Making out While Driving: Control, Coordination, and its Consequences in Algorithmic Labor

Job Market Paper (Draft)

Lindsey D. Cameron
Ph.D. Candidate, Ross School of Business, University of Michigan
Abstract

Increasingly, algorithms are changing how work is structured and navigated. Drawing on a 26-month ethnography of the ride hailing service industry, the largest sector of the on-demand economy, this paper describes how the shift from human to algorithmic managers affects the nature of managerial control and worker autonomy. I begin by describing how algorithm-based control systems differ from prior control systems and conceptualize *algorithmic work*—a set of job-related activities that are structured by algorithms. In this context, algorithms manage by structuring choice at each human-algorithm interaction via nudges, to which drivers respond with a set of work tactics: compliance, deviance, or feigned acquiescence. While these tactics appear to be at odds, drivers frame their actions as evidence of their personal autonomy, in that the actions allow them to build a continuous stream of income and work from a discontinuous set of tasks. This *contingent autonomy*, or circumscribed choice, demonstrates that though algorithms may be externally viewed as an impersonal and, at times, unforgiving taskmaster, workers perceive otherwise, actively navigating their work environment. Further, by requesting and acquiring consent from workers at each stage of the work process, these algorithmic systems enact control without authority. This paper contributes to the understanding of control in organizations by describing a new type of control system and theorizing how algorithms can be a means of exercising control through enabling autonomy. Lastly, worker autonomy is re-conceptualized as a product of dynamic, human-algorithmic interactions as opposed to a static job feature. In sum, this paper provides insight into how work is structured and performed in the contemporary workplace.

**Keywords:** algorithm; control; autonomy; labor process; gig economy; Uber
Increasingly a central part of the modern workplace, algorithms are allocating, optimizing, and evaluating the work of diverse populations ranging from traditional workers—such as subway engineers, warehouse workers and Starbucks baristas—to on-demand workers on platforms like Uber and TaskRabbit. In a 2016 report, the Brookings Institute estimated that more than 70% of jobs require interaction with digital technology, with the fastest growth in the service sector. Making decisions faster and far more efficiently than humans, algorithms are rapidly removing the need for human managers. Yet working with algorithms presents fundamentally different organizing challenges that have not been explored in the management literature. In this paper, I define and then explore the concept of algorithmic work—that is, work that is constituted, to some extent, by an algorithm or a set of instructions programmed by a computer—in relation to control and agency. Specifically, I ask the following questions: “What is algorithmic work and how does it structure work activities?” and “How do workers navigate algorithmic work?” Given the rapidly evolving modern workplace, understanding the impact and experience of algorithmic work is crucial for updating key organizational theories of managerial control and worker autonomy.

Algorithms are a defining feature of the on-demand economy, a labor market characterized by short-term work contracts where algorithms allow work and workers to be assigned, priced, and evaluated. Over the past decade, the number of workers outside of traditional organizations has doubled, with more than 15% of the U.S. workforce working as “free agents” moving between gigs (Katz & Krueger, 2016). Existing theories about managerial control (e.g., Taylor, 1947; Roy, 1952; Burawoy, 1976) were crafted in the mid-twentieth century, at the height of the bureaucratic age, with control being exercised through managers and peers (e.g., Roy, 1952, 1959; Burawoy, 1976; Barker, 1992). The rise of algorithms in the
modern workplace, and their effect on work coordination, opens up questions about how managerial control will be maintained and navigated. Algorithms further the distance between the organization and its workers, decentralizing and anonymizing procedures such as hiring, evaluations, and firing (Seavers, 2017). Compared to bureaucratic organizations, employer–worker relationships in on-demand organizations are more fluid and temporary: management, if present, keeps workers at arm’s length, since workers can be quickly replaced. In light of the highly individualized world of algorithmic work, organizations must develop new ways to exercise control in contrast to the way control has been previously theorized.

Drawing on an extensive qualitative field study of the ride hailing industry, the largest employer in the on-demand economy, I examine the intersection of algorithms, control and autonomy, exploring how algorithms structure work tasks and, correspondingly, how workers respond. To frame my findings, I review research on managerial control and worker autonomy as well as some of the literature on algorithms, which largely exists outside of organizational research. When possible, I integrate research on algorithms in organizational contexts. In addition, given the study’s context, the on-demand economy, I draw upon insights from research that discusses issues related to technology and the changing nature of work. I begin my findings section by defining the concept of algorithmic work. I then peer under the hood, describing how algorithms structure work, performing tasks that were previously done by managers. Lastly, I delve into the experience of algorithmic work itself, detailing worker activities in an environment without managers as workers piece together a living wage from a string of tasks. Taken together, this study puts algorithmic work on the map, laying out its structural elements and describing how workers actively navigate its landscapes. This study also opens the door for future research on human–algorithmic work interactions. Theoretically, this study makes several important
contributions to literatures on managerial control, worker autonomy, and human-algorithm interactions.

**Managerial Control Revisited in the Rise of the Algorithmic Revolution**

Control is management’s “most fundamental problem” (Van Maanen and Barley, 1984: 290). Organizational control is the attempt “to increase the probability that individuals will behave in ways that will lead to the attainment of organizational objectives” (Flamholtz, Das, & Tsui, 1985). Control systems are dynamic, evolving with capitalistic systems. In the mid-1800s, most industrial operations were small, with owner-entrepreneurs working and living in close contact with their workers. Control and motivation were handled in a simple, informal, and unstructured manner, since owner-entrepreneurs could easily observe and correct workers (Smith, 1827; Edwards, 1979). As firms grew in size, control structures evolved to compensate for the lack of direct observation. Foremen oversaw production (Roy, 1952), wages were linked to output (Burawoy, 1979), and technology, such as the assembly line, regulated the production process (Taylor, 1947). Edwards (1979) outlines three types of control: direct or simple; technical; and bureaucratic or rule-based. With the rise of non-unionized and non-production work in the mid-twentieth century, managerial interest turned to how to absorb workers psychologically into organizations and occupations. More recent work focuses on the psychological aspects of control, or social control, viewing the organization as an invisible hand that shapes workers’ minds by enriching jobs (Herzberg et al., 1967; Hackman & Oldham, 1978), sponsoring professional communities (Wenger, 2011), and engineering culture (Kunda, 2009).

As we enter the twenty-first century, technology is again reshaping work—this time through algorithms—and prompting another shift in the evolution of control systems.
The Oxford dictionary defines an algorithm as a “process or a set of rules to be followed in calculations or other problem-solving operations, especially by a computer.” Despite the frequent use of algorithms in high-tech contexts, the limits of the term *algorithmic* are determined by sociological constraints, not technological ones (Dourish, 2016). A data scientist working at Google in 2018, a lab manager setting a budget in 1980, a university mathematician working on a proof in 1940, and a doctor establishing treatment procedures in 1890 might all have claimed, correctly, to be working on algorithms. In this paper, I use the term *algorithm* to signal an idea initially defined by eighth-century Persian mathematician Muhammad ibn Musa al-Khwarizmi that is associated with symbolic (Boolean) logic. The concepts of algorithms and symbolic logic were further developed by the seventeenth-century philosopher and mathematician Gottfried Leibniz, who proposed a “calculus of reasons” (calculus ratiocinatus) and designed a calculating machine that used binary numbers to complete arithmetic operations. Although these concepts were subsequently advanced by George Boole, Charles Babbage, and Ada Lovelace, it was not until the Allied and Cold War defense strategists that symbolic logic and programming acquired great practical purpose. Today, algorithms are studied across a number of fields, including computer science, information science, communication, economics, and, more recently, anthropology, sociology, and psychology.

In the social sciences, two perspectives are emerging, where algorithms are viewed either from a structural or an interactionist perspective. The former sees algorithms as a black box to be penetrated—taken apart, figured out, and put back together (in a better way) by humans. Studies of algorithmic rankings and ratings, for example, attempt to understand why algorithms make certain decisions, such as those made by Google’s search engines, Facebook’s newsfeed, Netflix’s recommendations, or New York City’s predictive policing. For example, recent work
has explored how movie recommendations are ranked (Gomez-Urive and Kent, 2016) and how ride hailing services price (Borg, Candogan, Chayes, Lobel, Nazerzadeh, 2014) and match rides (Chen, Mislove and Wilson, 2016). A recent trend within this structural perspective involves audit studies that identify algorithmic bias, or potential racial and gender discrimination by algorithms. A series of studies on online platforms find that workers’ gender and race are significantly correlated with performance evaluations, which may affect employment opportunities (Rosenblat, Levy, Barocas and Hwang, 2016; Edelman, Luca, and Svirsky, 2017; Hannák et al., 2017). Relatedly, automated hiring platforms solicit increasingly personal information from applicants (e.g., personality assessments for hourly workers), and in turn, the algorithms use this information to perpetuate human biases and cull “riskier” job-seekers (Greene and Ajuma, 2017). A common theme across this work is an earnest attempt to make the algorithm and its decision-making process more visible so that it can be controlled, managed, and tweaked more easily. In response to the finding that guests with African-American names were less likely to be accepted than guests with distinctly white names (Edelman, Luca, and Svirsky, 2016, 2017), researchers suggested that AirBnB encourage renters to write reviews of African-American guests (Cui, Li, and Zhang, 2017), and the platform launched an public image campaign, emphasizing its anti-discrimination policy (Benner, 2016). Similarly, Textio, a platform that screens for gender-hostile language in job advertisements, was launched after a series of complaints about the gender and racial biases encoded within hiring algorithms and platforms (EEOC, 2007). In sum, this structural perspective on algorithms would suggest a hyper-Taylorized view of managerial control, in which algorithms are designed with optimal efficiency in mind. Furthermore, socially desired rules could be explicitly encoded within the algorithm, such that racial, gender, or other biases would be programmed away.
The second emerging perspective views algorithms as being enacted through interactions with humans. Drawing on performativity (Austin, 1962; MacKenzie and Milo, 2003), affordance theory (Gibson and Walker, 1984; Schrock 2015) and other practice-oriented approaches (Orlikowski, 2002; Carlile, 2002), this perspective argues that algorithms are not stable empirical objects and, thus, that access to the code or the rules embedded within the code is not enough to understand their effects “in the wild.” In a study of music recommendation systems, for instance, Seavers (2014; 2017) demonstrates there is rarely one algorithm to point to that results in, say, a particular song playing on Pandora, as results are personalized based on a “technological ecology” of interlocking inputs from advertising networks, users, and moderators. Similarly, in a study of an online dating site, Devendorf and Goodman (2014) found that various actors enacted the site’s algorithm differently: some engineers tweaked their code to mediate between the distinctive behaviors of male and female users, for example, while other users tried to game the algorithm, as they understood it, to generate more desirable matches. Yet another set of users took the algorithm’s matches as oracular pronouncements. Algorithmic enactments have real consequences. In the face of new technology adoption, status may play a role in whether workers accept or question the assumption embedded within the technology (Anthony, 2018). Noting the popularity of TripAdvisor and its “Popularity Index”-rating algorithm, which ranks hotels based on customer reviews (among other unnamed factors), Orlikowski and Scott (2013) reported that hoteliers felt on edge because they were viewing customers not as guests but as bosses. A common theme across this work is the assumption that there is no inner truth to the algorithm, since interactions with managers, coders, and non-technical outsiders change the algorithm’s usage. It is algorithmic interpretation and not algorithmic development that matters here. In sum, the interactionist perspective suggests that algorithms change how control systems
are interpreted and enacted such that experiences of managerial control through algorithms are personalized and situational. From this perspective, algorithms may both limit and enable worker autonomy in ways that are important to understand.

**Autonomy as a Form of Managerial Control**

Autonomy may be granted by management through the design of jobs (Hackman and Oldham, 1976) and the structure of teams (Hackman, 1983; Haas 2010), as well as supported through organizational practices (Blau, 1984; Michel, 2012). While autonomy is viewed as a marker of professional success (Abbot, 1988; Alvesson, Lee and Thomas, 2008), a number of studies document a “paradox of autonomy” (Mazmanian, Orlikowski, and Yates, 2013), in which workers will limit their autonomy in response to the demands of a job, a team, or a changing labor market (Kunda, 1992; Barker, 1993; Perlow, 1998; Barley and Kunda, 2004). In response to diminished autonomy, workers report feeling frustrated and trapped (Barker, 1993; Kunda, 1992; Perlow, 1998; Barley and Kunda, 2004). Barker’s (1993, 1999) noteworthy ethnographic study of the shift in managerial control from hierarchical, bureaucratic control to concertive control via the use of self-managing teams found that team members’ feelings of being controlled intensified as the team’s decision-making process went from value consensus to imposing moral values upon one another. Similarly, Michel’s (2011, 2014) ethnography of the control systems of two investment banks identified how the banks’ espoused values of autonomy and work-life balance contrasted with the habitual overwork that bankers experienced as self-chosen, which eventually led to body breakdowns.

Autonomy can also be relationally granted. In collaboration with their fellow workers, factory employees developed new ways to shirk work, such as through “goldbricking”—working as little as possible while giving the appearance of doing otherwise (Roy, 1952); “Banana
Time”—taking designated social breaks (Roy, 1959); or “making out”—playing games to outproduce one another while staying under the production quota (Burawoy, 1976). In contrast, in one the largest factories in the world, Bernstein (2012) found that line workers conspired to maintain higher productivity: they hid in plain sight to use “better” techniques and tricks that were not in line with organizational policies. Acts of autonomy can also strengthen workers’ relationship to collectives, such as to their occupational and professional identities. Anteby (2008) explains that while creating gifts from company materials on company time was explicitly forbidden, the practice continued, even under the threat of firing, as these “homers” served as a tangible artifact of the craftsmen’s skill and occupational identity. In another study, following the adoption of mobile email devices, Mazmanian and colleagues (2013) found that workers felt empowered, even though they were now continually available to their clients and co-workers, because the devices enhanced their image as responsible and competent professionals. Similarly, Perlow’s (1998, 2002) study of a high-tech organization found that engineers’ ethics and desire to appear committed to the organization led them to accept longer workdays and unpredictable demands on their time. Lastly, autonomy can be granted even outside the boundaries of the firm. In their work on freelance software contractors, Barley and Kunda (2004) found that even as these contractors had the freedom to select their jobs and hours, they seldom took advantage of this flexibility; they were perpetually worried about keeping their skills as sharp as those of their (imaginary) competitors on the next contract.

Research Setting, Methods, and Analysis

I explored human–algorithm interactions and the process of algorithmic work in the context of the ride-hailing industry, the largest sector of the on-demand economy. Algorithms are
the backbone of the ride-hailing industry. First launched in 2011, services such as Uber, Lyft, and Juno rely on algorithms to coordinate the labor process from hiring to firing and everything in between. Independent, distributed drivers with their own cars are algorithmically matched with customers within seconds and given block-by-block directions to their destination. Fares dynamically adjust based on demand. Performance is evaluated by customers’ ratings, and drivers have scant direct contact with company representatives. Even hiring and firing (access or blockage from the platform) is conducted completely online. Driving requirements vary across cities, but drivers across platforms are required to complete a reference check, criminal background investigation, and state vehicle inspection. After completing those requirements, which typically takes between one and three weeks, drivers are given access to the drivers app on their smartphone. Drivers are terminated through simply being denied access to the drivers app.

Given the emerging nature of on-demand work and my interest in theory development, I designed an in-depth field study and spent twenty-six months in the field. I used five overlapping data sources, which I triangulated to bolster validity (Eisenhardt, 1989): participant observation (150 hours as driver),\(^1\) conversational interviews (\(n = 109\)), semi-structured interviews in eleven North American cities (\(n = 93\)),\(^2\) focus groups with customers (\(n = 24\)), and analyses of social media (e.g., blogs, Reddit forums, Twitter) and print media (e.g., newspapers articles).

I analyzed data using a grounded theory approach (Charmaz, 1996; Locke, 2001) with field observations and interviews as my primary data sources and the foundation of my analysis.

---

\(^1\) Ninety of the 150 hours of driving (60\%) were completed by the first author. As ride-hailing platforms restrict driving to the state where the car is registered, a research assistant completed the remaining hours in a different state.

\(^2\) Geographic break-down of informant locations are as follows: 34\% Ann Arbor, Michigan or Detroit, 33\% Washington, DC, 33\% other cities. Interviews were conducted in two phases. Sixty-one individuals were interviewed during the first phase of data collection, from January 2016 to November 2017. Approximately one year after the initial interview, all participants who had driven more than 10 hours/month over the past year (83\% of all Phase 1 interviewees) were asked to complete a follow-up interview, of which 84\% accepted. Some declined to participate because they were no longer driving, had moved, or were no longer interested in the study. When possible, I conducted a short exit interview.
Data was analyzed and collected in for two-month waves, followed by two months of analysis and deep reflection, over a period of two years. A few examples of how data collection and analysis co-evolved follow. After collecting my first round of data, roughly 10 hours of driving and 20 interviews, I refined my research questions, interview schedule, and the structure of my field notes. Specifically, I noticed that both drivers and myself discussing the pricing structure frequently (incentives and surges) and setting daily/weekly earning goals. In subsequent interviews, I specifically probed about how drivers interacted with the pricing structure and noted how my own behavior towards it shifted over time (e.g., automatically dismissing some incentives because the goal was too high, scheduling shifts around projected surge times) and with changes in the company’s policy (e.g., the introduction of tipping at one platform company). Further interviews and field notes expanded to different structured embedded within the app’s work system (e.g., the ratings system).

Data analysis began in earnest roughly 18 months after collection started and was undertaken in several stages. While my preliminary analysis informed my way of thinking, as Charmaz would call “laying out the bones and finding the place of excavation”, I put the initial analysis aside in order to see my data with fresh eyes. First, I read over the my field notes to familiarize myself with their content and then turned to the interviews for more in-depth coding. Interviews and field notes were coded over five rounds. I began by open coding one-fifth of my transcripts selected on maximum variation of gender, number of hours worked, amount of time driving, and geographic location. From the initial codes three major theme emerged: narratives about the work experience (with a particular emphasis on identity claims and general (dis)like of the platform and the work itself), income (with a particular emphasis on maximizing income), and ratings (with a particular emphasis on grievances about ratings). In the next two coding
rounds, I started focused coding around those three themes and continued open coding identifying two additional themes – practices to create a good work day and interactions with other specific parts of the platform technology (i.e., accepting a ride request). No new major themes emerged in the last two rounds of coding. Throughout the process, I wrote memos on each of the emerging themes, met with advisors and colleagues, and workshopped early findings.

In the next stage of analysis I began axial coding and iterating between the data and existing theory. Based on my experience driving, I knew there was a rhythm to driving, so I began by first constructing a timeline of a typical day and a typical ride. I quickly noticed that both timelines were cyclical in that I often drove on the same streets (e.g., North Capitol, Wisconsin Avenue) and saw similar people based on when I drove (e.g., professionals in the morning, partiers on weekend evenings). The work tasks themselves were repetitive in that I repeated the same interactions with the platform (e.g., accepting a ride, rating rides). Across cities, informants used near-identical language to describe their days and best practices, suggesting to me that there was a typical day and a typical rides across my sample. Using stacks of index cards, I laid out the five thematic codes on top of the time cycles. And, as I had more data for typical rides than typical days, I focused my analysis on the former. It became clear to me that what made a ride typical were the routinized interactions with the app, so I turned to the literature on mobile devices, platform work, and algorithms. One thing that puzzled me in the literature that algorithms were typically described as a discrete entity as opposed to a system of distinct yet interlocking set of levers (which both myself and my informants experienced). Declining a ride, for an example, effected our ratings and surge pricing might effect when we would be matched with a ride. Realizing I was on to something, I re-coded my data around each mention of an algorithm-like function. (As my informants rarely used the word algorithm,
instead choosing to anthropomorphize the algorithms’ work, I relied on my own experiences to determine whether the informant’s described behavior was referencing an algorithm or not.) Eventually, I identified five distinct categories of algorithms: work matching, work instructions, pricing - incentive, pricing - surge, and ratings. Further coding clarified the purpose of each algorithm, how it interacted with drivers, how it was linked to other algorithms in the system, and whether it incentivized drivers through rewards or sanctions.

With the temporal work cycle and function of each of the five categories of algorithms clear, coding for the second half of my findings was relatively straightforward. My readings in critical sociology and labor process theory all suggested that workers would react negatively, likely resisting, to tightly structured work environments. Further, the literature suggested these the word tactics for these behaviors as they were enacted lower-powered individuals navigating within a larger system. Given my early stage of analysis, I chose to keep my coding approach open and broadly coded for any interactions with, reactions to, or perceptions to the platform, in general, or the algorithms, in particular, positive, negative, and neutral. After coding for these two categories (general/platform vs. specific/algorithmic), I realized I had more analytical leverage with the latter and focused my efforts on thematically categorizing my codes around human-algorithm interactions. Originally, I had only two tactics (compliance and deviance), but given that literature suggested a third category (resistance) I re-analyzed these two categories multiple times. Eventually, during a long walk, I realized that in my data did not fit classical conceptions of resistance (e.g., sabotage, unionizing) as it was dependent on workers’ intent, interaction with the platform itself, and behavior in the car. For example, in reference to a specific action on the platform (e.g., swiping right to accept a ride) a worker’s behavior may look like compliance while the worker’s actual intention and behavior is deviance (e.g., driving in the
opposite direction of the ride that was just accepted). Given this behavior did not match any literature-derived categories, I chose a new category name, feigned acquiescence.

At this point I had all of my data neatly laid out in front of me in a mass of index cards--the tactics linked to each algorithm and each algorithm linked to a different stage in the temporal work cycle. Repeatedly I asked myself, ‘What is the company trying to do?’ and ‘What are the workers trying to do?’ during long runs. In re-reading transcripts, I found that one of my informants had already answered these questions -- “The company is trying to make drivers take as many rides as possible. The driver is trying to make as much money as possible.” (Ralph, Detroit). Suddenly everything clicked. The platform driving was trying to structure work in such a way that drivers would find it easy --- nay, compelling -- to give as many rides as possible. The work was simple and discrete, so it could monitored and structured by an algorithm, yet also designed in a way to be motivating -- hence the incentives and advertisements alluding to the personal freedom of driving one’s car. In contrast, workers were drawn to the money. From my first day in the field, I saw that both drivers (and myself) were concerned about earning as much as possible and keeping our cars moving. However, our freedom was constrained in that we were always operating within the platform’s structure -- hence our inability to always meet our income goals. This insight led to my first theoretical idea of contingent autonomy or choice within constraint. With the idea of contingent autonomy in mind, I recoded the tactics data noting that some tactics were linked to the work cycle while others were linked to choosing when to begin or end a work shift. Thus, I realized contingent autonomy was multi-dimensional – both in response to a specific algorithm and as a set of interlocking parts along different timepoints in the overall work process – thus, giving me more confidence in this theoretical finding.
Once I had a better grasp of workers’ autonomy tactics, I went back to the first question of “What is the company trying to do?”. I found my original answer, that the platform company was micro-structuring work through algorithms and releasing autonomy-enhancing propaganda, unappealing – it lacked the nuance to explain what I was observing. Rereading Burawoy’s classic, *Manufacturing Consent*, I made parallel connections between his factory workers and my drivers. In the same way that consent was manufactured through playing games on the shop floors, in my context, consent was being manufactured through explicit requests at each human-algorithm interaction to continue to the next stage of the work cycle. Each human-algorithm interaction gives workers another opportunity to buy-into to the system, gradually create sense of psychological acquiescence to the algorithm. In this new work system, with the absence of any traditional management structure, this enables control without authority. With this insight in mind I returned to the literatures on control systems, autonomy, and algorithms to frame my findings.

**Algorithms and the Work Process**

*Algorithms as a Tool to Structure the Work Process*

From my first day in the field, I quickly realized how deeply embedded the algorithm was in everyday work practices. Algorithmic work is a set of job-related tasks and activities that are coordinated, to at least some extent, by an algorithm. In other words, if the completion of work activities depends on human and algorithms interacting then the work is algorithmic. Algorithms are the scaffolding of work system in the ride-hailing services as five different types of algorithm structure work: 1) work matching, 2) work instructions, 3) pricing (surge); 4) pricing (incentive); 5) performance evaluation or ratings. The smallest unit of work is a human-algorithmic
interaction (HAI) or work activity. A work cycle contains one or more HAI’s and a workflow contains one or more work cycles. The typical work cycle is a complete ride, namely 1) being matched with a passenger; 2) driving to passenger’s location; 3) waiting for passenger to enter vehicle; 4) starting ride with passenger; 5) engaging with passenger within car; 6) dropping passenger at their destination; 7) rating the ride. In contrast, an aborted work cycle would be: 1) being matched with a passenger; 2) driving to passenger’s location; 3) the passenger cancelling the ride. In a 4-hour shift, drivers may complete only twelve full work cycles (rides) yet have more than a hundred unique interactions with the algorithm. See Exhibit 1 for how algorithms are embedded within the work cycle and Exhibit 2 for more detailed descriptions of each algorithm.

Algorithms are not neutral in that they enable and constrain patterns of actions. In the same way a salesclerk designs a display to encourage the purchase of certain items, programmers create algorithms to influence or nudge behavior. In this context the computer programmer, with a heavy dash of insight from data scientist, are the choice architects drawing on an ever-changing mix of behavioral economics and consumer behavioral research to guide behavior (Scheiber, 2017). Nudges are a way to structure choices or provide options organized within a context by a choice architect (Thayer and Sunstein, 2008). In addition to structuring choice, my findings suggest that nudges also shape behavior through their structure and content. The two forms of nudge structure are: frequency, or how often a nudge is presented, and urgency or if responding to a nudge is critical to accomplishing work. The two types of nudge content are clarity or how easy workers can discern the algorithm’s motives and rewards (punishments) for (not) following nudges. From the perspective of the algorithm-designer, workers’ responses to nudges are not a straightforward stimulus-response reaction, but instead based on a numerous interlocking or
coupling factors inherent within the algorithm’s design. And while machine learning is inexplicable to the human mind, given that algorithms can be operationalized and optimized on countless dynamic factors (e.g., Orlikowski and Scott, 2013; Seavers, 2017; Kirilenko, Kyle, Samadi and Tuzun, 2017), through observation and engagement it is possible to describe some, if not all, the ways that algorithms nudge and, in turn, how workers respond to this circumscribed choice.

Algorithmic Nudges and the Work Cycle

In the next portion of the findings section, I provide an in-depth description of each of the five algorithms and how they shape the execution of work. Once a driver goes “on-line”, by swiping right, they are available to be matched with nearby passengers through the work assignment algorithm. In my fieldnotes from my first day of work, I note

First day. I’m sitting on a shady street two blocks from my house, nervously checking my phone every twenty seconds so I don’t miss a ping. My phone is in on my dashboard when it suddenly starts buzzing. Yay – a ride! I see a flashing circle with a timer, counting down. My hands are sweaty, the phone is vibrating, and while trying to swipe I drop the phone under the passenger seat. Darn! After a few seconds the phone goes quiet. I’ve lost my first ride.

When the algorithm matches a driver to a passenger, the driver’ smartphone buzzes and a fifteen-second countdown timer starts for drivers to decide whether to accept or decline. The app also presents distance to pick-up location (approximate), surge amount (if any), and details about the passenger (e.g., rating). Declining multiple rides in a row, either by outright rejecting or letting the timer run down, results in a series of escalating repercussions, such as a ratings penalty or being blocked from the platform for progressively longer period of times.
After the driver accepts a ride the work instructions algorithm takes over, timing the execution of work by directing the driving routing and setting waiting timers. In instructional material for drivers, the process is described as, “After you accept a request, tap 'Navigate.' The app automatically opens up your selected navigation app to guide you to the passenger. (Tap 'Settings' to choose which navigation app you want to use.)” The algorithm creates as a two-way communication between driver and rider along the way as the materials go on to describe “the passenger will see your car icon approaching on their app and your ETA. When you're getting close, we'll send them a text message.” Once the driver arrives at the passenger’s location, another countdown timer begins signifying how long the driver is required to wait for the passenger, which can be anywhere from sixty seconds to ten minutes, depending on if the ride is private or shared. In shared rides, the work instruction is critical as multiple individuals with different destinations share the same vehicle. The platform urges drivers to, “always follow the app's instructions. Keep a close eye on your app for shared rides. The route is built on efficiency, so the order of who is picked up and dropped off first varies from ride to ride.” In high-traffic areas, drivers are assigned to a queue with an estimated wait time until their next ride. In my fieldnotes, I describe my first time in the airport queue.

I’m circling around the airport trying to find waiting lot for drivers-- it’s my first time here... Grannely Point...private airstrip....packing warehouse...Finally when I’m at the Sunco [gas station] a timer pops up saying I am in the queue and the wait is 75 minutes. I guess the lot is nearby.

At the airport, this waiting timer is crucial -- without being in the queue drivers are unable to be matched to riders. Some drivers report waiting at the airport for hours, without receiving a ride, because they did not realize they did not notice the timer was not activated. In sum, the work instruction algorithm is crucial in that execution of work in that it dictates timing through the
flow of work (navigation) and suspending and restarting work (timer). In sum, the work assignment and work instruction provide the most structure in that the nudges clearly communicate a desired path of action and there are direct repercussions for not following nudges.

The pricing algorithm and its associated nudges structure drivers’ behavior less in that there is a greater variety in types of nudges and subsequent rewards are less clear. Two pricing algorithms - surge pricing and incentives - give drivers’ the ability to increase their base pay, a combination of mileage, driving time, and a flat pick-up fee. Surge pricing sets task pay above the base rate based on customer demand. Some surges are predictable, such as commuting hours, and others are more sporadic based on local events, traffic patterns, and weather. Drivers are alerted to surge pricing through SMS alerts or within the platform. Common SMS alerts include, “Demand is higher than usual in Center City. Take advantage of higher than normal fares!” or “Adele is playing at the Convention Center tonight! The streets will be full of people!!”. Surges may also be advertised in the notification section of their platform, such as “1.2 - 1.8x boost - 4:30PM - 7PM - downtown DC.” Real-time passenger demand is displayed on the platform’s heat map, with more heavily trafficked areas boldly outlined and in darker shades of red, that is displayed each time the driver logs into the app and completed a ride. Sarah, a Chicagoland driver, describes her interaction with the heat maps. “You turn on your app, and then you see that very orange, bright color around downtown area, that means there is a surge there. There is a high demand...so you rush into that area.” Overall, the surge algorithm is highly visible to the driver through multiple avenues (e.g., SMS alerts, frequent heat maps displays), drivers can take advantage of surges if desired and are not penalized for avoiding the nudge.
Incentive pricing provides a bonus amount for drivers competing a specific number of rides with the specific number being algorithmically determined based on the drivers' past behaviors. For example, a driver who meet their ride quota one week would get a more challenging incentive the following. For the weekend of 15 March 2018, my incentive was, “an extra $90 for completing 24 trips” and, after not meeting the goal, the following week’s quote was reduced to “$120 for completing 25 trips”. Benchmarks are clearly communicated to drivers through the platform itself (accessed via setting menu) and SMS alerts -- indeed, while taking a three-month hiatus from driving and I still received alerts twice a week. Further, these offers may incentive workers to drive at specific hours, such as peak-commuting hours or the bar closing shift. Both pricing algorithms are clearly communicated through multiple mediums and rewarded; however, in comparison to the work matching and instruction algorithm, neither are integral to accomplishing work nor incur penalties for non-compliance.

The rating system is two-way in that drivers’ rate riders and riders rate drivers on a one (poor) to five (excellent) scale. Riders’ evaluations of driver performance are important, as there are no human managers to evaluate performance, and high customer ratings (4.6+) are required for continued platform access. In this way, customers’ ratings of drivers serve as an invisible, looming threat in that they have the potential to ‘fire’ drivers. At the end of every ride, drivers are given the opportunity to rate the riders’ behavior. Instructional materials describe that “Ratings below 4 or 5 means the passenger wasn't up to par...Rating 3 or lower means you won't be matched with this passenger again.” Numerous factors may influence why a driver poorly rates a customer, such as a negative attitude or slamming the door, though, instructional materials do not give clear guidelines. Further, while drivers have the option to give a less than
excellent rating, the feedback form is pre-filled to give each rider five stars (excellent) and drivers must give the rider a rating before being matched to their next ride.

Nudges can also shape worker behavior outside of the work process/execution of the work itself. For example, drivers may receive texts such as, “You haven’t driven in three days. Go out there are make some money!” or that “Summer weekends are busy! Head to your promo hub [in the app] for you weekend incentives and surge pricing.” When logging off, the platform may offer nudges to encourage drivers to continue working such as “You’ve only driven 11 hours today!” or “Only $18 to go until you meet yesterday’s pay-out.” In each case, drivers must respond to this message before exiting the platform. In both instances, the algorithmic nudges encourage work on the platform.

Navigating the Algorithmic Work Environment

Keeping up the Flow: Making a Buck by Building a Steady Stream of Rides

Why do drivers drive? By far, making money was the prevalent motivation given for why drivers were active on the ride hailing platforms. Specifically, drivers were concerned with how to secure a continuous stream of income from a discontinuous set of rides and how to avoid standing still or “dead time.” Jonathan, a D.C. driver, notes, “If your car is not moving, you cannot earn money. Yeah. This is your investment. This is your tool to earn money for the car. That’s what the driving job is all about.” In order to maintain a steady flow of rides, drivers execute a series of tactics in response to algorithmic nudges. Tactics are different than strategies, which generally refer to the dominant player’s design for a system and to how the player moves toward a pre-defined goal. Tactics, therefore, are undertaken by less powerful players to navigate within the system (Certeau, 1980). Tactics allow players to use their small size, speed, and
flexibility to their advantage and to respond quickly to changes in their environment. Imagine, for example, the Algerian Front de Libération Nationale ambushing French colonizers in the casbah or the Rwandan Patriotic Front cutting off the key supply routes of the genocide-supporting regime: these are tactics, rather than strategies. In the context of ride hailing services, tactics provide insights about how workers manage to be agentic in an environment that is highly structured by algorithms so as to maintain a steady flow of rides. The remainder of this section is split into two halves: 1) tactics for navigating algorithmic work in the work cycle and 2) work entry and work exit. I first detail the three different work tactics—compliance, deviance, and feigned acquiescence—that workers employ in order to keep the rides flowing. (See Exhibit 3 for a summary of all tactics with respect to each algorithm.) I then detail the conditions when workers start (work entry) and complete (work exit) working. Taken together, I show that workers express considerable and varying amounts of autonomy throughout the work process.

**Algorithmic Work Tactics**

*Interpreting the Algorithm as Inevitable: Compliance Tactics.* Once drivers have logged in to the platforms, they enter a system where the algorithm sets the rules and nudges behavior; drivers, in turn, begin to navigate their work environment. With compliance tactics, workers see the algorithmic nudges as an inevitable feature of the environment and follow its suggestions. Jay, a D.C. driver, describes the way that he plans his work day around the two pricing algorithms, surges and incentives:

*The system is do the work or you don’t. There’s no other in-between. You got to be out here. If you are out here during the surge hours in the morning, the surge is between 7 a.m. and 9 a.m. Sometimes the surge is 2.0 and then you work throughout the day. Then, you’re going to be ahead of the game within those two hours, you can make $50 to $60. And then as the day goes on . . . you make $200. If you work during the surge in the*
afternoon, that adds up. So that’s the only thing you can really do. You can’t go around the system. The system is foolproof. You can’t cheat it. [laughs]

[Interviewer: Have you ever tried to?]

Not at all. Why? There’s no way. There’s no way. Yeah. No. There’s no way. I mean, the app determines the distance and determines how long you’re in the car and how much you’re going to get paid. So there is no way you can mess with it. . . . Like in any job, just do what you’re supposed to do and everything else will work itself out. It’s just staying on the road, ‘cause you gotta do the hours to make it come out right. You can’t cheat.

Jay rather straightforwardly describes the surge nudge as being embedded within a larger system of algorithmic work that does, to some extent, circumscribe his work activities. One either works within the algorithmic system or does not work at all. From Jay’s perspective, the system is foolproof and unbeatable. Earnings accumulate piece-rate from a series of rides; thus, timing shifts in conjunction with the surge nudge is necessary if a driver wants to take advantage of the more profitable earning hours. Overall, the work system is described as an iron cage, one that specifies how workers should behave in order to work successfully.

Incentive pricing is another nudge that is coupled to workers’ behavior: drivers receive nudges that offer bonuses for completing a variable number of rides. Catherine signs up for all of the incentives that are offered in Detroit and “get[s] 10 bucks or 15 bucks that I wouldn't have gotten otherwise. I don't do anything different so I feel like I'm just getting free money for that.” Being awarded extra money for routine work activities can engender positive emotions, encouraging workers to continue accepting the incentive offers. Kentucky is more deliberate than Catherine; he schedules his shifts in Philadelphia around incentives nudges:

Last weekend it was 50 rides and you get $150 bonus. If you give 75 rides you get a $250 bonus. If you give 90 rides you get a $350 bonus. I was trying to work towards the 90 rides, but on Saturday it didn’t work out because I got longer rides. I didn't get as many rides. I only got 21 rides. The first day I got 30. I was on track, but the second day screwed me. Then I got 80. This past weekend that just occurred, it was 60 rides for $175 bonus. 90 rides for $300 bonus and 105 rides for $375 bonus. That's [105] way too many rides. You could probably do it if you're out 13,
14 hours. That's crazy. That's a lot of rides. First day [I was out] eight or eight and a half [hours]. The second day was five and a half. Then yesterday was 10 and a half. So, I was out probably combined in driver mode, 24 hours this weekend. . . . With commuting, that was 30 hours total.

Kentucky chooses his output level—90 rides--from a set of choices provided by the algorithm. In the first week, Kentucky did not meet his goal, as the algorithm did not assign him the best mix of rides. However, he does not blame the platform, and he puts in even more driving hours, logging more than 30 hours in a 72-hour window. Technically, drivers can choose and adjust their benchmark, but most opt to aim for the highest benchmark, which means they act as if the benchmark is fixed, rather than taking the opportunity to exercise their autonomy. Thus, while the incentive algorithm allows for some autonomy in terms of choosing a specific incentive, in a broader sense, the psychological commitment of choosing a benchmark limits expressed autonomy.

Lastly, workers comply with the algorithms because it is easier to comply than to deviate.

In describing the ratings system, Jackson from Philadelphia notes that

I give everybody five stars. It's just not that deep, mentally, to me. To be giving somebody three stars instead of five. Like, why wouldn't I give five stars? As long as you stay back there, don't mess up my car, and don't bother me, you're five stars. I mean, I don't get why anybody would give anybody less stars.

Since the platform automatically prefills the customer’s rating as five stars, it takes less mental energy for the driver to accept the rating than to change it. Even if drivers were to assign a customer a low rating, doing so would have minimal consequences, in that while the driver will never be matched with that person again. In areas with large ridership pools, this consequence is not a serious economic threat. Overall, the idea that engaging with the algorithm is “not that deep” may suggest a more overwhelming viewpoint: that it is easier to align one’s actions with
the already suggested course of action, especially in a system where accomplishing (completing) the work flow depends on an assumption of general compliance.

Deviance Tactics: Interpreting the Algorithm as a Tool

In deviance tactics, drivers either ignore or actively counter the algorithm's nudges, typically because the worker believes the interests of the algorithms are not aligned with their own interests. For example, drivers may decline a work assignment from the matching algorithm if they decide that a ride that is more than a certain distance away from their current location is “not worth their time” (Sebastian, Detroit); they might say that it is not worth it to “drive 10 miles, drive them two minutes and make $3” (Tyrone, Montana), or they may “want to stay in the city and make my [a personally-set] quota” (Jay, D.C.). Surges are meant to draw drivers to areas with higher customer demand, yet, ironically, a common refrain on web forums is “Don’t chase the surge.” After several attempts to rush downtown to catch a disappearing surge, Sarah complains, “I just don’t understand . . . so now I don’t trust that [surge].” Jared, in Seattle notes, “It’s a little annoying because it’s oftentimes misleading or by the time you get there it’s [the surge] gone or whatever. They’ll send out a text message or something that says Adele is playing tonight, the streets will be filled with people. They send weird texts . . . where you’re like, okay, but I’m still going to be taking one person at a time. There’s going to be a lot of traffic and I’m going to be driving one person. They just exaggerate it. Maybe that’s a better word. It’s not misleading, they just exaggerate everything. You’ll make crazy cash this weekend, it’s almost like they’re insulting your intelligence [laughs].”

One of the reasons why drivers ignore and/or deviate from nudges is a lack of trust in the idea that the algorithm will help drivers maintain a steady stream of ride. In response to a misleading surge algorithm, Leo, in Detroit, decided to

Do it a little different. I don't really wait in the areas where they tell me to. I kind of do my own thing. I used to start my day out at the airport . . . and say it was a 2.0x surge, then you’d sit there for an hour and 20 minutes and you’d never get a ride, and the surge would go off, and you would get a ride from the airport. So, what they were doing is they were drawing people there,
but yet there were never any customers there to do it. What I do [now] is I pull up right to the actual arrival doors and I park right in front, and I put Lyft and Uber on, and whoever hits me first, I [take].

In outright deviance, Leo chooses to wait in front of the arrival doors instead of in the company’s mandated ride hailing parking lot.

Workers may also deviate from the algorithm's nudges for their own physical safety. Women and minorities, in particular, discuss denying ride requests based on distance, location, and riders’ ratings. After describing a string of sexual harassment episodes, Mary, a Detroit driver, notes, “If it's at night, usually if they're 4.0 or below, then I really don't really like to accept those, because they’re partiers.” Another Detroit driver, Robert, declines ride based on a combination of rating and location:

_Somebody requested a ride, number one it wasn't from a neighborhood I wanted to go to, because I've been there before. Nothing's ever happened, but it's just not a neighborhood I necessarily feel very safe in. That and then their rider rating was 4.3. Sorry, no. It's not going to happen. You didn't get that 4.3 rating for nothing. You got that rating for a reason and I don't want any part of it._

Lastly, workers deviate in order to protect their future employment. High ratings are a requirement to continue working, and drivers work hard to maintain high ratings, especially from passengers that are more troublesome and likely to give lower ratings. Describing a recent situation with a difficult passenger Roger, who is based in Washington, D.C., said,

_Right now, I'm 4.90, and before I was at a 4.93. I had just turned 4.93, I picked up a woman and her kid, and the Uber app took me to the back of where she lived, she was in the front, and it was really cold, she was holding the kid in her hands, she called me, she was all pissed off at me. I said, ma'am, I'm just going where the app sent me. She ran in the back, got in the car, destroyed me on the ratings, and I went from a 4.93 to a 4.90 just like that. And if you lose points it's real hard to get them back, and so what I've learned is that if you want to make sure that the person can't rate you, close out the ride right before you let them off. The ride will cancel—it will still pay you up until that point, but it's impossible for them to rate you. I tell them straight up, too. I tell them so that they understand, like, I'm canceling you because I don't want you to rate me._
Negative customer service encounters can have a disproportionately large effect on overall ratings. (The company’s websites states that ratings are not always calculated by a straight average of the last 500 rides, but no further information of this calculation is given.) In Roger’s situation, three interdependent factors—a malfunctioning work-instruction algorithm, the customer’s sour reaction, and the customer’s negative rating—pulled down his score by .03 points, a significant downgrade, since he had completed more than 5000 rides. While cancelling the ride before completion blocks the customers from rating, it is not in the driver’s financial interest, as it decreases their income earned from that ride. However, this deviant tactic allows the driver to have some autonomy within their work, since they are able to protect something that matters to them—the rating.

*Feigned Acquiescence: Interpreting the Algorithm as Malleable*

Feigned acquiescence tactic occurs when drivers’ interactions with the nudges are not aligned with their actual driving behavior. In other words, there is a mismatch between what the driver is “telling” the algorithm and what the driver is actually doing -- imagine an employee telling the boss that he or she is working on a report when, in actuality, the employee is golfing. This tactic is a larger expression of autonomy within an algorithmic work system; workers are trying to get what they want, while also remaining complaint within the larger system. One of the most reported feigned acquiescence tactic is when drivers try to have the algorithm match them with a pre-arranged passenger. Pound, a Detroit driver, describes trying to match with a friend who was already sitting in his passenger seat:

> [Paul asked.] “I’ve got to go to the airport at 4:30 p.m. on Friday, can you take me?” Sure. It used to be that you would get in the car and they’d request a ride and automatically goes to you. It’s changed dramatically. It takes maybe three or
Going against the company’s policy—in which drivers and riders are blindly assigned—Pound and his friend, Paul, repeatedly employ the work matching algorithm in order to be assigned to one another—and, eventually, they succeed, overriding the matching algorithm’s original intent. While drivers’ reasons for declining a string of rides to be matched with a pre-arranged one may vary; turning down too many rides in a row (usually three) means that both parties will face a series of escalating repercussions, such as the riders paying a cancellation penalty, or the drivers being locked out of the system. Referencing the misaligned motivations of ride hailing companies and their drivers, Ralph, a Detroit driver, notes,

*What does [the company] want me to do? They want me to take as many rides as possible. What do I want to do? I want to make as much money as possible. They punish me for it... However, I profit more than I hurt... [Describes turning down a series of rides waiting for a surge.] They were going to try to get me to work for a cheaper rate, and I didn't want that, but... if I miss [don’t accept] three rides, I get punished and I can't log in for half an hour. I figured out ways around it. I just request myself [laughs]. ... I use a separate e-mail for my passenger account and my rider account—and I'll go back online. There is a bit of an opportunity cost, but it's better than being locked out for like 30 minutes.*

While Ralph hopes to ride out the surge to get the highest possible fare, he is penalized after rejecting three rides in a row. To counter this penalty, he uses another phone, with the rider application, to request himself. This tactic incurs a cost, since riders are charged a fee for cancelling a ride, and it may take multiple attempts for a driver to be matched with a predetermined rider (in this case, with Ralph himself, in his own car). Yet even given the algorithm constraining choice, Ralph exhibits a certain amount of autonomy, in that he is able to feign acquiescence—i.e., the platform does not think that he is rejecting too many rides—in order to meet his goal of getting a higher surge price.
Fear of reprisal or losing platform access may also motivate workers to feign acquiescence and accept nudges. The fear of hurting his rating influenced Roger to take two highly incongruous actions simultaneously: accepting a ride while driving in the opposite direction. Roger describes,

*I had one time where I didn't want to hurt my 100 percent [acceptance rating]—if you let that [timer] time out—so I accepted [the ride request] and I just wanted the person to cancel. It was the night of when Donald Trump was inaugurated, and it was downtown, and you couldn't really get down there. So, people kept requesting me and I didn't want to keep canceling. Every single time someone gave me a request, I hit it, but then I would just take a whole bunch of time and they eventually would cancel.*

**Work Entry and Work Exit**

*Platform Choice and Selective Entry: Choosing to Go “On-Line”*

In addition to the three tactics described above, drivers have the highest degree of autonomy at two other points in their interaction with the ride hailing platform: when they enter the platform and when they exit. One of the most-touted benefits of working in the ride hailing industry is that drivers can choose when and where they want to drive. Incentives and surge notifications—such as “Summer weekends are busy! Head to your promo hub [in the app] for your weekend incentives and surge pricing”—may alert drivers to increased demand, but ultimately drivers make the choice. Workers can choose between different platform companies, exhibiting platform choice, to decide on the most favorable driving conditions. Many drivers often having multiple companies’ applications installed on their phone, choosing their preferred employer of the based on rider demand and incentives. It is at this point of the work process where workers have the largest amount of autonomy. Thus, it is at this point in the work process (along with the work entry and exit) that workers are able to exhibit the highest degree of autonomy. In deciding where to drive each evening Myrtle, who is based in Missoula, Montana,
leverages two applications—the drivers’ app and the riders’ app—in order to time her work entry so that she maximizes her earnings.

You would open the passenger app and it will show you the eight closest drivers and then you just go where they’re not. You could count all the other drivers on any given moment. It would be the 200 block of Ryman, but there were too many cars—it was too stressful. it wasn’t always a sure thing. So, I would go four blocks away where there were less people but more bars. And it would work out for me.

Selective Exit: Choosing to Go “Off-line”

Unlike traditional employment relationships, where voluntarily leaving the work system (quitting) has a high barrier for re-entry (rehiring), drivers can choose when to stop and start working at will. Thus, it’s at this point of the work process (along with work entry) that drivers have the largest amount of autonomy. Vox, in Montreal, likes “that I drive when I want, when I’m free. I can stop when I want to!” Common reasons for going off-line are: not receiving enough ride requests, meeting a personal quota of hours worked or rides completed, personal obligations, or physical and mental fatigue. Jamal, in Detroit, stops driving “if I get really bored [or] If it's not surging anymore, then I'll just go home.” Frustration with the work matching algorithm and with the accompanying tedium of travelling over the same bridge influences Sean, a driver in San Francisco, to stop working sooner than originally planned, even though surge algorithm is boosting.

Whatever I make in four hours is good enough for me. If I know it’s really slow, if I’m not making anything. .. Even if it’s not even four hours, I’ll go home. One time, I come from over the bridge. So, I drive over to [Stanford [University] and my first ride [laughs] I pick up, he wanted to go back to Union City basically where I came from. So, I’m thinking, “Oh man, oh my goodness. Are you kidding me?” So, I bring him back over there. So, I have my app on all the time and it’s not hot over there. So, I go back over the bridge. I pick up another rider. And she wants to go back to Freemont. I’m thinking, “Are you kidding me? So, I just came from there again.” So I dropped her off over there. And it’s only like two rides. But it was boosting that
night. So and those two rides I made $60. It was like $30 a ride. Yeah. So I’m thinking, okay, I’m good. I’m not going to waste my time going back and forth.

Towards a Framework of Contingent Autonomy

In the following section, I visually summarize my findings (see Exhibit 4), developing a framework on contingent autonomy or how autonomy is expressed within a constrained work environment. At its core my framework captures how autonomy is dynamic, fluctuating based on interactions with structure.

Platform Choice, Work Entry and Work Exit

At both work entry and work exit, workers have the largest degree of autonomy in the work process. For work entry, workers have three different dimensions of autonomy in that they can a) choose the platform on which they will drive (e.g., Uber, Lyft, Juno), b) decide what time they want to start working and c) decide where they want to start working. Pricing algorithms may influence what platform drivers choose and whether or not to drive; however, there are no sanctions for choosing not to respond to these incentives. Similarly, for work exit, drivers can choose when and where to stop driving. Algorithms may influence drivers to continue working (e.g., to meet an incentive quota), however; there are no sanctions for stopping work. This makes it possible for workers to control the pacing of work and to choose the platforms that are offering the most profitable working conditions at that particular moment. Overall, the autonomy expressed at work entry/exit most closely resembles the full-fledged autonomy one typically expects of ‘true’ independent gig workers.

Work Cycle

At each choice point in the work cycle workers interact with an algorithm, expressing greater or lesser degrees of autonomy. Algorithms such as the work matching and the ratings
system sanction or restrict behavior, so that workers must express less autonomy to remain compliant within the overall system. On the other, the pricing algorithms, which reward behavior, allow for greater autonomy in that workers may freely ignore or counter those nudges. The ability to express autonomy may make this type of work more palatable. A driver, for example, may disagree with the piece-rate pay system in general, but may enjoy the ability to create her own tactics for maximizing pay (which was include not following the surges) and thoughtfully rate each ride. While small, these smaller expressions of autonomy may make the work more tolerable and flexible given the potentially rigid structure of algorithmic work. However, it is important to remember, that no matter how much autonomy is being expressed, from the perspective of the algorithm, workers must remain complaint with the system in order to continue being allowed access to the platform and working. Thus, any autonomy expressed during the work cycle is less than during work entry/exit as it constrained by the larger algorithmic work system.

Contingent autonomy offers insights about how work is accomplished within an algorithmic environment. Algorithmic work runs the risk of being tightly scripted and structured so much so that there is little room for human expression, creativity, and freedom. Without these intrinsic motivators it is more likely that workers will be dissatisfied, disgruntled and demotivated --- which, especially for an organization relying on a contracted workforce, is potentially ruinous. By being able express autonomy within their work environment, workers are to satisfy key human needs and remained engaged in their work.

From the perspective of the platform company, each interaction with the algorithm can be viewed as an act of consent or “buy” into the work system. Accepting a surged ride signals buying into the system the same way as waiting in a designated airport parking lot for the next
pick-up. Within a given six-hour driving shift and individual may have hundreds of consent interaction with the algorithm with each act adding to an overall sense of psychological compliance toward the platform company. A driver might, for example, be more likely to categorize accepting a ride in a “bad” neighborhood or give a five-star rating to a rude customer as a one-time exception, though, in actuality he has already been conditioned to do accept the nudge by having completed the same action hundreds of time before. Taken together this suggests contingent autonomy, paradoxically, is associated with reinforcing the algorithmic control system.

**Discussion**

As algorithms become more embedded in different types of work, both in the on-demand and traditional work economy, it is important for organization scholars to develop grounded theoretical and empirical models reflecting the changing realities of work (Barley, Bechky, and Miliken, 2017). This study provides an important foundational study of how algorithms are embedded within the work process and how workers navigate an algorithmic work environment, shedding light on the control dynamics and work autonomy. Through this work, I open the doorway for more organizational research on human-algorithmic work interactions.

My contributions are both empirical and theoretical. The first, an empirical contribution, offers a grounded understanding of how control is exercised in algorithmic work environments. There is not “an” algorithm that shapes the work, but five. These algorithms structure choice and nudge to prompt desired behavior; in turn, workers respond with an array of tactics that both acquiesce and deviate from the algorithm's intent. In providing this descriptive account, I place algorithmic work “on the map,” providing a framework of algorithmic work systems as
well as defining key terms that provides a roadmap for further investigation of human-algorithm interactions by organizational scholars.

My theoretical contributions update and extend the control literature. Classical control literature conceptualizes control as restraint, assuming that control is achieved through the power of imposing constraints (Weber, 1956; Edwards, 1979). Constraint however is only one form of organizational control; autonomy is granted through the organization and is another form of control, whether it is granted through nurturing commitment (O’Reilly and Chatman, 1996), managerial leniency (Anteby, 2008), or schedule flexibility (Mazmanian, Orlikowski, and Yates, 2013). Games on the shop floor are real choices, however narrowly conceived (Burawoy, 1976), and in the same vein, tactics in response to algorithmic control are voluntary, though circumscribed. I call these choices contingent autonomy. This work suggests there is value in moving from a static conceptualization of autonomy to a more dynamic one, with a focus on the specific practices and conditions (e.g., work, cultural, technological, market) through which work autonomy is more or less likely to be produced. Yet, at the same time, it is crucial to remember that the presence of autonomy does not extinguish control systems. Shopworkers’ games reproduce the capitalistic labor system (Burawoy, 1976), and correspondingly, drivers’ tactics do not dismantle or destabilize the work system, but instead reinforce the precarity of on-demand work. These findings problematize the assumption that “good jobs” are characterized by high autonomy (Kalleberg, 2011), suggesting instead that autonomy is not a static characteristic inherent to a job and further proposing that one of the fruits of the on-demand economy is the birth of the “good bad job”.

More broadly, my work complicates the existing control literature by depicting how algorithmic work is infused across multiple dimensions of control. Critical perspectives (e.g.,
Kaplan, 2015; Davis, 2016; O’Neil, 2017) couple the rise of algorithmic work with a new, pan-optician control system that exploits, alienates, and kills (Smith, 2018). My findings argue for a more optimistic and humane future with algorithmic-work extending our conceptualizations of control. Yes, GPS systems dictate and monitor routes, matching algorithms set the pace of work, and rules are embedded within timers, incentives, and prompts and workers exercise autonomy within existing systems. Examining the rise of cognitive control mechanisms from more rational forms, Van Maanen and Kunda (1989: 28) note, “systems of managerial control build on, rather than replace, one another.” My findings support and extend this argument, suggesting that the introduction of algorithmic work becomes enmeshed with already existing control systems, creating a palimpsest or a system where levels of control are entwined with one another. The rules of bureaucratic control, for example, can be instantly updated with a re-programmed algorithmic nudge. Relatedly, the nature of technical control, has extended from how work is accomplished to the acquiring and dismissal of work itself. Even as algorithms and information flatten bureaucracy, reducing the need for human managers, technology remains grounded in, and contingent upon, the social worlds in which it operates. Thus, my findings suggest that while algorithms do not create an entirely new control system, they do extend already existing control frameworks. However, as the field of algorithmic studies and algorithmic work grows, future research should continue to revisit this conclusion as algorithms will continue to reshape how work is accomplished and structured.

At a more granular level, I provide insights into how control is maintained outside a collective. Prior control work rests on the assumption that control can be maintained only in the presence of others—managers (O’Reilly and Chatman, 1996; Kunda, 1992; Anteby, 2008), co-workers (Barker, 1993; Michel, 2012; Mazmanian, Orlikowski and Yates, 2013), and customers
(Liedner, 1993; 1999). By exploring how control is maintained in a hyper-individualized work environment, I challenge this fundamental assumption providing insights on how other types of distributed work can be structured and managed remotely. This finding is dual-edged in that it provides insights for how organizations can continue incorporating algorithmic-infused practices into their working environments to increase efficiency and reduce costs. At the same time managers may increasingly find themselves out of a job as more managerial decisions are embedded within software. Further, opportunities for collective action are limited as workers lacks a proverbial water cooler to gather around. While on-line forums provide a space for some information sharing (i.e., Stark and Rosenblat, 2016) my findings suggest that most workers are not active on the platform and hesitant to engage in any organizing, preferring to rely on themselves to navigate the workplace. The growing disconnect with organizations, managers, and workers may provide opportunities for algorithmic exploitation, even unintentionally, and future research should continue to keep an eye out on potential worker-implications.

Lastly, there has been a healthy skepticism suggesting these new forms of work are actually not new at all (e.g., Barley and Kunda, 2001). My work echoes this skepticism as the type of tactics workers engage in -- compliance, deviance, and feigned acquiescence -- are common across many workplaces and are adaptive work practices for an algorithmic work environment. A worker, for example, a may follow or not their manager’s request in the same way a driver can deny or accept a request. Alternatively, a worker can tell their manager they are working on a report, while they are actually golfing, in the same way a driver can accept a ride request while driving away from the rider. Overall, my findings provide additional support on adaptive work tactics that workers employ in response to the changing nature of work.
Conclusion

I began this research project with a simple question about how work is accomplished in an algorithmic work environment. My research describes a two-part framework where algorithms structure the work process, through employing rules, rewards, and sanctions, and suggesting behavior through nudges. Drivers, in turn, respond to the nudges with a set of tactics - compliance, deviance, or feigned acquiescence -- that give them a sense of autonomy within their constrained work environment. Taken together, this paper contributes to the understanding of control in organizations by describing a new type of control system and theorizing how algorithms can be a means of exercising control through enabling autonomy.
Exhibit 1: Algorithms and the Work Process
Algorithms As Tools to Structure the Work Process

<table>
<thead>
<tr>
<th>Algorithmic Design</th>
<th>Option Patterning - Nudge</th>
<th>In-app Depictions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Work Matching</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work Assignment Tightly Coupled</td>
<td>Assigns the work task to workers.</td>
<td></td>
</tr>
<tr>
<td>Navigation, Timers, Service Hotline Work Instructions Tightly Coupled</td>
<td>Specific work instructions for completing the mechanics of the tasks, such as how long to wait for customers and directions</td>
<td></td>
</tr>
<tr>
<td>Pricing (Incentives) Pay Linked to Output Moderately Coupled</td>
<td>Sets payment for a &quot;task bundle&quot; at a rate that encourages longer-term commitment to the organization.</td>
<td></td>
</tr>
<tr>
<td>Pricing (Surges) Pay Linked to Demand Moderately Coupled</td>
<td>Sets task pay above the base rate, based on customer demands.</td>
<td></td>
</tr>
<tr>
<td>Ratings Evaluation Loosely Coupled</td>
<td>Evaluations/quality control for tasks, with actual evaluation at the customer level. Populate it with a five.</td>
<td></td>
</tr>
</tbody>
</table>

Exhibit 2: Algorithms as Tool to Structure the Work Process
## Core Patterns of Algorithmic Work Tactics

<table>
<thead>
<tr>
<th>Types of Algorithm</th>
<th>Tactic Patterns</th>
<th>Compliance</th>
<th>Deviance</th>
<th>Feigned Acquiescence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Work Matching Work Assignment</td>
<td>Taking all rides</td>
<td>Declining rides that are too far away, in certain neighborhoods, or riders' have low rating</td>
<td>Trying to be matched with a rider already in the car; Accepting rides driver won't complete</td>
<td></td>
</tr>
<tr>
<td>Work Instructions Timer, Navigation</td>
<td>Waiting predetermined wait time; Following driving directions</td>
<td>Positioning car in non-approved spaces to avoid the waiting timer; Muting or disabling navigation</td>
<td>Driving away before the waiting timer expires</td>
<td></td>
</tr>
<tr>
<td>Pricing - Surges Linking Pay to Demand</td>
<td>Driving to surge areas; Scheduling hours around possible surge hours</td>
<td>Driving away from surges; Ignoring surge nudges</td>
<td>Selectively declining rides to secure a higher-priced ride; Turning off drivers' app to drive up surge prices to secure a higher fare</td>
<td></td>
</tr>
<tr>
<td>Pricing - Incentives Linking Pay to Output</td>
<td>Scheduling hours around hitting incentives; Working in densely populated areas to get more frequent, shorter rides to meet incentive</td>
<td>Ignoring incentive nudges</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td>Ratings Evaluations</td>
<td>Completing pre-filled rating metrics, giving all rides 5 stars regardless of poor customer behavior</td>
<td>Canceling rides that may give low ratings; Giving low ratings to riders for no reason</td>
<td>Accepting rides that a driver ‘forces’ rider to cancel in order to preserve rating</td>
<td></td>
</tr>
</tbody>
</table>

Exhibit 3: Core Patterns of Algorithmic Work Tactics
Exhibit 4: Contingent Autonomy
References (partial)

collection of
Administrative science quarterly, 408-437.
knowledge economy. Princeton Press.
identities, and work lives in the 21st century.
Bernstein, E. S. (2012). The transparency paradox: A role for privacy in organizational learning
and operational control. Administrative Science Quarterly, 57(2), 181-216.
pricing with
service guarantees. Management Science, 60(7), 1792-1811.
S94-S96.
Cappelli, Peter, H and Keller, JR. 2013. A Study of the Extent and Potential Causes of
analysis. Sage.
economy.
avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114.
Theoretical and Research Foundation. Mahwah, NJ: LEA.
review, 14(4), 532-550
Finch, David, Carola Hillenbrand, Norm O’Reilly and Paul Varella. 2015. Psychological
contracts and independent sales contractors: an examination of the predictors of


