



Beyond Automation: The Law & Political Economy of Workplace Technological Change

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Abstract: This article unpacks the relationship among advanced information technologies, employment law rules, and labor standards. Based on a detailed review of the capacities of existing technologies, it argues that automation is not a major threat to workers today, and that it will not likely be a major threat anytime soon. Companies are, however, using new information technologies in other ways that give them a power advantage vis-à-vis workers, all of which are enabled by existing employment laws. For example, they are increasingly using algorithms to monitor, direct, or schedule workers, in the process reducing workers' wages or autonomy. Companies are also using new technologies to "fissure" employment: outsourcing work tasks or processes and then disclaiming legal duties toward workers, all while closely monitoring workers' performance. These findings have policy implications. If the major threat facing workers is employer domination rather than job loss, then exotic reforms such as a universal basic income are less urgent. Rather, policymakers should expand the scope and stringency of companies' duties toward their workers, and/or enable workers to contest the introduction of new workplace technologies.

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INTRODUCTION

This article asks how new information technologies are really changing work. This is a subject of widespread public debate and speculation, driven by the recent economic growth of the tech sector and stunning developments in various technologies, including “big data” analytics, machine learning, and advanced robotics. Many have viewed the maturation of these technologies with apprehension, worrying that a looming automation wave will leave millions out of work. An oft-cited study by two Oxford researchers, for example, predicted that “about 47 percent of total U.S. employment” could be threatened by current technologies.¹ Nearly every major news magazine has run a cover story on the question, with titles such as “Welcoming Our New Robot Overlords,” “Learning to Love Our Robot Co-workers,” and “You Will Lose Your Job to a Robot—and Sooner Than You Think.”² Such fears are shared by law professors, labor leaders, and public intellectuals.³ And even commentators who are skeptical about the automation threat worry that new technologies will consign the rest of us to lifetimes of precarious work, as on-demand services such as Uber take over more and more swaths of economic activity.⁴

To date, however, such accounts have largely disregarded two important questions. One is socio-legal: How does the institutional context—in particular, the rules governing the workplace and labor markets—shape employers’ incentives to develop and deploy particular technologies?⁵ Another is more empirical: Can the underlying technologies actually accomplish what many are asking of them? This article takes up both questions.

Part I, below, addresses socio-legal matters. Working within the burgeoning field of law and political economy, which seeks to understand how law “gives shape to the relations between politics and the economy at every point,”⁶ it argues that workplace information is both an important input for contemporary information technologies and an important source of power in the modern workplace. Part I further illustrates how foundational rules of the labor contract give employers near-plenary

1. Carl Benedikt Frey & Michael A. Osborne, *The Future of Employment: How Susceptible Are Jobs to Computerisation?*, 114 *TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE* 254 (2017).

2. Sheelah Kolhatkar, *Welcoming Our New Robot Overlords*, *THE NEW YORKER*, Oct. 23, 2017; Kim Tingley, *Learning to Love Our Robot Co-workers*, *N.Y. TIMES MAGAZINE*, Feb. 23, 2017; Kevin Drum, *You Will Lose Your Job to a Robot—and Sooner Than You Think*, *MOTHER JONES*, Nov./Dec. 2017.

3. See generally Cynthia Estlund, *What Should We Do after Work? Automation and Employment Law*, 128 *YALE L.J.* 254 (2018); ANDY STERN (WITH LEE KRAVITZ), *RAISING THE FLOOR: HOW A UNIVERSAL BASIC INCOME CAN RENEW OUR ECONOMY AND REBUILD THE AMERICAN DREAM* 57–60 (2016); PEDRO DOMINGOS, *THE MASTER ALGORITHM: HOW THE QUEST FOR THE ULTIMATE LEARNING MACHINE WILL REMAKE OUR WORLD* (2015); MARTIN FORD, *RISE OF THE ROBOTS: TECHNOLOGY AND THE THREAT OF A JOBLESS FUTURE* (2015).

4. See e.g., GUY STANDING, *BASIC INCOME: A GUIDE FOR THE OPEN-MINDED* 104–107 (2017).

5. Important exceptions include Kathleen Thelen, *Transitions to the Knowledge Economy in Germany, Sweden, and the Netherlands*, ___ *COMP. POLITICS* ___ (forthcoming 2019); Frank Pasquale, *A Rule of Persons, Not Machines: The Limits of Legal Automation*, ___ *GEO. WASH. L. REV.* ___ (forthcoming); Ifeoma Ajunwa, Kate Crawford & Jason Schultz, *Limitless Worker Surveillance*, 105 *CALIF. L. REV.* 735 (2017); Pauline Kim, *Data-Driven Discrimination at Work*, 58 *WM. & MARY L. REV.* 857 (2017).

6. David Singh Grewal, Amy Kapczynski & Jedediah Purdy, *Law and Political Economy: Toward a Manifesto*, *LPEBLOG* (Nov. 6, 2017), available at <https://lpeblog.org/2017/11/06/law-and-political-economy-toward-a-manifesto/>. Law and political economy, or LPE, is methodologically and politically diverse. As discussed in Part I, *infra*, my own analysis of such issues draws on legal realism, institutional economics, and scholarship in comparative political economy.

power to gather work-related information, quantify it into usable data, and utilize it to reshape production processes.

Part II addresses the empirical question. In particular, it argues that automation fears are misplaced. There is no evidence that the pace of automation has accelerated in recent years—and in fact, productivity data, and data on job churn, indicates that automation has *slowed* in recent years. Theories that a wave of automation is imminent are equally flawed, as they tend to extrapolate from some impressive developments in machine learning and other technologies, but disregard major limitations of those technologies that are now coming into focus. Automation will displace certain workers and alter work for others by changing the mix of tasks they perform, as it has done since the beginning of capitalism, but it is not now a world-historic threat.

Part III then moves beyond existing debates to explore how companies *are* using data-driven technologies in the workplace, and how those uses tend to affect workers. Nearly all work is now performed with or in the shadow of data-gathering and analyzing devices, including mobile phones, handheld scanners, GPS and other physical tracking devices, and old-fashioned computers, many of which feed data directly into corporate intranets. As a result, companies today have vastly more information about production inputs and processes than at any time in history. And under current laws, employers have powerful incentives to use that data, and new technologies of data processing and analysis, to reduce labor costs.

As Part III.A shows, more and more companies are developing “algorithmic management” strategies, in which they use data analytics in employee hiring, scheduling, pay, discipline, and termination. Such efforts may benefit both workers and employers by creating new business opportunities, but can also negatively impact workers. For example, closely monitoring workers’ performance can enable companies to demand a faster pace of work, and data on customer flow may enable companies to schedule more leanly, giving workers less downtime on the job. Part III.B shows how companies also use data analytics to alter their industrial organization, again in ways that can affect workers’ livelihoods. Better data about internal cost structures and worker performance, and the ability to monitor suppliers and their workers through new technologies, can encourage companies to spin off or outsource functions in a process now known as the “fissuring” of employment.⁷

There are many examples of both algorithmic management and data-driven fissuring today, including among major low-wage employers such as Walmart, Amazon, Uber, and McDonald’s, and algorithmic management and fissuring strategies will likely predominate over automation in the low-wage workforce going forward. Many low-wage jobs are not susceptible to automation, and can’t be made much more productive through technology. As a result, companies in retail, fast food, and logistics will limit labor costs by demanding that workers increase their pace or effort levels or by limiting their legal responsibilities toward workers.

7. See generally DAVID WEIL, THE FISSURED WORKPLACE: WHY WORK BECAME SO BAD FOR SO MANY AND WHAT CAN BE DONE TO IMPROVE IT (2014).

Part IV draws out some broader implications of this account. One is that the three uses of data outlined above—automation, algorithmic management, and fissuring—are differentially susceptible to legal oversight.⁸ In brief, automation itself is difficult for lawmakers to govern, both because it generally enhances productivity and therefore gives companies a competitive advantage and because the knowledge underlying its processes has a public goods quality. Algorithmic management is more amenable to regulation, particularly where it has substantial and direct effects on labor standards such as wages, hours, and other terms of employment. Fissuring, finally, is quite susceptible to legal regulation and steering, since it often involves regulatory arbitrage. Even if preventing fissuring is not the aim, it may be desirable to alter companies' duties toward fissured workers, especially if they enjoy substantial economic or operational power over those workers.

Before moving on, I should note several limits of my argument. I focus largely on algorithm-based technologies including machine learning, data analytics, and earlier forms of data analysis. I do not discuss in detail blockchain, virtual reality, augmented reality, or wearable technologies. This is in part to enable a focused analysis and in part because I'm unconvinced any of those technologies will significantly alter labor contracts.

I also focus largely on the low-wage labor force, and say relatively little about higher-skilled workers, except in their capacity as managers, for a few reasons: there are better data sources on the low-wage labor market; that labor market is more homogenous in terms of job classifications than the mid-skill and high-skill market, which makes it easier to trace general trends; and underlying issues of economic and social equality are most acute in the low-wage labor market. I also focus largely on economic terms of employment, including wages, hours, and collective bargaining rights, saying less about how new data practices interact with employment discrimination.⁹ That being said, the low-wage labor markets that I discuss are disproportionately populated by historically disenfranchised groups, including African-Americans, Latinx individuals, other people of color and immigrants, and individuals with criminal records. As a result, virtually *all* the data practices I discuss have a disproportionately negative impact on such groups, even before unlawful or borderline-unlawful discrimination comes into the picture. In that regard, I hope this analysis can help advance efforts to understand the intersection of race, class, and other power structures in today's political economy.¹⁰

8. In what follows I focus on the rules directly governing the employment relationship and other work relationships. I do not focus on other legal rules that impact power relations between workers and firms, such as policies that alter workers' background entitlements and alternative employment options. Those include the availability and form of social insurance and welfare benefits, as well as macroeconomic factors including monetary policy and trade policy. I keep those issues in the background to enable a more discrete focus on the relationship between technological innovation and the employment relationship.

9. For treatments of the relationship between new information technologies and employment discrimination see Ifeoma Ajunwa, *Age Discrimination by Platforms*, 40 BERKELEY J. EMP. & LAB. L. ____ (forthcoming 2019); Kim, *supra* note 5; Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671 (2016); Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1 (2014).

10. As also discussed in Daria Roithmayr, *Racism is at the Heart of the Platform Economy*, LPEBLOG (Nov. 16, 2018), available at <https://lpeblog.org/2018/11/16/racial-capitalism-redux-how-race-segments-the-new-labor-markets/>.

I. THE LAW AND POLITICAL ECONOMY OF WORKPLACE INFORMATION

This part unpacks the legal and institutional structure in which workplace technological change occurs. The goal is to set the stage for the analysis in Parts II and III, which address the use of contemporary information technologies in the workplace. Part I.A outlines my methodological approach, which draws on legal scholarship and fields of social science that focus on how markets are constituted in large part by law. Part I.B summarizes how employment law allocates legal entitlements in workplace information. It argues that employers enjoy near-plenary legal powers to gather and use such information. Those powers arise both under background rules such as the employment-at-will doctrine and employers' common law property rights, and under foreground rules including workplace privacy doctrines. Part I.C then discusses how information has historically been an important form of power in work relationships, impacting employers' decisions over who to hire, what wages to pay, and whether to hire workers as employees or to contract for their labor.

I.A The Political Economy of Workplace Information

Labor is a peculiar commodity, quite different from tangible ones like soybeans. Because labor is always performed by a human being, it cannot be separated from workers and stored for future use. Also unlike soybeans, no two workers are interchangeable: we carry into the workplace different skills, desires, and moods, and interact with others in the course of our workdays. Moreover, workers' interests and employers' interests both overlap and diverge: they share an interest in company profitability, but companies have an incentive to reduce labor costs while increasing output, while workers have an incentive to increase their wages and benefits while not working too hard. Workers also need some degree of stability in their economic lives so that they can buy or rent housing, raise children, etc. As a sociologist recently put it, "The commodity 'labour' needs to reproduce, to restore itself and to consume. When it gets angry it can be troublesome."¹¹

As a result, understanding the labor contract—and the role of information within it—requires attention not just to forces of supply and demand but also to matters of *political economy*. By this I mean how workers' and employers' collective action affects the terms of the labor contract (with the firm itself as a form of lawful collective action),¹² as well as how such collective action both is shaped by and in turn shapes the broader legal and institutional structure. In what follows, I will draw freely on several bodies of scholarship that focus on political economy in this sense. Those include early twentieth-century legal realism,¹³ the "old" institutional economics of John Commons and his

11. Colin Crouch, *Redefining Labour Relations and Capital in the Digital Age*, in *WORK IN THE DIGITAL AGE: CHALLENGES OF THE FOURTH INDUSTRIAL REVOLUTION* 192 (Max Neufeind et al. eds., 2018).

12. See Claus Offe & Helmut Wiesenthal, *Two Logics of Collective Action: Theoretical Notes on Social Class and Organizational Form*, 1 *POL. POWER & SOC. THEORY* 67, 74 (1980) (describing firm as means of aggregating capital and subjecting it to centralized command); *Vegeahn v. Guntner* 167 Mass. 92, ___ (1896) (Holmes, J., dissenting) (describing labor unrest in competitive economies, arguing that "Combination on the one side [via a firm] is patent and powerful. Combination on the other [via unionization] is the necessary and desirable counterpart, if the battle is to be carried on in a fair and equal way.")

13. Robert Hale, *Coercion and Distribution in a Supposedly Non-Coercive State*, 38 *POL. SCI. Q.* 470, 472 (1918); Morris Cohen, *Property and Sovereignty*, 13 *CORNELL L. REV.* 8 (1927).

progeny,¹⁴ and the economics of imperfect information.¹⁵ I also draw from contemporary scholarship in comparative political economy,¹⁶ which seeks to understand the relationship between basic institutional structures and social outcomes within different advanced capitalist economies.¹⁷ While those disciplines diverge in many important respects, they share a qualitative focus on how labor markets are constituted in part by legal rules and other social factors, in ways that make them systematically different from markets for classic commodities.¹⁸

A focus on political-economic factors suggests that information plays two distinct roles in labor contracts. First, information is an essential input to contemporary technologies. Both exotic technologies such as machine learning and robotics and older information technologies including GPS tracking, other forms of workplace monitoring, and corporate intranets operate by gathering information, quantifying it as data, and analyzing that data using advanced algorithms. When and how employers can access information about work, workers, and workplace processes will therefore affect which sorts of new technologies they develop and deploy. Second, information is a source of power in the labor contract.¹⁹ Such power typically depends on informational asymmetry, where either

14. Bruce E. Kaufman, *Economic Analysis of Labor Markets and Labor Law: An Institutional/ Industrial Relations Perspective*, in RESEARCH HANDBOOK ON THE ECONOMICS OF LABOR AND EMPLOYMENT LAW 52, 78 (Cynthia L. Estlund & Michael L. Wachter eds., 2012) (explaining “institutional economics/industrial relations” perspective on labor economics, which focuses on the “institutional infrastructure of laws, property rights, and social relations that collectively set the rules of the game,” and in which “contending factions and classes endeavor to use the political power of sovereignty to shape the rules of the game to promote their interests.”) I also draw at times on “new” institutional economics of Coase & Williamson. See Michael L. Wachter, *Neoclassical Labor Economics: Its Implications for Labor and Employment Law*, in RESEARCH HANDBOOK ON THE ECONOMICS OF LABOR AND EMPLOYMENT LAW 20–51 (Estlund & Wachter eds., 2012) (seeking to incorporate transaction costs, information asymmetries, and other phenomena identified by “new” institutionalists into neoclassical model).

15. Joseph E. Stiglitz, *Information and the Change in the Paradigm in Economics* (Nobel Prize Lecture), 92 AM. ECON. REV. 460, 460 (2002).

16. See Wolfgang Streeck, *Taking Capitalism Seriously: Toward an Institutional Approach to Contemporary Political Economy*, MPIfG Discussion Paper, No. 10/15, at 6 (“Political economy looks at the interrelations between collective action in general and collective rule-making in particular, and ‘the economy,’ extending from economic and social policy-making to the way in which economic interests and constraints influence policy, politics and social life as a whole.”) See also Walter Korpi, *The Power Resources Model*, in THE WELFARE STATE READER 76 (Christopher Pierson & Francis G. Castles eds., 2d ed., 2006) (describing influential “power resources” model of welfare state formation, which understands the structure and generosity of welfare states largely as an effect of working-class political power.)

17. See, e.g., KATHLEEN THELEN, *VARIETIES OF LIBERALIZATION AND THE NEW POLITICS OF SOCIAL SOLIDARITY* (2014) (tracing evolution of bargaining structures, vocational training and labor market policy in various advanced capitalist economies); PETER A. HALL & DAVID SOSKICE, *VARIETIES OF CAPITALISM: THE INSTITUTIONAL FOUNDATIONS OF COMPARATIVE ADVANTAGE* (2001) (leading work proposing division of advanced capitalist economies into “liberal market economies” such as U.S. and U.K. and “coordinated market economies” such as Germany and the Nordic states); *but compare* LUCIO BACCARO & CHRIS HOWELL, *TRAJECTORIES OF NEOLIBERAL TRANSFORMATION: EUROPEAN INDUSTRIAL RELATIONS SINCE THE 1970s* (2017) (arguing, against Hall & Soskice, that European economies are converging on a more liberal model defined by greater employer discretion).

18. Granted, “new” institutionalism and the economics of imperfect information have been largely incorporated into standard models at this point. See *generally* Wachter, *supra* note 14.

19. I use the term in Weber’s sense of one party or group’s ability to “realize their own will in a communal action against the resistance of others.” H. H. GERTH & C. WRIGHT MILLS, *FROM MAX WEBER: ESSAYS IN SOCIOLOGY*, 180 (1946) (translating MAX WEBER, *WIRTSCHAFT UND GESELLSCHAFT* (ECONOMY AND SOCIETY), Part III, Chap. 3, pp. 631–40 (1922)). A similar understanding of power informs contemporary Marxist analyses of labor markets. See, e.g., Samuel Bowles & Herbert Gintis, *Contested Exchange: New Microfoundations for the Political Economy of Capitalism*, 18 POLITICS & SOCIETY 165, 184 (1990) (“those in positions of decision-making authority in capitalist firms . . . exercise power over employees”). Power in this sense does not always figure in standard economic theory. See Armen Alchian & Harold Demsetz, *Production, Information Costs, and Economic Organization*, 62 AM. ECON. REV. 777, 777–78 (1972) (asserting that employers have no more power over workers than a consumer has over any business).

workers or employers can prevent the other from gathering or utilizing information.²⁰ If workers possess information such as how quickly they can perform certain tasks and an employer lacks and cannot access it, workers can use that to drive up their wages; if an employer can access that information, it can use it to set a faster pace of work, or to lower wages.²¹

I.B How Employment Laws Allocate Rights in Workplace Information

Both faces of workplace information—as input to technology and as source of power—are shaped by laws governing labor contracts. Specifically, such laws determine firms’ rights to gather and to utilize workplace information, and workers’ correlative rights to prevent them from doing so.²² While that law is quite complex, the basic allocation of rights is clear: in the United States, employers have near-plenary rights to gather, quantify, analyze, and utilize work-related information. To be clear, the *effects* of employers’ use of information are regulated in various ways. For example, they cannot use superior information about a labor process to set pay below the statutory minimum wage for their own employees. (Though, as discussed below, firms’ ability to gather and utilize information at will *can* enable them to avoid such statutory obligations through various fissuring strategies.²³)

The specific doctrines here can be placed into two basic categories: background rules and foreground rules. The background rules establish a number of important default rules, and allocate rights to make decisions within the relationship. The foreground rules govern the gathering and use of information in specific contexts.

The first key background rule is the unusual American rule of “employment-at-will.” Under that rule, either party to an employment contract can terminate it, at any time, for any reason, or even a malicious reason, so long as doing so is not otherwise unlawful. While employment-at-will is no longer as robust as it once was, it is still the core background rule.²⁴ While it grants the employer and employee formally equal entitlements to end an employment contract, those rights redound to employers’ benefit in the run of cases, since employers engage in many employment contracts while workers typically engage in only one.²⁵ Employment-at-will effectively serves as a sort of “business

20. Information arguably plays a third role in labor contracts as well, as a transaction cost. Joseph Stiglitz won a Nobel Prize for a series of papers showing that “even a small amount of information imperfection could have a profound effect on the nature of the equilibrium.” Stiglitz, *Paradigm in Economics*, *supra* note 15, at 461. In what follows, I will discuss that aspect of information only in passing, on the theory that reducing transaction costs stands to benefit everyone. Put differently, the underexplored questions regarding information technology and contemporary labor markets are distributive rather than allocative.

21. See Kaufman, *supra* note 14, at 81; Bowles & Gintis, *supra* note 19, at 184–85 (discussing firms’ incentives to ensure an effective labor “extraction function” that obtains maximum labor effort, and workers’ incentives to collude in opposition to such a function). See discussion, *infra* Parts III.A. and III.B.

22. For ease of exposition, I will use the term “rights” to refer to the full spectrum of Hohfeldian entitlements, including “claims,” “privileges,” “powers,” and “immunities.” Wesley Newcomb Hohfeld, *Some Fundamental Legal Conceptions as Applied in Judicial Reasoning*, 23 YALE L.J. 16 (2013). I ask private law theorists to forgive the imprecision.

23. See discussion, *infra* Part III.B.

24. For example, there are various exceptions to and limitations on employment-at-will that have been developed under contract and tort doctrine, and via statute. See Cynthia Estlund, *Book Review: Rethinking Autocracy at Work*, 131 HARV. L. REV. 795, 803–805 (2018) (discussing partial erosion of employment-at-will in recent decades).

25. See Bowles & Gintis, *supra* note 19, at 184 (proposing that “those in positions of decision-making authority in capitalist firms occupy locations on the short side of the labor market and exercise power over employees.”)

judgment rule” for the firm’s employment decisions: unless there is evidence of other wrongdoing such as fraud or an independent statutory violation, it prevents courts from second-guessing companies’ decisions to terminate workers.²⁶ Moreover, since employment-at-will enables the termination of an employment contract without notice, it also enables employers to change the terms of that contract without notice. In many courts, workers’ decision to continue working when they have no duty to do so is accepted as consideration for what would otherwise be a unilateral change in the contract.²⁷ What’s more, employment-at-will means that workers who complain about working conditions that are not otherwise unlawful—including an employer’s efforts to monitor their work or otherwise gather information on workplace matters—can be disciplined or terminated without remedy.²⁸

The second background rule isn’t a single doctrine but rather a deeply rooted sense that the employer owns the enterprise and enjoys a sort of sovereignty over it, in a manner familiar from classical property law.²⁹ Employment-at-will itself reflects this assumption. While either party may end the relationship at any time, the employer has a unilateral (and asymmetric) power to exclude the employee from its premises. More generally, in nonunion workplaces the employer has near-total discretion to choose production technologies and processes, as an incident of their common law property rights. In contrast to some other advanced economies, most notably Germany, nonunionized workers have no rights to be consulted over technological change, including employer monitoring efforts or automation.³⁰ Indeed, even unionized workers in the United States have limited powers in this regard. On the one hand, employers may not make unilateral changes to wages or hours during the course of a collective bargaining agreement,³¹ or during contract negotiations.³² But employers have no duty to bargain over questions of firm strategy, investments, or other matters at the “core of

26. A point intuitively grasped by employment law scholars, but made directly by Edward Rock & Michael Wachter, *The Enforceability of Norms and the Employment Relationship*, 144 U. PENN. L. REV. 1913 (1996); also see generally Joseph E. Slater, *The “American Rule” That Swallows the Exceptions*, 11 EMP. RTS. & EMP. POL’Y J. 53 (2007) (discussing breadth of employment-at-will rule, and its tendency to undermine other workplace regulations); Richard Michael Fischl, *‘A domain into which the King’s writ does not seek to Run’: Workplace Justice in the Shadow of Employment-at-Will*, in LABOUR LAW IN AN ERA OF GLOBALIZATION: TRANSFORMATIVE PRACTICES AND POSSIBILITIES 253 (Joanne Conaghan, Richard Michael Fischl & Karl Klare eds., 2004).

27. *E.g.*, *Asmus v. Pacific Bell*, 999 P.2d 71 (Cal. 2000) (employees’ decision to continue work after employer’s unilateral change to employee handbook was consideration for employer’s revised promises, such that new handbook provisions were binding on employees); *Lucht’s Concrete Pumping, Inc. v. Horner*, 255 P.3d 1058 (Colo. 2011) (continued employment can constitute consideration for covenant not to compete); *Soto-Fonalledas v. Ritz-Carlton San Juan Hotel Spa & Casino*, 640 F.3d 471 (1st Cir. 2011) (bilateral promises to arbitrate constitute adequate consideration for arbitration clause).

28. If workers do so collectively, they are “protected” against retaliation under the NLRA. *Labor Board v. Washington Aluminum Co.*, 370 U.S. 9 (1962). If individual workers complain about unlawful conditions, such as wages that are below the statutory minimum, they will generally be protected by the antiretaliation provision of the Fair Labor Standards Act, 29 U.S.C. § 215 (a)(3) (2012). But an individual worker who complains that wages are *unfairly* low as opposed to *illegally* low will not be protected under either the FLSA or the NLRA.

29. See Morris Cohen, *Property and Sovereignty*, 13 CORNELL L. REV. 8 (1927).

30. See Matthew Dimick, *Productive Unionism*, 4 U.C. IRVINE L. REV. 679, 688, n.49 (2014) (discussing powers of German works councils to be consulted prior to technological changes). See generally JOEL ROGERS & WOLFGANG STREECK, EDS., *WORKS COUNCILS: CONSULTATION, REPRESENTATION, AND COOPERATION IN INDUSTRIAL RELATIONS* (1995). Such bodies are unlawful in nonunionized workplaces in the U.S. 29 U.S.C. 158(a)(2) (2018); *Electromation, Inc.* 309 NLRB 990 (1992).

31. *St. Vincent Hospital*, 320 NLRB 42, 42 (1995).

32. *Labor Board v. Katz*, 369 U.S. 736 (1962).

entrepreneurial control.”³³ The upshot is that employers need not bargain over their decision to displace workers through automation or outsourcing, though they may need to bargain over the effects of such decisions.³⁴ Again, though, these rules do not apply in the vast majority of workplaces in the U.S. which are not unionized.

The key foreground rules governing workplace information fall into two categories: those designed to protect workers against illicit discrimination, and those designed to protect workers’ privacy or dignity. As an example of the first, under the Americans with Disabilities Act employers may request information on workers’ ability to perform a task only after a conditional job offer is made, in order to ensure that prejudicial beliefs about individuals with disabilities do not taint the decision process.³⁵ Any information then gathered must be treated “as a confidential medical record,” kept in separate files from regular personnel files, and not disclosed to other employees except in certain defined circumstances.³⁶ Similarly, the Fair Credit Reporting Act³⁷ limits the gathering and use of data on employees and potential employees. The EEOC has argued that credit checks in employment screening may be unlawful when it has a disparate impact on the basis of race, though courts have not always agreed.³⁸

Workplace privacy protections are somewhat less discrete and well developed in the United States than rights against discrimination. In the United States, there is no general right to workplace privacy and privacy is not understood to be a fundamental right, as it is in Europe.³⁹ However, some workplace information, and other information on job applications, has been deemed off-limits by statute. For example, a number of states have banned employers from requesting applicants’ and employees’ social media passwords.⁴⁰ The National Labor Relations Act also protects employees’ privacy in some limited circumstances, prohibiting employers from surveilling or monitoring workers’ conversations for the purpose of preventing unionization or other lawful concerted action.⁴¹ And employees’ privacy is protected by a patchwork of common law privacy torts. The privacy torts,

33. *Labor Board v. Borg-Warner Corp.*, 356 U.S. 342 (1958) (distinguishing “mandatory” and “permissive” subjects of bargaining).

34. See *First Nat’l Maintenance Corp. v. NLRB*, 452 U.S. 666, 679–82, (1981); *Holly Farms Corp. v. NLRB*, 48 F.3d 1360 (4th Cir. 1995). The theory behind such “effects bargaining” is that it may enable workers to make concessions that save their jobs, or to demand compensation for job losses.

35. EQUAL EMPLOYMENT OPPORTUNITY COMMISSION, ENFORCEMENT GUIDANCE ON DISABILITY-RELATED INQUIRIES AND MEDICAL EXAMINATIONS OF EMPLOYEES UNDER THE AMERICANS WITH DISABILITIES ACT (ADA), (July 27, 2000), available at <https://www.eeoc.gov/policy/docs/guidance-inquiries.html>.

36. 42 U.S.C. § 12112(d) (2018); EEOC ENFORCEMENT GUIDANCE ON MEDICAL EXAMINATIONS, *supra* note 35. The Health Insurance Portability and Accountability Act (HIPAA) also restricts the use of health information that can be identified as coming from particular individuals. HIPAA Privacy Rule, 45 CFR Part 160 (2018); see generally, LITTLER MENDELSON, P.C., THE BIG MOVE TOWARD BIG DATA IN EMPLOYMENT 12–13 (2015) (discussing HIPAA regulations).

37. 15 U.S.C. §§ 1681 et seq (2018).

38. *EEOC v. Freeman*, 778 F.3d 643 (4th Cir. 2015) (upholding summary judgment for defendant in disparate impact claim based on background checks in part because EEOC’s expert testimony on matter deemed unreliable); *EEOC v. Kaplan Higher Ed. Corp.*, 748 F.3d 749 (6th Cir. 2014) (same).

39. See, e.g., European Court of Human Rights, Q&A: *Grand Chamber Judgment in the Case of Barbulescu v. Romania* (no. 61496/08) (Sept. 5, 2017) (summarizing judgment holding that private employee must be given notice before his electronic communications are viewed by his employer, and that the employer must consider whether means less intrusive of employee privacy could be used).

40. As of 2015, 21 states had passed such laws. See LITTLER MENDELSON, *supra* note 36, at 14.

41. See, e.g., *Local Joint Exec. Bd. v. NLRB*, 515 F.3d 942, 945–47 (9th Cir. 2008) (summarizing test for unlawful surveillance under NLRA).

however, distinguish between work-related and non-work-related conduct.⁴² Data generated in the workplace, during work hours, about work processes, is presumptively nonprivate under those torts. Plus, to obtain damages for an invasion of privacy, as through an unduly intrusive search, an employee must show that the employer's action was "highly offensive to a reasonable person."⁴³ That is a high bar, and lawyers will generally not find it worthwhile to pursue such claims on behalf of workers without substantial resources.

The net effect of these rules on workplace information is simple: employers have near-plenary power to gather and utilize work-related information, so long as it is not gathered or used to discriminate, or in a way that presents a substantial harm to workers' privacy or dignity.

I.C. Information and Power at Work: Three Examples

Three examples should help illustrate the import of information asymmetries and deficiencies—and employers' and workers' relative powers to exploit them—on labor contracts. Each is in part historical, but the basic dynamics carry over into the contemporary workplace and may be exacerbated by advanced information technologies.

The first, the historic battle between the craft ethic and so-called "scientific management," shows that control over work-related information has been central to how companies organize production processes and tasks. As labor historians and sociologists have documented, one key political-economic battle in the workplace has been between workers who seek to retain rare skills and firms that seek to replicate those skills and therefore save on labor costs.⁴⁴ For example, both historically and today, unions of skilled craft workers such as carpenters, machinists, and masons have exerted labor market power in part by controlling the labor supply, e.g., by limiting knowledge transfer to official apprenticeship programs. To become a union carpenter, one must generally apprentice with a master carpenter, or train in a union-sponsored program. Reflecting that, in the late nineteenth and early twentieth centuries, work practices were organized by workers themselves. Craft skills involved what we would today term an information asymmetry: only workers knew how to perform certain tasks, which gave them greater bargaining power vis-à-vis firms.

The development of modern factories required factory owners to capture some craft knowledge and to use it to mechanize production. This was the essence of "Taylorism," the system of "scientific management" developed by mechanical engineer and plant manager Frederick Winslow Taylor in the early twentieth century.⁴⁵ Taylor counseled factory managers to closely observe how jobs were being done; to break complex jobs down into simpler tasks; to assign less skilled (and less costly) workers

42. See, e.g., *O'Bryan v. KTIV Television*, 868 F. Supp. 1146 (N.D. Iowa 1994) (employer can search employee's desk area for work-related documents without violating employee's reasonable expectations of privacy); *Terrell v. Rowsey*, 647 N.E.2d 662 (Ind. Ct. App. 1995) (employer search of employee's personal vehicle was reasonable where done to investigate drinking on employer's property).

43. E.g., *K-Mart Corp. Store No. 7441 v. Trotti*, 677 S.W.2d 632, ___ (Ct. App. Tex. 1984).

44. HARRY BRAVERMAN, *LABOR AND MONOPOLY CAPITAL* (1974); DAVID MONTGOMERY, *WORKERS' CONTROL IN AMERICA: STUDIES IN THE HISTORY OF WORK, TECHNOLOGY, AND LABOR STRUGGLES* (1979); MICHAEL BURAWOY, *MANUFACTURING CONSENT: CHANGES IN THE LABOR PROCESS UNDER MONOPOLY CAPITALISM* (1982).

45. FREDERICK WINSLOW TAYLOR, *THE PRINCIPLES OF SCIENTIFIC MANAGEMENT* 63 (1911) (scientific management is "directly antagonistic to the old idea that each workman can best regulate his own way of doing the work.")

to the simple tasks; to measure workers' movements and their output; and ultimately to speed up the production process. In other words, Taylorism provided management with a set of tools for the "abstraction and rationalization of knowledge," whether by automating tasks or by "breaking up process-based knowledge into discrete, rationalized, low-skill tasks."⁴⁶ The effect of all of this was "the divorce of planning and doing," as management and industrial engineers would determine in minute detail how production would take place.⁴⁷

The technology with which companies replaced workers in these cases was not modern information technology, but the effect was often to displace skilled workers, to use new technologies to substitute for the labor of many skilled workers, and to reduce workers' discretion and wages.⁴⁸ Contemporary automation often continues this process, as I discuss below.

The second example, involving asymmetrical access to information during the hiring process, illustrates how work-related information, and rights to use or prevent the use of it, are an important determinant of terms and conditions of employment. During a job search the employer and potential employee each have limited information about the other. An employer will know relatively little about a potential employee when they walk in the door, such as whether they have the skills they claim to have and whether they are a diligent worker. A potential employee, similarly, will know little about an employer's internal policies, in particular whether the employer tends to terminate workers without just cause. Before an employment contract is entered, each party has an incentive to gather information that will allow them to draw inferences about how the other will perform.⁴⁹

The respective parties' abilities to gather this information are nevertheless asymmetric, for both legal and extralegal reasons. For example, employers have a right to request references or to require workers to pass an aptitude test (so long as such tests are not discriminatory), and in a labor market where workers are competing for a limited number of jobs employers will generally be able to do so. Employees, in contrast, can request internal company information, but it may be protected by trade secrets laws or other doctrines. Employees are well advised *not* to inquire into the company's policies around employee termination, however, since if they do so employers may assume they plan to work less diligently than others.⁵⁰ As I'll discuss more in Part III, these facts have important implications for wage-setting, the pace of work, and other aspects of the employment relationships.

The third example, concerning an employer's decision to either hire workers or bid out work to contractors, shows how imperfect information impacts the legal distribution of particular rights in the

46. Karen Levy, *The Contexts of Control: Information, Power, and Truck-Driving Work*, 31 THE INFO. SOCIETY 160, 161 (2015). See also BRAVERMAN, *supra* note 44, at 76–83 (arguing that Taylor sought to reorganize machine tool production for the purpose of disempowering workers).

47. Craig R. Littler, *Understanding Taylorism*, 29 BRITISH J. SOCIOLOGY 185, 188 (1978). See also Jill Lepore, *Not So Fast*, THE NEW YORKER, Oct. 12, 2009 (arguing that Taylor "fudged his data, lied to his clients, and inflated the record of his success," and that he asserted in congressional testimony that the "ordinary pig iron handler" is "too stupid" to shovel coal.)

48. See generally BRAVERMAN, *supra* note 44.

49. See, e.g., Stiglitz, *Paradigm in Economics*, *supra* note 15, at 463 (potential employer may seek to gather information to identify good employees, but only if it is possible to keep that information private and therefore to prevent other employers from hiring the worker at a higher wage).

50. Walter Kamiat, *Labor and Lemons: Efficient Norms in the Internal Labor Market and the Possible Failures of Individual Contracting*, 144 U. PENN. L. REV. 1953, 1958–60 (1996).

employment contract. For present purposes, an company’s decision of whether to make particular inputs in-house or to contract for them on the open market is momentous because it determines whether the workers making those inputs have rights vis-à-vis that company under various labor and employment regulations: employees are “inside” the firm, while independent contractors and workers for suppliers and subcontractors are “outside” of it. Indeed, the common law employment relationship was central to Ronald Coase’s own theory of the firm as a means of minimizing the transaction costs associated with market contracting.⁵¹ As Coase put it, “it is the fact of direction which is the essence of the legal concept of ‘employer and employee,’ just as it was in the economic concept” of the firm.⁵²

In a Coasean framework, companies’ make/buy decisions will be driven in part by their ability to access and utilize information about work processes. For example, information deficiencies can increase the transaction costs associated with market contracting: without effective communications technologies, locating suitable workers will be more difficult. More importantly, companies have historically had an incentive to bring work in-house when it is difficult to specify inputs with precision, to communicate with outside parties, or to monitor outside parties’ performance. In contrast, firms are more likely to buy in the market when “the input being purchased is standard rather than idiosyncratic,”⁵³ so that deliverables can be specified relatively precisely and easily, and when monitoring costs are low rather than high. This means that it pays to invest in information gathering and analysis in complex production processes, since doing so can reduce uncertainty. Moreover, when greater information about production enables outsourcing of tasks that would otherwise need to be performed in-house, companies can save on labor costs. I discuss this dynamic in more detail in Part III.B., below.

These examples—and the foregoing discussion more generally—suggest several ways in which attention to political-economic factors better reflects reality in labor markets than a standard neoclassical model. For example, it suggests that supply and demand should be understood as broad bands rather than curves.⁵⁴ Large changes in wage rates will clearly drive down demand, and wages are correlated with workers’ skills and the scarcity of those skills, but the relationship is far noisier than in neoclassical theory.⁵⁵ Among other things, wages may be influenced by employers’ ability to access information about workers’ performance, and workers’ rights to be consulted over, or to

51. See generally Ronald Coase, *The Nature of the Firm*, 4 *ECONOMICA* 386 (1937); Oliver Williamson, *The Economics of Organization: The Transaction Cost Approach*, 87 *AM. J. SOCIOLOGY*, 548 (1981).

52. Coase, *supra* note 51, at 404.

53. Wachter, *supra* note 14, at 37.

54. Kaufman, *supra* note 14, at 83. Compare Wachter, *supra* note 14, at 21–24 (summarizing “textbook model of a competitive labor market”). Neoclassical theory also fails to predict or explain various important phenomena in labor markets, such as long-term unemployment, see Stiglitz, *Paradigm in Economics*, *supra* note 15, at 460; intrafirm wage differentials for workers in the same occupation, Douglas Kinneer, *Two Sides of the Same Coin: Institutional Theories of Wage Rates and Wage Differentials*, in *THE INSTITUTIONALIST TRADITION IN LABOR ECONOMICS* 105, 105–106 (Dell P. Champlin & Janet T. Knoedler eds., 2004); and the persistence of illicit discrimination on the basis of race and sex, Kaufman, *supra* note 14, at 31.

55. It is also difficult to posit an airtight relationship between skills and wages, given the fact that many jobs considered “low-skill,” such as agricultural and domestic work, are excluded from full labor and employment law protections. *E.g.*, 29 U.S.C. § 152(3) (2018) (defining “employee” to exclude agricultural and domestic workers for purposes of NLRA); compare David H. Autor & David Dorn, *The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market*, 103 *AM. ECON. REV.* 1553, 1554 (2013) (chart in which “[o]ccupations are ranked by skill level, which is approximated by the mean log wage of workers in each occupation in 1980”).

bargain over, changes in workplace rules or technology.⁵⁶ What's more, a focus on political-economic factors suggests that labor time and labor effort are distinct. As a result, companies have incentives to invest in securing a high level of effort from workers while holding wages constant—for example, through monitoring—and workers have incentives to resist such efforts individually and collectively when possible.⁵⁷ I now turn to how advanced information technologies are affecting those dynamics.

II. THE OVERSTATED AUTOMATION THREAT

This part and Part III discuss how the growth of advanced information technologies is altering work and labor standards today. This part focuses on automation. Part II.A discusses machine learning, the branch of artificial intelligence (AI) that has generated extensive debate around a potential jobless future. It argues that machine learning is extremely unlikely to lead to massive technological unemployment, as its limits as a substitute for human cognition and judgment are becoming increasingly apparent. Part II.B ventures some more nuanced predictions about the future of automation, and about the labor market in the foreseeable future. Part III brings the power dynamics discussed in Part I back into the story, showing how firms are using these and related technologies to reshape work today where automation isn't possible.

II.A. About Machine Learning

This subpart discusses the current state of play in workplace automation. It may be helpful to state my conclusion at the outset: the hype around automation right now, particularly machine learning, is almost entirely unwarranted. Widespread technological unemployment will only result if enormous advances in technology are on the horizon, including the merger of artificial intelligence and robotics, and if those advances are cheap enough to implement at scale. There is no evidence that they are.

II.A.i The Potential of Machine Learning

A now standard argument that automation is likely to put many out of work goes something like this: artificial intelligence, or AI, and robotics have developed by leaps and bounds in recent years; such changes are accelerating as data sources expand and computing power continues to improve; our economy may not be able to adapt, as it has in the past, by creating new jobs, and as a result tens of millions will be left unemployed.⁵⁸ The major innovations that have driven this argument are in the subfield of AI known as machine learning. While machine learning is not new, several papers in the

56. See generally Kaufman, *supra* note 14.

57. Kaufman, *supra* note 14, at 81. See also Bowles & Gintis, *supra* note 19, at 184–85 (discussing firms' incentives to ensure an effective labor "extraction function" that obtains maximum labor effort, and workers' incentives to collude in opposition to such a function).

58. STERN, *supra* note 3, at 57–60 (discussing possibility of accelerating technological change); FORD, *supra* note 3, at 229–48 (same); DOMINGOS, *supra* note 3, at 43–45 (same). See generally KLAUS SCHWAB, THE FOURTH INDUSTRIAL REVOLUTION (2016).

early 2010s demonstrated how the technique could be used for purposes of image recognition,⁵⁹ which sparked extensive investment in machine learning by tech companies.

To illustrate the promise and possible limits of machine learning, it is helpful to contrast it with what is known as symbolic AI. The latter includes various approaches that rely on the manipulation of symbols and human-developed algorithms. Symbolic AI was dominant from the early days of AI research until the 1980s, and made a great deal of progress, but eventually ran out of steam due to the seemingly limitless complexity of many fields of human endeavor.⁶⁰ For decades, symbolic AI researchers tried to program a computer to recognize language by encoding grammatical rules in an “if-then” format. But this approach failed: human language is too complicated, and too nuanced, to be captured in such a set of rules. As a result, researchers were constantly plugging holes in their algorithms through ad hoc patches, while struggling to obtain decent outcomes.

Machine learning works quite differently. Rather than applying if-then rules to a data source, machine learning is “essentially a statistical technique for classifying patterns, based on sample data, using neural networks with multiple layers.”⁶¹ Neural networks themselves are programs made up of “connected units or nodes called artificial neurons which loosely model the neurons in a biological brain,” in that each “connection, like the synapses in a biological brain, can transmit a signal from one artificial neuron to another.”⁶² A machine learning algorithm has an “input layer” of data that represents pixels or words, multiple “hidden layers” of artificial neurons, and an “output layer” where the results of calculations appear. Programmers can “train” a network by giving it a large set of input data on which the appropriate outputs are labeled, then allowing the hidden layers to determine what it is about particular input units that correlates to particular outcomes.

For example, a relatively simple neural network can be trained to determine whether a particular picture is of a dog or a cat.⁶³ Programmers would do so by developing or using a commercially available dataset of thousands of pictures of dogs or cats. They would upload the pictures—the “training data”—into the machine, appropriately labeled as either “dog” or “cat.” The machine would then develop statistical correlations between the pixels in images labeled “dog” or “cat” and the outcomes “dog” and “cat,” respectively. Once the algorithm analyzed enough pictures to generate results, the researchers would test the machine by giving it pictures of dogs and cats that were not in the training data, to determine whether it could recognize them as being dogs or cats. Programmers would use a method known as back propagation to adjust the strength of the connections between different nodes in the hidden layers of the network, thus making the link between inputs and outputs

59. *E.g.*, Alex Krizhevsky et al., *ImageNet Classification with Deep Convolutional Neural Networks*, 60 COMMS. OF THE ACM 84 (June 2017); Dan Ciresan et al., *Multi-column Deep Neural Networks for Image Classification*, IDSIA Technical Report No. IDSIA-04-12 (Feb. 2012), available at <https://arxiv.org/abs/1202.2745>.

60. DOMINGOS, *supra* note 3, at 5.

61. Gary Marcus, *Deep Learning: A Critical Appraisal*, at 3 (Jan 2, 2018), available at <https://arxiv.org/abs/1801.00631>.

62. *Artificial neural network*, WIKIPEDIA, available at https://en.wikipedia.org/wiki/Artificial_neural_network (last visited Jan. 19, 2018).

63. *E.g.*, Sandipan Dey, *Dogs vs. Cats: Image Classification with Deep Learning using TensorFlow in Python*, DATA SCIENCE CENTRAL (Aug. 14, 2017), available at <https://www.datasciencecentral.com/profiles/blogs/dogs-vs-cats-image-classification-with-deep-learning-using>.

more robust. They might also add additional hidden layers and otherwise correct course where a machine went off track.

The results are quite often stunning. Even Gary Marcus, a psychology professor and cognitive scientist at NYU who is skeptical that machine learning can deliver what its boosters imagine, argues that “[i]n practice, results with large datasets are often quite good, on a wide range of potential mappings.”⁶⁴ Distinguishing cats from dogs is trivial, but image recognition may be able to assist in, for example, determining whether particular moles are cancerous or benign, and interpreting radiological scans.⁶⁵ Google uses a deep neural network known as RankBrain to help in search responses,⁶⁶ and its DeepMind network has gotten steadily better at the board game Go after essentially training itself how to play after being given some basic parameters.⁶⁷ During the most famous match, DeepMind made several moves that no human player would have made, since they went against all conventional wisdom, and often cost the machine in the short term. But those moves paid off in the end.⁶⁸

Perhaps the most impressive and useful consumer-facing application of machine learning so far is in speech recognition and translation. In speech recognition the input layer consists of sounds, and the output layer is words that correspond to those sounds. In translation, the input layer involves words, phrases, and sentences in one language, and outputs are words, phrases, and sentences in another language. Google’s Neural Machine Translation project has vastly outperformed symbolic AI approaches to the latter. Using literary works and other online sources available in multiple languages as a training set, the network has been able to give translations that are close enough, in terms of vocabulary, grammar, and syntax, for the meaning of a passage to be communicated.⁶⁹ When combined with speech recognition, Google has been able to develop rough-hewn real-time translation services on its latest-generation Android software.⁷⁰ Similar efforts underlay the IBM Watson’s successful match against two of *Jeopardy*’s leading winners.⁷¹

Machine learning developments are largely limited, so far, to online space, and to performing fairly discrete tasks. Nevertheless, many commentators see a wave of automation on the horizon. As noted above, machine learning is especially helpful in fields where there are large datasets that can be used to train neural networks, and modern technologies are not just *using* datasets but also

64. Marcus, *Critical Appraisal*, *supra* note 61, at 5.

65. Stanford ML Group, *MURA: Bone X-Ray Deep Learning Competition*, available at <https://stanfordmlgroup.github.io/competitions/mura/> (last visited Jan. 19, 2019).

66. Cade Metz, *AI Is Transforming Google Search. The Rest of the Web is Next*, WIRED (Feb. 4, 2016), available at <https://www.wired.com/2016/02/ai-is-changing-the-technology-behind-google-searches/>.

67. Google, *AlphaGo*, available at <https://deepmind.com/research/alphago/> (last visited Jan. 19, 2019).

68. Joon Ian Wong & Nikhil Sonad, *Google’s AI Won the Game Go by Defying Millennia of Basic Human Instinct*, QUARTZ (Mar. 25, 2016), available at <https://qz.com/639952/googles-ai-won-the-game-go-by-defying-millennia-of-basic-human-instinct/>.

69. Quoc V. Le & Mike Schuster, *A Neural Network for Machine Translation, at Production Scale*, GOOGLE AI BLOG (Sept. 27, 2016), available at <https://ai.googleblog.com/2016/09/a-neural-network-for-machine.html>.

70. AJ Dellinger, *Google Translate Adds Real-Time Translations for 13 New Languages*, ENGADGET (Oct. 11, 2018), available at <https://www.engadget.com/2018/10/11/google-translate-real-time-translations-new-languages/>.

71. Jo Best, *IBM Watson: The Inside Story of How the Jeopardy-Winning Supercomputer Was Born, and What It Wants to Do Next*, TECHREPUBLIC (no date available online), available at <https://www.techrepublic.com/article/ibm-watson-the-inside-story-of-how-the-jeopardy-winning-supercomputer-was-born-and-what-it-wants-to-do-next/> (last visited Jan. 19, 2019).

generating them. Mobile phones generate data about our whereabouts and patterns of calls that can be used to draw quite accurate inferences about who is in our social networks, which products we might be interested in, and the like. As more and more devices such as automobiles and household appliances are fitted with sensors and transmitters, ever more data is generated about our physical environment. Meanwhile, the cost of processing power continues to shrink. Intel founder Gordon Moore observed in 1965 that the number of transistors on a state-of-the-art integrated circuit tended to double roughly every two years. That pattern has held, at least until recently, and has become known as “Moore’s Law.”⁷² As a result, computer processing becomes both exponentially faster over time and less expensive. Assuming that trend continues, it should become substantially easier to utilize machine learning and related techniques as time goes on. This has led various commentators to predict an AI explosion, in which algorithms become ever more powerful at an exponential rate, leading to programs that are different in kind from what we have today.

As processing power, datasets, and machine sophistication increase continuously, the argument goes, we will eventually pass a threshold into “true” artificial intelligence, or AI that has some consciousness or can replicate perfectly important aspects of human cognition, and then into “artificial general intelligence,” or AI which can replicate all cognitive tasks that a human can perform.⁷³ And of course, in this view, once artificial general intelligence is developed, that would not be the end of the matter. As one prominent computer scientist puts it, such a machine “is the last thing we’ll ever have to invent because, once we let it loose, it will go on to invent everything else that can be invented.”⁷⁴ The rate of progress in all sorts of technologies would speed up. New production and distribution methods would be developed, as would new tools to determine and fulfill human desires.⁷⁵ In some versions of the story, a machine would go rogue, and seek to dominate human society, or to turn all known matter into paper clips or some such.⁷⁶

To be clear, the argument that current trends are leading to an imminent intelligence explosion is entirely speculative. I do not present it for its truth value or reasonableness. Rather, I present it to highlight that many prominent arguments for looming technological unemployment depend on this sort of “exponentialist” reasoning. They do not always believe that AI is a looming threat to humanity, but they do believe both that AI is progressing by leaps and bounds and that the pace of progress is accelerating. And if artificial general intelligence were developed, it would quickly become a cost-effective means of replacing human labor en masse. It won’t just lead to autonomous vehicles and fully automated factories but will also replace doctors, lawyers, CEOs, and even music composers, artists, and fiction writers.⁷⁷

72. *Moore’s law*, WIKIPEDIA, available at https://en.wikipedia.org/wiki/Moore%27s_law (last visited Jan. 19, 2019). But see Tom Simonite, *Moore’s Law Is Dead. Now What?*, MIT TECH. REV. (May 13, 2016), available at <https://www.technologyreview.com/s/601441/moores-law-is-dead-now-what/> (arguing that progress in chip speed has reached hard physical limits).

73. NICK BOSTROM, *SUPERINTELLIGENCE: PATHS, DANGERS, STRATEGIES* 26-62 (2014) (discussing paths to “superintelligence”).

74. DOMINGOS, *supra* note 3, at 25.

75. See DOMINGOS, *supra* note 3, at 43 (arguing that a “model of you will negotiate the world on your behalf, playing elaborate games with other people’s and entities’ models.”)

76. See BOSTROM, *supra* note 73, at 149–53 (2014).

77. *E.g.*, FORD, *supra* note 3, at 83–128 (discussing displacement of white collar jobs).

II.A.ii The Limits of Machine Learning

As Carl Sagan once put it, “Extraordinary claims require extraordinary evidence.”⁷⁸ No evidence of a looming intelligence explosion exists today. For one thing, AI is a field of academic research as well as engineering, with papers that are workshopped, peer-reviewed, and published. As a result, tracking what is written and published over time can provide a reasonable proxy for the state of the art. As one veteran roboticist and former MIT professor explains, recent publications in the subfield of AI research known as “artificial general intelligence” are typically modest and theoretical—they are not announcements of engineering successes that augur imminent sentient machines.⁷⁹ Similarly, one MIT project spanning decades has investigated the cell-level biology of a worm, *C. elegans*, which has only 959 cells, including just over 300 neurons. Researchers have mapped the worm’s entire brain, but still can’t explain how its neurons produce many of the worm’s behaviors.⁸⁰

Meanwhile, it is becoming quite clear that machine learning is not a path to “true” AI or artificial general intelligence. As the journalist Jason Pontin aptly put it, machine learning systems are “greedy, brittle, opaque, and shallow.”⁸¹ They are “greedy” in the sense that they require enormous processing power and human oversight to develop.⁸² IBM’s efforts to turn Watson, the program that won *Jeopardy*, into a healthcare product, have apparently hit major setbacks for this reason: medical records must be hand-coded in ways that enable the machine to access them, which makes on-the-ground progress quite slow.⁸³ A headline from a major health news publication reviewing the effort speaks for itself: “IBM pitched its Watson supercomputer as a revolution in cancer care. It’s nowhere close.”⁸⁴ Machine learning algorithms are “brittle,” meanwhile, in that they are robust with regard to their training data, but *only* that data. It is very difficult to transfer a machine learning algorithm’s findings into another domain. And they are “opaque” once mature in the sense that the operations of neural networks are often inscrutable to programmers, which makes it difficult to reverse-engineer them and replicate their success.

Most importantly, Pontin explained, “they are shallow because they are programmed with little innate knowledge and possess no common sense about the world or human psychology.”⁸⁵ This is related to their brittleness, since very minor changes in the input layer can lead systems to fail catastrophically. One study found that altering a single pixel in images uploaded for processing made an image-processing algorithm generate false results.⁸⁶ Another found that deep learning programs

78. Sagan standard, WIKIPEDIA, available at https://en.wikipedia.org/wiki/Sagan_standard (last visited Jan. 19, 2018).

79. Rodney Brooks, *The Origins of Artificial Intelligence*, RODNEY BROOKS (Apr. 27, 2018), available at <https://rodneybrooks.com/forai-the-origins-of-artificial-intelligence/>.

80. *Id.*

81. Jason Pontin, *Greedy, Brittle, Opaque, and Shallow: The Downsides to Deep Learning*, WIRED (Feb. 2, 2018), available at <https://www.wired.com/story/greedy-brittle-opaque-and-shallow-the-downsides-to-deep-learning/>.

82. See Rodney Brooks, *Machine Learning Explained*, RODNEY BROOKS (Aug. 28, 2017), available at <https://rodneybrooks.com/forai-machine-learning-explained/>.

83. David H. Freedman, *A Reality Check for IBM’s AI Ambitions*, MIT TECH. REV. (June 27, 2017), available at <https://www.technologyreview.com/s/607965/a-reality-check-for-ibms-ai-ambitions/>.

84. Casey Ross & Ike Swetlitz, *IBM Pitched its Watson Supercomputer as a Revolution in Cancer Care. It’s Nowhere Close*, STAT (Sept. 5, 2017), available at <https://www.statnews.com/2017/09/05/watson-ibm-cancer/>.

85. Pontin, *supra* note 81.

86. Jiawei Su et al., *One Pixel Attack for Fooling Deep Neural Networks*, ARXIV (Feb. 22, 2018), available at

often had difficulty recognizing the same animal in different frames of a video, identifying a single polar bear “as a baboon, mongoose, or weasel depending on minor shifts in the background.”⁸⁷ Young children with basic sense of object permanence don’t make such mistakes. In game play, DeepMind’s impressive victory in Go was dependent on the machine being trained on the standard 19-by-19 board. If the board had been changed to 18 by 18, DeepMind’s programmers admitted, it would have needed to be completely retrained.⁸⁸ A human would quickly adapt.⁸⁹

Machine learning’s limits are also apparent in efforts over the past few years to develop automated assistants. Facebook’s short-lived attempt, M, actually had humans do most of the back-end work, finding restaurants, making reservations, and sending flowers to people. The aspiration was to use humans to train an AI through supervised learning. However, the company shut down the project after a couple of years, later describing it as an “experiment.”⁹⁰ Chatbot services and other automated assistants, including by the companies X.ai, Expensify, and others, also often consist of humans making appointments, reading receipts, or performing other menial tasks through the artifice of “automated chat.”⁹¹ One psychologist aptly called this the “Wizard of Oz design technique.”⁹²

None of this should be surprising. Machine learning takes place in virtual spaces, not in the real world. While it is called “learning,” that is a metaphor. An algorithm that distinguishes pictures of dogs from cats doesn’t know what a dog or a cat is, what a picture is—or even that anything exists at all. It is, in essence, a very powerful means of advanced statistical analysis, one that has impressive applications to the real world. But we are very far from machines with anything approaching consciousness. This has recently led various experts, including a computer scientist who helped develop modern machine learning, to call for a return to symbolic AI, or AI that programs particular rules of behavior directly into machines, to at least give machines some context for what they are doing.⁹³

<https://arxiv.org/pdf/1710.08864.pdf>.

87. Aharon Azulay & Yair Weiss, *Why Do Deep Convolutional Networks Generalize So Poorly to Small Image Transformations?*, ARXIV (May 30, 2018), available at <https://arxiv.org/abs/1805.12177>.

88. Brooks, *Machine Learning*, *supra* note 82.

89. See, e.g., Marcus, *Critical Appraisal*, *supra* note 61, at 16 (describing machine learning program trained on even numbers that was baffled by odd numbers).

90. Kurt Wagner, *Facebook’s Virtual Assistant ‘M’ Is Super Smart. It’s Also Probably a Human*, RECODE (Nov. 3, 2015), available at <https://www.recode.net/2015/11/3/11620286/facebook-virtual-assistant-m-is-super-smart-its-also-probably-a-human>; Casey Newton, *Facebook Is Shutting Down M, Its Personal Assistant Service that Combined Humans and AI*, THE VERGE (Jan. 8, 2018), available at <https://www.theverge.com/2018/1/8/16856654/facebook-m-shutdown-bots-ai>.

91. Ellen Huet, *The Humans Hiding behind the Chatbots*, BLOOMBERG (Apr. 18, 2016), available at <https://www.bloomberg.com/news/articles/2016-04-18/the-humans-hiding-behind-the-chatbots>.

92. Quoted in Olivia Solon, *The Rise of ‘Pseudo-AI’: How Tech Firms Quietly Use Humans to Do Bots’ Work*, THE GUARDIAN (Jul. 6, 2018), available at <https://www.theguardian.com/technology/2018/jul/06/artificial-intelligence-ai-humans-bots-tech-companies>;

93. Gary Marcus, *In Defense of Skepticism about Deep Learning*, MEDIUM (Jan. 14, 2018), available at <https://medium.com/@GaryMarcus/in-defense-of-skepticism-about-deep-learning-6e8bfd5ae0f1>; see also Steve LeVine, *Artificial Intelligence Pioneer Says We Need to Start Over*, AXIOS (Sep. 15, 2017), available at <https://www.axios.com/artificial-intelligence-pioneer-says-we-need-to-start-over-1513305524-f619efbd-9db0-4947-a9b2-7a4c310a28fe.html> (programmer who developed “back-propagation” method that is at the heart of machine learning now believes it is a dead end).

II.A.iii The Limits of Robotics

These sorts of challenges quickly compound when algorithms begin to encounter the real world via robotics or autonomous vehicles. Until very recently there was a consensus in the tech and automotive sectors that autonomous vehicles were coming soon, and would be a game-changer. Google and Tesla predicted fully autonomous cars by 2018,⁹⁴ and General Motors recently pledged to put a fully autonomous car into production by 2019.⁹⁵ A very well-regarded labor reporter argued that this could threaten as many as five million jobs.⁹⁶ But as roboticist Rodney Brooks has put it, “Robotics, including self driving cars, is where Artificial Intelligence (AI) collides with the un-sanitized natural world. Up until now the natural world has been winning, and will probably continue to do so” for a while.⁹⁷

The problems are legion. For one thing, the room for failure is minimal: robots that can’t effectively navigate their environment can damage themselves or even kill people, which is why until very recently the vast majority of industrial robots had to work in cages. They move quickly and powerfully, and can’t always sense that humans are nearby, which has made them incredibly dangerous to work alongside.⁹⁸ Robots also lack common sense: humans understand that objects have the same color whether it is light or dark, but that our perception of them may change depending on conditions. Machines without even a one-year-old’s sense of object permanence can’t understand that.⁹⁹ Autonomous vehicles can make up for that a bit by using other sorts of sensors that humans don’t have, like sonar and radar and lidar, to get a 360-degree view of their surroundings in a way humans cannot. But advanced sensors are still no substitute for situational judgment, which autonomous vehicles need to be able to navigate an uncertain environment, reacting to objects and stimuli that they have never experienced before.

Most autonomous vehicles “employ a ‘sense-plan-act’ design,” in which a suite of sensors gathers information about the environment—lane markings, obstacles, other vehicles, etc.; algorithms including machine learning interpret that information; and then those algorithms plan how to respond.¹⁰⁰ But if a machine’s image recognition systems can be easily fooled, people may be killed. This happened in Uber’s self-driving car’s fatal crash with a pedestrian, the federal investigation of which indicated that the car’s image-recognition devices worked poorly: they spotted the object in the distance about six seconds before impact, and classified it “[first] as an unknown object, [and then] as

94. Russell Brandom, *Self-Driving Cars are Headed toward an AI Roadblock*, THE VERGE (July 3, 2018), <https://www.theverge.com/2018/7/3/17530232/self-driving-ai-winter-full-autonomy-waymo-tesla-uber>.

95. Andrew J. Hawkins, *GM Will Make an Autonomous Car without Steering Wheel or Pedals by 2019*, THE VERGE (Jan. 12, 2018), available at <https://www.theverge.com/2018/1/12/16880978/gm-autonomous-car-2019-detroit-auto-show-2018>.

96. Steven Greenhouse, *Autonomous Vehicles Could Cost America 5 Million Jobs. What Should We Do About It?*, L.A. TIMES (Sept. 22, 2016), available at <http://www.latimes.com/opinion/op-ed/la-oe-greenhouse-driverless-job-loss-20160922-snap-story.html>.

97. Rodney Brooks, *Domo Arigato Mr. Roboto*, RODNEY BROOKS (Aug. 28, 2017), available at <https://rodneybrooks.com/forai-domo-arigato-mr-roboto/>.

98. Will Knight, *A Radar for Industrial Robots May Guide Collaboration with Humans*, MIT TECH. REV. (Sept. 20, 2017), available at <https://www.technologyreview.com/s/608863/a-radar-for-industrial-robots-may-guide-collaboration-with-humans/>.

99. Rodney Brooks, *Steps toward Super Intelligence III, Hard Things Today*, RODNEY BROOKS (July 15, 2018), available at <http://rodneybrooks.com/forai-steps-toward-super-intelligence-iii-hard-things-today/>.

100. RAND CORPORATION: AUTONOMOUS VEHICLE TECHNOLOGY: A GUIDE FOR POLICYMAKERS 61–63 (2016).

a vehicle, and then as a bicycle with varying expectations of future path travel,” all of which led the vehicle not to respond in time.¹⁰¹

Even when autonomous vehicles are not dangerous, they can be annoying. In August of 2018, a blockbuster story showed that Waymo, the autonomous vehicle subsidiary of Alphabet (Google’s parent company), has found it extremely difficult to deploy autonomous vehicles in test sites outside Phoenix, Arizona. The cars get fooled by pedestrians, stop suddenly when other drivers violate traffic laws, and irritate neighbors stuck behind them as they wait to turn left. “More than a dozen individuals” who worked in the area “said the same three words when asked about the vans: ‘I hate them.’”¹⁰² Phoenix, it is worth noting, was chosen because it had near-perfect weather and traffic conditions. If autonomous vehicles can’t operate there, they have no chance of operating in crowded cities, in rain or in snow. And if autonomous vehicles aren’t on the near horizon after tens of billions of dollars of investment, advanced robotics are surely not on the horizon.¹⁰³ As of early 2019, it appears that companies in the sector are now seeking to “lower expectations about autonomous vehicles.”¹⁰⁴

II.B. The Realities of Workplace Automation

There are sound theoretical reasons to expect that future progress in automation will proceed much as it does now: by replacing particular tasks, and at a relatively slow and manageable pace. This is captured by what labor economist David Autor has deemed “Polanyi’s paradox” after Michael Polanyi’s observation that “we know more than we can tell.”¹⁰⁵ As Autor puts it,

When we break an egg over the edge of a mixing bowl, identify a distinct species of birds based only on a fleeting glimpse, write a persuasive paragraph, or develop a hypothesis to explain a poorly understood phenomenon, we are engaging in tasks that we only tacitly understand how to perform.

Basically, many tasks we perform all the time involve either motor skills or abstract skills that do not operate at a conscious level, which Polanyi termed “tacit knowledge.”¹⁰⁶

Autor and his coauthors argue that we can think of tasks that depend on tacit knowledge as “routine,” “abstract,” or “manual.” “Routine” tasks “follow an exhaustive set of rules and hence are readily amenable to computerization.” Those can be manual tasks, such as putting a bolt into an automobile chassis, or cognitive tasks such as spell-checking, multiplication, or data entry. Jobs made up primarily of such tasks, particularly in clerical, administrative support, and industrial production,

101. Filip Piekiewicz, *AI Winter Is Well on Its Way*, PIEKIEWICZ’S BLOG (May 28, 2018), available at <https://blog.piekiewicz.info/2018/05/28/ai-winter-is-well-on-its-way/>.

102. Amir Efrati, *Waymo’s Big Ambitions Slowed by Tech Trouble*, THE INFORMATION (Aug. 28, 2018).

103. Boston Robotics has recently admitted that its robots are not autonomous, but rather controlled by humans, and that it is unsure whether there is a market for them. Cade Metz, *These Robots Run, Dance and Flip. But Are They a Business?*, N.Y. TIMES (Sept. 22, 2018).

104. Cory Weinberg, *At CES, New Questions Emerge as Self-Driving Ambitions Narrow*, THE INFORMATION (Jan. 11, 2019).

105. David Autor, *Polanyi’s Paradox and the Shape of Employment Growth*, in FEDERAL RESERVE BANK OF ST. LOUIS: ECONOMIC POLICY PROCEEDINGS, REEVALUATING LABOR MARKET DYNAMICS 136 (2015), citing MICHAEL POLANYI, *THE TACIT DIMENSION* (1966).

106. *Id.*, at 136.

have already been hit hard by automation, and will continue to be automated.¹⁰⁷ Indeed, industrial automation is a major reason for the steady decline in manufacturing jobs in the United States since 1979—a decline that, it is worth noting, has *not* led to decreased manufacturing output.¹⁰⁸

The two other categories of tasks, however, have proven stubbornly resistant to automation. “Abstract” tasks “require problem-solving capabilities, intuition, creativity and persuasion.” Many high-wage professional, managerial, and technical jobs are made up primarily of abstract tasks. Such jobs often require individuals to keep up to date with best practices and technical literatures, and they often consist of making high-level situational judgments—does this patient have lung cancer? Is this lawsuit meritorious? Should we invest in this new line of business?—that others eventually implement. Advanced information technology can be substantially helpful in making such judgments—for example, by assisting in radiologic image recognition and in automated discovery practices—but humans still make the ultimate determination. Three Toronto Business School professors recently argued that for the foreseeable future, machine learning and AI will primarily aid in such decision making by delivering accurate predictions to professionals and managers, therefore increasing their power to make such decisions more quickly and with less uncertainty.¹⁰⁹

“Manual” tasks, in Autor’s words, involve “situational adaptability, visual and language recognition, and in-person interactions.” This category includes “food preparation and serving jobs, cleaning and janitorial work, grounds cleaning and maintenance, in-person health assistance by home health aides, and numerous jobs in security and protective services.”¹¹⁰ It also includes many jobs in retail, where shelf stocking, assisting customers, and checking customers out all require similar skills. And it may include work for “platform economy” firms such as Uber and Lyft, and other delivery services such as Deliveroo and Instacart. In all such jobs, workers utilize general skills that most humans have. But the manual dexterity, situational judgments, and language skills required have proven impossible to automate, for reasons discussed above. As I argue in Part III, the fact that such jobs can’t be either automated or made substantially more productive through technology encourages companies to save on labor costs through other means.

Autor’s analysis basically matches what the Bureau of Labor Statistics (BLS) has tracked over the past decade, and predicts going forward. From 2016 to 2026, the BLS expects expansion in healthcare and social assistance, professional and business services, and leisure and hospitality; little to no growth in mining, wholesale trade and utilities; and contraction in manufacturing.¹¹¹ The

107. *Id.*, at 135.

108. Economic Research at the Federal Reserve Bank of St. Louis, *All Employees: Manufacturing*, FRED, available at <https://fred.stlouisfed.org/series/MANEMP> (last accessed Jan. 2, 2018) (showing net number of employees); YiLi Chien & Paul Morris, *Is U.S. Manufacturing Really Declining?*, FEDERAL RESERVE BANK OF ST. LOUIS, ON THE ECONOMY BLOG (Apr. 11, 2017), available at <https://www.stlouisfed.org/on-the-economy/2017/april/us-manufacturing-really-declining> (last visited Jan. 2, 2018) (showing percentage of workers in manufacturing). The other major reason is globalization, especially the rise of China as a manufacturing powerhouse. Lawrence Mishel & Josh Bivens, *The Zombie Robot Argument Lurches On*, ECONOMIC POLICY INSTITUTE REPORT, at 5 (May 24, 2017) (noting that since 1980s “trade with China displaced three times as many jobs as did robots.”)

109. See generally AJAY AGRAWAL ET AL., PREDICTION MACHINES: THE SIMPLE ECONOMICS OF ARTIFICIAL INTELLIGENCE (2018). See also Autor, *supra* note 105, at 143 (computerization enables workers specializing in abstract tasks to further specialize).

110. Autor, *supra* note 105, at 138.

111. Kathleen Green, *Projected New Jobs by Major Industry Sector, 2016–26*, CAREER OUTLOOK, U.S. BUREAU

occupations that will grow the most, numerically, include personal care aides (almost 800,000 new jobs projected); food preparation and serving workers (almost 600,000); home health aides (over 400,000); and janitors and cleaners (over 200,000). Mid- to high-skill jobs that will add significant numbers include software developers, registered nurses, and other healthcare positions. Occupations that will contract most include secretaries and administrative assistants, industrial workers, data entry keys, and bank tellers—jobs consisting largely or primarily of “routine” tasks.¹¹² In other words, going forward, we will see fewer and fewer jobs that primarily involve routine tasks, but plenty that require abstract work or in-person manual work.

Autor’s analysis is also consistent with recent trends in labor productivity.¹¹³ In a period of technological upswing, with companies rapidly installing robotics and other automation devices, we should also see significant increases in labor productivity. In fact, productivity growth has recently been as slow as at any time since World War II.¹¹⁴ Moreover, productivity change in the manufacturing sector—where automation is easiest—has been especially tepid lately, at 0.7% over the last decade.¹¹⁵ On a related note, levels of “occupational churn,” or the net creation of jobs in growing occupations and loss of jobs in declining occupations, are also at historic lows.¹¹⁶ Nor is there economic evidence that an automation wave is on the horizon. If firms expected AI to be a major source of productivity growth in the near future, they would surely be investing in information technology. They aren’t. Computers and software constituted 13.5% of the value of companies’ investments from 2000 to 2007, as the internet was coming into wide use. Over the last decade that rate declined to 4.8%.¹¹⁷ Meanwhile, unemployment numbers are now falling in the United States rather than rising, even as higher minimum wage laws come into effect,¹¹⁸ and some European countries are facing labor shortages.¹¹⁹

This all suggests that the future of workplace automation will look a lot like the present. The vast majority of robotics and machine learning will be used to augment humans’ capabilities, rather than to replace them. Robots will not look like humans, nor will they simply step into humans’ shoes; AI-powered algorithms will not read books, synthesize research reports, hire workers, and communicate with us in full paragraphs. Rather, robots will look how they do now: they will be designed for a single

OF LABOR STATISTICS (Dec. 2017).

112. U.S. Bureau of Labor Statistics, *Projections of Occupational Employment, 2016–26* (Oct. 2017), available at <https://www.bls.gov/careeroutlook/2017/article/occupational-projections-charts.htm> (last visited Jan. 19, 2019).

113. See generally Daron Acemoglu et al., *Return of the Solow Paradox? IT, Productivity, and Employment in US Manufacturing*, 104 AM. ECON. REV. 394 (2014).

114. Productivity growth averaged 2.8% annually from 1945 to 1970, and 2.2% annually during the 1990s dot-com boom, but has been around 1.2% annually for the last decade. U.S. Bureau of Labor Statistics, *Labor Productivity and Costs*, available at <https://www.bls.gov/lpc/prodybar.htm> (last modified May 3, 2018).

115. U.S. Bureau of Labor Statistics, *Labor Productivity and Costs*, available at <https://www.bls.gov/lpc/prodybar.htm> (last modified May 3, 2018).

116. Robert D. Atkinson & John Wu, *False Alarmism: Technological Disruption and the U.S. Labor Market, 1850–2015*, INFORMATION TECHNOLOGY & INNOVATION FOUNDATION, at 20 (May 2017).

117. U.S. Bureau of Labor Statistics, *News Release, Multifactor Productivity Trends – 2017* (Mar. 21, 2018), available at https://www.bls.gov/news.release/archives/prod3_03212018.htm.

118. See U.S. Bureau of Labor Statistics, *Labor Force Statistics from the Current Population*, available at <https://data.bls.gov/timeseries/LNS14000000> (last visited Jan. 19, 2019) (showing unemployment falling under 4% starting in April of 2018).

119. Liz Alderman, *Danish Companies Seek to Hire, but Everyone’s Already Working*, N.Y. TIMES (Feb. 28, 2017), available at <https://www.nytimes.com/2017/02/28/business/economy/denmark-jobs-full-employment.html>.

purpose (like the Roomba and Amazon’s shelf-moving robots), or will be controlled by humans (like Boston Robotics’ PackBot), or will not actually be mobile (like assembly robots). They will be trained to perform specific tasks that make up the broader mix of tasks in a worker’s daily life. But because of that, companies and workers will generally have time to adapt to technological change, as they basically do today.

III. The Bigger Threats: Algorithmic Management and Fissuring

When automation isn’t possible, firms still have incentives to save on labor costs whenever possible. Machine learning and other forms of AI may help them in that process, functioning as especially powerful means of analyzing and quantifying ever more aspects of workplace and production processes. As discussed in Part I, above, companies can typically develop and deploy such technologies into the workplace at will. Below, I discuss two ways in which they are doing so. Part III.A discusses algorithmic management, or the use of algorithms to assist in hiring, oversight, and management. While at times algorithmic management improves productive efficiency, at others it directly disempowers workers, helping drive down wages and reduce workers’ autonomy. Part III.B discusses data-driven fissuring, or the use of new information technologies to shunt workers outside the corporate boundary, often denying them real rights under labor and employment laws. The two are not mutually exclusive. For example, an enhanced ability to monitor workers’ and suppliers’ performance through data-driven technologies can encourage fissuring. Nevertheless, they are distinct enough that I treat them separately.

III.A. Algorithmic Management

Researchers at Carnegie Mellon have used the term “algorithmic management” to describe contemporary companies’ use of data-driven algorithms to “manag[e] distributed human workers at a large scale.”¹²⁰ I borrow that term to refer to the full set of ways in which major companies use data developed through workplace quantification, fed into powerful algorithms, to manage workers today. While Uber, Lyft, and other on-demand companies are the most prominent examples of this phenomenon, they are far from alone; in fact, major retailers, fast food companies, and delivery companies have been using forms of algorithmic management for years, if not decades.

The underlying technologies here vary greatly. They include various sensors; for example, to determine where drivers are and whether they are speeding, as well as bar code scanners and inventory control devices of all sorts. They also include natural language processing, which companies can use to monitor employees’ speech and emails or to scan resumés. They include other sorts of machine learning and data analytics, including efforts to find data on job applicants that may correlate with job success or failure. And they include classic old information technologies such as mainframe computers and intranets, which can be used to communicate information between worksites and centralized servers that perform particular analyses. What unites the activities treated

120. Min Kyung Lee et al., *Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers* (working paper, 2015), available at <https://dl.acm.org/citation.cfm?doid=2702123.2702548>.

here are (a) gathering of data from workers and production processes to quantify particular aspects of work processes; (b) processing that data algorithmically, whether through machine learning or older technologies; and (c) making managerial decisions on the basis of those algorithms.

These efforts are admittedly less dramatic than full-job automation, since they often involve iterative changes to management processes, and to workers' jobs. To be clear, in many instances they *do* involve task automation, though the tasks being automated—inventory control, scheduling, workflow organization, oversight, payroll processing, etc.—were formerly carried out by managers. But algorithmic management may prove far more important than automation in the near term, and perhaps even in the long term. For one thing, neither robotics nor especially advanced forms of AI are required, which makes the implementation of such processes much easier. Moreover, the background rules governing the workplace, discussed above, generally enable employers to implement algorithmic management processes at will.

While the effects of algorithmic management are complicated, in many cases it will put downward pressure on labor standards, particularly for workers without specialized skills. Granted, where algorithmic management techniques enable greater productive efficiency without increasing the pace of labor or reducing wages, workers will tend to benefit. Algorithmic management techniques may often replace mind-numbing aspects of managerial work, and minimizing transaction costs can benefit everyone, by enabling more transactions to take place, and creating a consumer surplus.

However, as discussed in Part I, above, the workplace is a site of significant power disparities, and workers' and employers' incentives often diverge. Managers who can use the new tools of algorithmic management will be more effective and powerful. As two prominent economists put it, one result of incorporating modern information technologies into businesses is “a reduction in the vertical layers of middle managers engaged in supervision and an increase in the efficiency and quality of management oversight.”¹²¹ Basically, with better information about what is going on within an enterprise, and even among suppliers, oversight power is concentrated in fewer hands. Indeed, managers able to effectively use algorithmic management tools may be a paradigmatic case of the worker whose powers are amplified by technology, since they'll be able to oversee the work of far more workers.

Managed workers, meanwhile, tend to suffer. Some, of course, will thrive, since closer monitoring will illustrate their superior production skills, or since they'll learn how to use algorithms to their advantage. But many will find their autonomy on the job limited; they may be required to work faster or harder; they may have irregular schedules; and they may be subject to termination for rather arbitrary reasons.¹²² The remainder of this section discusses the tendency of algorithmic management to amplify the information asymmetries in the employer-employee relationship, in ways that systematically empower employers.

121. Laura Tyson & Michael Spence, *Exploring the Effects of Technology on Inequality*, in AFTER PIKETTY 182–83 (Heather Boushey et al. eds., 2017).

122. See Peter Skott & Frederick Guy, *A Model of Power-Biased Technological Change*, 95 ECON. LETTERS 124 (2007) (arguing that new information technologies “allow[] firms to monitor low-skill workers more closely, thus reducing the power of those workers.”) I am grateful to Heidi Shierholz for directing me to this paper.

III.A.i Algorithmic Hiring

As discussed above, information asymmetries plague the hiring process—potential employees and employers each have limited information about one another when they first meet, and so both may want to invest in producing better information about the other. Modern information technologies, including but not limited to machine learning and related algorithms, may alter those dynamics. If both parties have better information about the other, then job matching may improve, with firms finding the right workers and workers finding the right firms. However, the parties' ability to gather information on the other is unequal, for both legal and extralegal reasons, which can affect the outcome of hiring processes.

The theory behind algorithmic hiring is that data analytics and/or machine learning can help identify aspects of applicants' background or current activities that indicate they will be successful in particular positions. The underlying datasets may come from candidates' own submissions to recruitment websites, such as resumés that they upload; from candidates' social media profiles or other online activities that are visible to recruiters; or from background checks that recruiters perform on applicants.¹²³ This is superficially plausible, since today so many of us generate extensive data through our online and other activities. Initial efforts to fully automate recruitment failed, but subsequent efforts to bring machine learning and data analytics into the process in a more limited fashion seem at least moderately successful.¹²⁴ Ideal, a Toronto-based startup, has helped various large retailers with hiring by screening resumés, gathering information from applicants via chatbot regarding their shift availability and skills, and recommending qualified candidates.¹²⁵

Most McDonald's franchisees, meanwhile, use a centralized candidate screening system that the company hired a contractor to develop. The test asks applicants various questions designed to determine how diligent they are, such as how well they did in school and whether they tend to be on time for meetings; it also seeks to determine how applicants would respond to various social situations, such as an upset customer or coworker.¹²⁶ According to briefs filed in a case at the National Labor Relations Board, the test "eliminates prospective applicants through a screening tool which selects applicants for job skill and service propensity using a color-coded system (i.e., red, yellow and green)," where applicants coded "red" should not be interviewed, those coded "green" should be, and those coded "yellow" may be.¹²⁷ In the long term, the data gleaned from such tests, and from online applications, may enable McDonald's to make more precise determinations about which workers to interview or hire.

123. See Matt Rittel, *How Big Data is Playing Recruiter for Specialized Workers*, N.Y. TIMES (Apr. 28, 2013) (discussing companies' efforts to automate elements of recruitment).

124. Michelle V. Rafter, *Why Robots Won't Take Over HR Recruiting Any Time Soon*, PC MAGAZINE (Apr. 20, 2016), available at <https://www.pcmag.com/article/343627/why-robots-wont-take-over-hr-recruiting-any-time-soon> (quoting CEO of hiring startup Ideal: "A lot of people think recruiting can be totally automated and it's not possible. . . . We tried to develop the system thinking we could and we can't.")

125. Ideal, *Chatbot and Candidate Messaging Software*, available at <https://ideal.com/product/recruiting-chatbot/> (last visited Jan. 19, 2019).

126. Test for McDonald's applicants developed by Aon Assessment Solutions, on file with author.

127. Charging Parties' Post-Hearing Brief in Opposition to Proposed Settlement Agreements, *McDonald's USA LLC, a Joint Employer and Fast Food Workers Committee and SEIU*, National Labor Relations Board Cases 02-CA-093893 et al., and 04-CA-125567 et al. (Apr. 27, 2018).

The effects of such practices are complicated. On the one hand, if a company can use greater information about both employer needs and employee skills and desires to better match potential workers to jobs, all parties may benefit. Job searches are costly for both workers and employers, but the specific costs of searches differ based on industrial sector, geography, and many other factors.¹²⁸ On the other hand, if employers bear the costs of hiring new workers, they may pay above-market wages to reduce turnover and limit recruitment costs.¹²⁹ In those cases, search technologies may make certain labor markets behave more like classic commodity markets, which might reduce unemployment, while also reducing wages.

What *can* be said is that automated searches are only as good as their underlying data and programming, and that data and programming may reproduce various forms of bias, and power structures more generally, which already shape labor markets. A machine learning program that captures health or disability-related data may be per se discriminatory, for reasons discussed above. An algorithm that finds that workers tend to stay in jobs longer if they live near the worksite may exclude African American workers at a disproportionate rate if the worksite is in a white neighborhood in a segregated city.¹³⁰ Similarly, if machine learning algorithms draw a statistical inference that job applicants who have been unemployed for more than six months are unlikely to be a good match, it will be that much harder for unemployed workers to find jobs.¹³¹ In still other cases, machine learning and other automated recruitment strategies might be used to screen out applicants based on their political beliefs or social activities, in order to avoid a unionization drive. That would be a violation of the NLRA, but the provision is quite difficult to enforce.¹³²

III.A.ii Monitoring and Wage Setting

Imperfect information and power relationships also shape the parties' incentives after hiring. From the employer's perspective, workers who have been asked to perform a set of tasks may do so more or less diligently, but if the employer can't easily detect "shirkers," the pace of work may fall. Historically, if output was observable but effort was not, one employer strategy was to utilize piece rates, or payment of workers by the unit of goods produced. In theory, piece rates should align workers' and employers' incentives by giving workers an economic incentive to produce at a faster rate than they otherwise would.

But that is not how they typically worked in practice. Once an employer set a piece rate, workers would often produce more units in order to raise their pay. But that then created an incentive for the employer to lower the per-unit pay, or to increase the production level required for workers to make

128. Richard Rogerson et al., *Search-Theoretic Models of the Labor Market: A Survey*, NBER Working Paper 10655 (July 2004), available at <http://www.nber.org/papers/w10655>.

129. Joseph E. Stiglitz, *Alternative Theories of Wage Determination and Unemployment in L.D.C.'s: The Labor Turnover Model*, 88 Q. J. ECON 194 (1974).

130. See generally Barocas & Selbst, *supra* note 9; Kim, *supra* note 5.

131. On discrimination against the unemployed, see generally Gregor Jarosch & Laura Pilossoph, *Statistical Discrimination and Duration Dependence in the Job Finding Rate*, ___ REV. ECON. STUD. ___ (forthcoming), available at <https://doi.org/10.1093/restud/rdy055>.

132. See generally Nathan Newman, *UnMarginalizing Workers: How Big Data Drives Lower Wages and How Reframing Labor Law Can Restore Information Equality in the Workplace* (Aug. 8, 2016), available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2819142.

their ordinary wages. As a sociologist who studied the process explains, “Unless workers collectively restricted output they were likely to find themselves working much harder, producing much more, and earning only slightly higher wages.”¹³³ Of course, workers’ ability to collectively restrict output was in part an effect of employment law rules, including employment-at-will, and workers’ rights to unionize or take other collective action—once again demonstrating the complex relationship among law, power, and workplace information.

Employers’ ability to monitor workers’ performance may also affect wages. For example, monitoring costs are at the heart of some variants of “efficiency wage” theory, which arose to explain a phenomenon that puzzled neoclassical economists: why do labor markets rarely “clear,” with wages dropping to the point that unemployment approaches zero?¹³⁴ Per such theories, employers who can’t monitor workers’ performance easily may pay above-market wages to increase the costs of unemployment to workers, or to induce loyalty among workers.¹³⁵ Importantly, however, this theory assumed that employers were unable to cheaply observe workers’ effort or output levels.¹³⁶ This suggests that when firms are able to monitor work at low cost, they will have less incentive to pay above-market wages.¹³⁷

And firms are now using advanced information technologies to monitor workers’ performance in ever more perfect ways. For example, employers have long monitored telephone communications and email, and have utilized keystroke-monitoring programs to estimate workers’ productivity. A study by the American Management Association from 2007 found that, even then, 45% of employers tracked what employees did at computer workstations.¹³⁸ While peer-reviewed research on how such efforts impact wages is rare, one study found that when the platform Freelancer implemented a monitoring system that tracked keystrokes and the like, clients’ preferences “for bidders with a high effort-related reputation in time-based projects” fell. New users on the platform were able to find clients more easily, but the equilibrium price for time-based projects dropped by almost 7%.¹³⁹

133. DAN CLAWSON, *BUREAUCRACY AND THE LABOR PROCESS: THE TRANSFORMATION OF U.S. INDUSTRY, 1860–1920* 169–70 (1980), discussed in Robert Gibbons, *Piece-Rate Incentive Schemes*, 5 J. LABOR ECON. 413, 416 (1987).

134. Stiglitz, *Paradigm in Economics*, *supra* note 15, at 473.

135. Carl Shapiro & Joseph Stiglitz, *Equilibrium Unemployment as a Worker Discipline Device*, 74 AM. ECON. REV. 433, 433 (1984). See also Janet Yellen, *Efficiency Wage Models of Unemployment*, 74 AM. ECON. REV. 200, 203 (1984) (examining efficiency wages as a means of selecting for high-performing workers); George A. Akerlof, *Labor Contracts as Partial Gift Exchange*, 97 Q. J. ECON. 543 (1982) (arguing that efficiency wages arise due to norms of fair treatment within the firm or workplace).

136. Jeremy I. Bulow & Lawrence H. Summers, *A Theory of Dual Labor Markets with Application to Industrial Policy, Discrimination, and Keynesian Unemployment*, at 2, NBER Working Paper No. 1666 (July 1985), available at <https://core.ac.uk/download/pdf/6690394.pdf>. See also Yellen, *supra* note 135, at 200, 201 (arguing that efficiency wages may also be less important “in the secondary sector, where the wage-productivity relationship is weak or nonexistent”).

137. It is also important to note that efficiency wage theories do *not* predict that wage increases amount to a free lunch of sorts, on the grounds that higher wages will lead to increased productivity. Rather, they arose to explain persistent unemployment. Alex Tabarrok, *The False Prophets of Efficiency Wages*, MARGINAL REVOLUTION (Apr. 28, 2015), available at <https://marginalrevolution.com/marginalrevolution/2015/04/the-false-prophets-of-efficiency-wages.html>.

138. American Management Association, *The Latest on Workplace Monitoring and Surveillance* (2007), available at <https://www.amanet.org/training/articles/the-latest-on-workplace-monitoring-and-surveillance.aspx> (last visited Jan. 19, 2019).

139. Chen Liang et al., *Effects of IT-Enabled Monitoring on Labor Contracting in Online Platforms: Evidence from a Natural Experiment*, NET Institute Working Paper No. 16-01 (2016), available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2844920.

Companies also use point-of-sale systems to track sales, and in the process track workers' performance.¹⁴⁰ This is nothing new. In the 1970s, as supermarkets began to introduce bar code scanners at cashier stations, sociologist Harry Braverman warned that the technology could be used to track employee performance.¹⁴¹ But their sophistication has improved dramatically with the advent of corporate intranets. Today, those systems can give corporate headquarters previously unheard-of information about particular workers' and stores' performance.¹⁴² For example, in a wage theft case filed against Domino's Pizza, the New York State Attorney General argued that "Domino's possesses contemporaneous time records for all franchisee employees, not only the legally required time records showing hours worked, but more detailed records showing each employee's minute-by-minute actions each day," due to its use of an integrated timekeeping and POS system called PULSE.¹⁴³ Domino's used that data, regulators allege, to keep labor costs low.

Other companies use new technologies that integrate GPS tracking with other sensors to monitor remote workers' performance. United Parcel Service, for example, closely tracks everything that drivers do while on the road. As an NPR reporter put it in 2014, "From the time he punches in in the morning until he gets back to base at night, the company is trying to figure out how [the driver] can do his job quicker, more efficiently."¹⁴⁴ At the center of such efforts are "telematics" systems, or technologies that transmit data from remote sensors to a central point for analysis. Those include hundreds of sensors on individual trucks that "track everything from backup speeds to stop times to seat-belt use."¹⁴⁵ By combining that data with handheld scanners that track packages in a national or global corporate intranet, UPS has been able to dramatically increase its daily deliveries while simultaneously reducing its driver workforce.¹⁴⁶ One effect of the speed-up was a significant increase in workplace injuries.¹⁴⁷ Sociologist Karen Levy has documented similar systems used by long-haul trucking companies to monitor their drivers ever more closely, reducing their autonomy.¹⁴⁸

Perhaps the most dramatic recent success story in algorithmic management lies in Uber and other companies' transformation of the taxi sector.¹⁴⁹ Uber's app matches consumers and drivers more

140. Esther Kaplan, *The Spy Who Fired Me*, HARPERS (Mar. 2015), available at <https://harpers.org/archive/2015/03/the-spy-who-fired-me/?single=1>.

141. BRAVERMAN, *supra* note 44, at 256–58.

142. Walmart recently patented a device to monitor conversations near cashiers' stations, which it believes will help the company to determine how long customers were waiting in line, whether workers were adequately greeting guests, and whether they were bagging items quickly and efficiently. Sam Levin, *Walmart Patents Tech That Would Allow it to Eavesdrop on Cashiers*, THE GUARDIAN (July 12, 2018), available at <https://www.theguardian.com/business/2018/jul/12/walmart-surveillance-sound-sensors-employees>.

143. *People of the State of N.Y. v. Domino's Pizza*, Memorandum of Law in Support of Verified Petition at 3, [case number not available] (Nov. 4, 2016), available at <https://static1.squarespace.com/static/577e9d93b3db2b9290cd7005/t/5a5d1262652dea17cc58a79f/1516048997826/New+York+brief+in+Domino%27s+joint+employment+case.pdf>.

144. NPR Planet Money, *Episode 536: The Future of Work Looks Like a UPS Truck*, NPR (May 2, 2014), available at <https://www.npr.org/sections/money/2014/05/02/308640135/episode-536-the-future-of-work-looks-like-a-ups-truck>.

145. Kaplan, *supra* note 140.

146. Kaplan, *supra* note 140 (finding that UPS's package delivery numbers "grew by 1.4 million between 2009 and 2013, the years in which telematics was being rolled out—and these additional packages were delivered by a thousand fewer drivers.")

147. Kaplan, *supra* note 140.

148. See generally Levy, *supra* note 46.

149. See generally ALEX ROSENBLAT, *UBERLAND: HOW ALGORITHMS ARE REWRITING THE RULES OF WORK* (2018).

efficiently than street-hail systems; the company draws on data generated by past rides to determine appropriate routes and to predict demand; and it crowdsources the supervision of drivers, by requiring customers to rate them after each ride. Drivers who don't maintain a certain rating risk being "deactivated" from the platform. As two researchers put it, "the information and power asymmetries produced by the Uber application are fundamental to its ability to structure control over its workers."¹⁵⁰ For example, when it sends a ride request to a driver, the driver has only 15 seconds to accept it, and must do so without destination or fare information. Drivers who refuse too many fares, or who cancel fares after they have accepted them, risk deactivation. Such actions help ensure that customers can get rides as quickly as possible, but at the cost of driver autonomy. And finally, in a contemporary example of how piece rates are vulnerable to employer opportunism when workers have few rights to protest, Uber has several times changed pricing policies without notice in ways that reduced many drivers' pay.¹⁵¹

III.A.iii Scheduling and Timekeeping

Many if not most major companies today use timekeeping software that tracks when workers sign in and out of work, determines their net hours during each pay period, and interfaces with payroll-processing companies. More recently, fast food, retail, and other similar companies have begun using algorithms to schedule workers for their shifts. Those algorithms predict consumer demand based on past sales as well as factors such as weather reports, and schedule workers accordingly to ensure that worksites are neither overstaffed nor understaffed on particular days. Like some other forms of algorithmic management, this involves partial automation, though the tasks being automated are managerial.

Importantly, there is a worker-positive case for algorithmic scheduling: making schedules manually is a major hassle for managers, and can be quite difficult to learn to do. When workers can specify times they would ideally like to work, and an algorithm can figure out how to optimize the schedule for a manager, that can reduce a company's costs and also, in many cases, help ensure worker satisfaction.¹⁵² And while fixed schedules are highly desirable in most instances, many workers would like some flexibility, and workers may well prefer to be able to request a different shift via an app rather than in person with a manager. Automated scheduling may help ensure compliance with wage/hour laws,¹⁵³ or could help workers prove that they suffered discrimination if, for example, women or African American workers are frequently assigned less-desirable shifts.

That said, scheduling software often doesn't always take workers' needs into account. The practice of algorithmic scheduling came to light with Starbucks's practice of "clopenings," where

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

151. Patrick Hatch, *Drivers in Revolt over "Pay Cuts" as Uber Faces New Competition*, THE SYDNEY MORNING HERALD (July 29, 2018), available at <https://www.smh.com.au/business/companies/drivers-in-revolt-over-pay-cuts-as-uber-faces-new-competition-20180726-p4ztob.html>; Harry Campbell, *Is Uber Lowering Rates Again? Yes and No . . .*, THE RIDESHARE GUY (July 16, 2018), available at <https://therideshareguy.com/uber-lowering-rates/>.

152. Kronos, *Hannaford [Supermarkets] Uses Kronos Optimized Scheduling and Navigator to Streamline Workforce Management*, available at <https://www.kronos.com/customers/hannaford-supermarkets> (last visited Jan. 19, 2019).

153. *Id.*

workers were required to close the store one night then open it the next day, making it nearly impossible for them to sleep. Baristas protested the practice through Coworker.org, an online platform for worker organizing.¹⁵⁴ In the wake of media attention, the company revised its scheduling practices and promised more regular and predictable schedules in the future.¹⁵⁵ Starbucks's decision, it is worth noting, wasn't required under federal wage and hour laws, which don't guarantee steady hours, minimum hours, or maximum hours, and provide scant protections against unpredictable schedules or extensive on-call time.¹⁵⁶ Some states and localities have nevertheless begun to require employers to provide workers reasonable advance notice of their schedules.¹⁵⁷

There is also evidence that timekeeping software can actually undermine compliance. Three legal scholars reviewed common timekeeping software programs and found that most of them contributed to eroding compliance. Those programs enabled “employers to deprive employees of earned pay by editing down their hours worked, setting up automatic default rules that shave time, and discussing edits to employees' time records.”¹⁵⁸ Companies would have an incentive to do so, as they would then save on net labor costs, and perhaps avoid overtime pay. Underpayment of wages seems to be a major problem in the contemporary workplace, especially for low-wage workers. Walmart, for example, was ordered to pay nearly \$200 million to Pennsylvania workers who alleged in a class action suit that they had been deprived of mandatory breaks and required to perform work before they clocked in.¹⁵⁹

III.A.iv Summary

The examples cited above evince a trend: algorithmic management often enables employers to reduce informational asymmetries that historically favored workers, and/or create new information asymmetries that favor themselves. Efficiency wages often emerged because employers couldn't effectively monitor workers' efforts; once employers have near-perfect information about workers' performance, wages may be set closer to market levels. Similarly, in scheduling processes, at stake is who pays for unused labor power. The norm that firms hired employees and required them to stay on site for eight hours at a time provided firms with an incentive to give employees sufficient work for that period, but also meant that companies bore the risk of workers not being busy during the entire time. But if the pace of work can be monitored directly at very low cost, and firms can compensate workers only for time spent working, they tap all the excess labor power they can, while leaving

154. Coworker.org, *Victories*, available at <https://home.coworker.org/victories/> (last visited Jan. 19, 2019).

155. Jodi Kantor, *Starbucks to Revise Policies to End Irregular Schedules for Its 130,000 Baristas*, N.Y. TIMES (Aug. 14, 2014), available at <https://www.nytimes.com/2014/08/15/us/starbucks-to-revise-work-scheduling-policies.html>.

156. See 29 U.S.C. § 207 (2018) (maximum hours provision of FLSA, requiring overtime for work over 40 hours in a week, but not requiring regular or reasonable hours).

157. See Sara Eber Fowler & Lynn Kappelman, *As Predicted . . . On July 1, Oregon Will Become the First State with a Predictive Scheduling Law*, SEYFARTH SHAW EMPLOYMENT LAW LOOKOUT (June 28, 2018), available at <https://www.laborandemploymentlawcounsel.com/2018/06/as-predicted-on-july-1-oregon-will-become-the-first-state-with-a-predictable-scheduling-law/> (discussing newly enacted Oregon law as well as similar laws passed by municipalities).

158. Elizabeth Tippet, Charlotte Alexander & Zev Eigen, *When Timekeeping Undermines Compliance*, 19 YALE J. L. & TECH. 1, 3 (2017).

159. *Braun v. Wal-Mart Stores, Inc.*, 620 Pa. 292 (Sup. Ct. Penn., 2014), cert. denied 136 S.Ct. 1512 (Apr. 4, 2016).

workers uncompensated for any that is unused. While such processes do not today require machine learning, emerging information technologies may make them cheaper to implement and more powerful over time. By the same token, employers could use workplace data to ensure that they are in compliance with all legal mandates, if they have appropriate incentives to do so. As discussed in the next section, however, those incentives are often lacking.

III.B. Data-Driven Fissuring

Contemporary information technologies are also an important driving force behind changes in industrial organization. While the overall story is complex, varying based on industrial sector and other factors,¹⁶⁰ in general companies have incentives to produce goods in-house when it is difficult to specify outputs with precision, or to monitor outside parties' performance. At the same time, bringing workers in-house as employees makes companies responsible for substantial employment-related costs. Those include minimum wages, overtime pay, workers' compensation, rights to healthcare under the Affordable Care Act, and duties under antidiscrimination and collective bargaining laws. If new technologies enable a firm to ensure high-quality production through suppliers and outside contractors, that firm will have very strong incentives to exploit such technologies to reduce labor costs.

III.B.i The Law and Political Economy of Fissuring

Fissuring is possible because duties under labor and employment laws are limited to the employment relationship. A firm generally has no employment law duties toward independent contractors, subcontracted workers who are employed by a third party, or the employees of suppliers. The legal test for employment under most statutes derives from the common law of agency, which defines employment as a relationship of control. When one party consents that another party shall act on their behalf and under their control, an employment relationship is created.¹⁶¹ In contrast, a classic independent contracting relationship arises when the principal hires an independent businessperson with such specialized skills that the principal has neither the ability nor the desire to supervise.¹⁶² As one judge put it, the "paradigm of an independent contractor" is one who sells "only expertise."¹⁶³

Courts and administrative agencies have developed various multifactor tests for employment under the law of agency. Those tests require analysis of multiple factors, including whether the

160. See, e.g., Arvin Sahaym et al., *The Influence of Information Technology on the Use of Loosely Coupled Organizational Forms: An Industry-Level Analysis*, 18 ORG. SCI. 865 (2007) (finding that firms' organizational decisions varied in part with how other firms in their sector use technology. Greater disaggregation and outsourcing seen when other firms use the same technologies, when suppliers and principals use the same technologies, and when industry standards have been developed, which can reduce monitoring costs and mitigate holdup problems.) George Baker & Thomas Hubbard, *Make versus Buy in Trucking: Asset Ownership, Job Design, and Information*, 93 AM. ECON. REV. 551 (2003) (finding distinct effects on industrial organization of (a) technologies that reduce monitoring costs, which encourage in-house drivers, and (b) technologies that reduce coordination costs, which encourage use of contractors).

161. RESTATEMENT (SECOND) OF AGENCY § 220 (1958) (listing factors that should be used to determine whether a relationship constitutes employment). For an historical account of the evolution of the difference between employment and independent contracting within employment and labor law, see V. B. Dubal, *Wage Slave or Entrepreneur? Contesting the Dualism of Legal Worker Identities*, 105 CALIF. L. REV. 101 (2017).

162. See *Sec'y of Labor v. Lauritzen*, 835 F.2d 1529, 1540 (7th Cir. 1987) (Easterbrook, J., concurring).

163. *Lauritzen*, 835 F.2d at 1545 n.3 (Easterbrook, J., concurring).

putative employer exerted control over the work at issue, whether it had the right to control that work, whether the worker is in an independent trade, whether the agreement could be terminated at will, and the length of the relationship and the method of payment.¹⁶⁴ There is a robust and long-running debate among scholars and policymakers about whether such tests make sense for employment statutes. In brief, these tests emerged to determine when companies were responsible for harms their employees caused to third parties, and are a sensible way of allocating such costs.¹⁶⁵ But that rationale has little to nothing to do with employment regulations, which aim to protect workers against economic and social harms perpetrated by the employer, or to protect them against some of the harshest consequences of unrestricted market ordering.¹⁶⁶

The term “fissuring” analogizes such employment practices to the fissures that open in boulders and spread over time: fissuring creates a legal gap between workers and the companies that ultimately profit from their labor, a gap that is challenging to close under existing law.¹⁶⁷ One fissuring strategy is misclassification: legally classifying workers as independent contractors but still exerting enough control over them that they should rightly be classified as employees. This is common in the so-called “platform economy” of Uber and Lyft, among delivery firms (such as FedEx), and elsewhere in the logistics sector.¹⁶⁸ Another is subcontracting, in which user firms hire labor through agencies or third-party contractors. Workers then have a legal employer—the contractor—but user firms may exert substantial power over their working conditions. Subcontracting is especially common in building services, agriculture, and hotels.¹⁶⁹ A third strategy is franchising, in which large firms, especially in fast food and retail, license their trade dress and product line to independent businesses, who in turn employ line-level workers.¹⁷⁰ Franchisors may nevertheless retain substantial power over working conditions.¹⁷¹

164. See *Nationwide Mut. Ins. Co. v. Darden*, 503 U.S. 318, 323 (1992) (common law “control test” under law of agency applies to ERISA); *NLRB v. United Insurance*, 390 U.S. 254, 256 (1968) (affirming that test for employment under the NLRA is control test). The Fair Labor Standards Act also limits duties to the employer/employee relationship, but it defines “employ” more broadly than under the law of agency, to include to “suffer or permit to work,” 29 U.S.C. 203(g) (2012). *U.S. v. Rosenwasser*, 323 U.S. 360, 362–63 (1945) (noting difference between definitions).

165. Alan Hyde, *Legal Responsibility for Labour Conditions down the Production Chain*, in CHALLENGING THE LEGAL BOUNDARIES OF WORK REGULATION 94 (Judy Fudge et al. eds., 2012).

166. See, e.g., Noah Zatz, *Beyond Misclassification: Tackling the Independent Contractor Problem without Redefining Employment*, 26 ABA J. LAB. & EMPL. L. 279, 282–83 (2011); see also *Lauritzen*, 835 F.2d at 1544 (Easterbrook, J., concurring) (“the reasons for blocking vicarious liability have nothing to do with the purposes of the FLSA.”)

167. WEIL, *supra* note 7, at 7 (drawing this metaphor).

168. See, e.g., *Alexander v. FedEx Ground Package System, Inc.*, 765 F.3d 981 (9th Cir. 2014) (finding that FedEx misclassified drivers under California laws regarding wages, hours, and work-related expenses). See also *O’Connor v. Uber Techs.*, 82 F. Supp. 3d 1133 (N.D. Cal. 2015), *Cotter v. Lyft, Inc.*, 60 F. Supp. 3d 1067 (N.D. Cal. 2015) (separate opinions finding that question of employment status must go to a jury, and detailing facts of driver-platform relationship, many of which point in the direction of finding employment relationship).

169. Hard data on the incidence of subcontracting is difficult to come by. But as one data point, California has identified construction, janitorial and security services, garment, and farm labor as industries with a high incidence of subcontracting, and imposed enhanced duties on firms in those sectors as a result. California Labor Code § 2810 (___). See also WEIL, *supra* note 7, at 99–121 (discussing subcontracting and its effects).

170. See generally WEIL, *supra* note 7, at 122–58 (discussing franchising and its effects).

171. WEIL, *supra* note 7, at 158 (noting that franchisors still “creat[e], monitor[] and enforce[e] standards central to business strategy while . . . ducking responsibility” for labor).

Notably, a standard neoclassical economic model predicts that fissuring should not save money. Workers' wages should track their productivity, and contractors, franchisors, and others all follow the law, and pass costs of legal compliance on to principal firms, including wages, benefits, costs of workplace safety, insurance, and the like. Yet substantial evidence cutting across decades and industries shows that employees make more than contracted workers performing the same work.¹⁷² Similarly, a major study of franchises found substantially lower rates of compliance with wage/hour laws in franchise locations that were independently owned compared to those owned by the franchisor.¹⁷³ The reasons are not difficult to discern. A company relentlessly focused on cost saving may use judgment-proof contractors or franchisees, safe in the knowledge that employment law liabilities cannot be passed on to them.¹⁷⁴ And even when contractors and suppliers are not judgment-proof, regulators and workers face significant enforcement costs, including the costs of developing an extensive factual record about two different firms' conduct after the fact, with relatively low damages at stake, which makes it uneconomical for private attorneys to take on such cases. As a result, even where tests for employment are written to provide greater protection than existed under the common law, employees may have significant difficulty enforcing their rights.

Fissuring can also make effective collective bargaining impossible. Independent contractors have no collective bargaining rights under the NLRA, and subcontracted workers have such rights only against their immediate employers,¹⁷⁵ which makes it difficult to bargain with larger firms that are the real parties in interest.¹⁷⁶ What's more, a company generally does not violate the NLRA by terminating a subcontractor because its employees have unionized,¹⁷⁷ which creates powerful disincentives for such workers to organize. Indeed, subcontracted workers who do take industrial action against a user firm may often be terminated without consequence, on the grounds that such action is "unprotected" under the NLRA,¹⁷⁸ and unions that take such action can face injunctions, unfair labor practice charges, and hefty fines.¹⁷⁹

172. See, e.g., Samuel Berlinski, *Wages and Contracting Out: Does the Law of One Price Hold?* 46 BRIT. J. INDUS. RELNS. 59 (2008) (subcontracted janitors and security guards make less than 15% of what in-house workers doing same jobs make); Arandjit Dube & Ethan Kaplan, *Does Outsourcing Reduce Wages in the Low-Wage Service Occupations? Evidence from Janitors and Guards*, 63 INDUS. & LAB. RELNS. REV. 287 (2010) (finding smaller wage differential between subcontracted and in-house workers, but finding that in-house workers were less likely to receive health insurance); WEIL, *supra* note 7, at 88, discussing TRUMAN BEWLEY, WHY WAGES DON'T FALL DURING A RECESSION (1999) (showing different pay for employees and contractors performing the same job on the same worksite).

173. WEIL, *supra* note 7, at 131.

174. See *Reyes v. Remington Hybrid Seed Co.*, 495 F.3d 403, 409 (7th Cir. 2005) (Easterbrook, J.) (noting that user firms may have incentive to hire judgment-proof contractors and escape FLSA liability unless employment is defined broadly enough to capture subcontracted workers).

175. *NLRB v. United Insurance*, 390 U.S. 254, 256 (1968) (affirming that test for employment under the NLRA is control test).

176. The NLRB's "joint employer" standard is currently in flux, but most observers expect that the Trump board will eventually adopt a version of the standard in *Hy-Brand Industrial Contractors*, 365 NLRB No. 156 (Dec. 14, 2017), which requires workers to prove that a putative joint employer exercised "direct and immediate control" over their work. Under that standard, franchisee workers and many subcontracted workers will be unable to hold user firms responsible as joint employers.

177. *Plumbers Local 447 (Malbaff Landscape Construction)*, 172 NLRB 128, 129 (1968) (finding no 8(a)(3) violation in this situation).

178. E.g., *Preferred Building Services*, 366 NLRB No. 159 (Aug. 28, 2018).

179. 29 U.S.C. §§ 158(b)(4), 160(l) (2012) (banning almost all secondary boycotts, providing for expedited processes and injunctive relief in cases of certain secondary boycotts). By placing workers outside the firm,

It is difficult to overestimate the importance of fissuring for how the modern workplace is structured, and for workers' welfare more generally. As David Weil explores in great detail in his book *The Fissured Workplace*, over the last 30 or 40 years many occupations formerly performed within large, well-capitalized firms have come to be performed outside those firms. Some of the most important include janitorial services, security services, food service work, and hotel work. Similarly, a great deal of manufacturing has been fissured away from large, vertically integrated firms over the past few decades, as large companies increasingly purchase parts from third parties rather than making them, or rely on temporary agencies for workers in domestic factories. Many companies chose such strategies under pressure from shareholders to maximize returns by shedding business units that imposed high labor costs and were not central to firms' strategies.¹⁸⁰

III.B.ii Workplace Data and Fissuring: Examples

Advanced information technologies may encourage still more fissuring in the future. As two prominent economists argue in a recent book chapter, "Network-based information technology . . . [has] expanded the tools for managing complex global supply chains by enabling companies to source, monitor, and coordinate production processes at disparate locations quickly and cheaply."¹⁸¹ When documents and other information can be transferred across the globe at zero cost, global outsourcing becomes far more attractive due to lower labor costs abroad.¹⁸² Those same factors encouraged domestic fissuring. According to Weil, fissuring in the fast food, hospitality and other sectors depends on the low costs "of gathering information and undertaking monitoring in light of developments in the digital world."¹⁸³

Technology-enabled fissuring is quite clear in the on-demand economy of Uber, Lyft, and the like. As noted above, Uber uses one set of algorithms to match passengers to drivers, and another to oversee and discipline its workforce. It therefore has a clear sense of which drivers are among its best and worst, and manages an enormous and constantly changing workforce with almost no direct human supervision. Meanwhile, needless to say, Uber has disclaimed any duties toward its drivers under wage and hour, workplace safety, tax, and collective bargaining laws, by claiming they are independent contractors rather than employees. To date, the courts have mainly sided with the company despite powerful arguments that Uber drivers are in fact legal employees,¹⁸⁴ given the extensive control the company exercises over their labor.¹⁸⁵ Uber's avoidance of employment law

fissuring may also undermine norms of fair treatment. WEIL, *supra* note 7, at 81–85.

180. WEIL, *supra* note 7, at 43–60.

181. Tyson & Spence, *supra* note 121, at 187. ACCORD NATIONAL ACADEMY OF SCIENCES, INFORMATION TECHNOLOGY AND THE U.S. WORKFORCE: WHERE ARE WE AND WHERE DO WE GO FROM HERE?, at 66 (2017).

182. See Tyson & Spence, *supra* note 121, at 187 ("a key organizing principle for the spread of global supply chains has been labor arbitrage—reducing production costs by outsourcing or off-shoring work to locations with low-cost labor").

183. WEIL, *supra* note 7, at 61. See also *id.*, at 64–72 (discussing companies' monitoring strategies in retail and fast food). See also Erik Brynjolfsson et al., *Does Information Technology Lead to Smaller Firms?* 40 MGT. SCI. 1645–62 (1994) (finding "broad evidence that investment in IT is significantly associated with subsequent decreases in the average size of firms").

184. See *Razak v. Uber Techs*, 2018 U.S. Dist. LEXIS 61230 (E.D. Pa., Apr. 18, 2018) (granting defendant's motion for summary judgment on issue of employment status in FLSA case); *but see O'Connor v. Uber Techs.*, 82 F. Supp. 3d 1133, 1135, 1148–49 (N.D. Cal. 2015) (denying defendant Uber's motion for summary judgment in similar case under California law).

185. See generally Brishen Rogers, *Employment Rights in the Platform Economy: Getting Back to Basics*, 10

duties has helped it keep their wages down: a study by the Economic Policy Institute found that Uber drivers' pay averaged around \$9.21 an hour, after accounting for expenses and taxes, making them among the lowest-paid workers in the country.¹⁸⁶

What is so striking about Uber in historical perspective is not that it uses an independent contractor model—taxi companies have also done that—but that it does so while utilizing advanced information technology to supervise workers very closely. Historically, firms that outsourced labor often did so under the table, using a middleman but not engaging in active supervision. The “sweating system” in U.S. garment production, for example, involved jobbers hiring contractors to do production, who would in turn hire subcontractors or even let out work to individual sewers in their houses. Product specifications, piece rates, and ex post inspections ensured labor discipline. That is still the system in the Bangladeshi ready-made garment sector, where illegal subcontracting is rampant and many firms legitimately do not know in which particular shop their clothes were made.¹⁸⁷ Similarly, until very recently cab companies had little real-time knowledge of what particular workers are doing at any time. This is no longer the world we live in.

Nor are Uber and Lyft alone. As discussed above, companies such as FedEx use “telematics” devices to monitor drivers' delivery times, driving speed, and seatbelt usage; meanwhile, they have treated workers as independent contractors to avoid wage/hour obligations.¹⁸⁸ Advanced monitoring efforts can therefore give firms the best of both worlds: the powers traditionally associated with employment, without the duties and costs. As Weil put it in another context, the company uses such technology to “keep[] the production activity safely ensconced with the supplier,” even as it “carefully scrutinize[s] performance.”¹⁸⁹ And monitoring capabilities will surely become more powerful going forward as the underlying technology continues to develop.

Advanced information technologies have also been central to the transformation of the retail sector.¹⁹⁰ Walmart rose to become the world's largest retailer in large part due to its revolutionary “retail link” supply chain management system.¹⁹¹ That system utilized data on store-level inventory to

HARV. LAW & POL'Y REV. 479 (2016) (arguing that existing statutory tests for employment are broad enough, if interpreted purposively, for courts to find that Uber and Lyft employ drivers).

186. Lawrence Mishel, Economic Policy Institute, *Uber and the Labor Market* (May 15, 2018), available at <https://www.epi.org/files/pdf/145552.pdf>.

187. See Mark Anner et al., *Toward Joint Liability in Global Supply Chains: Addressing the Root Causes of Labor Violations in International Subcontracting Networks*, 35 COMP. LAB. L. POL'Y. J. 1 (2013).

188. See *Alexander v. FedEx Ground Package Services*, 765 F.3d 981 (2014) (overturning district court judgment that FedEx drivers were independent contractors as a matter of law, because FedEx exerted extensive control over their work).

189. WEIL, *supra* note 7, at 63. See also Wenjie Chen & Fariha Kamal, *The Impact of Information and Communication Technology Adoption on Multinational Firm Boundary Decisions*, 47 J. OF INT'L. BUS. STUD. 563 (2016) (finding that firms in industries where production processes can be more easily codified have less intrafirm coordination and more arm's-length transactions).

190. The retail transformation played out differently in different countries. See BARTHOLOMEW WATSON, *NATIONS OF RETAILERS: THE COMPARATIVE POLITICAL ECONOMY OF RETAIL TRADE*, UC Berkeley Political Science Dissertation (2011), available at <https://escholarship.org/uc/item/18z1138t> (arguing that in contrast to American “lean retailing model,” Denmark moved toward “relational contracting” model of close relations between retailers and suppliers, while France moved toward vertical integration of suppliers into retailers). Reflecting a general theme of the literature on comparative political economy, discussed *supra* notes 16 to 17, this suggests that there are myriad ways to organize a successful and profitable capitalist economy, with quite different distributive implications).

191. Erik Brynjolfsson, Lorin Hitt & Shinkyu Yang, *Intangible Assets: Computers and Organizational Capital*, Brookings Papers on Economic Activity, at 10 (2002).

optimize its supply chains, and by some accounts decisions about store inventories are made in the corporate office in Bentonville rather than locally.¹⁹² While Walmart workers are company employees, and therefore not fissured away from the company, the company centrally tracks wages and hours, and presses local stores to keep both at an absolute minimum. Walmart’s “retail link” also enabled it to put pressure on suppliers, whether by dictating specific contract terms to them or even requesting that they alter package sizes and shapes to make shipping and shelf stocking easier.¹⁹³ There is even evidence that Walmart has sought to control the wages that suppliers pay to their workers.¹⁹⁴

Amazon has followed Walmart’s lead, using sophisticated supply chain management techniques to grow rapidly. But it also uses fissured labor in much of its operations. It directly employs most of its warehouse workers, but is developing a captive delivery service that uses an on-demand model much like Uber’s, called “Amazon Flex,” in a long-term strategy to displace major delivery services. The company’s website says that drivers can “be [their] own boss[es], set [their] own schedule[s], and have more time to pursue [their] goals and dreams.”¹⁹⁵ In some distribution centers, the number of Flex drivers now exceeds the number of warehouse workers.¹⁹⁶ Where it doesn’t use Flex, Amazon often contracts with independent delivery services, who themselves contract workers, for other delivery.¹⁹⁷

Finally, fast food and other franchises again combine technologically enabled control and oversight of operations with legal and operational fissuring. McDonald’s, for example, is not a single legal enterprise but an amalgamation of tens of thousands of enterprises. At the center is McDonald’s corporate, at the edges are the many McDonald’s franchises that are independently owned and operated as separate corporations. The franchise business model enables expansion—and, where necessary, contraction—by pushing many startup costs and risks onto individual franchise owners.¹⁹⁸ Franchisees contribute the capital to start a franchise, and license McDonald’s products and other intellectual property to go into business.

Yet McDonald’s’ point-of-sale systems and payroll management systems are integrated between franchisees and corporate, which gives McDonald’s corporate a very good sense of which franchisees and workers are over- or underperforming. McDonald’s standardizes how work is performed across franchisees by training managers and other staff on exactly how to perform necessary tasks.¹⁹⁹ It also sets specifications for the performance of particular tasks down to the

192. NELSON LICHTENSTEIN, *THE RETAIL REVOLUTION: HOW WAL-MART CREATED A BRAVE NEW WORLD OF BUSINESS* 120 (2009).

193. LICHTENSTEIN, *supra* note 192, at 64. In contrast, auto manufacturers, for example, often collaborate with suppliers on design and work closely with them on their internal processes, in a strategy that several authors term “learning by monitoring.” Susan Helper, John Paul MacDuffie & Charles Sabel, *Pragmatic Collaborations: Advancing Knowledge while Controlling Opportunism*, 9 *INDUS. AND CORP. CHANGE* 443 (2000).

194. Nathan Wilmers, *Wage Stagnation and Buyer Power: How Buyer-Supplier Relations Affect U.S. Workers’ Wages, 1978 to 2014*, 83 *AM. SOC. REV.* 213, 216 (2018), discussed in Suresh Naidu, Eric A. Posner & Glen Weyl, *Antitrust Remedies for Labor Market Power*, 132 *HARV. L. REV.* 536, 597 (2018).

195. Amazon, *About Amazon Flex*, available at <https://flex.amazon.com/about> (last visited Jan. 19, 2019).

196. Author interview with Nick Rudikoff (Aug. 2018).

197. Abha Bhattarai, *Amazon is Helping Entrepreneurs Start Delivery Companies—As Long as They Deliver Amazon Packages*, *WASHINGTON POST* (June 28, 2018), available at https://www.washingtonpost.com/news/business/wp/2018/06/28/amazon-is-helping-entrepreneurs-start-delivery-companies-as-long-as-they-deliver-amazon-packages/?utm_term=.fc796f5307f7.

198. On the franchising business model, see *generally* WEIL, *supra* note 7, at 123–32.

199. Charging Parties’ Post-Hearing Brief, *supra* note 127, at 17–18.

second. The company allows “60 seconds maximum from the order being totaled until the order is presented . . . ,” provides that “[g]uests should wait no more than 90 seconds from your greeting to the completion of their order,” and that their “total experience time should not exceed 3 minutes, 30 seconds.”²⁰⁰ And it monitors franchisors’ performance and, by some accounts, monitors their labor costs as well. In so doing, it is able to ensure a particular sort of performance while (so far) disclaiming any responsibility for labor practices among franchisees. That has a clear effect on workers: as Weil documents, “The probability of [wage and hour] noncompliance is about 24% higher among franchisee-owned outlets than among otherwise similar company-owned outlets.”²⁰¹

III.C. Summary

As with algorithmic management, machine learning and other advanced information technologies can be expected to accelerate trends toward fissuring. Companies that have not yet outsourced nonessential functions have incentives to do so today, and new technologies often make those viable. Medical transcriptionists, for example, who until recently were mostly employed in-house at hospitals and doctor’s offices, are increasingly outsourced. Transcription work can be performed by the same workers at the hospital, who are simply employed by another company, or off-site, since audio files can be transferred electronically so cheaply and easily.²⁰² The franchise model also continues to expand in both fast food and hotels.

That said, there are limits to companies’ abilities to fissure even low-wage work. Under Supreme Court precedent, for example, it is difficult for a company to disclaim duties under wage and hour laws toward workers who perform tasks central to their business, on their premises.²⁰³ There are also clear limits to the on-demand economy model. Most low-wage employers still need workers to show up for scheduled shifts, stay for those shifts, and work well with others. The pure on-demand model, in which workers aren’t scheduled for shifts, hasn’t yet expanded beyond companies like Uber and Lyft, and seems increasingly unlikely to do so. Those caveats do not, however, change the underlying dynamics here. In general, we can expect that companies seeking to save on labor costs will exploit whatever combination of automation, algorithmic management, and fissuring strategies best fits their business model.

IV. Broader Observations and Policy Implications

This account of how companies are using new information technologies to reshape work has several broader implications. In brief, since employment law shapes employers’ powers to gather, control, and use workplace information, reforms to employment laws may alter both the path of and the effects of technological development. Yet the specific relationship between law and technological change on the ground is quite complex, in ways that have policy implications. Below, I first consider

200. Charging Parties’ Post-Hearing Brief, *supra* note 127, at 20.

201. WEIL, *supra* note 7, at 131.

202. Danny Vinik, *The Real Future of Work*, POLITICO, Jan./Feb. 2018.

203. *Rutherford Food Corp. v. McComb*, 331 U.S. 722 (1947).

the extent to which law can shape incentives in each case discussed above: automation, algorithmic management, and fissuring. I also sketch some policy reforms that would protect workers against harms stemming from technological change, and which would better ensure economic equality and other social goods generally.

While employment laws help enable all three phenomena discussed above—automation, algorithmic management, and fissuring—those three are differentially susceptible to regulation. For example, since automation ends the relationship between a worker and their employer, the traditional strategy of protecting workers by levying legal duties on the employer can't address the resultant harms. This has led some in public-facing debates to argue that the looming automation threat justifies a UBI.²⁰⁴ As should be clear, I disagree on empirical grounds: current rates of automation are historically low, and there is little or no reason to suspect they will increase appreciably. While there may be sound reasons to embrace a UBI, imminent technological unemployment is not among them.²⁰⁵

That being said, automation itself is certainly difficult for lawmakers to govern, in part because the knowledge underlying automation processes has a public goods quality. Industrial engineering, computer science, and robotics are all academic disciplines, in which new processes and scientific findings are shared with the public. Similarly, if one company develops an innovative production process or successful new consumer product, other companies quickly seek to replicate its success through reverse engineering and imitation. Other companies' ability to do so will be limited by market factors as well as intellectual property doctrines, but the basic point stands: scientific and engineering knowledge simply aren't that amenable to legal regulation. In cases where regulatory bodies have attempted to restrict the development of scientific knowledge—for instance, by restrictions on human cloning—regulators have been motivated by unusually strong moral or ethical considerations or an imminent danger to the public.

Moreover, automation is often good for workers, either individually or in the aggregate. For individual workers, task automation tends to displace fairly rote or boring tasks, and there are few reasons for policymakers to consign workers to lives of meaningless work if it is possible for them to make use of more creativity on the job. Automation also increases labor productivity, which is the only real way to sustainably ensure economic growth. Today, to be sure, less-skilled workers typically don't share in productivity gains. But that is largely an effect of legal policies that restrict workers' power rather than an inevitable effect of task automation. Perhaps most importantly, to the extent that automation enables production of goods at lower net energy cost, it will substantially assist in the transition to a green economy.

This all suggests that lawmakers should not seek to restrict automation per se. Policymakers can and should, however, do more to protect workers against the effects of automation. As noted above, under U.S. labor law, unionized companies have no duty to bargain over the decision to implement

204. See, e.g., Stern, *supra* note 3 and Ford, *supra* note 3.

205. I've written on this topic in the past. Brishen Rogers, *Basic Income in a Just Society*, BOSTON REV. FORUM (Spring 2018), available at <http://bostonreview.net/forum/brishen-rogers-basic-income-just-society>; Brishen Rogers, *Basic Income and the Resilience of Social Democracy*, ___ COMP. LAB. L. & POL'Y. J. ___ (forthcoming 2019), draft available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3283884.

new technologies, but often do have to bargain over the effects of such decisions. There is an important principle here, which could be expanded to the nonunion workplace: that companies should generally have free rein to pursue production strategies that enhance efficiency, but workers should have a voice in how those new strategies are implemented. German works councils, for example, give workers veto rights or bargaining rights over key issues such as scheduling, reductions in work, required overtime, and technological changes—regardless of those workers’ unionization status.²⁰⁶ That may enable workers to better ensure that they share in any enhanced profits resulting from task automation—or, in the alternative, to negotiate reasonable severance packages, or placement opportunities elsewhere within firms. Such consultative or bargaining rights would ensure that companies’ decisions around technology in the workplace are subject to at least some democratic norms.

Algorithmic management, meanwhile, is somewhat more amenable to legal regulation and steering. Granted, it often involves the automation of managerial tasks, which are difficult to govern for the reasons just stated. But it can also have substantial and direct effects on labor standards such as wages, hours, and other terms of employment. Policymakers can of course prohibit lowering labor standards below certain levels, by increasing minimum wages, or by guaranteeing workers reasonable notice of their work schedules or regular hours. Alternatively, policymakers can guarantee workers a greater voice in workplace process changes, again through a works council or similar model.

Another potential reform here would be to ensure that workers and regulators have reasonable access to companies’ data about workers’ performance. Once data on workplace performance is gathered and analyzed by companies, it is essentially costless to transfer it to regulators or workers. Regulators could use their own algorithms on that data; for example, to spot noncompliance with wage and hour or antidiscrimination laws. Workers, similarly, could use it for the same purposes in private suits. More generally, when workers are subjected to managerial power via algorithms—as when Uber drivers are deactivated for failure to maintain a particular passenger rating—basic concerns of fairness and due process suggest that they should get some access to that data, and an explanation of why a particular action was taken.²⁰⁷

Finally, changes in industrial organization are quite susceptible to legal regulation and steering. Fissuring often involves a degree of regulatory arbitrage, as the examples in Part III.B illustrate: Uber disclaims any responsibilities toward its drivers; McDonald’s and Domino’s toward their franchisees’ workers; and Amazon toward its Flex drivers. Other examples abound, in hospitality, building services, manufacturing, and elsewhere. Walmart and Amazon (and McDonald’s) also exercise substantial power over suppliers’ workers, yet owe them few or no duties under existing employment laws. The reason, as discussed in Part III.B., is that extant tests for employment require a worker to show that the employer exerted control over their work. Those tests are malleable, and workers can often establish an employment or joint employment relationship under them even when companies classify

206. See Dimick, *supra* note 30, at 688, n.49.

207. For an exploration of these ideas, see Citron & Pasquale, *supra* note 9.

them as independent contractors or subcontracted workers. Yet in the run of cases, companies can escape duties under labor and employment laws through fissuring strategies.²⁰⁸

There is no single legal solution to the problem of fissuring, but several different approaches are plausible and promising. Legislatures could expand definitions of employment under major labor and employment law statutes to capture the relationship between Uber and its drivers, or McDonald's and its franchisees' workers.²⁰⁹ Legislatures could also statutorily define work relationships as legal employment for purposes of particular statutes, mandating, for example, that major franchisors are jointly liable for wage/hour violations by their franchisees. Or legislatures and regulators could begin to take technological monitoring and management strategies into account when determining whether a firm employs particular workers. In the case of Uber or McDonald's, for example, evidence that the companies closely monitor how work is performed, help to schedule workers, and retain the right to terminate their contracts would be powerful evidence of employment status.²¹⁰ The theory behind such reforms is not that they would prohibit companies from organizing work relationships as they like, nor that they would limit the deployment of new technologies to manage work—but rather that companies should, regardless of the organizational strategy used, have duties toward workers over whom they enjoy substantial economic or operational power.

Reforms to protect workers against the worst consequences of fissuring and algorithmic management may have other salutary consequences for subsequent technological developments, and for the distribution of income more generally. One of the most important political-economic transitions of the last fifty years has been the decline of jobs in heavy industry, and the rise of the service sector jobs. This has hit workers very hard, since heavy manufacturing involves large investments in physical capital, which leads to high labor productivity, and historically enabled manufacturing enterprises to pay fairly high wages while remaining profitable.²¹¹ Manufacturing sectors were also heavily unionized, in part because collective bargaining laws were designed with manufacturing workers in mind. The decline of manufacturing has thus encouraged a more polarized

208. See discussion, *supra* Part III.B. See generally, Zatz, *supra* note 166; Hyde, *supra* note 165; WEIL, *supra* note 7; V. B. Dubal, *Winning the Battle, Losing the War? Assessing the Impact of Misclassification Litigation on Workers in the Gig Economy*, 2017 Wisc. L. REV. 739 (2017).

209. As the California Supreme Court did in a landmark 2018 decision, *Dynamex Operations West., Inc. v. Superior Ct. of Los Angeles*, 4 Cal. 5th 903 (Cal. 2018). Now in California, any worker performing services for pay is presumed to be an employee unless the company can prove the following:

- (A) that the worker is free from the control and direction of the hirer in connection with the performance of the work, both under the contract for the performance of such work and in fact;
- (B) that the worker performs work that is outside the usual course of the hiring entity's business;
- and (C) that the worker is customarily engaged in an independently established trade, occupation, or business of the same nature as the work performed for the hiring entity.

By shifting the burden of proof on this question, the so-called ABC test should capture a much broader set of work relationships than the standard "control" test under the law of agency.

210. For ideas along these lines, see Zatz, *supra* note 166; Hyde, *supra* note 165; Kate Andrias & Brishen Rogers, *Rebuilding Worker Voice in Today's Economy*, Roosevelt Institute at 16–20 (Aug. 2018) (discussing problems of fissured work in labor law/collective bargaining context, suggesting various solutions); Rogers, *Employment Rights in the Platform Economy*, *supra* note 185 (discussing misclassification suits against Uber and Lyft, and possible solutions); Brishen Rogers, *Toward Third-Party Liability for Wage Theft*, 31 BERKELEY J. EMP. & LAB. L. 1 (2010) (discussing relationship between supply chain management and employment status).

211. See, e.g., Dani Rodrik, *Premature Deindustrialization*, NBER Working Paper No. 20935 (Feb. 2015) (discussing importance of manufacturing to rising productivity in process of capitalist development).

income distribution by eliminating millions of mid-wage jobs,²¹² and by leaving workers without a substantial voice in politics, leaving political leaders disproportionately responsive to business interests and financial elites.²¹³

A major challenge facing all advanced economies in the near future is how to ensure a decent standard of living when the bulk of working-class jobs are not in manufacturing but in low-wage services, where the bulk of job growth since 1979 has occurred.²¹⁴ Unfortunately, the fact that those jobs are difficult to automate also means they are very difficult to render more productive through technological investment—which in turn means that raising wages for those workers involves fairly naked distributive conflict. For wages to go up for fast food workers, hotel workers, and retail workers, shareholders will need to accept lower returns, and/or consumers will need to pay more. This is, I believe, one major reason why fissuring and algorithmic management strategies predominate in those sectors: such strategies limit labor costs by keeping wages low, which enables financial interests to capture a greater share of profits.²¹⁵

Part of the necessary response here is to universalize more benefits, including healthcare, and to invest more in public goods, to ensure that even low-wage workers have access to the resources and services they need to thrive. Another part is perhaps the most important policy change: making it easier for workers to organize, unionize, and bargain collectively. A growing numbers of scholars and activists in the United States are now proposing that our laws be reformed to encourage sectoral or supply chain bargaining, and also suggesting reforms that would restore workers' key weapon, the right to strike.²¹⁶ That may be especially important for workers in sectors such as fast food, hospitality, retail, and logistics, where low wages and fissuring are today the norm, but where current industrial structures make worksite- or firm-based collective bargaining under U.S. law exceptionally difficult to obtain, and not very effective in any event.²¹⁷ Nearly every aspect of workplace power relations discussed above, including firms' abilities to monitor work, reorganize work, and terminate workers at will, could be opened to democratic contestation by labor law reforms that once again encourage

212. For data on this, and graphical representations of the shift, see Autor, *supra* note 105, at 150; Autor & Dorn, *supra* note 55, at 1553, 1554.

213. See generally Jacob S. Hacker & Paul Pierson, *Winner-Take-All Politics: Public Policy, Political Organization, and the Precipitous Rise of Top Incomes in the United States*, 38 *POLITICS & SOCIETY* 152 (2010); GRETA R. KRIPPNER, *CAPITALIZING ON CRISIS: THE POLITICAL ORIGINS OF THE RISE OF FINANCE* (2011); JAKE ROSENFELD, *WHAT UNIONS NO LONGER DO* (2014).

214. Autor, *supra* note 105, at 140.

215. My argument here overlaps with the now canonical account of “skill-biased technological change,” though I place a greater emphasis on the role of policy decisions and workplace power dynamics in generating income inequalities. On skill-biased technological change, see generally David Autor, Frank Levy & Richard J. Murnana, *The Skill Content of Recent Technological Change: An Empirical Exploration*, 118 *Q. J. ECON.* 1279 (2003); CLAUDIA GOLDIN & LAWRENCE KATZ, *THE RACE BETWEEN EDUCATION AND TECHNOLOGY* (2007); Autor & Dorn, *supra* note 55; Daron Acemoglu & Pascual Restrepo, *The Race between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment*, 108 *AM. ECON. REV.* 1488 (June 2018). But compare David Card & John E. DiNardo, *Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles*, 20 *J. LAB. ECON.* 733 (2002) (noting problems with canonical account including that “wage inequality stabilized in the 1990s” and that the hypothesis fails to explain racial and gendered wage gaps.)

216. E.g., Andrias & Rogers, *supra* note 210; Dylan Matthews, *The Emerging Plan to Save the American Labor Movement*, *Vox* (Sept. 3, 2018), available at <https://www.vox.com/policy-and-politics/2018/4/9/17205064/union-labor-movement-collective-wage-boards-bargaining>.

217. E.g., Andrias & Rogers, *supra* note 210.

organizing and collective bargaining. Such reforms could also encourage worker to form new sorts of unions, and to organize through new communications tools such as social media.²¹⁸

Conclusion

Firms are using advanced information technologies to change work, but not in the ways many believe. The pace of automation has not increased in recent years, and there is no evidence that it will soon become a more significant factor in the economy. But it is increasingly clear that companies can use new technologies to disempower workers in other ways, including algorithmic management and the fissuring of employment. Firms' ability to utilize such strategies, however, is largely a function of law, including both the basic rules governing the employment relationship, workplace privacy rules, and workers' rights (or lack of real rights) to unionize and bargain collectively. This suggests that appropriate policy responses include granting workers more generous workplace protections, and holding companies to duties toward a wider set of workers.

218. See Brishen Rogers, *Social Media and Worker Organizing under U.S. Law*, ___ INT'L J. COMP. LAB. L. & INDUSTRIAL RELNS ___ (forthcoming, 2019) (discussing impediments to worker organizing via social media under current law).