Expanding the Locus of Resistance: Understanding the Co-Constitution of Control and Resistance in the Gig Economy

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ABSTRACT

Existing literature examines control and resistance in the context of service organizations that rely on both managers and customers to control workers during the execution of work. Digital platform companies, however, eschew managers in favor of algorithmically mediated customer control—that is, customers rate workers, and algorithms tally and track these ratings to control workers' future platform-based opportunities. How has this shift in the distribution of control among platforms, customers, and workers affected the relationship between control and resistance? Drawing on workers' experiences from a comparative ethnography of two of the largest platform companies, we find that platform use of algorithmically mediated customer control has expanded the service encounter such that organizational control and workers' resistance extend well beyond the execution of work. We found that workers have the most latitude to deploy resistance early in the labor process, but must adjust their resistance tactics because their ability to resist decreases in each subsequent stage of the labor process. Our paper thus develops understanding of resistance by examining the relationship between control and resistance before, during, and after a task, providing insight into how control and resistance function in the gig economy. We also demonstrate the limitations of platforms' reliance on algorithmically mediated customer control by illuminating how workers' everyday interactions with customers can influence and manipulate algorithms in ways that platforms cannot always observe.

Keywords: algorithms, resistance, labor process theory, service work, gig economy, Uber, Lyft

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Scholars have documented how organizations, such as hospitals, universities, hotels and restaurants, increasingly use customers to monitor and control workers (Batt 1999, Korczynski 2013, Maffie 2020, Orlikowski and Scott 2014). In particular, when organizations cannot observe workers directly, they use customers to ensure worker compliance with company policies and rules (Rosenthal 2004, Lopez 2010). Organizations, for instance, provide customers with feedback surveys after service encounters, deploy mystery shoppers to surreptitiously observe and report on workers' behaviors, and use electronic monitoring systems to gauge customer satisfaction (Fuller and Smith 1991, Leidner 1993, Sutton and Rafaeli 1988). Traditionally, organizations relied on managers to incorporate customer feedback with their own observations to formulate worker performance evaluations (Bolton and Houlihan 2005, Lopez 2010, Rosenthal 2004). In recent years, however, organizations have reduced managers' role in monitoring and evaluating workers by deploying emerging technology, particularly algorithms, to collect customer feedback and use these data to evaluate workers' performance in real-time (Zuboff 2019). The rise of this algorithmically mediated customer control to monitor and evaluate individuals has effectively given many workers a new, digital "boss" (Lee et al. 2015, Vallas and Schor 2020).

Nowhere is algorithmically mediated customer control more evident than in platform companies, which use digital infrastructure to connect workers with customers for short-term assignments (Lei 2021, Rahman 2021, Stark and Pais 2021). Digital labor platforms such as Uber, TaskRabbit, and Upwork embed customers as a foundational layer of control by using customer ratings as input for their algorithmic systems to determine workers' visibility, eligibility for incentives, and continued employment (Leung 2014, Maffie 2020, Pallais 2014). This new configuration of control has brought startling efficiencies to platform organizations by reducing the administrative and financial burden of hiring managers to oversee workers (Aloisi 2015, Dubal 2017). However, this control system has placed workers in a precarious situation by granting customers control over them with virtually zero accountability for their actions toward workers (Maffie 2020). Indeed, some scholars suggest that customers' abuse of workers, including wage theft (O'Brien and Yurieff 2020), sexual harassment (Ticona and Mateescu 2018), and verbal attacks (Maffie 2020), is higher in platform settings than other service settings (Ticona et al. 2018). While researchers are beginning to highlight how workers mount collective resistance in platform settings (Chen 2018, Lei 2021, Rizzo and Atzeni 2020), we know less about how individual workers resist algorithmically mediated customer control in their day-to-day work.

Prior studies examine workers' covert resistance – hard-to-observe actions that undermine organizations' attempts at control (Hollander and Einwohner 2004, Prasad and Prasad 1998, 2000) – during the execution of work, in part because this is when workers' interactions with customers typically occur (Korczynski 2013, Lopez 2010, Rosenthal 2004). Indeed, research in traditional service work settings focuses on workers' covert resistance during service-delivery, such as the "seat belt squeeze" (amusement park workers rapidly cinch a required seatbelt for a ride so that the passenger doubles over at the departure point and is uncomfortable for the ride's duration [Van Maanen and Kunda 1989:67]); the smile withdrawal (a convenience store clerks halts all pleasantries when lines become too long [Sutton and Rafaeli 1988]); and "flicking" (customer service representatives hang up on or redirect rude callers in ways that management cannot track [Van den Broek 2002]). However, compared to other types of service workers, platform-based gig workers encounter both greater depth and breadth of control through increased, real-time surveillance by both the platform's algorithm and customers' monitoring and feedback, which influence future work opportunities (Kellogg et al. 2020, Wood et al. 2019). This increased control raises a critical question: How have changes in the distribution of control among platforms, customers, and workers affected the relationship between control and covert resistance?

We examine this question in a strategic research site (Merton 1987) based on two platform companies, RideHail and FindWork (pseudonyms). Specifically, we draw on three years of participant observation (as both a worker and customer), interviews (n = 189), and archival sources. We found that the configuration of control in platform work lengthens the service encounter such that organizational control extends well beyond the execution of work, as related to stages of the labor process (before, during, or after a task). Moreover, we found that workers' latitude to deploy covert resistance changes during each labor-process stage. In the first stage, before a task begins, platforms use a matching algorithm to assign workers to tasks, and customers have limited ability to monitor or control workers. Consequently, workers have the most latitude to deploy covert resistance tactics in this stage. However, in subsequent stages, the configuration of control shifts such that worker latitude to deploy covert resistance decreases. We thus argue that platforms' use of algorithmically mediated customer control has extended the service encounter, thereby broadening the span of both organizational control and workers' resistance: workers adjust their resistance tactics because algorithms and customers control workers with varying intensity during each stage of the labor process.

By considering how control arrangements vary outside of task execution, we gain insight into the dynamic between control and resistance in the gig economy. Our study also demonstrates the limitations of platforms' reliance on customer control, by revealing how workers' everyday interactions with customers can influence and game algorithms in ways platforms cannot always observe.

LITERATURE REVIEW

Examining the Relationship Between Control and Covert Resistance in Service Organizations

Scholars have viewed control, broadly defined as a set of efforts to align worker behavior with organizational goals, as management's "fundamental problem," (Van Maanen and Barley 1984:290) in part because workers often resist organizations' attempts to control their behavior (Cardinal et al. 2017). As a result, studies of resistance (i.e., actions that subvert an organization's control system) conceptualize the relationship between control and resistance as mutually co-constitutive, or two sides of the same coin (Hodson 1995). In direct control systems, for example, organizations rely on managers to closely supervise and discipline workers (Edwards 1978). In response to such oversight, workers' resistance tactics often involve attempts to regain their autonomy and dignity (Thompson 1989). Scholars have examined different types of control systems and resistance tactics in various organizations and settings, but most relevant to this study are service organizations' attempts to control individual workers' covert resistance tactics (Morrill et al. 2003).

“The customer is king” is a common refrain among service organizations, emphasizing the mission to prioritize customer satisfaction. Frontline workers are essential to organizations’ desire to satisfy customers, because they directly interact with customers on a daily basis (Batt 1999, Korczynski et al. 2000, Leidner 1993). Therefore, to ensure consistent service encounters, organizations curate and control customer-worker interactions by prescribing service rules and feeling scripts that emphasize certain behaviors (usually a friendly and open demeanor, Leidner 1993). When workers violate these rules, they are sanctioned (Bolton and Houlihan 2005). Traditionally, service organizations have relied on managers to directly observe customer-worker interactions (Holman et al. 2002, Lee et al. 2019, Van Maanen 1991). Managers, however, typically cannot monitor workers in real time or oversee all their interactions with customers (Korczynski 2009). As a result, in customer-oriented control systems, workers often use resistance tactics to target customers, allowing workers to regain their dignity and maintain some autonomy over their work (Sutton and Rafaeli 1988, Van Maanen and Kunda 1989). Waitresses have long developed strategies to thwart or punish rude or lascivious customers, such as the proverbial spitting in the soup (Hall 1996, Paules 1991, Spradley and Mann 1975). Supermarket cashiers ignore customers, sing, or move even slower to deflect or diffuse customers’ anger (Sutton and Rafaeli 1988). Workers may also use an organization’s control mechanisms to resist customers’ demands. For instance, McDonald’s workers embraced routinization because it allowed them to emotionally distance themselves from rude customers and to deflect requests that would require extra effort (Liedner, 1993). Because managers have difficulty controlling workers’ covert resistance tactics, service organizations have devised measures to reign in workers’ latitude with customers.

One way service organizations have tried to redress covert resistance tactics is by outsourcing performance monitoring to customers (e.g., using mystery shoppers [Sherman 2007] or customer feedback surveys [Groth 2005]). More recently, organizations have also attempted to extend their oversight through emerging technologies, such as electronic monitoring systems (Bain and Taylor 2000). Using voice monitoring software, call centers monitor the technical (i.e., duration) and social (i.e., tone) elements of exchanges, offering real-time corrections to workers (Carroll 2008, Holman et al. 2002, Lee et al. 2019, Rothbard and Wilk 2011). Some organizations use surveillance cameras to see if workers follow protocols and interact with customers appropriately (Anteby and Chan 2018). Thus, in contrast to relying on managers' direct supervision, emerging technologies provide organizations with real-time monitoring to ensure workers' interactions with customers meet expectations (Rosenthal 2004).

Control and Resistance in Platform Organizations

Platform companies extend the trend and scale of integrating customer control into organizational management and control systems. Platforms rely on a different configuration of control than traditional service work has used: platforms match workers with customers and compute workers' overall evaluation scores, but they outsource the task-by-task monitoring and evaluation of interactions to customers (Shapiro 2017, Wood et al. 2019). In algorithmically mediated customer control, platforms use "customers as an additional layer of managerial control by empowering customers to direct, monitor, and/or evaluate workers" (Maffie 2020:5). Platforms' algorithms track these ratings, computing an overall score for workers that then affects workers' access to future work assignments (Ravenelle 2019, Rosenblat 2018, Schor et al. 2020). Workers with lower ratings, for instance, may have lower visibility in platforms' search results, be matched more slowly to incoming assignments, or lose access to the platform (Leung 2014, Pallais 2014, Rahman 2021). This control arrangement represents a conceptual departure from traditional modes of managing service workers in that the platform and the customer have control over workers during different stages of the work process (Kornberger et al. 2017, Vallas and Schor 2020).

In this control system, workers often face demands to display certain behaviors and emotions (which may be inconsistent with their true feelings) alongside competing pressures to conform to an algorithm's measures and metrics (Cameron 2021a, Purcell and Brook 2020, Shapiro 2017). Workers on the grocery-delivery platform Instacart, for example, purchase out-of-stock items out of pocket in other stores to keep customers satisfied (Cameron et al. 2021a, Milkman et al. 2020). Similarly, workers provide free services or reduce their hourly wage to gain customers' trust and ensure a high rating (Rahman 2021). To manipulate the platforms' algorithms, ride-hailing drivers sometimes pay friends and family to request a ride from them to boost their acceptance rate (Cameron 2021b). In another gaming practice, Amazon delivery drivers hang their phones on trees located near distribution centers, so the matching algorithm will interpret their location as “closer” (Soper 2020). Thus, emerging literature highlights how workers develop differentiated tactics to contend with both platforms and customers.

Accordingly, the resistance literature focuses on how workers resist either the platforms or the customers. For instance, in an early study of platform algorithms that rely on customer feedback, Lee et al. (2015) describe how drivers on ride-hailing platforms counter the algorithm’s nudges by hiding in plain sight. To qualify for guaranteed hourly wages, drivers park in locations where the algorithm can detect them but where they are unlikely to get a request. In a more sophisticated technique, delivery drivers deploy bots, or automated computer programs, to force platforms’ matching algorithms to assign them more-lucrative assignments (Chapman and Mehrotra 2020). Other research highlights how workers can manipulate customers, such as encouraging ride-hailing passengers to use a competitor that has more favorable conditions for drivers (Maffie 2020), or workers may pretend to complete a project to boost their ratings but, in reality, outsource the project to others (Kinder et al. 2019). Scholars have hinted at workers’ covert resistance tactics on platforms (e.g., Lee et al. 2015, Shapiro 2017), but the literature lacks a theoretical framework to understand how platforms’ increased use of algorithms and their reliance on customer control shapes workers’ covert resistance tactics. One step toward answering these questions, involves a closer examination of the relationship between control and resistance through each stage of the labor process in platform settings.

RESEARCH SETTING, DATA COLLECTION, AND ANALYSIS

Research Setting

FindWork and RideHail are labor market intermediaries (Cappelli and Keller 2013, Spreitzer et al. 2017) that use a digital infrastructure to match workers with customers instantaneously or on demand. FindWork was an open labor market in which customers could hire workers to complete complex, high-skilled tasks such as software, mobile, and web development; graphic design and animation; or sales and marketing. On a daily basis, freelancers searched and applied for projects, replied to customers’ questions or requests, and submitted completed work for customer evaluations. In contrast, RideHail was a closed labor market in which drivers were assigned rides from customers on demand via the digital platform.[1] On a daily basis, drivers were matched with a ride, followed GPS directions to the customers' pickup and drop-off locations, and then rated customers. The similarities and differences between the platforms allow rich comparison. Scholars with expertise in comparative qualitative studies note that identifying common mechanisms from dissimilar sites is useful for generating novel theories robust to contextual variation and with enhanced generalizability (Barley 1996, Bechky and O'Mahony 2015).

These platforms' designs have salient similarities and differences. Both platforms relied on algorithmically mediated customer control. Algorithms shaped which tasks workers were assigned, and customers rated each worker after the completion of a task. The algorithm used customers' ratings to reward and discipline workers. However, the platforms differed in how visible the algorithm and its choices were to workers and in the extent to which these choices were embedded in the labor process. Below we provide an overview of two key features of each platform: the matching and rating algorithms.

Matching Algorithm on FindWork. As an open labor market, FindWork provided customers full discretion in choosing which freelancers to work on their projects; however, the platform's matching algorithm facilitated this process in two ways. First, customers could enter keywords into FindWork's search engine (e.g., "design a video game") and/or use FindWork's filtering criteria (e.g., rating thresholds, location, earnings, experience) to refine their searches. FindWork's matching algorithm then presented customers with a list of freelancers they could invite to apply for their job. Second, FindWork's matching algorithm used customers' project descriptions and preferred freelancer qualifications (e.g., desired level of experience, skills required) to suggest freelancers to customers and projects to freelancers. Once a project was posted, any freelancer could submit a bid, or a customer could solicit bids from specific workers they found in their search results. Customers could review freelancers' prior history on the platform, including past assignments, education, location, and any feedback received from previous

[1] In this study, we describe RideHail as one company, but some informants worked for up to four different ride-hailing companies. All companies had similar business models and used technology in similar ways (Cameron 2021, Rosenblat 2018); thus, we combined all interview data under RideHail.

customers. When a worker completed a project, the name of the project and the freelancer's earnings, ratings, and hours worked were posted to their public profile. Freelancers were free to work on multiple projects simultaneously, and customers could hire multiple freelancers to work on the same project.

Matching Algorithm on RideHail. As a closed labor market, RideHail used algorithms that were more deeply embedded into the labor process. Once workers had access to the platform, they were algorithmically matched with customers' ride requests in a process that was not visible to workers. Drivers' personal information was available on the platform (e.g., photo, languages spoken, blurbs about their interests) but was not communicated to customers before matching and, to the best of our knowledge during our data collection stage, was not used by the algorithm for matching. Instead, drivers were assigned rides based on their ratings, physical proximity to the customer, acceptance and cancellation rates, and the vehicle and ride type requested (e.g., luxury rides, shared rides). Drivers could reject incoming ride requests and cancel rides after accepting, but the algorithmic ratings system penalized both behaviors. Customers who canceled a ride after assignment were charged a small cancellation fee.

Ratings Algorithm on FindWork. FindWork used a ratings algorithm to evaluate, sort, and suggest matches between customers and freelancers. These ratings were highly visible and prominently displayed next to users' profile names in search results. When a project ended, the customer rated the worker along six dimensions—availability, communication, cooperation, deadlines, quality, and skills—on a scale of 1 to 5. The ratings algorithm averaged these scores to form a single overall rating for each project; the freelancer's profile page displayed an overall rating score based on all ratings from the past six months. Customers could leave optional qualitative feedback in a free-text field, but the ratings algorithm did not incorporate this feedback in evaluating freelancers. Customers and freelancers could not see the ratings and feedback that each party provided about the other until both parties completed the feedback process. Although freelancers rated customers, in practice these ratings were meaningless. Not only did freelancers say they universally gave customers perfect ratings to signal to future customers that they were easy to work with, but also FindWork did not allow freelancers to sort the platform by customers' past ratings.

Ratings Algorithm on RideHail. To evaluate drivers, RideHail used the same five-point scale as FindWork did. At the end of every ride, customers rated the ride, and the algorithm used this rating to calculate an overall score based on the driver's ratings over the past 500 rides. Ratings were highly visible, and drivers could see them immediately upon logging into the app. Customers could leave additional feedback, choosing from a set of options (e.g., great conversationalist, clean car, smooth braking and acceleration), or provide qualitative feedback in a free-text field. Drivers could not see which customers provided which feedback. Similar to FindWork, drivers' ratings of customers were meaningless,[2] although drivers would not be matched again with a rider they rated poorly; however, in most markets this was not an issue, as there were as many drivers as riders. Drivers also received scores, calculated by the algorithm, based on their acceptance and cancellation rates.

Data Collection

The FindWork data comprise proprietary, anonymized data chronicling private communications between freelancers and customers during projects, interviews (n = 77), and information collected by the second author as a customer and freelancer. The RideHail data draw on the first author's three-year qualitative study consisting of participant observation (as a driver and customer), interviews (n = 107), and archival social media data. Each author independently collected each data set as part of other projects; through conversations, the authors found complementary data about how the matching and rating algorithms were central to worker experiences. Thus, we decided to integrate these data for this study.

RideHail. The participant observation, interviews, and social media data on RideHail come from the first author's larger five-year qualitative study. The ethnographic data are from 2016 to 2019[3], when the first author worked as a driver in a major U.S. city, using both a personal car and a rental car, the latter obtained through a platform-sponsored program. To examine drivers' experiences in different geographic

[2] Not until 2017, five years after the company's inception, were customers of one ride-hailing company able to check the ratings that drivers gave them. As of early 2020, when this article was submitted, customers at another ridehailing company were still unable to check these ratings.
[3] Due to the comparative nature of this paper, the first author limited the RideHail data used for this study to data that roughly overlaps with FindWork's ethnographic data.

locations, the author enlisted a research assistant to drive for RideHail in another U.S. city.[4] Ethnographic notes included reflections on work performance, busyness, ratings, surge pricing and bonuses, interactions with technical support, accidents, car care, and road conditions. During the same time period, the first author kept notes as a rider on nearly all rides (*n* = 112) taken. These rides were both personal and specifically for the research, including spending afternoons taking rides around a new area of town. Logs included information about how the author hailed the ride, the car's condition, app malfunctions, and overall impressions, including the author's rating of the ride.

The first author conducted interviews (*n* = 107) with 63 drivers over the same three-year period and held focus groups with customers (*n* = 22 participants). Interviews were semi-structured and focused on drivers' everyday experiences, including interactions with the app, customers, and RideHail. The author used several sampling approaches to ensure maximum variation and participant anonymity. The author met roughly half the informants through ride-hailing, either as part of everyday life (e.g., traveling to the airport) or through outings to a new area. The author recruited the other half of the sample via advertising (e.g., airport parking lots, Facebook groups), convenience sampling, and snowball sampling.[5] Interviews ranged from 35 minutes to 2.5 hours, with an average length of 65 minutes. Focus group members were high-volume users (10+ rides/month) recruited from [University's] community subject pool; focus groups averaged one hour in length.

Finally, archival and social media materials served as useful support for triangulation (Shah and Corley, 2006); these data sources included newspaper and magazine articles, social media posts, YouTube videos, how-to guides, blogs, discussion boards, and materials from company websites. Overall, the perspectives of the data sources complemented one another.

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[4] The first author completed 100 of the driving hours used for the study. Ride-hailing platforms restrict driving to the state in which a car is registered, so a research assistant completed the remaining hours in a different state.

[5] By far, snowball sampling was the least productive technique, because most drivers did not know other drivers. Three drivers had multiple members of their household driving. The first author chose not to interview more than two people from the same household, to ensure largely independent perspectives.

FindWork. FindWork provided access to 200 anonymized customer-freelancer communication records related to project work. The projects occurred between 2013 and 2014 and were randomly selected by the platform from among the contracts completed during that stage. On average, projects lasted three months. None of the customers and freelancers previously worked together.

The real-time communication data included messages sent using FindWork's shared messaging system, which customers and freelancers used to convey instructions, files, and project information, as well as to discuss ideas. Communications included messages between customers and freelancers about the project's duration, including situations when a project was suspended and later resumed. These messages represented one of the best ways to understand which tactics freelancers used to navigate work, as customers and freelancers had no consistent way to interact outside of the messaging system.[6]

In addition to collecting these data, the second author conducted 59 interviews with freelancers and 18 interviews with customers. The second author conducted these interviews from 2016 to 2018, overlapping with the data collection stage for RideHail. To gain a range of insights, the author selected informants with diverse platform tenure: 45% had been registered on the platform for one to five years, 39% for more than five years, and 16% for less than one year. Interviews were semi-structured and focused on workers' experiences on the platform. The second author collected data both as a result of working as a registered freelancer and as a customer on the FindWork platform over the course of four years (2015 to 2019). These data included firsthand experience using the platform as well as information from blog posts, community discussion boards, and help articles. Taken together, these data provided complementary perspectives that helped the authors triangulate insights gleaned from each source.

[6] Because of the sensitivity of the data, FindWork's user agreement, and legal terms, a third-party firm was hired to anonymize and remove identifying information from the conversation histories. This requirement included removing any identifying information from message content. Additionally, to protect customers' and freelancers' identities, FindWork did not provide information (e.g., public profile information) that could potentially link conversations to specific people.

Data Analysis

We used inductive, qualitative methods to analyze our comparative field data (Barley 1996, Bechky and O'Mahony 2015). The technique involved comparing specific instances in our field notes and interviews to build theoretical categories that served as the basis for analysis (Charmaz 2006, Corbin and Strauss 2014). In the process of data gathering and analysis, each author independently became interested in the platforms' matching and rating algorithms and workers' resistance to each, and thus focused initial coding on this theme. This parallel interest motivated the authors to collaborate and develop a comparative theory of tactics that workers in online labor markets use to manipulate ratings. Although comparative qualitative studies are less common than more traditional research, Bechky and O'Mahony (2015) and Barley (1996) provide guidelines for analyzing such data.

Specifically, each author independently coded their data and wrote descriptive memos (i.e., emic analysis). During this step, we strove to capture as much detail as possible about the circumstances in which the matching and rating algorithms were used, who was involved, and how these details shaped relevant outcomes. After this step, we shared our open coding and emic analysis from each site, to understand similarities and differences between our data. Through a process of constant comparison, we began relating our emic analysis to broader themes (i.e., etic analysis). This process involved creating several tables and figures to compare our data and settings. Table 1 shows the similarities and differences we found between the two platforms.

As we explored these themes, we observed that both platforms used similar rating algorithms and that workers perceived the ratings to be consequential for their success on the platform. Moreover, workers on both platforms tried to manipulate the rating algorithms. Throughout these steps, we iterated between the literature and our findings to identify novel insights that could extend our understanding of the relationship between resistance and control. For instance, when comparing our data with insights from prior work, we found that workers used different types of resistance tactics within the same task. To more systematically analyze this theme, we organized our data temporally and observed that workers' resistance tactics changed depending on the stage of the labor process. This initial insight led us back to the literature discussing the relationship between control and covert resistance, and we observed that past studies analyze mainly what happens at the execution point of work. Thus, we began to build an inductive model that examined the control arrangements among the platform, customer, and worker in each stage of the labor process and how changes in these control arrangements affected workers' resistance tactics. These insights became the foundation of our analysis and enabled us to identify how expanding the locus in which we examine individuals' work activities extends our understanding of the relationship between resistance and control.

To indicate the data source, we use "I" for interview, "DB" for discussion board, "FN" for field notes from observations as a customer on RideHail, and "CR" for data from FindWork's communication data. We use "FW" for FindWork and "RH" for RideHail to indicate the platform from which a given data originates. For instance, we label an interview quote from FindWork as "FW-[Pseudonym]-I."

THE TEMPORAL CO-CONSTITUTION OF CONTROL AND RESISTANCE ON DIGITAL PLATFORMS

In the following sections, we analyze how the control arrangement shifted among the platform, customer, and worker in each stage of the labor process on RideHail and FindWork. Figure 1 provides an overview of the model that we derived inductively from our findings. The figure reveals the shifting control arrangements during each stage of the labor process and corresponding effect on workers' resistance tactics and rating outcomes. The funnel shape in the far right column depicts workers' decreasing latitude to deploy resistance tactics in each subsequent stage of the labor process.

Our inductive model depicts how, before a task begins, the control arrangement provides workers with the most latitude to enact covert resistance tactics because the platform matches customers with workers, but customers have little information about workers' activities and cannot rate workers at this point. In each subsequent stage of the labor process, the control arrangement changes such that customers' ability to control workers increases, restricting workers' ability to enact resistance tactics. As customers' ability to control workers increases, workers' latitude to deploy resistance tactics decreases, as they often must involve customers to protect their ratings. To depict changes in the control arrangements,

Figure 1 uses solid (stronger control) and dashed (weaker control) lines between each actor in the service triangle. Our model also illuminates the relationship between rating outcomes when workers successfully deploy corresponding tactics for each control arrangement (see *Rating Outcome* column).

Before presenting our findings, we first describe the importance of customer ratings for workers and why workers believe they should be able to manipulate them. The combination of lack of customer accountability and workers' short-term contract employment with the company creates a context in which workers know ratings are important but also believe they are inaccurate indicators of performance. This context makes ratings ripe for manipulation.

Setting the Foundation: Importance of Ratings

Workers in both settings conveyed that ratings were important to ensure continued access to the platform. A FindWork freelancer, for instance, remarked, "On [FindWork] your rating is everything," and the rating received from a customer "is going to go a long way in getting you a new job" (FW-Susan-I). Some freelancers described the rating as "more important than money," because the rating helped secure additional work and advance their careers on FindWork (FW-Bryan-I). As an open labor market, FindWork enabled customers to sort and search the platform based on workers' ratings, reinforcing the importance of high ratings. One customer, for instance, said, "I only look at workers with high-ratings" when determining whom to hire (FW-Adam-I).

As a closed labor market, RideHail algorithmically matched drivers to customers, and high ratings were required for drivers' continued platform access. In its community guidelines, RideHail warned drivers that ratings below a certain threshold were grounds for deactivation. Drivers judged their own performance by their rating score. When asked, "How do you know if you're doing a good job?" most drivers responded with their rating score to the hundredth-decimal place: "I know by my ratings. I got a 4.83. You guys give me good stars" (RH-George-I). Most drivers checked their rating after every ride. Routines, such as offering snacks (e.g., gum), calling before pickup (to verify the rider's pickup location), opening the car door, and complimenting customers, seeded positive customer interactions and potentially higher ratings. Explaining how he keeps a high rating, one driver noted, "I keep my car immaculate—it looks like it just drove off the lot. I keep water in the back cooler in case people might want a drink. It's mostly the discussion that we have and maybe the music I'm selecting. Ever since I've been back on, I haven't had anything less than a five-star rating" (RH-Tom-I).

In sum, customer ratings were a highly visible metric, and platforms used them to monitor, evaluate, and reward/discipline workers. To maintain high ratings, workers went out of their way to create favorable impressions for customers before the official work started.

Sowing the Seeds of Resistance: Ratings Subjectivity and Lack of Voice

On both platforms, workers recognized that ratings were a central component of their success, but they believed the rating algorithms were significantly flawed because they were based on customers' subjective, and hence potentially biased, perceptions. In particular, ratings derived from relatively brief interactions with customers, who were not held accountable for their evaluations. Some workers thus believe the rating algorithm was not an actual performance evaluation to help them learn how to improve but, instead, a reflection of customer whims. A RideHail driver said, "There's a sense of accountability to it [ratings algorithm], but it's not real . . . it's arbitrary, it's valuable, but it's very subjective" (RH-Quentin-I). On describing why two individuals on the same shared ride might give different ratings, a driver explained: "You have two passengers—one is satisfied, another completely not. Just the mood, just something happened that day with him, or whatever" (RH-Moose-I).

Even though FindWork freelancers and customers had longer, more in-depth exchanges online, freelancers still complained that customers gave arbitrary ratings. One freelancer shared how a customer gave him a low rating, without warning or an opportunity to respond:

> Long story short, my customer wanted a name card but he suddenly ended our contract right after I sent him the draft of the name card without leaving a single message or comment. However, I still completed the job by following up with him asking if the design is okay and sent him the file for him to make amendments on the contact details by himself. A week later I found out that he gave me only 3.65 stars rating which is terribly unfair to me because he ended the contract without even giving me chances to improve on my design. If he really thinks I am not suitable for the job, he should communicate with me instead of ruining someone's profile. (FW-Amy-DB)

Because the platforms maintained minimal relationships with workers, workers felt they could not voice concerns or influence the platforms' decisions, especially decisions related to the rating algorithms. Indeed, workers felt dehumanized in their interactions with the support function on both platforms, as their questions were answered only by a machine. Compared to traditional service work, in which workers can ask questions to managers, the platforms' messaging systems gave robotic replies that were frustrating to workers. A driver said, "If you work in a restaurant, you can talk to the customer, you can find the problem [and] solve right away. You don't need to talk to the computer. You can say, 'Sorry.' You can say, 'Help me.' You can laugh. But here, nothing—it's a computer, a machine" (RH-Dennis-I). A freelancer described a similar experience when inquiring about a ratings drop: "I went to support for help and all that I got is copy and paste answers. . . . Sometimes I think 'Is there any real human being . . . behind these name[s]?'" (FW-Tom-I). Together, these conditions created a work context ripe for resistance: workers believed ratings were important to their success but also fundamentally flawed because the algorithmic rating system could not observe why customers gave apparently arbitrary ratings, or account for customer biases.

Stage One: Control Arrangements and Preemptive Resistance Tactics

Control Arrangement Before Paid Work Starts. Before customers and workers began working together, the platform matched them together. This matching process differed for each platform. On FindWork, the platform controlled which freelancers were most visible in customers' search results and suggested potential matches, but it was ultimately up to the pair to decide whether to work together. On RideHail, drivers were automatically assigned to customers when the latter requested a ride; however, until drivers actually picked up the customer, they were not earning money and could not be rated. Drivers could refuse rides, but they were discouraged from doing so because their acceptance rate, which influenced future assignments, would drop. Thus, at this stage of the work process, both platforms had some control over matching workers with customers, especially RideHail, which could sanction drivers who did not accept multiple rides. Customers, however, had no control over workers at this point: they could not rate workers, and they had limited information about workers' activities.

Vetting Customers. Both platforms prohibited workers from discussing their potential ratings with customers before a task began. Workers, however, believed that the platforms did not actively monitor or sanction what workers and customers discussed with each other, even when these communications occurred through the platform. Thus, before starting a task and before a customer had an opportunity to rate them, workers in both settings took preemptive steps to ensure that customers would not leave a low rating or would provide a high rating. In particular, workers preemptively probed and looked for cues regarding the rating a customer would provide. Although it was against RideHail company policy, drivers used an in-app feature to call customers before pickup, ostensibly to verify their name but really to ask their destination, which the platform purposefully obfuscated. Drivers acted as if these calls were not monitored even though they placed the calls through the app; if they believed a prospective customer had a nasty attitude, many would cancel the ride immediately, noting that riders who misbehaved were more likely to give low ratings. If a customer called first, the driver would assess their behavior. A customer who called to change their pickup location "can be picked up but only if they pass the attitude test. I never start the trip for a passenger with a bad attitude because that means bad ratings. If they act like it is my fault or seem upset, they don't get a ride because I can't afford their bad rating on my account" (RH-Steve-DB). Another driver described a similar incident before preemptively cancelling the ride request:

> Today I accepted a RideHail "shared" ride. I was already in the car so I was moving immediately. I was only a couple of minutes from the pick-up. Then the message comes in: "In front of the house. I am in a rush." Of course, I couldn't cancel fast enough. Chances are the rider is going to be in a bad mood, is not gonna be happy that you choose to stop for a yellow light rather than barrel through it, and if you don't get them where they're going on time it's probably going to affect your rating. (RH-Jake-DB)

Drivers were also evaluated on their cancellation rates, but they paid the penalty to avoid a potentially low rating from an irate customer.

On FindWork, freelancers also contacted customers before a project began and, in some instances, asked customers if they would leave perfect ratings as a precondition to starting. Similar to workers on RideHail, freelancers assumed that the platform did not monitor, or at least analyze, these illicit requests. One freelancer, for instance, sent the following message before a project began: "There is one thing I require [before starting the project]—a promise of 5 stars and a nice review" (FW-Terry-I). Without this assurance, the freelancer was not willing to work on the project. Another freelancer said, "I put in a very low bid for a project, but told the customer I am putting in a lower bid so that they guarantee a perfect rating [after the project ended]" (FW-Alex-I). By securing such assurances before a project started, workers hoped to ensure a high rating. Because both platforms' policies stated that customers should only rate workers *after* a ride or project was completed, workers could have had their accounts deactivated if customers reported this behavior. Yet, because workers' experiences showed that platforms did not actively monitor these conversations (or at least did not take actions against workers based on these conversations), we found workers actively flouting the platforms' rules to vet customers in hopes of securing a high rating.

Encouraging Customers to Cancel. In addition to using customer ratings, RideHail held drivers accountable through their ride acceptance and cancellation rates, and they could face penalties (e.g., charged fees, matched with less profitable rides) if these ratings fell below a threshold. One driver noted, "You have the ability to cancel rides . . . but, they [customers] retaliate against that [through] lower[ing] your ratings. I had a 4.93. They gave me a warning, 'If you decline this [ride], it's going to affect your rating,' and I didn't think much of it. I just declined it. And it was the last time I did that [because of a rating drop]" (RH-Oscar-I). Due to these sanctions, drivers encouraged customers to cancel rides they did not want to complete.

The most common example of this tactic is when drivers called customers before picking them up, ostensibly to verify their location. Drivers used this tactic most often at airports and large events, where drivers may wait in long queues. Describing the scene at airport waiting lots, a driver said, "If they don't like where the passenger is going, [drivers] come up with some sob story and request that the passenger cancels the request. Unfortunately, most passengers don't know this is against policy, and they go ahead and cancel. Since the passenger canceled, the driver is left at the top of the [airport] queue. [Drivers] repeat the process until they get a ride they like" (RH-Zeke-DB). Similarly, if drivers thought a ride was not worth their time because the pickup location was far away, they pressured customers to cancel the ride request, claiming that other drivers were closer or, if there is a surge in requests, that customers should wait for the surge to die down to save money. For example, the first author was encouraged to cancel when a driver could not find them at their geolocation marker:

> The driver must have had to really hold his nerve to be patient. He couldn't find me (seems he was on the other side of the building) and—at least three times in a monotone, robotic voice—he kept on saying, "I don't see you. You dropped the wrong pin [geo-location marker]. It's not my fault. There is nothing else you can do. You need to cancel the ride." His flat and restrained voice reminded me of a parent trying not to show their kid that they are angry. Why didn't he want to cancel the ride [instead of asking me to cancel]?? Of course, it would hurt his rating and he gets money if I cancel—and I pay if I cancel!! (FN from RH. 9 March 2017)

Dropping the wrong geo-marker is common and easily resolved through additional communication between a driver and customer. However, when drivers did not want to pick up a customer, they nudged customers to cancel the ride, thereby averting a cancellation fee and a penalty by the matching and rating algorithms. The rating algorithm did not penalize drivers for customer cancellations, as this action was attributed only to the customer.

In summary, before a task began, workers had the most latitude to deploy resistance: even though the platform matched workers to customers, workers used their knowledge of the work process to their advantage to safeguard their ratings. Customers had limited information about workers' motives and the work process overall, and the platforms did not appear to monitor and sanction communications between workers and customers. Taking advantage of the information asymmetry in this control configuration, workers preemptively screened out customers who may have given them a lower rating, either by cancelling the project/task themselves or encouraging the customers to do so. When successfully executed, these tactics help workers avoid potentially toxic customers, maintain a high rating, and position themselves to receive more work assignments from the platforms' matching algorithms.

Stage Two: Control Arrangements and Interactive Resistance Tactics

Control Arrangements Once Work Starts. When a task started, the platforms relied on customers to monitor and observe workers' behaviors (e.g., professionalism, friendliness, communication, competence). On FindWork, freelancers and customers were in constant communication on the platform about project specifics, such as determining the project's scope, clarifying tasks, and negotiating timelines. Most communications between freelancers and customers occurred via the digital platform, but both parties behaved as if FindWork did not actively monitor these exchanges. RideHail workers assumed a similar level of privacy. To the best of our knowledge, the platform did not actively monitor conversations in the car between drivers and riders; RideHail did monitor the vehicles' locations but did not routinely scrutinize these logs unless there was a customer complaint. At this stage of the work process, customers had increased control over workers because they were now actively monitoring their performance. Furthermore, both parties knew that the platform would ask the customer to rate the worker upon the task's completion. Thus, as customers' control increased, workers had less latitude to deploy resistance tactics and, as a result, had to devise more-interactive resistance tactics to ensure that they did not alienate customers.

Segmenting Work. On FindWork, freelancers and customers structured their project contracts as they wished (e.g., creating one or more contracts for a single project); however, the platform's ratings system interpreted each contract as a new project. Freelancers took advantage of customers' lack of knowledge (or care) about how the platform organized work, by spreading a single project over multiple contracts, which allowed them to receive separate ratings for each apparently new project. One freelancer described working on a computer game and providing regular updates:

> I have the project created in Unity.[7] I have all the images you've sent me imported into the project. I have a background drop ready to be a building level [in the game]. And I'm ready . . . to get the main player moving around. (FW-Mark-CR)

As the freelancer completed portions of the project, the customer expressed his approval and satisfaction. Replying to the worker's latest update, the customer said, "Looks awesome as a working platform. Hopefully I can get you the main character script and background for the level soon. Thanks, looks good" (FW-Liz-CR). The customer not only indicated his satisfaction with the freelancer's progress, but also signaled increased trust and a desire to continue working together by providing

[7] Unity is a game development platform commonly used to create 2D and 3D games for deployment across mobile, desktop, and other platforms.

additional parameters to continue development of the game. Later in the project, sensing the customer was pleased with his work, the freelancer suggested [emphasis added],

> Let's close the contract after this last milestone so we can give each other a rating. Once we've closed the contract you can invite me on a separate bid and we can work together on ***what we already have in progress now***. (FW-Mark-CR)

The customer responded, "Yes, no problem." The freelancer waited to make this request until he was sure the customer was pleased, and knew the customer depended on him for further development of the game. For the customer, providing multiple five-star ratings took virtually no extra time, communicated goodwill (as the customer had agreed to the freelancer's request), and enabled him to continue working with a trusted, competent freelancer. To the best of our knowledge, customers were unaware of how multiple contracts and related ratings boosted freelancers' overall rating, because most customers interacted with freelancers only once, and many did not return to the platform after a completed project. Freelancers thus took advantage of their more comprehensive understanding of the rating algorithm: each rating appeared to new potential customers as if the worker had, in fact, completed numerous, unique projects, all of which received perfect ratings; that made the freelancer a more attractive candidate and more visible in the platform's search results. In addition, the inflated rating provided a buffer in case a worker received a low rating on another assignment in the future.

Holding Work Hostage. In some cases, if FindWork freelancers sensed that a customer would leave a low rating, they negotiated with the customer to exchange part of the work for a high rating. For example, a customer hired a worker to develop an Android application, and although the freelancer initially made progress, he stopped providing updates. The customer became concerned:

> I need to see some [additional] results. You are making me nervous [for not providing updates]. . . . Please show me something that works like the live dashboard mockup I sent you. (FW-Sharon-CR)

The freelancer responded:

> Hello, I have received your message. I worked for over 20 hours for this job. But I did not get good results [i.e., could not complete the project]. So I will delete [i.e., refund] 2 hours

> and finish the job and will provide good feedback and a review about you. I am going to send the source code to you after you end the job. (FW-Lee-CR)

Worried that the customer would provide a low rating when the project ended, the freelancer preemptively refunded a portion of his wages and offered to provide positive feedback. At the same time, he also attempted to hold some leverage over the customer by keeping the source code until he could see the customer's rating. The customer responded:

> You can keep the source code. I will start again and re-build the mobile application using a different developer. The contract will be finished and I will give you a bad [rating]. I am very unhappy with your services. (FW-Sharon-CR)

Alarmed at the threat of a negative rating, the freelancer offered to refund a larger amount, contingent on receiving positive feedback: "I will refund 8 hours of your money. But please provide good feedback." Realizing that portions of the project work could still be used, the customer requested that the freelancer provide the partial source code in exchange for a higher rating: "I see the refund, thank you. I will provide good feedback, if you send the source code." Eager to avoid a low rating, the freelancer said, "After giving good [qualitative] feedback and five-marks [a perfect rating of five stars] I will send the source code." Agreeing to this proposal, the customer gave the freelancer a perfect rating, and the freelancer sent the source code. Such negotiations were risky, because customers could report such behavior to the platform; however, freelancers banked on the fact that customers did not care about the ratings they provided, in part because there was no accountability for customer ratings.

Ending Work Prematurely. If workers on either platform believed they were not meeting customers' expectations, they would end the task prematurely to prevent customers from rating them—even if this meant a reduction in their earnings. On a ride-hailing forum, a driver noted, "If you tell pax [passengers] they can't eat or drink and they get upset about it, still do the ride. But at the end of the trip, don't complete it as normal, cancel it . . . you won't be able to rate them and they can't rate you" (RH-Amy-DB). These behaviors had financial consequences. Drivers were paid based on mileage, so they did not receive the full fare if they canceled a ride before arriving at the customer's destination. Furthermore, ending a ride early exposed drivers to extra risk because they were not covered by the platform's insurance policy during the gap; even so, some workers saw forgoing income and insurance coverage as an acceptable tradeoff to maintain a high rating. Customers were unlikely to notice the premature ending, as it was near their scheduled drop-off time; even if they did notice, customers were unlikely to report this behavior, as a premature ending meant that they saved money.

Similarly, FindWork freelancers sometimes stopped work on a project prematurely and returned customers' money to avoid a negative rating. A freelancer recounted one customer who "was totally inexperienced and unprofessional and could have left me an extremely bad feedback [rating]" (FW-Zak-I). As a result, even after working 20 hours on the project, the freelancer canceled the project to avoid a possible low rating because "[if] no money exchanged hands, [the customer] can't leave a rating" (FW-Zak-I). Similarly, another freelancer said,

> Recently, I received a contract offer to work on a website and accepted it. I started and developed a beta version based on the job description where I had to edit an html template. I edited it and sent the links of the beta site to the customer to review it. He was disappointed because I didn't re-design the template. In the job description . . . he told me that I have to replace the content and make custom pages (to position the content), and never said to do custom header (to redesign the original one and other). I canceled the contract because the job was not as described . . . and to avoid an unfair rating. (FW-Brandon-DB)

By cancelling a contract, workers prevented customers from leaving a negative rating. As a result, freelancers maintained their high ratings average. In general, because FindWork relied on customer control and did not observe the circumstances leading to a project's cancellation, workers could use these tactics to avoid low ratings.

In summary, once the work began, customers had more control over workers, thereby decreasing workers' latitude to deploy resistance tactics. Workers were acutely aware that platforms outsourced control to customers and that customers could leave ratings that could diminish their future work opportunities. As a result, workers devised more-interactive resistance tactics, which required customers' involvement yet also took advantage of customers' lack of information (or care) about the broader effects of their actions on workers (e.g., splitting a single project into multiple contracts). When successfully executed, these tactics helped to inflate workers' ratings (e.g., by segmenting work) or safeguarded them from negative ratings (e.g., by ending work prematurely).

Stage Three: Control Arrangements and Reactive Resistance Tactics

Control Arrangement Once Work Is Complete. When work neared completion, the salience of the ratings increased for both customers and workers: customers now had the opportunity to formally evaluate the work, and workers were aware of the forthcoming evaluation and how the platform used this information to determine future work assignments. On both platforms, customers were asked to leave a rating (1 to 5) and qualitative comments. On FindWork, the platform used customers' ratings to influence freelancers' future work opportunities, such as their ranking in the search results and whether the platform automatically recommended them to clients. The platforms also prominently featured customers' ratings in freelancers' profiles; the prominence of these ratings signaled their value as a measure of competence to potential customers. On RideHail, customer ratings influenced the speed and price at which drivers were matched with incoming ride requests. High ratings unlocked bonuses such as lower commissions and discounts on gas and car insurance. Drivers who received a string of low ratings or a serious customer complaint could be immediately blocked from the platform with limited recourse. While workers on both platforms could leave ratings, these ratings were inconsequential for customers because the platform did not use them to sanction customers. Thus, at this stage of the work process, customers and the platform had the most direct and indirect control over workers, who had the least latitude to deploy resistance.

Mediated Retaliation. When RideHail drivers suspected they were likely to receive a low rating from a customer, they reacted by giving the customer a low rating first. Drivers hoped that the two low ratings would cancel each other out such that the driver would not receive any sanctions from the platform (e.g., being less likely to be matched to high-value rides). Because drivers believed that RideHail's interests were more aligned with customers than with their own and that the company's arbitration policies favored the former, retaliating against customers by giving a low rating was a quicker, more surefire option. More important, workers gave these low ratings not to indicate customers' poor behavior (the company's intended purpose for the ratings system) but, instead, to signal to RideHail that drivers were being rated unfairly. A driver describes such an incident:

> And at the end of the day, we went to the place and she realized the fee was too much. She was angry. [Laughs.] Right in front of me, she told me, "I'm going to give you one star and I'm going to give you bad comments." And when that happens, right there, you give that person one star, too, and give them bad comments. Otherwise, she's going to get away with it. If she gives you bad star[s] with a bad comment, and you give her five star, they will know it's obviously she's right. But when she says bad about you and the driver that says bad about them [sic], RideHail [is] going to [compare] it—it's not going to affect you. (RH-Brandon-I)

While drivers did not have firsthand information about how the algorithmic rating system worked, they developed last-ditch efforts to protect their ratings and believed they were less likely to be reprimanded if they gave a low rating when they suspected that a customer would as well.

Filing Disputes ("Hail Mary"). When workers knew they had received a low rating, they filed a dispute with the platform company to try to nullify the rating's effect on their ability to secure future work. This move was an act of resistance against customers, which workers could enact via formal organizational channels. Yet, workers on both platforms saw this move as a "Hail Mary," because they believed that FindWork and RideHail unduly privileged customers and that this tactic was therefore unlikely to be successful. A freelancer on FindWork's discussion board, for instance, shared, "I do not believe that FindWork's dispute system is designed to 'decide upon a fair outcome.' I do not believe that there are effective ways for a freelancer to successfully 'win' a dispute with a [difficult] client" (FW-Pedro-DB). Another freelancer added that FindWork had few options for workers who encountered difficult customers: "I am pointing out here is FindWork should have better protection for us, freelancers, especially the top-rated ones. Those kinds of [dispute] decisions…are clearly only in favor of customers" (FW-Claire-DB). Despite believing they were unlikely to succeed in a dispute, freelancers saw filing a dispute as their final option to try to rectify a situation with misbehaving customers. A freelancer on the discussion board shared, "[FindWork] was about to close the dispute so I brought up my feedback concerns (which was my greatest concern all along). To my understanding, the Client had already had to give feedback when she got upset and [unfairly] ended the contract, so I'm assuming the feedback is terrible. I asked the Client if she could make sure the feedback reflected my work and not our conflict, but she didn't reply" (FW-Aliyah-DB).

Similarly, RideHail drivers filed disputes as a final attempt to salvage their ratings. Drivers reported that customers often "scammed" the RideHail system: to get a refund, riders claimed that drivers behaved inappropriately (e.g., smoking weed), which led to drivers being deactivated. Roger was deactivated after completing a shared ride in which he called out a customer who was late, causing a delay in reaching other customers waiting for the shared ride: "[The notification said] your account needs attention. You've been deactivated off the platform . . . for inappropriate conversations in the vehicle. I was pissed because I'm like, inappropriate conversations? There was no inappropriate conversation. . . I had no idea customers had so much power" (RH-Roger- I). Albert faced a similar experience when he woke up one morning and realized he could no longer open the app and work. Only after he went to the RideHail resource center did he learn that a customer had reported him for falling asleep behind the wheel and was issued a refund. In making his case to RideHail, he said, "Some people [customers] are really not fair. I don't know who did this kind of report but I did not do something like this" (RH-Albert-I). In these types of situations, when drivers felt that customers had been untruthful and no other options were available, the drivers reached out to RideHail as a last resort.

Worried that RideHail would not believe them, drivers offered additional proof from dashcam footage to substantiate their claims. After being temporarily blocked by a dishonest customer, Roger purchased a dashcam "for my protection . . . [it] saved me on numerous occasions because people would say, 'Well, I'm just going to tell RideHail this, this and that,' and I'd be like, 'Dash cam. I'm just going to send them the dash cam of y'all having me saying this.'" In a similar situation, Andre used footage to refute a customer's refund request and avoid deactivation:

> I have the whole thing on video. The person that climbed into my car knew my name, knew the name of the passenger on the account, and knew the destination address that was entered into the app at the time of his arrival request. Then I sent them a couple of screenshots. I said, "I'm going to put this video up on the cloud. You can download it and see that I followed every single appropriate procedure to verify that I had the correct person in the car. If it was not the correct person, what is the statistical probability that I would get the wrong person with the same name

> going to the exact same address?" They came back to me later and said, "Here's your credit." (RH-Andre-I)

Drivers believed that such data from their own monitoring systems allowed them to better protect themselves from customers' false charges and to resist unfair downward ratings adjustments.

In summary, after workers completed a task, they had the least latitude to deploy resistance tactics because they were forced to negotiate directly with the platform to salvage their ratings. On RideHail, drivers believed that the company would notice low ratings only if the rating was asymmetrical (i.e., low customer rating, high driver rating); therefore, drivers gave customers a low rating if they thought that customers would rate them poorly, even if customers' behavior did not warrant a low rating. In such cases, drivers' overall rating declined, but they avoided the more severe penalties they anticipated. When filing disputes, workers engaged directly with the company, hoping the platform would remove a negative rating from their overall average and thereby salvage their rating. The tactics in the last stage of the labor process were highly unlikely to succeed, but many workers' felt it was their last and best attempt to protect their ratings. Table 2 summarizes the covert resistance tactics we observed on both platforms.

Discussion

Our comparative analysis of two platforms using algorithmically mediated customer control shows how control arrangements among the platform, customer, and workers shift at each stage of the work process, revealing a temporal co-constitution between control and covert resistance. This temporal co-constitution highlights workers' diminishing latitude to deploy resistance tactics in each sequential stage. Before a task begins, workers have the most latitude to deploy covert resistance tactics: platforms have matched customers with workers, but customers cannot yet observe workers' actions or rate them. Once a task begins, the co-constitution between control and resistance shifts: customers gain more control over workers through their increased ability to monitor worker activities. As a result, workers' latitude to deploy resistance tactics decreases, and to enhance or safeguard their ratings they must devise more interactive tactics involving customers. Workers can deploy these tactics by taking advantage of the information asymmetry between customers and themselves. In the final labor process stage, customers provide ratings that platform algorithms use to make consequential decisions about workers' future opportunities on the platform. Faced with even less latitude and fewer feasible options, workers resort to last-ditch, Hail Mary efforts to counteract negative customer ratings.

Figure 1 summarizes our model elaborating control and resistance that we inductively derived from our findings. This model captures the temporal changes among the control arrangements of the platform, customer, and worker in each stage of the labor process, how these changes affected workers' latitude to deploy resistance tactics, and the effect on rating outcomes.

Contributions to Our Understanding of Control and Resistance

Issues at the nexus of control, resistance, and emerging technology have captured scholars' attention for more than a century, yielding research that associates control systems with specific resistance tactics (Edwards 1978, Hodson 1995, Hollander and Einwohner 2004, Roy 1959). Much of the extant literature considers the relationship between control and resistance at the execution of work (Anteby and Chan 2018, Burawoy 1979), such as when call-center workers field calls (Batt 1999). In a manner similar to these prior studies, we show that at the service-delivery point, customers are involved in overseeing workers' activities, and workers must carefully deploy resistance tactics to avoid negative customer feedback (Leidner 1993, Rosenthal 2004). Unlike prior studies, however, our study highlights how workers can take advantage of platforms that rely only on customers to monitor activity at the execution of work. We found that workers used their superior knowledge of how the platform worked to dupe customers into not leaving a negative rating, or enlisted amenable clients to help inflate their ratings. Such actions are less likely to occur in traditional workplaces, where managers are more likely to notice the behaviors because they oversee workers directly and can adjust their control tactics to deter such behavior (e.g., Anteby and Chan 2018).

Our paper thus highlights how emerging technologies have extended the scope of control and resistance in the labor process in ways that previous studies have not considered. Before an encounter begins, platform algorithms play a key role in matching customers and workers by measuring workers' acceptance rates which then influences workers' access to future platform-based opportunities. As a result, our study shows that the stage before work begins is now an important site of control and resistance. This finding contrasts with previous studies (Leidner 1993, Rosenthal 2004, Van Maanen 1991), which describe organizations that have relatively little input into the customer-worker matching process, because customers are paired randomly with workers (e.g., taxi drivers have little information about which customer enters a cab; stores have minimal influence over which cashier a shopper selects). Correspondingly, organizations' control efforts and workers' subsequent resistance tactics occurred primarily during the execution of work (e.g., the point of sale; Sherman 2007, Sutton and Rafaeli 1988)

Similarly, little research has examined resistance after workers' interaction with a customer. In traditional independent contractor work, when an individual received a negative rating, the impact was minimal because workers had control over how much information, if any, they disclosed to new customers, in part because their prior evaluations were not posted publicly (Barley and Kunda, 2004). As an example, in traditional taxi work, a service encounter is complete when the ride is finished, but the customer's feedback and experience are not automatically transmitted to the next rider (Luedke 2010). While riders could, in theory, complain to a dispatcher, the process is comparatively arduous, and customers are typically unaware of the outcomes of their complaints. Thus, our study suggests that compared to prior service work, platform workers' "Hail Mary" complaints against customers are supplicatory because workers are essentially begging platforms for continued access to platform-based work. Indeed, platform algorithmic management systems and their ability to exclude workers form the crux for much legal research arguing that these features make work on digital platforms more controlling than typical independent-contractor work (Dubal 2017, Hyman et al. 2020).

Our findings also have implications beyond traditional service settings, because more organizations are using technology to integrate customers throughout their business processes. For example, many hospitals request real-time feedback from their patients, not only about the care they receive but also regarding their experience with scheduling, registration, parking, and food (Pope 2009). Similarly, airlines request real-time feedback from passengers about their non-flight experience, including buying tickets, checking bags, passing through security, and the boarding process (Saha and Theingi 2009). Furthermore, there is increasing evidence that technology can extend an organization's control beyond the standard service encounter (Finn 2017, Zuboff 2019). Automakers increasingly place sophisticated algorithms in new vehicles to monitor how drivers use their cars, and deactivate features when drivers take actions that automakers do not approve (e.g., seeking repairs at an unauthorized shop; Alsever 2021). Taken together, these examples of emerging technologies that extend service encounters and organizational control suggest that our process model (Figure 1) applies well beyond traditional service work. Future research should further investigate how emerging technologies are evolving and reshaping our traditional conceptualization and understanding of work and organizing.

Overall, the lengthening of the service encounter on digital platforms has created an environment in which workers must contend with control for a longer period compared to previous service work settings, in part because their rating follows them throughout their lifecycle on the platform. This prolonged period of control over workers presents opportunities for resistance outside the execution of work, but our study suggests that it also contributes to worker fatigue because service providers are required to be vigilant for longer periods to maintain high ratings and access to the platform.

Implications of Shifting Control Arrangements for Workers, Customers, and Platform Companies

The expanded scope of control to include before, during, and after a task has implications for workers, customers, and platforms companies. For workers, the shifting control arrangements and decreasing latitude to deploy resistance tactics in each subsequent stage of the labor process highlight the tacit knowledge that workers must acquire to succeed in the gig economy. Simply doing good work cannot protect workers from difficult customers who may give negative ratings for reasons unrelated to the quality of the work (Wood et al. 2019). Nor can workers rely on managers to intervene and buffer the effect of negative customers, as previous studies document (e.g., Rosenthal 2004). Instead, our study shows that the most highly rated workers not only do good work but also develop deep knowledge of the labor process, assessing customers' demeanor and anticipating their actions, deciphering how the platforms' algorithms collect and use their data, and deciding when they can deploy resistance tactics that increase, maintain, or salvage their ratings. Moreover, the savviness that workers develop in platform settings is reminiscent of the skills that successful contractors develop in traditional external labor markets, in which workers must convince potential clients that they can work on complex projects despite not having the requisite formal experience (Barley and Kunda 2004, O'Mahony and Bechky 2006).

For customers, the shifting control arrangements in the labor process contribute to an inverted U-shape regarding their control over workers. Our study shows that customers have relatively little control over workers before a task begins, relying on platforms to shape who is visible in their search results and match them with workers. Once the work begins, however, customers are in a temporary position of power over workers as they monitor and evaluate them (i.e., the apex of the "U"). Because of their transactional relationship with the platform and with workers, customers generally lack information about how their own or workers' actions during a task affect the labor process. During a task, workers must devise interactive tactics involving customers that exploit this information asymmetry, to dupe customers into believing that certain actions are in the customers' interest when, in fact, the actions are intended to help worker ratings. We saw this dynamic on RideHail when workers convinced customers to initiate a cancellation request, and on FindWork when workers convinced customers to split a project into multiple contracts. Thus, while previous studies highlight customers' greater control over workers during a task in the gig economy (Calo and Rosenblat 2017, Schor 2020, Shapiro 2017), our study identifies a limitation in this arrangement by revealing how workers can exploit platforms' reliance on customer control.

For platforms, the shifting control arrangements within the labor process reflect a U-shaped relationship regarding their control over workers: platforms can decentralize their control of workers while maintaining power overall (Vallas and Schor 2020). Platforms have the most control over workers during the matching process and after work is completed, with limited control during the execution of the work as they source the monitoring and evaluations to customers (i.e., the nadir of the "U"). Such dynamics highlight the power asymmetries inherent in platform work (Rosenblat and Stark 2016, Vallas and Schor 2020). Our findings suggest that customers are not vested in platforms' outcomes because customers are not held accountable for their ratings and they do not have a long-term relationship with the platform company or workers (Dzieza 2015, Rahman and Valentine 2021). At times, customers apathy toward platform outcomes can benefit workers, because it gives them latitude for resistance tactics, but it may be detrimental overall to the platform company (Garg and Johari 2021). Relying solely on customer feedback for performance evaluations is risky, as customers may give poor ratings out of thoughtlessness or negative intent, or they may not provide any rating, thereby increasing the disproportional effect of a single negative rating (Leung 2014, Pallais 2014). Given that platform companies' business model relies on having a large, always available labor pool, deactivating workers based on dubious customer feedback could slow their growth trajectory and, even if workers are reinstated, could tarnish workers' goodwill and commitment to the platform (Purcell and Brook 2020). By highlighting a basic internal limit of platforms' reliance on customer control, this study raises concerns about the sustainability of the gig economy, or why "Uberification" will not take over the world (Faraj and Pachidi 2021, Fleming et al. 2019). Figure 2 depicts the shifting control arrangements in each stage of work, as described above.

Note that workers' resistance tactics in the first two stages largely rely on fragile information asymmetries: workers assume and then take advantage of the idea that platforms do not monitor their communications with customers. Platforms could, of course, change this policy at any moment and adjust their algorithms, decreasing information asymmetries and reducing workers' latitude to deploy resistance tactics. Platforms, however, must be careful of how much explicit control they exert over workers, to avoid the impression that they treat workers as employees (Aloisi 2015, Scheiber 2018). After this study's data collection efforts, for example, the second author observed that FindWork implemented an algorithm that reminded workers and customers that they could not move their conversations off platform when they shared contact information before a project started. The platform, however, stopped short of taking action against workers and customers who violated the policy. This example is a reminder that platforms can monitor workers' communications on the platform, but there is a dance between platforms updating their algorithms to counteract existing resistance tactics and workers devising new resistance tactics to respond to these updates.

Our study also provides a more nuanced understanding of the relationship between control and covert resistance. Prior studies suggest that workers' covert resistance ultimately reinforces organizations' control over workers: resistance provides only temporary relief, as workers ultimately remain enmeshed within the organization (Morrill et al. 2003, Prasad and Prasad 2000). Our study, however, reveals that workers' covert resistance tactics can both enable and weaken platforms' control systems. In the first stage, when workers' resistance tactics lead them to reject certain customers, the platform must match customers again with new workers, resulting in increased costs and inefficiencies. Once work begins, workers sometimes safeguard their ratings by forgoing income and cancelling an in-progress assignment; in such cases, the platform does not receive a percentage of the wage the worker would have received, nor does the company receive the customer's rating data. Even in the final stage when workers file disputes to try to salvage their ratings, the platform must dedicate resources to arbitrating these disputes. Studies have found that updating algorithms to try to counteract workers' covert resistance takes considerable time, money, talent, and energy (Gillespie 2018, Keller 2018, Möhlmann et al. 2020). Thus, our study suggests that platforms bear increased costs when workers devise and implement covert resistance tactics.

Differences Between Closed and Open Platforms

Our comparative ethnographic approach helps to identify key distinctions between platform companies, particularly differences between the customer's role in the control arrangement and the type of tasks that platforms facilitate. By identifying these key distinctions, we hope future research can continue to build more theoretically informed arguments that reflect platforms' unique characteristics.

Our study reveals the different roles of customers in algorithmically mediated customer control systems. On open labor market platforms such as FindWork, the matching decision is ultimately left to customers and workers, who choose whether they will work together. As a result, compared to closed labor market platforms, customers and workers in open platforms can exercise greater control at the beginning of the labor process. In closed labor markets, however, workers face sanctions for refusing matches that the platform makes. Indeed, throughout all stages of the labor process in closed labor markets, workers face stricter sanctions and possible removal from the platform. Differences in temporal stages have been noted in legal debates regarding platforms, especially closed platforms, such as with insurance coverage and misclassification complaints (Dubal 2017, Hyman et al. 2020). Thus, one salient difference our study reveals is that the extent to which platforms control the matching process affects workers' latitude to deploy resistance.

Another natural advantage of comparing our sites concerns the type of work that each platform facilitates, as FindWork facilitates more complex work and RideHail facilitates more-routine work. Projects on FindWork are largely complex and iterative. As a result, customers and workers have comparatively more opportunities to communicate, which presents workers with more opportunities to deploy interactive resistance tactics. We observed this in workers' ability on FindWork to convince customers to split a single project into multiple contracts and when workers negotiated with customers at the end of a project. These interactions are difficult to police in higher-skilled work because they may be legitimate, depending on the type of project or customers' preferences. For RideHail, in contrast, the nature of work was comparatively more routine: the platform specifies how fast workers should respond to ride requests, how long it should take them to complete a ride, and which times and areas workers should prioritize. As a result, we found that platforms facilitating routine work can set stricter penalties for workers not meeting their expectations: the platforms clearly define good work, making it more difficult for workers to deploy resistance tactics. Other scholars have noted similar differences between complex and routine work (Rahman and Barley 2017), as attempts to quantify complex work backfire and reduce productivity because of the work's intricate nature (Ranganathan and Benson 2020). Additionally, more routine work means that the workforce is more easily replaceable: when workers are lower skilled, organizations are less concerned about retention and, thus, enforce stricter sanctions (Hyman et al. 2020). Our study thus highlights how differences in customers' roles in platform labor markets (open or closed) and tasks offered (non-routine or routine) contribute to differences in how control is exercised and how workers deploy resistance tactics.

Boundary Conditions and Limitations

Our qualitative study provided a comparative analysis of workers' covert resistance tactics on two different platforms. As in any research study, important limitations bound our claims and suggest opportunities for future research. First, we focused on workers' experiences because we did not have any data from FindWork or RideHail on the internal development of their algorithms. The lack of these data limits our ability to verify whether these organizations were aware of or concerned about workers' routine resistance tactics. Understanding platforms' perspectives would certainly be valuable, but the absence of these data does not diminish our study's contributions, as our study focused on building theory about workers' resistance tactics in relation to the algorithms. In her review on building theory from qualitative research about algorithms in the contemporary workplace, Christin (2020:7–8) explains that "ethnographers can only study places and practices to which they have access. The different dimensions of algorithmic opacity …. (e.g., corporate secrecy, technical illiteracy, unintelligibility, and size) make it inherently difficult for ethnographers to center their analysis on algorithms. Rather, ethnographers can examine the reception side of algorithmic systems, analyzing the practices and representations of users." Consistent with this perspective and other qualitative, theory-building studies (e.g., Barley and Kunda 2004), our data collection centered on workers' practices and experiences. Future research could focus on the designers of algorithms and their work practices and experiences.

We note that platforms rarely, if ever, go on the record discussing their proprietary algorithms, as their competitive advantage relies on keeping such details secret (Burrell 2016, Christin 2020, Dourish 2016, Pasquale 2015). When platforms have shared data for research, they have been accused of providing curated data to maintain a positive public image (Griswold 2018, Kerr 2020). Even more alarming, platform companies have targeted scholars, former employees of platform companies, and elected officials with physical harassment and cyberbullying for revealing too much about the companies' practices (Hiltzik 2020, Isaac 2017, 2019). Notwithstanding these limitations, many influential studies have successfully examined algorithmic processes in organizations, with little to no information from the organizations themselves (e.g., Curchod et al. 2019 [eBay], Irani 2015 [Amazon mTurk], Ravenelle 2019 [sharing economy]). Thus, while platform companies continue to guard their algorithms closely, researchers continue to gain valuable insights by collecting data from multiple sources, including workers, who are most affected by the algorithms.

Our study also examined the nature of covert resistance enacted at an individual level. There are other types of resistance, including unwitting and overt, the latter of which has spiked during the COVID-19 pandemic as workers seek hazard pay, personal protective equipment, and sick leave (Bond 2020, Cameron et al. 2021b). Workers have launched their own co-operatives that allow them to maintain more of their income and that use customer ratings as a more instructional, rather than punitive, measure (Conger 2021). Stakeholders are closely watching such initiatives, which signal a growing initiative to redress the difficulties that workers face when using platforms. Finally, our sampling strategy did not allow us to identify variations among participants in terms of national culture, tenure, hours worked per week, gender, or previous work history. Thus, other factors likely also shape the relationship between control and resistance on platforms. Future research could explore the prevalence of different types of resistance tactics and how other factors (e.g., work configurations, gender, tenure) shape the relationship between control and resistance. Workers, for example, might defect to a competing platform (e.g., switching from Uber to Lyft), akin to a digital whipsaw strike (Hirsch 1969), without the platform company's awareness. Other scholars note that emerging legislation is compelling platforms to provide workers with greater access to the data that platforms use to control them, potentially impacting workers' ability to devise and deploy resistance tactics (Thomason et al. 2019).

Emerging technologies and shifting organizing paradigms are reconfiguring the workplace, signaling a broader need to re-examine and update mainstream organizational theories (Barley et al. 2017). This study extends our understanding of what control and resistance entail in the new, gig-based economy finding that control and resistance extend well beyond the execution of work. As the nature of technology and work changes, we anticipate the relationship between control and resistance will continue evolve in ways that will require innovative data collection and theory building opportunities.

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Table 1. Similarities and Differences Between FindWork and RideHail

Field Setting Dimension	FindWork	RideHail
Similarities		
Ratings Algorithm	One–five star rating based on customer reviews.	One–five star rating based on customer reviews.
Importance of Ratings to Workers	High; Used by algorithm to sort and display worker profiles to customers	High; Used by algorithm to match drivers, and affects future work opportunities
Accountability of Customer's Rating	None; Customers could give rating without justification or being subject to oversight from the platform	None; Customers could give rating without justification and would give low ratings for factors outside of drivers' control and/or to get a free ride
Significance of Workers' Ratings of Customers	Low; Most customers were unaware that they were rated by workers; ratings did not influence platform outcome	Low; Most customers did not know even their own ratings; these ratings did not influence any platform outcome
Differences		
Type of Labor Market and Work	Open; Variety of services offered, primarily knowledge work	Closed; Routine tasks of driving offered
Matching Algorithm	Used in ranking freelancers in search results and used to suggest potential freelancers to customers	Automatically assigns drivers to rides based on location, rating, and other factors; workers face penalties if they reject too many rides
Customer Role	Responsible for hiring and rating worker	Responsible for rating worker
Consequences of Low Ratings	Workers less visible in search results	Possible deactivation (firing), and influences future work opportunities

Table 2. Resistance Tactics on FindWork and RideHail

Type of Resistance Tactic	FindWork	RideHail
Preemptive: Working to achieve higher ratings without customer involvement	Vetting customers	Vetting customers Duping customers to cancel rides
Interactive: Workers nudge customers to help ensure they achieve or maintain high ratings, without customers knowing they are engaging in unsanctioned actions	Segmenting work into multiple contracts Holding work hostage Ending work prematurely	Duping customers to cancel rides Ending work prematurely
Reactive: Last-resort tactics workers use to avoid or minimize the effect of customers leaving a negative rating	Filing Disputes	Mediated retaliation

Figure 1. Shifting Control Arrangements, Worker Resistance Tactics, and Rating Outcomes

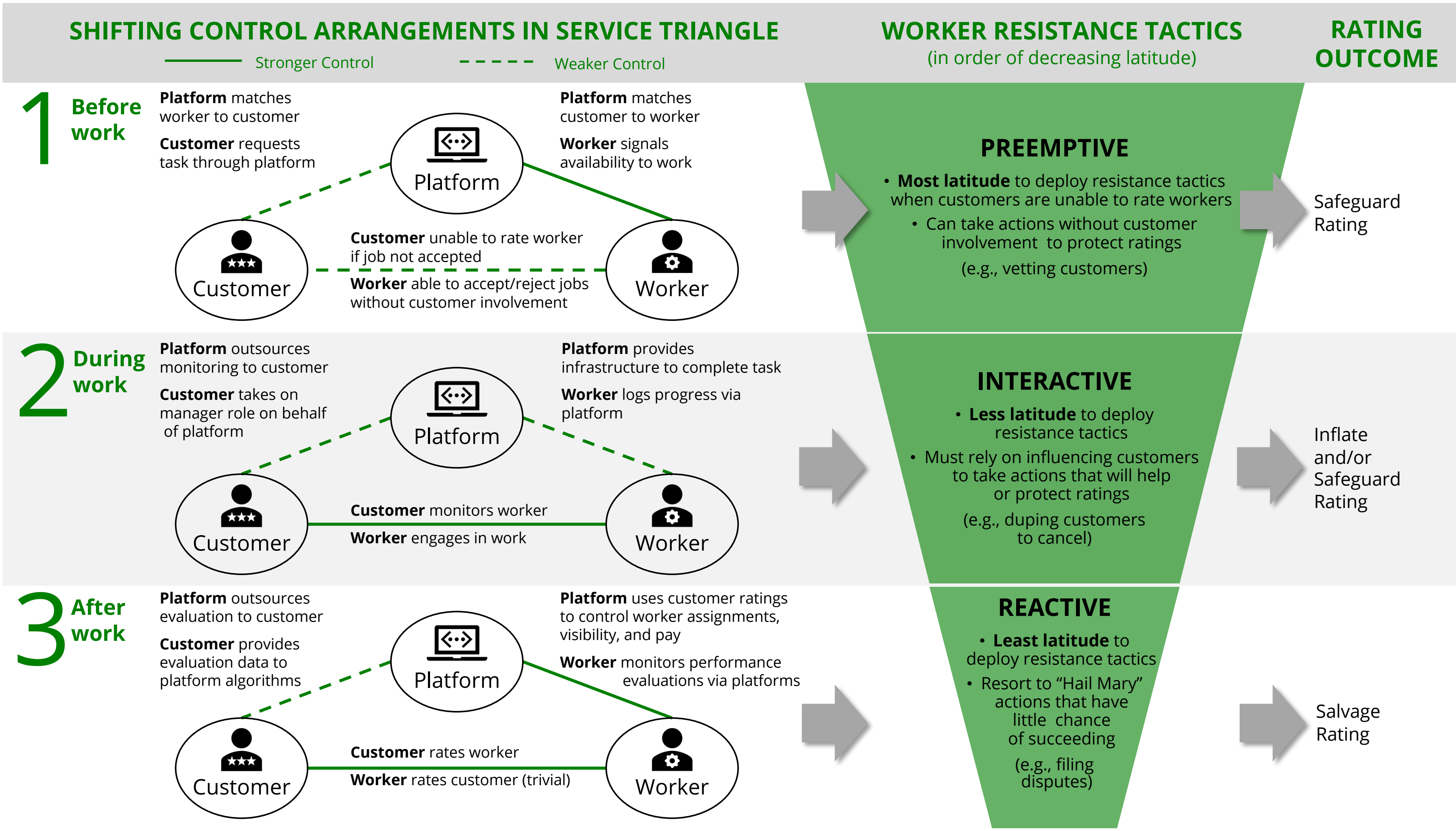

Figure 2. Visualizing Shifting Control Arrangements in Each Stage of Work