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On Algorithmic Wage Discrimination

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ON ALGORITHMIC WAGE DISCRIMINATION

*Veena Dubal**

Abstract: Recent technological developments related to the extraction and processing of data have given rise to widespread concerns about a reduction of privacy in the workplace. For a growing number of low-income and subordinated racial minority workforces in the United States, however, on-the-job data collection and algorithmic decision-making systems are having a much more profound yet overlooked impact: these technologies are fundamentally altering the experience of labor and undermining the possibility of economic stability and mobility through work. Drawing on a multi-year, first-of-its-kind ethnographic study of organizing on-demand workers, this Article examines the historical rupture in wage calculation, coordination, and distribution arising from the logic of informational capitalism: the use of granular data to produce unpredictable, variable, and personalized hourly pay. Rooted in worker on-the-job experiences, I construct a novel framework to understand the ascent of digitalized variable pay practices, or the transferal of price discrimination from the consumer to the labor context, what I identify as *algorithmic wage discrimination*.

Across firms, the opaque practices that constitute algorithmic wage discrimination raise central questions about the changing nature of work and its regulation under informational capitalism. Most centrally, what makes payment for labor in platform work fair? How does algorithmic wage discrimination change and affect the experience of work? And, considering these questions, how should the law intervene in this moment of rupture?

To preface an assessment, Part I examines the rise of algorithmic wage discrimination and its historic legalization in California and Washington state as crucial occasions to understand how data from labor and algorithmic decision-making systems are changing wage practices in service and logistics sectors. The section also considers the extent to which these new laws

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comport with legal and cultural expectations about moral economies of work arising from and embedded in longstanding wage equalization statutes—namely, minimum wage and anti-discrimination laws. Part II uses findings and analysis from ethnographic research to assess how data from labor is used to produce algorithmic wage discrimination in ride-hail work and how workers subjectively experience and respond to the practice. I find that workers describe the variable payment structures as forms of gambling and trickery, and that these experiences, in turn, produce profoundly unsettling moral expectations about work and remuneration. Part III assesses both how workers’ groups have leveraged existing data privacy and business association laws to contest algorithmic wage discrimination and the limitations of these approaches. The Article concludes by proposing a non-waivable legal restriction on its practice, which will in turn also restrict harmful data extraction and deter firm fissuring practices.

INTRODUCTION

Over the past two decades, technological developments have ushered in extreme levels of workplace monitoring and surveillance across many sectors.¹ These automated systems record and quantify the movement or activities of workers, their personal habits and attributes, and even sensitive biometric information about stress and health levels.² Amassed datasets on workers’ lives are then fed into machine learning systems to make hiring determinations, to influence behavior, to increase worker productivity, to intuit potential workplace problems (including worker organizing), and, as I highlight in this Article, to determine worker pay.³

To date, policy concerns about informational capitalism’s incursions into

¹ See, e.g., Ifeoma Ajunwa, Kate Crawford, and Jason Schultz, “Limitless Worker Surveillance,” 105 CALIFORNIA LAW REVIEW 735 (2017).; Matthew T. Bodie, “The Law of Employee Data: Privacy, Property, Governance,” SSRN Scholarly Paper (Rochester, NY, April 14, 2021), accessible at <https://papers.ssrn.com/abstract=3819897>.; Brishen Rogers. “The law and political economy of workplace technological change.” 55 HARV. CR-CLL REV. 531(2020).

² Ifeoma Ajunwa, Kate Crawford, and Joel S. Ford. “Health and big data: An ethical framework for health information collection by corporate wellness programs.” JOURNAL OF LAW, MEDICINE & ETHICS 44, no. 3 (2016): 474-480.

³ As Matthew Bodie writes about the role of data extraction at work under systems of informational capitalism, “Workers find themselves on the wrong end of this data revolution. They are the producers of data, but the data flows seamlessly from their work and personal experience to corporate repositories. Employers can capture the data, aggregate it into meaningful pools, analyze it, and use it to further productivity. Individual employees cannot tap into that value, nor can independent contractors. They are trapped: the more data they provide, the more powerful their employers become.” Matthew Bodie. “The Law of Employee Data: Privacy, Property, and Governance.” 97 INDIANA L. J. 1 (2020-2021).

the workplace have largely mirrored the apprehensions articulated by consumer advocates, including limitations on worker privacy and autonomy, the potential for society-level discrimination to seep into machine learning systems, and a general lack of transparency.⁴ For example, in October 2022, the White House Office of Science and Technology Policy released a non-legally-binding handbook identifying five principles that “should guide the design, use, and deployment of automated systems to protect the American public in the age of artificial intelligence.”⁵ These principles called for automated systems that (1) were safe and effective, (2) protect individuals from discrimination, (3) offer users control over how their data is used, (4) provide notice and explanation that an automated system is being used, and (5) allow users access to a person who can remedy any problems they encounter. The “Blueprint for an AI Bill of Rights” (hereinafter, “Blueprint”) specified that these enumerated rights extended to “Employment-related systems...[including]...workplace algorithms that inform all aspects of the terms and conditions of employment including, but not limited to, *pay or promotion*, hiring or termination algorithms, virtual or augmented reality workplace training programs, and electronic workplace surveillance and management systems.”⁶ (my italics)

Under each principle, the Blueprint provides “illustrative examples” of the kinds of harms that the principle is meant to address. One such example, used to specify what defines unsafe and ineffective automation in the workplace, involves an unnamed company that has installed AI-powered cameras in their delivery vans to monitor the driving habits of workers for alleged safety reasons. The Blueprint states that the system “*incorrectly* penalized drivers when other cars cut them off...As a result, drivers were *incorrectly* ineligible to receive a bonus.”⁷ (my italics) Thus, the specific

⁴ Antonio Aliosi and Valerio De Stefano have argued convincingly in a comprehensive review of technology, law, and work that concerns about the supposed “disappearance of work” to algorithmic intelligence are less urgent than the myriad challenges raised by the incipient practices of algorithmic management at work. These nascent practices, they argue, have intensified any number of problems including the devaluation of work, the maldistribution of risks and privileges, the health and safety of workers, the assault on dignity, and of course, the destruction of individual and collective worker privacy. Antonio Aliosi Valerio De Stefano. *YOUR BOSS IS AN ALGORITHM*. (2022).

⁵ “Blueprint for an AI Bill of Rights,” THE WHITE HOUSE, accessed October 4, 2022, <https://www.whitehouse.gov/ostp/ai-bill-of-rights/>. P3.

⁶ “Examples of Automated Systems,” THE WHITE HOUSE, accessed October 4, 2022, <https://www.whitehouse.gov/ostp/ai-bill-of-rights/examples-of-automated-systems/>.

⁷ “Blueprint for an AI Bill of Rights” supra note 3, 17, referring to reporting by Lauren Kaori Gurley. Amazon’s AI Cameras Are Punishing Drivers for Mistakes They Didn’t Make. *Motherboard*. VICE. Sep. 20, 2021. Available at <https://www.vice.com/en/article/88npjv/amazons-ai-cameras-are-punishing-drivers-for-mistakes-they-didnt-make>.

harm that is identified is a mistaken calculation by an automated variable pay system developed by the company.

What the Blueprint does not specify, however, is that the company in question—Amazon—does not directly employ the delivery workers. Rather, the company hires Delivery Service Providers (DSPs), who they treat as contractors. In this putative non-employment arrangement, Amazon does not provide workers’ compensation, unemployment insurance, health insurance, or the protected right to organize. Nor does it guarantee individual DSPs minimum wage or overtime compensation.⁸ Instead, the company pays DSPs a variable hourly rate based on fluctuations in demand and routes, along with “bonuses” based on a quantified digital evaluation of the DSP’s on-the-job behavior, including “service, safety, client experience.”⁹ Some DSPs, while completely reliant on Amazon for business, are encouraged to hire drivers as employees.¹⁰ These Amazon-created and -controlled small businesses rely

⁸ If a DSP has a fleet of cars, they may hire drivers and treat them as their employees. This tiered process further insulates Amazon from liability and risk associated with direct employment. As economist Brian Callaci explains, “A key benefit for Amazon is that the DSPs are the employer of delivery drivers, bearing any liability for accidents or workplace safety. This also means that DSP workers do not fall under Amazon’s \$15 an hour minimum wage, despite working for Amazon in everything but name. And the contracts usually stipulate flat delivery rates, restricting the wages the DSP can offer. Amazon is even able to ensure these drivers remain non-union through a contractual mandate that they serve as at-will employees. If the workers unionize, Amazon can terminate the contract and find a new DSP, which is much easier than fighting a union campaign itself.” Brian Callaci, “Entrepreneurship, Amazon Style,” THE AMERICAN PROSPECT, September 27, 2021, available at <https://prospect.org/api/content/1923a910-1d7c-11ec-8dbf-1244d5f7c7c6/>.

⁹ “How are Amazon DSPs Paid?” ROUTE CONSULTANT. Available at <https://www.routeconsultant.com/industry-insights/how-are-amazon-dsps-paid>. The scorecards that determine “bonuses” are calculated in constantly changing ways. The DSP scorecards I reviewed four different categories: safety and compliance, reliability, quality, and team. The “scores” for these categories—and for each driver employed by the DSP—are determined algorithmically. See also, <https://www.youtube.com/watch?v=-mBOYfBZs9I> The example in the Blueprint, for example, lowered the score enough to undermine the ability of the DSP to get a bonus. By contract, Amazon is guaranteed the data it wants from the DSPs (they cannot reject the use of cameras, for example)—not just while servicing Amazon but for three years afterwards. In addition to using this data to calculate bonuses, Amazon can also use it to terminate contracts, terminate specific underperforming workers, and punish DSPs with fees.

¹⁰ When an individual DSP hires other drivers, the DSP may appear more like a company that is legally separate from Amazon. This may protect Amazon from unionization efforts and from downstream liability that may otherwise be incurred based on allegations that the DSPs are employees, not contractors, of Amazon. To my knowledge, FedEx was the first delivery company to utilize this tactic after re-drafting their contracts with drivers in response to the *Alexander v. FedEx Ground Package Sys., Inc.*, 765 F.3d 981 (9th Cir. 2014), the 9th circuit decision that held that their drivers were employees, not independent contractors. Rather than changing the drivers’ status in response to the decision, FedEx drafted their contracts to make the drivers appear more like independent contractors. This included

heavily on their automated “bonuses” to pay for support, repairs, and driver wages. As one DSP complained to an investigator, “Amazon uses these [AI surveillance] cameras allegedly to make sure they have a safer driving workforce, but they’re actually using them not to pay [us]...They just take our money and expect that to motivate us to figure it out.”¹¹

Presented with this additional information, we should ask again: what exactly is the harm of this automated system? Is it, as the Blueprint states, the algorithm’s *mistake*, which prevented the worker from getting his bonus? Or, is it the structure of Amazon’s payment system, rooted in evasion of employment law, data extraction from labor, and digitalized control?

Amazon’s automated control structure and payment mechanisms represent an emergent and undertheorized firm technique arising from the logic of informational capitalism: the use of *algorithmic wage discrimination* to maximize profits and to exert control over worker behavior. By algorithmic wage discrimination, I mean to refer to a practice in which individual workers are paid different hourly wages—calculated with ever-changing formulas using granular data on location, individual behavior, demand, supply, and other factors—for broadly similar work. As a wage pricing technique, algorithmic wage discrimination encompasses not only digitalized payment for work completed, but critically, digitalized decisions to allocate work, which are significant determinants of hourly wages and levers of firm control. These methods of wage discrimination have been made possible through dramatic changes in cloud computing and machine learning technologies in the last decade.¹²

mandating that the drivers purchase more service areas, which in turn made drivers hire others to complete the deliveries. VEENA DUBAL. WINNING THE BATTLE LOSING THE WAR. 2017 WISC. LAW. REV. 791-2 (2017).

¹¹ Gurley *supra* note 4.

¹² In a forthcoming article, Zephyr Teachout has created a useful taxonomy of five different forms of “personalized wages” have emerged in the labor market: (1) extreme Taylorism, in which “high degrees of surveillance [result in]... rewarding productivity;” (2) gamification, in which psychological tools are used to incentivize task completion; (3) behavioral price discrimination in which workers get paid more if they make certain lifestyle choices, like exercising, which can be tracked through fitness apps; (4) dynamic labor pricing, which, she argues, is based primarily on demand; and (5) experimentation, in which firms test “assumptions about what will lead to the firm gathering the highest output for the wages it pays.” Zephyr Teachout. *Algorithmic Personalized Wages*. POLITICS AND SOCIETY. *Forthcoming*. In all of these instances, wages are rooted in data extracted from labor. Based on my data, I might simplify this taxonomy to two main ways of thinking of algorithmic wage discrimination: (1) wages based on productivity analysis alone (which we see most clearly in the employment context), and (2) wages based on productivity, supply, demand, and other personalized data that is intended to minimize labor costs, whether that happens through gamification or psychological tricks discussed in Part III. This second form of algorithmic wage discrimination is most common in on-demand work where workers are treated as independent contractors.

Though firms have relied upon performance-based variable pay for some time (e.g., the use of bonuses and commission systems to influence worker behavior),¹³ my research on the on-demand ride hail industry suggests that algorithmic wage discrimination raises new and distinctive set of concerns. In contrast to more traditional forms of variable pay, algorithmic wage discrimination—whether practiced through Amazon’s “bonuses” and scorecards or Uber’s work allocation systems, dynamic pricing and incentives—arises from (and functions akin to) to the practice of “price discrimination,” in which individual consumers are charged as much as a firm determines they are willing to pay.¹⁴ As a labor management practice, algorithmic wage discrimination allows firms to personalize and differentiate wages for workers in ways unknown to them, paying them to behave in ways that the firm desires, perhaps as little as the system determines that they may be willing to accept. Given the information asymmetry between workers and the firm, companies can calculate the exact wage rates necessary to incentivize desired behaviors, while workers can only guess as to why they

¹³ Non-algorithmic variable payments systems with transparent payment structures are also not without controversy. They are hotly debated in the human relations and management literature with critics pointing to variable pay mechanisms as a contributor to income gaps by gender and race. Other critics suggest variable pay has psychological costs for workers and other unforeseen consequences. See, e.g., Annette Cox, “The Outcomes of Variable Pay Systems: Tales of Multiple Costs and Unforeseen Consequences,” *THE INTERNATIONAL JOURNAL OF HUMAN RESOURCE MANAGEMENT* 16, no. 8 (August 1, 2005): 1475–97, <https://doi.org/10.1080/09585190500220697>. Farmworkers are also paid through bonus systems California are paid: <https://twitter.com/UFWupdates/status/1577795973476220930>

¹⁴ To date, scholars and analysts who have written about what I term “algorithmic wage discrimination” have predominantly adopted the language of pricing, though they describe wage and not product pricing. For example, in her 2021 Enlund Lecture at DePaul University School of Law, Professor Zephyr Teachout referenced some of these practices as “labor price discrimination.” Niels van Doorn, in a seminal piece in which he analyzes the pay structures of on-demand Deliveroo riders in Berlin, writes of “the algorithmic *price-setting* power of food delivery platforms” which he understands as a “monopsonistic power that is not only market-making but also potentially livelihood-taking.” (my italics). Niels van Doorn. “At What Price: Labour Politics and Calculative Power Struggles in On-demand Food Delivery.” *14 WORK ORGANIZATION: LABOUR AND GLOBALISATION* 136, 138 (2020). But in the political and legal context, adopting the language of “pricing” for wage-setting is politically and legally consequential. Since at least the rise of neoliberalism, price controls in the U.S. (and elsewhere) have been highly disfavored as economic interferences in the “free market,” raising conservative critiques of socialism and “planned economies.” See, generally, Benjamin C. Waterhouse, *LOBBYING AMERICA: THE POLITICS OF BUSINESS FROM NIXON TO NAFTA* (2013). Wage controls in the form of minimum wage and overtime laws, on the other hand, have been contested but culturally naturalized as a necessary (or at least, accepted) part of economic regulation. In this sense, re-conceptualizing the digitalized wages received by workers not as firm price-determinations, but as firm wage-determinations is a critical political—and legal—corrective.

make what they do.¹⁵

In addition to being “ineffective” and rife with calculated mistakes that are difficult to ascertain and correct (as the Blueprint example underscores), algorithmic wage discrimination creates a labor market in which people who are doing the same work, with the same skill, for the same company, at the same time, may receive different hourly pay. Moreover, this personalized wage is determined through an obscure, complex system that makes it nearly impossible for workers to predict or understand their constantly changing, and frequently declining, compensation.

Drawing on Karl Polanyi’s notion of *embeddedness*—the idea that social relations are embedded in economic systems¹⁶—I excavate the norms around payment that constitute what we might consider a moral economy of work to help situate this contemporary rupture in wages.¹⁷ Although the U.S.-based system of work is largely regulated through contracts with a strong deference

¹⁵ Aaron Shapiro, “Dynamic Exploits: Calculative Asymmetries in the on-Demand Economy,” *NEW TECHNOLOGY, WORK AND EMPLOYMENT* 35, no. 2 (2020): 162–77, <https://doi.org/10.1111/ntwe.12160>. Uber, for its part, has stated that “suggestions that Uber offers variable pricing based on user-profiling is completely unfounded and factually incorrect.” There is no way to know whether this statement is true. “Managed by Bots Report,” *WORKER INFO EXCHANGE*, accessed October 18, 2022, <https://www.workerinfoexchange.org/wie-report-managed-by-bots>. P26.

¹⁶ In 1957, Karl Polanyi wrote, “Instead of economy being embedded in social relations, social relations are embedded in the economic system. The vital importance of the economic factor to the existence of society precludes any other result. For once, the economic system is organized in separate institutions, based on specific motives and conferring special status, society must be shaped in such a manner as to allow that system to function...” Karl Polanyi, *THE GREAT TRANSFORMATION: THE POLITICAL AND ECONOMIC ORIGINS OF OUR TIME* (Beacon Press, 2001). 57. One interpretation of this important excerpt, as I use it here, is that Polanyi was referring to the ways in which society adapts to and reorganizes itself “by demanding new social institutions that can constrain market forces and compensate for market failures.” Bob Jessop and Ngai-Ling Sum, “Polanyi: Classical Moral Economist or Pioneer Cultural Political Economist?,” *ÖSTERREICHISCHE ZEITSCHRIFT FÜR SOZIOLOGIE* 44, no. 2 (June 1, 2019): 153–67, <https://doi.org/10.1007/s11614-019-00338-3>. P158. This, in essence, is what he calls “the embedded economy”: that in order to prevent a Hobbesian war of all against all, a market society must limit—through law, politics, and morality—the range of legitimate activities of economic actors motivated by material gain.

¹⁷ The notion of “moral economy” in relationship to labor and work has been explored in a variety of disciplines, including political theory, anthropology, and sociology, as way to think about and assess various systems of economic distribution and their impacts on everyday life. See, e.g., Bolton, Sharon C., and Knut Laaser. “Work, employment and society through the lens of moral economy.” 3 *WORK, EMPLOYMENT AND SOCIETY* 27 508 (2013); Bolton, Sharon C., Maeve Houlihan, and Knut Laaser. “Contingent work and its contradictions: Towards a moral economy framework.” 111 *JOURNAL OF BUSINESS ETHICS* 121 (2012); Murphy, James Bernard. “The moral economy of labor: Aristotelian themes in economic theory.” (1993); William Greider. *THE SOUL OF CAPITALISM: OPENING PATHS TO A MORAL ECONOMY*. (2003).

to the “managerial prerogative,”¹⁸ two general restrictions with respect to wages have emerged from social and labor movements: minimum wage and overtime laws, which set a price floor for the purchase of labor (in relation to time), and prohibitions on discrimination in the terms, conditions, and privileges of employment, which require firms to provide “equal pay for equal work.” Both sets of wage laws can be understood as forming a core moral foundation for the regulation of most work in the U.S. In turn, certain ideals of fairness have become embedded in cultural and legal expectations about work. Part I examines how recently passed laws in California and Washington state that specifically legalize algorithmic wage discrimination for certain sectors of work compare with and destabilize more than a century of legal and social norms around fair pay.

In Part II, I draw on first-of-its-kind, long-term ethnographic research to understand the everyday, grounded experience of workers earning through and experiencing algorithmic wage discrimination.¹⁹ Specifically, I analyze the experiences of on-demand ride-hail drivers in California before and after the passage of an important industry-initiated law (Proposition 22) that legalized this form of variable pay to illuminate the experiences of work under compensation systems that make it difficult for workers to predict and ascertain their hourly wages. Then, I examine the practice of algorithmic wage discrimination in relationship to workers’ on-the-job meaning making and their moral interpretations of their wage experiences. Though many

¹⁸ This legal deference to the managerial prerogative is controversial in the scholarly literature. See, e.g., Gali Racabi. Abolish the Employer Prerogative, Unleash Work Law. 43 *BERKELEY J. EMP. & LAB. L.* 79 (2022).

¹⁹ The ethnographic research that informs this article reflects six years of embedded research amongst self-organizing Uber and Lyft drivers concentrated in the San Francisco Bay Area, beginning in 2014 after the first protest in front of Uber headquarters. This research includes thousands of hours of participant observation and action at drivers’ meetings, protests, in meetings with regulators, on group phone calls and texts, in government hearings, on social media, and one-on-one conversations. As a result, I also occasionally observed and studied workers who labored in other parts of the state and the country when they were organizing with and alongside local workers. With some drivers, who I came to know over a period of time, my ethnography continued into social spaces. All the workers in the drivers’ groups I studied were Uber or Lyft drivers, and many worked for other gig platforms as well, including Wonolo, Doordash, Instacart, UberEats, and Postmates (which was purchased by Uber during my research). During my ethnographic research, I interacted with hundreds of drivers of many backgrounds. The findings from my in-depth interviews reflected and were reinforced by the realities I observed through participant observation and everyday conversations with workers. Alongside and at the behest of drivers, I attended protests, spoke at townhalls, wrote public essays, and spoke to newspaper editorial boards about the potential impacts of the proposed law on the intended workforce. In this Article, to protect the identity of most workers in my research, I have used first name pseudonyms. For workers who assumed a public role by speaking publicly or writing opinion pieces, I use their real first and last name.

drivers are attracted to on-demand work because they long to be free from the rigid scheduling structures of the Fordist work model, they largely conceive of their labor through the lens of the model's payment structure: the hourly wage.²⁰ Workers find that, in contrast to more standard wage dynamics, being directed by and paid through an app involves opacity, deception, and manipulation.²¹ Those who are most economically dependent on income from on-demand work frequently describe their experience of algorithmic wage discrimination through the lens of gambling. As a normative matter, I contend that workers laboring for firms (especially large, well-financed ones like Uber, Lyft, and Amazon) should not be subject to the kind of risk and uncertainty associated with gambling as a form of work. In addition to the salient constraints on autonomy and threats to privacy that accompany the rise of on-the-job data collection, algorithmic wage discrimination poses significant problems for worker mobility, for worker security, and for worker collectivity, both on the job and outside of it. Because the on-demand workforces that are remunerated through algorithmic wage discrimination are primarily made up of immigrants and racial minority workers, these harmful economic impacts are also necessarily racialized.²²

²⁰ It should be noted that nothing about employment status necessitates an inflexible work schedule. This is a business decision associated with, not mandated by, employment. See Veena Dubal. "Wage slave or Entrepreneur?: Contesting the dualism of legal worker identities." 105 CALIFORNIA LAW REVIEW 65 (2017). For discussion of the legal rules defining employment status. In California, after the passage of a law in 2019 that made it much harder to misclassify workers, at least one labor platform company hired their previously contracted workers. Research conducted before and after the change found that employment status did not affect worker flexibility. Hannah Johnston, Ozlem Ergun, Juliet Schor, and Lidong Chen. "Is employment status compatible with the on-demand platform economy: Evidence from a natural experiment." *On file with author*.

²¹ These findings comport with findings across sociology, communications, and media studies literatures on algorithmic management. See, e.g., Steven Vallas and Juliet B. Schor. "What do platforms do? Understanding the gig economy." 46 *Annual Review of Sociology* 273 (2020); Rafael Grohmann, Gabriel Pereira, Abel Guerra, Ludmila Costhek Abilio, Bruno Moreschi, and Amanda Jurno. "Platform scams: Brazilian workers' experiences of dishonest and uncertain algorithmic management." 7 *NEW MEDIA & SOCIETY* 1611 (2022); Elke Schüßler, Will Attwood-Charles, Stefan Kirchner, and Juliet B. Schor. "Between mutuality, autonomy and domination: rethinking digital platforms as contested relational structures." 19 *SOCIO-ECONOMIC REVIEW* 1217 (2021); Aloisi, Antonio; "Platform work in Europe: Lessons learned, legal developments and challenges ahead." *EUROPEAN LABOUR LAW JOURNAL* 13, no. 1 (2022): 4-29.; Goanta, Catalina, and Sofia Ranchordás, eds. *THE REGULATION OF SOCIAL MEDIA INFLUENCERS*. (2020); Daniel Susser, Beate Roessler, and Helen Nissenbaum. "Technology, autonomy, and manipulation." 2 *INTERNET POLICY REVIEW* 8 (2019).

²² In the United States, such work is conducted primarily by immigrants and subordinated minorities. Lyft estimates that 69% of their U.S. workforce identifies as racial minorities. One study estimates that in the San Francisco Bay Area in 2019, immigrants and people of color comprised 78% of Uber and Lyft drivers, most of whom relied on these jobs

Finally, in Part III, I explore how workers and worker advocates have used existing data privacy laws and cooperative frameworks to address or at least minimize the harms of algorithmic wage discrimination. In addition to mobilizing against violations of minimum wage, overtime, and vehicle reimbursement laws, workers in California—drawing on the knowledge and experience of their co-workers in the United Kingdom—have developed a sophisticated understanding of the laws governing data at work. In the United Kingdom, a self-organized group of drivers called the App Drivers and Couriers Union have not only sued Uber for worker status, but they have also used General Data Protection Regulation (GDPR) to lay claim to a set of positive rights with regard to the data and algorithms that determine their pay. As a GDPR-like law went into effect in California in 2023, drivers there are positioned to do the same. Other workers in both the U.S. and Europe have responded by creating “data cooperatives” to fashion some transparency around the data extracted from their labor, to attempt to understand their wages, and to assert ownership over the data they collect at work. In addition to examining both approaches to addressing algorithmic wage discrimination, I argue that the constantly changing nature of machine-learning technologies and the asymmetrical power dynamics of the digitalized workplace minimize the impact of these attempts at transparency and may not mitigate the objective and subjective harms of algorithmic wage discrimination. Taking into consideration the potential for this practice to spread into other sectors of work, I propose instead an approach that addresses the harms directly: a narrowly structured, non-waivable peremptory ban on the practice.

While this Article is focused on algorithmic wage discrimination as a labor management practice in “on-demand” or “gig work” sectors, where workers are commonly treated as “independent contractors” without protections, its significance is not limited to that domain. So long as this practice does not run afoul of minimum wage or anti-discrimination laws, nothing in the laws of work makes this form of digitalized variable pay

as their primary source of income. Chris Benner, Erin Johansson, Kung Feng & Hays Witt, *On-Demand and on-the-Edge: Ride-Hailing and Delivery Workers in San Francisco*, UC SANTA CRUZ INST. FOR SOC. TRANSFORMATION, <https://transform.ucsc.edu/on-demand-and-on-the-edge/> [<https://perma.cc/N6CJ-U9Z6>]. Yes on Proposition 22 campaign representatives confirm that people of color and immigrants make up the vast majority of drivers who labor for Uber and Lyft in California. In addition to the nationwide Lyft data, we know that in New York City, 9 out of 10 ride-hail drivers are immigrants, and in Seattle 72% are immigrants and 50% Black. Gina Bellafante, *Uber and the False Hopes of the Sharing Economy*, N.Y. TIMES (Aug. 9, 2018), <https://www.nytimes.com/2018/08/09/nyregion/uber-nyc-vote-drivers-ride-sharing.html> [<https://perma.cc/26R9-FF4H>]; James A. Parrot & Michael Reich, *A Minimum Compensation Standard for Seattle TNC Drivers* (July 2020), https://irle.berkeley.edu/files/2020/07/Parrott-Reich-Seattle-Report_July-2020.pdf [<https://perma.cc/NW6K-QV6N>].

illegal.²³ As Zephyr Teachout argues, “Uber drivers’ experiences should be understood not as a unique feature of contract work, but as a preview of a new form of wage setting for large employers.”²⁴ The core motivations of labor platform firms to adopt algorithmic wage discrimination—labor control and wage uncertainty—apply to many other forms of work. Indeed, algorithmic wage discrimination has already seeped into the healthcare sector, impacting how porters, nurses, and nurse practitioners in some hospitals are allocated work and remunerated.²⁵ If left unaddressed, the practice will continue to be normalized in other sectors of employment, including retail, restaurant, and computer science, producing new cultural norms around remuneration for low-wage work.²⁶ The on-demand sector thus serves as an important and portentous site of forthcoming conflict over longstanding moral and political ideas about work and wages.

I. Wage Laws in Relation to Moral Economies of Work

Under the regime of private sector at-will employment in the United States, contracts regulate a large complex economy. Where contracts are silent—particularly around scheduling and payment decisions—a general

²³ Anti-trust laws, however, are a more promising way to address these practices when and if workers are classified as independent contractors. In Part III, I discuss a California lawsuit filed in 2022 by Rideshare Drivers United workers against Uber alleging that their payment structures amount to price-fixing and that they are violating state laws against fraud. Still, as a payment practice, algorithmic wage discrimination may not be limited

²⁴ Zephyr Teachout. *Algorithmic Personalized Wages*. POLITICS AND SOCIETY. *Forthcoming*.

²⁵ For example, one company, which has branded itself “Uber for Hospitals” has developed AI staffing software for hospitals. This software uses “smart technology” to allocate work tasks and to judge the performance of porters, nurses, and nurse practitioners. The technology company’s “performance analysis” is then used to determine the pay for these healthcare workers. For more information on this company, see “Oxford Tech Raises £9 Million for ‘Uber for Hospitals’ AI Platform.” BUSINESS INNOVATION MAGAZINE (2020). Available at <https://www.businessinnovationmag.co.uk/oxford-tech-raises-9-million-for-uber-for-hospitals-ai-platform/>.

²⁶ Companies across the world are using this practice in both employment and contracting settings to incentivize certain behaviors. Technology capitalists have foreshadowed its growth. See, e.g., Venture capitalist Shawn Carolan wrote an essay after the passage of Proposition 22 in which he foreshadowed investments to make these sectors on-demand. WHAT PROPOSITION 22 NOW MAKES POSSIBLE THE INFORMATION, <https://www.theinformation.com/articles/what-proposition-22-now-makes-possible> (last visited Oct 28, 2022). As Keith Hylton has warned in reference to the power of algorithms, “There is a case to be made that the working logics of these algorithms not only shape user practices, but lead users to internalize their norms and priorities...” Keith Hylton. *Digital Platforms and Antitrust Law*. 98 NEB. L. REV. 272 (2019).

judicial deference to the managerial prerogative has reigned. Wage regulation laws are important exceptions. Both minimum wage laws and anti-discrimination statutes reflect and have contributed to the legal consensus around what constitutes a moral economy of work regarding compensation for labor. By moral economy, I refer to an understanding of economic activities that “accounts for class-informed frameworks involving traditions, valuations and expectations.”²⁷ A theoretical and empirical focus on “moral economy” is a useful way to understand how class relations and inequalities emerging from those relations have been negotiated through law and to distinguish the values that are embodied in the prevailing legal frameworks. In this section, I argue that the passage of wage-related laws, in response to social and labor movements, have served to address and legitimize concerns about certain kinds of distributive injustices—concerns that the practice of algorithmic wage discrimination raises anew. In general, minimum wage laws have created cultural and legal expectations that employers will compensate work at or above a particular wage floor, giving rise to agreement that payment for work should be both fair and predictable. For their part, anti-discrimination laws have created the expectation that individuals will not be paid differently because of their protected status—a cultural expectation of or aspiration towards equality of payment for equal work.

Algorithmic wage discrimination—which personalizes wages to specific workers and moments—is not addressed by any such laws. This gives rise to two outcomes that conflict with existing legal and cultural wage norms. First, different workers can earn vastly different amounts for substantially similar work, making payment unequal. And second, the same worker can earn vastly different amounts in other moments, making wages highly unpredictable. In these instances, wages can be so low as to fall well below what legislatures have determined to be the lowest minimum hourly compensation. How can we understand these earnings outcomes within and in relation to the moral economy of work that has developed through a century of wage regulations?

In Karl Polyani’s terms, algorithmic wage discrimination is a disembedding phenomenon—a practice that eschews existing norms around social, economic, and political relations between firms and their workers. It is, in essence, an economic practice—even an economic project—that is changing social imaginaries with regard to the kinds of remuneration practices that are considered normal, acceptable, and fair. Because the vast majority of people who endure the unpredictable, low, and variable pay associated with algorithmic wage discrimination are immigrants and

²⁷ Jaime Palomera & Theodora Vetta, *Moral Economy: Rethinking a Radical Concept*, 16 ANTHROPOLOGICAL THEORY 413, 413–432 (2016)

subordinated racial minorities, the practice may also exacerbate existing racialized economic inequalities and for these populations, impede the possibility of economic security and mobility through work.

Though my primary objection to this practice is normative—that is, I think we have good reason to reject the form of payment it imposes on workers—I root this critique in a historical analysis of labor practices and labor laws, and, in particular, the values and customs that have guided the regulation of wages since the transition to industrialization. Before I turn to that analysis, however, I first describe how algorithmic wage discrimination has been specifically legalized in two state-level laws, one through the initiative process and the other through state legislature.

A. The Legalization of Algorithmic Wage Discrimination

In 2020, amidst the COVID-19 pandemic and Presidential debates, a scholarly dispute about worker wages made its way to the *New York Times*. The newspaper's labor reporter, Noam Scheiber, wrote that the most contested question about the gig economy is not the employment status of its workers, but exactly how much gig workers make.²⁸ In the lead up to legislative battles in California and Washington state over the employment status of ride-hail drivers, Uber shared select data with a historian, Louis Hyman, and several Cornell economists known for their association with Democratic administrations. Hyman's research, paid for by Uber and later touted by Uber CEO Dara Khoshrowshahi, found that a typical Uber driver in Seattle made about \$23 an hour, with 92% of workers earning above the local minimum wage.²⁹ However, using similar data, an alternative analysis by two labor economists, James Parrott and Michael Reich, and commissioned by the city of Seattle, arrived at a very different number: \$9.74

²⁸ Noam Scheiber. "Are Uber Drivers Well Paid? It Depends on the Study." N.Y. TIMES. July 2020, available at <https://www.nytimes.com/2020/07/12/business/economy/uber-lyft-drivers-wages.html>.

²⁹ PLATFORM DRIVING IN SEATTLE PLATFORM DRIVING IN SEATTLE. <https://ecommons.cornell.edu/handle/1813/74305> (last visited Oct 28, 2022). Note that the costs of the \$120,000 study were covered by Uber. Also, in late 2022, Uber whistleblower Mark MacGann testified before the European Parliament stating that during his time at Uber, the company paid for studies providing skewed data sets, "While at Uber, we paid academics to use skewed data sets to produce numbers that favoured Uber's position. Data that would show high earnings because it wouldn't take account of wait times. Data that would show drivers wanted to be independent, but based on carefully designed driver surveys. As Mark Twain famously wrote, there are *"lies, damned lies and statistics"*". GIG ECONOMY PROJECT - UBER WHISTLEBLOWER MARK MACGANN'S FULL STATEMENT TO THE EUROPEAN PARLIAMENT BRAVE NEW EUROPE, <https://braveneweuropa.com/uber-whistleblower-mark-macganns-full-statement-to-the-european-parliament> (last visited Oct 28, 2022)

per hour, with the majority of drivers earning far less than the minimum wage.³⁰ The difference between the two figures turned in large part on how the groups calculated overhead costs for workers.³¹ In the Hyman-Uber analysis, Uber insisted that the investigators not include costs associated with the vehicle—which the firm claims are incidental to the work.³² By contrast, the economists Parrott and Reich insisted that, because workers often purchase cars (and are even induced to do so by the companies³³) and must maintain their vehicles to labor (based on requirements set forth by Uber), the cost should be included.³⁴

Notably absent in the coverage of this debate, however, was that *both* studies found that some workers earned well under the minimum wage (for Hyman-Uber the number was 8% and for Parrott-Reich-Seattle the number was 75%), that workers who performed substantially similar work received dramatically different wages, and that, in general, the wages that an individual worker would receive were impossible to precisely ascertain or predict. Even over the span of just a few days, individual workers made dramatically different amounts for the same amount of work. In my own long-term research among on-demand drivers, I found that, retrospectively, many workers are not sure how much money they made—or in some cases, lost. For firms, this uncertainty is a way to obscure the harms of algorithmic wage discrimination. But, as discussed in Part II, for workers, this uncertainty is itself a harm.

As a highly personalized and variable form of compensation, algorithmic wage discrimination was adopted by on-demand, labor platform companies to solve a particular problem that accompanies the (mis)classification of their

³⁰ James A. Parrot & Michael Reich, *A Minimum Compensation Standard for Seattle TNC Drivers* (July 2020), https://irle.berkeley.edu/files/2020/07/Parrott-Reich-Seattle-Report_July-2020.pdf [<https://perma.cc/NW6K-QV6N>].

³¹ James A. Parrot & Michael Reich, *A Comparison of Two Seattle Studies* (July 2020), <https://irle.berkeley.edu/files/2020/07/Comparison-of-two-Seattle-studies.pdf>

³² *Id.*

³³ The FTC accused Uber in 2017 of both exaggerating earnings claims and misleading them with claims about the terms of the vehicle loans they provided or facilitated. UBER AGREES TO PAY \$20 MILLION TO SETTLE FTC CHARGES THAT IT RECRUITED PROSPECTIVE DRIVERS WITH EXAGGERATED EARNINGS CLAIMS FEDERAL TRADE COMMISSION, <https://www.ftc.gov/news-events/news/press-releases/2017/01/uber-agrees-pay-20-million-settle-ftc-charges-it-recruited-prospective-drivers-exaggerated-earnings> (last visited Oct 28, 2022). Alissa Orlando, former Uber executive, tweeted, “When I was at Uber, we encouraged drivers to take out three-year car loans, knowing we were going to cut prices by 35%...[W]e knew we were encouraging drivers to take out debt [that] they couldn’t service w/o 70+hr work weeks.” [Tweet on file with author] September 18, 2020.

³⁴ OPEN LETTER AND PRINCIPLES FOR ETHICAL RESEARCH ON THE GIG ECONOMY MEDIUM, <https://medium.com/@gigeconomyresearchersunited/open-letter-and-principles-for-ethical-research-on-the-gig-economy-3cd27924cc08> (last visited Oct 28, 2022)

workers as independent contractors. Since drivers are not treated as employees of the firm and the primary legal indicia of employment status is control exerted by the hiring entity over the means and manner of work, firms do not directly order workers as to where they must go and when they must go there, which would be the simplest way to calibrate supply and demand.³⁵ Instead, the firms use data extracted from workers' labor and fed into automated tools to incentivize temporal and spatial movement. In other words, the companies use algorithmic wage discrimination to solve the problem of meeting demand.

Companies like Uber refer to some of the mechanisms by which they determine driver pay under the label of “dynamic pricing,” explicitly drawing a connection to the practice of price discrimination. This latter practice typically involves segmenting consumers by their willingness to pay, rather than charging a flat price. Coupons, student discounts, and bulk purchases are among some of the most common forms of price discrimination. As these examples make clear, price discrimination long pre-dates algorithmic computing. However, individualized data collection and machine learning makes the practice much more powerful and profitable for companies.³⁶ As one CEO of a dynamic pricing search engine notes, they are able to use “data to change pricing based on where a shopper is located, how much they’ve spent previously, and other behavioral indicators.”³⁷ While price discrimination is illegal if it is intentionally based on race or gender, in many sectors, for many decades, sociologists have found poor people and people of color pay more for goods and services.³⁸ More recent research suggests that consumer price discrimination in hospital services, hospitality, air travel,

³⁵ V.B. Dubal, Wage Slave or Entrepreneur?: Contesting the Dualism of Legal Worker Identities, 105 CALIF. L. REV. 65, 120–22 (2017); V.B. Dubal, The Drive to Precarity: A Political History of Work, Regulation, & Labor Advocacy in San Francisco's Taxi & Uber Economies, 38 BERKELEY J. EMP. & LAB. L. 73, 75–77 (2017).

³⁶ Aaron Shapiro, “Dynamic Exploits: The Science of Worker Control in the On-Demand Economy - Media, Inequality & Change Center Aaron Shapiro,” accessed October 5, 2022, <https://www.readkong.com/page/dynamic-exploits-the-science-of-worker-control-in-the-4565192>. at 8.; HOSPITAL PRICE DISCRIMINATION IS DEEPENING RACIAL HEALTH INEQUITY NEJM CATALYST INNOVATIONS IN CARE DELIVERY, <https://catalyst.nejm.org/doi/full/10.1056/CAT.20.0593> (last visited Oct 28, 2022); HOW RACIAL DISPARITIES IN HOME PRICES REVEAL WIDESPREAD DISCRIMINATION BROOKINGS, <https://www.brookings.edu/testimonies/how-racial-disparities-in-home-prices-reveal-widespread-discrimination/> (last visited Oct 28, 2022).

³⁷ See, e.g., Howard Kunreuther (1972), “Why the Poor May Pay More For Food: Theoretical and Empirical Evidence,” in SV - Proceedings of the Third Annual Conference of the Association for Consumer Research, eds. M. Venkatesan, Chicago, IL : Association for Consumer Research, Pages: 660-678.

³⁸ Robert Masson, *Costs of Search and Racial Price Discrimination*, 11 WESTERN ECONOMIC JOURNAL , 167 (1973).

housing, and ride-hail sectors exacerbates racial inequities, even absent intentional discriminatory profiling.³⁹

In 2017, Uber somewhat pulled back the curtain with respect to its use of price discrimination (what it calls “route-based pricing”) to set fares for riders. Prior to this moment, Uber had calculated fares using a combination of mileage, time, and surge multipliers based on geographic demand. In an interview with Bloomberg, Uber’s head of product explained that “the company applies machine-learning techniques to estimate how much groups of customers are willing to shell out for a ride. Uber calculates riders’ propensity for paying a higher price for a particular route at a certain time of day. For instance, someone traveling from a wealthy neighborhood to another tony spot might be asked to pay more than another person heading to a poorer part of town, even if demand, traffic and distance are the same.”⁴⁰ Despite the implication in this hypothetical, extant empirical research suggests that surge pricing is more complicated and unpredictable, causing riders who start in non-white, low-income areas to have to wait extended periods of time for a ride while in other instances, price gouging consumers who were fleeing disaster.⁴¹

While price discrimination is familiar within the consumer context, Uber and similar companies have broken new ground by using related methods to determine worker pay. As a 2017 exposé in the *New York Times* reported, Uber “is engaged in an extraordinary behind-the-scenes experiment in behavioral science to manipulate [drivers] in the service of its corporate growth.”⁴² Indeed, the journalist found that “Employing hundreds of social scientists and data scientists, Uber has experimented with video game techniques, graphics and noncash rewards of little value that can prod drivers into working longer and harder — and sometimes at hours and locations that are less lucrative for them.”⁴³ U.S.-based Uber drivers were previously paid a base fee based on mileage (amounts that varied per geographic location)

³⁹ See FN 26.

⁴⁰ “Is Uber’s Price Discrimination Bad? Economists Say Maybe Not — Quartz,” accessed October 3, 2022, <https://qz.com/990131/uber-is-practicing-price-discrimination-economists-say-that-might-not-be-a-bad-thing/>.

⁴¹ Stark, J., & Diakopoulos, N. Uber seems to offer better service in areas with more white people. That raises some tough questions. THE WASHINGTON POST (2016).; “Caldor Fire Evacuees Report Tahoe Ride-Hail Price Gouging of More Than \$1,500,” KQED, accessed October 25, 2022, <https://www.kqed.org/news/11887558/caldor-fire-evacuees-report-tahoe-ride-hail-price-gouging-of-more-than-1500>.

⁴² Noam Scheiber, “How Uber Uses Psychological Tricks to Push Its Drivers’ Buttons,” N.Y. TIMES, April 2, 2017, sec. Technology, <https://www.nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html>, <https://www.nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html>.

⁴³ Id.

and time. However, since the passage of Proposition 22 in California, which (among other things) legalized the practice of algorithmic wage discrimination, drivers have received a base fare rooted in what Uber calls “Upfront Pricing”—an amount based on a black-box algorithmic determination. In addition to this base fare, Uber drivers rely upon any number of offers, bonuses, surges, quests, and other “wage manipulators” from which to raise their base fare, which in most cases is untenably low by itself. Uber uses this practice across the world.

These wage manipulators—the additional financial incentives and dynamic pricing structures—are designed and deployed to influence individual worker behavior without directly telling a driver what to do. While I detail some of these wage manipulators in Part II, the relevant point here is that these are not the same for every driver, nor are they the same across time. For example, the surge multiplier that Diego is presented may not be the same as the multiplier that is sent to Marta, even if both workers are working in the same area at the same time. The bonus offer that Ahmed receives on any given week is not the same as the offer sent to Sanjeev. The reasons that underlie these differences are opaque—the logic hidden inside black-box algorithms. But based on what we know about price discrimination in the consumer context, we can postulate that these wage manipulators are personalized based on what Uber’s machine learning systems knows about the habits, practices, and income targets of individual workers. Despite Uber’s pleadings to the contrary, since drivers are best conceived as workers whose labor provides a service, rather than consumers of Uber technology, “dynamic pricing” as it pertains to driver income is better understood as *algorithmic wage discrimination*.

One of the central levers that Uber uses to manipulate worker behavior—and crucial to its practice of algorithmic price discrimination—is the rate at which it offers rides to various drivers. Uber and other on-demand companies do not pay workers for what they variably refer to as “non-engaged time,” “non-passenger platform time,” or P1 time, the time during which workers spend awaiting a fare and which accounts for roughly (but unpredictably) 40% of overall time on the job.⁴⁴ Importantly, this waiting time is not purely a factor of demand or driver quality or quantity. The company’s goal is to keep as many drivers on the road in order to quickly address fluctuations in rider demand; thus, they are motivated to elongate the time between sending fares to any one driver, so long as that wait time does not lead the driver to end their shift. The company’s machine-learning technologies may even predict the amount of time a specific driver is willing to wait for a fare. In contrast to firms like Caviar, which uses disincentives to limit the number of

workers that can log on at any specific time,⁴⁵ Uber primarily addresses the situation of the number of workers exceeding the number of customers by keeping workers waiting and unpaid, while offering tantalizing bonuses and offers that keep drivers on the road with the possibility of receiving a larger fare in the near future. As discussed in the following sections, these practices run afoul of basic legal and cultural expectations around work and violate the prevailing moral economy norms reflected in most low-wage work over the past century.

And yet, this is the default practice of many on-demand firms across the economy.⁴⁶ Indeed, in at least nine states, state legislatures have legally encased these practices in the ride-hail sector by passing statutes that classify workers laboring for “transportation network companies” like Uber and Lyft as independent contractors and leaving the terms of the payment to be settled entirely through contracts between companies and drivers—contracts that are frequently updated by the companies, sent through the app, and that drivers must accept in order to labor. And in two states—California and Washington—the non-payment for non-engaged time has been explicitly legalized, thus leaving workers’ hourly wages and their determination to the whim of the hiring entities.

In California, the passage of Proposition 22 sanctioned, among other things, this tool of algorithmic wage discrimination: the practice of not paying workers for time when a worker is laboring, but has not been allocated work.⁴⁷ Instead, workers receive a guarantee of 120% of the minimum wage for the area in which they are working—but only for “engaged time,” that is, after they have been dispatched a fare (or an order, in the case of food delivery platforms).⁴⁸ In Washington state, a similar piece of state-level legislation, negotiated by Uber and Teamsters Local 117, requires workers to be paid \$1.17 per mile and \$0.34 per minute, including a minimum pay of \$3.00 per trip, while legalizing the practice of not paying workers for non-engaged

⁴⁵ Shapiro at 14.

⁴⁶ The one exception to this in the U.S. is the New York City ride-hail sector where all workers by local law have a time-based wage floor. When the New York City Council passed this law, 85% of drivers laboring in NYC were making less than the minimum wage, according to former TLC director Meera Joshi. Veena Dubal, Fieldnotes, On File with Author; Emma Fitzsimmons and Noah Scheiber. NEW YORK CITY CONSIDERS NEW PAY RULES FOR UBER DRIVERS THE NEW YORK TIMES, <https://www.nytimes.com/2018/07/02/nyregion/uber-drivers-pay-nyc.html> (last visited Oct 28, 2022).

⁴⁷ Veena Dubal, *The New Racial Wage Code*, 15 HARVARD LAW AND POLICY REVIEW 511 (2021). The Yes on Proposition 22 campaign, supported by Uber, Lyft, DoorDash, Postmates, and Instacart, invested \$223 million dollars to pass the initiative. Many of their tactics were widely believed to include voter deception.

⁴⁸ Dubal, *supra* FN 37.

time.⁴⁹ In effect, this legislation, like Proposition 22, provides official sanction for one central aspect of algorithmic wage discrimination: the power of firms to provide digitalized variable pay with no hourly floor guarantee. At the same time, it is silent on the other aspects of the practice—including the data collection that makes the algorithmic wage discrimination possible and the variable dispersal of wage manipulators that facilitate driver control.

With this background in place, I consider how the practice and legalization of algorithmic wage discrimination comports with longstanding U.S. wage laws and regulations and the moral and cultural norms they created.

B. Calculative Fairness & Minimum Wage Regulation

Algorithmic wage discrimination represents a dramatic rupture in the moral economy of work. To illustrate this, I consider the practice in relation to the history of the wage and work laws in the U.S. More specifically, I examine it against the background of minimum wage regulations that arose during the transition from craft-based to the Fordist structures of work and the interpretations of distributive fairness—both in terms of the calculation of wages and their minimum sum—that were embedded in these laws.

The exchange of wages for time worked seems natural today. But in the transition to industrial capitalism, this payment regime was contested by a wide variety of workers, many of whom sought to be or to remain independent producers.⁵⁰ In the transition from artisanal production to industrialization in the late 19th century, craftsmen frequently demonstrated their independence from factory owners by refusing to work regular shifts—defying the capitalist’s control over time, which workers viewed as a “degrading portent of proletarianization”⁵¹ or, as was commonly stated, “wage slavery.”⁵² Many labor reformers and collectives of workers attempted to exert control over wages via campaigns for shorter days, while reimagining workers as “merchants of time.”⁵³ This conceptualization led to the fight for the eight-hour day and for “a living wage”—both of which, reformers argued, would give workers the means to live and the time to engage in civic life and

⁴⁹ In an unusual break with the Teamsters local union that negotiated the bill with Uber, the Teamsters International President, Sean O’Brien opposed the law and urged the Governor of Washington to veto it. Josh Eidelson, *Teamsters Chief Seeks to End His Union’s Uber Bill in Washington*, BLOOMBERG BUSINESS, Mar. 31, 2021, <https://www.bloomberg.com/news/articles/2022-03-31/teamsters-chief-seeks-to-end-his-union-s-uber-bill-in-washington> (last visited Oct 28, 2022)

⁵⁰ See generally, Glickman, *supra* FNx.

⁵¹ Glickman at 99.

⁵² *Id.*

⁵³ *Id.*

consumption.⁵⁴

As reformers gained legislative victories for minimum wage and maximum hour regulations, however, the Supreme Court ruled that such regulations were a violation of the state's police power to govern commerce. In these "*Lochner*-era decisions," the Court endorsed the view that wages and hours should be decided through private contract, and generally determined by abstract market forces. Yet careful review of these cases reveals a more nuanced approach to the regulation of payment for work. Even within the *Lochner*-era, we can identify a judicial commitment to an ideal of calculative fairness in the workplace: that wages should be predictable and reached in ways that are honest, clear, and fair. For example, the early twentieth century Supreme Court case, *Adkins v. Children's Hospital of D.C.* ("*Adkins*") is remembered for infamously striking down minimum wage laws and upholding freedom of contract. But in doing so, *Adkins* also highlighted the importance of wage calculability and predictability for workers. Citing to two previous Supreme Court cases, *McLean v. State of Arkansas* ("*McLean*") and *Knoxville Iron Company v. Samuel Harbison* ("*Knoxville Iron*"), *Adkins* outlined normative notions of fairness regarding wage calculation and distribution.

Writing on behalf of the Court, Justice Sutherland in *Adkins* struck down an Act that created a wage board to ascertain, for women living in the District of Columbia, "what wages are inadequate to supply the necessary cost of living...to maintain them in good health and to protect their morals."⁵⁵ While Justice Sutherland maintained that "There is, of course, no such thing as absolute freedom of contract," he characterized the minimum wage law as "a price fixing law... which has no relation to the capacity or earning power of the employee."⁵⁶ And yet, legal scholars who study *Adkins* often overlook Justice Sutherland's articulation of a broader notion of fairness beyond a wage floor: "A statute," he wrote, "requiring an employer to pay in money, to pay at prescribed and regular intervals, to pay the value of the services rendered, even to pay with fair relation to the extent of the benefit obtained from the service, would be understandable."⁵⁷

In other words, even a Court that cast the minimum wage as "a naked,

⁵⁴ Labor reformers debated whether minimum wage laws would hurt or benefit the labor movement more broadly. Many, including leaders in both the more conservative AFL and the more radical IWW, were skeptical of state intervention in negotiations between firms and collective groups—even in providing a basic wage floor from which to bargain. This skepticism has largely left the labor movement as minimum wage laws have become the cultural norm.

⁵⁵ *Id.* at 395.

⁵⁶ *Id.* at 400.

⁵⁷ *Id.* at 402.

arbitrary exercise of power,”⁵⁸ which was unfair to business and broadly interfered in the workers’ freedom to contract, recognized the importance of fairness of payment in form and time. Indeed, citing to *McLean* and *Knoxville Iron*, the Court explained that the Court had upheld previous wage regulations because the “tendency and purpose was to prevent unfair... methods in the payment of wages...”⁵⁹ In *McLean*, the Court considered the regulation of a mining company that paid workers according to the quantity of the coal they mined. The law in question stated that the contract between a mining company and a miner could not stipulate payment to the worker based on “screened coal” but instead based on weights of coal “originally produced in the mine.”⁶⁰ In this sense, the method of payment, the Court concluded, must be fair with regard to “honest weights and measures.”⁶¹ More specifically, the weight of the coal mined could not be measured through the use of a technology that would result in lower payment than was fair. The Court upheld the law as a reasonable legislative restriction on contract. It held that the company had violated it through not only “the introduction of screens as a basis of paying the miners for screened coal only,” but also because “after the screens had been introduced, differences had arisen...thereby preventing a correct measurement of the coal as the basis of paying the miner’s wages.”⁶² In *Knoxville Iron*, a law that required that a coal mining company pay their workers in money or goods – but only if those goods were the same value as the money – was also upheld by the Court on fairness grounds.⁶³

In both cases, the “technology” through which wages were calculated— instruments to measure coal weight and the calculated worth of a non-monetary good—had to be fair in form and method. That is, the company could not deduct value from the workers’ labor by introducing a new, obscuring instrument for payment. In the *McClean* Court’s words, the wage practices which the state legislature made illegal by statute, had a “reasonable relation to the protection of a large class of laborers in the receipt of their *just* dues.”⁶⁴ Thus, the law’s regulation of contract not only passed the muster of the Court’s police powers analysis, but the Court’s logic was that it did so because it addressed the problem of calculative fairness in the wage-setting practices of employers.

This value of calculative fairness, embedded even in *Lochner*-era Supreme Court decisions, is worth contrasting with the practice of

⁵⁸ *Id.* at 402

⁵⁹ *Adkins v. Children's Hosp. of the D.C.*, 261 U.S. 525 (1923).

⁶⁰ *McLean v. State of Arkansas*, 211 U.S. 539, 548 (1909).

⁶¹ *McLean v. State of Arkansas*, 211 U.S. 539, 550 (1909).

⁶² *Id.* at 539.

⁶³ *Knoxville Iron Co. v. Harbison*, 183 U.S. 13, (1901).

⁶⁴ *McLean* at 550.

algorithmic wage discrimination, in which the calculation of wages—again through the introduction of new technologies—is arrived at through an entirely unpredictable and opaque means. The worker cannot know what the firm has algorithmically decided their labor is worth, and the technological form of calculation makes each person’s wages different. In contrast to the wage regulations that the *Adkins* Court considered common sense, the practice of algorithmic wage discrimination obscures the possibility of discerning whether workers are paid “the value of the services rendered” or “even...with fair relation to the extent of the benefit obtained from the service.”⁶⁵ As these cases make clear, this unpredictability is a matter of fairness quite apart from the fact that some workers make so little as to fall below the minimum wage. Algorithmic wage discrimination raises not just the problem of wage value, but also of the wage-setting process.

Adkins was overturned by *West Coast Hotel v. Parish*, marking a sharp shift in the Court’s stance toward minimum wage regulations.⁶⁶ Laws guaranteeing a time-based wage floor that were once derided as “a form of theft” were now “required for bringing about distributional justice.”⁶⁷ Importantly, many minimum wage advocates asserted that wages themselves were a social construction and that they should thus be allocated justly, not only to “secure existence” but also, in the words Walter Lippmann, to “make life a rich and welcome experience.”⁶⁸ Vital to the Court’s interpretation of “distributional justice” in *West Coast Hotel*, then, was that an hourly wage was based not on an abstract or “true” value of the work, but on an *adequate* measure of basic needs.⁶⁹ This transformation—and the norms about labor compensation embedded in it—led to growing minimum wage movements in states and cities across the nation and ultimately resulted in the passage of the Fair Labor Standards Act in 1937, which, with notable exceptions in the agricultural and domestic sectors made up primarily of women and subordinated racial minority workers, created a wage floor for workers.

Thus, minimum wage laws, as intrinsic to “moral capitalism” and a “need-centered pay system” coupled with more conservative ideas about worker consumption and “purchasing power,” have come to reflect standard economic practice and expectations about fair (and lawful) work. Despite a

⁶⁵ *Adkins* at 402.

⁶⁶ *W. Coast Hotel Co. v. Parrish*, 300 U.S. 379 (1937). As historian Lawrence Glickman points out, this change in recognition of the importance of distributional justice by the Court finds its origins in the advocacy of late 19th century U.S. workers who invented the language of the “living wage” and from whom the New Dealers adopted and modified the language.” Glickman at 155.

⁶⁷ Edward James McKenna & Diane Catherine Zannoni, *Economics and the Supreme Court: The case of the minimum wage*, 69 REVIEW OF SOCIAL ECONOMY, 189–210 (2011)

⁶⁸ Glickman at 151-152.

⁶⁹ *Id.* at 153.

staggeringly low federal minimum wage, to be considered fair, payment for work is still expected to be predictable, arrived at with calculative fairness, and with few exceptions, all time that one spends laboring must be accounted for in the labor price.⁷⁰ The profound contemporary association between these ideas of fairness, the minimum wage, and “blue collar” work is reflected in the way in which Proposition 22 is written – with direct reference to the minimum wage. And yet, the actual effect of Proposition 22, as discussed *infra*, is to obfuscate the minimum wage—and the notion of a living wage. The only worker-led study (discussed in Part III) on worker wages in an on-demand sector, for example, found a variable average hourly wage for on-demand ride-hail drivers in California that fell well below one-half (and sometimes one-third) of the minimum wage of urban areas.

Minimum wage laws—and the laws that came before them—embedded cultural norms and expectations about calculative fairness, wage predictability, and fair labor remuneration that prevail today in our conceptualization of what constitutes a moral economy of work. This conceptualization becomes particularly important as we see how workers make sense of their encounters with algorithmic wage discrimination.

C. “Equal Pay for Equal Work” Anti-Discrimination Laws

Despite a persistent pay gap across social groups (between men and women, and racial minorities and the white majority), U.S. anti-discrimination laws (including Title VII of the U.S. Civil Rights Act of 1964, the Age Discrimination in Employment Act, the Equal Pay Act, and the Americans with Disabilities Act) formally prohibit differential pay “because of” or on the basis of race, color, religion, sex, national origin, age, or disability. These laws, which were adopted in response to social and labor movement demands, have also embedded values and expectations around “fair work” in relationship to identity. With regard to Title VII, the underlying normative dictate is that workers within a firm should not be treated differently as to the terms, conditions, and privileges of employment, if that difference is related to a protected identity. The Equal Pay Act, by contrast, which emerged out of the “equal pay for equal work” movement, emphasized something slightly different, but with the same effect.⁷¹ Rather than

⁷⁰ The exceptions are narrow, but under the Fair Labor Standards Act, some workers may not be remunerated for “on-call time.” Fact sheet #22: Hours worked under the Fair Labor Standards Act (FLSA), UNITED STATES DEPARTMENT OF LABOR, <https://www.dol.gov/agencies/whd/fact-sheets/22-flsa-hours-worked> (last visited Oct 28, 2022).

⁷¹ In her manifesto *Equal Pay for Equal Work*, published in 1910, Grace Charlotte Strachan wrote on the problematics of unequal pay within a workforce, “Who will deny that

legislating against differential pay based on a protected status or identity, the Equal Pay Act legislated affirmatively for sameness: within firms, the same pay for the same work, regardless of gender.⁷² In doing so, the Act attempted to remedy that women had long been paid less than men even when doing substantially similar work.

Though the “equal pay for equal work” movement gained some recognition in the wake of World War I, it was not until World War II that the campaign gained significant traction. Both the American Federation of Labor and the Congress of Industrial Organizations urged the inclusion of equal pay clauses in labor contracts, and women’s groups brought the issue before the War Labor Board in 1942, resulting in a rule establishing “the principle of equal pay for equal work.” In one important War Board opinion involving General Motors, the Board wrote that it “accepted the general principle of equal pay for equal work. *There should be no discrimination between employees [within a firm] whose production is substantially the same on comparable jobs.*”⁷³ (my italics) In the same decade, nine states passed equal pay laws, which were modeled after an equal pay bill written by the United States Women’s Bureau and supported by the union movement and the League of Women Voters. But the movement achieved its most significant victory in 1963, with the passage of the Federal Equal Pay Act, an amendment to the Fair Labor Standards Act that held that no difference in pay between the two sexes can exist when the employees are performing work that requires “equal skill, effort, and responsibility” and is “performed under similar working conditions.”⁷⁴

In practice, demonstrating that women are performing work “with the

a railroad track with one of its rails depressed three feet below the other is dangerous to all who travel on it! I hold that all who are connected with the enforcement and the operation of our unjust salary schedules are in danger of moral degeneration. Therefore, I hold that the entire community should fight the unjust salary schedules ... as immoral and as a menace to the welfare of the State.” Strachan led the Interborough Association of Women Teachers in New York City, and a year after the publication of this book, the New York legislature passed a law mandating equal pay for equal work in teaching. Grace Strachen. EQUAL PAY FOR EQUAL WORK (1910).

⁷² A useful anecdote that was used during the fight for the Equal Pay Act early in the industrial revolution was as follows: John Jones earned good wages braiding military tunics in a factory. When he fell ill, the factory allowed him to work from home. John’s illness worsened, and so he taught his wife Jane how to do the work. Jane would take the tunics to the factory, and in turn, the factory would disburse to her John’s normal wages. When John died, Jane continued the work. But after the factory bosses discovered that he had passed and that they were paying for Jane and not John’s work, they docked her pay by two thirds. Id.

⁷³ Marguerite J. Fisher, “Equal Pay for Equal Work Legislation,” INDUSTRIAL AND LABOR RELATIONS REVIEW 2, NO. 1 (1949): 50–57.

⁷⁴ EQUAL PAY FOR EQUAL WORK. Department of Labor. <https://www.dol.gov/agencies/oasam/centers-offices/civil-rights-center/internal/policies/equal-pay-for-equal-work> (accessed October 28, 2022).

same quality and quantity of productivity” as their male counterparts has been a major impediment to achieving equal pay across the genders. Yet, however difficult to enforce, the Act contains a relatively straightforward normative principle of fairness: workers within a firm should receive equal pay for equal work. While the Act itself focuses on the fact that women, as a class, should earn similar pay to men for similar work, this focus is explained by fact that men were, at the time, largely being paid comparable amounts for comparable work. Algorithmic wage discrimination upends this assumption.

Some—including Uber chief economist Jonathan Hall—have suggested that “the gig economy” can help to narrow the persistent wage gap (not adequately remedied by the Equal Pay Act) between men and women in the economy by lowering “the job-flexibility penalty.”⁷⁵ And yet, Hall and his coauthors in a 2020 study show that despite the fact that “neither the pay formula nor the dispatch algorithm for assigning riders to drivers depend on a driver’s gender,”⁷⁶ women working for Uber make roughly seven percent less than men.⁷⁷

On its own terms, the publication of this finding signals a troubling moral shift in how firms understand the problem of gender discrimination and their legal responsibility to avoid it. Since at least the Supreme Court’s 1971 decision in *Griggs v. Duke Powers*, firms have been reticent to reveal pay differentials as they pertain to protected categories of workers for fear of incurring liability. Even absent intentional discrimination, such widespread wage differences between genders could trigger disparate impact liability under Title VII of the Civil Rights Act of 1964. In publicizing and interpreting the gendered wage difference in the Uber work force, this article reflects Uber position that anti-discrimination laws do not apply to them, or at least, that they do not fear liability under the laws. In ignoring (or diverting attention from) the role of the firm’s wage-setting process in creating the gendered wage gap, the article also does the cultural work of alleging that the gendered wage gap arises organically from individual worker—and not firm—choices.

The authors attribute this gendered wage difference to three factors: (1) “the logic of compensating differentials (and the mechanisms of surge pricing and variation in driver idle time),” (2) “rideshare specific human capital,” and (3) “average driver speed.” In essence, they argue that men earn more because of the techniques they use to drive, their greater experience in working for Uber, and the fact that they drive faster. Somewhat

⁷⁵ Cody Cook et al., “The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers,” *THE REVIEW OF ECONOMIC STUDIES* 88, no. 5 (October 1, 2021): 2210–38, <https://doi.org/10.1093/restud/rdaa081>.

⁷⁶ *Id.* at 2211.

⁷⁷ *Id.*

counterintuitively, “hour-within-week differences are a small part of the gender gap.” While women might work around child-rearing or family responsibilities, they do not appear to pay a large financial price for this.

The authors of the study describe the factors to which they attribute the gender pay gap as worker “preferences or constraints,” casting them as the result of individual driver decisions. They analogize the gender pay gap found among ride-hail drivers to that found among JD and MBA graduates, which studies have determined are due largely to individual preferences that correlate with gender, such as a preference to work fewer hours or to work at lowering pay jobs. However, unlike in the case of lawyers or MBAs, the pay differential between Uber drivers cannot be explained by women workers choosing to work fewer hours or even certain hours. Rather, the determinants that result in lower pay for women drivers are driven in large part by the structure of wage setting—by algorithmic wage discrimination. This, according to Uber’s own research, results in gender pay discrimination.⁷⁸ But it also means that there are individualized or personalized pay differences that run afoul of the norm undergirding the Equal Pay Act: that people should earn substantially similar amounts for similar work.

Thus, algorithmic wage discrimination belies decades of legal norms—and compromises—around wages for work. It creates a structure in which wages are unpredictable and variable from person to person and hour to hour.

II. The Operation & Experience of Algorithmic Wage Discrimination

“Modern production seems like a dream of cyborg colonization work, a dream that makes the nightmare of Taylorism seem idyllic.” – Donna Haraway, A Cyborg Manifesto

The previous section examined the introduction of “algorithmic wage discrimination” by on-demand platform labor companies, the explicit legalization of parts of this practice in state law, and the tension between this practice and the norms embedded in the wage laws that have long shaped our contemporary moral expectations around work and wage regulation. In this section, I take a closer look at the operationalization of algorithmic wage

⁷⁸ While neither the EEOC nor private plaintiffs have attempted to hold Uber liable for this wage differential (under Title VII, this would only be possible as a disparate impact lawsuit, since disparate treatment lawsuits would require a showing of intentional discrimination), this is in large part because the threshold question in such a lawsuit would be whether or not the drivers are employees. If not, they are not covered by the Equal Pay Act or Title VII.

discrimination as a system of labor control, as well as how the practice is subjectively experienced and understood by workers. Following economic sociologist Viviana Zelizer, I maintain that this practice—as a nascent economic and legal phenomenon—is laden with new and old meanings, institutions, and structures of social relations.⁷⁹ As a result, workers experience algorithmic wage discrimination in relation to and as a disjuncture from long-held wage practices. A focus on moral economy, then, continues to be a useful analytical to understand, not just how this practice objectively departs from existing legal norms, but also how workers experience and describe this form of labor control. Many workers, I find, experience algorithmic wage discrimination as fundamentally in conflict with what they understand as the purpose of work: economic stability and security.

In section (A) I analyze algorithmic wage discrimination—as it is practiced by on-demand firms like Uber—within the broader history of scientific management theory. I show how by obscuring the rules of the workplace, algorithmic wage discrimination departs from the foundations of Taylorism, creating a work environment in which drivers must guess the logic of the algorithms to earn. Building on this, in section (B), I examine how workers subjectively experience and make sense of this practice. Though both management science scholars and critical science and technology scholars have examined algorithmic management as a technical or structural matter, we know little about how workers understand or experience algorithmic management with respect to wage distribution.⁸⁰ To the extent that scholarship has focused on workers, it has tended to look instead at their attempts to counter-manage the management: how they “gamify” or try to resist the algorithm, rather than how they make sense of their remuneration.⁸¹

⁷⁹ Viviana Zelizer, *THE PURCHASE OF INTIMACY* (2000).

⁸⁰ See, e.g., Niels van Doorn. “At What Price? Labour Politics and Calculative Power Struggles in On-Demand Food Delivery.” *WORK ORGANISATION, LABOUR & GLOBALISATION* 14, no. 1 (2020): 136-149.; Aaron Shapiro. “Dynamic Exploits: Calculative Asymmetries in the On-Demand Economy.” *NEW TECHNOLOGY, WORK AND EMPLOYMENT* 35, no. 2 (2020): 162-177.; M. Chen and Michael Sheldon. “Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber platform.” *Ec* 16 (2016): 455.; Siddhartha Bannerjee, Ramesh Johari, and Carlos Riquelme. “Dynamic Pricing in Ridesharing Platforms.” *ACM SIGecom Exchanges* 15, no. 1 (2016): 65-70.; Kelle Howson, Fabian Ferrari, Funda Ustek-Spilda, Nancy Salem, Hannah Johnston, Srujana Katta, Richard Heeks, and Mark Graham. “Driving the Digital Value Network: Economic Geographies of Global Platform Capitalism.” *Global Networks* 22, no. 4 (2022): 631-648.

⁸¹ Krzywdzinski, Martin, and Christine Gerber. “Between automation and gamification: forms of labour control on crowdwork platforms.” *Work in the Global Economy* 1, no. 1-2 (2021): 161-184.; Hamari, Juho, Jonna Koivisto, and Harri Sarsa. “Does gamification work?—a literature review of empirical studies on gamification.” In *2014 47th Hawaii international conference on system sciences*, pp. 3025-3034. Ieee, 2014.; Vasudevan, Krishnan, and Ngai

Foregrounding worker subjective understandings and experiences is important if we are to identify the everyday impacts that this new technology of pay and control has on workers, as well as to begin to formulate the appropriate regulatory interventions.

Drawing on findings from a long-term ethnographic study of Uber drivers in California, I show that the values and norms embedded in both anti-discrimination laws and minimum wage laws discussed in Part I have become schema through which workers frame their work experiences as harmful. In defining the algorithmic payment structures as unfair and unjust, workers in my research frequently complained of their low-hourly wages, despite the fact that they were not paid by the hour. In describing the harms they suffered, they drew on the language of anti-discrimination law, condemning not just the variability of their income over time, but more specifically the variability of their income in comparison to other drivers. The fact that different workers made different amounts for largely the same work was a source of grievance defined through inequities that often-pitted workers against one another, leaving them to wonder what they were doing wrong or what others had figured out. This feature of algorithmic wage discrimination—because of its divisive effects—may also undermine the ability of workers to organize collectively to raise their wages and working conditions.

In addition to complaints about the unfairness of the low, variable, and unpredictable hourly pay, workers made two other moral judgements about the techniques through which they were remunerated. First, as my research progressed and the techniques of algorithmic wage discrimination deployed by on-demand firms both lowered pay and became increasingly obscure, drivers described the process of attempting to earn not through the lens of gaming, but through the lens of gambling. And second, they portrayed the algorithmic changes or interventions that prevented them from earning as they had hoped or expected as trickery or manipulation enacted by the firm. Vacillating between feeling possibility and impossibility, freedom and control, workers experienced algorithmic wage discrimination as a practice in which the structures and functions of the machine boss were designed to take advantage of them by providing the illusion of agency. As Dietrich, a part-time driver in Los Angeles said, “[It’s] constant cognitive dissonance. You’re free, but the app controls you. You’ve got it figured out, and then it all changes.”

Drawing on these insights, I argue that algorithmic wage discrimination is a deeply predatory and extractive labor management practice—a practice that preys on feelings of hope of vulnerable workers while limiting real possibility of economic certainty and stability.

Keung Chan. "Gamification and work games: Examining consent and resistance among Uber drivers." *new media & society* 24, no. 4 (2022): 866-886.

A. *Labor Management through Algorithmic Wage Discrimination*

How can we position algorithmic wage discrimination in the history of scientific management and technology? Is it a departure from or merely a continuation of the general quest for optimization and efficiency?

The purpose of traditional industrial forms of scientific management has been “to find ways to incorporate ever smaller quantities of labor time into ever greater quantities of product.”⁸² In early 20th century scientific management, firms broke down the motions of factory workers into “elementary components” and defined each component into a fraction of a second to discover how best to divide the labor process and to determine how long worker movements should or could take.⁸³ Through observation and synthesis of workflows, scientific management attempted to optimize the processes through which work was completed in order to increase productivity.

But scientific management was never merely about efficiency. Early theorists also understood it through the lens of fairness and even through workplace democracy. For example, Frederick Taylor, the author of *Principles of Scientific Management*, observed that scientific management substituted “exact knowledge for guesswork...[seeking] to establish a code of natural laws equally binding upon employers and workmen.” He went so far as to argue that “No such democracy has ever existed in industry before.”⁸⁴

Taylor’s primary contention was that through the effort to maximize efficient production, rules became knowable—to both workers and their bosses. Workers would know what was expected of them and could, in theory, use a “code of law” developed through scientific management to justify complaints to management. Scholars have shown that other features of Taylorism—such as the fact that it deskilled workforces and made exacting demands of worker bodies, treating them, in essence, as a standardized part of the machine—significantly undermine its conduciveness to workplace democracy.⁸⁵ While Taylor’s analysis lacked a realistic assessment of the

⁸² Harry Braverman, *LABOR AND MONOPOLY CAPITAL: THE DEGRADATION OF WORK IN THE TWENTIETH CENTURY* (1998), 118.

⁸³ Because these kinds of studies could not account for the continuous uninterrupted motions of the human body and velocity produced through movement, management scientists went to great lengths to gather data approximating human movement via motion pictures, magnetic fields, photoelectric waves. Id.

⁸⁴ Friedrich Taylor cited in Marcuse, Herbert. “Some Social Implications of Modern Technology.” *ZEITSCHRIFT FÜR SOZIALFORSCHUNG* 9, no. 3 (1941): 414-439. 146.

⁸⁵ Marcuse, Herbert. *ONE-DIMENSIONAL MAN: STUDIES IN THE IDEOLOGY OF ADVANCED INDUSTRIAL SOCIETY*. (2013), 143.

power dynamic of most workplaces and the impacts of his systems of control, his emphasis on the importance of clear expectations and transparency is useful for thinking about what has constituted normative notions of fairness in the workplace. At the very least, knowable rules and expectations on work behavior and pay have long been agreed upon as customary in the workplace.

But Taylor’s system of scientific management relied on an assumption that no longer remains under informational capitalism: that labor overhead is directly proportional to time spent laboring. Today, facilitated by independent contractor status, algorithmic wage discrimination turns the basic logic of scientific management on its head. Instead of using data and automation technologies to increase productivity by enabling workers to work more efficiently in a shorter period (to decrease labor overhead), on-demand companies like Uber and Amazon use data extracted from labor, along with insights from behavioral science, to engineer systems in which workers are *less productive* (they perform the same amount of work over longer hours) and receive lower wages, thereby maintaining a large labor supply while simultaneously keeping labor overhead low. These systems generally operate through complex incentive structures (variably called “surges,” “promotions” and “bonuses” in the UberX context and “scorecards” in the Amazon DSP context), which are intentionally opaque and highly adaptive to both general demand and to worker behaviors.

As in earlier iterations of the application of scientific management to labor, subjective human decision-making is replaced by what is understood as objective calculations. But because this is achieved through a combination of data science, machine learning, and social psychology—rather than through direct command—algorithmic control is much less legible to the worker. Firms like Uber and Amazon influence worker behavior not just by learning how workers move, but also how they think: using data and machine learning to reinforce behavior that they want using financial rewards and to punish behavior that they do not by withholding work (and therefore wages).⁸⁶

As Aaron Shapiro has shown, the management science literature examining the on-demand labor platform economy focuses on solving labor control problems for workers who cannot be directly controlled because of their independent contractor status. Accordingly, it offers some useful insights into the logic behind the operation of algorithmic wage discrimination.⁸⁷ Management scholars, per Shapiro’s analysis, have argued that algorithmic levers of control can produce “optimal solutions” to the

⁸⁶ In Tarleton Gillespie’s terms, the relationship between algorithms and people is “a recursive loop between the calculations of the algorithm and the ‘calculation of people.’” “The Relevance of Algorithms.” *MEDIA TECHNOLOGIES*. (2014), 183.

⁸⁷ Shapiro at 12.

logistical challenges that firms face when they do not want to exert clear control as bosses.⁸⁸ They do so primarily by influencing work time (e.g., through incentives) and work location (e.g., through fare multiplier or surges).⁸⁹ These two variables, alongside individualized information about worker wage goals and habits, play a critical role in determining individual worker wages on any given day. Indeed, Shapiros analysis of the literature suggests that firms use and monitor “dynamic pricing” (an example and component of algorithmic wage discrimination for firms like Uber) to determine the exact pay rates necessary to attract a sufficient volume of workers to specific areas. Algorithmic wage discrimination thus helps ensure that workers labor during busy hours, for long periods of time, and in specific areas.

To serve this purpose, however, the “wage manipulators”—in the case of Uber, surges, offers, localized incentives, quests, boosts, bonuses, guarantees—must be personalized to each driver (thus differing between drivers) and adapt from week to week and day to day. Let us consider in slightly more detail three levers that Uber uses to influence driver behavior: base fares, geographic surges, and quests. Until 2022, drivers in California were paid a base fare rooted in what appeared to be an objective calculation: time and mileage. Although the amounts that Uber drivers were paid for time and mileage dropped precipitously over time, between 2014 and 2022, drivers understood the calculation of the base wage per fare, even if they could not predict the number of fares that they were allocated or the distance per fare. In the Fall of 2022, however, Uber replaced the time and mileage calculation with a system called “Upfront Pricing.” Drivers are presented with a base fare—or the upfront pricing—but they do not know how it is calculated. California drivers have argued that upfront pricing has lowered their overall earnings. One driver explained, “The new algorithm [that determines upfront pricing] is lowering driver base pay ... And it’s not adjusting the fares for extended trips by riders...It’s a pay cut in disguise.”

Because base fares are generally quite low, drivers rely heavily on surges and quests (alongside other “offers” or wage manipulators) to increase their earnings. But, as drivers explain, even within a particular locale, the surge rate is highly variable between drivers. According to Ben, an active driver and organizer with Rideshare Drivers United, “Everyone has different levels of surge at any given time. If the median surge is 2.5, someone else might have 5.0. We don’t know what this is based on. It’s not transparent.” Many drivers also rely on bonuses from “quests,” in which, for instance, a driver is told that if he completes one hundred rides per week, he will receive a bonus of \$50-\$200. But quests are not offered every week, not everyone receives a

⁸⁸ Id.

⁸⁹ Id.

quest when they are offered, and not everyone who is offered a quest is offered the same bonus amount. Moreover, according to many drivers, as they approach the required number of rides to reach their quest, Uber slows down the rate at which it sends them rides.

	Example of Levers of Wage Control	Influences
Base Fare	Upfront Pricing (How this is calculated is unknown)	Decision to Accept Ride
Fare Multiplier	Surge Set by Uber, Varies per Driver	Location of Driver & Amount of Time Worked
Incentives or Wage Manipulators	Quests, Pay Guarantees, Pro Status (varies per drivers)	Location of Driver, Amount of Time Worked, and Timeframe Worked

As a result of the opacity, variability, and unpredictability with which wages are determined, drivers often earn much less than they expect or plan for. While Proposition 22 in California guarantees workers 120% of the minimum wage of the area in which they are driving, as mentioned above, this only applies to P1 or “engaged time.” Theoretically, workers could labor for an entire shift and legally earn nothing if they are not allocated a fare during that time.

After the passage of Proposition 22, Rideshare Drivers United (“RDU”)—a group of independent, self-organizing drivers in California—conducted a study based on their membership. They found that drivers earned, on average, \$6.22 per hour (after accounting for expenses and lost benefits).⁹⁰ Revealingly, many drivers simply did not believe the findings, given the high variability of their individual incomes and how difficult it is to calculate net pay. As Nicole Moore, a part-time driver and RDU leader said, “After we released the study, we met with 65 drivers from across the state. No one believed they were making so little. I didn’t believe it. But we worked through the numbers with them, and they went from, ‘I don’t believe it’ to ‘Tell me something I don’t know’ to drivers saying, ‘How are we doing to fight for wages we can live on?’”

In striking contrast to Taylor’s description of scientific management as bringing democracy to work because everyone—workers and bosses—knows the workflows and the rules governing them, algorithmic scientific management deployed by on-demand firms is opaque—and purposively so. As a result of this opacity, workers cannot trust the firm’s or their own market

⁹⁰ Eliza McCullough, Brian Dolber, Justin Scoggins, Edward-Michael Muña, and Sarah Treuhart. “Prop 22 Depresses Wages and Deepens Inequities for California Workers”. NATIONAL EQUITY ACCESS. <https://nationalequityatlas.org/prop22-paystudy>

forecasts, nor can they rely on the incentive structures (or wage manipulators) created by the firm. The time that they must labor to meet their income target—the primary way in which workers in my research structured their work—is ever changing. Through this process, hard work and long hours become disconnected from any certainty of economic security. Thus, algorithmic wage discrimination, by keeping workers in a state of deep uncertainty, creates profoundly precarious working conditions and wages that belie long held norms of a moral economy of work.

B. A Bundle of Harms: Calculative Unfairness, Trickery, & Gamblication

As the Rideshare Drivers United study referenced above makes clear, one significant problem with algorithmic wage discrimination is the fact that it allows companies to pay workers less than the minimum wage. However, the harms of algorithmic wage discrimination extend well beyond low wages. Worker’s expectations, grounded in long-standing work law and culture—that they will receive predictable wages, comparable to other drivers—are upended. Drivers in my research often described the fact that they are paid differing amounts at different times and compared to other workers as fundamentally “unfair.” Emphasizing the ubiquity of this problem, Carlos, a driver organizer, told me and a group of organizing drivers:

I need a real living wage. Not some fake minimum wage where I get \$3 more at the end of one shift and \$5 at the end of another. I’m from Cuba and I’m not a socialist; I’m a social democrat. When I’m in the car, I think this is worse than socialism. It is the violence of unbalanced capitalism. There everyone has the same shoes. Here, we don’t have money to buy shoes. I am not asking for a revolution. I am asking for fairness. I am asking to make enough to live. *To know how much I am going to make from one day to the next. To have some predictability.* (my italics)

In the following sections, I examine how workers talk about the lack of predictability that Carlos describes. They objected not just to the low pay, but also to feeling constantly tricked and manipulated by the automation technologies. As wages for on-demand ride hail drivers in California dropped over the course of my research, I increasingly heard drivers complain about the “casino culture” generated by on-demand work. These pervasive experiences and feelings run counter to the widespread moral expectation that work should, as discussed in Part I, provide a stable means of survival and even consumption.

1. Calculative Unfairness

Algorithmic wage discrimination leads to different forms of perceived calculative unfairness among drivers, rooted both in the variability of their pay and the differences in their pay. Experienced drivers generally report having to work longer hours to earn the amount that they earned early in their career. This is both because the collective wages for Uber drivers have been reduced dramatically since the firm was founded, and because drivers generally believe that the firms offer new drivers better fares and bonuses to entice them to work for the company and become financially reliant on the work. As Nicole, who started driving for Lyft because of a bad mortgage, told me,

“I was promised 80% of the fares [when I started], and within two months there was no relationship between what the passenger was paying and what I was earning. So, I had started making about \$200 a day and within two months it was \$150. And after a while, I was having a hard time even making a \$100! So, I had to add on an extra day to pay for my mortgage. I’ve never had a job like this before. It felt fundamentally unfair.”

In addition to decreasing wages over time—due both to systemwide “pay cuts” and to the personalized nature of algorithmic wage discrimination—workers in my research who labored for longer hours complained that they earned less per hour than workers who worked shorter hours. Uber’s chief economist Jonathan Hall and his co-authors confirmed this in their study on gendered wage disparities, noting a “decreasing return [for drivers] within-week work intensity.”⁹¹ Thus, a worker who labors for thirty hours a week tends to earn less per hour than a worker who labors for twenty hours per week. Again, this phenomenon runs counter to moral expectations about work: that those who work long hours will earn the same for those hours, or even more per hour after laboring for a certain number of hours (due to overtime laws).

Drivers also notice that even among those who drive roughly similar routes and hours, some make more than others. Adil, a Syrian refugee who supports five kids and his wife began driving for Uber after arriving in the Bay Area via Dubai. Many of his friends drove for Uber and showed him screenshots of how much they could earn. Hoping to follow in their footsteps, he bought a car and started driving. He lived two hours outside of the city and

⁹¹Cook, et al. *supra* FNx at 2229.

drove to San Francisco, where he labored for three days in a row—sleeping in his car when he felt tired. Adil would spend one day out of each week at home with his family. But at the time of our conversation, Adil was not earning enough to make his rent and pay for his car, which was on the verge of being recalled. The perception that others were able to make more money than him was a nagging data point that kept Adil driving.

“My friends they make it, so I keep going, maybe I can figure it out. It’s insecure, and I don’t know how people they do it. I don’t know how I am doing it, but I have to. I mean, I don’t find another option. In a minute, if I find something else, oh man, I will be out immediately. I am a very patient person, that’s why I can continue. But...now for the past two days I was like, I am stupid. I should not be dragged like this [by this company]. I started praying recently. Maybe God can help me. I am working hard, why can’t I make it?”

In contrast to Adil, who experienced his poor fortunes in relationship to other drivers as largely mysterious, some drivers possessed clear explanations for what they were experiencing. Diego told me, “Any time there’s some big shot getting high pay outs, they always shame everyone else and say you don’t know how to use the app. I think there’s secret PR campaigns going on that gives targeted payouts to select workers, and they just think it’s all them.”⁹² For many drivers like Adil and Nicole and Diego, the fact that they cannot make as much as they once did or as others claim that they can becomes a source of inner conflict—producing feelings not only of unfairness but also of personal failure and hopelessness. These experiences contradict what contract-based work has been understood to provide under industrial capitalism—the security of labor in exchange for a stable wage. But it also creates a divisiveness within the workforce that makes it harder for workers to collectivize and address the harms of this form of remuneration and control.

2. Trickery and Gamblification

In response to algorithmic prodding enacted through wage manipulators discussed above, workers must make decisions—asserting calculative

⁹² Diego’s interpretation of how on-demand wages work is not dissimilar from how multi-level marketing schemes work. See generally, Taylor, Jon M. “The Case (for and against Multi-level Marketing.” *Appendix A: The History of Pyramid Schemes and Multi-level Marketing*, Consumer Awareness Institute, Jon M. Taylor (2011).

agency.⁹³ They do this by drawing on both their acquired knowledge of the algorithmic systems, as well as their knowledge of urban spaces. This agency is circumscribed, however, by the opaque and constantly changing algorithmic systems and wage manipulators that they are offered. As a result, drivers, especially those who have figured out a technique that helps them earn or who have come to rely on weekly quests, often feel manipulated or tricked as the system changes. Given the information asymmetry that exists between the worker and the firm, this variability generates a great deal of suspicion about the algorithms that determine their pay.

Tobias, a longtime Uber driver, shared how he and his driver friends experience the information asymmetries:

“For us drivers, a lot of it is just suspicion. They [Uber] operate in very opaque ways, they are collecting your information and, they know everything about you. They know what route your taking, your personal information, where you are going, but when it comes to the output of the algorithm, that is all obscured. There is no way to know why the app is making these decisions for me.”

Such obscurity generates many concerns about manipulation of wages. Domingo, for example, felt like overtime, he was being tricked into working longer and longer, for less and less. He gave me an example,

“It feels like the algorithm is turned against you. There was a night at the end of one of week, if felt like the algorithm was punishing me. I had 95 out of 96 rides for a \$100 bonus... it was ten o’clock at night in a popular area. It took me 45 min in a popular area to get that last ride. The algorithm was moving past me to get to people who weren’t closer to their bonus. No way to verify that, but that’s what it felt like was happening. I was putting the work in the way I was supposed to, but the app was punishing me because it was cheaper to give it to someone else. So I got 45 min of

⁹³ This characterization is influenced by the work of Michel Callon and Fabian Muniesa, who, in an influential organizational study paper, theorize the calculative character of markets by defining their three constitutive elements: economic goods, economic agents, and economic exchanges. They introduce the notion of “calculative distributed agencies” to understand how economic agents make sense of and respond to the calculability of goods. Michel Callon and Fabian Muniesa, “Peripheral Vision: Economic Markets as Calculative Collective Devices,” *ORGANIZATION STUDIES* 26, no. 8 (August 1, 2005): 1229–50, <https://doi.org/10.1177/0170840605056393>.

dead time, hoping that I would go home and give up. Really feels like you are being manipulated – not random chance but literally feels like you're being punished by some unknown spiteful God.”

Domingo believed that Uber was not keeping its side of the bargain. He had worked hard to reach his quest and attain his \$100 bonus, which he had budgeted to buy groceries that week, but he found that the algorithm was using that fact against him. Many drivers articulated similar suspicions. Melissa told me quite succinctly, “When you get close to the bonus, the rides start trickling in more slowly.... And it makes sense. It's really the type of sh*t that they can do when it's okay to have a surplus labor force that is just sitting there that they don't have to pay for.”

Perhaps no wage manipulator received more suspicion from drivers in my research than surges—which is a major portion of overall driver income. Drivers overwhelmingly believed that surges are a form of trickery enacted upon them by Uber, and they reported either not responding to surges or using another app to judge whether a surge was real or not—in other words, to independently determine whether there was actual demand in a given area, or whether Uber was simply trying to trick them into changing their location. The first time I heard about surge trickery was in 2016 from Derrick, a middle-aged African-American driver who frequently picked up passengers from the San Francisco International Airport. He told me how he dealt with surges:

Derrick: Uber will make the airport surge bright red like it's 3.0 [three times the base fare]...you get a 3.0 trip from the airport downtown, that might be like \$60 a trip, you know. Uber will make it surge on there even though no flights coming in, so everybody can look at the app and [think], ‘Man, it's surging at the airport, let me go back to the airport.’ [But] You go to the airport, once the lot get kind of full, then the surge go away. They cut it off. So they just want you back.

Dubal: So, wait, when you see the surge you don't respond?

Derrick: No. I don't even go to it. (laughs) It took me a minute to figure that out. It took me maybe, I won't say a year, but it took me a minute. Actually, there was this lady who worked at the Uber office in Sacramento, and she called me and pulled me to the side...She said ‘Don't be chasing that surge or nothing like that.’ She said, ‘Look, when you

figure out how they play their game,’ she said, ‘You will be all right.’ She said, ‘Just watch. Think about how they play their game; you will be all right.’ She worked for Uber. And I figured it out. I said okay, I see what they do. So, I stopped chasing surges.

After hearing about this strategy from Derrick, I started asking drivers about it. Many explained that they were on group texts with other drivers who would “call out” fake surges. After being added to one of these text threads, I received text messages that alerted drivers to avoid certain areas (e.g., “I’m in the Marina. It’s dead. Fake surge.”). The expectation that not only is information withheld from workers, but also that some information provided by firms is “fake” has become a well-known phenomenon among those who study the field. Two management scientists, Harish Guda and Upinder Subramanian, have even proposed that on-demand firms “misreport” demand information to control worker behavior.⁹⁴ As Shapiro explains, “Guda and Subramanian argue that as workers learn that ‘chasing the surge’ is futile, they become suspicious of platform information, and [they] recommend that firms exploit this suspicion by ‘misrepresenting market forecasts to exaggerate the need for workers to move’—in other words, misleading workers...”⁹⁵

This sense that algorithmic wage discrimination is used to manipulate drivers through trickery and misinformation has led many workers to feel angry and alienated. It has also motivated several to become involved in driver activism for better working conditions and wages. Inmer, who owned a small construction company and who worked for Uber on the side to help pay the medical expenses for his disabled child, offered this explanation for his decision to join a group of drivers who were fighting against the on-demand system:

It’s like being gaslit every day being told you are independent and being manipulated in all these different ways. Every single day they are figuring out how to exploit you in different ways. It drives me to anger that bubbles inside me because I’m being taken advantage of. The state of work is going to deteriorate in this country in a way such that it’s not recognizable anymore. It already is.

⁹⁴ Harish Guda and Upinder Subramanian, “Your Uber Is Arriving: Managing On-Demand Workers Through Surge Pricing, Forecast Communication, and Worker Incentives,” *MANAGEMENT SCIENCE* 65, no. 5 (May 2019): 1995–2014, <https://doi.org/10.1287/mnsc.2018.3050>.

⁹⁵ Shapiro, *supra* FNX at 16. Shapiro cites a previous version of Guda and Subramanian’s article that was posted online.

Inmer and Adil, both expressed remorse and even guilt about not finding other, more secure jobs, because they, like many others in my research, viewed it as a form of gambling. The trickery and opacity that is involved in setting wages made the work feel not just like a game, in which the labor was to drive, accept fares, and navigate the firm's incentives, but also like a gamble, in which the financial outcome of those incentives was always unpredictable.

The “gaming” of on-demand work has been described by media theorists as a process that “scaffolds tedious work tasks [through] ‘puzzles’ and ‘challenges’ that offer workers the potential to earn ‘points,’ ‘badges’..[and other rewards]” in exchange for labor consent.⁹⁶ But these “games”—in the form of surges or quests may better be conceived as *gambles* or in Ulrich Beck's terms, “manufactured uncertainties”⁹⁷ which predicate earnings on worker consent to the risk. By design, they are work activities connected to earnings that limit choice and present high financial risk.⁹⁸

Workers describe how the very structure of the system—seemingly random patterning of incentive allocation—is designed to produce subjective shifts in which they feel possibility and impossibility, freedom and unfreedom. The occasional good fare or high surge allocation keeps many workers convinced to keep going. As they begin to feel hopeless and think about looking for other work, they might get another good fare—effectively keeping them in the labor force for longer. Nicole explained:

The system is designed to make sure people never earn a certain amount...Who knows what the magic number is for Uber when they start sending us less desirable rides, but that

⁹⁶ Vasudevan and Chan, *supra* FN 869. Vasudevan and Chan also note that gamification of labor “becomes predatory” when it is “designed to cultivate ‘obsessive behavior,’ while limiting ‘rational self reflection.’” *Id.* at 869. While gamification may indeed incite obsessive behavior, the larger point that I make is that even workers who are not “addicted” to the work find that the uncertain rules and payouts of the game are gambling-like.

⁹⁷ Here, I am drawing on the description by sociologist Ulrich Beck. Ulrich Beck. “World risk society as cosmopolitan society? Ecological questions in a framework of manufactured uncertainties.” *THEORY, CULTURE & SOCIETY* 13, no. 4 (1996): 1-32.

⁹⁸ Vili Lehdonvirta notes that this is also true of online (as opposed to in-person) on-demand workers who labor under a different model of algorithmic wage discrimination (this model is discussed in detail in Alex Wood, Mark Graham, Vili Lehdonvirta, Isis Hjorth. “Good Big, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy.” *33 WORK, EMPLOYMENT, AND SOCIETY* 56 (2019). Lehdonvirta finds that MTurk workers “effectively gamble with their time, forgoing modest but certain rewards for a chance to earn bigger rewards.” Vili Lehdonvirta. “Flexibility in the Gig Economy: Managing Time on Three Online Piecework Platforms.” *NEW TECHNOLOGY WORK AND EMPLOYMENT*. (2018).

calculation is happening. If someone is making \$40 above expenses, and that's a good ride... you are only getting that once a week. They will give that to someone to incentivize them to keep going. It keeps people in the loop a little longer. It's the *casino mechanics*. You need to have that good ride to know that they come every now and again. (my italics)

In another one of my conversations with Ben, he affirmed this logic to me, right before he had to go back to work:

It's like gambling! The house always wins... This is why they give tools and remove tools – so you accept every ride, even if it is costing you money. You always think you are going to hit the jackpot. If you get 2-3 of these good rides, those are the screenshots that people share in the months ahead. Those are the receipts they will show. Hey, [laughing, as he gets off the phone] it's almost time to roll the dice, I gotta go!

In dynamic interactions between a worker and the app, the machine—like a supervisor—is a powerful, personalized conduit of firm interest and control. But unlike a human boss, the machine's one-sided opacity, inconsistencies, and cryptic designs create shared worker experiences of risk and limited agency. Perhaps most insidiously, however, the manufactured uncertainties of algorithmic wage discrimination also generate hope (hope that a fare will offer a big payout or hope that next week's quest guarantee will be higher than this week's) that temporally defers or suspends the recognition that the “house always wins.” The cruelty of those temporary moments of optimism become clear once again when workers get their payout and subtract their costs.⁹⁹

Even if on-demand companies are *not* using algorithmic wage discrimination to offer vulnerable workers lower wages based on their willingness to accept work at lower prices, the possibility remains that they can do so, as can other employers. Together with low wages, the unfairness, gambification, and trickery create an untenable bundle of harms that run afoul of moral ideals of formal labor embedded in long-standing social and legal norms around work.

⁹⁹ I am drawing conceptually on Lauren Berlant's idea of cruel optimism. Lauren Berlant. *CRUEL OPTIMISM*. (2011).

III. RE-ORIENTING GOVERNANCE OF DIGITALIZED PAY:
TOWARD A NON-WAIVABLE PEREMPTORY BAN ON ALGORITHMIC WAGE
DISCRIMINATION

“Humans Aren’t Computers! End AI Oppression!” –Sign held by of protesting Uber driver

Writing of the food riots precipitated by the rising prices of wheat and poor harvests in eighteenth-century England, historian E.P. Thompson observed that:

“It is of course true that riots were triggered by soaring prices, by malpractices among dealers, or by hunger. But these grievances operated with in a popular consensus as to *what were legitimate and illegitimate practices* in marketing, milling, baking, etc. This in its turn was *grounded upon a consistent traditional view of social norms and obligations, of the proper economic functions of several parties with the community...* An outrage to these moral assumptions, quite as much as the actual deprivation, was the usual occasion for direct action.”¹⁰⁰ (my italics)

Thompson’s description of the famous riots should not be read as a form of nostalgia for a more “traditional system” on the part of the protestors. During an era of industrial upheaval, the protestors’ actions in this historical moment of transformation were future looking. As Marc Edelman has written, “[T]hey [protested] to define entitlements and rights, forms of social responsibility and obligation, tolerable levels of exploitation and inequality, meanings of dignity and justice.”¹⁰¹ Their protests were intended to demarcate the boundaries of what they believed a moral economy should look like in the coming century.

In this contemporary historic moment of rupture in the legal and social relationship between firms and workers under informational capitalism, we

¹⁰⁰ E.P. Thompson, in this famous essay on the moral economy of the English crowd, is talking about the shifting moral economy from subsistence economy to the economy in which there is a wage nexus, but explain why it is a foundational text for understanding contemporary moral economy. Edward P. Thompson “The moral economy of the English crowd in the eighteenth century.” 50 PAST & PRESENT 76 (1971). Thompson, in his 1991 revisit to this article, made clear that industrial capitalism was not an “amoral economy.” In doing so, he sought to clarify that his essay was about a shift from a particular moral economy to a new moral economy. Thompson argues that under a “free market” approach, policies attempted to divest moral imperatives from market relations and in doing so, created new kinds of moral problems. (1991), 89-90; 271. He calls the idea that the free market was “amoral” or without morality a “superstition.”

¹⁰¹ Palomera and Vetta, *supra* FNX, at 424.

see a great deal of popular mobilization on the basis of beliefs about illegitimate wage calculation and compensation systems through systems of digital pay. Through direct actions, strikes, protests, and lawsuits, on-demand workers all over the world have asserted discontent and outrage over the practices of control and remuneration that I have theorized as *algorithmic wage discrimination*.

In these acts of resistance, workers have frequently demanded the traditional wage floor associated with employment status. But, recognizing that this would not solve all the harms that arise from their digitalized variable pay (gambification and trickery, after all, can and do in some contexts exist alongside a minimum wage floor), many organized groups of workers and labor advocates have more recently turned their attention to the data and algorithms that are invisible to them. In this sense, they are not just calling for or protesting for a return to the Fordist employment system, but rather attempting to re-define the terms of work in relationship to informational capitalism and its indeterminate future(s).

As a first step, these workers have sought to make transparent both the data and algorithms that determine their pay (including those that determine work allocation). In this section, I examine two important, worker-engaged forms of resistance that attempt to deal with the inter-related problems of pay and data in the on-demand economy and discuss their promises and limitations. Using the legal frameworks on data privacy available to them, some workers have sought to leverage GDPR and analogous U.S. state laws, including the California Privacy Protection Act (“CPPA”), to demand what data is extracted from their labor and how the algorithms that govern their pay. Others have creatively used business association laws to maximize the financial gain and control of workers through parallel data collection, collective data ownership, and sale of datasets.

In Parts A and B, I argue that both data collectives and data transparency approaches are critical forms of resistance, but also that they cannot by themselves address the social and economic harms produced by algorithmic wage discrimination and associated practices. In Part C, I propose that addressing the harms caused by the algorithmic wage discrimination detailed throughout this Article requires not merely shifting control over the data—e.g., democratizing data relations in the workplace—but rather, envisaging a peremptory restriction on the practice altogether. This, in turn, may disincentivize or even eliminate the collection and use of certain forms of data collection and digital surveillance at work that has long troubled privacy and work law scholars.

I am thus inviting scholars of data governance to think more expansively not just about the legal parameters of what happens to the data after it is collected, but also about the legal abolition of digital data extraction or what

I have called the “data abolition” objective.¹⁰² Data extraction at work is neither an inevitable nor—especially when analyzed through the lens of moral economy—a necessary instrument of labor management.

A. The Limits of Data Transparency & Algorithmic Legibility

Complementing a global fight to recognize the employment status of many on-demand workers (including Uber drivers), the most frequently proposed policy reforms for platform labor concern algorithmic transparency and legibility. Workers, scholars, and regulators alike have argued that a first step to labor regulation in on-demand work sectors is to make the “black box” of algorithmic wage processes and labor controls more comprehensible and transparent to workers, consumers, and governing bodies. Those who have tried or are trying to use data privacy laws like GDPR and similar laws in the U.S. to shed light on labor conditions and pay in on-demand sectors maintain that such knowledge can help equalize the playing field between workers and platforms by helping workers understand their pay calculations, the grounds for their dismissal or suspension, and the ways in which their working conditions are otherwise influenced or controlled by automated systems.

James Farrar, a former Uber driver and current organizer in the United Kingdom, discovered the importance of knowledge and control over data in the context of his legal disputes with Uber over his employment status. Along with his co-worker, Yaseen Aslam, Farrar founded a union of on-demand workers called the App Drivers and Couriers Union (ADCU), and in 2015, they sued Uber for basic workers’ rights, including the minimum wage. Farrar and Aslam (and their 25 co-plaintiffs) won their case after six years of litigation, receiving a historic, positive judgement from the U.K. Supreme Court in February 2021. The Court found (among other things) that the drivers were entitled to minimum wage protections for all the time spent

¹⁰² I use the term “data abolition” to invite scholars and advocates to think about how ending digital data extraction can be a movement aspiration, accomplished via statute or bargained for by contract. Using the term “abolition,” I draw upon W.E.B. Du Bois’s articulation of “abolition democracy.” W.E.B. Du Bois. *BLACK RECONSTRUCTION* 1935 (2012 Edition). In Du Bois’s making, the promise of Reconstruction on Black labor was undermined by the extraordinary power that remained allocated to employers to subordinate and oppress workers—both Black and white. What was left, Du Bois wrote, was “an oligarchy similar to the colonial imperialism of today, erected on cheap colored labor and raising raw material for manufacture.” *Id.* at 78. Data abolition at work, as I conceive of it, is a means of intervening in these oligarchic, neocolonial formations. It is an objective that would prevent the ubiquitous extraction of digital data on workers—whether that data is extracted to control labor individually or collectively. Data abolition is of course just one instrument in the struggle towards coordinating more racially just, equitable workplaces and economies, but under informational capitalism, is an imperative one.

logged onto the app, including P1 or non-engaged time.¹⁰³ Still, to date, Uber has refused to pay workers with a guaranteed minimum wage floor and for all the time that they labor, claiming instead that the on-the-ground facts have changed since the case was adjudicated and so the holding no longer applies to their operations.¹⁰⁴ Through this litigation, Farrar came to understand the role of data extracted from his labor in maintaining his subjugation and that of his on-demand worker colleagues. Reflecting on the case, he noted that “Uber challenged me with my own data, and they came to the tribunal with shelves of paper that detailed every hour I worked, every job I did, how much I earned, whether I accepted or rejected jobs. And they tried to use all this against me. And I said we cannot survive and cannot sustain worker rights in a gig economy *without some way to control our own data.*”¹⁰⁵ (my italics)

Prompted by this realization, Farrar founded Worker Info Exchange—a U.K.-based nonprofit dedicated to using GDPR to help workers across on-demand sectors understand what data is being collected by labor platform companies and how it is being processed to manage and remunerate them. Farrar and Worker Info Exchange have since sued several on-demand companies for not sharing basic information on what data they collect from the labor from workers. But as Farrar states, “[W]hat we really want are *inference data*. What decisions has [the app] made about me? How has it profiled me? How does that affect my earnings? This is what Uber has not

¹⁰³ *Uber BV v. Aslam* UKSC 5 (2021).

¹⁰⁴ In 2021, soon after the High Court ruling finding Uber drivers are workers and deserve minimum wage protections, the company reached a private agreement with the largest union in the United Kingdom—GMB, which funded the ADCU litigation. The GMB, like the Machinists Union in New York City that formed the Independent Drivers Guild, an unelected worker association that receives funding from Uber and Lyft, gets to organize drivers at hubs and contest driver termination. Natasha Bernal. “Uber’s Union Deal Doesn’t Mean the Battle is Over.” WIRED MAGAZINE. (2021). Available at <https://www.wired.co.uk/article/uber-gmb-recognition-deal/> But, the GMB, like the IDG, do not insist that the company pay workers for all the time that workers spend laboring, appearing to completely forego collective bargaining on pay. *Id.* Instead, under the GMB-Uber agreement, Uber continues to pay workers a minimum wage only for “engaged time.” One critique of this agreement is that it neutralizes the worker led fight for an hourly wage and for employment status more generally. In practice, it also sanctions algorithmic wage discrimination as a form of insecure pay and labor control and leaves the issues raised by data extraction untouched. Months after GMB agreed to these terms, the UFCW in Canada signed a similar agreement with Uber. David Doorey. “The Surprising Agreement Between Uber and UFCW in Canada in Legal Context.” ONLABOR. (2022). Available at <https://onlabor.org/the-surprising-agreement-between-uber-and-ufcw-in-canada-in-legal-context/>

¹⁰⁵ “With One Huge Victory Down, UK Uber Driver Moves on to the Next Gig Worker Battlefront,” Inequality.org, accessed October 17, 2022, <https://inequality.org/research/uk-uber-drivers/>.

given us.”¹⁰⁶

The California Privacy Protection Act went into effect for workers in January 2023. Drivers organizing with Rideshare Drivers United (RDU), drawing on Farrar’s work, are positioned to pursue similar legal inquiries. Both RDU and Worker Info Exchange ground their actions and understanding of the data extraction and algorithmic processes that determine their pay in three aspirational rights: (1) the right to access the data extracted from their labor and the algorithms that pay and direct them, (2) the right to contest the validity of the data that is collected through their labor, and (3) the right to “explainability” of the algorithms that pay and direct them. These “rights to know” how they are governed and remunerated by automation technologies are largely reflective of the rights that scholars of informational capitalism, including those who authored the Blueprint, have argued the general public needs regarding data and machine learning: models of governance built on consent and transparency.

Although these efforts should be understood as powerful attempts to leverage GDPR and draw attention to the use of data and opaque algorithms to control workers and their wages, efforts by Farrar and others to gain transparency about—and even to “reverse engineer”—the labor management structures that produce algorithmic wage discrimination have yet to change firm practices.¹⁰⁷ In theory, Article 22¹⁰⁸ of the GDPR should protect workers from some algorithmic wage discrimination practices, as it provides them with a right to know how they have been subjected to automated decision-making and to challenge these decisions if they “produce legal effects.” But a recent district court decision suggested that the wage discrimination experienced by Uber drivers does not give rise to “significant legal effects” and therefore is not unlawful under GDPR.¹⁰⁹ Article 15¹¹⁰ of GDPR grants

¹⁰⁶ Id.

¹⁰⁷ Niels van Doorn, for example, discusses how a “calculative experiment” among Deliveroo riders in Berlin—an experiment to understand dynamic pricing—created a web-based tracker app. He notes that it was a “minor calculative power shift,” but that it could be used to grow union power and to politicize workers around the problems of pricing. Niels van Doorn, “At What Price? Labour Politics and Calculative Power Struggles in on-Demand Food Delivery,” WORK ORGANISATION, LABOUR & GLOBALISATION, January 1, 2020, <https://doi.org/10.13169/workorgalaboglob.14.1.0136>. P146.

¹⁰⁸ Article 22 of GDPR states, in part, “The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her.”

¹⁰⁹ *Uber v. ADCU*. Amsterdam District Court. C / 13/687315 / HA RK 20-20 (March 11, 2021). 4.66-4.68. Available at <https://ekker.legal/en/2021/03/13/dutch-court-rules-on-data-transparency-for-uber-and-ola-drivers/>.

¹¹⁰ Article 15 of GDPR states, “1. The data subject shall have the right to obtain from the controller confirmation as to whether or not personal data concerning him or her are being processed, and, where that is the case, access to the personal data and the following

data subjects the right to receive a copy of their personal data and to attain information about how that data is processed and shared. To date, some on-demand companies, like Amazon, have made data downloads available to workers who request them.¹¹¹ Other firms have fought off attempts by workers to achieve some level of work rule transparency and accountability under GDPR. Companies like Uber and Ola have argued that “the safety and security of their platform may be compromised if the logic of such data processing is disclosed to their workers.”¹¹²

Even in cases where the companies have released the data, little information has been released about the algorithms informing their wage systems. In one suit, Worker Info Exchange challenged Uber’s refusal to provide information under GDPR on data processed in Upfront Pricing. In deciding the matter, the lower court ruled that “the drivers did not substantiate that they wanted to be able to verify the *correctness* and lawfulness of the data processing” – only that they had “a wish to gain insight” into how Uber uses the data in its algorithms.¹¹³ It concluded that GDPR section 15 does not support this goal. The court also denied the workers’ request for information about work allocation, another central feature of algorithmic wage discrimination in the on-demand context.¹¹⁴ Like in the Blueprint

information: (1) the purposes of the processing; (2) the categories of personal data concerned; (3) the recipients or categories of recipient to whom the personal data have been or will be disclosed, in particular recipients in third countries or international organisations; (4) where possible, the envisaged period for which the personal data will be stored, or, if not possible, the criteria used to determine that period; (5) the existence of the right to request from the controller rectification or erasure of personal data or restriction of processing of personal data concerning the data subject or to object to such processing; (6) the right to lodge a complaint with a supervisory authority; (7) where the personal data are not collected from the data subject, any available information as to their source; (8) the existence of automated decision-making, including profiling, referred to in Article 22(1) and (4) and, at least in those cases, meaningful information about the logic involved, as well as the significance and the envisaged consequences of such processing for the data subject. 2. Where personal data are transferred to a third country or to an international organisation, the data subject shall have the right to be informed of the appropriate safeguards pursuant to Article 46 relating to the transfer. 3. The controller shall provide a copy of the personal data undergoing processing. For any further copies requested by the data subject, the controller may charge a reasonable fee based on administrative costs. Where the data subject makes the request by electronic means, and unless otherwise requested by the data subject, the information shall be provided in a commonly used electronic form. 4. The right to obtain a copy referred to in paragraph 3 shall not adversely affect the rights and freedoms of others.”

¹¹¹ Worker Info Exchange. “Managed by Bots Report.” Available at <https://www.workerinfoexchange.org/wie-report-managed-by-bots>. P43.

¹¹² Id. at 44.

¹¹³ *Uber v. ADCU*. Amsterdam District Court. C / 13/687315 / HA RK 20-20 (March 11, 2021). Available at <https://ekker.legal/en/2021/03/13/dutch-court-rules-on-data-transparency-for-uber-and-ola-drivers/>.

¹¹⁴ Worker Info Exchange at 71.

published by the White House, the primary focus of courts interpreting GDPR has been on transparency specifically related to potential mistakes or violations of the law.

Drawing on Frank Pasquale's work, I argue that workers and worker groups who succeed in obtaining some degree of transparency about the data extracted and deployed through algorithms to remunerate them face a formidable task in asserting any power or control over the automated decision-making management structures. Absent a ban on algorithmic wage discrimination under Article 22 or through collective bargaining agreements, transparency requests are by themselves fairly ineffectual.¹¹⁵ For example, through a GDPR data request, Worker Info Exchange succeeded in gaining access to data collected by Amazon, as well as a guidance document from Amazon Flex. Nevertheless, this knowledge has not ended digitalized variable pay or control for DSPs in Europe.

In other words, firm transparency or a worker right to algorithmic explainability—while crucial to understanding the logic of existing practices—does not by itself shift the power dynamics that enable algorithmic wage discrimination. Nor does it do much to mitigate the culture of labor gamblification described in Part II that is becoming endemic to the on-demand economy—and to more conventional workplaces. While knowing generally how the algorithm works might mitigate the feeling of being manipulated, given the rapid rate at which machine learning systems change in comparison to the temporal tendencies of legal requests and subsequent adjudication, this knowledge will have little impact on drivers' ability to exert control on the job or to standardize their wages in a way that is fair and predictable.

This is not to say that workplace transparency and these forms of resistance by workers are not crucial to building worker power and drawing public attention to the wage and control practices of on-demand companies. They are essential steps to those ends and the only tool that workers have under existing laws. But transparency and legibility *alone* do not address the harms caused by algorithmic wage discrimination because they seek to understand, not directly impede the source of these social harms.

Put differently, it is not, primarily, the secrecy or lack of consent behind digitalized workflows that result in low and unpredictable wages, but rather, the extractive logics of well-financed firms in these digitalized practices and comparatively small institutional power of workers that cause both individual and workforce harms.

¹¹⁵ Frank Pasquale. *THE BLACK BOX SOCIETY*. (2016).

B. Experiments with Data Cooperatives

In addition to pressing for greater transparency and algorithmic legibility in the on-demand economy using privacy laws, some scholars and labor advocates have argued that data cooperatives would give platform workers power over their labor by allowing them to “compare their respective incomes across similar routes, areas, and distances” and accordingly, to know whether they are being paid equitably or not.¹¹⁶ With this in mind, at least two novel data cooperative projects, the Driver’s Seat Coop (in the U.S.) and WeClock (in Europe), have been launched. These cooperative efforts, which counter-collect data collected by on-demand firms using a separate app, reflect the belief that if workers can collectively pool and exert ownership and control over their data, then, they will be able to better understand their work experiences and “control their destiny at work.”¹¹⁷

To be sure, such cooperatively organized collection of personal data has been useful for workers who are able to contest unfair suspensions or terminations based on errors in facial recognition or in geolocation checks conducted by the companies. However, most workers in the U.S. do not have the option to make such contestations. Indeed, a common complaint of workers in my research is the lack of a formal appeals mechanisms in relationship to termination or suspension decisions by the companies for which they labor. A worker may go to a physical Uber or Lyft “hub” to complain or attempt to engage with the firm via their app, but getting reinstated or having a wrong corrected is difficult, if not impossible, regardless of whether the automated suspension or termination is based on incorrect data. This, then, is primarily a structural problem, not necessarily one that is rooted in control over and legibility of data.

Collective data ownership through data cooperatives does not address the most significant harms posed by algorithmic wage discrimination because—by itself—it does not fundamentally intervene in the economic relationship between the hiring entities and the workers. Having some knowledge of the data that is extracted from one’s labor does not give rise to the power to negotiate over the use of that data, or to restrict or even ban its future collection. Worse, like other proposals that claim that “data is labor,”¹¹⁸ these approaches may reify widespread data collection as a social good, thus ignoring problems of individual and social harm that result from broad

¹¹⁶ Alex Pentland and Thomas Hardjono. “Building New Economies: Data Cooperatives.” *Work in Progress*, Available at <https://assets.pubpub.org/c2g7vkvs/f0013654-2966-4def-a81f-3117ce0724f3.pdf>. P2.

¹¹⁷ Id at 82.

¹¹⁸ See, e.g., Eric A. Posner and E. Glen Weyl. *RADICAL MARKETS*. Princeton University Press, 2018.

surveillance, categorization, and data derivative processing.¹¹⁹ While Jaron Lanier, Richard Posner, and Greg Wyle’s basic presumptions about how workers and consumers are not remunerated for the data that they provide to firms is correct, their solution—to pay them for it—raises more problems than it solves.¹²⁰

The central logic of data cooperatives—that data extraction is an inevitable form of labor for which workers should be remunerated—risks reifying the extraction itself. The on-the-job surveillance which gives rise to the data is not an inescapable practice. And in the bargain between workers and firms over data control, workers—even those in data cooperatives—are badly positioned both because of their relative lack of power and because of the vast expense and general inaccessibility of digital architectures to store, clean, understand, and leverage data.¹²¹ For one, the value (and quality) of such workplace-derived datasets to the firm itself and to downstream buyers is unknown and fluctuating. As Salomé Viljoen argues, paying data subjects—workers in this case—for their data may also further degrade worker privacy because workers may decide that the downstream risk of privacy loss is worth the payment provided, even when the actual value of that data is indeterminant.¹²² To date, data extraction [from workers]...[has provided a] stream of capital that is infinitely speculatable...with minimal downward redistribution.”¹²³

This is not to say that these worker data cooperatives do not have any role to play in the current regulatory environment. To the contrary, data cooperatives have played an important role for regulators in several cities and states to understand the erratic and low wages of workers laboring for on-demand firms and to write policy accordingly. The Rideshare Drivers United wage study, released in 2022 and referenced in Part II, was made possible

¹¹⁹ See Viljoen, Salome. “A relational theory of data governance.” 131 YALE L.J. 573 (2021).

¹²⁰ Posner and Weyl’s book *Radical Markets*, supra FN109, draws on Jaron Lanier’s description of data as “the new oil” and suggests that the solution to the problems raised by informational capitalism is to “pay people from whom the data is gathered.” See Jaron Lanier. “Stop the Stealing.” PACIFIC STANDARD (2015). <https://psmag.com/economics/the-future-of-work-stop-the-stealing-and-pay-us-for-our-online-data> . This obfuscates the first order question: should the data be gathered in the first place?

¹²¹ For an interesting critique of the Lanier, Posner, Wyle contentions in *Radical Markets*, see Beatriz Botero Arcila. “The System is Rigged Against Users: Another Reason Why Getting Compensated for Data is Not a Good Idea.” BERKMAN KLEIN CENTER COLLECTION. (2020). Available at <https://cyber.harvard.edu/story/2020-02/system-rigged-against-users> .

¹²² Viljoen at FN 115.

¹²³ Sam Adler-Bell and Michelle Miller. “The Datafication of Employment: How Surveillance and Capitalism Are Shaping Workers’ Futures without Their Knowledge.” THE CENTURY FOUNDATION (2018).

through collaboration with the Driver’s Seat Coop. The Driver’s Seat Coop, run by longtime labor organizer Hays Witt and supported, in part, by the Ford Foundation, is a cooperative of ride-hail and delivery workers who share in profits from their data collection. The cooperative has sold the pooled data to cities and transportation agencies who, in turn, desire to use the data to address governance issues. Drivers can also use the data to make analytical assessments about their work. For example, Driver’s Seat Coop helps workers to deduce their “true hourly rate,” to figure out what time it might be most lucrative to work, and to identify which platform is giving the workers the better hourly wage.

Drawing on the critiques of data as labor/property more generally, the limitations with this approach are three-fold. As an initial matter, the assessments made through this cooperative are constantly changing, as the practices of algorithmic control continue to change. This limits the cooperative’s ability to provide workers with the stability and predictability they seek. For example, in my research, I found that drivers who “figured out” a way to hit their income target for a few months (and came to rely on these techniques) would often be devastated when their knowledge about the system was inevitably upended by changes in the algorithms. In other words, while data cooperatives might give workers some derivative knowledge over the kinds of data that is collected about them, they are not able to exert sustained control over the (constantly changing) automation processes that control them and determine their pay. Second, selling cooperatively collective data might be a small income source for workers and that data might be occasionally useful to regulators—especially since on-demand firms often deny access to data on privacy or intellectual property grounds—but it also assumes that these kinds of collection and sale do not carry social risks when utilized to make private or public decisions in other contexts.¹²⁴ Workers cannot know whether the data collected will, at the population level, violate the civil rights of others or amplifies their own social oppression.

Finally, perhaps the most troubling problem with worker data cooperatives is the complicated (and expensive) nature of automated digital data collection and their subsequent reliance on third party data brokers. Workers who sign up to be members of the Driver’s Seat Coop, for example, have two options. They can manually generate their data which relies on the driver “to record their activity by swiping trip start/end buttons and filling out daily earnings logs,” which is an unrealistic series of steps for most workers. Alternatively, drivers can opt for automatic tracking, which is a “hassle -free way of tracking their gig work.”¹²⁵ Extracting data from the variety of

¹²⁴ See, generally, Shoshanna Zuboff, *SURVEILLANCE CAPITALISM*. (2019).

¹²⁵ Driver’s Seat Cooperative, *DRIVER’S SEAT*, <https://driversseat.co/> (last visited Oct 28, 2022).

different apps that its members use turns out to be extremely complicated, so the Driver's Seat Coop relies on a third-party service called Argyle to connect to the on-demand labor platforms and import their earnings data and activities.¹²⁶ But Argyle is itself a data broker that watchdog organizations such as Co-worker.org have flagged for potentially fraudulent practices, like phishing workers to extract their employment data.¹²⁷ The company claims to have the employment data of 80% of “gig workers,” which it makes available for sale as its primary source of profits.¹²⁸ This arrangement calls into question the long-term efficacy of workers “owning” their own data, since well-capitalized data brokerage firms have the same datasets. For example, Argyle, through a partnership with DigiSure which claims to give “mobility and sharing platforms [the power] to own their,” uses these datasets to sell and deny hybrid car insurance to gig workers.¹²⁹ This then raises a host of other concerns about downstream harm: can companies use this data collected in collaboration with Driver's Seat Coop to create and sell data derivatives that trap workers into certain wage brackets based on their income history? Can they (do they) use this data to target workers for predatory pay day loans or to deny other kinds of credit?

As workers formulate and re-formulate paths towards re-defining “tolerable levels of exploitation and inequality, meanings of dignity and justice” in the context of labor management practices emerging from informational capitalism, my analysis of possibilities and limitations of existing business and data laws suggests they could benefit from other legal tools more fitting of their moral outrage toward the harms emerging from these digitalized remuneration practices.

C. A Non-Waivable Ban on Algorithmic Wage Discrimination

Given the limitations of both worker cooperative ownership of data and attempts at data transparency and legibility under existing laws, I propose a

¹²⁶ Id.

¹²⁷ Wilneida Negrón. “Little Tech is Coming for Workers.” Coworker.org. (2020). Available at <https://home.coworker.org/wp-content/uploads/2021/11/Little-Tech-Is-Coming-for-Workers.pdf>. Negrón makes the related point that the firm practices that give rise to algorithmic wage discrimination are then used to produce other data extraction products to supposedly help workers. These products include payday loan firms and management software which not only leverage existing datasets with worker information but create new datasets that have potential downstream impacts on workers. Id. at 22.

¹²⁸ Driver's Seat Cooperative, DRIVER'S SEAT, <https://driversseat.co/> (last visited Oct 28, 2022).

¹²⁹ “Argyle and DigiSure Partner to Supercharge Screening and Risk Assessment for Gig Drivers.” GLOBAL NEWSWIRE. (2022). Available at <https://www.globenewswire.com/en/news-release/2022/07/13/2479144/0/en/Argyle-and-DigiSure-Partner-to-Supercharge-Screening-and-Risk-Assessments-for-Gig-Drivers.html>

more direct solution: a statutory or regulatory non-waivable ban on the practice of algorithmic wage discrimination, including, but not limited to, a ban on remuneration through digitalized piece pay.¹³⁰ This would, in effect, not only put an end to the gambification of work and the uncertainty of hourly wages, but it would also disincentivize certain forms of data extraction and retention that may harm low-wage workers down the road, addressing the urgent privacy concerns that others have raised.

Similar to proposed bans on targeted advertising, which attempt to limit the use of “deep stores of personal data to make money from targeted ads,”¹³¹ a preemptory ban on algorithmic wage discrimination might also disincentivize the growth of fissured work under informational capitalism. If firms cannot use gambling mechanisms to control worker behavior through variable pay systems, they will have to find ways to maintain flexible workforces while paying their workforce predictable wages under an employment model.¹³² If a firm cannot manage wages through digitally-determined variable pay systems, then the firm is less likely to employ algorithmic management in certain circumstances.

This kind of ban is not without precedent. Indeed, reflecting the moral and legal norms embedded in wage laws, the spirit of a ban on algorithmic wage discrimination is embedded in both federal and state level anti-trust laws. Indeed, Zephyr Teachout has argued that consumer price discrimination “from the 1870s through the 1970s was [also] understood through a political, moral, and economic lens.”¹³³ At the federal level, the Robinson-Patman Act bans sellers from charging competing buyers different prices for the same “commodity” or discriminating in the provision of “allowances”—like compensation for advertising and other services. The Federal Trade Commission currently maintains that this kind of price discrimination “may give favored customers an edge in the market that has nothing to do with their superior efficiency.”¹³⁴ Though price discrimination is generally lawful, and the Supreme Court’s interpretation of the Robinson-Patman Price

¹³⁰ This could take several different forms, in the on-demand ride-hail and food-delivery sectors, it could mean only allowing the collection of data on distance, driving time, location, and time of day to determine pay on top of a uniform wage floor for all workers receive for all hours that they labor.

¹³¹ Taylor Hatmaker, “New Privacy Bill Would Put Major Limits on Targeted Advertising,” TECHCRUNCH (blog), January 19, 2022, <https://techcrunch.com/2022/01/18/banning-surveillance-advertising-act/>.

¹³² Notably, there is precedent for this kind of agreement in some union contracts.

¹³³ Zephyr Teachout. *Algorithmic Personalized Wages*. POLITICS AND SOCIETY. *Forthcoming*.

¹³⁴ “Price Discrimination: Robinson-Patman Violations.” FEDERAL TRADE COMMISSION, available at <https://www.ftc.gov/advice-guidance/competition-guidance/guide-antitrust-laws/price-discrimination-robinson-patman-violations>

Discrimination Act of 1936 suggests it may not apply to services like those provided by many on-demand companies, the idea that there is a “competitive injury” endemic to the practice of charging different buyers a different amount for the same product clearly parallels the legally-enshrined moral expectations about work and wages discussed in Part I.¹³⁵ Workers—like buyers—understand “moral economies of work” as reflecting systems in which they get predictable, “equal pay for equal work” and in which wages rise above a certain level or value (at least the minimum wage). If, as on-demand companies assume, workers are consumers of their technology and not employees, we may understand digitalized variable pay in the on-demand economy as violating the spirit of the Robinson-Patman Act.

Plaintiffs from Rideshare Drivers United, represented by Towards Justice, a non-profit legal organization based in Colorado, have filed a complaint based on state-level anti-trust law in California court, alleging something very similar. They seek to use California anti-trust law to permanently enjoin Uber and Lyft “from fixing prices for rideshare services, *withholding fare and destination data from drivers when presenting them with rides*, imposing other non-price restraints on drivers, such as minimum acceptance rates, and *utilizing non-linear compensation systems based on hidden algorithms* rather than transparent per-mile, per-minute, or per-trip pay.¹³⁶ (my italics) If successful, the lawsuit, alleging violations of the Cartwright Act and California Business and Professions Codes that prevent secret commissions and other fraudulent practices, would stop the use of algorithmic price discrimination by these specific on-demand companies. But, it would not necessarily prohibit variations on the practice all together, especially for firms who classify their workers as employees. In those contexts, gamblification could continue, as long as it did not fall below the minimum wage of the geographic area where a worker is laboring or create disparate incomes for workers based on their protected identities.¹³⁷ This makes the consideration of an affirmative legal prohibition against the practice of algorithmic wage discrimination an imperative.

The precise limits of a proposed non-waivable ban need to be explored.

¹³⁵ Keywana Griffith argues that the Congress should consider amending the Robinson-Patman Act to include “services” and not just “commodities” so as to address the problem of “surge pricing” by Uber and similar firms. Surge pricing, Griffith argues, hurts consumers and is anti-competitive in effect. Keywana Griffith, *The Uber Loophole That Protects Surge Pricing*, 26 VA. J. Soc. POL’y & L. 34 (2019).

¹³⁶ This complaint can be accessed at <https://towardsjustice.org/wp-content/uploads/2022/06/Uber-Lyft-Complaint.6.20.2022-3.pdf>. This is on-going litigation.

¹³⁷ Healthcare is one sector where algorithmic wage discrimination (or what firms call “incentive payment systems” is being used to control employee work assignment and pay for nurses and janitorial staff.

This Article seeks to identify and theorize the practice of algorithmic wage discrimination in relationship to long-standing ideas of what constitutes a moral economy and to invite scholars and regulators concerned with labor management practices in on-demand sectors of work to think about it as a distinct problem that has troubling implications for work and remuneration. I also hope to shine a light on a possible legal path forward. But many questions remain in the statutory construction of such a ban and in its coverage. For example, would such a prohibition, as Zephyr Teachout has suggested, comport with monopoly principles, and only affect firms with a controlling market share?¹³⁸ Or, would it rule out digitalized variable pay between workers, such that it would allow a firm to pay all workers some declining or increasing rate based on an algorithmic assessment? Would it prevent the use of digital bonuses entirely, or would it allow such bonuses if they were offered consistently to all workers? Alternatively, and more expansively, would such a law cover all digitalized variable pay practices across industries, espousing the ethos of data abolition?

CONCLUSION

Algorithmic wage discrimination—in contrast to other forms of offline pay variability systems—is made possible through the ubiquitous, invisible collection of data extracted from labor and the creation of massive data sets on workers. These data sets, combined with machine learning science and insights from behavioral psychology, have come to form, what I suggest in this Article, are morally objectionable techniques of work control and remuneration. They have the effect of circumscribing autonomy and economic mobility for highly racialized workforces, and they have the great potential to seep into the firm practices of other sectors.

In some instances, algorithmic wage discrimination practices produce pay that falls well below what is guaranteed to employees by law. For example, in California in 2020, the Labor Commission sued Uber and Lyft claiming the companies had failed to pay drivers over \$1.3 billion dollars for all hours worked, including unpaid overtime, paid sick leave violations, and reimbursement of business expenses.¹³⁹ But violations of wage and hour laws are not the only harms caused by algorithmic wage discrimination. Low pay is accompanied by extractive labor processes that go against the moral norms embedded in over a century of U.S. statutes and case law, creating jobs akin to gambling and using personalized data to generate feelings of possibility

¹³⁸ Zephyr Teachout. *Algorithmic Personalized Wages*. POLITICS AND SOCIETY. *Forthcoming*.

¹³⁹“Labor Commissioner’s Wage Theft Lawsuits Against Uber and Lyft.” CALIFORNIA LABOR COMMISSIONER. Available at <https://www.dir.ca.gov/dlse/Lawsuits-Uber-Lyft.html>

that are in turn crushed to create value for the firm.

As a predatory practice enabled by informational capitalism, algorithmic wage discrimination profits from the cruelty of hope: appealing to the desire to be free from both poverty and from employer control (and the scheduling norms of the Fordist economy), while simultaneously ensnaring workers in structures of work that offer neither security nor stability. These practices, even alongside employment status and the guarantees of a wage floor, contradict long-standing norms about fairness as they pertain to wage practices and wage regulations. To address these problems, this Article invites lawmakers and regulators to direct their attention, not just to the problems of transparency and accuracy of automation technologies at work, but also to an evaluation of the social harms embedded in the logic of the algorithmic systems themselves.