

ON ALGORITHMIC WAGE DISCRIMINATION

*Veena Dubal**

Recent technological developments related to the extraction and processing of data have given rise to concerns about a reduction of privacy in the workplace. For many low-income and subordinated racial minority workforces in the United States, however, on-the-job data collection and algorithmic decisionmaking systems are having a more profound yet overlooked impact: These technologies are fundamentally altering the experience of labor and undermining economic stability and job mobility. 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.

The Article constructs a novel framework rooted in worker on-the-job experiences to understand the ascent of digitalized variable pay practices, or the importation of price discrimination from the consumer context to the labor context—what this Article identifies as algorithmic wage discrimination. Across firms, the opaque practices that constitute algorithmic wage discrimination raise fundamental questions about the changing nature of work and its regulation. What makes payment for labor in platform work fair? How does algorithmic wage discrimination affect the experience of work? And how should the law intervene in this moment of rupture? Algorithmic wage discrimination runs afoul of both longstanding precedent on fairness in wage setting and the spirit of equal pay for equal work laws. For workers, these practices produce unsettling moral expectations about work and remuneration. The Article proposes a nonwaivable restriction on these practices.

* Professor of Law, University of California, Irvine; Postdoctoral Fellow, Stanford University; Ph.D. 2014, University of California at Berkeley; J.D. 2006, University of California at Berkeley School of Law; B.A. 2003, Stanford University. I thank Aziza Ahmed, Amna Akbar, Abbye Atkinson, Aslı Bâli, Corinne Blalock, James Brandt, Raúl Carillo, Angela Harris, Amy Kapczynski, K-Sue Park, Fernando Rojas, Karen Tani, and Noah Zatz, all of whom offered comments on an early conceptualization of this Article. I am also grateful to Yochai Benkler, Scott Cummings, Sam Harnett, Sarah Myers West, Aziz Rana, Aaron Shapiro, and Meredith Whittaker, who provided critical feedback on drafts and to the brilliant editors of the *Columbia Law Review*, especially Zakiya Williams Wells. This Article was written at the Center for Advanced Study in the Behavioral Sciences at Stanford University, where I was a fellow from 2022 to 2023. I dedicate it to John Crew, a wonderful mentor and dear friend whose lifelong dedication to justice and fairness shaped both my understandings of and ways of being in this world and who died while I was writing it.

INTRODUCTION	1930
I. WAGE LAWS IN RELATION TO MORAL ECONOMIES OF WORK	1942
A. The Legalization of Algorithmic Wage Discrimination.....	1944
B. Calculative Fairness and Minimum-Wage Regulation	1952
C. “Equal Pay for Equal Work”: Antidiscrimination Laws.....	1957
II. THE OPERATION AND EXPERIENCE OF ALGORITHMIC WAGE DISCRIMINATION	1961
A. Labor Management Through Algorithmic Wage Discrimination	1964
B. A Bundle of Harms: Calculative Unfairness, Trickery, and Gamblification.....	1969
1. Calculative Unfairness.....	1970
2. Trickery and Gamblification	1972
III. REORIENTING GOVERNANCE OF DIGITALIZED PAY: TOWARD A NONWAIVABLE PEREMPTORY BAN ON ALGORITHMIC WAGE DISCRIMINATION	1976
A. The Limits of Data Transparency and Algorithmic Legibility	1979
B. Experiments With Data Cooperatives	1985
C. A Nonwaivable Ban on Algorithmic Wage Discrimination	1989
CONCLUSION	1992

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 workers’ movement or activities, their personal habits and attributes, and even sensitive biometric information about their stress and health levels.² Employers then feed amassed datasets on workers’ lives 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 this Article highlights, to determine worker pay.³

1. See, e.g., Ifeoma Ajunwa, Kate Crawford & Jason Schultz, *Limitless Worker Surveillance*, 105 *Calif. L. Rev.* 735, 738–39 (2017) [hereinafter Ajunwa et al., *Limitless Worker Surveillance*]; Matthew T. Bodie, *The Law of Employee Data: Privacy, Property, Governance*, 97 *Ind. L.J.* 707, 712–17 (2022); Brishen Rogers, *The Law and Political Economy of Workplace Technological Change*, 55 *Harv. C.R.-C.L. L. Rev.* 531, 535–36 (2020).

2. See Ifeoma Ajunwa, Kate Crawford & Joel S. Ford, *Health and Big Data: An Ethical Framework for Health Information Collection by Corporate Wellness Programs*, 44 *J.L. Med. & Ethics* 474, 474–75, 477–78 (2016) (describing the comprehensive data collection practices and capacities of worker wellness programs).

3. See, e.g., Annette Bernhardt, Linda Kresge & Reem Suleiman, *Berkeley Lab. Ctr., Data and Algorithms at Work: The Case for Workers’ Technology Rights* 6, 15–17 (2021),

To date, policy concerns about growing technological surveillance in the workplace have largely mirrored the apprehensions articulated by consumer advocates. Scholars and advocates have raised concerns about the growing limitations on worker privacy and autonomy, the potential for society-level discrimination to seep into machine learning systems, and a general lack of transparency on workplace rules.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.⁶ The *Blueprint for an AI Bill of Rights* (hereinafter

<https://laborcenter.berkeley.edu/wp-content/uploads/2021/11/Data-and-Algorithms-at-Work.pdf> [<https://perma.cc/TC3U-458E>]. As employment law scholar Matthew Bodie has written in reference 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.

Bodie, *supra* note 1, at 736.

4. See generally Bernhardt et al., *supra* note 3 (arguing that data-driven technologies harm workers through discrimination and work intensification at the expense of safety, depriving workers of their autonomy and dignity); Ajunwa et al., *Limitless Worker Surveillance*, *supra* note 1 (“[T]here has been a shift in focus from collecting personally identifying information, such as health records, to wholly acquiring unprotected and largely unregulated proxies and metadata, such as wellness information, search queries, social media activity, and outputs of predictive ‘big data’ analytics.”); Bodie, *supra* note 1 (“As the data collected in this new environment has become increasingly individualized, the line between person as individual and person as employee has become significantly blurred.”); Rogers, *supra* note 1 (“[L]abor and employment laws . . . and the broader political economy of work that they help sustain, also encourage employers to use new technologies to exert power over workers.”). Labor law scholars Antonio Aloisi and Valerio De Stefano have argued convincingly in a comprehensive review of technology, law, and work that concerns about the supposed “disappearance of work” lost 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 Aloisi & Valerio De Stefano, *Your Boss Is an Algorithm: Artificial Intelligence, Platform Work and Labour* 9, 23–24, 98–101, 104–05 (2022).

5. White House Off. of Sci. & Tech. Pol’y, *Blueprint for an AI Bill of Rights* 3 (2022), <https://www.whitehouse.gov/wp-content/uploads/2022/10/Blueprint-for-an-AI-Bill-of-Rights.pdf> [<https://perma.cc/A62C-TV47>].

6. *Id.* at 5–7.

Blueprint) specified that these enumerated rights extended to “[e]mployment-related systems [such as] . . . 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.”⁷

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 workers’ driving habits, ostensibly for “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.”⁸ Thus, the specific harm 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 contracts with Delivery Service Providers (DSPs), small businesses that Amazon helps to establish. In this putative nonemployment arrangement, Amazon does not provide to the DSP drivers workers’ compensation, unemployment insurance, health insurance, or the protected right to organize. Nor does it guarantee individual DSPs or their workers minimum wage or overtime compensation.⁹ Instead, DSPs receive a variable hourly rate based on fluctuations in demand and routes, along with “bonuses” based on a quantified digital evaluation of on-the-job behavior, including “service, safety, [and] client experience.”¹⁰

7. *Id.* at 53 (emphasis added).

8. *Id.* at 17 (emphasis added) (citing Lauren Kaori Gurley, Amazon’s AI Cameras Are Punishing Drivers for Mistakes They Didn’t Make, *Vice* (Sept. 20, 2021), <https://www.vice.com/en/article/88npjv/amazons-ai-cameras-are-punishing-drivers-for-mistakes-they-didnt-make> [<https://perma.cc/HSF4-EG4M>]).

9. As economist Brian Callaci explains, since the DSPs legally employ the delivery drivers, the DSPs, rather than Amazon, bear “liability for accidents or workplace safety,” and DSP drivers, classified as Amazon’s contractors, “do not fall under Amazon’s \$15 an hour minimum wage.” Brian Callaci, *Entrepreneurship*, *Amazon Style*, *Am. Prospect* (Sept. 27, 2021), <https://prospect.org/api/content/1923a910-1d7c-11ec-8dbf-1244d5f7c7c6/> [<https://perma.cc/AV2H-59YA>]. Meanwhile, Amazon’s contracts with DSPs “[restrict] the wages the DSP can offer” drivers and mandate that drivers remain nonunion by stipulating that “they serve as at-will employees.” *Id.* If the drivers unionize, “Amazon can terminate the contract and find a new DSP, which is much easier than fighting a union campaign itself.” *Id.*

10. *How Are Amazon DSPs Paid?*, *Route Consultant*, <https://www.routeconsultant.com/industry-insights/how-are-amazon-dsps-paid> [<https://perma.cc/684P-WLKB>] (last visited Aug. 14, 2023). The scorecards that determine “bonuses” are calculated in constantly changing ways. The DSP scorecards I reviewed include four 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 *Peak Delivery Driver, Amazon DSP Scorecard Deep Dive*, YouTube, at 1:04–1:58, 2:48–3:10 (Sept. 10, 2021),

DSPs, while completely reliant on Amazon for business, must hire a team of drivers as employees.¹¹ These Amazon-created and -controlled small businesses rely heavily on their automated “bonuses” to pay for support, repairs, and driver wages.¹² As one DSP owner–worker 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.”¹³

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.¹⁴ “Algorithmic wage discrimination” refers to a practice in which

<https://www.youtube.com/watch?v=mBOYfBZs9I> (on file with the *Columbia Law Review*). The example in the *Blueprint*, for instance, lowered the score enough to undermine the DSP’s ability to get a bonus. White House Off. of Sci. & Tech. Pol’y, *supra* note 5, at 17. By contrast, Amazon is guaranteed the data it wants from the DSPs (they cannot reject the use of cameras, for example)—not just while the DSP is servicing Amazon but also for three years afterward. In addition to using such data to calculate bonuses, Amazon can also use it to terminate contracts, terminate specific “underperforming” workers, and punish DSPs with fees. Josh Eidelson & Matt Day, *Drivers Don’t Work for Amazon but Company Has Lots of Rules for Them*, *Det. News* (May 5, 2021), <https://www.detroitnews.com/story/business/2021/05/05/drivers-dont-work-amazon-but-company-has-lots-rules-them/4955413001/> [<https://perma.cc/7REA-NKRU>].

11. When a DSP hires other drivers, it may appear more like a company that is legally separate from Amazon. This may protect Amazon from unionization efforts and downstream liability that it may otherwise incur based on allegations that the DSPs are its employees, not contractors. Callaci, *supra* note 9. It appears FedEx was the first delivery company to use this tactic after redrafting its contracts with drivers in response to *Alexander v. FedEx Ground Package Sys., Inc.*, 765 F.3d 981 (9th Cir. 2014), the Ninth Circuit decision that held that its drivers were employees, not independent contractors. Rather than changing the drivers’ status in response to the decision, FedEx drafted its contracts to make the drivers appear more like independent contractors. V.B. Dubal, *Winning the Battle, Losing the War?: Assessing the Impact of Misclassification Litigation on Workers in the Gig Economy*, 2017 *Wis. L. Rev.* 739, 791–92. This included mandating that the drivers purchase more service areas, which in turn made drivers hire others to complete the deliveries. *Id.*

12. Lauren Kaori Gurley, *Amazon’s AI Cameras Are Punishing Drivers for Mistakes They Didn’t Make*, *Vice* (Sept. 20, 2021), <https://www.vice.com/en/article/88npjv/amazons-ai-cameras-are-punishing-drivers-for-mistakes-they-didnt-make> [<https://perma.cc/HSF4-EG4M>].

13. *Id.* (internal quotation marks omitted) (quoting the owner of a Washington-based Amazon delivery company).

14. “Informational capitalism” or “information capitalism” as a descriptor of the contemporary digital-age world system is generally attributed to sociologist Manuel Castells.

individual workers are paid different hourly wages—calculated with ever-changing formulas using granular data on location, individual behavior, demand, supply, or other factors—for broadly similar work. As a wage-pricing technique, algorithmic wage discrimination encompasses not only digitalized payment for completed work 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.¹⁵

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),¹⁶ my research on the on-demand ride hail industry

Castells first introduced the term in his three-volume study, *The Information Age*, published between 1996 and 1998. In describing a shift from industrial capitalism to information capitalism, Castells wrote in Volume I, “A technological revolution, centered around information technologies, is reshaping, at accelerated pace, the material basis of society. Economies throughout the world have become globally interdependent, introducing a new form of relationship between economy, state, and society, in a system of variable geometry.” Manuel Castells, *The Rise of Network Society* 1 (2d ed. 2000). In legal scholarship, Julie Cohen uses the term “informational capitalism” to explore the relationships between political, legal, and economic institutions amidst the propertized expansion of data and information exchange. See generally Julie Cohen, *Between Truth and Power: The Legal Constructions of Informational Capitalism* (2019).

15. Zephyr Teachout has created a useful taxonomy of five different forms of “personalized wages” that have recently emerged in the labor market: (1) extreme Taylorism, in which “[h]igh degrees of surveillance [result in] . . . rewarding productivity”; (2) gamification, in which employers use psychological tools 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*, 51 *Pol. & Soc’y* 436, 437, 442–44 (2023) [hereinafter Teachout, *Algorithmic Personalized Wages*].

In all these instances, wages are rooted in data extracted from labor. My data indicate the potential to further simplify this taxonomy to two main ways of thinking about algorithmic wage discrimination: (1) wages based on productivity analysis alone (most evident in the employment context), and (2) wages based on productivity, supply, demand, and other personalized data used to minimize labor costs. This second form of algorithmic wage discrimination appears most commonly in on-demand work that treats workers like independent contractors.

16. Nonalgorithmic variable payment systems with transparent payment structures are more familiar to many people. See, e.g., United Farm Workers (@UFWupdates), Twitter (Oct. 15, 2022), <https://twitter.com/UFWupdates/status/1577795973476220930> (on file with the *Columbia Law Review*) (showing how California companies use a variable bonus system for some farmers’ pay). They are, nonetheless, controversial. Some critics in the human relations and management literature point to variable pay mechanisms as a contributor to income gaps by gender and race. See, e.g., Emilio J. Castilla, *Gender, Race, and Meritocracy in Organizational Careers*, 13 *Am. J. Socio.* 1479, 1502–17 (2008) (finding variable salary bias in salary increases and promotions on the basis of gender, race, and nationality). Others suggest variable pay has psychological costs for workers and other unforeseen consequences. See, e.g., Annette Cox, *The Outcomes of Variable Pay Systems:*

suggests that algorithmic wage discrimination raises a 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 wage incentives—arises from (and may function akin to) the practice of “price discrimination,” in which individual consumers are charged as much as a firm determines they may be willing to pay.¹⁷ 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 for as little as the system determines that the workers may be willing to accept.¹⁸ Given the information asymmetry between workers and firms, companies can calculate the exact wage rates necessary to incentivize desired behaviors, while workers can only guess how firms determine their wages.¹⁹

Tales of Multiple Costs and Unforeseen Consequences, 16 *Int’l J. Hum. Res. Mgmt.* 1475, 1483–93 (2005) (discussing unexpected costs to both employers and employees resulting from variable salary systems).

17. To date, scholars and analysts who have written about what this Article terms “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.” Zephyr Teachout, Professor, Fordham Univ. Sch. of L., Enlund Lecture at DePaul University School of Law (Apr. 15, 2021). Niels van Doorn, in an article analyzing the pay structures of on-demand Deliveroo riders in Berlin, describes “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.” Niels van Doorn, *At What Price? Labour Politics and Calculative Power Struggles in On-Demand Food Delivery*, 14 *Work Org. Lab. & Globalisation*, no. 1, 2020, at 136, 138. But adopting the language of “pricing” for wage setting is politically and legally consequential. Since at least the rise of neoliberalism, price controls in the United States (and elsewhere) have been highly disfavored as economic interferences in the “free market,” raising conservative critiques of socialism and “planned economies.” See Benjamin C. Waterhouse, *Lobbying America: The Politics of Business From Nixon to NAFTA* 106–23, 132–39 (2013) (describing how American businesses rejected government price setting in the Nixon, Ford, and Carter administrations). 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. See Amina Dunn, *Most Americans Support a \$15 Federal Minimum Wage*, *Pew Rsch. Ctr.* (Apr. 22, 2021), <https://www.pewresearch.org/short-reads/2021/04/22/most-americans-support-a-15-federal-minimum-wage/> [<https://perma.cc/CX5Z-YX9Z>] (surveying support for minimum-wage laws across the United States). In this sense, conceptualizing the digitalized wages received by workers not as firm price determinations but as firm wage determinations is a critical political—and legal—corrective.

18. See *infra* Part II.

19. See Aaron Shapiro, *Dynamic Exploits: Calculative Asymmetries in the On-Demand Economy*, 35 *New Tech. Work & Emp.* 162, 162–63 (2020) [hereinafter Shapiro, *Dynamic Exploits: Calculative Asymmetries*] (arguing that “independent service providers” for “on-demand service platforms” are workers and not independent contractors because the platforms set wages and “exhibit substantial information asymmetries”). Uber, for its part, has stated that “suggestions that Uber offers variable pricing based on user-profiling is completely unfounded and factually incorrect.” Cansu Safak & James Farrar, *Worker Info*

The *Blueprint* example underscores how algorithmic wage discrimination can be “ineffective” and rife with calculated mistakes that are difficult to ascertain and correct. But algorithmic wage discrimination also 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.²⁰ Digitally personalized wages are often determined through obscure, complex systems that make it nearly impossible for workers to predict or understand their constantly changing, and frequently declining, compensation.²¹

Drawing on anthropologist Karl Polanyi’s notion of *embeddedness*—the idea that social relations are embedded in economic systems²²—this Article excavate the norms around payment that constitute what one might consider a moral economy of work to help situate this contemporary

Exch., *Managed by Bots: Data-Driven Exploitation in the Gig Economy* 26 (2021), https://5b88ae42-7f11-4060-85ff-4724bbfed648.usrfiles.com/ugd/5b88ae_8d720d54443543e2a928267d354acd90.pdf [https://perma.cc/TLV3-R2EE] (internal quotation marks omitted) (quoting Letter from Uber Data Protection and Cybersecurity Team to Cansu Safak (Dec. 3, 2021), https://5b88ae42-7f11-4060-85ff-4724bbfed648.usrfiles.com/ugd/5b88ae_f12953beac7e4fd9b6057375cce212b5.pdf [https://perma.cc/LL6M-KVGV])). We have no way to judge the accuracy of this statement.

Since a draft of this Article was posted online, Uber drivers have adopted the term “algorithmic wage discrimination,” testified to how it reflects how they are paid, and documented how they are offered different base pay for the exact same ride when sitting next to each other. See, e.g., *The RideShare Guy, The Age of Algorithmic Wage Discrimination for Uber & Lyft Drivers and More?!*, YouTube, at 2:16 (Apr. 16, 2023), <https://www.youtube.com/watch?v=MfFujB0IY6A> (on file with the *Columbia Law Review*); *The RideShare Guy, MORE Algorithmic Wage Discrimination?? Show Me The Money Club*, YouTube, at 6:25, 1:01:03 (June 20, 2023), <https://www.youtube.com/watch?v=8mwzsB41-f4> (on file with the *Columbia Law Review*).

20. See *infra* Part II.

21. See *infra* Part II.

22. 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 a special status, society must be shaped in such a manner as to allow that system to function according to its own laws.

Karl Polanyi, *The Great Transformation: The Political and Economic Origins of Our Time* 60 (Beacon Press 2001) (1944). One interpretation of this important excerpt, as used in this Article, 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 & Ngai-Ling Sum, *Polanyi: Classical Moral Economist or Pioneer Cultural Political Economist?*, 44 *Österreichische Zeitschrift für Soziologie* 153, 158 (2019). 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. Fred Block, *Karl Polanyi and the Writing of *The Great Transformation**, 32 *Theory & Soc’y* 275, 297 (2003).

rupture in wages.²³ Although the United States–based system of work is largely regulated through contracts and strongly defers to the managerial prerogative,²⁴ two restrictions on wages have emerged from social and labor movements: minimum-wage laws and antidiscrimination laws. Respectively, these laws set a price floor for the purchase of labor relative to time and prohibit identity-based discrimination in the terms, conditions, and privileges of employment, requiring firms to provide equal pay for equal work.²⁵ Both sets of wage laws can be understood as forming a core moral foundation for most work regulation in the United States. 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, which specifically legalize algorithmic wage discrimination for certain firms, compare with and destabilize more than a century of legal and social norms around fair pay.

Part II draws on first-of-its-kind, long-term ethnographic research to understand the everyday, grounded experience of workers earning

23. Various disciplines, including political theory, anthropology, and sociology, have explored the notion of “moral economy” in relationship to labor and work as a way to think about and assess various systems of economic distribution and their impacts on everyday life. See, e.g., William Greider, *The Soul of Capitalism* 39 (2003) (“The logic of capitalism is ingeniously supple and complete, self-sustaining and forward-looking. Except for one large incapacity: As a matter of principle, it cannot take society’s interests into account.”); James Bernard Murphy, *The Moral Economy of Labor* 42 (1993) (applying moral reason to the social division of labor and technology); Sharon C. Bolton, Maeve Houlihan & Knut Laaser, *Contingent Work and Its Contradictions: Towards a Moral Economy Framework*, 111 *J. Bus. Ethics* 121, 123–124 (2012); Sharon C. Bolton & Knut Laaser, *Work, Employment and Society Through the Lens of Moral Economy*, 27 *Work Emp. & Soc’y* 508, 509 (2013) (using a moral economic approach in a sociological inquiry); Marion Fourcade, Philippe Steiner, Wolfgang Streeck & Cornelia Woll, *Moral Categories in the Financial Crisis 2* (Max Planck Sciences Po Ctr. on Coping With Instability in Mkt. Societies (MaxPo) Discussion Paper, Working Paper No. 13/1, 2013), <https://www.econstor.eu/bitstream/10419/104613/1/757489362.pdf> [<https://perma.cc/4ZJ4-QYC4>] (analyzing the reconfiguration of the moral economy surrounding income inequality in France following the 2008 financial crisis).

24. See Gali Racabi, *Abolish the Employer Prerogative, Unleash Work Law*, 43 *Berkeley J. Emp. & Lab. L.* 79, 82 (2022) (“The employer [or managerial] prerogative is the default governance rule in the workplace . . .”). This legal deference to the managerial prerogative is controversial in the scholarly literature. See, e.g., *id.* at 138 (“[P]erhaps the employer prerogative’s most sinister effect is convincing work law movements, scholars, and activists that it is a state of nature, a necessary theoretical benchmark for both pragmatic and normative discussions of work law. It is not.”).

25. At the federal level, the Fair Labor Standards Act of 1938, 29 U.S.C. §§ 201–219 (2018), establishes a national floor for minimum-wage and overtime. *Id.* at §§ 203, 206, 207. The central federal laws that prohibit wage discrimination based on protected identities or classes are the Equal Pay Act, 29 U.S.C. § 206(d) (requiring that men and women in the same workplace be given equal pay for equal work); Title VII of the Civil Rights Act of 1964, 42 U.S.C. § 2000e-2 (2018) (prohibiting employment discrimination based on race, color, religion, sex, and national origin); the Age Discrimination in Employment Act, 29 U.S.C. §§ 623, 631 (prohibiting employment discrimination based on age for workers older than forty); and the Americans with Disabilities Act, 42 U.S.C. § 12112 (prohibiting employment discrimination based on disability).

through and experiencing algorithmic wage discrimination. Specifically, Part II analyzes the experiences of on-demand ride-hail drivers in California before and after the passage of an important industry-initiated law, Proposition 22, which legalized this form of variable pay. This Part illuminates workers' experiences under compensation systems that make it difficult for them to predict and ascertain their hourly wages. Then, Part II examines the practice of algorithmic wage discrimination in relationship to workers' on-the-job meaning making and their moral interpretations of their wage experiences.²⁶ Though many drivers are attracted to on-demand work because they long to be free from the rigid scheduling structures of the Fordist work model,²⁷ they still largely conceptualize their labor through the lens of that model's payment structure: the hourly wage.²⁸ Workers find that, in contrast to more standard wage dynamics, being directed by and paid through an app involves opacity, deception, and manipulation.²⁹ Those who are most

26. The social construction of meaning is a central concern of sociologists and anthropologists who seek to account for the variability and diversity of human understandings and experiences. Compare Michèle Lamont, *Meaning-Making in Cultural Sociology: Broadening Our Agenda*, 29 *Contemp. Socio.* 602, 603–05 (2000) (offering a detailed taxonomy of sociological literature that takes up how people make sense of their worlds through their experiences of race, ethnicity, immigration, and inequality), with Richard A. Posner, *Economic Analysis of Law* 3–4 (9th ed. 2014) (describing rationality as grounded within self-interested economic maximization of scarce resources).

27. Philosopher Antonio Gramsci used the term “Fordism” to refer to an emergent system of material production—routine, intensified labor—under the regime of Ford. But due in large part to corresponding political and economic forces, namely the laws and policies passed in response to upheaval during the Great Depression, the Fordist work structure in much of the mid-twentieth century often corresponded to an hourly (living) wage and a forty-hour work week. See Antonio Gramsci, *Americanism and Fordism*, in *Selections From the Prison Notebooks of Antonio Gramsci* 561, 561–63 (Quentin Hoare & Geoffrey Nowell Smith eds. and trans., 1999). For more on the demise of Fordism, see generally Luc Boltanski & Ève Chiapello, *The New Spirit of Capitalism* (2007).

28. See Michael Dunn, *Making Gigs Work: Digital Platforms, Job Quality and Worker Motivations*, 35 *New Tech. Work & Emp.* 232, 238–39, 241–42 (2020) (discussing the motivations of gig workers, including flexible work hours, despite often needing to maintain the same work structures as traditional employment). 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. For a discussion of the history of businesses contesting the legal rules defining employment status to avoid legal responsibility for basic employment safeguards, see Veena B. Dubal, *Wage Slave or Entrepreneur?: Contesting the Dualism of Legal Worker Identities*, 105 *Calif. L. Rev.* 65, 86–88 (2017) [hereinafter Dubal, *Wage Slave or Entrepreneur?*]. Notably, the passage of California's AB5 law made it much harder to misclassify workers in this way. See Hannah Johnston, Ozlem Ergun, Juliet Schor & Lidong Chen, *Is Employment Status Compatible With the On-Demand Platform Economy? Evidence From a Natural Experiment* 6 (2021) (unpublished report) (on file with the *Columbia Law Review*). When at least one labor platform company, called Bring Your Package, went on to hire their previously contracted workers in anticipation of AB5 restrictions, this transition did not precipitate any reduction in workers' desired scheduling flexibility nor in firm efficiency. See *id.* at 14, 24, 26–27.

29. These findings comport with research findings from across sociology, communications studies, and media studies literatures on algorithmic management. See,

economically dependent on income from on-demand work frequently describe their experience of algorithmic wage discrimination through the lens of gambling.³⁰ As a normative matter, this Article contends 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 condition of their 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, worker security, and 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.³¹

e.g., Antonio Aloisi, Platform Work in Europe: Lessons Learned, Legal Developments and Challenges Ahead, 13 *Euro. Lab. L.J.* 4, 10–11 (2022) (discussing how platform management tends to unfold in misleading, opaque ways); Rafael Grohmann, Gabriel Pereira, Abel Guerra, Ludmila Costhek Abilio, Bruno Moreschi & Amanda Jurno, Platform Scams: Brazilian Workers' Experiences of Dishonest and Uncertain Algorithmic Management, 24 *New Media & Soc'y* 1611, 1614 tbl.1 (2022) (presenting case studies of the types of dishonesty and deception that workers experience in platform work); Elke Schüßler, Will Attwood-Charles, Stefan Kirchner & Juliet B. Schor, Between Mutuality, Autonomy and Domination: Rethinking Digital Platforms as Contested Relational Structures, 19 *Socio-Econ. Rev.* 1217, 1224 (2021) (outlining common theories of the position of power that platforms hold over their workers); Steven Vallas & Juliet B. Schor, What Do Platforms Do? Understanding the Gig Economy, 46 *Ann. Rev. Socio.* 273, 279–81 (2020) (conducting a literature review of the predominant sociological views of platform work, which often conceptualize this work as an extension of existing neoliberal models of work without any of the worker protections); Daniel Susser, Beate Roessler & Helen Nissenbaum, Technology, Autonomy, and Manipulation, 8 *Internet Pol'y Rev.*, no. 2, 2019, at 1, 8 (explaining how gig economy services covertly influence an individual's decision-making through "online manipulation").

30. See *infra* section II.B.

31. In the United States, such work is conducted primarily by immigrants and subordinated minorities. Lyft estimates that 73% of their U.S. workforce identify as racial minorities. Lyft, Economic Impact Report 5 (2022), https://s27.q4cdn.com/263799617/files/doc_downloads/esg/Lyft-Economic-Impact-Report-2022.pdf [<https://perma.cc/8BUG-NGAV>]. One study estimates that in the San Francisco Bay Area in 2019, immigrants and people of color composed 78% of Uber and Lyft drivers, most of whom relied on these jobs as their primary source of income. Chris Benner, Erin Johansson, Kung Feng & Hays Witt, UC Santa Cruz Inst. for Soc. Transformation, On-Demand and On-The-Edge: Ride-Hailing and Delivery Workers in San Francisco, Executive Summary 2 (2020), https://transform.ucsc.edu/wp-content/uploads/2020/05/OnDemandOntheEdge_ExecSum.pdf [<https://perma.cc/DFH8-7VSY>]. In addition to the nationwide Lyft data, we know that in New York City, 90% of ride-hail drivers are immigrants, and in Seattle, ride-hail drivers are 50% Black and "nearly three times more likely to be immigrants than all Kings County workers." James A. Parrott & Michael Reich, Ctr. on Wage & Emp. Dynamics & New Sch. Ctr. for N.Y.C. Affs., A Minimum Compensation Standard for Seattle TNC Drivers 23 (2020), https://irle.berkeley.edu/files/2020/07/Parrott-Reich-Seattle-Report_July-2020.pdf [<https://perma.cc/QA9F-FV47>] [hereinafter Parrott & Reich, Minimum Compensation Standard]; Ginia Bellafante, Uber and the False Hopes of the Sharing Economy, *N.Y. Times*

Finally, Part III explores how workers and worker advocates have used existing data privacy laws and cooperative frameworks to address or at least to 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 coworkers in the United Kingdom—have developed a sophisticated understanding of the laws governing data at work.³² In the United Kingdom, a self-organized group of drivers, the App Drivers & Couriers Union, has not only successfully sued Uber to establish their worker status³³ but also used the General Data Protection Regulation (GDPR) to lay claim to a set of positive rights concerning the data and algorithms that determine their pay.³⁴ As a GDPR-like law went into effect in California in 2023, drivers there are positioned to do the same.³⁵ Other workers in both the United States 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.³⁶ In addition to examining both approaches to addressing algorithmic wage discrimination, this Article argues 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 or subjective harms of algorithmic wage discrimination. Considering the potential for this form of discrimination to spread into other sectors of work, this Article proposes instead an approach that addresses the harms directly: a narrowly structured, nonwaivable 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

(Aug. 9, 2018), <https://www.nytimes.com/2018/08/09/nyregion/uber-nyc-vote-drivers-ride-sharing.html> (on file with the *Columbia Law Review*).

32. See *infra* Part III.

33. Kate Duffy & Theo Golden, Uber Just Lost a Major Legal Battle Over Whether Its UK Drivers Count as Workers and Are Entitled to Minimum Wage, *Bus. Insider* (Feb. 19, 2021), <https://www.businessinsider.com/uber-driver-lost-uk-legal-battle-court-worker-rights-employment-2021-2> [<https://perma.cc/CT27-K2ZP>].

34. Jeffrey Brown, In New European Lawsuit, Uber Drivers Claim Company’s Algorithm Fired Them, *Geo. L. Tech. Rev. Legal Impressions* (Nov. 2020), <https://georgetownlawtechreview.org/in-new-european-lawsuit-uber-drivers-claim-companys-algorithm-fired-them/GLTR-11-2020/> [<https://perma.cc/887P-RET4>] (“The GDPR . . . imposes obligations on companies which collect personal information if that data is related to EU consumers, regardless of the consumer’s physical location in the world. Under Article 22, individuals have ‘the right not to be subject to a decision based solely on automated processing.’” (quoting Council Regulation 2016/679, art. 22, 2016 O.J. (L 119) 1 (EU))).

35. Cal. Civ. Code § 1798.100 (2023) (imposing limits on businesses’ collection of consumer personal information and requiring notice of the purposes behind data collection).

36. See *infra* section III.B.

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 antidiscrimination laws, nothing in the laws of work makes this form of digitalized variable pay illegal.³⁷ As Professor 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”³⁸ 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, extant evidence suggests that algorithmic wage discrimination has already seeped into the healthcare and engineering sectors, impacting how porters, nurses, and nurse practitioners are paid.³⁹ If left unaddressed, the practice will continue to be normalized in other employment sectors, including retail, restaurant, and computer science, producing new cultural norms around compensation for low-wage work.⁴⁰

37. See *supra* note 25. Antitrust laws, however, are a more promising way to address these practices when and if workers are classified as independent contractors. Part III discusses a California lawsuit filed in 2022 by Rideshare Drivers United workers against Uber alleging that the company’s payment structures amount to price fixing and that it is violating state antifraud laws.

38. See Teachout, *Algorithmic Personalized Wages*, *supra* note 15, at 437.

39. For example, a company that brands 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. See Nicky Godding, *Oxford Tech Raises £9 Million for ‘Uber for Hospitals’ AI Platform*, *Bus. Mag.* (May 21, 2020), <https://thebusinessmagazine.co.uk/technology-innovation/oxford-tech-raises-9-million-for-uber-for-hospitals-ai-platform/> [<https://perma.cc/8593-M9U7>] (“Hospitals can use [this technology] to assign tasks to healthcare teams based on their location. . . . This helps to ensure . . . full visibility of vulnerable patient movement between departments, and connects porters directly with staff . . .”). The technology company’s “performance analysis” may then be used to determine the pay for these healthcare workers. *Id.*

IBM Japan is also using digital surveillance systems to help set wages for their workers. In 2019, the company introduced human relations software created by Watson to use as a “compensation advisor.” The Japan Metal, Manufacturing, Information and Telecommunication Workers’ Union (JMITU), which represents IBM Japan workers, requested disclosure of the data the Watson AI acquired and used, an explanation for how it was evaluating workers, and how these evaluations were involved in the wage-setting process. IBM Japan refused to disclose the information. JMITU subsequently lodged a complaint with the Tokyo Labor Relations Commission. The union argues that the software is being used to unfairly target union members. According to one report, “[i]n awarding summer bonuses in June 2019, the individual performance rate assessed by the company was only 63.6% on average for union members, compared to an average of 100% for all [other] employees. In addition, an exceptional 0% assessment was made for many union members.” Hozumi Masashi (ほづみ まさし), *AIによる賃金査定にどう向き合うか: 日本IBM事件(不当労働行為救済申立)の報告* [How to Face AI-Based Wage Assessments: Report on the IBM Japan Case (Unfair Labor Practice Relief Petition)], 338 *季刊 労働者の権利* [Worker Rights Quarterly], no. 10, 2020, at 101, 102.

40. See, e.g., Min Kyung Lee, Daniel Kusbit, Evan Metsky & Laura Dabbish, *Working With Machines: The Impact of Algorithmic and Data-Driven Management on Workers*, *in* CHI 15: Proceedings of the 33rd Annual CHI Conference on Human Factors in Computing Systems 1603, 1603–04 (2015) (discussing how algorithms used across industries can

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. When contracts are silent—particularly around scheduling and payment decisions—a general judicial deference to the managerial prerogative has reigned.⁴¹ Wage-regulation laws are important exceptions. Both minimum-wage laws and antidiscrimination statutes reflect and have contributed to the legal consensus around what constitutes a moral economy of work regarding compensation for labor. “Moral economy,” here, refers to an understanding of economic activities that “accounts for class-informed frameworks involving traditions, valuations and expectations.”⁴² Moral economy, as a theoretical and empirical focus, is a useful way to understand how class relations and resultant inequalities have been negotiated through law and to distinguish the values embodied in the prevailing legal frameworks. This Part argues that wage-related laws, passed 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.⁴³ For their part, antidiscrimination laws have created

produce new norms of allocation of, evaluation of, and compensation for work). Companies across the world use wage algorithms in both contracting and permanent employment settings to incentivize certain behaviors. Technology capitalists have foreshadowed its growth. See, e.g., Shawn Carolan, Opinion, What Proposition 22 Now Makes Possible, *The Info.* (Nov. 10, 2020), <https://www.theinformation.com/articles/what-proposition-22-now-makes-possible> (on file with the *Columbia Law Review*) (predicting increased venture capitalist investment in “all sorts of industries” after the passage of Proposition 22). As Tarleton Gillespie has warned regarding the power of algorithms, “[t]here is a case to be made that the working logics of these algorithms not only shape user practices, but also lead users to internalize their norms and priorities.” Tarleton Gillespie, *The Relevance of Algorithms*, in *Media Technologies: Essays on Communication, Materiality, and Society* 167, 187 (Tarleton Gillespie, Pablo J. Boczkowski & Kirsten A. Foot eds., 2014).

41. See Racabi, *supra* note 24, at 82–83 (discussing employer prerogative as the “default governance rule in the workplace”).

42. Jaime Palomera & Theodora Vetta, *Moral Economy: Rethinking a Radical Concept*, 16 *Anthropological Theory* 413, 415 (2016).

43. As an illustration, at jobs where employees customarily receive more than \$30 in tips per month, federal law requires that an employer pay the tipped minimum wage of “\$2.13 [per hour] in direct wages if that amount combined with the tips received at least equals the federal minimum wage. If the employee’s tips combined with [those] direct wages . . . do not equal the federal minimum hourly wage, the employer must make up the difference.” *Tips*, DOL, <https://www.dol.gov/general/topic/wages/wagestips> [[https://](https://www.dol.gov/general/topic/wages/wagestips)

the expectation that individuals will not be paid differently because of their protected status—a cultural expectation of or aspiration toward equality of payment for equal work.⁴⁴

Algorithmic wage discrimination—which personalizes wages to specific workers and moments—is not addressed by any such laws. This gap 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 different 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 allowable 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 Polanyi'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.⁴⁵ It is, in essence, an economic practice—even an economic project—that is changing social imaginaries as to the kinds of compensation practices that are considered normal, acceptable, and fair. Because, to date, most people who endure the unpredictable, low, and variable pay associated with algorithmic wage discrimination are immigrants and subordinated racial minorities,⁴⁶ the practice may also exacerbate existing racialized economic inequalities and, for these populations, impede the possibility of economic security and mobility through work.

This Article's primary objection to this practice is normative—that is, there is good reason to reject the form of wage setting it imposes on workers—but the Article's critique is rooted in a historical analysis of labor practices and labor laws, particularly the values and customs that have guided wage regulation in the United States since industrialization. Before this Article turns to that analysis, however, this Part will first describe how two state laws—one passed through the initiative process and the other

perma.cc/X6KU-NGBK] (last visited Aug. 14, 2023). Because employers often fail to comply with the law and make up the difference when tips are not sufficient to meet the minimum wage, seven states (Alaska, California, Minnesota, Montana, Nevada, Oregon, and Washington) require a full minimum wage for all workers. See Kate Bahn, *Enacting a Minimum Wage Is on the Ballot in Two Cities. Here's What the Research Says*, Wash. Ctr. for Equitable Growth (Nov. 4, 2022), <https://equitablegrowth.org/enacting-a-minimum-wage-for-tipped-workers-is-on-the-ballot-in-two-u-s-cities-heres-what-the-research-says/> [<https://perma.cc/LR2A-C4KH>]; Minimum Wages for Tipped Employees, DOL, <https://www.dol.gov/agencies/whd/state/minimum-wage/tipped> [<https://perma.cc/J7QX-E4N9>] (last visited Aug. 14, 2023). Thus, while tipped workers' earnings are unpredictable, their wages are still subject by law to an hourly minimum-wage floor.

44. See *infra* section I.C.

45. See Polanyi, *supra* note 22, at 60.

46. See *supra* note 31.

through a state legislature—specifically legalized algorithmic wage discrimination.

A. *The Legalization of Algorithmic Wage Discrimination*

In 2020, amid 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.⁴⁷ 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 historian Louis Hyman and several Cornell economists known for their association with Democratic administrations.⁴⁸ Hyman’s research, paid for by Uber and later touted by Uber CEO Dara Khosrowshahi, found that a typical Uber driver in Seattle made about \$23 an hour; 92% of workers earned above the local minimum wage, which, in 2020, was \$16.39 for large employers.⁴⁹ But an alternative analysis using similar data conducted by labor economists James Parrott and Michael Reich and commissioned by the City of Seattle arrived at a very different number—\$9.74 per hour—and found that the majority of drivers earned far less than the city’s minimum wage.⁵⁰ The difference between the two figures turned largely on how the groups calculated overhead costs for workers.⁵¹ In the Hyman-Uber

47. Noam Scheiber, *When Scholars Collaborate With Tech Companies, How Reliable Are the Findings?*, *N.Y. Times* (July 12, 2020), <https://www.nytimes.com/2020/07/12/business/economy/uber-lyft-drivers-wages.html> (on file with the *Columbia Law Review*) (last updated Nov. 4, 2021).

48. See *id.*

49. Louis Hyman, Erica L. Groshen, Adam Seth Litwin, Martin T. Wells, Kwelina P. Thompson & Kyrylo Chernyshov, *Cornell Univ., Platform Driving in Seattle 10* (2020), https://ecommons.cornell.edu/bitstream/handle/1813/74305/Cornell_Seattle_Uber_Lyft_Project_Report_Final_Version_JDD_accessibility_edits_7_14_2020.pdf [<https://perma.cc/6XCT-74FW>]. Note that Uber and Lyft covered the costs of the \$120,000 study. *Id.* at 20. Also, in late 2022, Uber whistleblower Mark MacGann testified before the European Parliament that, during his time at Uber, the company paid for studies providing skewed datasets. *Gig Economy Project—Uber Whistleblower Mark MacGann’s Full Statement to the European Parliament*, *Brave New Europe* (Oct. 25, 2022), <https://braveneweuropa.com/uber-whistleblower-mark-macganns-full-statement-to-the-european-parliament> [<https://perma.cc/KCR3-U46U>] (“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.”).

50. See Parrott & Reich, *Minimum Compensation Standard*, *supra* note 31, at 55, 59 (noting “\$9.73 as net pay” and finding that “only app-reported earnings from the survey at the 90th percentile rise above the Seattle minimum wage.”).

51. See James Parrott & Michael Reich, *Ctr. on Wage & Emp. Dynamics & Inst. for Rsch. on Lab. & Emp., Comparison of Two Seattle TNC Driver Studies 2–3* (2020), <https://irle.berkeley.edu/files/2020/07/Comparison-of-two-Seattle-studies.pdf> [<https://perma.cc/N9RP-MCYX>] [hereinafter Parrott & Reich, *Two Seattle Studies*] (“The Parrott- Reich study recognizes the full array of expenses borne by drivers seeking a living

analysis, Uber insisted that the investigators not include costs associated with the vehicle—which the firm claims are incidental to the work.⁵² By contrast, economists Parrott and Reich asserted that, because workers often purchase cars (and are even induced to do so by the companies⁵³) and must maintain their vehicles to labor (based on requirements set forth by Uber),⁵⁴ those costs should be included.⁵⁵

Notably absent in the coverage of this debate, however, was that *both* studies found that *some* workers earned well under the minimum wage,⁵⁶ that workers who performed substantially similar work received dramatically different wages, and that the wages that an individual worker would receive were generally impossible to precisely ascertain or predict.⁵⁷ Even over the span of just a few days, individual workers made dramatically

from driving, whereas the Uber-Lyft-Hyman excludes numerous expenses by taking a minimalist ‘marginal’ perspective . . .”).

52. See *id.* at 2.

53. In 2017, the FTC accused Uber of both exaggerating earnings claims and misleading workers with claims about the terms of the vehicle loans they provided or facilitated. See Press Release, FTC, Uber Agrees to Pay \$20 Million to Settle FTC Charges that It Recruited Prospective Drivers With Exaggerated Earnings Claims (Jan. 19, 2017), <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> [<https://perma.cc/M77X-VM8C>]; Rideshare Professor, Thank You Alissa Orlando Former Uber Employee. Whistleblower Exposing Disgusting Uber & Lyft Tactics, YouTube, at 0:21 (Sept. 22, 2020), <https://www.youtube.com/watch?v=SfxUKvEa-os> (on file with the *Columbia Law Review*) (“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 they couldn’t service without 70-plus-hour work weeks.” (quoting tweet posted by Alissa Orlando (@AlissaOrlando))).

54. E.g., Vehicle Requirements: New York City, Uber, <https://www.uber.com/us/en/drive/new-york/vehicle-requirements/> (on file with the *Columbia Law Review*) (last visited Aug. 14, 2023).

55. Parrott & Reich, Two Seattle Studies, *supra* note 51, at 2–3 (“By contrast, the Parrott-Reich study includes all costs associated with driving (fixed costs) Since most trips are completed by full-time drivers, whose primary use of the vehicle is for TNC purposes, it makes little sense to exclude the bulk of expenses associated with driving.”); see also Gig Econ. Rschers. United, Open Letter and Principles for Ethical Research on the Gig Economy, Medium (July 30, 2020), <https://medium.com/@gigeconomyresearchers/united/open-letter-and-principles-for-ethical-research-on-the-gig-economy-3cd27924cc08> [<https://perma.cc/C2G4-LG4M>] (arguing that “[c]osts borne by workers include those directly related to driving and to health of workers”).

56. Compare Hyman et al., *supra* note 49, at 1 (finding that “many drivers earn below the minimum wage”), with Parrott & Reich, Minimum Compensation Standard, *supra* note 31, at 55 (finding that “[o]nly app-reported earnings from the survey at the 90th percentile rise above the Seattle minimum wage”).

57. Compare Hyman et al., *supra* note 49, at 5 (“In a normal service economy job, at Starbucks, Wal-Mart or McDonald’s, the variation in worker earnings is very low. For platform drivers, the opposite is true.”), with Parrott & Reich, Minimum Compensation Standard, *supra* note 31, at 37 (referring to the “considerable variation” in the individual driver earnings data).

different amounts of money for the same amount of work.⁵⁸ 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.⁵⁹ 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.

On-demand labor platform companies adopted algorithmic wage discrimination, a highly personalized and variable form of compensation, to solve a particular problem that accompanies the (mis)classification of their workers as independent contractors. Since drivers are not treated as employees of the firm and the primary legal indicium of employment status is control the hiring entity exerts over the means and manner of work, firms often 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.⁶⁰ Instead, the firms use data extracted from workers' labor and fed into automated tools to incentivize temporal and spatial movement.⁶¹ In other words, the companies use algorithmic wage discrimination to direct workers' behaviors without explicitly directing them—and to solve the problem of meeting demand.

Companies like Uber refer to some of the mechanisms by which they determine driver pay as “dynamic pricing,” explicitly drawing a connection to the practice of price discrimination.⁶² This latter practice typically

58. See Parrott & Reich, *Minimum Compensation Standard*, *supra* note 31, at 36–40 & exh.25 (depicting a variation of over \$20 between the fifth and ninety-fifth percentiles for hourly driver earnings reported during the week of December 2–8).

59. See, e.g., Research Assistant Justin Donner's Fieldnotes, San Francisco (Apr. 8, 2016) (on file with author).

60. See Dubal, *Wage Slave or Entrepreneur?*, *supra* note 28, at 90. See generally 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 (2017) (discussing the growth of worker precarity in the United States resulting from differentiation between “employees” and “independent contractors” through the lens of the San Francisco chauffeur industry).

61. See Safak & Farrar, *supra* note 19, at 25 (discussing how Uber incentivizes employees to meet “performance goals”).

62. See, e.g., Aaron Shapiro, *Media, Inequality & Change Ctr.*, *Dynamic Exploits: The Science of Worker Control in the On-Demand Economy* 8 (2019), https://www.asc.upenn.edu/sites/default/files/2020-11/DynamicExploits_Final1.pdf [<https://perma.cc/UH2G-R3QU>] [hereinafter Shapiro, *Dynamic Exploits: Worker Control*] (“Dynamic pricing (also called ‘surge,’ ‘demand,’ or ‘time-based pricing’) is the most commonly used technique to influence worker decision-making. Dynamic pricing involves the manipulation of a product or service’s commercial value based on perceived changes in market conditions.”); Jessica Phillips, *How Uber’s Dynamic Pricing Model Works*, *Uber Blog* (Jan. 21, 2019), <https://www.uber.com/en-GB/blog/uber-dynamic-pricing/> [<https://perma.cc/7J69-7LU4>] (explaining how Uber’s “dynamic pricing” works for consumers). In 2022, in a variety of jurisdictions, including California, Uber began to use “upfront pricing” to determine drivers’ base pay. Rather than a rate card that showed workers how much they earned per mile, per minute, the company created an opaque system that offered workers a variable base payment for particular rides. For more on upfront pricing and the shift, see generally

involves segmenting consumers by their willingness to pay rather than charging a flat price. Coupons, student discounts, and bulk purchases are some of the most common forms of price discrimination. As these examples make clear, price discrimination long predates algorithmic computing.⁶³ But individualized data collection and machine learning makes the practice much more powerful and profitable for companies.⁶⁴ As Andrew Pole, a statistician for Target, explained to the *New York Times*, companies like Target use data algorithms to keep track of customer behavior and shopping habits in order to more efficiently market to them.⁶⁵ While price discrimination is illegal if it is intentionally based on race or gender,⁶⁶ sociologists have for many decades found that poor people and people of color often pay more for goods and services.⁶⁷ More recent research suggests that consumer price discrimination in hospital

Yujie Zhou, Five Claims From Uber's Rosy 2022 Recap, Fact-Checked, Mission Local (Jan. 19, 2023), <https://missionlocal.org/2023/01/five-claims-uber-2022-recap-fact-checked/> [<https://perma.cc/HQV6-F7JR>].

63. See, e.g., Alan Kaplan & Daniel O'Neill, NEJM Catalyst, Hospital Price Discrimination Is Deepening Racial Health Inequity 2–3 (2020), <https://catalyst.nejm.org/doi/pdf/10.1056/CAT.20.0593> [<https://perma.cc/EE5X-HF2G>] (explaining that private health plans have covered increasingly higher prices since the 1990s, which contributes to the quality health services' inaccessibility to Medicaid recipients); How Invidious Discrimination Works and Hurts: An Examination of Lending Discrimination and Its Long-Term Economic Impacts on Borrowers of Color: Virtual Hearing Before the Subcomm. on Oversight & Investigations of the H. Comm. on Fin. Servs., 117th Cong. app. at 55 (2021) (prepared statement of Andre M. Perry, Senior Fellow, Metro. Pol'y Program, Brookings Inst.) (“Sociologists Junia Howell and Elizabeth Korver-Glenn found homes in metropolitan areas increased, on average, by \$68,000 from 1980 to 2015 after adjusting for inflation. But homeowners in disproportionately Black and Latino or Hispanic neighborhoods are gaining wealth at around half the speed as homeowners in disproportionately white neighborhoods.”).

64. See Shapiro, Dynamic Exploits: Worker Control, *supra* note 62, at 8 (“[Individualized data] can then be used to modulate prices according to statistical forecasts of supply and demand and to maximize profit.”).

65. Charles Duhigg, How Companies Learn Your Secrets, *N.Y. Times Mag.* (Feb. 16, 2012), <https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html> (on file with the *Columbia Law Review*) (“Almost every major retailer, from grocery chains to investment banks to the U.S. Postal Service, has a ‘predictive analytics’ department devoted to understanding not just consumers’ shopping habits but also their personal habits, so as to more efficiently market to them.”); see also Rishi Gummakonda, The Ugliness of Dynamic Pricing, *MyPermissions: Blog* (July 30, 2017), <https://mypermissions.com/blog/2017/07/30/the-ugliness-of-dynamic-pricing/> [<https://perma.cc/M8WA-CWPX>] (quoting a CEO corroborating how companies can use data to change pricing based on a shopper’s geography and shopping habits).

66. 42 U.S.C. § 2000a (2018).

67. See, e.g., Howard Kunreuther, Why the Poor May Pay More for Food: Theoretical and Empirical Evidence, 46 *J. Bus.* 368, 368 (1973) (“To the extent that poor people shop at these smaller stores, they pay higher prices for the same quality food than if they had purchased their groceries at a chain store.”); Robert Tempest Masson, Costs of Search and Racial Price Discrimination, 11 *W. Econ. J.*, 167, 167 (1973) (“There is some evidence that [B]lack[] [people] pay more for consumer durables than do white[] [people].”).

services,⁶⁸ housing,⁶⁹ and ride-hail sectors exacerbates racial inequities, even absent intentional discriminatory profiling.⁷⁰

In 2017, Uber pulled back the curtain somewhat on its use of price discrimination (what it calls “route-based pricing”) to set fares for riders.⁷¹ Previously, 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:

[T]he company applies machine-learning techniques to estimate how much groups of customers are willing to shell out for a ride. Uber calculates riders’ propensities for paying higher prices for particular routes at certain times 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.⁷²

Despite the implication in this hypothetical, extant empirical research suggests that surge pricing is more complicated and unpredictable, causing longer wait times for riders who start in nonwhite, low-income areas⁷³ and, in other instances, price gouging consumers who were fleeing disaster.⁷⁴

While price discrimination is familiar within the consumer context, Uber and similar companies have broken new ground by using related

68. See Kaplan & O’Neill, *supra* note 63, at 6.

69. See Perry, *supra* note 63, at 5.

70. See Jonathan A. Lanning, Evidence of Racial Discrimination in the \$1.4 Trillion Auto Loan Market, ProfitWise News & Views, no. 1, 2023, at 1, 8, https://www.chicagofed.org/-/media/publications/profitwise-news-and-views/2023/pnv2023-1.pdf?sc_lang=en [<https://perma.cc/J6TB-EUXV>] (“Given that approximately 60% of Black households and around one-half of Hispanic households are [low or moderate income (LMI)], these findings [that non-White borrowers pay higher interest rates than their non-Hispanic White counterparts] imply a substantial risk that racial/ethnic prejudice may significantly limit the economic mobility of non-White LMI households.”).

71. Alison Griswold, Uber Is Practicing Price Discrimination. Economists Say This Might Not Be a Bad Thing, Quartz (May 24, 2017), <https://qz.com/990131/uber-is-practicing-price-discrimination-economists-say-that-might-not-be-a-bad-thing> [<https://perma.cc/6SW9-9LTW>].

72. *Id.* (internal quotation marks omitted) (quoting Eric Newcomer, Uber Starts Charging What It Thinks You’re Willing to Pay, *Bloomberg* (May 19, 2017), <https://www.bloomberg.com/news/articles/2017-05-19/uber-s-future-may-rely-on-predicting-how-much-you-re-willing-to-pay> (on file with the *Columbia Law Review*)).

73. Jennifer Stark & Nicholas Diakopoulos, Uber Seems to Offer Better Service in Areas With More White People. That Raises Some Tough Questions., *Wash. Post* (Mar. 10, 2016), <https://www.washingtonpost.com/news/wonk/wp/2016/03/10/uber-seems-to-offer-better-service-in-areas-with-more-white-people-that-raises-some-tough-questions/> (on file with the *Columbia Law Review*).

74. Sam Metz & Scott Sonner, Caldor Fire Evacuees Report Tahoe Ride-Hail Price Gouging of More Than \$1,500, *KQED* (Sept. 3, 2021), <https://www.kqed.org/news/11887558/caldor-fire-evacuees-report-tahoe-ride-hail-price-gouging-of-more-than-1500> [<https://perma.cc/W6PF-XPKE>].

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.”⁷⁵ Indeed, the journalist found that, by “[e]mploying 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.”⁷⁶ United States–based Uber drivers were previously paid a base fee based on mileage (amounts that varied per geographic location) and time.⁷⁷ But 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.⁷⁸

In addition to this base fare, Uber drivers rely upon what this Article calls *wage manipulators*: any number of offers, bonuses, surges, and quests that can raise their base fare, which in most cases is untenably low by itself. Uber uses this practice across the world.⁷⁹ 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 Part II details some of these wage manipulators, 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 presented to Diego may differ from the multiplier presented 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 one Sanjeev receives. The reasons underlying these differences are opaque—the logic hidden inside black-box algorithms. But based on what is known about price discrimination in the consumer context, these wage manipulators appear to be personalized based on what Uber’s machine learning systems know about the habits, practices, and income targets of individual workers. Despite Uber’s pleadings to the contrary,⁸⁰ since drivers are best conceived of as workers whose labor provides a service,

75. Noam Scheiber, *How Uber Uses Psychological Tricks to Push Its Drivers’ Buttons*, *N.Y. Times* (Apr. 2, 2017), <https://www.nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html> (on file with the *Columbia Law Review*) [hereinafter Scheiber, *Uber’s Psychological Tricks*].

76. *Id.*

77. Amos Toh, *Opinion, Gig Workers Think They Work for Themselves. They Don’t*, *S.F. Chron.* (Oct. 17, 2022), <https://www.sfchronicle.com/opinion/openforum/article/gig-workers-17509777.php> (on file with the *Columbia Law Review*).

78. See *id.*; *infra* note 86 and accompanying text.

79. Scheiber, *Uber’s Psychological Tricks*, *supra* note 75.

80. For more discussion of how Uber has attempted to argue that it is merely a technology intermediary, see Julia Tomassetti, *Does Uber Redefine the Firm? The Postindustrial Corporation and Advanced Information Technology*, 34 *Hofstra Lab. & Emp. L.J.* 1, 13–16 (2016).

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 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 workers spend awaiting a fare, which accounts for roughly (but unpredictably) 40% of overall time on the job.⁸¹ Importantly, this waiting time is not purely a factor of demand or of driver quality or quantity. The company’s goal is to keep as many drivers as possible on the road 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 decrease the number of workers that log on at any specific time,⁸² 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 them 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 United States–based low-wage work over the past century.

And yet this is the default practice of many on-demand firms across the economy.⁸³ Indeed, in many states, legislatures have legally encased these wage practices in the ride-hail sector by passing statutes that classify workers laboring for “transportation network companies” like Uber and

81. Memorandum from Melissa Balding, Teresa Whinery, Eleanor Leshner & Eric Womeldorff, Fehr & Peers, to Brian McGuigan, Lyft, & Chris Pangilnan, Uber, Estimated TNC Share of VMT in Six U.S. Metropolitan Regions (Revision 1) 9 (Aug. 6, 2019), https://issuu.com/fehrandpeers/docs/tnc_vmt_findings_memo_08.06.2019 (on file with the *Columbia Law Review*).

82. Shapiro, *Dynamic Exploits: Worker Control*, *supra* note 62, at 14–15.

83. The one exception to this norm in the United States is the New York City ride-hail sector, where local law mandates a time-based wage floor for all drivers. When the New York City Council passed this law, 85% of N.Y.C. drivers were making less than the minimum wage, according to former Taxi & Limousine Commission (TLC) director Meera Joshi. Author’s Fieldnotes, New York (Sept. 30, 2022) (on file with author); see also Emma G. Fitzsimmons & Noam Scheiber, *New York City Considers New Pay Rules for Uber Drivers*, *N.Y. Times* (July 2, 2018), <https://www.nytimes.com/2018/07/02/nyregion/uber-drivers-pay-nyc.html> (on file with the *Columbia Law Review*) (“The [local law] would make New York the first major American city to establish pay rules to grapple with the upheaval caused by ride-hailing[] companies that has decimated the yellow cab industry and left many drivers in financial ruin.”).

Lyft as independent contractors.⁸⁴ Terms of payment are settled entirely through contracts between the companies and the drivers—contracts that the companies frequently update and send to drivers through the app and that the drivers must accept in order to labor.⁸⁵ And in two states—California and Washington—nonpayment for nonengaged time has been explicitly legalized, 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 they are laboring but have not been allocated work.⁸⁶ 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).⁸⁷ In Washington State, a similar piece of state-level legislation, negotiated by Uber and Teamsters Local 117, requires workers be paid \$1.17 per mile and \$0.34 per minute, including a minimum pay of \$3.00 per trip, but legalizes the practice of not paying workers for nonengaged time.⁸⁸ This legislation, like Proposition 22, effectively sanctions one central aspect of algorithmic wage discrimination in app-deployed work: firms’ power to provide digitalized

84. Ruth Berins Collier, V.B. Dubal & Christopher L. Carter, *Disrupting Regulation, Regulating Disruption: The Politics of Uber in the United States*, 16 *Persps. on Pol.* 919, 921–28 (2018) (“The majority of these test cases involve the misclassification of Uber drivers as independent contractors, a status that denies them the labor and employment rights available only to employees.”).

85. See, e.g., *New Driver Agreements as of July 1, 2021 FAQ*, Uber, <https://help.uber.com/driving-and-delivering/article/new-driver-agreements-as-of-july-1-2021-faq?nodeId=3948cdfd-b5de-4781-991f-888f5c792403> [<https://perma.cc/23YZ-F3SG>] (last visited Sept. 7, 2023).

86. Veena Dubal, *The New Racial Wage Code*, 15 *Harv. L. & Pol’y Rev.* 511, 528 (2021) [hereinafter Dubal, *New Racial Wage Code*]. The Yes on Proposition 22 campaign, supported by Uber, Lyft, DoorDash, Postmates, and Instacart, invested \$223 million to pass the initiative. Many of their tactics were widely believed to include voter deception. Brian Chen & Laura Padin, *Prop 22 Was a Failure for California’s App-Based Workers. Now, It’s Also Unconstitutional.*, *Nat’l Emp. L. Project: Blog* (Sept. 16, 2021), <https://www.nelp.org/blog/prop-22-unconstitutional/> [<https://perma.cc/CN7S-MPXD>].

87. See Dubal, *New Racial Wage Code*, *supra* note 86, at 533 (“On paper, [transportation] and [delivery] workers are entitled to 120% of the applicable minimum wage and 30 cents per mile reimbursement. But these wages and reimbursements are tied to ‘engaged time’ and ‘engaged miles’” (footnote omitted)).

88. Brad Dress, *Washington Passes First-Ever State Law Creating Minimum Pay for Ride-Hailing Companies*, *The Hill* (Apr. 1, 2022), <https://thehill.com/homenews/3256469-washington-passes-first-ever-state-law-creating-minimum-pay-for-ride-sharing-companies/> (on file with the *Columbia Law Review*). In an unusual break with the Teamsters local union that negotiated the bill with Uber, 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 Bus.* (Mar. 31, 2021), <https://www.bloomberg.com/news/articles/2022-03-31/teamsters-chief-seeks-to-end-his-union-s-uber-bill-in-washington> (on file with the *Columbia Law Review*).

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 facilitates control over drivers.

With this background in place, the next section considers how the practice and legalization of algorithmic wage discrimination comport with longstanding U.S. wage laws and regulations as well as the moral and cultural norms they created.

B. *Calculative Fairness and Minimum-Wage Regulation*

Algorithmic wage discrimination represents a dramatic rupture in the moral economy of work. To illustrate this, this section considers the practice in relation to the history of the wage and work laws in the United States. More specifically, it examines it against the background of minimum-wage regulations that arose during the transition from craft-based work 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, many workers contested waged labor, seeking instead to become or remain independent producers.⁸⁹ In the transition from artisanal production to industrialization in the late nineteenth 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”⁹⁰ or, as was commonly called, “wage slavery.”⁹¹ Many labor reformers and worker collectives attempted to exert control over wages via campaigns for shorter days while reimagining workers as “merchants of time.”⁹² This conceptualization led to the fight for the eight-hour day and “a living wage”—both of which, reformers argued, would give workers the means to live and the time to engage in civic life and consumption.⁹³

89. See Lawrence B. Glickman, *A Living Wage: American Workers and the Making of Consumer Society* 11–12 (1999) (reviewing the history of wage labor in America, including the discourse around wage labor as a form of slavery).

90. *Id.* at 99.

91. *Id.* at 18.

92. *Id.* at 99.

93. Labor reformers debated whether minimum-wage laws would hurt or benefit the labor movement more broadly. Many, including leaders in both the more conservative American Federation of Labor (AFL) and the more radical Industrial Workers of the World (IWW), were skeptical of state intervention in negotiations between firms and collective groups—even in providing a basic wage floor from which to bargain. Melvyn Dubofsky, *We Shall Be All: A History of the Industrial Workers of the World* 90 (Joseph A. McCartin ed., 2000); see also Laura Murphy, *An “Indestructible Right”: John Ryan and the Catholic Origins of the U.S. Living Wage Movement, 1906–1938*, *Labor*, Spring 2009, at 57, 77

As reformers gained legislative victories for minimum-wage and maximum-hour regulations, however, the Supreme Court ruled that such regulations violated the state's police power to govern commerce.⁹⁴ 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.⁹⁵ Yet careful review of these cases reveals a more nuanced approach to the regulation of payment for work. Even *Lochner*-era judges committed to an ideal of calculative fairness in the workplace: 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.* infamously struck down minimum-wage laws and upheld freedom of contract.⁹⁶ 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. Arkansas*⁹⁷ and *Knoxville Iron Co. v. Harbison*,⁹⁸ *Adkins* outlined normative notions of fairness regarding wage calculation and distribution.⁹⁹

(noting that most AFL leaders did not think legislation was the appropriate means). This skepticism has largely left the labor movement as minimum-wage laws have become the cultural norm. Howard D. Samuel, *Troubled Passage: The Labor Movement and the Fair Labor Standards Act*, *Monthly Lab. Rev.*, Dec. 2000, at 32, 37 ("By 1944, . . . the AFL vowed to guard against 'any attempt to weaken [the FLSA]' Two years later, the AFL began its drive to raise the legal minimum wage to \$1 an hour. By early 1955, . . . Labor's doubts about the creation of statutory wage and hour standards had disappeared." (quoting AFL Convention Proceedings 158 (1938))); see also Minimum Wage Tracker, Econ. Pol'y Inst. (July 1, 2023), <https://www.epi.org/minimum-wage-tracker/> [<https://perma.cc/86ET-RZEN>] (explaining that forty-two states currently have minimum-wage laws).

94. See *Lochner v. New York*, 198 U.S. 45, 57–58 (1905), overruled in part by *Ferguson v. Skrupa*, 372 U.S. 726 (1963).

95. See, e.g., *Adkins v. Child.'s Hosp. of D.C.*, 261 U.S. 525, 557 (1923) (condemning minimum-wage laws because "[t]o the extent that the sum fixed exceeds the fair value of the services rendered . . . [the law] amounts to a compulsory exaction from the employer"), overruled by *West Coast Hotel Co. v. Parrish*, 300 U.S. 379 (1937); *Adair v. United States*, 208 U.S. 161, 282 (1908) (invalidating federal law that prohibited contracts barring employees in the interstate railroad business from joining a union), abrogated by *Lincoln Fed. Lab. Union No. 19129, AFL v. Nw. Iron & Metal Co.*, 335 U.S. 525, 536 (1949); *Hammer v. Dagenhart*, 247 U.S. 251, 276 (1918) (striking down a federal regulation on child labor), overruled in part by *United States v. Darby*, 312 U.S. 100 (1941).

96. See *Adkins*, 261 U.S. at 561 ("To sustain the individual freedom of action contemplated by the Constitution is not to strike down the common good . . . for surely the good of society as a whole cannot be better served than by the preservation against arbitrary restraint of the liberties of its constituent members.").

97. 211 U.S. 539 (1909).

98. 183 U.S. 13 (1901).

99. *Adkins*, 261 U.S. at 547. In *Adkins*, Chief Justice Taft wrote in dissent: [T]here are decisions by this court which have sustained legislative limitations in respect to the wage term in contracts of employment. In *McLean v. Arkansas*, 211 U.S. 539, . . . it was held within legislative power to make it unlawful to estimate the graduated pay of miners by weight after screening the coal. In *Knoxville Iron Co. v. Harbison*, 183 U.S. 13, . . . it was held that stores orders issued for wages must be redeemable in cash.

Writing on behalf of the Court, Justice George 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.”¹⁰⁰ While Justice Sutherland maintained that “[t]here 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.”¹⁰¹ And yet in focusing on the holding alone, 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.”¹⁰²

In other words, even a Court that cast the minimum wage as “a naked, arbitrary exercise of power”¹⁰³ that was unfair to business and broadly interfered in the workers’ freedom to contract recognized the importance of fair payment in form and time. Indeed, citing to *McLean* and *Knoxville Iron*, the Court explained that it had upheld previous wage regulations because their “tendency and purpose w[ere] to prevent unfair . . . methods in the payment of wages.”¹⁰⁴

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 required that the contract between a mining company and a miner stipulate payment to the worker based not on “screened coal” but instead based on weights of coal “originally produced in the mine.”¹⁰⁵ In this sense, the method of payment, the Court concluded, must be fair as to “honest weights and measures.”¹⁰⁶ More specifically, the weight of the coal mined could not be measured by using technology that would result in lower payment than was fair. The Court upheld the law as a reasonable legislative restriction on contract and held that the company had violated it not only by “introduc[ing] . . . 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.”¹⁰⁷ In *Knoxville Iron*, the Court also upheld on fairness grounds a law that

261 U.S. at 565 (Taft, C.J., dissenting).

100. *Id.* at 540 (majority opinion) (internal quotation marks omitted) (quoting Act of Sept. 19, 1918, ch. 174, § 9, 40 Stat. 960, 962).

101. *Id.* at 554–55.

102. *Id.* at 559.

103. *Id.*

104. *Id.* at 547.

105. *McLean v. Arkansas*, 211 U.S. 539, 548 (1909).

106. *Id.* at 550.

107. *Id.*

required a coal mining company to pay their workers in money or goods—but only if those goods were the same value as the money.¹⁰⁸

In both cases, the “technology” through which wages were calculated—instruments to measure coal weight and the calculated worth of a nonmonetary 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 *McLean* Court’s words, the wage practices outlawed by the state legislature had a “reasonable relation to the protection of a large class of laborers in the receipt of their *just dues*.”¹⁰⁹ Thus, the law’s regulation of contract not only passed the muster of the Court’s police powers analysis, but also—per the Court’s logic—did so because it addressed the problem of calculative fairness in employers’ wage-setting practices.

This value of calculative fairness, embedded even in *Lochner*-era Supreme Court decisions, is worth contrasting with the practice of algorithmic wage discrimination, in which employers calculate wages—again through the introduction of new technologies—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, 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.”¹¹⁰ These cases make clear that wage unpredictability is a matter of fairness, distinct from the fact that some workers earn below the minimum wage. Algorithmic wage discrimination thus raises the problem not just of wage value but also of the wage-setting process.

Adkins was overturned by *West Coast Hotel Co. v. Parrish*, marking a sharp shift in the Court’s stance toward minimum-wage regulations.¹¹¹ Laws guaranteeing a time-based wage floor that were once derided as “a form of theft” were subsequently “required for bringing about distributional justness.”¹¹² Importantly, “many minimum wage advocates . . . asserted” that wages themselves were a social construction and should thus be allocated justly, not only to “secure existence” but also, in the words of reporter Walter Lippmann, to “make life a rich and

108. *Knoxville Iron Co. v. Harbison*, 183 U.S. 13, 19–20 (1901).

109. *McLean*, 211 U.S. at 550 (emphasis added).

110. *Adkins v. Child’s Hosp. of D.C.*, 261 U.S. 525, 559 (1923).

111. 300 U.S. 379, 400 (1937). As historian Lawrence Glickman points out, this change in the Court’s recognition of the importance of distributional justice finds its origins in the advocacy of late nineteenth-century U.S. workers who invented the language of the “living wage” and from whom the New Dealers adopted and modified the language. Glickman, *supra* note 89, at 155.

112. Edward James McKenna & Diane Catherine Zannoni, *Economics and the Supreme Court: The Case of the Minimum Wage*, 69 *Rev. Soc. Econ.*, 189, 190 (2011).

welcome experience.”¹¹³ Vital to the Court’s interpretation in *West Coast Hotel*, then, was earlier minimum-wage advocates’ conception of “distributional justice”: that an hourly wage was based not on an abstract or “‘true’ value of [the work]” but on an “adequate measure [of basic] needs.”¹¹⁴ 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 (FLSA) in 1938, which—with notable exceptions in the agricultural and domestic sectors, made up primarily of women and subordinated racial minority workers¹¹⁵—created a wage floor for workers.¹¹⁶

Thus, minimum-wage laws, as intrinsic to “moral capitalism” and a “need-centered pay system” and 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.¹¹⁷ Despite a staggeringly low federal minimum wage, “fair” payment demands predictability, calculative fairness, and, minus a few exceptions, a correlation to time labored.¹¹⁸ Proposition 22, in fact, directly refers to the minimum wage,¹¹⁹ reflecting the profound contemporary association between these ideas of fairness, the minimum wage, and “blue collar” work. And yet the actual effect of Proposition 22, as discussed below, is to obfuscate the minimum wage—and the notion of a living wage. The only worker-led study on worker wages in an on-demand sector (discussed in Part III), for example, found a variable average hourly wage for on-

113. Glickman, *supra* note 89, at 151–52 (internal quotation marks omitted) (quoting Walter Lippmann, Campaign Against Sweating, *New Republic*, Mar. 27, 1915, reprinted in *Selected Articles on Minimum Wage* 42–55 (Mary K. Reely ed., 1917)).

114. See *id.* at 153 (emphasis added) (describing the position of pre-*West Coast Hotel* minimum-wage advocates).

115. See Marc Linder, Farm Workers and the Fair Labor Standards Act: Racial Discrimination in the New Deal, 65 *Tex. L. Rev.* 1335, 1372–75 (1987) (arguing that racial animus in FLSA’s legislative history explains the inclusion of exemptions for domestic and agricultural workers).

116. See Fair Labor Standards Act of 1938, ch. 676, § 6, 52 Stat. 1060, 1062–63 (1938).

117. Glickman, *supra* note 89, at 155 (internal quotation marks omitted) (first quoting Lizabeth Cohen, *Making a New Deal: Industrial Workers in Chicago, 1919–1939*, at 209, 286 (1990); then quoting Nelson Lichtenstein, *The Most Dangerous Man in Detroit: Walter Reuther and the Fate of American Labor* 221 (1995)).

118. The exceptions are narrow, but under FLSA, some workers may not be remunerated for “on-call time.” See Fact Sheet #22: Hours Worked Under the Fair Labor Standards Act (FLSA), DOL, <https://www.dol.gov/agencies/whd/fact-sheets/22-flsa-hours-worked> [<https://perma.cc/6KHR-BUR2>] (last modified July 2008) (explaining that “on-call time” may need to be compensated if there are “constraints on the employee’s freedom”).

119. See Legis. Analyst’s Off., Proposition 22: Analysis of Measure 2 (2020), <https://lao.ca.gov/ballot/2020/Prop22-110320.pdf> [<https://perma.cc/V5YQ-2872>] (referring to “120 percent of the minimum wage” for driving hours, not including wait time, as a way to address concerns about driver minimum-wage protections); Chen & Padin, *supra* note 86.

demand ride-hail drivers in California that fell well below half (and sometimes a third) of the minimum wage in urban areas.

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

C. *“Equal Pay for Equal Work”: Antidiscrimination Laws*

Despite a persistent pay gap across social groups (between men and women¹²⁰ and between racial minorities and the white majority),¹²¹ U.S. antidiscrimination 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.¹²² 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. Regarding 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 treatment is related to a protected identity.¹²³ The Equal Pay Act, by contrast, which emerged out of the “equal pay for equal work”

120. See, e.g., Press Release, DOL, Equal Pay Day 2023 (Mar. 14, 2023), <https://www.dol.gov/newsroom/releases/osec/osec20230314> [<https://perma.cc/G3BB-MS4V>] (“In the U.S., women who work full-time, year-round, are paid an average of 83.7 percent as much as men, which amounts to a difference of \$10,000 per year. The gaps are even larger for many women of color and women with disabilities.”).

121. See Valerie Wilson & William Darity Jr., *Econ. Pol’y Inst., Understanding Black–White Disparities in Labor Market Outcomes Require Models that Account for Persistent Discrimination and Unequal Bargaining Power* 10 (2022), <https://files.epi.org/uploads/215219.pdf> [<https://perma.cc/E4ZN-TN6J>] (“In 2019, the typical (median) [B]lack worker earned 24.4% less per hour than the typical white worker. This is an even larger wage gap than in 1979, when it was 16.4%.”).

122. See *supra* note 25 and accompanying text.

123. Section 703 of Title VII of the Civil Rights Act of 1964 reads, in part:

It shall be an unlawful employment practice for an employer—

(1) to fail or refuse to hire or to discharge any individual, or otherwise to discriminate against any individual with respect to his compensation, terms, conditions, or privileges of employment, because of such individual’s race, color, religion, sex, or national origin; or

(2) to limit, segregate, or classify his employees or applicants for employment in any way which would deprive or tend to deprive any individual of employment opportunities or otherwise adversely affect his status as an employee, because of such individual’s race, color, religion, sex, or national origin.

Civil Rights Act of 1964, Pub. L. No. 88-352, tit. VII, § 703, 78 Stat. 253, 255 (codified at 42 U.S.C. § 2000e-2(a) (2018)).

movement, emphasized something slightly different but with the same effect.¹²⁴ Rather than 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.¹²⁵ In doing so, the Act attempted to remedy that women had long been paid less than men even when doing substantially similar work.¹²⁶

Though the “equal pay for equal work” movement garnered some recognition in the wake of World War I, it was not until World War II that the campaign gained significant traction.¹²⁷ Both the American Federation of Labor and the Congress of Industrial Organizations urged the inclusion of equal pay clauses in labor contracts,¹²⁸ 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.”¹²⁹ 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*

124. In her 1910 manifesto *Equal Pay for Equal Work*, Grace Charlotte Strachan wrote powerfully on the problematics of unequal pay within a workforce:

Who will deny that 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.

Grace C. Strachan, *Equal Pay for Equal Work* 10 (1910). 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. See Act of Oct. 30, 1911, ch. 902, 1911 N.Y. Laws 2749–50 (amending the Greater New York City Charter to require that “[i]n the schedules of [teacher] salaries hereafter adopted there shall be no discrimination based on the sex of the [teacher]”); Robert E. Doherty, *Tempest on the Hudson: The Struggle for “Equal Pay for Equal Work” in the New York City Public Schools, 1907–1911*, 19 *Hist. Educ. Q.* 413, 428 (1979) (“Chapter 902 of the 1911 Laws of New York . . . outlawed any form of sex discrimination [in teacher salaries] . . .”).

125. A useful anecdote used during the fight for the Equal Pay Act early in the industrial revolution involved a widow who took over her husband’s job after his death. John Jones, the husband, had earned wages braiding military tunics in a factory. When he fell ill, the factory allowed him to work from home. John’s illness worsened, 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. See Millicent G. Fawcett, *Equal Pay for Equal Work*, 28 *Econ. J.* 1, 1 (1918).

126. H.R. Rep. No. 88-309, at 2–3 (1963), as reprinted in 1963 U.S.C.C.A.N. 687, 688; see also S. Rep. No. 88-176, at 1 (1963) (noting that the Equal Pay Act of 1963 aimed to counter the historical practice of American industry, which paid men more for the same work due to outdated beliefs about a man’s role in society).

127. See Donald Elisburg, *Equal Pay in the United States: The Development and Implementation of the Equal Pay Act of 1963*, 29 *Lab. L.J.* 195, 195–97 (1973).

128. James C. Nix, *Equal Pay for Equal Work*, 74 *Monthly Lab. Rev.* 41, 42 (1952).

129. Marguerite J. Fisher, *Equal Pay for Equal Work Legislation*, 2 *Indus. & Lab. Rels. Rev.* 50, 51 (1948).

*discrimination between employees [within a firm] whose production is substantially the same on comparable jobs.*¹³⁰ In the same decade, nine states passed equal pay laws 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.¹³¹ But the movement achieved its most significant victory in 1963 with the passage of the Federal Equal Pay Act, an amendment to FLSA that banned difference in pay between the two sexes when the employees are performing work that requires "equal skill, effort, and responsibility" and is "performed under similar working conditions."¹³²

In practice, demonstrating that women are performing work "with the same quality and quantity of productivity" as their male counterparts has been a major impediment to achieving equal pay across the genders.¹³³ Yet the Act, however difficult to enforce, 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 idea that women, as a class, should earn similar pay to men for similar work, this focus is explained by the fact that men were, at the time, largely being paid comparable amounts for comparable work relative to other men.

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 between men and women in the economy (which the Equal Pay Act did not adequately remedy) by lowering "the job-flexibility penalty."¹³⁴ And yet Hall and his coauthors in a 2020 study show that even though "neither the pay formula nor the dispatch algorithm for assigning riders to drivers depend on a driver's gender," women working for Uber make roughly seven percent less than men.¹³⁵

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 Power Co.*, firms have been reticent to reveal pay differentials as they pertain to protected categories of workers for fear

130. *Id.* (emphasis added).

131. *Id.* at 52.

132. Equal Pay for Equal Work, DOL, <https://www.dol.gov/agencies/oasam/centers-offices/civil-rights-center/internal/policies/equal-pay-for-equal-work> [<https://perma.cc/FZ6C-BSSQ>] (last visited Aug. 14, 2023).

133. For an overview of reasons the Equal Pay Act has failed—and potential solutions, see generally Kimberly J. Houghton, *The Equal Pay Act of 1963: Where Did We Go Wrong?*, 15 *Lab. Law.* 155 (1999).

134. Cody Cook, Rebecca Diamond, Jonathan Hall, John List & Paul Oyer, *The Gender Earnings Gap in the Gig Economy: Evidence From Over a Million Rideshare Drivers*, 88 *Rev. Econ. Stud.* 2210, 2211 (2021). For more on the moral stigma associated with job flexibility, see generally Joan Williams, Mary Blair-Loy & Jennifer Berdahl, *Cultural Schemas, Social Class, and the Flexibility Stigma*, 69 *J. Soc. Issues* 209 (2013).

135. Cook et al., *supra* note 134, at 2211.

of incurring liability.¹³⁶ 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, the article coauthored by Hall reflects Uber's position that antidiscrimination laws do not apply to them, or at least, that they do not fear liability under the laws. By 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—not firm—choices.

Hall and his coauthors, Cody Cook, Rebecca Diamond, John List, and Paul Oyer, 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 driving speed."¹³⁷ 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 counterintuitively, "hour-within-week differences are a small part of the gender gap."¹³⁸ While women might work around child-rearing or family responsibilities, they do not appear to "pay a large financial price for this."¹³⁹

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.¹⁴⁰ They analogize the gender pay gap found among ride-hail drivers to that found among J.D. and M.B.A. 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 lower paying jobs.¹⁴¹ Unlike in the case of lawyers or M.B.A.s, however, 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 largely by the structure of wage setting—by algorithmic wage discrimination.¹⁴² This, according to Uber's own research, results in gender pay discrimination.¹⁴³ But it also means that

136. In *Griggs v. Duke Power Co.*, the Supreme Court unanimously ruled that employment policies that produce a disparate impact on protected classes of people may violate Title VII, even absent a showing of discriminatory intent. 401 U.S. 424, 435–36 (1971).

137. Cook et al., *supra* note 134, at 2211–12.

138. *Id.* at 2222.

139. *Id.*

140. *Id.*

141. *Id.* at 2237.

142. *Id.* at 2236–37.

143. 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

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.

Part I 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. Part II draws on original ethnographic research to examine the operationalization of algorithmic wage discrimination as a system of labor control and to understand how the practice is subjectively experienced and understood by workers.

II. THE OPERATION AND 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.¹⁴⁴

The findings in this Part reflect over eight years of first-of-its-kind, embedded ethnographic research among 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 included thousands of hours of participant observation and my own action at drivers’ meetings and protests, in meetings with regulators, on group phone calls and texts, in government hearings, on social media, and

lawsuit because disparate treatment lawsuits would require a showing of intentional discrimination), this is largely because the threshold question in such a lawsuit would be whether the drivers are employees. See 42 U.S.C. § 2000e-2 (2018) (describing unlawful employment practices under Title VII); Noah Zatz, *Beyond Misclassification: Gig Economy Discrimination Outside Employment Law* (Jan. 19, 2016), <https://onlabor.org/beyond-misclassification-gig-economy-discrimination-outside-employment-law/> [<https://perma.cc/MXF9-KWTD>]. If not, they are not covered by the Equal Pay Act or Title VII. See 42 U.S.C. § 2000e(a) (defining “employer” under Title VII); id. § 2000e-2(a) (defining “unlawful employment practices” to extend only to the activities of “employer[s]”); id. § 2000e-2(k)(1)(A)(i) (providing the burden-shifting framework for establishing disparate impact liability under Title VII); see also Dubal, *Wage Slave or Entrepreneur?*, *supra* note 28, at 90 & n.77 (“Control over the means and manner of production as required under the common law definition of the employee was, arguably, limited in transportation work. . . . Over and over again, courts found that taxi drivers who leased their cabs were ‘independent contractors’ under the common law.” (footnote omitted)).

144. Donna J. Haraway, *A Cyborg Manifesto: Science, Technology, and Socialist-Feminism in the Late Twentieth Century*, in *Simians, Cyborgs and Women: The Reinvention of Nature* 149, 150 (1991).

through one-on-one conversations. With some drivers, the research continued into social spaces. All the workers in the drivers' groups studied were Uber or Lyft drivers, and many worked for other labor platforms as well, including Doordash, Instacart, Uber Eats, and Postmates (which Uber purchased during the research period). The findings here also reflect participant observation and everyday conversations with workers.¹⁴⁵ This Article analyzes interviews and fieldnotes for how workers described and experienced the digitalized variable pay structures through which they earn.

Drivers described the wage-setting practices of Uber and Lyft—described in section I.A as algorithmic wage discrimination—in relation to and as a disjuncture from long-held wage practices and cultures. Following economic sociologist Viviana Zelizer, this Article maintains that algorithmic wage discrimination—as a nascent economic and legal phenomenon—is thus laden with new and old meanings, institutions, and structures of social relations.¹⁴⁶ Many workers experienced algorithmic wage discrimination as fundamentally in conflict with what they understand as the purpose of work: economic stability and security. A focus on moral economy, then, is a useful analytic to understand not just how this practice objectively departs from existing legal norms but also how workers make sense of this form of labor control and remuneration.

Section II.A analyzes algorithmic wage discrimination—as practiced by on-demand firms like Uber—within the broader history of scientific management theory. It shows how, by obscuring the rules of the workplace, algorithmic wage discrimination departs from the foundations of Taylorism—the management practice of increasing workplace efficiency by breaking production into repetitive tasks and rules—thus creating an environment in which drivers must guess the logic of the algorithms to earn. Building on this, section II.B examines 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,¹⁴⁷

145. Alongside and at the behest of drivers, I also attended protests, spoke at townhalls and in legislative hearings, wrote public essays, and spoke to journalists, unions, lawyers, and (at their requests) lawmakers and regulators about app-deployed work. To protect the identity of most workers in my research, this Article uses first-name pseudonyms. For workers who assume a public role by speaking publicly or writing opinion pieces, this Article uses their real names.

146. See Viviana A. Zelizer, *The Purchase of Intimacy* 41 (2000) (noting that the book will sketch changes in the legal treatment of intimacy issues but “never reconstruct in detail the legal process that produced the changes or deal systematically with their implications”); see also, e.g., Lee et al., *supra* note 40, at 1610 (“[M]any complications . . . can occur when one relies too heavily on quantified metrics without deeper consideration of their meanings and nuances.”).

147. See, e.g., Shapiro, *Dynamic Exploits: Worker Control*, *supra* note 62, at 14–16 (suggesting that management science literature enables a lack of ethical accountability in the platform economy); Kafui Attoh, Katie Wells & Declan Cullen, “We’re Building Their

we know little about how workers understand or experience algorithmic management with respect to wage setting. To the extent that scholarship has focused on workers, it has tended to look instead at their attempts to countermanage the management: how they “gamify” or try to resist the algorithm rather than how they make sense of their compensation.¹⁴⁸ Foregrounding workers’ subjective understandings and experiences is important in order to identify this new technology of pay and control’s everyday impact on workers and to begin to formulate the appropriate regulatory interventions.

The values and norms embedded in both antidiscrimination laws and minimum-wage laws discussed in Part I have become schemas through which workers frame their work experiences as harmful. In defining algorithmic payment structures as unfair and unjust, workers frequently complained of their low hourly wages, even though they were not paid hourly. In describing the harms they suffered, they drew on the language of antidiscrimination law, condemning the variability of their income not just over time but more specifically compared 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

Data”: Labor, Alienation, and Idiocy in the Smart City, 37 *Env’t & Plan. D: Soc’y & Space* 1007, 1011–18 (2019) (using interviews with Uber drivers to understand their working conditions); Siddhartha Bannerjee, Ramesh Johari & Carlos Riquelme, *Dynamic Pricing in Ridesharing Platforms*, 15 *ACM SIGecom Exchs.* 65, 70 (2016) (studying “equilibrium effects of pricing policies in a two-sided marketplace” in revenue management); Kelle Howson, Fabian Ferrari, Funda Ustek-Spilda, Nancy Salem, Hannah Johnston, Srujana Katta, Richard Heeks & Mark Graham, *Driving the Digital Value Network: Economic Geographies of Global Platform Capitalism*, 22 *Glob. Networks* 631, 640–41 (2022) (“These complex, algorithmically managed ratings systems form the cornerstone of Upwork’s digital governance.”); Lee et al., *supra* note 40, at 1608–09 (finding that the “numeric [algorithmic] systems that made drivers accountable for all interactions . . . created negative psychological feelings in drivers”); Alex Rosenblat & Luke Stark, *Algorithmic Labor and Information Asymmetries: A Case Study of Uber’s Drivers*, 10 *Int’l J. Comm’n* 3758, 3765–67 (2016) (describing workers’ experiences with surge pricing); van Doorn, *supra* note 17, at 136 (highlighting the “central role of dynamic pricing” in the algorithmic management of on-demand labor); M. Keith Chen & Michael Sheldon, *Dynamic Pricing in a Labor Market: Surge Pricing and Flexible Work on the Uber Platform 2* (Dec. 11, 2015), https://www.anderson.ucla.edu/faculty/keith.chen/papers/SurgeAndFlexibleWork_WorkingPaper.pdf [<https://perma.cc/H2XS-NLX2>] (unpublished manuscript) (seeking to measure how the dynamic pricing of tasks on online “sharing” and “gig” economy platforms influence the supply of labor on the intensive margin”).

148. See Martin Krzywdzinski & Christine Gerber, *Between Automation and Gamification: Forms of Labour Control on Crowdwork Platforms*, 1 *Work Glob. Econ.* 161, 167 (2021) (noting that studies suggest that “platform workers may also use these digital infrastructures to build networks of solidarity and resistance”); Krishnan Vasudevan & Ngai Keung Chan, *Gamification and Work Games: Examining Consent and Resistance Among Uber Drivers*, 24 *New Media & Soc’y* 866, 874 (2022) (finding that oppositional play is a mode of work in which Uber drivers “actively resist Uber’s gamification”); see also Juho Hamari, Jonna Koivisto & Harri Sarsa, *Does Gamification Work?—A Literature Review of Empirical Studies on Gamification*, in *47th Hawaii International Conference on System Science* 3025, 3029 (2014) (finding that “gamification does work”).

workers against one another, leaving them to wonder what they were doing wrong or what others had figured out.¹⁴⁹ This feature of algorithmic wage discrimination—because of its divisive effects—may also undermine workers’ ability to organize collectively to raise their wages and improve their working conditions.

In addition to complaints about the unfairness of low, variable, and unpredictable hourly pay, workers made two other moral judgements about the techniques through which they were paid. First, as 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. 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 machine boss’s structures and functions 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.”¹⁵⁰

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

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.”¹⁵¹ In early-twentieth-century scientific management, firms broke down factory workers’ motions into “elementary components” and defined each component into a fraction of a second in order to discover how best to divide the labor process and to determine how long worker movements should or could take.¹⁵² Through observation and synthesis of workflows, scientific management attempted to optimize the processes through which work was completed in order to increase

149. See *infra* section II.B.

150. Author’s Fieldnotes, Los Angeles (Mar. 29, 2019) (on file with author).

151. Harry Braverman, *Labor and Monopoly Capital: The Degradation of Work in the Twentieth Century* 118 (1998).

152. See *id.* at 120–22 (noting that management scientists made efforts to “find a means of gaining a continuous, uninterrupted view of human motion” by using, for example, photoelectric waves, magnetic fields, and motion pictures).

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*, was characterized as observing that scientific management substituted “exact knowledge for guesswork, . . . seek[ing] to establish a code of natural laws equally binding upon employers and workmen.”¹⁵³ He went so far as to argue, “No such democracy has ever existed in industry before.”¹⁵⁴ 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.¹⁵⁵ Scholars have shown that other features of Taylorism—such as the fact that it deskilled workforces and made exacting demands of workers’ bodies, essentially treating them as a standardized part of the machine—significantly undermine its conduciveness to workplace democracy.¹⁵⁶ While Taylor’s analysis lacked a realistic assessment of the 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 for work behavior and pay have long been agreed upon as customary in the workplace.

Taylor’s system of scientific management relied on an assumption that no longer remains true 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

153. See Herbert Marcuse, *Some Social Implications of Modern Technology*, in *9 Studies in Philosophy and Social Science* 414, 422 (1941) (internal quotation marks omitted) (quoting Robert F. Hoxie, Appendix II: The Labor Claims of Scientific Management According to Mr. Frederick W. Taylor, in *Scientific Management and Labor* 140, 140 (1916)).

154. Robert F. Hoxie, Appendix II: The Labor Claims of Scientific Management According to Mr. Frederick W. Taylor, in *Scientific Management and Labor* 140, 140 (1916).

155. Id. (arguing that the code of laws would settle any of the workmen’s complaints).

156. See, e.g., Braverman, *supra* note 151, at 119.

“scorecards” in the Amazon DSP context), which are intentionally opaque and highly adaptive to both general demand and worker behaviors.

As in earlier iterations of the application of scientific management to labor, subjective human decisionmaking 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 by learning not just 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 want by withholding work (and therefore wages).¹⁵⁷ In communications researcher Tarleton Gillespie’s terms, the relationship between algorithms and people is “a recursive loop between the calculations of the algorithm and the ‘calculations’ of people.”¹⁵⁸ As Professor 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.¹⁵⁹ Management scholars, per Shapiro’s analysis, have argued that algorithmic levers of control can produce “optimal solutions” to the logistical challenges that firms face when they do not want to exert clear control as bosses (so as to avoid the risk of being legally considered employers).¹⁶⁰ They do so primarily by influencing work time (e.g., through incentives) and work location (e.g., through fare multiplier or surges).¹⁶¹ 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, Shapiro’s 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.¹⁶² Algorithmic wage discrimination thus helps ensure that workers labor

157. Gillespie, *supra* note 40, at 183.

158. *Id.*

159. See Shapiro, *Dynamic Exploits: Calculative Asymmetries*, *supra* note 19, at 168 (observing that management science models are created within the regulatory constraints of workers’ independent-contractor classification).

160. See *id.* at 163 (arguing that surge pricing is an exemplary calculative asymmetry that allows firms to exert control over workers at the aggregate level while still classifying them as independent contractors).

161. See *id.* at 169, 171 (observing that when labor supply is positively elastic, workers respond in predictable ways to wage adjustment as an incentive and also that the platforms depend on spatial incentives).

162. See *id.* at 168 (noting that managers can produce the most desirable outcomes from management’s perspective by calculating the exact wage rates needed in a given situation).

during busy hours, for long periods of time, and in the firm's preferred zones.

To serve this purpose, however, the wage manipulators—in the case of Uber, surges, offers, localized incentives, quests, boosts, bonuses, and 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, California drivers were paid a base fare rooted in what appeared to be an objective calculation: time and mileage. Although drivers claim that the amounts that Uber paid them for time and mileage dropped precipitously over time between 2014 and 2022,¹⁶³ they 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 Fares.”¹⁶⁴ Drivers are presented with a base fare—or the upfront pricing—but do not know how it is calculated.¹⁶⁵ California drivers have argued that upfront pricing has lowered their overall earnings.¹⁶⁶ 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 [I]t's a pay cut in disguise.”¹⁶⁷

Because base fares are generally quite low, drivers rely heavily on surges and quests (alongside other wage manipulators, which, inside the app, are called “offers”) to increase their earnings. But as drivers explained, the surge rate is highly variable between drivers, even within a particular locale. According to Ben, an active driver and organizer with Rideshare Drivers United, “[e]veryone has different levels of surge at any given time. If the median surge is 10, someone else might have 8. We don't know what this is based on. It's not transparent.”¹⁶⁸ 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 to

163. Author's Fieldnotes (July 27, 2022) (on file with author).

164. See Toh, *supra* note 77. Lyft also transitioned to this model and called it “Upfront Pay.” See *id.* For more on upfront pricing, see generally Alison Griswold, *The Devilish Change Uber and Lyft Made to Surge Pricing*, *Slate* (Aug. 23, 2023), <https://slate.com/technology/2023/08/lyft-uber-surge-prime-time-upfront-pricing.html> [<https://perma.cc/53YP-6VYA>].

165. See Toh, *supra* note 77 (reporting that with the Upfront Fares initiative, Uber “will be switching to an algorithm to calculate fares that is more opaque than before”).

166. See Dara Kerr, *Secretive Algorithm Will Now Determine Uber Driver Pay in Many Cities*, *The Markup* (Mar. 1, 2022), <https://themarkup.org/working-for-an-algorithm/2022/03/01/secretive-algorithm-will-now-determine-uber-driver-pay-in-many-cities> [<https://perma.cc/9DLL-MZZ6>] (“Some drivers say . . . that they've mostly seen lower earnings overall since the change [to Upfront Fares] . . . [and] it seems like Uber is taking a bigger cut of fares.”).

167. Telephone Interview with Ben, Driver, Uber (Sept. 26, 2022).

168. *Id.*

\$200.¹⁶⁹ But “quests are not offered every week, not everyone receives a quest when they are offered, and not everyone who is offered a quest is offered the same bonus amount.”¹⁷⁰ Moreover, drivers claim that as they approach the required number of rides to reach their quest, Uber slows down the rate at which it sends them rides.¹⁷¹

TABLE I. LEVERS OF WAGE CONTROL OF PLATFORM WORKERS

	Example of Levers of Wage Control †	Influences
Base Fare	Upfront Pricing	Decision to Accept Ride
Fare Multiplier	Surge Set by Uber	Location of Driver & Amount of Time Worked
Wage Manipulators	Quests, Pay Guarantees, Pro Status	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 to or plan for. While California’s Proposition 22 guarantees drivers 120% of the minimum wage of the area in which they are driving, as mentioned above, this applies only to P1 or “engaged time.”¹⁷² 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—joined with the National Equity Atlas to conduct a study based on their membership. They found that drivers earned, on average, \$6.20 per hour

169. For more on how Uber describes how “Quests” work, see How Does Quest Work?, Uber Help, <https://help.uber.com/riders/article/how-does-quest-work?nodeId=3a43fa72-4fc2-42d0-bc1d-63c4c0bddb9d> [<https://perma.cc/7D22-ANMG>] (last visited Aug. 14, 2023).

170. Interview with Nicole Moore, Rideshare Driver’s United (Sept. 21, 2021); Author’s Fieldnotes (Sept. 21, 2021) (on file with author).

171. Drivers who had driven for more than six months repeatedly raised this concern. This came up in interviews and fieldnotes twenty-eight times between 2020 and 2022.

† As described herein, each of these levers varies overtime and across drivers.

172. See California Proposition 22, App-Based Drivers as Contractors and Labor Policies Initiative (2020), Ballotpedia, [https://ballotpedia.org/California_Proposition_22,_App-Based_Drivers_as_Contractors_and_Labor_Policies_Initiative_\(2020\)](https://ballotpedia.org/California_Proposition_22,_App-Based_Drivers_as_Contractors_and_Labor_Policies_Initiative_(2020)) [<https://perma.cc/Q67K-5DSF>] (last visited Aug. 14, 2023) (explaining that the labor and wage policies enacted by Proposition 22 included an earnings floor based on the minimum wage and a driver’s “engaged time”).

(after accounting for expenses and lost benefits).¹⁷³ Revealingly, many drivers simply did not believe the findings, given the high variability of their individual incomes and the difficulty in calculating their net pay.¹⁷⁴ As Nicole Moore, a part-time driver and RDU leader, said:

After we released the study, we met with sixty-five 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 going to fight for wages we can live on?'¹⁷⁵

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 purposefully so. Because of this opacity, workers cannot trust the firm's or their own market forecasts, nor can they rely on the firm-created incentive structures (or wage manipulators). The time that they must labor to meet their income targets—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, and Gambification*

As the RDU study referenced above makes clear, one significant problem with algorithmic wage discrimination is that it allows companies to pay workers subminimum wages.¹⁷⁶ But the harms of algorithmic wage discrimination extend well beyond low wages. It also upends workers' expectations, grounded in longstanding work law and culture, that they will receive predictable wages that are comparable to other drivers'. Drivers 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 his fellow organizing drivers:

173. See Eliza McCullough, Brian Dolber, Justin Scoggins, Edward-Michael Muña & Sarah Treuhaft, Prop 22 Depresses Wages and Deepens Inequities for California Workers, Nat'l Equity Atlas (Sept. 21, 2022), <https://nationalequityatlas.org/prop22-paystudy> [<https://perma.cc/6BA7-V835>] ("[T]he National Equity Atlas partnered with Rideshare Drivers United and 55 rideshare drivers working across the state's major rideshare markets to collect and analyze driver data from November 1, 2021, to December 12, 2021 . . .").

174. Telephone Interview with Nicole Moore, Rideshare Drivers United (Sept. 23, 2021).

175. *Id.*

176. See *supra* note 173 and accompanying text.

I need a real living wage. Not some fake minimum wage. 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.*¹⁷⁷

The following sections examine how workers talk about the lack of predictability that Carlos describes. Drivers like Carlos object 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 in 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 Moore, 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.¹⁷⁸

In addition to decreasing wages over time—due both to systemwide “pay cuts” and to the personalized nature of algorithmic wage discrimination—workers who labored for longer hours complained that they earned less per hour than workers who worked shorter hours. Hall and his coauthors confirmed this in their study on gendered wage disparities, noting a “decreasing return [for drivers] to within-week work intensity.”¹⁷⁹ Thus, a worker who labors for thirty hours a week tends to

177. Author's Fieldnotes, New York (Sept. 29, 2022) (on file with author) (emphasis added).

178. Telephone Interview with Nicole Moore, Rideshare Drivers United (Aug. 6, 2019).

179. See Cook et al., *supra* note 134, at 2229 (“This [analysis] shows that, at least for Uber drivers, there is significant financial value in accumulated experience and a mildly decreasing return to within-week work intensity.”).

earn less per hour than a worker who labors for twenty hours a week. Again, this phenomenon runs counter to moral expectations about work: 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 got a loan, bought a car, and started driving. He lived two hours outside of the city and 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 each week at home with his family. But at the time of our conversation, Adil was not earning enough to make his rent or pay for his car, which was on the verge of being repossessed. 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 unsecure, 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, they find something else, oh man, I will be out immediately . . . I am a very patient person, that's why I can continue . . . 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?¹⁸⁰

In contrast to Adil, who experienced his poor fortunes compared to other drivers as largely mysterious, some drivers had clear explanations for their experiences. Diego told me, “Anytime there’s some big shot getting high payouts, 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.”¹⁸¹ For many drivers like Adil, Nicole, and Diego, their inability to 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 the understanding of what contract-based work provides under industrial capitalism: the security of labor in exchange for a stable wage. But it also

180. Interview with Adil, Driver, Uber, S.F., Cal. (Mar. 4, 2016).

181. Interview with Diego, Driver, Uber, S.F., Cal. (May 5, 2017). Diego’s interpretation of how on-demand wages work is not dissimilar from how multilevel marketing schemes work. See Jon M. Taylor, Consumer Awareness Inst., *The Case (for and) Against Multi-Level Marketing* ch. 2, at 24 (2011) (“There is seldom any functional justification for five or more levels in [a multilevel marketing] hierarchy of participants[,] other than to encourage recruiting and the illusion of very large potential incomes—which only a few enjoy.”).

creates a divisiveness within the workforce that makes it harder for workers to collectivize and address the harms of this form of compensation and control.

2. *Trickery and Gambification.* — In response to algorithmic prodding enacted through wage manipulators discussed above, workers must make decisions—asserting calculative agency.¹⁸² They do this by drawing on both their acquired knowledge of the algorithmic systems and their knowledge of urban spaces. This agency is circumscribed, however, by the opaque and constantly changing algorithmic systems and wage manipulators that firms offer them. 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 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 you're 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.¹⁸³

Such obscurity generates many concerns about wage manipulation. For example, Domingo felt over time like 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 the weeks, it felt like the algorithm was punishing me. I had ninety-five out of ninety-six rides for a \$100 bonus It was ten o'clock at night in a popular area. It took me forty-five minutes 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. 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 forty-five minutes of dead time, hoping that I would go home and give up. Really feels like you are being

182. The work of Michel Callon and Fabian Muniesa influenced this characterization. In an influential organizational study paper, they theorize the calculative character of markets by defining their three constitutive elements: economic goods, economic agents, and economic exchanges. Michel Callon & Fabian Muniesa, *Peripheral Vision: Economic Markets as Calculative Collective Devices*, 26 *Org. Stud.* 1229, 1245 (2005) (“Economic calculation . . . is not a purely human mechanical and mental competence; it is distributed among human actors and material devices. . . . These three elements (goods, agents, and exchanges) constitute three possible starting-points for exploring markets as complex calculative devices.”).

183. Interview with Tobias, Driver, S.F., Cal. (Sept. 21, 2021).

manipulated—not random chance but literally feels like you’re being punished by some unknown spiteful god.¹⁸⁴

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.”¹⁸⁵

Perhaps no wage manipulator received more suspicion from drivers than surges—which are a major portion of overall driver income. Drivers overwhelmingly believed that surges are a form of trickery Uber enacts upon them, and they reported either not responding to surges or using another app to judge whether a surge was real or not. In other words, they independently determined whether there was actual demand in a given area or whether Uber was instead 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.¹⁸⁶

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

184. Author’s Fieldnotes, San Francisco (May 20, 2020) (on file with author).

185. Telephone Interview with Melissa, Driver (Feb. 2020).

186. Interview with Derrick, Driver, Burlingame, Cal. (Mar. 9, 2017).

threads, I received text messages that alerted drivers to avoid certain areas (e.g., “I’m in the Marina. It’s dead. Fake surge.”).¹⁸⁷ The expectation not only that firms withhold information from workers but also that some information firms provide is “fake” has become a well-known phenomenon among those who study the field. Management scientists Harish Guda and Upender Subramanian have even proposed that on-demand firms “misreport” demand information to control worker behavior.¹⁸⁸ As Shapiro explains, Guda and Subramanian encourage firms to “mislead[]” workers by exaggerating surges more and more as workers “become suspicious of platform information.”¹⁸⁹

This sense that algorithmic wage discrimination techniques are 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 worked for Uber on the side to help pay his disabled child’s medical expenses, explained why he decided to join a group of workers 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 up 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.¹⁹⁰

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 ride-hailing work as a form of gambling. The trickery and opacity 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.¹⁹¹ But these

187. Author’s Fieldnotes, San Francisco (Apr. 10, 2017) (on file with author).

188. Harish Guda & Upender Subramanian, *Your Uber Is Arriving: Managing On-Demand Workers Through Surge Pricing, Forecast Communication, and Worker Incentives*, 65 *Mgmt. Sci.* 1995, 2000 (2019).

189. Shapiro, *Dynamic Exploits: Worker Control*, supra note 62, at 16. Shapiro cites a previous version of Guda & Subramanian’s article, supra note 188, that was posted online prior to its final publication.

190. Author’s Fieldnotes (Mar. 15, 2022) (on file with author).

191. Vasudevan & Chan, supra note 148, at 869 (quoting Tae Wan Kim & Kevin Werbach, *More Than Just a Game: Ethical Issues in Gamification*, 18 *Ethics Info. Tech.* 157, 157 (2016)). Scholars Krishnan Vasudevan and Ngai Keung Chan also note that gamification of labor “becomes predatory” when it is “designed to cultivate ‘obsessive

“games”—in the form of surges or quests—may better be conceived as *gambles*, or in sociologist Ulrich Beck’s terms, “manufactured uncertainties,”¹⁹² 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.¹⁹³

Workers describe how the very structure of the system—seemingly random patterning of incentive allocation—produces subjective shifts in which they feel possibility and impossibility, freedom and unfreedom.¹⁹⁴ The occasional good fare or high surge allocation keeps many workers 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. Moore 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 calculation is happening. If someone is making forty dollars 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.¹⁹⁵

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

behavior,’ while limiting ‘rational self-reflection.’” Id. (quoting Tae Wan Kim & Kevin Werbach, *More Than Just a Game: Ethical Issues in Gamification*, 18 *Ethics Info. Tech.* 157, 164 (2016)). While gamification may indeed incite obsessive behavior, the larger point 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.

192. See Ulrich Beck, *World Risk Society and Manufactured Uncertainties*, 1 *Iris* 291 (2009) (“[Manufactured uncertainties] are distinguished by the fact that they are . . . created by society itself, immanent to society and thus externalizable, collectively imposed and thus individually unavoidable . . .”).

193. Economic sociology scholar 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. For example, Lehdonvirta finds that Mechanical Turk 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*, 33 *New Tech. Work & Emp.* 13, 22 (2018). For more on this model, see generally Alex J. Wood, Mark Graham, Vili Lehdonvirta & Isis Hjorth, *Good Gig, Bad Gig: Autonomy and Algorithmic Control in the Global Gig Economy*, 33 *Work Emp. & Soc’y* 56 (2019) (finding that although remote gig workers experienced “high levels of autonomy . . . [and] potential spatial and temporal flexibility” these same qualities produced by “algorithmic control” also resulted in “overwork, sleep deprivation, and exhaustion” since they often “[had] little real choice” in how, where, or for how long they worked).

194. See Rosenblat & Stark, *supra* note 147, at 3777 (discussing how Uber drivers do not experience the freedom and flexibility that Uber advertises).

195. Telephone Interview with Nicole Moore, Rideshare Drivers United (Mar. 29, 2019) (emphasis added).

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 two to three 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!¹⁹⁶

In dynamic interactions between a worker and the app, the machine—like a supervisor—is a powerful, personalized conduit of firm interests 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.¹⁹⁷ Perhaps most insidiously, however, the manufactured uncertainties of algorithmic wage discrimination also generate hope (that a fare will offer a big payout or that next week's quest guarantee will be higher than this week's) that temporarily defers or suspends the recognition that the “house always wins.”¹⁹⁸ The cruelty of those temporary moments of optimism becomes clear when workers get their payout and subtract their costs.¹⁹⁹

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 longstanding social and legal norms around work.²⁰⁰

III. REORIENTING GOVERNANCE OF DIGITALIZED PAY: TOWARD A NONWAIVABLE PEREMPTORY BAN ON ALGORITHMIC WAGE DISCRIMINATION

“Humans Aren't Computers! End AI Oppression!”

— Sign held by a protesting Uber driver.

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

196. Telephone Interview with Ben, Driver, Uber (Aug. 22, 2022) [hereinafter August 2022 Interview with Ben].

197. See, e.g., Rosenblat & Stark, *supra* note 147, at 3764 (discussing how Uber hides its pay structure from drivers).

198. See August 2022 Interview with Ben, *supra* note 196.

199. This Article draws conceptually on Lauren Berlant's idea of “cruel optimism.” Lauren Berlant, *Cruel Optimism* 1 (2011) (“A relation of cruel optimism exists when something you desire is actually an obstacle to your flourishing.”).

200. See Bolton & Laaser, *supra* note 23, at 512 (discussing a morality-driven theory of labor that emphasizes the humanity of the labor force).

[R]iots were triggered off by soaring prices, by malpractices among dealers, or by hunger. But these grievances operated within a popular consensus as to *what were legitimate and what were 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 within the community*. . . . An outrage to these moral assumptions, quite as much as actual deprivation, was the usual occasion for direct action.²⁰¹

But 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.²⁰² During a historic era of industrial upheaval, protestors' actions were future looking.²⁰³ As anthropologists Jaime Palomera and Theodora Vetta have 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."²⁰⁴ Their protests were intended to demarcate the boundaries of what they believed a moral economy should look like in the coming century.²⁰⁵

In this contemporary moment of rupture in the legal and social relationship between firms and workers under informational capitalism, there is a great deal of popular mobilization on the basis of beliefs about illegitimate wage calculation and digital compensation systems.²⁰⁶ Through direct actions, strikes, protests, and lawsuits, on-demand workers all over the world have asserted discontent and outrage over the practices

201. E.P. Thompson, *The Moral Economy of the English Crowd in the Eighteenth Century*, 50 *Past & Present* 76, 78–79 (1971) [hereinafter *Thompson, Moral Economy*] (emphasis added). In this foundational text on moral economy, Thompson discusses the shift from the subsistence economy to the wage economy. Id. Thompson revisited this article in 1991 and made clear that industrial capitalism was not an amoral economy. E.P. Thompson, *Customs in Common* 270–71 (1991) [hereinafter *Thompson, Customs*]. In doing so, he clarified that his essay was about a shift from a particular moral economy to a new moral economy. Id. Thompson argued that free market theories that attempted to divest moral imperatives from market relations created new kinds of moral problems. Id.

202. Thompson, *Moral Economy*, supra note 201, at 79.

203. See Thompson, *Customs*, supra note 200, at 340–41 (praising a forward-looking definition of moral economy when discussing the protests); Palomera & Vetta, supra note 42, at 424 (arguing that the riots described by Thompson were "future-oriented").

204. Palomera & Vetta, supra note 42, at 424.

205. Thompson, *Moral Economy*, supra note 201, at 79 ("[The protestors' convictions were] grounded upon a consistent traditional view of social norms and obligations, of the proper economic functions of several parties within the community, which, taken together, can be said to constitute the moral economy of the poor.").

206. See, e.g., Faiz Siddiqui, *Uber and Lyft Drivers Strike for Pay Transparency—After Algorithms Made It Harder to Understand*, *Wash. Post* (May 8, 2019), <https://www.washingtonpost.com/technology/2019/05/08/uber-lyft-drivers-strike-pay-transparency-after-algorithms-made-it-harder-understand/> (on file with the *Columbia Law Review*) (discussing numerous demonstrations by Uber and Lyft drivers to lobby for improved pay and increased transparency).

of control and compensation that this Article theorizes as algorithmic wage discrimination.²⁰⁷

In these acts of resistance, workers have frequently demanded the traditional wage floor associated with employment status.²⁰⁸ But, recognizing that this would not solve all the harms that arise from digitalized variable pay (after all, gamblification and trickery could still exist alongside a minimum-wage floor), many organized worker groups and labor advocates have turned their attention to the data and algorithms that are invisible to them.²⁰⁹ In this sense, they are not just calling for a return to the Fordist employment system but rather attempting to redefine the terms of work in relation to informational capitalism and its indeterminate future(s).²¹⁰

As a first step, these workers have sought to make transparent both the data and the algorithms that determine their pay (including those that determine work allocation).²¹¹ This Part examines two important, worker-engaged forms of resistance that attempt to deal with the interrelated problems of pay and data in the on-demand economy and discusses their promises and limitations. Some workers have sought to leverage the European General Data Protection Regulation (GDPR) and analogous U.S. state laws, including the California Privacy Protection Act (CPPA), to learn what data are extracted from their labor and how the algorithms govern their pay.²¹² Others have creatively used business association laws to maximize workers' financial gain and control through parallel data collection, collective data ownership, and sale of datasets.²¹³

Sections III.A and III.B argue that both data transparency approaches and data collectives are critical forms of resistance but also that they cannot by themselves address the social and economic harms produced by

207. See Ioulia Bessa, Simon Joyce, Denis Neumann, Mark Stuart, Vera Trappmann & Charles Umney, *A Global Analysis of Worker Protest in Digital Labour Platforms 8–10* (Int'l Lab. Org., Working Paper No. 70, 2022), https://www.ilo.org/wcmsp5/groups/public/-dgreports/-inst/documents/publication/wcms_849215.pdf [<https://perma.cc/5F4E-ZZVQ>] (outlining various forms of protest by on-demand workers in opposition to issues like algorithmic management).

208. *Id.* at 8 (discussing on-demand digital platform workers' campaigns for minimum-wage legislation).

209. *Id.* (discussing worker unrest regarding algorithmic management).

210. See Rana Foroohar, *How the Gig Economy Could Save Capitalism*, *Time* (June 15, 2016), <https://time.com/4370834/sharing-economy-gig-capitalism/> [<https://perma.cc/7QZG-T2C7>] (“[T]he platform technologies of the ‘sharing economy’ might offer the possibility of empowering labor in a new way, creating a more inclusive and sustainable capitalism.”).

211. See, e.g., Siddiqui, *supra* note 206; see also *infra* section III.A.

212. See, e.g., Natasha Lomas, *Drivers in Europe Net Big Data Rights Win Against Uber and Ola*, *TechCrunch* (Apr. 5, 2023), <https://techcrunch.com/2023/04/05/uber-ola-gdpr-worker-data-access-rights-appeal/> [<https://perma.cc/3TSU-JE59>] (discussing drivers' actions against Uber and Ola under the GDPR).

213. See *infra* section III.B.

algorithmic wage discrimination and its associated practices. Section III.C proposes that addressing the harms caused by the algorithmic wage discrimination detailed throughout this Article requires not merely shifting control over the data—for example, by democratizing workplace data relations—but rather envisaging a peremptory restriction on the practice altogether. This, in turn, may disincentivize or even eliminate certain forms of data collection and digital surveillance that have long troubled privacy and work law scholars (and, of course, workers themselves).

This Article thus invites scholars studying about 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: what I have called the “data abolition” objective.²¹⁴ Data extraction at work is neither an inevitable nor necessary instrument of labor management—especially when analyzed through the lens of moral economy.

A. *The Limits of Data Transparency and Algorithmic Legibility*

One of the most frequently proposed policy reforms for platform labor in the global fight to recognize the employment status of many on-demand workers (including Uber drivers) concerns 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 setting and labor controls more comprehensible and transparent to workers, consumers, and governing bodies.²¹⁵ Those who have tried or are trying to use data privacy laws such

214. The term “data abolition” invites scholars and advocates to think about how ending digital data extraction can be a movement’s aspiration, accomplished via statute or bargained for by contract. Using the term “abolition” draws upon W.E.B. Du Bois’s articulation of “abolition democracy.” W.E.B. Du Bois, *Black Reconstruction in America: Toward a History of the Part Which Black Folk Played in the Attempt to Reconstruct Democracy in America, 1860–1880*, at 163 (Routledge 2017) (1935) (“[One theory of the future of America] was abolition-democracy based on freedom, intelligence and power for all men; the other was industry for private profit directed by an autocracy determined at any price to amass wealth and power.”). In Du Bois’s making, employers’ extraordinary power to subordinate workers—both Black and white—undermined the promise of Reconstruction for Black labor. 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 211. 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 toward coordinating more racially just and equitable workplaces and economies. But under informational capitalism, it is an essential one.

215. See, e.g., S.B. 23-098, 74th Gen. Assemb., Reg. Sess. (Colo. 2023); Sara Wilson, *Colorado Bill Aims to Increase Transparency for Uber, Lyft Driver Pay*, Colo. Newline (Jan. 31, 2023), <https://coloradonewline.com/2023/01/31/colorado-transparency-uber-lyft-driver-pay/> [<https://perma.cc/Q483-58YF>] (“It’s about transparency. Companies would

as GDPR and analogous U.S. laws 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 coworker, Yaseen Aslam, Farrar founded a union of on-demand workers called the App Drivers & Couriers Union (ADCU), and in 2015, they sued Uber for basic workers' rights, including the national minimum wage.²¹⁶ Farrar and Aslam (and their twenty-five coplaintiffs) won their case after six years of litigation, receiving a historic positive judgement from the U.K. Supreme Court in February 2021.²¹⁷ The Court found (among other things) that the drivers were entitled to minimum-wage protections for all the time they spent logged

have to disclose the take rates to the drivers and customers before it happens. Sometimes that is not disclosed to a driver before we accept a ride.” (internal quotation marks omitted) (quoting Brian Winkler, Organizer, Colo. Indep. Drivers United)); Press Release, Council of the EU, Rights for Platform Workers: Council Agrees Its Position (June 12, 2023), <https://www.consilium.europa.eu/en/press/press-releases/2023/06/12/rights-for-platform-workers-council-agrees-its-position/> (on file with the *Columbia Law Review*) (“Digital labour platforms regularly use algorithms for human resources management. As a result, platform workers are often faced with a lack of transparency The Council wants to ensure that workers are informed about the use of automated monitoring and decision-making systems.” (emphasis omitted)). For examples in the academic literature, see, e.g., Dan Calacci & Alex Pentland, Bargaining With the Black-Box: Designing and Deploying Worker-Centric Tools to Audit Algorithmic Management, 6 Proc. ACM Hum-Comput. Interaction (CSCW2), art. 428, 2022, at 1, 20 (noting that “data access for platform workers is also a larger project than just ‘bargaining with the black box’ for higher wages” because that data itself has other value to the workers); Toby Jia-Jun Li, Yuwen Lu, Jaylexia Clark, Meng Chen, Victor Cox, Meng Jiang, Yang Yang, Tamara Kay, Danielle Wood & Jay Brockman, A Bottom-Up End-User Intelligent Assistant Approach to Empower Gig Workers Against AI Inequality 1, 2 (CHIWORK Symposium on Human-Computer Interaction for Work 2022), <https://arxiv.org/pdf/2204.13842.pdf> [<https://perma.cc/FPM9-WN7M>] (noting that the use of AI in the gig economy disadvantages workers that have neither access to their data nor the tools to analyze it); Antonio Aloisi, Valerio De Stefano & Six Silberman, A Manifesto to Reform the Gig Economy, Wolters Kluwer: Glob. Workplace L. & Pol’y (May 1, 2019), <https://global-workplace-law-and-policy.kluwerlawonline.com/2019/05/01/a-manifesto-to-reform-the-gig-economy/> [<https://perma.cc/6K4D-RS72>] (advising the development of standards and regulations to “temper the impulse to technological novelty . . . with sustained and serious action to safeguard workers’ rights and build worker power in digital labour platforms”).

216. About Us, App Drivers & Couriers Union, <https://www.adcu.org.uk/about-us> [<https://perma.cc/CEF4-P928>] (last visited Aug. 14, 2023).

217. Mary-Ann Russon, Uber Drivers Are Workers Not Self-Employed, Supreme Court Rules, BBC News (Feb. 19, 2021), <https://www.bbc.com/news/business-56123668> [<https://perma.cc/EXD7-E3V>].

onto the app, including P1 or nonengaged time.²¹⁸ Still, to date, Uber has refused to guarantee a minimum-wage floor or pay workers for all the time that they labor, claiming the holding no longer applies to their operations because the on-the-ground facts have changed since the case was adjudicated.²¹⁹ 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:

Uber challenged me with my own data, and they came to the tribunal with sheaves 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*.²²⁰

Prompted by this realization, Farrar founded Worker Info Exchange—a United Kingdom–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 compensate them. Farrar and Worker Info Exchange have since sued several on-demand companies for not sharing basic information on what data they collect from their workers’ labor. But as Farrar states, “[W]hat we really want are *inference data*. What decisions has [the

218. See *Uber BV v. Aslam* [2021] UKSC 5 [138] (Eng.).

219. In 2021, soon after the High Court ruling finding that Uber drivers are workers and deserve minimum-wage protections, the company reached a private agreement with the United Kingdom’s largest union—the GMB, which funded the ADCU litigation. The GMB, like the Machinists Union in New York City that formed the Independent Drivers Guild (IDG) (an unselected worker association that receives funding from Uber and Lyft), gets to organize drivers at hubs and contest driver termination. See Natasha Bernal, *Uber’s Union Deal Doesn’t Mean the Battle Is Over*, *Wired* (May 27, 2021), <https://www.wired.co.uk/article/uber-gmb-recognition-deal/> [<https://perma.cc/QZ4V-KU4G>]. But the GMB, unlike the IDG, does not insist that the company pay workers for all the time that workers spend laboring and appears to completely forgo collective bargaining on pay. *Id.* Instead, under the GMB–Uber agreement, Uber continues to pay workers a minimum wage only for “engaged time.” UK Business Model Change, *Uber* (Feb. 24, 2022), <https://www.uber.com/en-GB/blog/driver-terms-faq/> [<https://perma.cc/SSR2-P654>] (“It’s important to note that these changes do not affect the worker protections that we provide to drivers on the Uber app . . . You are still guaranteed to earn at least the National Living Wage for the engaged time you spend on the app . . .”). 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 the GMB agreed to these terms, the United Food and Commercial Workers International (UFCW) in Canada signed a similar agreement with Uber. David Doorey, *The Surprising Agreement Between Uber and UFCW in Canada in Legal Context*, *OnLabor* (Jan. 31, 2022), <https://onlabor.org/the-surprising-agreement-between-uber-and-ufcw-in-canada-in-legal-context/> [<https://perma.cc/6KGT-5YU5>].

220. Bama Athreya, *With One Huge Victory Down, UK Uber Driver Moves On to the Next Gig Worker Battlefield*, *Inequality.org* (Apr. 5, 2021), <https://inequality.org/research/uk-uber-drivers/> [<https://perma.cc/ZMC6-97VR>] (emphasis added) (internal quotation marks omitted) (quoting interview with James Farrar).

app] made about me? How has it profiled me? How does that affect my earnings? This is what Uber has not given us.”²²¹

CPPA went into effect for workers in January 2023. Drivers organizing with RDU, drawing on Farrar’s work, are positioned to pursue similar legal inquiries. Both RDU and Worker Info Exchange base 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.²²² Workers’ “rights to know” how they are governed and remunerated by automation technologies largely reflect what scholars of informational capitalism, including those who authored the White House *Blueprint*, have argued the public needs: technological 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,²²³ efforts by Farrar and others to gain transparency over—and even to “reverse engineer”—the labor management structures that produce algorithmic wage discrimination have yet to change firm practices.²²⁴ In theory, Article 22 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 decisionmaking and to challenge these decisions if they “produce legal effects.”²²⁵ Article 15 of the GDPR grants data subjects the right to receive a copy of their personal data and to attain information about how that data is processed and shared.²²⁶ To date, some

221. *Id.*

222. Author’s Fieldnotes (Apr. 30, 2022) (on file with author).

223. Media studies scholar 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. See van Doorn, *supra* note 17, at 146. 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. *Id.*

224. *Id.* at 148 (declaring a need for labor organizers and workers to continue working against the “unchecked power” of gig platforms).

225. Article 22 of the 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.” Council Regulation 2016/679, 2016 O.J. (L 119) 46 (EU).

226. 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 information:

(a) the purposes of the processing;
(b) the categories of personal data concerned;

on-demand companies have made data downloads available to workers who request them.²²⁷ 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.”²²⁸

Even in cases where the companies have released the data, they have released little information 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.²²⁹ A lower court ruling found 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

(c) 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;

(d) where possible, the envisaged period for which the personal data will be stored, or, if not possible, the criteria used to determine that period;

(e) 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;

(f) the right to lodge a complaint with a supervisory authority;

(g) where the personal data are not collected from the data subject, any available information as to their source;

(h) 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.

2016 O.J. (L 119) 43.

227. Safak & Farrar, *supra* note 19, at 43.

228. *Id.* at 44.

229. WIE and ADCU Challenge Uber and Ola on Data Access and Automated Decision-Making, Worker Info Exch. (May 18, 2022), <https://www.workerinfoexchange.org/post/worker-info-exchange-and-adcu-challenge-uber-and-ola-on-data-access-and-automated-decision-making> [<https://perma.cc/4FK8-CR8J>] (“ADCU and Worker Info Exchange challenge Uber and Ola Cabs on behalf of 11 UK and Portugal based drivers for data access and algorithmic transparency at the Amsterdam Court of Appeal.”).

uses the data in its algorithms.²³⁰ In April 2023, however, the Amsterdam appellate court overturned the decision, finding that Uber “must explain how driver personal data and profiling is used in Uber’s upfront, dynamic pay and pricing system.”²³¹ But like in the *Blueprint* 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.²³²

Drawing on Professor Frank Pasquale’s analysis, this Article argues 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 automated decisionmaking management structures. Absent a ban on algorithmic wage discrimination under Article 22 of the GDPR or through collective bargaining agreements, transparency requests are by themselves ineffectual.²³³ Knowledge alone will not end or mitigate the precarities of digitalized pay.

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 gambification 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 diminish the feeling of being manipulated, given the rapid rate at which machine learning systems change compared 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 on wage standardization in a fair and predictable way.

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 tools that

230. Safak & Farrar, *supra* note 19, at 71 (emphasis added); see also RBAMS Amsterdam 24 februari 2021, RvdW 2021, C/13/696010 / HA ZA 21-81 m.nt (Uber B.V.) (Neth.) (ordering reinstatement of plaintiff drivers and payment of monetary damages); Jenny Gasley, Netherlands: Amsterdam District Court Classifies Uber Drivers as Employees, *Libr. Cong.* (Sept. 29, 2021), <https://www.loc.gov/item/global-legal-monitor/2021-09-29/netherlands-amsterdam-district-court-classifies-uber-drivers-as-employees/> [<https://perma.cc/52X8-J38E>].

231. Historic Digital Rights Win for WIE and the ADCU Over Uber and Ola at Amsterdam Court of Appeal, *Worker Info Exch.* (Apr. 4, 2023), <https://www.workerinfoexchange.org/post/historic-digital-rights-win-for-wie-and-the-adcu-over-uber-and-ola-at-amsterdam-court-of-appeal> [<https://perma.cc/2YE5-3EQ5>].

232. See, e.g., White House Off. of Sci. & Tech. Pol’y, *supra* note 5, at 7.

233. See Frank Pasquale, *The Black Box Society: The Secret Algorithms that Control Money and Information* 8 (2015) (“Transparency is not just an end in itself, but an interim step on the road to intelligibility.”).

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 results in low and unpredictable wages; rather, it is the extractive logics of well-financed firms in these digitalized practices and workers' comparatively small institutional power that cause both individual and workforce harms.²³⁴

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.²³⁵ With this in mind, advocates have launched at least two novel data cooperative projects: Driver’s Seat Cooperative (in the United States) and WeClock (in Europe).²³⁶ These cooperative efforts, which countercollect data collected by on-demand firms using separate apps, 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.”²³⁷

To be sure, such cooperatively organized collections of personal data have been useful for workers who have been able to contest unfair suspensions or terminations based on errors in facial recognition or in geolocation checks conducted by the companies.²³⁸ But most U.S. workers 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 for termination or suspension decisions (often made algorithmically).²³⁹ A worker may go to a physical Uber or Lyft “hub” to complain or may attempt to engage with the firm via their app, but getting

234. Jathan Sadowski, *Too Smart: How Digital Capitalism Is Extracting Data, Controlling Our Lives, and Taking Over the World* 104 (2020) (“Even if we had access to all the data collected about us, ‘what individuals can do with their data in isolation differs strikingly from what various data collectors can do with this same data in the broader context of everyone else’s data’” (quoting Mark Andrejevic, *The Big Data Divide*, 8 *Int’l J. Commc’n* 1673, 1674 (2014))).

235. Thomas Hardjono & Alex Pentland, *Data Cooperatives: Towards a Foundation for Decentralized Personal Data Management* 3 (May 15, 2019) (on file with the *Columbia Law Review*) (unpublished manuscript).

236. See Driver’s Seat, <https://driversseat.co/> [<https://perma.cc/925C-P6WU>] (last visited Aug. 15, 2023); WeClock, <https://weclock.it/> [<https://perma.cc/UG5H-2PP6>] (last visited Aug. 15, 2023).

237. Safak & Farrar, *supra* note 19, at 82.

238. See, e.g., *id.* at 17–25.

239. Author’s Fieldnotes (Feb. 21, 2019) (on file with author).

reinstated or correcting a wrong is difficult, if not impossible, regardless of whether the automated suspension or termination is based on incorrect data.²⁴⁰ 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 hiring entities and workers. Having some knowledge of the data 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 production is labor,”²⁴¹ these approaches may reify widespread data collection as a social good, thus ignoring individual and social harms that result from broad surveillance, categorization, and data derivative processing.²⁴² While scholars Jaron Lanier, Eric Posner, and Glen Wyle’s basic presumptions about how workers and consumers are not compensated for the data that they provide to firms is correct, their solution—to pay them for it—raises more problems than it solves.²⁴³

The underlying assumption 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 that 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.²⁴⁴ For one, the value (and quality) of such workplace-derived datasets to the firm itself and to downstream buyers is unknown

240. *Id.*

241. See, e.g., Eric A. Posner & E. Glen Weyl, *Radical Markets: Uprooting Capitalism and Democracy for a Just Society* 230 (2018).

242. See Salomé Viljoen, *A Relational Theory of Data Governance*, 131 *Yale L.J.* 573, 643 (2021) (“[B]y forming and then acting on population-level similarities in oppressive and dominating ways, datafication may materialize classificatory acts of oppressive-category formation that are themselves unjust.”).

243. Posner and Weyl’s book *Radical Markets*, *supra* note 241, draws on Jaron Lanier’s work 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, Pac. Standard* (Sept. 15, 2015), <https://psmag.com/economics/the-future-of-work-stop-the-stealing-and-pay-us-for-our-online-data> (on file with the *Columbia Law Review*) (last updated June 14, 2017) (suggesting that under an “information economy . . . if you’re not paid for your tweets, then you’re being ripped off”). This obfuscates the first order question: Should the data be gathered at all?

244. See Beatriz Botero Arcila, *The System Is Rigged Against Users: Another Reason Why Getting Compensated for Data Is Not a Good Idea*, *Medium* (Feb. 23, 2020), <https://medium.com/berkman-klein-center/the-system-is-rigged-against-users-another-reason-why-getting-compensated-for-data-is-not-a-good-ebb2192a3209> (on file with the *Columbia Law Review*) (critiquing Lanier, Posner, and Weyl’s contentions).

and fluctuating. As Professor 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 indeterminate.²⁴⁵ To date, “data extraction [from workers] . . . [has provided] a stream of capital that is infinitely speculatable . . . with minimal . . . downward redistribution.”²⁴⁶

This is not to say that these worker data cooperatives have no role in the current regulatory environment. To the contrary, data cooperatives have been important 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 RDU wage study, released in 2022 and referenced in Part II, was made possible through collaboration with the Driver’s Seat Cooperative. The Driver’s Seat Cooperative, run by longtime labor organizer Hays Witt, is a cooperative of ride-hail and delivery workers who share in profits from their data collection.²⁴⁷ The cooperative has sold the pooled data to cities and transportation agencies, who, in turn, desire to use the data to address governance issues.²⁴⁸ Drivers can also use the data to make analytical assessments about their work.²⁴⁹ For example, Driver’s Seat Cooperative helps workers to deduce their “true hourly earnings,” 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.²⁵⁰

In light of the critiques of data as labor and property more generally, this Article argues that this approach’s limitations are threefold. As an initial matter, the assessments made through this model are constantly changing as algorithmic control practices continue to change. This may limit the cooperative’s ability to give workers 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 (and came to rely on these techniques) would often be devastated when their knowledge about the system was inevitably upended by changes in the system.²⁵¹ In other words, while data cooperatives might give workers some derivative knowledge

245. See Viljoen, *supra* note 242, at 618–22.

246. Sam Adler-Bell & Michelle Miller, Century Found., *The Datafication of Employment: How Surveillance and Capitalism Are Shaping Workers’ Futures Without Their Knowledge* 2–3 (2018), <https://production-tcf.imgix.net/app/uploads/2018/12/03160631/the-datafication-of-employment.pdf> [<https://perma.cc/9REN-4JM9>].

247. See *People: Hays Witt*, Platform Coop. Consortium, <https://platform.coop/people/hays-witt/> [<https://perma.cc/V9WV-RYEZ>] (last visited Aug. 14, 2023).

248. See *Data Customers*, Driver’s Seat, https://driversseat.co/data_customers/1689706532362x298241080674223940 [<https://perma.cc/JJ9S-9L7E>] (last visited Oct. 20, 2023).

249. See *Index*, Driver’s Seat, <https://driversseat.co/index/1689706532362x298241080674223940> [<https://perma.cc/Y3SK-CHSR>] (last visited Oct. 20, 2023).

250. *Id.*

251. See *supra* Part II.

over the kinds of data that are collected about them, they cannot exert sustained control over the (constantly changing) automation processes that control them and determine their pay. Second, selling cooperatively collected data might be a small income source for workers and that data might be 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 carry no social risks when used to make private or public decisions in other contexts.²⁵² As Viljoen has argued elsewhere, workers cannot know whether the data collected will, at the population level, violate the civil rights of others or amplify their own social oppression.²⁵³

Finally, perhaps the most troubling problem with worker data cooperatives is the complicated (and expensive) nature of automated digital data collection and cooperatives' subsequent reliance on third-party data brokers. Workers who sign up to be members of the Driver's Seat Cooperative, 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"—an unrealistic series of steps for most workers.²⁵⁴ Alternatively, drivers can opt for automatic tracking, a "hassle-free way of tracking their gig work."²⁵⁵ Extracting data from the variety of different apps that its members use is extremely complicated, so the Driver's Seat Cooperative relies on a third-party service called Argyle to connect to the on-demand labor platforms and import their earnings data and activities.²⁵⁶ 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.²⁵⁷ The company claims to have a "longitudinal" dataset of "quality information willingly generated by gig workers," which it sells

252. See Shoshanna Zuboff, *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power* 90 (2019) ("Decision rights confer the power to choose whether to keep something secret or to share it. . . . Surveillance capitalism lays claim to these decision rights. . . . In the larger societal pattern, privacy is not eroded but redistributed, as decision rights over privacy are claimed for surveillance capital.").

253. See Viljoen, *supra* note 242, at 622–23, 651 (arguing that downstream uses of collected data can lead to infringements of civil rights).

254. Frequently Asked Questions, Driver's Seat, <https://driversseat.co/faq/1694143366421x418725978104454800> [<https://perma.cc/P93Q-7SAK>] (last visited Sept. 8, 2023).

255. *Id.*

256. *Id.*

257. Wilneida Negrón, *Little Tech Is Coming for Workers: A Framework for Reclaiming and Building Worker Power* 31 (2021), <https://home.coworker.org/wp-content/uploads/2021/11/Little-Tech-Is-Coming-for-Workers.pdf> [<https://perma.cc/E68P-VM4C>]. 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 24–27.

as its primary source of profits.²⁵⁸ 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 data and customer experience,” uses these datasets to sell and deny hybrid car insurance to gig workers.²⁵⁹ This then raises a host of other concerns about downstream harm: Can companies use this data collected through the Driver’s Seat Cooperative to create and sell data derivatives that trap workers into certain wage brackets based on their income history? Can they (and do they) use this data to target workers for predatory payday loans or to deny other kinds of credit?

As workers formulate and reformulate paths toward redefining “tolerable levels of exploitation and inequality, meanings of dignity and justice” in the context of labor management practices emerging from informational capitalism,²⁶⁰ this Article’s analysis of possibilities and limitations of existing business and data laws suggest that other legal interventions are necessary. Such interventions—including a potential legislative ban on digitalized variable pay—better reflect the harms emerging from these digitalized remuneration practices.

C. *A Nonwaivable 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, this Article proposes a more direct solution: a statutory or regulatory nonwaivable ban on algorithmic wage discrimination, including, but not limited to, a ban on compensation through digitalized piece pay.²⁶¹ This would effectively not only put an end to the gambification of work and the uncertainty of hourly wages but 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 information to make money from

258. See Data Customers, *supra* note 248.

259. Press Release, Argyle Sys., Argyle and DigiSure Partner to Supercharge Screening and Risk Assessment for Gig Drivers, Globe Newswire (July 13, 2022), <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> [https://perma.cc/J6K3-47SK].

260. See Palomera & Vetta, *supra* note 42, at 424.

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

targeted ads,”²⁶² a preemptory ban on algorithmic wage discrimination might also disincentivize the growth of fissured work under informational capitalism.²⁶³ 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.²⁶⁴ If a firm cannot manage wages through digitally determined variable pay systems, then it is less likely to employ algorithmic management in certain circumstances.

This kind of ban is not without precedent. Reflecting the moral and legal norms embedded in wage laws, the spirit of a ban on algorithmic wage discrimination underpins both federal and state antitrust laws. Indeed, Professor Teachout has argued that consumer price discrimination “from the 1870s through the 1970s was [also] understood through a political, moral, and economic lens.”²⁶⁵ 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.²⁶⁶ The FTC 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.”²⁶⁷ Though price discrimination is generally lawful, and the Supreme Court’s interpretation of the Robinson–Patman Act 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.²⁶⁸ Workers—like buyers—understand “moral economies of work” as reflecting systems in which they get predictable “equal pay for equal work”

262. Taylor Hatmaker, *New Privacy Bill Would Put Major Limits on Targeted Advertising*, TechCrunch (Jan. 18, 2022), <https://techcrunch.com/2022/01/18/banning-surveillance-advertising-act/> (on file with the *Columbia Law Review*).

263. “The fissured workplace,” a term developed by economist David Weil, describes the firm trend of focusing on core business competencies and outsourcing or subcontracting other work (including, for example, accounting, payroll, and human resources). This typically lowers labor costs and liabilities for the core firm. David Weil, *The Fissured Workplace: Why Work Became So Bad for So Many and What Can Be Done to Improve It* 3–4 (2014).

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

265. Teachout, *Algorithmic Personalized Wages*, *supra* note 15, at 451.

266. Robinson–Patman Price Discrimination Act of 1936, 15 U.S.C. § 13 (2018).

267. Price Discrimination: Robinson–Patman Violations, FTC, <https://www.ftc.gov/advice-guidance/competition-guidance/guide-antitrust-laws/price-discrimination-robinson-patman-violations> [<https://perma.cc/Vs6L-E3RH>] (last visited Aug. 15, 2023).

268. Keyawna Griffith argues that 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 anticompetitive in effect. Keyawna Griffith, Note, *The Uber Loophole that Protects Surge Pricing*, 26 Va. J. Soc. Pol’y & L. 34, 36, 60 (2019).

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 Colorado-based nonprofit legal organization, have filed a complaint based on state antitrust law in California court, alleging something very similar. They seek to use California antitrust 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.”²⁶⁹ 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 altogether, especially for firms who classify their workers as employees. In those contexts, gambification 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.²⁷⁰ This makes considering an affirmative legal prohibition against the practice of algorithmic wage discrimination an imperative.

The precise limits of a proposed nonwaivable ban need to be explored. This Article seeks to identify and theorize the practice of algorithmic wage discrimination in relationship to longstanding 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. This Article is also designed 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 Teachout has suggested, comport with monopoly principles and affect only firms with a controlling market share?²⁷¹ Or

269. Class Action Complaint at 4, *Gill v. Uber Techs., Inc.*, No. CGC-22-600284 (Cal. Super. Ct. filed June 21, 2022) (emphasis added); see also Class and Collective Action Complaint at 28–29, *Gill v. Uber Techs., Inc.*, No. 3:23-cv-00518 (N.D. Cal. filed Feb. 3, 2023). This is ongoing litigation in federal and state court.

270. Healthcare is one sector in which firms use algorithmic wage discrimination (or what firms call “incentive payment systems”) to control employee work assignment and pay for nurses and janitorial staff. See *supra* note 39 and accompanying text.

271. See Teachout, *Algorithmic Personalized Wages*, *supra* note 15, at 452 (outlining “different ways in which new labor monopsony provisions could interact with personalized labor pricing”).

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 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 datasets on workers. These datasets, combined with machine learning science and insights from behavioral psychology, have come to form what are, as this Article suggests, morally objectionable techniques of work control and compensation. They circumscribe autonomy and economic mobility for highly racialized workforces, and they are seeping into other sectors' labor practices.

In some instances, algorithmic wage discrimination practices produce pay that falls well below what is guaranteed to employees by law. For example, in 2020, California's Labor Commission sued Uber and Lyft, claiming the companies had failed to pay drivers over \$1.3 billion for all hours worked, including unpaid overtime, paid sick leave violations, and reimbursement of business expenses.²⁷² But wage and hour law violations 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 that firms in turn crush to create value for themselves.

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 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 longstanding fairness norms as they pertain to wage practices and wage regulations. To address these problems, this Article invites scholars, lawmakers, and regulators to direct their attention not just to the transparency and accuracy problems of automation technologies at work but also to an evaluation of the social harms embedded in the logic of the algorithmic wage-setting systems themselves.

272. Labor Commissioner's Wage Theft Lawsuits Against Uber and Lyft, Cal. Dep't of Indus. Rels. (Oct. 2020), <https://www.dir.ca.gov/dlse/Lawsuits-Uber-Lyft.html> [<https://perma.cc/FWC4-L3NF>].