Algorithmic Harms to Workers in the Platform Economy: The Case of Uber

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Technological change has given rise to the much-discussed "gig" or "platform economy," but labor law has yet to catch up. Platform firms, most prominently Uber, use machine learning algorithms processing torrents of data to power smartphone apps that promise efficiency, flexibility, and autonomy to users who both deliver and consume services. These tools give firms unprecedented information and power over their services, yet they are little-examined in legal scholarship, and case law has yet to meaningfully address them. The potential for exploitation of workers is immense, however the remedies available to workers who are harmed by algorithm design choices are as yet undeveloped.

This Note analyzes a set of economic harms to workers uniquely enabled by algorithmic work platforms and explores common law torts as a remedy, using Uber and its driver-partners as a case study. Part II places the emerging "platform economy" in the context of existing labor law. Part III analyzes the design and function of machine learning algorithms, highlighting the Uber application. This Part of the Note also examines divergent incentives between Uber and its users alongside available algorithm design choices, identifying potential economic harms to workers that would be extremely difficult for workers to detect. Part IV surveys existing proposals to protect platform workers and offers common law causes of action sounding in tort and contract as recourse for workers harmed by exploitative algorithm design.

I. INTRODUCTION

The past two decades have seen the rise of algorithmic management — the use of algorithms to allocate, manage, optimize, and evaluate workers across a wide range of industries.[1] This trend, coupled with the widespread adoption of smartphones, has given rise to what has been variously termed the "gig economy," the "sharing" economy, the "on-demand economy," or the "platform economy" an ill-defined[2] grouping meant to describe firms that facilitate peer-to-peer services via digital platform marketplaces. These include, most prominently, the transportation network companies Uber and Lyft, as well as firms providing a host of other services, such as moving, cleaning, delivery, repair, or even personal massage.[3] Proprietary algorithms match workers to customers who summon them with the tap of a smartphone, promising a seamless, optimized transaction to users on both sides of the market. In return, the firm providing the platform marketplace collects a percentage of the cost of the service in addition to valuable user data.[4]

The premise of the platform economy is simple: technology firms create app-based digital marketplaces where buyers and sellers can transact in perfect algorithmic harmony. Ostensibly, the interests of buyers, sellers, and platform providers are aligned: classical microeconomic theory predicts that nearly-frictionless online marketplaces will be governed efficiently by

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1. *See* Min Kyung Lee et al., *Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers*, *in* CHI '15 PROC. 33RD ANN. CONF. ON HUMAN FACTORS IN COMP. SYS. 1603 (Seoul, S. Kor., April 18–23, 2015).

2. *See* Charlie Warzel, *Let's All Join the AP Stylebook in Killing the Term "Ride-Sharing,"* BUZZFEED NEWS (Jan. 8, 2015), https://www.buzzfeednews.com/article/charliewarzel/lets-all-join-the-ap-stylebook-in-killing-the-term-ride-shar [perma.cc/YRV7-ENCW].

3. These include TaskRabbit and Dolly for moving or handyman assistance; Handy for maid services; Postmates, DoorDash, and Caviar for food delivery; and Soothe for in-home massage services. *See* Jeff Desjardins, *The 150 Apps that Power the Gig Economy*, VISUAL CAPITALIST (May 6, 2019), https://www.visualcapitalist.com/150-apps-power-gig-economy [https://perma.cc/2GSZ-TF9U].

4. *See* Alex Moazed, *Can Uber Reach Profitability?*, INC. (Feb. 18, 2018), https://www.inc.com/alex-moazed/ubers-path-to-profitability.html [perma.cc/ZU7W-AQZE]. *See also How the Gig Economy Will Bring Big Data to Every Market*, INSIDE BIG DATA (Apr. 16, 2019), https://insidebigdata.com/2019/04/16/how-the-gig-economy-will-bring-big-data-to-every-market [https://perma.cc/B4EE-JJHA].

supply and demand.[5] The more transactions occur, the more customers' needs are met, the more workers earn, and the more the platform operators collect. Machine learning algorithms with theoretically perfect information on the market and instructions to maximize profits will get better and better at matching buyers and sellers of services, and everybody wins.

The reality is not so simple. A closer look at the incentives and constraints on platform firms illuminates a set of situations where their interests diverge from, and may directly oppose, those of their users. The vast asymmetries of information and market power that firms enjoy over their users invite closer scrutiny of the power dynamics at play and the behavior of platform firms compared with how they represent themselves to users.[6] The remedies available to workers who are harmed by these effects are as yet undeveloped, but common law principles applied to these novel challenges may yield the first steps towards a regime for regulating the platform economy.

This Note analyzes a set of economic harms to workers uniquely enabled by algorithmic work platforms and explores common law torts as a remedy, using Uber and its driver-partners as a case study.[7] Part II describes the rise of the "platform economy"[8] and surveys the current state of employment law

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5. *See* Alison Griswold, *Uber's Secret Weapon Is Its Team of Economists*, QUARTZ (Oct. 14, 2018), https://qz.com/1367800/ubernomics-is-ubers-semi-secret-internal-economics-department [perma.cc/Z5JQ-9VUU].

6. Ryan Calo & Alex Rosenblat, *The Taking Economy: Uber, Information, and Power*, 117 COLUM. L. REV. 1623, 1649 (2017).

7. Uber is one of the most widely-recognized and widely-studied work platforms. Analysis of harms resulting from decisions made in the design and implementation of machine learning algorithms [hereinafter, "algorithmic harms"] to workers on the Uber platform will necessarily involve a degree of speculation, as Uber's algorithm is a "black box" whose particulars are closely-guarded intellectual property. There is, however, a small but growing body of observations by researchers and drivers in addition to publicly-available information about the app and analogies to algorithms used in similar contexts that allow for inferences about design choices made by its developers and how those impact driver-partners. *Id.* at 1654.

8. There is no widely agreed-upon definition of this sector, nor a consistent terminology used by scholars for this group of workers. The terms "platform economy" and "platform worker" have been chosen because they are relatively neutral, in contrast to the misleadingly benign or altruistic-sounding "sharing economy" or the dismissive "gig economy." The word "platform" also usefully serves to highlight the legal precarity of workers who rely on smartphone applications such as Uber, TaskRabbit, or Handy for their incomes. *See generally* Juliet B. Schor et al., *Dependence and Precarity in the Platform Economy* (2018) (unpublished paper), https://www.bc.edu/content/dam/bc1/schools/mcas/sociology/pdf/connected/Dependence%20and%20Precarity%20Aug%202018.pdf [https://perma.cc/YH9T-E2KJ] (on file with Colum. J.L. & Soc. Probs.).

as it applies to workers who use algorithmically-mediated smartphone platforms to directly mediate labor. Part III analyzes the design and function of machine learning algorithms, highlighting the Uber application to illustrate a range of potential economic harms to workers enabled specifically by the two-sided platform model resulting directly from the firm's design choices.[9] Part IV explores possible legal and regulatory responses to these emerging issues, proposing common law causes of action for breach of the implied duty of good faith and fair dealing and the tort of misrepresentation as a recourse to workers whose interests have been harmed by algorithmic design choices in platform markets. This Note concludes by arguing that causes of action against platform employers generally, and Uber in particular, are viable under existing law and may represent a promising approach for protecting the interests of this new and growing class of workers against abusive practices or economic harms unique to algorithmically-mediated work.

II. THE RISE OF THE "PLATFORM ECONOMY" AND THE LEGAL STATUS OF PLATFORM WORKERS

To understand the worker-firm relationships that define the platform labor model and the legal rights and responsibilities they may give rise to, it is helpful to first examine how they emerged and what they replaced. Part II.A identifies structural economic and technological factors that increase the viability of the platform model. Part II.B then surveys the current state of labor law applied to the platform economy, focusing on gaps in prevailing worker classification schemes and the litigation these have given rise to. The design and structure of the algorithms that mediate platform work is analyzed in greater detail in Part III.

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9. This Note analyzes in detail specific practices and design choices, both documented and hypothetical, building on the work of Alex Rosenblat, Ryan Calo, and others who have studied algorithmically-mediated work platforms and drawn attention to information asymmetries and potential for harm and abuse inherent in these models. *See generally* Calo & Rosenblat, *supra* note 6.

A. STRUCTURAL FACTORS SUGGEST GROWTH OF PLATFORM MODEL

There is no consensus on how big the platform economy is, or how big it will get, but high-end estimates put the number of full-time platform workers at fifteen percent of the working population.[10] Setting aside the hype[11] and the somewhat ambiguous[12] data[13] on the growth of "gig" or platform work, economic theory suggests that this model offers substantial efficiencies.

Platform company boosters assert that these new organizational models have disrupted the most basic unit of economic organization — the firm.[14] In *The Nature of the Firm*, economist Ronald Coase provided a theory to explain why firms emerged in markets where individuals were free to independently contract for goods or services in supposedly-efficient open markets.[15] A firm is, essentially, a closed internal market; they are able to subsist to the extent that the benefits of internalized transaction costs exceed the costs of overhead (maintaining capital and labor) and inefficiencies of resource allocation.[16]

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10.   *See* Steven Dubner, *What Can Uber Teach Us About the Gender Pay Gap?*, FREAKONOMICS: RADIO (Feb. 6, 2018), http://freakonomics.com/podcast/what-can-uber-teach-us-about-the-gender-pay-gap [perma.cc/V7A5-G2RF].

11.   Jon Bruner, *Platform Economies: A Conversation with Erik Brynjolfsson and Jon Bruner*, O'REILLY MEDIA (2015), https://www.oreilly.com/radar/platform-economies [https://perma.cc/DT43-ZYCC].

12.   *See* Caleb Gayle, *US Gig Economy: Data Shows 16M People in 'Contingent or Alternative' Work*, GUARDIAN (June 7, 2018), https://www.theguardian.com/business/2018/jun/07/america-gig-economy-work-bureau-labor-statistics [https://perma.cc/B4G9-AF35]. Many workers interviewed were unsure how to define their app-based platform work; Uber drivers, for example, expressed confusion as to whether they were "employees" of Uber or independent small business owners. *Id.*

13.   *See* Natasha Bach, *Everyone Thought the Gig Economy Was Taking Over. Turns Out It's Not*, FORTUNE (June 8, 2018), http://fortune.com/2018/06/08/gig-economy-shrinking-data [perma.cc/XY3D-UMT9]. The U.S. Department of Labor has been cautious in defining platform work; the most recent Bureau of Labor Statistics Survey included a caveat that it would report on app-based electronically-mediated employment at a later date. *See Contingent and Alternative Employment Arrangements Summary*, U.S. BUREAU OF LABOR STAT. (June 7, 2018), https://www.bls.gov/news.release/conemp.nr0.htm [perma.cc/3ZFE-8XXZ].

14.   *See* Bruner, *supra* note 11.

15.   *See generally* R.H. Coase, *The Nature of the Firm*, 4 ECONOMICA 386 (1937). Classical economic models had previously ignored the costs inherent in contracting on an open market — i.e., the searching, bargaining, and policing of rules endemic to all transactions. Firms reduce these by formalizing relationships with laborers and suppliers, reducing the need to search and bargain in the course of each individual transaction. *See id.*

16.   *Id.*

Information technology has been altering this equation for some time. Coase, after all, was writing in an era predating the modern fax machine. In the middle of the twentieth century, the vertically-integrated industrial conglomerates that dominated Western economies increasingly sought to reduce the costs of maintaining a workforce by subcontracting, franchising, and externalizing their supply chains.[17] Advances in information technology made it possible for globalized, "fissured" firms to externalize many of the costs of production while maintaining centralized control.[18] For example, Nike does not exactly "make" shoes: it directs their design, marketing, manufacture, and distribution.[19]

Digital networks have accelerated this trend. In 2002, Yochai Benkler used Coase's theory of transaction costs to explain the then-emerging trend of networked peer-to-peer production.[20] He applied Coase's theory to online networks and marketplaces, arguing that individuals with differing motivations and goals can nonetheless productively collaborate on large-scale projects via digital networks.[21] This "third model" of production — the platform — found its purest expressions in decentralized platforms such as Wikipedia and Napster, where individuals were able to participate in information exchange via a digital network according to their own motivations and abilities, without central control or direction.

Over the past fifteen years, digital platforms have proliferated.[22] The rise of Big Data and machine learning, along with the ubiquity of smartphones, has unlocked a new market for firms, workers, and consumers in the form of "on-demand" "gig econo-

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17.   *See generally* DAVID WEIL, THE FISSURED WORKPLACE: WHY WORK BECAME SO BAD FOR SO MANY AND WHAT CAN BE DONE TO IMPROVE IT 122–24, 159–60 (2014).

18.   *Id.* at 53–55.

19.   "Nikefication" refers to the transformation of a firm into a "nexus of contracts." *See* Gerald F. Davis, *What Might Replace the Modern Corporation? Uberization and the Web Page Enterprise*, 39 SEATTLE U. L. REV. 501, 502 (2016). Nike was one of the first firms to outsource the production of shoes to suppliers overseas while still maintaining control of the brand. *See id.*

20.   Yochai Benkler, *Coase's Penguin, or, Linux and The Nature of the Firm*, 112 YALE L.J. 369, 375 (2002).

21.   *Id.*

22.   Professor Julie Cohen has argued that platforms (defined expansively to include online marketplaces like eBay, or desktop and mobile operating systems such as Android) represent nothing less than a replacement of markets as the core organizational form of the information economy. *See generally* Julie Cohen, *Law for the Platform Economy*, 51 U.C. DAVIS L. REV. 133 (2017).

my" services.[23]   Smartphones gather reams of data about their users, allowing firms to track the behavior of all participants within a platform market and use machine-learning algorithms to gather, analyze, and leverage market information.[24] Platforms grant the firms that operate them extraordinary information advantages while simultaneously raising questions about competition, privacy, and manipulation.[25]

The firms themselves have not been shy about promoting the tantalizing promise of machine learning algorithms and their ability to "perfect" markets, and in doing so distinguish themselves from traditional firms.[26] Companies such as Lyft and Uber efficiently "disrupt" traditional businesses such as taxi operators, but insist that they are not becoming what they displace. They instead present themselves as "transportation network companies" or simply "technology companies."[27] In their telling, they operate in the new "sharing economy" as benevolent innovator-matchmakers enabling independent entrepreneurs to drive, host, and share their way to a freer, better work-life balance. However, as in other markets where algorithms are entrusted with decision-making, there is great potential for harm and abuse.

B. WORKER CLASSIFICATION AND TRANSPORTATION NETWORK COMPANIES: LITIGATION WITHOUT RESOLUTION

Most of the legal scrutiny in this emerging field has focused on the classification of the workers who use these platforms: are they employees, independent contractors, or something in between?[28] Recent high-profile cases brought by drivers against Uber and Lyft have focused on the issue of worker classification

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23.   Professor Orly Lobel has described a "transaction costs revolution" enabled by algorithm-driven digital platforms that promises a virtuous cycle of efficiency to "perfect" the market. *See* Orly Lobel, *The Law of the Platform*, 101 MINN. L. REV. 87, 106–07 (2016).

24.   *See* Kenneth A. Bamberger & Orly Lobel, *Platform Market Power*, 32 BERKELEY TECH. L.J. 1051, 1053 (2017).

25.   *Id.*

26.   Bamberger & Lobel, *supra* note 23, at 99–101. Platform companies have strong legal and public-relations incentives to define themselves in particular ways; "definitional defiance" is, in many cases, central to platform companies' business models. *Id.* These are discussed in more detail in Part III, *infra*.

27.   *See* O'Connor v. Uber Techs., Inc., 82 F. Supp. 3d 1133, 1137 n.10 (N.D. Cal. 2015).

28.   See Pamela A. Izvanariu, *Matters Settled but Not Resolved: Worker Misclassification in the Rideshare Sector*, 66 DEPAUL L. REV. 133, 137 (2016).

and have highlighted the difficulties of applying existing employment law to novel work relationships.[29]

O'Connor v. Uber Technologies was the first major test of worker classification as applied to the platform economy.[30] In 2015, a group of drivers filed a putative class action lawsuit against Uber in the Northern District of California asserting that they were employees of Uber and thus entitled to various protections under California law. Uber sought a summary judgment declaring that drivers who used its platform were independent contractors as a matter of law. Judge Edward Chen denied Uber's motion, holding that the plaintiffs had met their burden of showing performance of services and that a genuine issue of material fact remained as to the extent of control exercised over the drivers by Uber, a key element of the classification test.[31] In the opinion, Judge Chen rejected Uber's claim that it is merely a "technology company" rather than a transportation provider. Judge Chen's opinion contained language that has potentially far-reaching implications for the platform economy at large, stating:

> Uber engineered a software method to connect drivers with passengers, but this is merely one instrumentality used in the context of its larger business. Uber does not simply sell software; it sells rides. Uber is no more a 'technology company' than Yellow Cab is a 'technology company' because it uses CB radios to dispatch taxi cabs.[32]

Following the denial of summary judgment, a federal appeals court agreed to review an order certifying the drivers as a class, leading Uber to ultimately settle with the plaintiffs for $100 million.[33] Drivers for Lyft brought a nearly identical suit in California in 2015; it, too, was settled along similar lines.[34]

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29. *See, e.g.*, Cotter v. Lyft, Inc., 176 F. Supp. 3d 930 (N.D. Cal. 2016).
30. *See O'Connor*, 82 F. Supp 3d at 1133.
31. *Id.* at 1141, 1148.
32. *Id.* at 1141.
33. *Uber Drivers Remain Independent Contractors as Lawsuit Settled*, 30 No. 20 Westlaw J. Emp. 1, 1 (Apr. 26, 2016). According to the terms of the settlement agreement, the status of drivers as independent contractors was unchanged, though the plaintiffs' attorney maintained that nothing in the agreement prevented future courts or agencies from determining that drivers are employees. *Id.*
34. *See* Izvanariu, *supra* note 28, at 161.

During the same period that these high-stakes cases were moving through the court system, Uber and Lyft embarked on a nationwide lobbying and public-relations campaign aimed at fending off unwelcome regulation. The rapid expansion of their services was mirrored by the aggressiveness with which they conducted their legislative campaign.[35] Uber typically enters a marketplace and begins operating without consulting local authorities, pressing them to "update" local regulations on terms favorable to the company.[36] This has led to friction with local authorities and incumbent taxi providers, who take exception to what they view as the arrogant flouting of local laws. It also leads to a rapidly-growing base of drivers and riders who can be mobilized to apply pressure to local officials.[37] Uber has married this insurgent approach with a traditional lobbying apparatus. As of 2015, Uber had registered 250 lobbyists and twenty-nine lobbying firms nationwide, outspending the likes of Wal-Mart.[38] By 2016, Uber was paying 370 active lobbyists in forty-four states.[39]

In the past five years, forty-eight states and the District of Columbia have passed legislation pertaining specifically to self-identified transportation network companies (TNCs).[40] In forty-one states, such laws preempt local municipal regulation of these industries to varying degrees.[41] However, Uber and Lyft have scored significant successes, perhaps most crucially in defining themselves as TNCs rather than as taxi dispatch services. Uber and Lyft have also been successful in gaining carve-outs to ensure that drivers who use their platforms are not classified as employees; in twenty-five states, drivers are explicitly or presumed to be independent contractors, and in eleven states, they have been

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35.   Karen Weise, *This is How Uber Takes Over a City*, BLOOMBERG (June 23, 2015), https://www.bloomberg.com/news/features/2015-06-23/this-is-how-uber-takes-over-a-city [perma.cc/4MUG-9GP4].

36.   *See id.*

37.   *See id.*

38.   *See id.*

39.   *See* Joy Borkholder et al., *Uber State Interference: How Transportation Network Companies Buy, Bully and Bamboozle Their Way to Deregulation*, NAT'L EMP. L. PROJECT 5 (Jan. 2018), https://www.forworkingfamilies.org/sites/default/files/publications/Uber%20 State%20Interference%20Jan%202018.pdf [https://perma.cc/FKW9-28GL].

40.   *Id.*

41.   These laws are not uniform, and often represent "compromises" between Uber and Lyft and local authorities seeking to impose requirements such as insurance minimums, background checks for drivers, and other measures to protect the public. *Id.*

granted a mix of specific exemptions from state employment laws.[42]

In fairness, the grassroots support TNCs receive from their users is genuine. Services like Uber and Airbnb are wildly popular with consumers, and many consumer advocates have praised their utility. Uber and Lyft, for example, provide reliable on-demand transportation to low-income urban areas that previously lacked taxi services.[43] These firms' legislative victories would not have been possible without pressure generated by users of the services, both riders and drivers, who were willing to vocally support these companies.

Barring a significant legislative reversal, platform workers seem destined to remain independent contractors for the foreseeable future.[44] For that reason, scholars have begun to explore alternatives to employee classification as avenues for protecting workers or regulating platform firms, such as consumer protection law.[45] Part III of this Note builds on that work by identifying specific algorithmic harms that may be inflicted on platform workers and exploring possible causes of action that a worker might have against the operators of a platform algorithm.

III. ALGORITHMIC DESIGN AND THE POTENTIAL FOR HARMS TO WORKERS

As big data and machine learning algorithms increasingly permeate modern life, their use poses a growing threat to individual rights and values.[46] Courts and legal scholars are begin-

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42. *Id.* at 13.

43. One study found that 99.8% of households in Los Angeles were able to access the services of ridehailing companies, including neighborhoods with limited car ownership, representing a significant increase in equitable access to mobility. *See generally* Anne E. Brown, *Ridehail Revolution: Ridehail Travel and Equity in Los Angeles*, UCLA ELECTRONIC THESES AND DISSERTATIONS (2018), https://escholarship.org/uc/item/4r22m57k [https://perma.cc/RM63-TC7P].

44. In September of 2019, the state of California passed legislation aiming to reclassify platform economy workers as employees, rather than independent contractors, requiring that businesses provide them with labor protections such as a minimum wage and paid parental leave. *See* AB-5 Worker Status: Employees and Independent Contractors, Cal. Assembl. (Cal. 2019); *see also* Alexia F. Campbell, *California Just Passed a Landmark Law to Regulate Uber and Lyft*, VOX (Sep. 18, 2019), https://www.vox.com/2019/9/11/20850878/california-passes-ab5-bill-uber-lyft [https://perma.cc/YL3H-DARR].

45. *See generally* Calo & Rosenblat, *supra* note 6.

46. *See* EXEC. OFFICE OF THE PRESIDENT, BIG DATA: SEIZING OPPORTUNITIES, PRESERVING VALUES 1–3 (May 2014), https://obamawhitehouse.archives.gov/sites/default/files/docs/big_data_privacy_report_may_1_2014.pdf [https://perma.cc/8H6H-2P69]. "Big

ning to grapple with the implications of algorithmic decision-making in contexts as varied as credit scoring,[47] medical malpractice,[48] predictive policing,[49] and hiring.[50] This emerging body of scholarship explores the harms that can arise from the use of machine learning algorithms to make decisions and also adds to the growing debate about how to address these harms and who should be responsible for doing so.[51]

In the employment context, legal scholars have generally focused on bias and discrimination in hiring decisions.[52] To supplement traditional practices, such as interviewing candidates and considering their education and experience, machine learning algorithms process thousands of data points about an individual, often gathered by third parties.[53] While proponents argue that algorithms hold the promise of removing "human bias" from hiring decisions, skeptics note that data sets often themselves are not neutral, and the uncritical use of workplace analytics may

Data" has no single definition but generally refers to the practice of using algorithms to analyze massive digital data sets, identifying patterns and generating insights made possible by vast computing resources. *Id.* at 2.

47.   *See* Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 17–18 (2014).

48.   *See* Shailin Thomas, *Artificial Intelligence, Medical Malpractice, and the End of Defensive Medicine*, PETRIE-FLOM CTR.: BILL OF HEALTH (Jan. 26, 2017), http://blog.petrieflom.law.harvard.edu/2017/01/26/artificial-intelligence-medical-malpractice-and-the-end-of-defensive-medicine [https://perma.cc/8835-429Q].

49.   *See generally* Andrew Guthrie Ferguson, *Big Data and Predictive Reasonable Suspicion*, 163 U. PA. L. REV. 327 (2015).

50.   *See* Pauline T. Kim, *Data-Driven Discrimination at Work*, 58 WM. & MARY L. REV. 857, 884–92 (2017). Predictive algorithms designed to be neutral with respect to protected characteristics, such as race and gender, nonetheless deliver results that are biased along these lines due to the nature of machine-learning and design choices that fail to account for proxy variables or other correlations that deliver biased results. *Id.*

51.   Citron & Pasquale, *supra* note 47, at 14. Naturally, issues that implicate constitutional rights have attracted the most criticism. Disparate and adverse impacts of algorithmic decisions on protected classes have been documented in a range of circumstances; for example, credit rating algorithms have been found to deliver biased results against women and racial minorities, leading to diminished access to credit for these groups and entrenching inequality. *Id.* Similarly, algorithms meant to predict recidivism have delivered troubling outcomes that raise questions about equal protection. For example, in *State v. Loomis*, the Wisconsin Supreme Court held that the use of an algorithmic recidivism risk assessment tool to aid sentencing did not violate the defendant's due process rights, despite the inclusion of his gender as a factor of consideration. 881 N.W.2d 749, 767 (Wis. 2016).

52.   *See generally* Kim, *supra* note 50.

53.   Data that is "neutral" along lines of protected class may nonetheless serve as a proxy for protected characteristics. For example, a firm may seek to improve employee retention by favoring candidates who live closer to the workplace. This "neutral" choice may, however, reinforce a legacy of racially discriminatory housing policies that have led to segregation in many cities. *Id.* at 861, 863.

actually exacerbate or introduce new forms of bias along lines of class, race, and gender.[54]

Most scholarship on algorithmic harms in the platform economy has also focused on racial discrimination and bias. Evidence from multiple studies and experiments suggests that platforms that incorporate a reputational or rating component will often reflect the racial biases of their service providers: for instance, a study on Airbnb revealed that guests with African-American sounding names are sixteen percent less likely to have their reservation requests accepted,[55] while another study focusing on Uber showed that female and African-American passengers suffered from various forms of discrimination by drivers, including longer wait times, increased cancellations, and, particularly in the case of female riders, more circuitous routes taken by drivers.[56]

While these problems deserve attention, there is reason to think that platform workers are vulnerable to substantial economic harms that are less easy to identify and detect. A number of scholars, notably Alex Rosenblat and Ryan Calo, have drawn attention to the incentives and opportunities for abuse inherent in the platform model.[57] The information asymmetries that define platform marketplaces allow for firms to leverage information in ways that exploit the divergent interests of workers and firms and undermine the joint-profit premise of the platform economy.[58]

It is worth noting here that algorithmic management of platform workers is different from other potentially problematic algorithmic-decision situations (such as a hiring algorithm unfairly denying an applicant) because the potential harms are not one-off; algorithmically-determined, labor-assignment transactions are recurrent.[59] This is crucial because even marginal harms that are individually insignificant will accumulate over time. A five percent inefficiency on a given route may be negligible, perhaps costing a driver only a few dollars or cents, but an algorithm

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54. *See id.* at 865. Systematic errors, such as errors in the data or data collection that reflects human bias, may inadvertently deliver biased results despite the intentions of algorithm designers. *See id.*

55. *See* Benjamin Edelman et al., *Racial Discrimination in the Sharing Economy: Evidence from a Field Experiment*, 9 AM. ECON. J. 1, 2 (2017).

56. Yanbo Ge et al., *Racial and Gender Discrimination in Transportation Network Companies* 18–19 (Nat'l Bureau of Econ. Research, Working Paper No. 22776, 2016).

57. *See generally* Calo & Rosenblat, *supra* note 6.

58. *See id.*

59. *See generally* Lee et al., *supra* note 1.

that results in consistent five percent losses for a driver could mean thousands of dollars of lost income over the course of a year.[60] This observation is intimately linked with the problem of calculating damages.[61] Algorithmic outputs that cause marginal losses to workers have the potential to be substantial over recurrent transactions and could amount to vast sums when considering millions of drivers as a class. This Part addresses this more subtle problem — how to provide recourse to platform workers who are victims of algorithmic design choices that are opaque and marginal, yet in the aggregate cause substantial loss.

A. SPECIFIC HARMS FROM THE DESIGN AND USE OF MACHINE LEARNING ALGORITHMS

Before addressing the use of machine learning algorithms in the platform economy and the impacts on workers, it is helpful to examine how these algorithms operate and the extent to which they are designed and controlled by their operators. Closely examining the definitions, inputs, parameters, adjustments, and developers' ability to even understand how machine learning algorithms make decisions is crucial to evaluating the potential liabilities faced by firms for any harms resulting from an algorithm's use.

Machine learning algorithms have myriad designs and applications, but they share certain basic characteristics. Broadly defined, machine learning refers to an automated process for identifying relationship between variables in a data set and making predictions based on those relationships.[62] Those relationships accumulate into a "model," or algorithm, which can then be used to make predictions or decisions based on new data.[63] At a fundamental level, an algorithm's job is to discriminate; data mining is itself a form of rational discrimination, and often one with legitimate ends and means.[64] The problems arise when this dis-

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60. Jacob Bogage, *How Much Uber Drivers Actually Make Per Hour*, WASH. POST (June 27, 2016), https://washingtonpost.com/news/the-switch/wp/2016/06/27/how-much-uber-drivers-actually-make-per-hour [perma.cc/J88P-LKNK].

61. *See* i*nfra* Part IV.C.5.

62. KEVIN P. MURPHY, MACHINE LEARNING: A PROBABILISTIC PERSPECTIVE 1 (2012).

63. MICHAEL BERRY & GORDON LINOFF, DATA MINING TECHNIQUES FOR MARKETING, SALES, AND CUSTOMER RELATIONSHIP MANAGEMENT 8–11 (2d ed. 2004).

64. *See* Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CAL. L. REV. 671, 677 (2016).

crimination takes place along lines that are legally or ethically impermissible and place individuals at a systematic disadvantage.[65] These problems are further complicated by the extent to which algorithms are in a "black box," opaque not only to those affected by algorithmic decisions, but also to the very designers and operators of the algorithms themselves.[66] A close examination of the human role in various stages of algorithmic design and operation is thus essential to understanding potential liability.

The process of developing and deploying machine learning algorithms can be broken down into eight steps, each with varying degrees of human input and transparency.[67] David Lehr and Paul Ohm have divided steps one through seven, which they characterize as "playing with the data," or developing, training, and refining the algorithm, from the last step, which they call "running the model," i.e., deploying the algorithm to process new data and make decisions in the field.[68]

The first three of Lehr and Ohm's steps involve setting the basic parameters of the algorithm: problem setting, or defining abstract goals (i.e., "predicting whether a borrower is likely to default"), assigning specific variables and measurements to these goals, and choosing which variables will be included in the "training data" that the algorithm will use to build its model of relationships.[69] At this stage, the selection of parameters is entirely in the hands of the algorithm's designers and necessarily involves deliberate normative choices. While the training data itself is "objective," it may contain errors or reflect pre-existing human biases.[70] Developers may choose to "clean" this data, either by substituting estimates for missing variables or deleting subjects with incomplete data; in any event, this too involves choices on the part of the developers.[71]

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65. *See id.*

66. *See* Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1094 (2018).

67. David Lehr & Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653, 655 (2017).

68. *Id.*

69. Selbst & Barocas, *supra* note 64, at 677–92. Training data consists of a pre-selected set of input data where the target outcome is already known. *See id.* at 680. Designers use training inputs to evaluate the performance of an algorithm's results against the known empirical results, and thus refine and improve their performance. *See* Tom Dietterich, *Overfitting and Undercomputing in Machine Learning*, 27 ACM COMPUTER SURVEYS 326, 326 (1995).

70. Lehr & Ohm, *supra* note 67, at 665.

71. *Id.* at 681–82.

Having selected variables and assembled training data, developers will review summary statistics of each input and output variable to correct for common errors.[72] Developers review summary statistics such as the mean, median, and standard deviation of each variable and identify outliers that might distort a given model.[73] In addition, they seek to identify and remove "false positive" relationships and correlations — a problem known as "overfitting."[74] Machine learning algorithms will often identify correlations between variables that have no plausible connection, for example, correlating high intelligence with a preference for curly fries.[75]

Having reviewed the data, developers must then select a model — generally speaking, selecting output variables to optimize according to selected criteria.[76] For instance, in a credit scoring algorithm, the goal of the model may be minimizing the risk of default, or, for a taxi dispatch algorithm, maximizing the fares collected. Once a model has been selected, developers "train" the algorithm by running the data set through the model, allowing the algorithm to "learn" the rules to make decisions in accordance with the developers' goals.[77] This occurs over multiple iterations, as developers assess the performance of the algorithm and make adjustments to the model.[78] It is the "learning" stage that is most opaque: the actual source code that results from the training and learning process may be unintelligible even to its developers if it was not specifically designed to be explainable.[79]

Only after this extensive development and training process is the algorithm deployed in the real world to process new data. "Running algorithms" will often dynamically adjust to incorporate new data, regularly and automatically "retraining" to improve performance.[80] Developers can continue to monitor, adjust

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72. *Id.* at 683–85.
73. *Id.*
74. *Id.*
75. Michal Kosinski et al., *Private Traits and Attributes Are Predictable from Digital Records of Human Behavior*, 110 PROC. NAT'L ACAD. SCI. 5802, 5804 (2013).
76. Lehr & Ohm, *supra* note 67, at 687–95.
77. *Id.* at 695–97.
78. *Id.* at 698.
79. Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. PA. L. REV. 633, 640–41 (2017). Merely disclosing the source code or program audit logs is insufficient to allow for an explanation of "why" an algorithm made a decision. For full transparency and accountability, algorithm designers need to deliberately build in tools that can communicate partial information about program processes in a way that is intelligible. *Id.* at 647–50.
80. Lehr & Ohm, *supra* note 67, at 702.

and retrain algorithms as they operate in the real world. Thus, while much of the commentary on the harmful effects of algorithmic decisions assumes that the machine learning process is almost fully automated, and thus somehow objective, nonintuitive or inscrutable, the reality is that deliberate, normative choices made by humans are involved throughout the process of building and deploying machine learning algorithms.[81]

B. DIVERGENT INTERESTS AND PROBLEMATIC INCENTIVES IN THE TWO-SIDED MARKET PLATFORM MODEL

There is a fundamental problem with the two-sided platform market that is glossed over by sunny proclamations about the virtues of the platform economy: a persistent oversupply of workers benefits both customers and the operators of the platforms themselves, while driving down wages and work opportunities for workers.[82] This problem is compounded by the fact that the mechanisms of platform markets are opaque and entirely in the hands of the firms that operate them.[83] For all the talk about platform work "liberating" workers or giving them increased flexibility, the fact remains that the vast amounts of data and the means to leverage it are in the hands of billion-dollar privately-held corporations, a paradox that gives them even more power than in a traditional marketplace.[84]

In a traditional firm, it is taken for granted that low-level employees need not be involved in high-level managerial decisions, but in the context of platform work, opacity and power asymmetry is complicated by a relationship promising workers flexibil-

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81. Selbst & Barocas, *supra* note 64, at 1109–15.

82. *See* Noam Scheiber, *How Uber Uses Psychological Tricks to Push Drivers' Buttons*, N.Y. TIMES (Apr. 2, 2017), https://www.nytimes.com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks.html [perma.cc/WY8C-7RTR].

83. Neil Richards & Jonathan King, *Three Paradoxes of Big Data*, 66 STAN. L. REV. 41, 42–43 (2013). The platform economy illustrates what Professors Neil Richards and Jonathan King have identified as two paradoxes of machine learning, specifically the "Transparency Paradox" and the "Power Paradox," both of which raise salient issues in the context of work. The "Transparency Paradox" is that firms are able to collect ever-growing volumes of data about workers and their performance, yet the collection of this data is almost imperceptible and its uses opaque. The "Power Paradox" is the fact that big data analytics give large, powerful actors, such as governments and corporations, unprecedented insights and ability to leverage them over individuals. *Id.* at 44–45.

84. *Id.* at 44.

ity and autonomy.[85] The incentives and potential for harms or abuse in this emerging area merit more consideration, especially when the owners and operators of the algorithms in question disclaim a formal employment relationship with the users who depend on their platforms for income. Workers who are given to misunderstand their relationship to a platform firm are more vulnerable to manipulation and abuse.

Uber calls its drivers "driver-partners," suggesting a joint-profit-maximizing enterprise.[86] But the partnership is not equal. As the all-seeing intermediary, Uber enjoys near-total control in determining not just individual offers of driving assignments, but the overall strategy and goals of the firm.[87] Most crucially, Uber has sole knowledge of, and discretion over, the parameters, data inputs, and goals of its dispatch algorithm.

This tension is problematic because the interests of a venture-financed technology firm playing to capture and keep a multi-billion-dollar market are simply not the same as those of a worker who drives so that she can pay the bills at the end of the month. Uber is valuable, but it is not profitable.[88] The privately-held company was estimated to be worth $76 billion in August of 2018 (up from $48 billion in February of the same year) despite losing money every year since its inception.[89] Many tech startup firms seek to leverage network effects to claim a winner-take-all market position; Facebook, for example, thrives only because everybody uses it, making it exceedingly difficult for challengers to enter the market and compete.[90] The dominant strategy for any platform seeking long-term profitability is to rapidly grow its user base while maintaining operating losses that are sustainable

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85.   Alex Rosenblat & Luke Stark, *Algorithmic Labor and Information Asymmetries: A Case Study of Uber's Drivers*, 10 INT'L J. OF COMM. 3758, 3759 (2016).

86.   *See generally* Jonathan Hall & Alan Krueger, *An Analysis of the Labor Market for Uber's Driver-Partners in the United States*, 71 INDUS. & LAB. REL. REV. 705 (2016).

87.   Rosenblat & Stark, *supra* note 85, at 3758.

88.   *See Breaking Down Uber's Valuation: An Interactive Analysis*, FORBES (Feb. 22, 2018), https://forbes.com/sites/greatspeculations/2018/02/22/breaking-down-ubers-valuation-an-interactive-analysis [perma.cc/MNA4-JSD5].

89.   Alex Barinka, & Eric Newcomer, *Uber Valued at $120 Billion in an IPO? Maybe*, BLOOMBERG (Oct. 16, 2018), https://www.bloomberg.com/news/articles/2018-10-16/uber-valued-at-120-billion-in-an-ipo-maybe [perma.cc/W4YS-XQJ5].

90.   Gigi Levy Weiss, *Network Effects Are Becoming Even More Important on Emerging Platforms*, FORBES (Mar. 18, 2018), https://www.forbes.com/sites/startupnationcentral/2018/03/18/why-a-network-effect-is-the-only-way-your-startup-can-win/#77f96cfc7527 [perma.cc/AEM4-3FD3]; *see also supra* Part II.A (describing the economics of the platform model).

only in the short term. Uber's valuation (and ability to continue to attract investment) depends on its continued growth of monthly active users.[91] Uber claims to view its drivers as an asset, but high turnover among them has done little to dampen the firm's value.[92]

This disconnect points to a fundamental problem for platform workers inherent in the model of the two-sided market for rides: a persistent oversupply of drivers benefits both riders and the firm that operates the platform.[93] A surplus of drivers on the platform results in a shorter average wait time for riders, as there is more likely to be a driver nearby. Furthermore, because the "surge" pricing algorithm determines fares by matching the supply of available drivers against the demand of prospective riders, a regular overbalance of supply results in consistently lower fares — great news for riders, but harmful to the earnings of drivers, who do not earn a guaranteed hourly wage and are solely responsible for the costs of maintaining their vehicles.[94] Uber, like other platform operators, has effectively outsourced its costs of production. It costs the firm nothing (and indeed, benefits it tremendously) to have its drivers idling, waiting for a fare, and so its profits are limited only by its ability to satisfy rider demand.

In sum, Uber leads drivers to believe that the interests of riders, drivers, and the firm are aligned, when in fact they are divergent and often opposed. Uber enjoys total control of its algorithm and faces strong incentives to design it in such a way as to maximize its own growth and earnings at drivers' expense. The problem is that the novel types of harms that drivers may incur as a result are often individually small but significant in aggregate, but invisible to workers and regulators.

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91.   Breaking Down Uber's Valuation: An Interactive Analysis, *supra* note 88.

92.   *See* Amir Efrati, *How Uber Will Combat Rising Driver Churn*, INFORMATION (Apr. 20, 2017), https://www.theinformation.com/articles/how-uber-will-combat-rising-driver-churn [perma.cc/Z2DF-WDSP]. One report showed that only twenty-five percent of drivers who partner with Uber are still using the platform a year later. *See id.* Turnover remains high despite Uber's 2015 redesign of the driver-facing app, which was prompted by the firm's realization that the platform catered almost exclusively to the rider side of the market. *See id.*; *see also* Jessi Hempel, *Inside Uber's Mission to Give its Drivers the Ultimate App*, WIRED (Oct. 13, 2015), https://www.wired.com/2015/10/uberredesign [perma.cc/K39F-M7Y8].

93.   *See* Scheiber, *supra* note 82.

94.   *See id.*

C. IDENTIFYING POTENTIAL ALGORITHMIC HARMS TO UBER DRIVERS

It bears emphasis that Uber and other platform firms closely guard their intellectual property, and these firms carefully limit publicly-available information about how their algorithms work. There is, however, a growing body of evidence from journalists,[95] researchers,[96] drivers,[97] and representatives of the firm itself that imply a variety of possible design choices and algorithmic inputs.[98] This evidence, in conjunction with the widely-understood workings of machine learning algorithms, allows for strong inferences about the Uber algorithm design and the data inputs it uses to calculate fares, assign rides, and deliver messages and incentives to drivers. To illustrate these problems, the following subparts consider a set of more concrete hypothetical practices and design choices that are within the firm's capability to both execute and conceal from its users.

1. *The Uber Interface*

To explain the nature of the economic harms to which Uber drivers are vulnerable, it is necessary to examine the application in detail. Because Uber is the paradigmatic platform market firm, it provides a useful illustration of specific potential algorithmic harms to workers.[99] A rider types a destination into the

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95.   *See* Scheiber, *supra* note 82 (reporting on a variety of nudging techniques employed by Uber to alter drivers' behavior, including arbitrary earnings targets, push notifications to encourage more time on the road, and virtual badges as rewards for meeting benchmarks related to driving time or customer service).

96.   *See generally* Calo & Rosenblat, *supra* note 6.

97.   Online driver forums, such as RideSharing Forum, offer a window into the experiences of drivers and the issues that they deal with. One striking feature of the conversations in these spaces is the lack of information that Uber makes available to drivers about the workings of the application, and the mistrust of Uber exhibited by forum contributors. *See* RIDESHARING FORUM, www.ridesharingforum.com [https://perma.cc/2WKU-F7WB] (last visited Oct. 25, 2019).

98.   Shankar Vedantam & Maggie Penman, *This Is Your Brain on Uber*, NAT'L PUB. RADIO (May 17, 2016), https://www.npr.org/2016/05/17/478266839/this-is-your-brain-on-uber [perma.cc/F65G-25CV].

99.   This focus is mostly due to the prominence of Uber, the amount of litigation it has faced, and the volume research that has been conducted on its drivers and its application. While it is one platform market among many, "Uber for X" has become an effective shorthand for new entrants to the platform economy, and the structure of its relationship to its users and workers is comparable to other firms in this space. *See* Alexis C. Madrigal, *The Servant Economy*, ATLANTIC (Mar. 6, 2019), https://www.theatlantic.com/technology/archive/2019/03/what-happened-uber-x-companies/584236 [https://perma.cc/8YVJ-BCZE].

Uber app on her smartphone, and Uber quotes her the cost of the ride as determined by Uber's "surge" pricing algorithm.[100]   The app also estimates the time it will take for a driver to reach the rider and for the rider to reach her destination, showing a sample route and icons to indicate the presence of nearby drivers.[101] When the rider accepts, Uber offers the ride as a commission to a nearby driver, whose smartphone shows the name, customer rating, location and destination of the rider, and how much the driver will earn for the ride, again determined by Uber's surge pricing algorithm.[102] The driver has a few moments to accept; if she does not, Uber offers the ride commission to another driver nearby. Once a driver accepts the commission, the rider sees the name and rating of her driver, along with an updated estimated time of arrival, and a real-time animation of the car's location on a map. The driver picks up the rider, takes her to her destination, and Uber collects the fare by charging the rider's credit card and remits a portion of the charge to the driver's account. Afterward, rider and driver assign each other a rating out of five stars to indicate their satisfaction. This data is used to give feedback to drivers and riders, and, in some cases, remove them from the platform for bad behavior or performance.

Crucially, not all trips are worth the same to drivers, and experienced drivers will accept or decline fares strategically.[103] Uber pays its drivers a constant percentage of the fare as commission, and the value of a given ride is determined by the distance and time it takes to complete on top of a minimum fare. The result is that longer rides in lower traffic are, by definition, the most profitable for drivers.[104] The percentage of a driver's time spent actively transporting a passenger effectively determines her hourly earnings. Longer trips mean less downtime and are

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100.   Lee et al., *supra* note 1, at 1.

101.   Uber has stated that these do not necessarily correspond to the actual locations of nearby drivers, but merely represent to riders that some drivers are nearby. *See* Calo and Rosenblat, *supra* note 6, at 1630.

102.   Lee et al., *supra* note 1, at 1605. The "surge" algorithm dynamically adjusts prices in real time, so that the fare that a rider or driver is offered for the same route may change from minute to minute. *See id.* at 1607.

103.   Harry Campbell, *How to Make More Money with Uber & Lyft (Maximize Earnings)*, RIDESHARE GUY (Oct. 1, 2019), https://therideshareguy.com/how-to-make-more-money-with-uber [https://perma.cc/L3AT-J7CY].

104.   Nat, *The Complete Guide to Long-Distance Uber Rides (for Passengers and Drivers)*, RIDESTER (July 24, 2018), https://www.ridester.com/long-distance-uber [https://perma.cc/Z3J9-ERPV].

thus more profitable for drivers. Similarly, certain destinations, such as a city's central business district, are likely to result in a shorter post-drop-off wait time for a new fare than others. These differences are crucial because work assignments are not perfectly interchangeable, and any bias or inefficiency in the algorithm that distributes rides will lead to disparate earnings between drivers over the long term.

2. *The Uber Algorithm*

Platform economy firms like Uber deploy a specific model known as a "supplier pick matching algorithm" to pair providers and consumers of a given service.[105] "Supplier pick" refers to the fact that suppliers — in this case drivers — ultimately determine whether to complete an offered transaction. Uber asserts that the distance from rider to prospective driver is the key input variable, and that it seeks to optimize both rider and driver experience by minimizing rider wait time and maximizing frequency of trips for drivers (seemingly in that order).[106] These goals are countervailing because an oversupply of drivers reduces wait times for riders while increasing wait times for drivers while also decreasing both rider costs and driver earnings per ride.[107]

A crucial and controversial element of the platform is Uber's surge pricing algorithm, which the company uses to adjust pricing in real time. Like a supply-and-demand graph come to life, Uber adjusts the price of a ride by computing information about the number of riders and drivers within a certain distance of each other. The "surge" algorithm is intended to create an equilibrium between supply and demand; an increasing price should motivate more drivers to become active, while reducing ride requests from price-sensitive riders.[108] Uber owns a patent for its dynamic pricing system, which describes a mechanism for adjust pricing "based, *at least in part,* on the determined amount of requesters

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105.   *How the Matching Algorithm Works in the On-Demand Economy*, JUNGLEWORKS, https://jungleworks.com/matching-algorithm-works-demand-economy-part-three-user-journey-series [https://perma.cc/LBL7-KM5L] (last visited Oct. 11, 2019).

106.   Bradley Voytek, *Optimizing a Dispatch System Using an AI Simulation Framework*, UBER: NEWSROOM (Aug. 11, 2014), https://www.uber.com/newsroom/semi-automated-science-using-an-ai-simulation-framework [https://perma.cc/HKP4-HSTB].

107.   *See* Scheiber, *supra* note 82.

108.   Ben Popper, *Uber Surge Pricing: Sound Economic Theory, Bad Business Practice*, VERGE (Dec. 18, 2013), https://www.theverge.com/2013/12/18/5221428/uber-surge-pricing-vs-price-gouging-law [https://perma.cc/NW9F-7REE].

and the determined amount of available service providers."[109] The application collects undefined "requester data" and "provider data" from participants' smartphones, and then feeds that data into the algorithm that in turn determines prices and offers rides.[110]

Uber does not disclose all of the information that makes up the "Requester Data" and the "Provider Data" transmitted to the device interface, nor does it reveal precisely how the algorithm uses that data. The volume and richness of the data, however, is potentially vast. In addition to a GPS chip, smartphones contain gyroscopes, accelerometers, and, of course, the torrents of personal data that users input.[111]

Uber has, however, revealed that it measures inputs beyond location. An Uber researcher revealed in an interview that the firm had evidence that low battery in a phone correlated with the user's willingness to pay a higher surge price (though, the company later clarified, that information was "absolutely not" used to charge higher prices to riders).[112] Researchers who have studied the surge algorithm's workings by placing a network of Uber-enabled phones across grids in Manhattan and San Francisco have noticed inconsistencies in surge pricing, though Uber claimed that these were simply "bugs."[113]

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109. System and Method for Dynamically Adjusting Prices for Services, U.S. Patent Application No. 13/828,481, Publication No. 2013/0246207 A1 (filed Mar. 14, 2013) (published Sept. 19, 2013) (Mark Novak & Travis Kalanick, applicants) (emphasis added). The patent application does not contain any details on the extent to which information other than the numbers of available riders and drivers influences the price of a given ride. *See id.*

110. *See* Figure 1*, id.*

111. David Nield, *All the Sensors in Your Smartphone, and How They Work*, GIZMODO (July 23, 2017), https://gizmodo.com/all-the-sensors-in-your-smartphone-and-how-they-work-1797121002 [https://perma.cc/Q5EQ-GJCF]. Modern smartphones contain an array of sophisticated sensors. For instance, the accelerometer measures the phone's movement, and allows a phone to measure the number and rate of steps taken by a person carrying it in her pocket. *See id.* The gyroscope assists the accelerometer in determining the position and orientation of the phone. *See id.* Most smartphones contain other instruments, such as barometers, proximity sensors, and ambient light sensors, all of which provide data that is accessible to app developers. *See id.*

112. Adam Withnall, *Uber Knows When Your Phone is Running Out of Battery*, INDEPENDENT (May 22, 2016), https://www.independent.co.uk/life-style/gadgets-and-tech/news/uber-knows-when-your-phone-is-about-to-run-out-of-battery-a7042416.html [https://perma.cc/3KKV-85MC]. Left unanswered is the question of how Uber determined riders' willingness to pay higher prices when their batteries were low without actually presenting similarly-situated riders with varying prices.

113. Le Chen et al., *Peeking Beneath the Hood of Uber*, *in* IMC '15 PROCEEDINGS OF THE 2015 INTERNET MEASUREMENT CONF. 495–508 (ACM New York, Oct. 28, 2015).

It is not clear whether Uber creates rider or driver profiles in the way that Facebook or Google might, but the means and incentives for it to do so surely exist. Uber's value depends on its ridership, and so the firm has every incentive to increase rider satisfaction and loyalty. Each trip is incredibly data-rich: Uber knows the origin and destination, the time of day, the route taken, the level of traffic, the speed and smoothness of the ride, and the rider's satisfaction (as measured by driver rating). It clearly stores and analyzes this data over the long term, as evidenced by the research that Uber and its academic collaborators have released.[114] Uber already collects all of the data it needs to identify a rider's preferences and a driver's tendencies; why would it not leverage these to improve its product, or enhance its profitability?

Finally, Uber employs a team of PhD economists who have access to what is essentially the world's largest and most detailed real-time behavioral economics experiment.[115] This provides Uber with the human capital to maximize the profitability of its platform by leveraging economic insights and perfect the "nudges" it sends to drivers and riders.[116] Uber has also increasingly partnered with unpaid academic researchers to publish studies using its unrivaled data sets, which critics speculate is a way for Uber to gain the academic credibility needed to influence the public policy discourse surrounding the platform economy and favorably influence future legislation.[117]

3. *Specific Worker Harms Enabled by the Uber Platform Model*

What follows is a framework for thinking about harms to platform workers, along with examples of design choices that could lead to these harms, using the Uber model to illustrate how harms to workers might occur. At one end are purely incidental harms resulting from legitimate or well-intentioned algorithm design choices. These bad outcomes are unintentional and possibly unforeseeable, and resemble analogous issues in other settings where algorithms make decisions.[118] At the other end of the

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114.   *See, e.g.*, Hall & Krueger, *supra* note 86, at 705–06.
115.   *See* Griswold, *supra* note 5.
116.   *See* Scheiber, *supra* note 82.
117.   *See* Griswold, *supra* note 5.
118.   Vasant Dhar, *When To Trust Robots With Decisions, and When Not To*, HARV. BUS. REV. (May 17, 2016), https://hbr.org/2016/05/when-to-trust-robots-with-decisions-and-when-not-to [https://perma.cc/5N9Y-C3L6].

spectrum are practices or design choices that would exploit the platform's inherent lack of transparency to deliberately deceive or exploit users for the benefit of the firm. In most cases, these would be extremely difficult to detect in practice, but there is evidence that Uber has at least experimented with some of them.[119] The following subparts also examine a range of algorithmic design choices that fall somewhere in between, classified as "divergent-interest" harms, which include incidental algorithmic harms, abusive practices, and design choices that undermine the premise of a mutually-beneficial partnership between drivers and the firm.

a. *Incidental Algorithmic Harms*

Incidental harms are likely to result from unintended consequences of decisions made at various stages of algorithm development, including data selection, problem setting, variable assignment and tuning.[120] The overfitting problem is endemic to machine learning, and well-intentioned choices in the algorithmic design process often lead to confounding or harmful results.[121] It is easy to imagine real-time adjustments (either automated or developer-initiated) to Uber's matching algorithm having unforeseen consequences that harms drivers, for instance, by nudging them to areas that are not actually price surging, sending them on inefficient routes, or failing to match them with the closest available rider.

As discussed above, there has been evidence of racial discrimination on peer-to-peer service platforms, though the evidence suggests that this has primarily harmed consumers of platform services rather than the workers themselves.[122] However, depending on the variable inputs chosen by developers, such as driver profiles, algorithms have the potential to reinforce bias or discrimination along lines of race, gender, or other protected classes.

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119. *See generally* Calo & Rosenblat, *supra* note 6 (describing practices such as "false surges" and "phantom cars"); *see generally* Shankar & Penman, *supra* note 98 (describing behavior experiments revealing user irrationality).

120. *See generally* Lehr & Ohm, *supra* note 67.

121. David Lazer et al., *The Parable of Google Flu: Traps in Big Data Analysis*, 343 SCI. 1203 (Mar. 14, 2014), https://gking.harvard.edu/files/gking/files/0314policyforumff.pdf [https://perma.cc/7P5P-VU6M]; *see also* Lehr & Ohm, *supra* note 67, at 683–85.

122. *See* Edelman, *supra* note 55, at 2.

One interesting example affecting drivers involves gender disparity. Uber's own research has shown a pay gap for female drivers, which researchers attributed to the fact that female drivers drive more slowly on average.[123] While this explanation is plausible, it may not tell the whole story. Imagine that Uber sets a seemingly innocent goal for its algorithm: match drivers with riders who are likely to give them a high rating. Such a parameter is not obviously problematic until we consider that Uber's algorithm may be collecting and using data in ways that could run afoul of equal protection. What if the "high rating match" instruction, in a reflection of rider bias, began pairing riders and drivers based on race, class or gender? As previously noted, not all routes are equally profitable for drivers; rides to and from the airport, for instance, represent not just high-value fares, but also tend to be longer and thus reduce driver down-time, thereby increasing earnings-per-hour.[124] People headed to the airport, on balance, may be in more of a hurry than others, and more likely to assign a low driver rating to a slower, more cautious driver.

It is conceivable, and even likely, that a machine learning algorithm could, by finding linkages between driver rating, gender, and high-urgency routes, systematically deprive female drivers of more profitable fares in response to design parameters intended to simply improve overall rider satisfaction. Such a scenario is one example of what is likely to be a larger set of harmful outcomes that may be unintentional and unforeseen by an algorithm's designers, but which could nonetheless create liability.

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123.   Cody Cook et al., *The Gender Earnings Gap in the Gig Economy: Evidence from Over a Million Rideshare Drivers* 33 (Mar. 8, 2019) (unpublished working paper) (on file with Colum. J.L. & Soc. Probs.), https://web.stanford.edu/~diamondr/UberPayGap.pdf [https://perma.cc/WB6S-TG58].

124.   *See* UBERPEOPLE.NET, https://uberpeople.net [https://perma.cc/5NXW-X5ZG] (last visited Oct. 22, 2019). Driver web forums often contain advice from experienced drivers in response to questions and complaints from novices. *See, e.g.*, *id.* *See also* RIDEGURU, https://ride.guru/lounge/p/when-driving-for-uber-which-trips-are-more-profitable-longer-trips-or-shorter-trips [https://perma.cc/3PAC-AQDK] (last visited Nov. 13, 2019). While there is disagreement among drivers posting to forums as to whether long trips are more profitable, there is general agreement that drivers seek to minimize downtime. *See* Scheiber, *supra* note 82.

b. *Abusive Practices*

Abusive practices sit at the other extreme of algorithmic harms. These harms are more straightforward and could take many forms. It would not be hard for designers of an algorithm to deliberately deceive drivers, incenting behavior that works against their economic interests but improves the firm's profitability.[125] Similarly, firms have the ability and potentially the incentive to deliberately use information in impermissible ways.[126] These practices would amount to clear ethical breaches, and there is preliminary evidence that Uber has at least experimented with some of these.[127]

Such practices would be both difficult for users to detect and simple for the firm to employ given the information asymmetries it enjoys. For example, Uber's app shows a price to riders upfront by estimating the time the ride will take, but it calculates its driver fare according to the distance and time it ends up actually taking. Journalists have documented cases where the Uber app has shown passengers and drivers drastically different fare amounts for the same ride, with the driver having earned substantially less than the customer paid (setting aside Uber's commission) even when the ride took approximately the time and distance estimated.[128] Such deceptive market manipulation, if proven, is surely actionable as a breach of the duty of good faith and fair dealing.

Driver forums are replete with advice from experienced drivers to new ones, and a common refrain is "don't chase the surge."[129] Because of the opacity and dynamic nature of surge pricing, it would be easy for Uber to manipulate surge pricing as a tool to shift riders to areas where it deemed them most valuable (for reasons described previously, such as market establishment),

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125. *See* Calo & Rosenblat, *supra* note 6, at 1654.

126. *Id.*

127. *Id.* (describing a number of practices reported by drivers and users, such as false or misleading information displayed on the application interface about the availability of drivers or rides and other evidence of unfair manipulation of the platform market).

128. Alison Griswold, *Uber Drivers Are Using This Trick To Make Sure The Company Doesn't Underpay Them*, QUARTZ (Apr. 13 2017) https://qz.com/956139/uber-drivers-are-comparing-fares-with-riders-to-check-their-pay-from-the-company/   [https://perma.cc/9WQR-PMXD].

129. *See* Calo & Rosenblat, *supra* note 6, at 1656.

even if these were not necessarily areas of the highest demand or potential for driver profit.[130]

Every startup seeking to rely on network effects has the chicken-and-egg problem: users benefit from the presence of other users and suffer from their absence. Rides cannot be offered without drivers, but drivers have no reason to get on the road without any prospect of finding customers. So how does Uber move into a new market?

Uber already defines "surge zones" within cities as geographic segments that are effectively localized markets.[131] Suppose Uber wanted to increase ridership in the West Village neighborhood of New York City, and imagine, further, that Uber has market research data that shows it takes an average of four minutes for a passenger to hail a traditional yellow cab there. Uber's engineers could set specific goals for its machine learning algorithm: "maximize driver presence in the West Village" or "reduce passenger wait times in the West Village below three minutes," and then train the algorithm to accomplish these goals. Even without nefarious intent or methods, these instructions could deliver incidentally harmful or inefficient results: drivers being routed out of their way to pass through the neighborhood, for example, or unduly prioritizing riders whose destinations were in the West Village.[132] More perniciously, Uber engineers could permit its algorithm to systematically misrepresent a surge to drivers within that area to encourage greater driver saturation — a possible explanation for the phenomenon known as the "false surge" that has drawn driver complaints.[133]

Uber also has the ability to leverage user information to exploit willingness-to-pay, and, presumably, willingness-to-work. As discussed above, the firm let slip its finding that riders with a low phone battery tolerated higher prices for rides.[134] Given the reams of data that smartphones collect, there is no shortage of levers that a platform firm could experiment with to manipulate

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130. *Id.* at 1662–63.
131. *See* Chen, *supra* note 113.
132. While decisions about where to operate or expand are questions of legitimate business strategy, they could also have the unintended effect of systematically denying or limiting service availability to members of protected classes. *See supra* Part III.C.3.c (discussing "gray area" harms that reflect divergent interests among riders, drivers, and the firm).
133. Rosenblat & Stark, *supra* note 87, at 3766.
134. *See* Withnall, *supra* note 112.

its users' behavior. Uber could effectively wage-discriminate against its drivers for a variety of purposes, for example, by offering only low-value fares to drivers who demonstrated a willingness to accept them, or reserving high-value fares for drivers whom it determined were on the verge of ending their "shift" or leaving the platform entirely. In short, the sheer volume of data available to Uber and the opportunity to deliberately yet imperceptibly manipulate the behavior of drivers and riders invites more scrutiny.

c. *Divergent Interests in the Short Term: The Gray Area*

In between the extremes, there exists an intermediate zone of harms resulting from algorithmic parameters or design choices that undermine the joint-profit premise. Uber's drivers are essentially participating in a vast behavioral economics experiment.[135] This is problematic because a platform firm is likely to sacrifice short-term profitability in the interest of long-run market capture, and there is little to protect workers from high-level decisions that sacrifice their individual earnings in order to increase a firm's market share or the performance of its algorithm. The benefits of these improvements accrue mostly to the owner of the algorithm, while the costs of errors and inefficiencies are borne by the workers.

Take, for instance, the use of A/B testing and "multi-arm bandit algorithms," which systematically test a range of options randomly on a population of users, gather data on the effectiveness of alternatives, and then adjust accordingly.[136] Applied to surge-

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135.   *See* Griswold, *supra* note 5.
136.   *See* Calo & Rosenblat, *supra* note 6, at 1669. An A/B test is a controlled experiment where a user is randomly presented with one of two different options, and the outcomes are recorded and used to influence future presentations. *See* Shaw Lu, *Beyond A/B Testing: Multi-armed Bandit Experiments*, TOWARDS DATA SCI. (Apr. 3 2019), https://towardsdatascience.com/beyond-a-b-testing-multi-armed-bandit-experiments-1493f709f804 [https://perma.cc/V9NG-VUK3]. For instance, a clothing website might show different users two different photographs on its homepage and measure which group — those who saw photo "A" or photo "B" — is more likely to make a purchase. Multi-arm bandit algorithms function essentially the same way, except that they are able to adapt in real-time to optimize the presentation of a wider range of options. *Id.* In the above example, a clothing website deploying a multi-arm bandit algorithm might show users one of a dozen photographs, while tracking who eventually made a purchase; as some photographs begin performing better (i.e., leading to more purchases) than others, the algorithm will begin automatically showing the high-performing photographs to more users, and, over time, provide the operators of the algorithm with information about the characteristics of photographs that tend to be more successful. *Id.*

area assignments, adjusted "boost" incentives (offering a higher rate of compensation) or alternative routes between destinations, this practice would necessarily involve sending a certain percentage of drivers to areas that are likely to increase their wait times between rides, and thus reduce their earnings. Uber has acknowledged that it uses A/B testing to improve its algorithms.[137]

Uber has an interest in learning as much as it can about driver behavior and an unlimited ability to adjust its algorithm to help it answer specific questions. For instance, Uber could find out what is the longest amount of time a driver is willing to wait for a ride before logging off the app; what is the farthest a driver would go to pick up a rider; and how far from home is a driver willing to range in the course of a day's work.

In addition to studying driver behavior generally, Uber could also track the behavior of individuals. Would the firm adjust drivers' ride opportunities based on individual behavior profiles as a way to extract maximum value? Platform firms have the incentives and opportunities to engage in these behaviors, and because their algorithms are protected as intellectual property, their design choices are not subject to public scrutiny.

As these examples illustrate, the overall model raises ethical questions about experimentation and control in a market where people's livelihoods are at stake. In running a machine learning algorithm, Uber is building up its intellectual property by conducting a vast field experiment where drivers have not been informed or given meaningful consent and do not understand they are participating. Uber's terms of service are constantly shifting, and often a driver will have no meaningful alternative to simply agreeing to an update when she opens the app to begin work.[138] Drivers are being paid for giving rides, but they are not seeing any profit (and may, in fact, incur losses) from the development of these algorithms and the insights about transportation that Uber is able to gain. This would be less problematic if drivers were employees of the company — nobody would question whether a firm had the right to leverage data on employees to improve

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137. Jeremy Hermann & Mike Del Balso, *Meet Michelangelo: Uber's Machine Learning Platform*, UBER: ENG'R (Sept. 5, 2017), https://eng.uber.com/michelangelo [https://perma.cc/5JA6-ECAJ].

138. David Horton, *The Shadow Terms: Contract Procedure and Unilateral Amendments*, 57 UCLA L. REV. 605, 649–50 (2010).

productivity, or experiment with different work assignments. The more difficult question is what responsibility Uber has to its "partners," and whether the firm is meeting it.

IV. PROPOSALS FOR LEGAL PROTECTION OF UBER DRIVER-PARTNERS AND OTHER PLATFORM WORKERS

A growing body of scholarship is addressing the problem of protecting workers in the platform economy. Much of this scholarship has already examined the role of worker classification laws and has described proposals for revising such laws. Part IV.A of this Note identifies challenges facing platform workers who occupy a gap in existing labor protections. Part IV.B surveys various proposals and concludes that these proposals are ultimately insufficient to address the novel harms enabled by algorithmically-mediated platform work. Part IV.C proposes specific causes of action sounding in tort and contract jurisprudence as a means of redress for workers who have been harmed by the practices and design choices previously identified in Part III.

A. OBSTACLES FACING PLATFORM WORKERS

There are numerous structural factors that may make it difficult for platform workers to assert or vindicate their interests against platform firms. First and foremost is their independent contractor status. Because the law treats the drivers, maids, and masseuses of the platform economy as small-business owners, a host of statutory worker protection schemes, such as the Fair Labor Standards Act (FLSA), are not available to them.[139] Uber's standard contract with its "driver-partners" contains provisions limiting Uber's liability in a variety of circumstances.[140] Drivers

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139. *See, e.g.*, Kerce v. W. Telemarketing Corp., 575 F. Supp. 2d 1354, 1359 (S.D. Ga. 2008) (holding that only workers classified as employee can bring actions under FLSA); Padjuran v. Aventura Limousine & Transp. Serv., Inc., 500 F. Supp. 2d 1359, 1361–62 (S.D. Fla. 2007) (same).

140. *See, e.g.*, Rasier LLC Technology Services Agreement §§ 2.2–2.3 (last updated Dec. 11, 2015), https://s3.amazonaws.com/uber-regulatory-documents/country/united_ states/RASIER%20Technology%20Services%20Agreement%20Decmeber%2010% 202015.pdf [https://perma.cc/RVV2-QG7K] (recent version of Uber's contract with one of its "driver-partners," Rasier LLC, a wholly-owned subsidiary of Uber). *See also* Mohamed v. Uber Techs., Inc., 109 F. Supp. 3d 1185, 1190 (N.D. Cal. 2015), aff'd in part, rev'd in part and remanded, 836 F.3d 1102 (9th Cir. 2016), and aff'd in part, rev'd in part and remanded, 848 F.3d 1201 (9th Cir. 2016).

must agree to terms stating that they are independent contractors who receive transportation services from Uber, and agree to a disclaimer of a formal employment relationship or the right to pursue claims outside of arbitration, though the enforceability of these provisions is in doubt.[141]

Independent contractors do not receive employee protections under statutes such as the Employment Retirement Income Security Act (ERISA) or FLSA because they are thought to be more self-sufficient than employees, having greater bargaining power due to their ability to potentially contract with multiple parties. As independent contractors, Uber drivers are forbidden from organizing or bargaining collectively under antitrust law.[142]

Accordingly, the existing employment law landscape is poorly suited to address the novel challenges of platform work. Nonetheless, scholars have proposed various potential responses to these obstacles, which will be examined in the following subpart. While there are benefits and drawbacks to each, they signal an emerging recognition that platform workers need additional legal protections.

B. PROPOSALS FOR STATUTORY AND REGULATORY PROTECTION OF PLATFORM WORKERS

There is widespread agreement that the existing worker classification scheme is poorly suited to work relationships in the platform economy. In the words of Judge Vincent Chhabria, a jury asked to determine a TNC driver's employment status "will be handed a square peg and asked to choose between two round holes."[143]   Platform companies using similar employment-mediation models are very likely to encounter the same difficulty.

Economist Joseph V. Kennedy has identified three potential programs for updating labor law to better address the platform

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141.   *See, e.g.*, Cotter v. Lyft, Inc., 176 F. Supp. 3d 930, 943 (N.D. Cal. 2016) ("Even beyond the possibility that Lyft has waived the right to force the class members to arbitration, there is at least some authority suggesting the arbitration provision is unenforceable entirely, because it violates the National Labor Relations Act.").

142.   Under section 6 of the Clayton Act, organized labor activities were specifically exempted from antitrust prohibitions on anti-competitive behavior. *See* 15 U.S.C. § 17. However, later Supreme Court decisions narrowed the exemption by prohibiting independent contractors from organizing. *See* Columbia River Packers Ass'n v. Hinton, 315 U.S. 143 (1942); L.A. Meat & Provision Drivers Union, Local 626 v. United States, 371 U.S. 94 (1962).

143.   *See Cotter*, 176 F. Supp. 3d at 1081.

economy.[144] Broadly stated: regulators and legislators could create a new, third category of worker; Congress could revise each of the country's major labor laws (FLSA, ERISA, etc.) to update them to ensure that they continue to achieve their goals; or legislators can draft carve-outs to existing labor laws that ensure that workers, customers and platforms all benefit.[145]

In 2015, economists Seth Harris and Alan Krueger published a detailed proposal for the option of a third class of "independent workers."[146] According to their research, at that time there were 600,000 workers, or 0.4% of the U.S. workforce, who used a platform intermediary to secure work, a number which was then growing rapidly.[147] They identify challenges in regulating this sector, including the immeasurability of "hours worked," which is tied to eligibility for programs such as the Affordable Care Act; the ability to collectively bargain; and the absence of civil rights protection afforded to employees.[148] The class of workers they propose designating would receive some employee protections, including the right to organize and employer contributions to Social Security and Medicare payroll taxes, but would not receive benefits such as overtime.[149]

While this proposal is appealingly pragmatic, further analysis exposes some weaknesses. Other industrialized nations have classifications similar to what Harris and Krueger propose, and their experience suggests that adding a third category to the existing scheme will increase opportunities for manipulation and only marginally protect the intended workers, while increasing the volume of litigation required to enforce the more complex classification scheme.[150] The experiences of Canada, Italy, and Spain, each of which has some version of an intermediate category sharing some characteristics with the "Independent Worker"

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144.   Joseph V. Kennedy, *Three Paths to Update Labor Law for the Gig Economy*, INFO. TECH. & INNOVATION FOUND. 1, 2 (Apr. 2016), http://www2.itif.org/2016-labor-law-gig-economy.pdf [https://perma.cc/H278-PPHV].

145.   *Id.*

146.   *See* Seth Harris & Alan Krueger, *A Proposal for Modernizing Labor Laws for Twenty-First-Century Work: The "Independent Worker,"* BROOKINGS: HAMILTON PROJECT 2 (2015), https://www.hamiltonproject.org/assets/files/modernizing_labor_laws_for_twenty_first_century_work_krueger_harris.pdf [https://perma.cc/6RPP-L4LE].

147.   *Id.*

148.   *Id.* at 14–18.

149.   *Id.* at 27.

150.   *See generally* Miriam Cherry & Antonio Aloisi, *"Dependent Contractors" in the Gig Economy: A Comparative Approach*, 66 AM. U. L. REV. 635 (2017).

classification proposed by Harris and Krueger, are instructive. Canada's "dependent contractor" had the most success at expanding worker protections by essentially expanding the definition of "employee"; at the other end of the spectrum, Italy's framework allowed businesses to use the third category as a less tax-burdened alternative to traditional employment classification with the same essential features, resulting in a series of "emergency" interventions by the Italian legislature and rampant confusion and abuse.[151]

Other scholars have been more willing to accept platform firm's characterizations of themselves as providers of platform market services, but have called for more oversight to ensure that these markets operate fairly. In 2016, the Federal Trade Commission hosted a workshop on issues in the "sharing economy" where participants adopted much of the terminology and narratives favored by platform firms, and expressed a range of concerns including "protectionism of incumbent [taxi or hotel] suppliers" as a consumer harm and "balancing its regulatory goals and encouraging innovation."[152]

This approach disappointed many observers. Professors Ryan Calo, Orly Lobel, Kenneth Bamberger and others have highlighted the need for closer scrutiny of the practices of platform firms, and for regulators to demand more granular information about the workings of their algorithms.[153] Similarly, Professors Mark Anderson and Max Huffman have proposed an antitrust analysis of Uber's business model, characterizing Uber's structure as having similarity to a cartel.[154] These critics and others charge that the conduct of Uber and its peers is more serious than regulators currently understand.

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151. *Id.* at 676. By expanding the ambit of employee protections to include more independent contractors, the plan was able to provide more benefits and coverage than reforms in other countries. *See id.*

152. FED. TRADE COMM'N, THE "SHARING" ECONOMY: ISSUES FACING PLATFORMS, PARTICIPANTS AND REGULATORS 53 (Nov. 2016), https://www.ftc.gov/system/files/ documents/reports/sharing-economy-issues-facing-platforms-participants-regulators-federal-trade-commission-staff/p151200_ftc_staff_report_on_the_sharing_economy.pdf [https://perma.cc/M4B2-TNCZ].

153. *See* Bamberger & Lobel, *supra* note 24, at 1051; *see also* Calo & Rosenblat, *supra* note 6, at 1633.

154. *See generally* Mark Anderson & Max Huffman, *The Sharing Economy Meets the Sherman Act: Is Uber a Firm, A Cartel, or Something in Between?*, 2017 COLUM. BUS. L. REV. 859 (2017).

Transparency in this context is both desirable and problematic, due to the nature of machine learning algorithms and firms' interests in intellectual property.[155] Professor Paul Ohm has called for requirements that firms that deploy consumer-facing algorithms be not just transparent, but also "forthright," advocating for an affirmative obligation to warn consumers about their services.[156]

While many of these proposals are measured and thoughtful, they fail to address the core challenges of algorithmically-mediated work. The harms that are enabled by the platform model are subtle and difficult to detect, yet potentially vast when considered at scale. Although comprehensive regulation may eventually offer a solution, the law should first address new, discrete harms as they arise and build from common law principles to determine how best to regulate an emerging and sophisticated model of labor relations.

C. CAUSES OF ACTION FOR ALGORITHMIC HARMS TO PLATFORM WORKERS

This Part of the Note proposes common law causes of action sounding in contract and tort jurisprudence as a potential response to algorithmic harms to platform workers. The law is slow to adapt to structural economic change. The modern worker protection regimes were not drafted overnight, but rather came in the wake of decades of litigation between workers and employers, with courts laying down the principles that would animate these laws through case-by-case adjudication. In our present moment, where the reach and import of machine learning algorithms continues to expand dramatically while regulations and laws pertaining to them remain scant, the courts might play a similar role in extending the law from common principles.

However, there are some caveats to this approach. At present, there is little direct proof of the abusive or otherwise harmful practices as outlined in Part III.[157] As a procedural matter, Uber driver-partners might struggle to overcome dismissals of their complaints under Federal Rule of Civil Procedure 12(b)(6), given that evidence of specific and concrete algorithmic harms is lim-

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155. *See supra* Part III.A.
156. *See generally* Paul Ohm, *Forthright Code*, 56 HOUS. L. REV. 471 (2018).
157. *See supra* Part III.

ited by the very nature of their operation and the monopoly of control over them that firms enjoy.[158] However, given the incentives faced by start-up platform firms and the control they have over their algorithms, it seems highly plausible that some platform operator sooner or later will commit some version of these abuses and get caught. A plaintiff who was able to overcome dismissal of the complaint would have a great deal of leverage to settle, given the jealousy with which firms guard their trade secrets and intellectual property.

The following subparts apply a tort framework to the three categories of harms — abusive, incidental, and divergent-interest — and analyze how different tort theories may apply to specific examples of algorithmic harms.[159] There is presently no court that has ruled on an issue pertaining specifically to pecuniary harms to platform workers. The body of case law dealing with algorithmic harms generally is limited, but provides useful conceptual analogies to develop legal theories that could be used by Uber driver-partners harmed by the firm's conduct.

1. *The Tort of Misrepresentation and its Potential Application to Uber*

The tort of misrepresentation resulting in pecuniary loss holds promise for a worker who enters into a contract with a platform firm and is harmed by the result.[160] Misrepresentation torts in the employment context have, to this point, typically been litigated based on representations made at hiring. So-called "truth-in-hiring" claims arise when employees accept job offers or positions

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158.   In *Bell Atl. Corp. v. Twombly*, the Supreme Court clarified that a complaint "requires . . . enough factual matter (taken as true) to suggest that" the alleged conduct actually occurred, effectively heightening the requirements of the well-pleaded complaint rule. 550 U.S. 544, 556 (2007). In *Ashcroft v. Iqbal*, the Court reinforced this requirement in finding the plaintiff's claim of racial discrimination lacked enough factual basis to cross "the line from conceivable to plausible." 556 U.S. 662, 680 (2009). Driver plaintiffs who seek redress for practices described in Part III, *supra*, could find themselves facing similar obstacles in the face of a motion to dismiss. As drivers have no access to the data that Uber uses to assign routes and calculate fares, they would have difficulty making a factual showing at the pleading stage. However, there are scholars who suggest that the workings of Uber's algorithms may be discoverable through field experiments that reverse-engineer the platform. *See generally* Chen et al., *supra* note 113. Furthermore, at least one court has sustained claims of harm resulting from a defective algorithm design where plaintiff provided expert testimony. *See infra* Part IV.C.3 (discussing *Wickersham v. Ford*).

159.   *See supra* Part III.C.3.

160.   *See* Restatement (Second) of Torts ch. 22, §§ 525–557 (Am. Law Inst. 1977).

in reliance on false statements or promises the employer made to entice the worker to accept the position.[161] The case of platform work is analogous, but different: each transaction effectively amounts to an offer of a new contract.[162]   A platform worker would be harmed by misrepresentations as a course of conduct, rather than a single misrepresentation made at the initial point engagement — that is, a pattern of reduced fares or diminished opportunities. As emphasized before, while any one individual algorithmic decision may cause a relatively small pecuniary loss to a driver, these accumulate over the course of continued transactions.

Misrepresentation may be fraudulent,[163] negligent,[164] or innocent.[165] The analysis of this Note focuses on the first two; the sophistication and comprehensiveness of Uber's data mining give the firm a "god's eye" view of drivers and riders in the field, which is to say that its developers either know or could know everything about the effects of algorithm design choices on the earnings of drivers.[166] Therefore, "innocent" or unknowing misrepresentation is not applicable.

Section 525 of the Second Restatement of Torts imposes liability on "one who fraudulently makes a misrepresentation of fact, opinion, intention or law for the purpose of inducing another to act or to refrain from acting in reliance upon it" for pecuniary losses that result.[167] Section 522 of the Second Restatement of Torts imposes liability for negligently doing the same. Professor Frank Cavico identifies seven specific situations where a worker can bring a successful misrepresentation claim against an employer, four of which are particularly relevant in the context of

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161.   *See* Richard P. Perna, *Deceitful Employers: Common Law Fraud as a Mechanism to Remedy Intentional Employer Misrepresentation in Hiring*, 41 WILLAMETTE L. REV. 233, 234 (2005). *See, e.g.*, Johnson v. George J. Ball, Inc., 617 N.E.2d 1355 (Ill. App. Ct. 1993) (upholding a claim for fraudulent misrepresentation against an employer for misleading descriptions of the position at issue).

162.   *See* Calo & Rosenblat, *supra* note 6, at 1660–61.

163.   Restatement (Second) of Torts ch. 22, § 525 (Am. Law Inst. 1977).

164.   *Id.* § 552(1).

165.   *Id.* § 552C.

166.   Chris Welch, *Uber Will Pay $20,000 Fine in Settlement Over "God View" Tracking*, VERGE (Jan. 6, 2016), https://www.theverge.com/2016/1/6/10726004/uber-god-mode-settlement-fine [perma.cc/8XBR-UQMV].

167.   Restatement (Second) of Torts, ch. 22, § 525 (Am. Law Inst. 1977).

platform work.[168] These occur where an employer misrepresents the terms or conditions of employment;[169] misrepresents the employer's financial condition, profitability, or the employee's income potential;[170] makes false statements regarding the legality, propriety or fairness of employment practices;[171] or misrepresents salary, commissions, insurance or other benefits.[172] Many or all of these claims could be employed against platform operators engaging in abusive or misleading practices.

2. *Uber's Duty to its Driver-Partners*

Uber's driver-partner contract seeks to exculpate the firm from liability broadly, including claims of misrepresentation. It contains specific provisions disclaiming guarantees of service provision, error-free service, or of the app providing any requests for transportation whatsoever.[173] Some scholars doubt the enforceability of these types of contracts due to their status as "contracts of adhesion," the inability of consumers to carefully scrutinize complex terms on the fly, or a "fleeting unconscionability" that results when a driver-partner is forced to agree to new terms before logging into the app.[174]

As a general matter, a party cannot contract around its liability for fraud; it can, however, contract away its liability for negligence. In most American jurisdictions, a contractual relationship implies a covenant of good faith; fraud is, by definition, a breach of the duty of good faith.[175] Negligent misrepresentation arises

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168.   Frank J. Cavico, *Fraudulent, Negligent, and Innocent Misrepresentation in the Employment Context: The Deceitful, Careless, and Thoughtless Employer*, 20 CAMPBELL L. REV. 1, 4 (1997).

169.   *See* Hamlen v. Fairchild Indus., Inc., 413 So.2d 800, 801–02 (Fla. Dist. Ct. App. 1982); Bemmes v. Pub. Emps. Ret. Sys. of Ohio, 658 N.E.2d 31, 35–36 (Ohio Ct. App. 1995).

170.   *See* Berger v. Sec. Pac. Info. Sys., Inc., 795 P.2d 1380, 1383–84 (Colo. Ct. App. 1990); Clement-Rowe v. Mich. Health Care Corp., 538 N.W.2d 20, 23–24 (Mich. Ct. App. 1995).

171.   *See* Russ v. TRW, Inc., 570 N.E.2d 1076, 1083–84 (Ohio 1991).

172.   *See* Sandler v. New York Times Inc., 721 F. Supp. 506, 512 (S.D.N.Y. 1989); Duck Head Apparel Co., Inc. v. Hoots, 659 So.2d 897, 904–05 (Ala. 1995).

173.   Rasier LLC Technology Services Agreement, *supra* note 140, cl. 11.

174.   *See* OREN BAR-GILL, SEDUCTION BY CONTRACT: LAW, ECONOMICS, AND PSYCHOLOGY IN CONSUMER MARKETS 141–45 (2012); *see also* David Horton, *The Shadow Terms: Contract Procedure and Unilateral Amendments*, 57 UCLA L. REV. 605, 649–50 (2010).

175.   Steven J. Burton, *Breach of Contract and the Common Law Duty to Perform in Good Faith*, 94 HARV. L. REV. 369, 370 (1980).

from the defendant's failure to exercise reasonable care and competence in determining underlying facts or information or in communicating that information to the worker.[176] A claim of negligent misrepresentation, however, can create difficulty for the plaintiff to convince the court of the defendant's duty. Some courts look for "special circumstances" to convince them to impose tort duties on one party to a contractual relationship; for instance, the Fourth Circuit has held that a contract must involve "special circumstances," such as a doctor-patient relationship or lawyer-client relationship, to impose tort duties in addition to contractual duties.[177]

Uber has none of the special professional duties of a doctor or lawyer. The independent-contractor model presumes two commercial parties on equal footing, and contract law typically takes the position that these parties should protect themselves (or not) purely through the terms of their contract. However, the extreme information asymmetry and unilateral control Uber enjoys over the dispatch algorithm counsel in favor of Uber owing drivers a duty of care in making representations to driver-partners, whether in its "partnership" joint-profit-maximizing representations to drivers at the outset of the relationship, their representations about the neutrality of the dispatch algorithm, or in providing granular information to drivers about the locations of "surge zones." The ease with which Uber could undermine its own representations to further its own interests at their drivers' expense coupled with the near-impossibility for driver-partners to police the terms of the bargain militate in favor of holding Uber to a special standard of care.

3. *Design Choices that May Amount to a Breach of Duty*

Assuming that Uber has a duty to its driver-partners in making good-faith or non-negligent representations about the functionality of the work platform, driver's potential earnings overall or in a given surge area, or the basic nature of the "partnership," the next question is what types of algorithm design choices amount to a breach of that duty. As described previously, these

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176. Cavico, *supra* note 168, at 56.
177. McNierney v. McGraw-Hill, Inc., 919 F. Supp. 853, 862 (D. Md. 1995) (citing Martin Marietta v. Int'l Telecomm. Satellite Org., 991 F.2d 94, 98 (4th Cir. 1992)).

design choices and resultant harms can be broadly categorized as abusive, divergent-interest, or incidental.[178]

The breach element of the tort is fairly straightforward for the cases of abusive and divergent-interest design choices, as these will amount to breaches of the duty of good faith. Abusive practices are the most easily dispatched. At a basic level, if Uber represents to driver-partners that its algorithm is designed to help maximize their earnings, any design choices not geared to that result arguably represent a breach. The most flagrant examples would be deliberately showing a false surge to drivers or wage-discriminating by offering drivers only the lowest-value rides that they were likely to accept.[179]

Divergent-interest practices are not quite as clear cut but would still breach the duty of good faith. Nowhere in its marketing materials or terms of service does Uber advertise to drivers that they are part of a vast real-world behavioral economics experiment meant to improve and enhance Uber's intellectual property. Yet, if it deploys a bandit algorithm that routinely sends drivers to test areas or alternative routes with the aim of gathering data rather than generating fares for drivers, it breaches its duty of good faith. Similarly, if the algorithm sends off-line drivers a "nudge" message to get on the road at a certain time due to "high demand,"[180] whether measured or anticipated, it is essentially representing to drivers that they can expect higher-than-average earnings. However, supply may quickly overwhelm demand; the algorithms (or its operators) may have the reduction rider wait times as the actual goal, with oversupplying drivers as the means to that end.

Incidental harms resulting from design choices are trickier. Pecuniary losses to driver partners as a result of "overfitting" offer perhaps the least blameworthy case; as discussed in Part III.A of this Note, overfitting is endemic to machine-learning algorithms and requires active measures by developers to overcome.[181] Some courts have held algorithm proprietors liable for

178.   *See supra* Part III.C.3.

179.   *See* Calo & Rosenblat, *supra* note 6, at 1766.

180.   *See* Scheiber, *supra* note 93 ("Many companies in the gig economy simply do not have enough workers, or rich enough data about their workers' behavior, to navigate busy periods using nudges and the like. To avoid chronic understaffing, they have switched to an employee model that allows them to compel workers to log in when the companies most need them.").

181.   *See* Lehr & Ohm, *supra* note 67, at 683.

defects in the design of their algorithms resulting in economic harm to plaintiffs. Specifically, in the case of *Gambles v. Sterling Infosystems*, the plaintiff, Gambles, brought suit against a provider of background checks that used algorithms to provide recommendations to prospective employers.[182] Gambles alleged that the firm's algorithm "(1) contained information about addresses where he had not lived in more than seven years; (2) incorrectly, inconsistently, or duplicatively reported the dates that Gambles had lived at various addresses; and (3) used false and derogatory terms to describe certain addresses . . . [and that] these statements depicted him as itinerant, unstable, and unattractive" and harmed his employment prospects.[183]

The court sustained plaintiff's allegations that the algorithm's design (specifically, developers' failure to "clean" the data to a reasonable degree)[184] did not meet the Fair Credit Reporting Act's requirement that "reasonable procedures be used to assure the maximum possible accuracy of credit reports."[185] While there is no statute currently requiring platform firms to use reasonable procedures to ensure the accuracy or fairness of their algorithms' decisions, a misleading representation of economic opportunity coupled with a failure to reasonably design the algorithm to ensure the represented outcome could meet a common-law negligence standard.

Product liability torts offer another conceptual frame for dealing with this issue, in the form of design defects. In the case of *Wickersham v. Ford*, the plaintiff's estate was able to sustain a claim against a carmaker that an algorithm designed to deploy an airbag in the event of a crash was designed defectively.[186] The plaintiff's expert witness, an automotive engineer, testified that the algorithm in question had been negligently designed. The algorithm was allegedly "trained" using crash test data that did not account for the type of crash that occurred in the instant case. Thus, the court held that it was a question of fact whether Ford was negligent in not conducting more thorough testing.[187]

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182. Gambles v. Sterling Infosystems, Inc., 234 F. Supp. 3d 510, 515 (S.D.N.Y. 2017).
183. *Id.* at 513.
184. *See* Lehr & Ohm, *supra* note 67, at 656.
185. *Gambles*, 234 F. Supp. 3d at 513.
186. Wickersham v. Ford Motor Co., 194 F. Supp. 3d 434, 438 (D.S.C. 2016).
187. *Id.* at 438.

The same logic could apply to the hypothetical case where the dispatch algorithm "unintentionally" or "carelessly" discriminates against certain drivers or classes of drivers.[188] If Uber represents to drivers that they can expect consistent earnings per hour worked in a given area, but then fails to adequately test or train the algorithm to ensure this outcome, the firm could be liable for negligence in making that representation.

4. *Causation Requirements*

The causation element of misrepresentation torts presents perhaps the most difficult challenge to would-be driver-partner plaintiffs. To show causation in any tort context, a plaintiff must show that the defendant's actions (or lack thereof) were the "but-for cause" of the harm or a "substantial factor" in causing the harm.[189] To prevail on claim of fraudulent misrepresentation, a plaintiff must show both that the defendant intended to deceive her and intended to induce her to rely on the misrepresentation and act on that reliance.[190] Therefore, a driver-partner would need to show that a misrepresentation made by Uber — either in its general representations of how the algorithm works, the nature of the partner relationship, or communicated through the app — was a substantial factor in causing her economic harm. The plaintiff would also need to show actual reliance on that misrepresentation that was reasonable or justifiable under the circumstances.[191]

A driver-partner should be able to show justifiable reliance with little difficulty; by simply supplying a vehicle and using the app to make income, she is acting based on Uber's representations about its algorithm working to efficiently match riders with drivers and earn drivers money.[192] To the extent that a plaintiff accepted and acted on the justifiable belief that the algorithm was designed to maximize (or even reasonably promote) driver

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188.   *See supra* Part III.C.3 (discussing the possibility that Uber's documented lower pay for female drivers is the result of unintended consequences of choices made in the design of the dispatch algorithm).

189.   *See* Cavico, *supra* note 168, at 41.

190.   *See id.* at 34, 39. In the case of negligent misrepresentation, the intention element is displaced by a lack of reasonable care. *Id.*

191.   *Id.* at 44.

192.   *See* Hall & Krueger, *supra* note 86; *see also* Voytek, *supra* note 106 (describing Uber engineers' efforts to "optimize" the dispatch algorithm).

profits, her actions are substantially caused by those representations.

The key difficulty for driver-partner plaintiffs would be making a showing of what algorithm design choices were made, why developers made those choices, how the results of those choices differed from representations made by the firm, and then showing that the choice was a substantial factor in an economic loss. Uber voluntarily shares the broad outlines of how its dispatch algorithm works but is also highly secretive about its specific parameters.[193] To sustain a claim, a plaintiff might need a disgruntled whistleblower inside the firm or a leak of internal documents describing abusive or divergent-interest algorithm design choices and an awareness on the part of developers that the results of these decisions would undermine or directly contravene representations to driver-partners.[194]

5. *Calculating Damages for Economic Harms to Uber Driver-Partners*

A plaintiff who seeks to recover damages based on an employer's misrepresentation must show a legally recognizable injury or loss as a result of the misrepresentation.[195] Assuming the defendant's misrepresentation legally causes the plaintiff to suffer actual damages, courts typically permit juries to award compensatory monetary damages based on a "general" measure of "direct" damages, in addition to "indirect" damages, which can comprise "benefit of the bargain" damages (placing the plaintiff where she would have been if the representation had been accurate) or the recovery of out-of-pocket losses.[196]

For Uber driver-partners, "benefit of the bargain" damages might amount to the difference between actual earnings and the amount they would have earned in the absence of abusive, divergent-interest, or incidental design choices not made in service of the fundamental joint-profit partnership premise.[197] Out-of-pocket losses might be measured by the costs of maintaining and operating a vehicle, or perhaps the opportunity cost to drivers

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193.   *See supra* Part III.C.2.
194.   See *supra* note 158, for a more detailed discussion of this point.
195.   Cavico, *supra* note 168, at 52.
196.   *Id.*
197.   *See supra* Part III.B.

who spend hours idling or "chasing surges" that might have been spent in more gainful employment.

In fact, calculating these damages is an even more formidable task than simply identifying and presenting evidence of the harmful design choices that give rise to these losses. With uninhibited access to Uber's data and algorithm, and with the assistance of sophisticated data scientists, a plaintiff might be able to "run the model"[198] to simulate the effects of different designs on driver earnings. Uber is unlikely to share this information unless compelled to in discovery.

Other market enforcement contexts give clues to how such losses might be calculated, however. The New York Stock Exchange (NYSE), in the course of investigating electronic stock trading fraud, has developed and deployed algorithms to identify stock transactions where "specialist firms" exploited delays in public stock orders to gain an unfair market advantage.[199] The algorithm developed by the NYSE (and later used by the Department of Justice in its criminal prosecution of specialist firms) was not only able to identify the specific transactions that violated trading rules, but also the number of disadvantaged shares and the dollar amounts by which they were disadvantaged.[200]

While in that case, the NYSE had the advantage of full access to the data in question, it at least demonstrates the principle that highly-complex market-based transactions can be tracked, evaluated, and compared against but-for outcomes to measure damages. One previously-noted difficulty in a hypothetical lawsuit against Uber is that the individual economic harm suffered by an Uber driver-partner (in the form of a single ride commission denied or an extra ten minutes spent idling) might be very small; over time, however, the damages could add up substantially. The NYSE case shows that the practical obstacles to Uber driver plaintiffs achieving a similar measurement are various and formidable, but not impossible to overcome.

In short, claims brought by driver-partners against Uber would face a number of headwinds but are firmly grounded in established common-law principles. While proposed regulatory responses or worker classification reforms are steps in the right direction, these will have limited impact as long as the workings

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198.   *See supra* Part III.A.
199.   *In re* NYSE Specialists Sec. Litig., 260 F.R.D. 55, 66 (S.D.N.Y. 2009).
200.   *Id.*

of Uber and other platforms remain opaque. Lawsuits brought by driver-partners may be especially useful in revealing the actual contours of the relationship between Uber and its users and force the legal system to evaluate these against established law.

V. Conclusion

Black-box algorithms may prove impervious to misrepresentation torts; to meet pleading requirements, plaintiffs who have been economically harmed by abusive, divergent-interest, or incidental algorithm design choices simply do not have access to the facts that they would need to sustain a claim against a motion for dismissal. A breach of information or security by a firm like Uber, however, could well reveal actionable discrepancies between the representations it makes to its driver-partners and the goals it sets for its algorithm, if there is in fact anything to hide.

As the modern economy continues to change, it is clear that algorithms will play a growing role in mediating employment relationships. As in other areas where algorithms are entrusted to make consequential decisions, regulators, legal scholars, and, especially, the operators of work platform algorithms have a responsibility to consider the impacts of their use. As yet, there is little legislation or regulation of the use of algorithms to manage workers. Courts are only beginning to encounter claims of algorithmic harms. Partly due to the complexity and opacity of machine learning algorithms, the legal academy has been slow to articulate the potential harms of automated decision-making and to propose and develop policy solutions.[201]

As such, common law principles applied to new situations can point the way towards a fair and efficient regime for regulating platform work. The promise of platform labor markets should not be discounted, and concerns about "stifling innovation," while sometimes strategic and overblown, are still worth considering. Eventually, statutes tailored to the unique problems presented by platform work may be necessary or desirable. But before legislators attempt to draft comprehensive regulation, it may make sense to first address individual abuses as they arise and allow the law to develop gradually from existing principles.

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201. *See* Lehr & Ohm, *supra* note 67, at 655.