequently work for multiple competing applications. In response, some platforms have used GPS data to track and identify these drivers who work for their competitors, sometimes providing additional work to these drivers as a means of keeping them away from competitors.

Collective Action in the Gig Economy

Despite a growing number of workers relying on 'gig' work as either their primary or a supplemental income source, there has been very little research on how collective action might function in this area of work. For several reasons, these workers fall outside of the traditional union organizing model. First, 'gig' workers do not have 'co-workers' or 'supervisors' – their entire relationship to a company is through an app or web browser. Furthermore, many 'hot shop' triggers, such as mandatory overtime or wage reductions, do not elegantly map onto a workspace where workers can set their own hours, have no promotion opportunities, and use their own capital goods. At the most foundational level, unions rely on some form of an internal labor market (Doeringer & Piore, 1970), but these are largely absent from gig-based work. Complicating this further, much of the union-organizing literature has grown out of traditional industrial production (T. A. Kochan, 1979).

In the face of these difficulties, there are several examples of gig workers engaging in collective acts to protest falling wages and poor working conditions. Amazon Mechanical Turk was one of the earliest sites of conflict over working conditions in the gig economy (L. Irani & M. Silberman, 2015). Unlike online marketplaces like eBay, Amazon refused to act as a mediator in the event of a conflict between buyers and sellers on their marketplace. Instead, Amazon allowed buyers to unilaterally refuse work products if the buyer claimed that the work fell below an acceptable standard. Buyers, however, were allowed to keep the work that was sent to them by the seller. Predictably, this ballooned an area for abuse since buyers did not need to demonstrate that the seller's work was not satisfactory. mTurkers, through an online message board, workers began to identify buyers who repeatedly used this tactic to avoid paying for a product.

These problems have spurred several collective worker actions. In 2014, a group of mTurk workers wrote to Amazon President Jeff Bezos in an attempt to humanize the workforce and asked for better workplace protections. Yet, perhaps the most the effective means of addressing poor working conditions in the mTurk marketplace came from outside the informal bargaining process altogether. In 2014**,** a group of academics at Stanford who created a Chrome browser plug-in called "Turkopticon" that allows mTurk workers to rate *sellers* and alert other mTurk workers if a seller had previously cancelled payments arbitrarily. Much like passenger ratings in the rideshare app Uber, this plugin allowed workers to pool their work experience for the mutual aid of other workers. By linking together workers' collective information through the "cloud", it allowed mTurkers to avoid problematic sellers and created a public record of the abusive payment system.

Turkoption demonstrated that workers faced a similar set of challenges when navigating the mTurk market. While the software designers were initially wary of using the term ‘union’, they later found that workers had warmed to the idea:

> “When we first began Turkopticon, the reaction workers had was, ‘We don’t want to be in a labor union. Is this going to turn into a union thing?’” Irani says. (Turkopticon is not a labor union and was not founded with formal unionization in mind.) “But over the years, it seems workers have become more open to how unions can help them. They see how recalcitrant Amazon has been on making changes.” (Greenhouse, 2016)

Today, over 20,000 mTurkers use Turkopticon on a daily basis. This software demonstrated the power of a nontraditional labor organizing techniques and that highlighting systematic labor abuses may cause workers to see their grievances in a collective fashion.

Similar evidence has emerged in the rideshare industry. Recent research is beginning to examine how Uber and Lyft drivers use online social networking tools, like Facebook groups, to help spread information about the labor conditions in their industry. This research has found that drivers frequently exchange information about compensation, such as unexpected pay cuts, possible insurance hurdles, how to dispute disciplinary actions, and how to handle Uber’s various class action settlements (Rosenblat, 2018). One of these groups, the New York City Uber drivers’ Facebook group, began examining how Uber calculated its percentage of the overall fare. By posting dozens of receipts to the page, drivers identified that Uber was incorrectly calculating its portion of the fare, resulting in overcharging drivers tens of millions of dollars. In order to remedy this miscalculation, Uber was forced to compensate drivers nearly $70 million in back wages.

The reluctance of gig companies to provide workers with the basic information about their jobs has created demand for these networks. Most gig companies do not onboard their workers or inform workers of the platform's policies and procedures because doing so may place these companies at risk of employment misclassification litigation. Yet this lack of instruction causes drivers to seek out this information, either through online groups or a in the emerging constellation of online information brokers, such as Harry Campbell "The Rideshare Guy" or "Uberdriver.net". These informal networks help drivers understand the nuances of the rideshare industry and spread information about changes in compensation, insurance plans, tax law, and rideshare company policies. For example, rideshare drivers with law degrees began offering advice to other drivers when Uber changed its arbitration policy. To scholars of labor relations, these online networks are beginning to resemble mutual aid or support for fellow workers. Despite anecdotal claims that these networks may improve workers' views on union or collective action, there has yet to be systematic evidence on this matter.

Power of Online Networks

Many researchers have studied the capacity for online networks to spillover into "real world" events. Bryson et al., (2010) argue that the structure of Web 2.0 lends itself to the construction of online worker networks because these forums create "engagement" – essentially, active communication -- between participants. For community users, this engagement allows them to participate in close-knit communities and share interests and ideas. Additionally, these web communities have institutional memories, as demonstrated when Uber driver forums alerted members in January 2017 that Uber had previously cut wages in January 2016.

Additionally, scholars have argued that social media has the capacity to overcome existing bottlenecks in information distribution. For example, McGarth et al. (2012) highlight several cases where "e-participation" could increase citizens' engagement in social movements. Anecdotally, the authors argue that unions could utilize social networks as a means of spreading information about the strategic goals of the union and also connect with other collective organizations. Furthermore, Hogan et al. (2010) argues that workers can use social media to alert a global audience to precarious working conditions:

> The ability of workers to relay information on wage rates, bad work conditions, management policies, and government failures to tackle bad employment practices and conditions instantaneously across the world at minimal cost provides new levels of transparency and new conditions for harvesting solidarity.

The distributed nature of information technology makes it easy for workers to access others' experiences at the touch of a button. Previous restrictions on contacting workers, such as an employer's ability to bar union organizers from the physical workplace, may be less effective when workers can discretely and instantaneously contact one another.

Beyond these arguments, researchers in the field of information science provide some psychological pathways that support a relationship between online community and "real world" activism. Scholars have extensively examined how Computer Mediated Communication (CMC) changes the way individuals exchange information. Researchers have found that the open nature of Internet forums, blogs, and social media allow people to become members of these larger communities (Snow, 2001). Through repeated interactions with online communities and their symbols, narratives, and images, studies have found that individuals begin to more strongly identify with those causes (Earl & Kimport, 2011). Furthermore, the flexible nature of digital spaces allow individuals to craft areas where they are less likely to encounter resistance or retaliation for their identities (Choi & Park, 2013). Additionally, people can anonymously browse these spaces, allowing workers to read about the working conditions in the industry without fearing that Uber or, in a traditional workplace, their supervisor, discovering them reading about labor organizations. With weak labor protections surrounding retaliation, providing a forum for workers to engage without fear of discovery is a promising development for collective labor action. Finally, research has linked CMC's ability to gather together people of similar interest to larger, offline social movements (Gil de Zúñiga et al., 2012). Together, this research suggests that online connections have the capacity to spillover into actions in the offline world.

Union Attitudes and Support

There is extensive research on why workers choose to support a union and the best predictors of union support (Godard, 2008). The core literature identifies three main areas of variation: union instrumentality, job satisfaction, and demographic characteristics (Davey & Shipper, 1993; T. A. Kochan, 1979). Union instrumentality refers to an individual's belief that a union will be able to address their problems at work, such as unequal discipline or pay. Research that examines union instrumentality asks workers about their views on how unions influence workplace conditions, pay, and overall organizational performance. Generally, union instrumentality is considered the strongest predictor of how an individual will vote in a union certification election (Deshpande & Fiorito, 1989; Fiorito, Lowman, & Nelson, 1987), but some studies have found that job dissatisfaction can have an equal effect on voting behavior (Fiorito et al., 1987; T. A. Kochan, 1979). Instrumentality is considered a useful predictor of an individual's voting behavior because some studies find it is a "veto" criteria: if workers do not believe a union can effectively resolve their concerns, then dissatisfaction is not likely to be associated with increased union support (Wheeler & McClendon, 1991; Youngblood, DeNisi, Mollseton, & Mobley, 1984). Much of this literature argues that workers view unions through an expected value lens and ask themselves, 'are there conditions that I wish to improve in the workplace and how likely is the union to resolve those concerns' (Farber & Saks, 1980)? In studies comparing the three main sources of variation, instrumentality has largely been able to explain the greatest variation in voting behavior, correctly categorizing more than 75% of votes cast in multiple studies and has the highest correlation with intent to vote (DeCotiis & LeLouarn., 1981; Montgomery, 1989; S. Premack & Hunter, 1988). The strength of the union instrumentality variable has been reproduced in a variety of settings, including laboratory environments (LaHuis & Mellor, 2001) and unionization drives (DeCotiis & LeLouarn., 1981).

Second, some research suggests that individuals with a lower job satisfaction will see unions more favorably because they believe the union may be able to improve their working conditions (Riley, 1997). Generally, job satisfaction is grouped into two categories, economic (job security, opportunity for promotions, pay, etc.) and noneconomic (freedom, creativity in one's job, variety of work, etc.) forms of workplace satisfaction (Deshpande & Fiorito, 1989; Fiorito et al., 1987; Riley, 1997). Although previous research has found a relationship between job satisfaction and union support (S. Premack & Hunter, 1988), other studies have found that it only operates through instrumentalities (Park, McHough, & Bodah, 2006).

Additionally, research suggests demographic characteristics are correlated with individual's voting behavior. One of the strongest demographic characteristics is if a worker is a former union member or has a family member who is a union member (Deshpande & Fiorito, 1989; T. A. Kochan, 1979; Riley, 1997). This is most likely a proxy for union instrumentality because these workers have experience with a union's influence on wages and working conditions. For the purposes of this study of the rideshare industry, another important predictor is if an individual works full- or part-time, with people who work part-time reporting lower union support than those who are working full time (Riley, 1997). Part-time workers may see less value in unionization because they are less likely to stay with a company for a prolonged period of time or may not be as economically reliant on the job for their income, both of which would decrease the expected value of unionization. This would be consistent with previous research that shows workers view the benefits of unionization through an expected-value lens, where workers who are the top of existing pay charts being less likely to support unions than workers who are lower on the pay scale (Farber & Saks, 1980). Finally, past studies have found some general demographic characteristics, such as age, gender, race, and marital status to be correlated with intent to support a union, but these associations are often weak and inconsistent across studies (Godard, 2008; T. A. Kochan, 1979; Youngblood et al., 1984).

Although there has been a gradual decline in union density and collective bargaining coverage since the mid-1950s, workers still express a strong desire for due process and representation at work (Osterman et al., 2001). In fact, compared to current union membership, many more workers express a positive view toward unions and say they would vote for union if given a chance (Freeman & Rogers, 2002). This mismatch has led scholars to explore potential alternative organizing models that may avoid some of the common pitfalls of traditional unions, such as organizing through the Internet ('e-organizing'), nonexclusive bargaining units ('open-source unionism') (Freeman & Rogers, 2002), or targeting non-traditional workers, like managers ('next-generation unionism') (Osterman et al., 2001). Since rideshare (and most gig workers) are classified as 1099-MISC exempt workers, collective bargaining would constitute a violation of the Sherman Antitrust Act (Harris & Krueger, 2015). Given this legal hurdle, unions have been exploring alternative organizing models, such as the Independent Drivers' Guild in New York City (Johnston & Land-Kazaluskas, 2018). Despite these organizing efforts, rideshare companies have maintained that workers do not want union representation because it may impinge on their flexibility to select their own hours (Heller, 2017). Given workers' general interest in collective voice and due process at work, this study will also explore drivers' interest in worker associations in addition to traditional unions.

Research Question

Do rideshare drivers who more frequently engage with other rideshare drivers on social media have more positive views of unions than those who less frequently do so? And is this limited to online interactions, or do "offline" interactions have similar effects? Anecdotally, others have observed that work-driven networks in both the rideshare industry and in the Amazon Mechanical Turk marketplace increase workers' support for collective action, yet no study has systematically studied this relationship between social media and workers' views on unions. As workplaces become increasingly fractured, finding new means of connecting workers for collective labor activism is a central interest for labor researchers and activists. Yet currently, the link between *worker* developed social networks and workers' union attitudes is only theoretical. Since rideshare workers have yet to file for a union election, and legally this seems to be several years in the future, this paper empirically seeks to test if rideshare drivers who more frequently use social media to interact with other rideshare drivers express more positive views on unions' ability to resolve the problems they face at work than those who use interact less frequently with other rideshare drivers. Going beyond traditional unions, this paper also tests if greater social interaction between drivers is associated with more positive views on worker associations.

Data and Key Measures

Rideshare drivers were recruited for this study in three ways. The first set of study participants (N=226) were recruited with the aid of a worker organization in a large northeastern metropolitan area. The worker organization sent out both text messages and emails to its members notifying them of the study. Workers were informed that this study would be about labor conditions in the rideshare industry. At the end of the three-week signup period, 226 drivers had registered to participate.

A second recruitment channel utilized the “popular worker gathering spot” research strategy (Eigen, 2008a; Lind et al., 2000; Rosenblat & Stark, 2016). In the world of digital work, this means using online gathering spots to identify and recruit participants. Since Uber (and other gig companies) do not provide onboarding or much other information about how to use the service, drivers frequently turn to online resources in order to troubleshoot problems they experience while working.

Harry Campbell, a former rideshare drive, has one of the most popular online websites for rideshare drivers. Campbell’s website is routinely cited by major news outlets, such as the New York Times, Washington Post, and Time Magazine. Campbell posted a call for participants on his website in summer 2017 and sent an email to his mailing list notifying drivers about the study. This recruitment method yielded 234 participants.

Finally, I engaged in targeted Facebook recruitment (Kapp & Oliver, 2013) in an attempt to recruit drivers who had only recently started driving rideshare. Previous research has studied targeted Facebook recruitment and found that it can be appropriate for statistical inference (Fenner Y et al., 2012; Ramo & Prochaksa, 2012). Three closed Facebook groups were identified because they require drivers to send moderators proof of their driver status in order to join the group. Two of the three groups “pinned” the request at the top of their page for 7 days. This recruitment method yielded 26 participants.

After users signed up to participate in the study, they were sent the study documents via a Qualtrics online server. The study documents were optimized so drivers could respond while waiting for rides. Of the 490 drivers who signed up for the study, 488 provided semi-complete responses. Since this was not a random draw of drivers, drivers demographic information was checked against three previous demographic studies of rideshare drivers. In comparison to these three benchmarking studies, the participants in this study were slightly older and less racially diverse than previous studies of the rideshare market. Accordingly, models were reweighted to reflect the data found in Hall and Krueger (2015), but this did not change any of the outcomes variables of interest. Given how close the demographics of this study match previously conducted research, this is not unexpected.

Key Independent Variables

A. Social Connection to Other Drivers

The social connection scale was derived from qualitative interviews conducted from August 2016 to August 2017 with 75 rideshare drivers from across the United States. Drivers were recruited in several ways for these semi-structured interviews. First, I interviewed drivers as they entered and exited Uber's main New York City offices on 28th street. After that office closed, I interviewed drivers outside Uber's Long Island office. Additional drivers were recruited online with the help of Harry Campbell, "The Rideshare Guy". I used snowball sampling in order to reach additional rideshare drivers. Interview questions were updated as new interviews provided information regarding additional methods of connecting with other drivers.

Once these interviews reached theoretical saturation (Glaser & Strauss, 1968), researchers returned to early interviewees for member-checks (Lincoln & Guba, 1985). While much of the existing literature on rideshare driver communities focuses on online interactions, drivers reported other less visible means of connection as well. The qualitative data gathered in this study generated four distinct methods of communication: texting with other drivers, physically meeting other drivers, reading websites, and engaging with drivers on social media.

Conceptually, these four categories were derived to reflect how drivers used online and offline networks to learn about the labor conditions in the rideshare industry. Physically meeting up with other drivers was more commonly reported in smaller driver communities. Some of these drivers indicated they had such frequent interaction with other rideshare drivers they could identify them by their vehicle. Drivers also reported they would meet fellow rideshare drivers in gas stations or parking lots while waiting for a passenger. In these driver meet ups, workers indicated they discussed many different topics, including their experiences with the app and interactions with rideshare companies. Texting was also a way drivers interacted with other drivers, usually in a group chat. In these text conversations, drivers would ask how the road conditions were, if there were police checkpoints, and if the night was busy or “dead”. Drivers indicated that social media is a less intimate way of engaging with other drivers compared to either driver meet ups or texting. Finally, drivers said that engaging with drivers over websites, such as Facebook, Reddit, Twitter, and other Web 2.0 apps, was a way for drivers to share their experiences and learn about previous rideshare industry practices.

Since this paper looks to test the relationship between the frequency of driver interaction and views on union instrumentality, these four measures ranged from (1) Never to (4) Frequently (for means and standard deviations, see Appendix 1). The four elements of driver interaction (texting, websites, meetups, social media) were summed into a "social interaction" scale and returned a Cronbach's alpha of 0.80. This paper also will look at a subsection of that scale, the social media variable, to test the specific social media interaction frequency to see if it is associated with stronger views on union instrumentality.

Key Dependent Variable: Union Instrumentality.

This study tests the relationship between drivers' social interactions and (1) their views on union instrumentality and (2) driver's interest in joining a rideshare association. Existing research suggest that union instrumentality is a strong predictor of an individual's voting behavior (Montgomery, 1989; S. L. Premack & Hunter., 1988), making it a useful since certification election data is unavailable in the rideshare industry. Other research has argued that union instrumentality is particularly useful at predicting voting behavior with newly-hired workers because these workers are unlikely to have strong views about their current employer (LaHuis & Mellor, 2001). Since rideshare drivers usually leave the industry after six months, instrumentality is an especially useful predictor for rideshare drivers. Drawing on this literature, this study uses a previously validated union instrumentality scale to measure drivers' views on unions efficacy at resolving the problems they face at work (Davey & Shipper, 1993; T. A. Kochan, 1979). In addition, this paper also tests the relationship between drivers' social media interaction and their interest in joining a rideshare drivers' association. If social media is exposing drivers to the systematic economic problems of their industry, thus prompting them to support collective action, drivers may hold divergent views regarding unions in general compared to their views on the necessity of a union in the rideshare industry. To test this, a specific measure asked drivers' if they would consider joining a drivers' association.

Union Instrumentality. Previous research has documented several barriers to directly measuring the relationship between union attitudes and voting behavior (Fiorito, Daniel G. Gallagher, & Greer., 1986; Wheeler & McClendon, 1991). These problems are further complicated since drivers have yet to hold a unionization vote in the rideshare industry. To account for this complication, this study draws on research that examines their views on union instrumentality, a measure that has been previously shown to reasonably predict how workers will vote in an upcoming election (Johnson-Laird, 1983; Montgomery, 1989; Schriesheim, 1978).

Davey and Shipper discuss two other scales that were not used for this paper, (1) social pressure and (2) job satisfaction (Davey & Shipper, 1993). The "social pressures" scale largely assumes workers who interact with other employees in a traditional workplace (e.g., "How many, if any, of the people you know at work do you think will vote for the union?"). Likewise, the job satisfaction scale asks about supervision, which is not applicable to the 'gig' workplace. Instrumentality, however, asks general questions about workers' views on how unions change the workplace (e.g., union make sure workers are fairly treated or receive better pay) that could reasonably apply to gig based work. Drivers were asked to fill out the four-item union instrumentality scale, all of which were on a five-point Likert scale (means, standard deviations available in the Appendix). Consistent with past research, these items returned a 0.72 Cronbach's alpha.

Drivers' Association Measure. Directly asking about a drivers' interest in joining a drivers' association is complicated by the ongoing union drives in Seattle and other cities. In these campaigns, Uber has created podcasts that will automatically load within the drivers' application and informs drivers that they may lose their ability to set their own hours if the union vote succeeds. While there are considerable reasons to doubt this assertion, it could create additional variance when asking drivers if they would like to join a drivers' association. To account for this possible complication, the survey asked drivers their interest in joining a drivers' association and stated that the association would not change drivers' ability to set her/his own hours. In doing so, it allowed drivers to express their interest in joining an association outside of the messaging currently surrounding the union drives in Seattle and other cities. The drivers' association question was a five-point question, ranging from Strongly Disagree (1) to Strongly Agree (5) (mean = 3.77, SD = 1.16). This is very close to the union instrumentality scale (mean = 3.41, sd=0.89). The correlation between the two measures is 0.62, but a t-test returned a significant difference between the two measures ($t = -5.44$, $p<0.0001$)

Control variables. Several self-reported variables from the driver survey were included to control for possible co-variation with union attitudes. First, age was collected as a categorical variable but is used as a continuous variable to save degrees of freedom. Neither specification changed the models explanatory power or variables of interest. Race, full-time vs. part-time driver status, marital status, and gender variables were collected in the same fashion as Hall and Krueger (2015). These variables are included as dummy variables. Additionally, health care status was asked as a multiple part question about driver's source of coverage (e.g., other work, self-insured, government, spouse, no health care) but was collapsed into a binary variable (insured vs. not insured). Neither specification changed any outcome variable. Drivers were asked about if they had ever worked in a union or if a family member had worked in a union. Respondents could select multiple options (self, self and family, family, neither). To control for possible co-linearity between these options, this was collapsed into a binary variable: those who have previous experience (self or family) with unions (coded as 1) and those who do not (coded 0).

Some elements of the rideshare market do not easily map onto the industrial economy but still could influence drivers' relative bargaining power or change the dynamics of local rideshare markets. Local regulations vary significantly in this industry: some cities require drivers to purchase additional commercial insurance, undergo driver safety training, and purchase a professional driver's license. These licensing requirements require drivers to pay more upfront in order to work in the industry, changing the composition of the workforce, but also creating a greater labor scarcity. In order to control for this variation, respondents were asked if their local rideshare market required them to purchase a rideshare license. Additionally, drivers can work for multiple competing services simultaneously (e.g., Uber, Lyft, Amazon, Via, Juno, etc.). Consistent with previous research on bargaining power (Bacharach, 1986; Mishel, 1986), platform research suggests that the more competing services a driver can choose between, the greater bargaining power drivers will have (Srnicek, 2016). In order to control for these differences in bargaining power, models include the total number of rideshare platforms a driver uses.

Methods

Tables 1 and 2 displays the distributions and summary statistics for the categorical and continuous variables. The key dependent variables, the social connection scale and social media frequency, are continuous 1-5 variables. Accordingly, the models used in this paper are OLS models testing the relationship between social connection and union instrumentality. The first set of models regresses only the key dependent variables on the key independent variables. This acts as a test of association. Tables 3 and 4 display the regression analyses. Models' residuals did not return a significant skew while qqPlots indicated a continuous effect throughout the distribution. Model diagnostics indicated the presence of influential observations, so models were run both with and without these observations. Removing these variables did not change the variables of interest but did improve model fit. The models reported in this paper are those without outliers.

This study uses two different dependent variables, general union attitudes and a driver's interest in joining a rideshare association. The models test the association of these two dependent variables with the two key independent variables, the social interaction scale and a driver's use of social media. This configuration creates four separate models.

Results

Table 3 tests the association of the social interaction scale on the key independent variables, union instrumentality (model 1) and interest in joining a rideshare drivers' association (model 2) accounting for economic and demographic covariates. In model 1, driver's views on union instrumentality acts as the key dependent variable while the social interaction scale acts as the key independent variable. This model returned a significant ($p<0.01$) positive association (0.122) between general social interaction and driver's views on union instrumentality. For scale, roughly a four-point swing in the social interaction scale would be required to shift the key dependent variable by one standard deviation (0.89). This finding suggests that, as drivers increase their social interactions with other rideshare drivers, online or offline, it is associated with a more positive view of union instrumentality. Model 2 reports the relationship between the social interaction scale and respondent's reported views on joining a rideshare drivers union. In this model, the social interaction scale acts as the key independent variable while the respondent's views on a rideshare driver's association is the key dependent variable. This significant ($p<0.01$) positive association (0.252) suggests that greater social interaction with other drivers, either online or offline, is associated with more positive view toward joining a rideshare driver's association. For scale, it would take slightly more than a four-point swing in the social interaction scale in order to move the rideshare driver's association measure by one standard deviation (1.16).

Table 4 regresses the key dependent variables, views on union instrumentality (model 1) and interest in joining a rideshare association (model 2), on the isolated social media variable. In model 1, respondent's views on union instrumentality act as the key dependent variable while frequency of social media interaction acts as the key independent variable. This model reports a significant ($p<0.01$) positive (0.072) association between the frequency of social media interaction with other drivers and workers' views on union instrumentality. This finding suggests that digital interaction with other drivers has a positive effect on how workers view unions ability to resolve the problems they face at work. For scale, it would take roughly a four-point change in the social media variable to move the dependent variable by half of a standard deviation. In model 2, driver's interest in joining a rideshare driver's association acts as the key dependent variable while frequency of interacting with other drivers on social media acts as the key independent variable. This model reports a significant ($p<0.01$) positive (0.158) association between frequency of social media interaction and driver's interest in joining a rideshare drivers association. This suggests that greater social media interaction improves drivers' views on a rideshare drivers' association. For scale, it would take a roughly a five-point change in order to move the dependent variable by one standard deviation (1.16).

Discussion

In the traditional industrial relations literature, unionization drives are centered on institutional actors: laws, unions, and collective bargaining agreements. Yet as the informal sector of the economy continues to expand, workers are seeking out new methods of organizing and exerting collective pressure on management. With the rise of new communication and networking structures, industrial relations scholars must develop new frameworks for understanding how these form of community – both online and off – influence individuals' views on unions. This paper begins to test how CMC and alternative work arrangements can garner new insights into behaviors of workers in emerging forms of work.

This paper provides the first empirical data linking *worker-led* networks with union attitudes. Unions or other institutional actors did not build these networks; these networks emerged from drivers' own desire for more information about their industry. Platforms made the strategic decision to withhold onboarding information or tell drivers about the back-end of their algorithm, leaving workers without reliable information on the matching process, driver evaluations, how to handle difficult passengers, or the underlying surge calculations. From that void, workers began building their own online networks to help parse the best work practices, understand the performance evaluation system, and ask other drivers about their work experiences. Just like in the mTurk marketplace, those message boards, group chats, and Facebook groups allowed drivers to uncover systematic problems in the industry, such as miscalculated payments. It appears that the same technology that accelerated the gig economy – networked communication – is now being used by labor to identify problems within the industry and connect workers in a disconnected workplace.

For unions looking to organize nontraditional workers, these results provide some guidance. First, previous experience with trade unions, either directly or through a family member, was associated with stronger support for joining a rideshare association. While the binary formulation of this variable returned an insignificant association with workers' views on union instrumentality, other models (not shown) that used the four categories ("I have been a union member", "I have a family member who was a union member", "Both I and a family member have been union members", "Neither"), returned a strong significant association between a family member working in a union and workers' views on union instrumentality. This is consistent with before-and-after union election tests and studies of other industries. Since some cities have unionized transportation workers, identifying these workers could be beneficial to union organizers. In contrast, this study found that workers who enter the industry seeking part-time work generally held worse beliefs about union instrumentality and were less likely to express an interest in joining a drivers' association. One intriguing finding is that drivers with a graduate degree or less than a high school education hold stronger views of unionization than those with 2- or 4-year college degrees. While several factors may be driving this result, it is consistent with previous research that workers who have either higher education or lower bargaining power generally hold more positive general views on union instrumentality. For unions looking to target workers for union organizing drivers in the gig economy, this provides some insight into the demographic predictors of general union support in this area of work.

For lawmakers looking to craft legislation governing collective action, this study provides some insight into the divisions of interest that exist within the rideshare space. This study suggests that one of the strongest predictors of union support is if a worker is a full- or part-time driver. Other research, such as Uber-funded research, has touted that many rideshare drivers work for fewer than 40-hours a week. If the majority of workers seek out rideshare work because it allows them to schedule work around their other life obligations, a new model of union representation may be better able to balance labors' diverse interests in this category of work. While existing union drives indicate there is some interest in collective action to address existing problems in the rideshare industry, this split between part- and full-time workers suggests that lawmakers must think carefully about how to define a "community of interests" for these workers.

Third, this work brings together the information science literature on CMC and labor relations research on union organizing. The information science literature has documented that not only have advances in CMC increased the number of connections individuals have, but that these interactions may transmit information in different ways than face-to-face communication. For scholars of dispute resolution who have compared asynchronous online mediation against in-person mediation, this is a familiar finding. Yet the field of information science has documented that different forms of CMC have created entirely new types of communication and ways that information is transmitted between users. These new forms of communication, combined with the ubiquity of SNS, provide a possible opening for labor organizations to recruit union members and provide unfettered access to workers. These channels could sidestep two of the central challenges to existing union campaigns: identifying workers and gaining access to the workplace. With the spread of smartphones and increasing SNS density, labor organizations can communicate messages to workers both inside and outside the workplace without needing to perform house calls or gain access to the workplace. The asynchronous nature of SNS communication also allows workers to consume information at their own pace and return to previous conversations. Broadly, this study suggests these networks may have constructed a new institutional entity in union organizing: the worker-constructed network.

Limitations

This study has several limitations. First, theses data come from a cross-sectional survey, raising the risk of reverse causality. While it is unlikely that driver's views on unionization increase their social media behavior, these data cannot rule it out. Since there has yet to be a union election in the gig economy space, we cannot test the relationship between social media consumption and pre- and post-election behaviors. Yet previous research has documented that union instrumentality is a reliable predictor of future union voting behavior. These measures will need to be further validated when drivers in either Seattle, San Francisco, or New York hold a union certification election.

Second, since some participants were recruited from a social media website, this could bias the sample by including workers who are from the higher-end of the of the social media distribution. Model residuals were not clearly skewed in the direction of higher social media engagement and qqPlots indicated a consistent effect throughout the distribution. This suggests that even if this is from a higher end of the distribution, it is not driving the model results. Furthermore, when removing the data (N=26) from drivers who were recruited via other sources, it did not change the key results (some controls became less significant, but this is most likely due to the decrease in model power).

Third, sample participants were not randomly drawn from the population of rideshare drivers. As other scholars have pointed out, it is difficult to sample from nonstandard workers because it is hard to identify these workers and many quickly move in and out of nonstandard work. This problem is compounded in gig arrangements where workers have no obligation to work for any amount of time, can move between companies at will, and even the platforms themselves do not know the total number of workers on the platform. In short, even a random draw from a gig company may not yield a representative sample because some workers may intentionally *avoid* certain companies. Yet as seen in Chapter 1's appendix, this sample is close to the randomly drawn sample of Uber drivers in Hall and Krueger (2015), the random draw of Yahoo! users found Kooti et al. (2017), and Harry Campbell's nonrandom (but cross-platform) demographic benchmarks. Due to this, the nonrandom nature of participants is less likely to be driving the results.

Conclusion

Today, interactions are virtual and physical, text-based and vocal, asynchronous and simultaneous, broad and narrow. The emergence of SNS and CMC have forged new links between people and changed the way information is transmitted between workers. Can these new links be used to rekindle the labor movement? This study provides three insights into this question. First, worker-designed networks may have the ability to reinforce or change other workers' views on unions and about the role of collective action in their industry. In workplaces where workers may not have physical contact with others, these online gathering spots may become the "digital water coolers" where people can exchange their experiences. Second, these networks could overcome some of the existing bottlenecks in the American industrial system. Unions frequently face difficulty in accessing the workplace and contacting workers, yet now workers can simultaneously exchange information and literature while at, or away from, work. Workers can also read information anonymously and without fear of reprisal, lowering the cost of entering these conversations. Third, these networks show that non-traditional actors in the industrial system may play an important role in developing collective action in the gig economy. While much of the industrial relations literature focuses on union campaigns by established labor institutions, worker-driven networks are spreading information outside of these formal structures. In short, the same technology responsible for the emergence of platforms appears to be connecting workers in new ways as well, and in doing so, may change the way workers view the role of unions in emerging types of work.

Tables and Figures

Table 1: Sample Description – Categorical Variables	
Married	62.80%
Age 18-29	8.64%
30-39	21.81%
40-49	25.99%
50-64	39.21%
65+	1.60%
Education – Some High School	1.85%
High School or Eq	9.88%
2 Year College	29.01%
4 Year College	40.33%
Graduate Degree	18.93%
Gender – Female	17.60%
Rideshare License	54.80%
Full Time	38.90%
Part Time	30.37%
Transitional Work	17.40%
Work Rideshare - Other Reason	13.30%
White Non-Hispanic	60.29%
Black Non-Hispanic	10.70%
Asian Non-Hispanic	12.55%
Other Non-Hispanic	5.35%
Hispanic	10.49%
Union Membership [Yes]	48.66%

Table 2: Distribution of Continuous Variables		
	Mean	**S.d.**
Social Scale	2.35	0.76
Loyalty Scale	2.47	0.76
Total Time Driving (months)	21.17	14.58
Social Media Frequency	2.23	1.19
Number of Platforms	2.19	1.02
Rideshare Association Interest	3.77	1.16
Union Instrumentality	3.41	0.89

Table 3: Regressing (OLS) Drivers' Views on Interest in Joining a Rideshare Association and Union Instrumentality on Social Interaction Scale.		
	Union Instrumentality	Interest in Joining a Rideshare Association
Some High School	**0.751****	-0.31
	0.312	0.436
Some College	0.073	0.02
	0.144	0.18
Two Year College	-0.171	-0.128
	0.173	0.22
Four Year College	0.052	0.154
	0.145	0.181
Graduate Degree	0.185	**0.415****
	0.153	0.193
Black Non-Hispanic	**0.311****	**0.329****
	0.12	0.164
Native American	0.1	**1.201***
	0.429	0.701
License - Yes	**0.259*****	**0.363*****
	0.09	0.122
Part Time	**-0.399*****	**-0.412*****
	0.092	0.124
Other Work	**-0.248****	-0.023
	0.123	0.16
Union [Yes]	**0.128***	**0.39*****
	0.073	0.098
Job Satisfaction	**-0.086***	**-0.139****
	0.048	0.064
Total Time Working Rideshare [Months]	0.001	0.005
	0.003	0.004
Platform Count	**-0.098****	-0.011
	0.042	0.058
Social Scale	**0.122****	**0.252*****
	0.052	0.07
Nobs	415	406
R-Squared	0.170	0.229

*** = p<0.01, ** = p<0.05, * = p<0.10. "---" indicates variables not used for that regression. Number of observations changes based on the number of complete cases for each regression.

Table 4: Regressing (OLS) Drivers' Views on Interest in Joining a Rideshare Association and Union Instrumentality on Social Media Interaction		
	Union Instrumentality	Interest in Joining a Rideshare Association
Some High School	**0.866*** **	-0.212
	0.306	0.433
Some College	0.142	0.074
	0.139	0.177
Two Year College	-0.097	-0.022
	0.166	0.217
Four Year College	0.123	0.197
	0.14	0.178
Graduate Degree	**0.276** **	**0.460** **
	0.148	0.19
Female	0.113	-0.108
	0.097	0.131
Black Non-Hispanic	**0.330*** **	**0.364** **
	0.119	0.163
Hispanic	0.023	0.027
	0.129	0.171
License - Yes	**0.280*** **	**0.396*** **
	0.088	0.121
License - Don't Know	-0.372*	-0.092
	0.191	0.273
Part Time	**-0.4*** **	**-0.365*** **
	0.091	0.123
Union [Yes]	**0.141* **	**0.352*** **
	0.072	0.097
Job Satisfaction	**-0.099** **	**-0.165** **
	0.048	0.063
Total Time Working Rideshare [Months]	0.001	0.005
	0.003	0.003
Platform Count	**-0.089** **	-0.01
	0.041	0.056
Social Media Interaction	**0.072** **	**0.158*** **
	0.03	0.041
Nobs	416	408
R-Squared	0.179	0.231

*** = p<0.01, ** = p<0.05, * = p<0.10. "---" indicates variables not used for that regression. Number of observations changes based on the number of complete cases for each regression.

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CHAPTER 5: CONCLUSION

What do these studies suggest about the future of industrial relations? First, these studies indicate that the resolution of platform conflict is associated with desirable outcomes for both platform workers and operators. Platforms are seeking to expand rapidly, both on their labor-side and customer-side, in order to prevent competitors from entering their market-space. Due to this strategy, platforms use their investment capital to attract and retain both workers and customers. Users of these platforms are familiar with these strategies: “first three rides are free”, “refer a friend for $15 off your next ride” or “guaranteed $X if you work 2 hours at this time” and others. By largely focusing on economic factors, these strategies assume that customers (and labor) are primarily price-conscious and give other factors little, if any, weight when deciding between rideshare platforms. If this were the case, then a labor-management relationship between drivers and platforms would not have a significant effect on key organizational outcomes.

The results of this dissertation suggest otherwise. These studies suggest conflict has taken on a new dimension; it operates both upward (labor-platform conflict) and across platform (between users), requiring platform managers to consider how they write the rules regulating consumer-labor interactions. The current state of these rules reflects platforms’ general perspective that labor is more dependent on platforms than customers, resulting in work rules that favor customers to workers in the event of a dispute. This strategy may be changing, though; as driver churn accelerated in 2016 and 2017, both Uber and Lyft developed new driver-side accommodations in order to improve their overall user experience, including providing new forms of driver support. Uber announced their '180 days' of change in June of 2017, while Lyft has been slowly rolling out new features to give drivers greater control over their work. As these markets develop and labor can exercise greater autonomy on platforms, this may naturally result in platforms raising their labor standards.

This is the most optimistic outlook for platform labor, though. Existing research suggests that platforms naturally converge into monopolies, like Google for search engines, Twitter for microblogging, and Facebook for social interaction. If the results of this study are correct, that drivers generate bargaining power by whipsawing competing platforms, this would suggest a dark future for platform workers once platforms converge into a single dominant organization. This is not only possible, but also the very likely endpoint for this industry: all current rideshare companies are running at large financial losses, ranging from Uber's $4 billion to Lyft's roughly $1 billion losses in 2017. These platforms are relying upon the convergence of markets into a digital monopoly so they can raise their prices and finally pay their creditors. If they are unable to do this, then rideshare platforms will become the latest examples in a long-line of platform causalities.

Yet if rideshare companies do consolidate, that poses significant questions for both regulation and drivers' bargaining power. In a market dominated by a single organization, rideshare platforms will be able to act as monopolists and exert their market power over riders, drivers, and cities in order to increase profits. Drivers will not have alternative platforms to use as leverage, leaving them to with few options outside of exit. Additionally, given drivers' low barriers to entry, there is no institutional protection for drivers in the event of platform consolidation. The popular press is already publishing stories of drivers sleeping in their cars and committing suicide due to their precarious economic condition, but labor conditions may become worse in the near future. Without unions or other labor organizations, labor standards are likely to fall as rideshare companies consolidate market share.

Cities, too, should be deeply worried that they will become overly reliant on rideshare platforms for providing public transportation. In 2015, Uber launched "De Blasio mode" that displayed longer wait times and higher prices to each customer in New York City. A popup message would then state that these times and prices would be the result of De Blasio's proposed regulation and displayed a number customers could call to voice their opposition to De Blasio's proposed measures. The city government was flooded with angry calls and the city quickly dropped their proposal. Uber used the same strategy in Austin, Texas, threatening to cease service in Austin if the city required drivers to undergo a fingerprint background check. In June 2016, Uber and Lyft left Austin over the dispute. A single rideshare platform that controls transportation in most major cities and sets transportation prices across the United States poses serious labor and public policy problems given the complete absence of an institutional counterbalance.

Furthermore, the question of work rules has yet to be determined in this category of work. For example, do platforms need to specifically state the conditions to stay connected to their networks? There are similar issues in social media platforms, such as determining when Twitter users are removed from the platform for invoking hate speech or “doxxing” someone (the platform even had to append its code of conduct to regarding ‘threats of violence’ after the President of the United States threatened to start a nuclear war with North Korea via tweet. Government actors are now excluded). Unlike standard employment, where the ‘terms and conditions of employment’ are generally available to workers, platforms make modifications to their code on a near daily basis. The opacity of these terms can present problems for workers, such as Uber’s floating “acceptance rate” requirement or what “star rating” a driver must maintain in order to stay connected to the platform. It seems reasonable to assert that workers need to be made aware of the platform standards and rules so that they can make informed decisions about how to allocate their labor. Yet currently, regulators have been silent on this point and platforms have adopted varying levels of opacity with regard to their matching algorithms, disciplinary decisions, and terms and conditions of work.

This suggests that, absent institutional intervention, conflict between workers and platforms has yet to peak. Existing laws, like the National Labor Relations Act or institutions, like Federal Mediation and Conciliation Service, are ill suited for handling these disputes given the locations and dynamics of platform-conflict. Instead, it appears that new institutions, like flexible unions that act like platforms, may be one method of rebalancing the labor-platform relationship. “Unions as platforms” could allow workers to promise either a certain number of hours or relinquish the right to work for competing platforms for a determined period of time in order to gain better terms and conditions for employment. For example, a Lyft driver could foreswear the use Uber’s application for three weeks and drive for at least 20 hours a week in exchange for better compensation per minute or mile (or access to insurance, health care, etc.). A different and more provocative solution lies in allowing workers to control platforms themselves. If it is true that rideshare platforms are mainly digital dispatch services, then the dominate model in this space may be one that allows workers to control the means of production themselves instead of relinquishing 30% of their work product to a rideshare company. This could potentially solve the multi-homing problem because it would better align workers' interests with those of the platform.

Despite the changes in market structures and institutions, this dissertation argues that the resolution of workplace conflict is a pressing concern for platform operators. Although the locations, tactics, and methods have changed, workers make important work decisions based both on the quality of their work lives and the compensation promised from a platform. This means there may not be a single solution for firms to maximize their share of the market; in fact, firms may find that supporting workers is the more durable long-term strategy. With an industry that is only ten years old, strong projections in the future is a risky practice, but the results of this study suggest that resolving conflict and improving labor-management relationships is a critical element of the 'gig' economy.

Appendix – Survey Instrument

Do you work as a rideshare driver as a full-time, part-time, transitional, or other form of work?
My full-time job: this is my primary occupation and I am not looking for other work [38.9%]
Part-time job: I have another job but work as a rideshare driver as for additional income [30.3%]
Transitional job: I am between jobs and am using rideshare as a way of bridging under-/un-employment [17.4%]
Other: I drive for other reasons (please specify) [13.3%]

Please select your highest educational attainment:
Some high school [1.8%]
High school or equivalent [9.8%]
Some college/Associate's [29.0%]
2-year College [9.4%]
4-year College [30.7%]
Graduate or post-college degree [19.0%]

Please let us know your age:
18-24 [6.9%]
25-29 [19.4%]
30-39 [23.1%]
40-49 [34.3%]
50-64 [14.1%]
65+ [1.6%]

Please select your gender:
Male [82.3%]
Female [17.6%]

Please select how you racially identify:
Black Non-Hispanic [10.6%]
Hispanic [10.45%]
Caucasian/White Non-Hispanic [60.4%]
Asia/Pacific Islander Non-Hispanic [12.5%]
Native American [0.6%]
I choose not to specify [5.3%]

Please check all that apply:
I am married [37.2%]
I have children at home [59.2%]
I am currently attending school [5.9%]
I am retired [86%]
I am a military veteran [9.4%]
I am a citizen of the United States [77.0%]

Do you set an amount you wish to make each day (a 'target' amount) and stop driving after reaching that amount?
Yes [43.4%]
Sometimes [34.3%]
No [22.2%]

What city and state do you primarily drive in?

Prior to becoming a rideshare driver, did you have professional experience in the transportation industry? (Check all that apply)
Taxi driver [13.5%]
Public transportation (example: Metro driver) [2.8%]
Black car service [12.2%]
Other private transportation services (example: limousine driver) [13.7%]
No transportation experience [67.2%]

Do you currently have health insurance?
Yes, from my spouse/partner [16.9%]
Yes, employer-provided from another job [14.2%]
Yes (other) [13.8%]
Yes - Medicare or other government health care provider [36.7%]
I do not have health insurance [18.3%]

Do you carry supplemental rideshare insurance?
Yes [38.4%
No [59.6%]
I used to but I do not anymore [1.8%]
Don't know []

What type of vehicle do you primarily use when you are working for a rideshare company:
Small Sedan [15.9%]
Medium Sedan [35.6%]
Large Sedan [11.2%]
4 Wheel Drive SUV [22.7%]
Minivan [5.7%]
Other [8.6%]

Why do you drive for a rideshare company?
To earn more income to better support myself or my family [67.7%%]
To be my own boss and set my own schedule [47.7%]
To have more flexibility in my schedule and balance my work with my life and family [45.2%]
To help maintain a steady income because other sources of income are unstable/unpredictable [27.2%]
Laid off from other job [12.5%]
To offset any swing in income from my other job [9.6%]
Other [9.2%]

Does your city require rideshare drivers to possess an additional license to drive for a rideshare company? (For example, in New York City, drivers must have a driver license and a livery license.)
Yes [43.5%]
No [52.7%]
Don't Know [3.7%]

When working for a rideshare company, I typically drive:
Daytime hours (6AM-5PM) [48.9%]
Evening hours (7PM-10PM) [43.3%]
Nights (10PM-4AM) [34.4%]
Weekends Only [10.0%]
Whenever I am free [35.2%]

When did you begin driving for a rideshare company?
Year:
2009: 0.6%
2010: 0.2%
2011: 0.2%
2012: 2.4%
2013: 4.9%
2014: 14.7%
2015: 26.8%

2016: 32.4%
2017: 17.8%

Month:
Jan: 11.2%
Feb: 7.9%
March: 9.2%
April: 7.9%
May: 10.4%
June: 6.1%
July: 5.9%
August: 9.2%
Sept: 7.7%
Oct: 6.1%
Nov: 7.1%
Dec: 6.3%

Using the scale below, please identify the option that best represents your experience with the following statements/events:
1. I interact with an unruly or disruptive passenger [Median: 2.0, Mean: 2.96, SD: 1.48]

2. I file a cleanup fee due to a passenger damaging my vehicle [Median: 1.0, Mean: 2.89, SD: 0.94]

3. Passengers attempt to "squeeze" too many passengers into my vehicle beyond the legal limit [Median: 2.0, Mean: 2.25, SD: 1.41]

4. I receive incorrect compensation from a platform (e.g., you did not receive the full fare for a ride) [Median: 2.0, Mean: 2.89, SD: 1.54]

5. I file a complaint with a rideshare company over passenger behavior [Median: 2.0, Mean: 2.25, SD: 1.22]
Range: “Every time I drive” (6), “Every Week” (5), “Once a Month” (4), “Less than Once a Month” (3), “Almost Never”(2), “Never” (1)

On the first platform you started driving for, has there been a reduction in how much they pay per mile or by the minute?
Yes [63.7%]
No [23.5%]
Can't remember [12.7%]

How much has this reduction impacted the total amount you make on this platform?
1-10% less [17.4%]
11-20% [34.7%]
21-30% [22.5%]
31-40% [13.1%]
41-50% [6.4%]
more than 50% [5.4%]

Have you worked for any of the following online platforms (check all that apply):
TaskRabbit [1.2%]
Amazon Mechanical Turk [12.2%]
Catalant (3) [0%]
Honor (4) [0%]
Handy (5) [0.6%]
PeoplePerHour (6) [0.2%]
Fiverr [0.6%]
Upwork [1.4%]
Postmates [8.4%]
Grubhub [2.8%

Have you or a family member ever worked in a union?

Yes, I have worked in a union [21.5%]
Yes, a family member has worked in a union [18.6%]
No, neither I nor a family member has worked in a union [51.2%]
Both a family member and I have been a member of a union [8.4%]

Which platforms are available where you drive (select all that are available even if you do not drive for them):
Uber [97.7%]
RideAustin [2.6%]
Lyft [94.0%]
Juno [36.2%]
Wingz [4.9%]
Flywheel [3.6%]
Curb [9.2%]
Gett [30.7%]
Hailo [2.2%]
Summon [0.0%]
Amazon Flex/Prime [27.6%]
Shuddle [0.0%]
Boomerang [0.0%]
Buckle [0.0%]
Via [29.7%]

Using the scale below, please identify the option that best represents your experience with the following statements/events: [Options: Frequently, Sometimes, Rarely, Never]
I speak with other rideshare drivers Mean: 2.2, SD = 0.97
I communicate with other drivers over text message. Mean = 2.95, SD = 1.09
I interact with other drivers using social media (e.g., Facebook, Twitter, etc.) Mean = 2.22, SD = 1.2
I read websites about the rideshare industry Mean = 1.69, SD = 0.87
I meet up with other drivers socially 3.17 SD = 1.06
I listen to podcasts about the rideshare industry Mean = 2.95, SD = 1.11
I talk with other drivers about how to manage the problems I encounter while driving Mean = 2.62, SD = 1.08

Using the scale below, please rate the extent to which you agree or disagree with the following statements: [Options: Strongly Agree, Agree, Neither Agree nor Disagree, Disagree, Strongly Disagree] [*Note: Question loops for each rideshare company*]

I feel my rideshare company has treated me fairly
[Strongly Agree: 66.5%, Agree: 22.5%, Neither Agree nor Disagree: 5.3%, Disagree: 1.2%, Strongly Disagree: 0.0%]

Driver support is an important part of any rideshare service
[Strongly Agree: 57.7%, Agree: 25.6%, Neither Agree nor Disagree: 9.8%, Disagree: 1.2%, Strongly Disagree: 1.0%]

Pay is the most important aspect of a ride share service
[Strongly Agree: 51.6%, Agree: 30.9%, Neither Agree nor Disagree: 9%, Disagree: 4%, Strongly Disagree: 0.0%]

I control how much I make as a rideshare driver
[Strongly Agree: 11.0%, Agree: 30.1%, Neither Agree nor Disagree: 18.4%, Disagree: 17.8%, Strongly Disagree: 11.4%]

It is easy to drive for multiple services
[Strongly Agree: 18.8%, Agree: 34.6%, Neither Agree nor Disagree: 30.3%, Disagree: 18.8%, Strongly Disagree: 3.8%]

Using the scale below, please rate the extent to which you agree or disagree with the following statements: [Strongly Agree, Agree, Neither Agree nor Disagree, Disagree, Strongly Disagree]
Unions make sure that workers are fairly treated by supervisors Mean = 2.3, SD=1.14
Unions help working men and women to get better wages. Mean = 2.11, SD = 1.07
I believe that a drivers union would harm my work as a rideshare driver Mean = 3.47, SD = 1.28
Unions interfere with good relations between companies and employees Mean = 2.01, SD = 1.24
I would consider joining a drivers union if the union did not prevent me from setting my own hours Mean = 2.23, SD = 1.16

How long do you plan to continue to drive as a rideshare driver?
[Mean = 3.3, SD = 1.13]
0-3 more months (1)
4-6 more months (2)
6 months to a year (3)
I have no plans to stop driving as a rideshare driver (4)

Using the scale below, please let us know the extent to which you agree or disagree with the following statement: My view of these services is better than when I started driving for them. [Carry forward all companies driver currently works for. Options: Strongly Agree, Agree, Neither Agree nor Disagree, Disagree, Strongly Disagree]

Uber – Strongly Agree, (7.7%), Agree (10.4%), Neither Agree nor Disagree (18.6%), Disagree (21.7%), Strongly Disagree (26.2%), [No response: 15.1%]

Lyft – Strongly Agree (10.0%), Agree (16.5%), Neither Agree nor Disagree (23.5%), Disagree (13.1%), Strongly Disagree (8.8%) [No response: 27.8%]

If a friend was looking to start driving as a rideshare driver, I would recommend s/he use the following services: [Carry forward all companies that operate in the driver's area. Options: Highly Recommend, Recommend, Neutral, Would Not Recommend, Strongly Would not Recommend, N/A]

Uber – Highly Recommend (10.4%), Recommend, (26.4%), Neutral (23.3%), Would Not Recommend (14.1), Strongly Would not Recommend (18.8%), NA: 0.8%

Lyft – Highly Recommend (21.5%), Recommend (29.5%), Neutral (18.6%), Would not Recommend (8.6%), Strongly Would not Recommend (7.7%), NA: 4.0%

Using the scale below, please indicate the extent to which you agree or disagree with the following statement for $[lm://Field/1]

1. I represent $[lm://Field/1] favorably to outsiders
Uber: Median: 3.0 Mean: 3.23, SD: 1.26
Lyft: Median: 4.0 Mean: 3.91, SD: 1.06

2. I do not go out of my way to defend $[lm://Field/1] from criticism
Uber: Median: 2.0 Mean: 2.23, SD: 1.13
Lyft: Median: 3.0 Mean: 2.87, SD: 1.06

3. I tell others that [lm://Field/1] is a good place to work
Uber: Median: 3.0 Mean: 2.32, SD: 1.16
Lyft: Median: 4.0 Mean: 3.54, SD: 1.07
4. I actively promote $[lm://Field/1]'s service to others
Uber, Median: 3.0 Mean: 2.76, SD: 1.20
Lyft: Median: 4.0 Mean: 3.41, SD: 1.18

5. I would accept a job at a competing rideshare company if they offered me more pay
Uber, Median: 1.0, Mean: 1.58, SD: 0.87
Lyft: Median: 2.0 Mean: 1.87, SD: 0.99

6. I would invest in $[lm://Field/1] if it were a public company
Uber, Median: 3.0, Mean: 2.74, SD: 1.27
Lyft: Median: 3.0, Mean: 3.31, SD: 1.23

Using the scale below, please indicate the extent to which you agree or disagree with the following statement or [company. Options: Strongly Agree, Agree, Neither Agree nor Disagree, Disagree, Strongly Disagree]:

I encourage passengers to join [company]
Uber: Strongly Agree (0.8%), Somewhat Agree (21.9%), Neither Agree nor Disagree (29.9%), Somewhat Disagree (10.0%), Strongly Disagree (15.3%)
Lyft: Strongly Agree (20.9%), Somewhat Agree (21.1%), Neither Agree not Disagree (20.6%), Somewhat Disagree (3.0%), Strongly Disagree (5.9%)

I encourage drivers from other rideshare companies to work for [company]
Uber: Strongly Agree (5.1%), Somewhat Agree (18.8%), Neither Agree nor Disagree (24.5%), Somewhat Disagree (14.5%), Strongly Disagree (22.1%)
Lyft: Strongly Agree (17.2%), Somewhat Agree (22.5%), Neither Agree nor Disagree (21.2%), Somewhat Disagree (3.6%), Strongly Disagree (7.3%)

I prefer working for [company] over other rideshare services
Uber: Strongly Agree (7.7%), Somewhat Agree (15.3%), Neither Agree nor Disagree

(18.4%), Somewhat Disagree (5.9%), Strongly Disagree (21.3%)
Lyft: Strongly Agree (19.2%), Somewhat Agree (19.6%), Neither Agree nor Disagree (18.4%), Somewhat Disagree (5.9%), Strongly Disagree (8.6%)

When working, I intentionally stay online with [company] more than my other rideshare platforms
Uber: Strongly Agree (20.6%), Somewhat Agree (19.2%), Neither Agree nor Disagree (20.4%), Somewhat Disagree (8.4%), Strongly Disagree (15.5)
Lyft: Strongly Agree (13.1%), Somewhat Agree (12.0%), Neither Agree nor Disagree (22.5%), Somewhat Disagree (12.7%), Strongly Disagree (11.2%)

I feel that [company] values me as a driver

Uber: Strongly Agree (2.4%), Somewhat Agree (7.5%), Neither Agree nor Disagree (15.1%), Somewhat Disagree (19.6%), Strongly Disagree (39.95)
Lyft: Strongly Agree (22.3%), Somewhat Agree (22.3%), Neither Agree nor Disagree (21.5%), Somewhat Disagree (7.7%), Strongly Disagree (9.4%)

I am satisfied working for [company]
Uber: Strongly Agree (3.9%), Somewhat Agree (20.4%), Neither Agree nor Disagree (18.6%), Somewhat Disagree (20.0%), Strongly Disagree (21.3%)
Lyft: Strongly Agree (10.6%), Somewhat Agree (27.4%), Neither (17.4%), Somewhat Disagree (8.6%), Strongly Disagree (7.1%)

If I had a problem with [company] 's service or a passenger, [company] would provide the necessary support.
Uber: Strongly Agree (7.1%), Somewhat Agree (19.4%), Neither (17.0%), Somewhat Disagree (20.6%), Strongly Disagree (20.4%)
Lyft: Strongly Agree (11.8%), Somewhat Agree (21.9%), Neither (21.5%), Somewhat Disagree (6.7%), Strongly Disagree (8.8%)

Have you deliberately stopped driving for any of these services: [Carry forward all the operate, but not selected as driving with] [Choices Carry Forward]

[No deactivations reported]

Have you been deactivated from any of these services? (Please select even if you have been reactivated) [Carry forward all that operate in the area]

[None]

When did you download your second rideshare application?
Month:
Jan: 8.1%
Feb: 4.3%
March: 9.0%
April: 6.5%
May: 8.4%
June: 6.7%
July: 4.3%
August: 6.7%
Sept: 6.9%
Oct: 2.4%
Nov: 4.5%
Dec: 3.2%

Year:
2011: 0.0%
2012: [NA]
2013: 1.1%
2014: 9.2%
2015: 21.4%
2016: 42.3%
2017: 25.3%

Why did you decide to begin driving on a second rideshare service (select all that apply)?
Better chance of catching a fare [58.5%]
Poor Customer Service Experience on First Service [15.9%]
Incident With a Passenger on First Service [3.8%]
Recruitment Bonus From Second Service [26.0%]
Compensation Reduction on First Service [16.3]
Disliked Business Practices of First Service [21.9%]
Felt the Service Did Not Care About Drivers [27.6%]
Second Service Pays Better [27.0%]
Other [8.4%]

Please rank your selections your reasons, from most important (#1) to least important (highest number), for why you started driving for a second service: [carry forward all checked above]
Better Chance of Catching a Fare (Mean = 2.12, SD = 1.51)
Poor Customer Service Experience (Mean = 3.29, SD = 1.53)
Incident with a Passenger (Mean = 2.12, SD = 2.12)
Recruitment Bonus (Mean = 2.7, SD = 1.64)
Compensation Reduction (Mean = 2.89, SD = 1.82)
Business Practices (Mean = 3.26, SD = 1.68)
First Service Didn't Care About Drivers (Mean = 2.99, SD = 1.52)
Second Service Pays Better (Mean = 2.94, SD = 1/77)

Which order did you download your rideshare applications: [Carry forward all that the driver works for]
Uber [Mean: 1.29, SD = 0.57]
Lyft [1.88, SD = 0.65]

Imagine you were able to make the same amount of money (same number of rides, compensation per mile, etc.) regardless of which service you drove for. In this scenario, please rank your the rideshare services you would drive for from best (#1) to worst (highest number): [carry forward all services a driver works for]
Uber [Mean = 2.07, SD = 0.87]
Lyft [Mean = 1.72, SD = 0.91]

Do you boot up your rideshare platforms in a set order? (in other words, do you always log into one service first, then wait for a set period of time before logging into other rideshare services?).
Yes [43.0%]
No [56.9%]

Please let us know the order which you turn on your ride share platforms:
Uber [Mean = 1.55, SD = 0.81]
Lyft [Mean = 1.94, SD = 0.81]

How much time (in hours) were you online on each platform? (include time when the app was open and you were waiting for a ping)
Uber: 24.16 Hours (SD = 20.97)
Lyft: 17.39 Hours (SD = 17.55)

Appendix II – Second Survey Instrument

Did you drive for a rideshare company last week?

Yes [82.4%]

No [17.5%]

Do you plan to drive for a rideshare company in the foreseeable future?

Yes [96.0%]
No [3.91%]

In the last seven days, did any of the following occur while you were driving for a rideshare company? [Checkbox, all that apply]

Verbal confrontation (e.g., argument) with a passenger
Passengers trying to squeeze too many people into your car
Routing dispute with a passenger
Passenger(s) attempted to bring an open container of alcohol into your vehicle
You filed for a cleanup fee
Rideshare application crashed while using it
Passenger damaged your vehicle
A passenger left an item in your car

How many times did each of these events occur in the last week? [Carry forward answers from above] [Count variable]

Verbal confrontation (e.g., argument) with a passenger Mean = 2.97, SD = 1.48
Passengers trying to squeeze too many people into your car Mean = 2.89, SD = 1.41
Routing dispute with a passenger Mean = 2.51, SD = 2.69
Passenger(s) attempted to bring an open container of alcohol into your vehicle Mean = 2.55, SD = 2.53
You filed for a cleanup fee Mean = 3.29 SD = 5.62
Rideshare application crashed while using it Mean = 3.71, SD = 3.35
Passenger damaged your vehicle Mean = 1.59, SD = 1.5
A passenger left an item in your car Mean = 1.77, SD = 2.04

For how many of these events did you file a report (customer service email or phone call) with the rideshare service?

Verbal confrontation (e.g., argument) with a passenger Mean = 1.58 SD = 2.24
Passengers trying to squeeze too many people into your car Mean = 1.7, SD = 3.23
Routing dispute with a passenger Mean = 1.81, SD = 2.91
Passenger(s) attempted to bring an open container of alcohol into your vehicle Mean = 0.86, SD = 1.71

You filed for a cleanup fee Mean = 3.29, SD= 5.22
Rideshare application crashed while using it, Mean = 1.39, SD = 1.8
Passenger damaged your vehicle Mean = 0.4 SD = 0.51
A passenger left an item in your car Mean = 1.76, SD = 3.34

Over the last week, how many hours were you online on each of these platforms (please include time while you were online and waiting for a passenger): [Carry forward all services from above]
Uber: Mean = 18.56, SD = 18.86
Lyft: Mean = 12.79, SD = 15.02

Over the last week, how much did you earn on each platform? (in US dollars)? [Carry forward all services]
Uber: Mean = 381.94, SD = 284.7
Lyft: Mean = 216.98, SD = 208.06

At your **non-rideshare job**, please let us know about the hours you worked last week:

I was not able to work at my other job last week [0.0%]

I worked more hours than I would have preferred last week [4.7%]

I worked fewer hours than I would have preferred last week [6.4%]

I worked the hours I wanted last week [15.0%]

I do not work hourly [6.9%]

Rideshare full time [65.9%]

Please evaluate the following statements: [Options: Definitely yes, Probably yes, Might or might not, Probably not, Definitely not]

As a consumer, will you use rideshare in the future? Mean = 1.75, SD = 0.98
Did your experience as a driver influence which rideshare companies you will use as a consumer? Mean = 2.01, SD = 1.17

Please let us know the order that you would use these applications **as a consumer** (1 = the first app you would open, 2= the second app you would open, etc.):
Uber: 1.90, SD = 0.95
Lyft: 1.76, SD = 1.05

Do you boot up your rideshare platforms in a set order? (In other words, do you always log into one service first, then wait for a set period of time before logging into other rideshare services?)
Yes [44.0%]
No [55.9%]

When you decided to stop driving rideshare, did you sign off of all your platforms at once?
Yes, I stopped driving for all platforms at once [100%]
No, I stopped using some platforms before others [0.0%]