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TO THINE OWN SELF BE TRUE? INCENTIVE PROBLEMS IN PERSONALIZED LAW

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ABSTRACT

Recent years have seen an explosion of scholarship on “personalized law.” Commentators foresee a world in which regulators armed with big data and machine learning techniques determine the optimal legal rule for every regulated party, then instantaneously disseminate their decisions via smartphones and other “smart”

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devices. They envision a legal utopia in which every fact pattern is assigned society's preferred legal treatment in real time.

But regulation is a dynamic process; regulated parties react to law. They change their behavior to pursue their preferred outcomes—which often diverge from society's—and they will continue to do so under personalized law: They will provide regulators with incomplete or inaccurate information. They will attempt to manipulate the algorithms underlying personalized laws by taking actions intended to disguise their true characteristics. Personalized law can also (unintentionally) encourage regulated parties to act in socially undesirable ways, a phenomenon known as moral hazard.

Moreover, regulators seeking to combat these dynamics will face significant constraints. Regulators will have imperfect information, both because of privacy concerns and because regulated parties and intermediaries will muddle regulators' data. They may lack the authority or the political will to respond to regulated parties' behavior. The transparency requirements of a democratic society may hinder their ability to thwart gamesmanship. Concerns about unintended consequences may further lower regulators' willingness to personalize law.

Taken together, these dynamics will limit personalized law's ability to optimally match facts to legal outcomes. Personalized law may be a step forward, but it will not produce the utopian outcomes that some envision.

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INTRODUCTION

Imagine a new technology that lets us measure each individual's health perfectly, immediately, and at no cost. Such a technology would have tremendous potential value; it would enable society to allocate and distribute medical care in the best possible way. We could perfectly take into account how sick people are, what benefits they stand to gain from treatment, and any other factors society deems relevant when deciding what medical care everyone should receive and when they should receive it. We could update our medical care distribution plan in response to new developments—for example, if someone suddenly takes a turn for the worse, we could move her up the queue and treat her earlier. Our new technology would let us maximize the potential gains from medical care in a way that simply was not possible before its invention.¹

This vision sounds utopian. And all is well in utopia—until Bob, who has a bad liver, realizes that he can move his way up the liver transplant queue by drinking a bottle of champagne and making his liver worse. This self-destructive behavior may help Bob if moving up the queue advantages Bob more than becoming sicker hurts him. Meanwhile, Bob's actions make everyone else in the queue unambiguously worse off. The Bobs of the world can wreak havoc on our carefully designed healthcare system—and make care more expensive to provide, as beneficiaries become sicker than they otherwise would be. Thus, paradoxically, precisely targeting benefits can sometimes produce *worse* outcomes than allocating them in a simpler, more straightforward way (for example, first come, first served).²

The utopian care queue that drove Bob to drink exemplifies “personalized law.” Personalized law is a rapidly growing phenomenon in legal thought, the subject of a bevy of articles³ and even a

1. Cf. Anthony J. Casey & Anthony Niblett, *The Death of Rules and Standards*, 92 IND. L.J. 1401, 1412-16 (2017) (discussing a similar example concerning a diagnostic machine that predicts the timing of patients' surgeries).

2. For example, if liver patients receive care sequentially based on the dates on which they request care, Bob would have no incentive to aggravate his condition.

3. See, e.g., Miriam H. Baer, *Evaluating the Consequences of Calibrated Sentencing: A Response to Professor Kolber*, 109 COLUM. L. REV. SIDEBAR 11, 12 (2009); Omri Ben-Shahar

symposium in the *Chicago Law Review*.⁴ The basic idea underlying personalized law is that regulators can use sophisticated analytical techniques, large amounts of data, and powerful computers to draw exacting distinctions between similar (but not identical) circumstances and assign them different legal outcomes.⁵ Individualized decision rules can be instantaneously distributed to regulated parties via smartphones, smart cars, and other “smart” devices.⁶ Thus, the law can weigh all the important facts, instantly analyze what actions should be permitted, and tell us the results in a clear, easy-to-understand way: personalized law “will provide ex ante behavioral prescriptions finely tailored to every possible scenario,” thereby achieving “all of the benefits of both rules and standards without the costs of either.”⁷ At the same time, it will “mitigate economic and legal inequality”⁸ and provide “ultimate transparency.”⁹ Scholars have asserted that personalized law “will only increase” over time;¹⁰ indeed, they have repeatedly dubbed it “the wave of the future.”¹¹

& Ariel Porat, *Personalizing Negligence Law*, 91 N.Y.U. L. REV. 627 (2016); Anthony J. Casey & Anthony Niblett, *Self-Driving Contracts*, 43 J. CORP. L. 1 (2017); Anthony J. Casey & Anthony Niblett, *Self-Driving Laws*, 66 U. TORONTO L.J. 429 (2016) [hereinafter Casey & Niblett, *Self-Driving Laws*]; Casey & Niblett, *supra* note 1; Caryn Devins, Teppo Felin, Stuart Kauffman & Roger Koppl, *The Law and Big Data*, 27 CORNELL J.L. & PUB. POL'Y 357 (2017); Adam J. Kolber, *The Subjective Experience of Punishment*, 109 COLUM. L. REV. 182 (2009); John O. McGinnis & Steven Wasick, *Law's Algorithm*, 66 FLA. L. REV. 991 (2014); Ariel Porat & Lior Jacob Strahilevitz, *Personalizing Default Rules and Disclosure with Big Data*, 112 MICH. L. REV. 1417 (2014); see also Cass R. Sunstein, *Deciding by Default*, 162 U. PA. L. REV. 1 (2013); George S. Geis, *An Experiment in the Optimal Precision of Contract Default Rules*, 80 TUL. L. REV. 1109 (2006); Ian Ayres, *Preliminary Thoughts on Optimal Tailoring of Contractual Rules*, 3 S. CAL. INTERDISC. L.J. 1, 4-5 n.15 (1993); Ian Ayres & Robert Gertner, *Majoritarian vs. Minoritarian Defaults*, 51 STAN. L. REV. 1591, 1593, 1596-1602 (1999).

4. Symposium, *Personalized Law*, 86 U. CHI. L. REV. 217 (2019).

5. See Casey & Niblett, *supra* note 1, at 1402-04, 1410, 1414.

6. See *id.* at 1431-32.

7. *Id.* at 1403.

8. Philip Hacker & Bilyana Petkova, *Reining in the Big Promise of Big Data: Transparency, Inequality, and New Regulatory Frontiers*, 15 NW. J. TECH. & INTELL. PROP. 1, 35 (2017).

9. Andrew Verstein, *Privatizing Personalized Law*, 86 U. CHI. L. REV. 551, 567 (2019).

10. Devins et al., *supra* note 3, at 368; see also Thorsten Kaeseberg, *The Code-ification of Law and Its Potential Effects*, 2 STAN. J. BLOCKCHAIN L. & POL'Y 232, 236 (2019).

11. Christoph Busch, *Implementing Personalized Law: Personalized Disclosures in Consumer Law and Data Privacy Law*, 86 U. CHI. L. REV. 309, 309, 324, 331 (2019); Porat & Strahilevitz, *supra* note 3, at 1420, 1476; Sunstein, *supra* note 3, at 10, 11, 57.

The personalization revolution is already well under way in business.¹² Companies now have unprecedented levels of information about their customers, including where they go, what they view online, what they purchase, and whom they communicate with.¹³ They use this information to finely tailor their services and products to customers' individual preferences.¹⁴ Many of the new economy's biggest successes—Google, Amazon, Facebook, Uber, and others—are built on using this kind of information to provide consumers with exactly what they want.¹⁵

But there are important differences between matching consumers to products and matching facts to legal outcomes. In particular, customers want to be directed to their preferred products, so they generally do not resist such personalization efforts.¹⁶ But in many circumstances, the legal outcome that policymakers prefer will *not* be the outcome that the regulated party desires. Accordingly, regulated parties may react to personalized laws in ways that—from the perspective of policymakers—are undesirable. These responses by regulated parties can limit the effectiveness of personalization efforts, or even thwart them outright.

Businesses have already encountered these dynamics when personalization is against customers' interests. For instance, companies have often attempted to use big data to engage in price discrimination.¹⁷ If Uber can tell how much individual consumers are willing to pay for rides, it can offer lower prices to people who

12. See, e.g., Casey & Niblett, *supra* note 1, at 1424-25, 1445.

13. Oren Bar-Gill, *Algorithmic Price Discrimination When Demand Is a Function of Both Preferences and (Mis)Perceptions*, 86 U. CHI. L. REV. 217, 224-26, 231 (2019).

14. *Id.* at 225-26, 231.

15. *Id.* at 225, 231; see Orly Lobel, *The Law of the Platform*, 101 MINN. L. REV. 87, 94, 96-99, 102 (2016). Many old economy firms have also made aggressive use of the same techniques to bolster their businesses, including Target, Proctor & Gamble, and many others. Charles Duhigg, *How Companies Learn Your Secrets*, N.Y. TIMES MAG. (Feb. 16, 2012), <https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html> [<https://perma.cc/9FPN-KXU7>].

16. See Aniko Hannak, Gary Soeller, David Lazer, Alan Mislove & Christo Wilson, *Measuring Price Discrimination and Steering on E-commerce Websites*, 2014 ACM INTERNET MEASUREMENT CONF. 305, 306 (2014).

17. Bar-Gill, *supra* note 13, at 217-19, 224-27; Gerhard Wagner & Horst Eidenmüller, *Down by Algorithms? Siphoning Rents, Exploiting Biases, and Shaping Preferences: Regulating the Dark Side of Personalized Transactions*, 86 U. CHI. L. REV. 581, 585-86 (2019); see also Hannak et al., *supra* note 16, at 305-06; Jakub Mikians, Lažló Gyarmati, Vijay Erramilli & Nikolaos Laoutaris, *Detecting Price and Search Discrimination on the Internet*, 11 ACM WORKSHOP ON HOT TOPICS IN NETWORKS 80 (2012).

are strongly price-sensitive and higher prices to those who are not.¹⁸ This means that consumers have powerful incentives to convince Uber that they *are* very price-sensitive—even if they are not—so that Uber will offer them lower prices.¹⁹ For example, consumers could signal price sensitivity to Uber’s algorithm by checking prices on their usual routes and then declining to request a ride.²⁰ Amazon and other retailers have also tried similar price discrimination strategies and seen similar responses.²¹ These consumer responses have made it harder for companies to tell who is truly price sensitive and thus have limited the efficacy of personalized pricing strategies.²²

The potential of personalized law is likewise bounded. Regulated parties will react to personalized laws by changing their behavior; they will alter or disguise their circumstances in order to improve their regulatory treatment.²³ They will respond to a given regulatory regime in unanticipated and undesirable ways; in some instances, personalized law may produce affirmatively *worse* outcomes than a depersonalized legal regime.²⁴ These behaviors will constrain the law’s ability to draw fine distinctions between circumstances—in other words, how personalized the law can actually be in practice—and therefore its ability to achieve optimal outcomes.²⁵

18. See Scott Duke Kominers, *Uber’s New Pricing Idea Is Good Theory, Risky Business*, BLOOMBERG (June 13, 2017, 2:35 PM), <https://www.bloomberg.com/opinion/articles/2017-06-13/uber-s-new-pricing-idea-is-good-theory-risky-business> [<https://perma.cc/2ZEC-Q6QP>].

19. *Id.*

20. *Id.*

21. See, e.g., Wagner & Eidenmüller, *supra* note 17, at 585-86, 588-89; Ismat Sarah Mangla, *3 Tricks to Help You Snag the Best Deals Online*, MONEY (Sept. 8, 2014), <http://money.com/money/dynamic-pricing-amazon-best-buy-walmart/> [<https://perma.cc/8L8B-8UDQ>]; Kyle James, *6 Ways to Avoid Sneaky Online Price Changes*, WISEBREAD (Aug. 5, 2015), <https://www.wisebread.com/6-ways-to-avoid-sneaky-online-price-changes> [<https://perma.cc/B6FP-F5M3>].

22. See Kominers, *supra* note 18.

23. Cf. Wagner & Eidenmüller, *supra* note 17, at 588-91.

24. Cf. Baer, *supra* note 3, at 13-15, 17-19 (discussing how prisoners could respond to personalized sentencing).

25. To our knowledge, this is the first paper on personalized law to address these issues in depth. Porat and Strahilevitz consider the possibility of strategic responses, but they rely explicitly on the fact that they are only discussing the use of personalized law to create default rules, not binding legal rules. They note that “expanding personalization beyond waivable default would magnify the problem” of strategic behavior that we discuss here and that “the strategic behavior problem would be substantially magnified in a world where most terms were nonnegotiable.” Porat & Strahilevitz, *supra* note 3, at 1455-56; see also Casey & Niblett,

More precisely, we should expect rational actors to change their behavior whenever they have an incentive to do so. Thus, a personalized legal regime that perfectly matches circumstances to legal outcomes will only function as designed if none of the parties that it governs has an incentive to change its behavior. In economics terms, the personalized legal regime must be “incentive compatible.”²⁶

It is exceedingly difficult to make personalized law incentive-compatible. That difficulty is further compounded by several significant constraints on regulators’ ability to personalize law and to respond to perceived gamesmanship by regulated parties.

The first such constraint is informational. Yes, new technologies make it easier to gather and analyze data; however, that does not mean that regulators will have all of the information that they might want.²⁷ For instance, regulators may be prohibited from collecting or considering certain types of information due to privacy or other concerns.²⁸ Even when regulators have data, regulated parties may intentionally muddle it as a means of thwarting regulators’ efforts.²⁹

Regulators’ behavior is also constrained by the scope of their authority.³⁰ Certain types of perceived misbehavior may fall outside of a regulator’s prescribed jurisdiction.³¹ Regulators may have limited ways of penalizing misconduct.³² And even when regulators have all the legal authority they need, they may lack the political

supra note 1, at 1420 n.63; Anthony J. Casey & Anthony Niblett, *A Framework for the New Personalization of Law*, 86 U. CHI. L. REV. 333, 347-48 (2019).

26. *See, e.g.*, ANDREU MAS-COLELL, MICHAEL D. WHINSTON & JERRY R. GREEN, MICROECONOMIC THEORY 493 (1995).

27. *See infra* Part III.B.

28. *See infra* Part III.C.

29. *See infra* Part III.A.

30. *See infra* Part III.C.

31. *See, e.g.*, *Loving v. IRS*, 742 F.3d 1013, 1015 (D.C. Cir. 2014) (holding that the IRS lacked authority to regulate tax-return preparers); *Bus. Roundtable v. SEC*, 905 F.2d 406, 407 (D.C. Cir. 1990) (holding that the SEC lacked authority to prohibit securities exchanges from listing companies that engaged in transactions that disparately reduced the per-share voting rights of existing common stockholders); *see also* Lynne L. Dallas & Jordan M. Barry, *Long-Term Shareholders and Time-Phased Voting*, 40 DEL. J. CORP. L. 541, 595-96 (2016) (discussing the D.C. Circuit’s decision in *Business Roundtable*).

32. *See, e.g.*, I.R.C. § 5000A(g)(2) (curtailing the enforcement options available to the IRS for enforcing the Patient Protection and Affordable Care Act’s “individual mandate”).

will to use it.³³ These issues feed into each other; for example, an aggressive regulator may trigger a political backlash that reduces its jurisdiction or its ability to impose penalties.

Democratic oversight requires that regulators maintain a certain amount of transparency, which creates additional complications. Transparency can serve as a tonic for concerns about a regulator's power; at the same time, greater transparency may facilitate regulated parties' attempts to manipulate personalized laws.³⁴

All of these issues interact and overlap in complicated ways that will fluctuate over time. These dynamics may create substantial uncertainty for regulators regarding which actions will earn them plaudits and which will result in a political backlash.³⁵ That concern will sit atop the uncertainty that regulators face regarding how regulated parties will react to personalized laws.³⁶ These uncertainties will likely encourage regulators to be conservative in their efforts to personalize law and respond to gamesmanship.³⁷

These constraints on regulators, combined with regulated parties' responses to personalized law, will reduce the law's ability to optimally match circumstances to outcomes. We do not mean to be overly dour; personalized law will likely be a valuable tool in the regulatory tool kit, and it may represent a major step forward in policy making. But proponents of personalized law should curb their enthusiasm: the strictures of incentive compatibility will generally prevent personalized law from producing the utopian outcomes that some envision. Personalized law may be "the future of law",³⁸ that does not make it a panacea.

This Article proceeds as follows. Part I begins with the relevant background on personalized law. Part II explains how personalized law will lead to personalized avoidance responses in the form of false elicitation, false signaling, and moral hazard and illustrates these phenomena through a combination of both stylized and real-world examples. Part III turns to the problems that real-world regulators will face *ex ante* when shaping the law to deal with these

33. See *infra* Part III.C.

34. See *infra* Part III.D.

35. See *infra* Part III.E.

36. See *infra* Part III.E.

37. See *infra* Part III.E.

38. Casey & Niblett, *supra* note 1, at 1402.

anticipated avoidance problems and when responding to perceived misbehavior *ex post*. This analysis draws upon private actors' experiences implementing personalized regimes. We then summarize our conclusions.

I. PERSONALIZED LAW

Laws vary in how much they incorporate specific circumstances. At one end of the spectrum are blunt, one-size-fits-all rules, such as a speed limit that everyone must obey.³⁹ At the other end of the spectrum are laws that calibrate outcomes based on the facts and circumstances in each case. For example, in the speeding context, some western states used to permit drivers to travel at any speed that was "reasonable and proper" under the circumstances.⁴⁰ Most laws fall somewhere in between these extremes; for instance, some states impose varying speed limits for different kinds of motor vehicles or for nighttime versus daytime driving.⁴¹

It is easy to see the appeal of more tailored laws, which can better match circumstances to legal results. As Professors Anthony Casey and Anthony Niblett noted, "The idea that the law should be tailored to better fit the relevant context to which it applies is obvious and has been around as long as the idea of law itself."⁴²

At the same time, more finely tailored laws raise their own issues. The two most common ways of making a law highly responsive to

39. We note that several other articles have used the speed limit example to illustrate the concept and implications of personalized law. *See, e.g., id.* at 1404; Verstein, *supra* note 9, at 564-65.

40. For example, until 1998, Montana had no speed limits on certain highways:

A person ... driving a vehicle ... on a public highway of this state shall drive ... in a careful and prudent manner and at a rate of speed no greater than is reasonable and proper ... taking into account the amount and character of traffic, condition of brakes, weight of vehicle, grade and width of highway, condition of surface, and freedom of obstruction to the view ahead. The person ... shall drive the vehicle so as not to unduly or unreasonably endanger the life, limb, property, or other rights of a person entitled to the use of the ... highway.

MONT. CODE ANN. § 61-8-303(1) (1998).

41. *See, e.g., id.* § 61-8-303 (2019) (providing faster speed limits on highways in rural areas, slower speed limits for heavy trucks, and slower speed limits at night); *Speed Limits*, MONTANA.GOV, <https://www.mdt.mt.gov/visionzero/roads/speedlimits.shtml> [<https://perma.cc/C86C-6YF5>] (providing a summary table).

42. Casey & Niblett, *supra* note 25, at 333.

circumstances are to use a broad standard that can flexibly take into account a wide variety of facts and circumstances or to use multiple rules that prescribe different outcomes in different scenarios.⁴³ Each approach has its advantages and disadvantages.⁴⁴

Standards are flexible, but offer less certainty, which can make it difficult for people to know whether they are complying with the law.⁴⁵ Sticking with the speed limit example, exactly what speed is “reasonable and proper” for a rural interstate on a dry and sunny day?⁴⁶ When people cannot determine what the law actually is and whether particular conduct violates it, that raises deep concerns about the rule of law.⁴⁷

Rules, by contrast, can provide certainty about whether specified conduct is legal or illegal.⁴⁸ Theoretically, one can use a large number of (possibly complicated) rules to match any given set of circumstances to any desired legal outcome.⁴⁹ In practice, complicated rules make it harder for people to understand what the law is and how to comply with it.⁵⁰ Such laws can also be harder for the government to administer.⁵¹ Imagine a law that defines the speed limit at any given time using a seventeen-variable equation that

43. Compare Isaac Ehrlich & Richard A. Posner, *An Economic Analysis of Legal Rule-making*, 3 J. LEGAL STUD. 257, 257 (1974) (discussing a regime that eschews specific rules in favor of broad standards), with MONT. CODE ANN. § 61-8-303 (2019) (denoting a regime with different rules for different scenarios).

44. See, e.g., WARD FARNSWORTH, *THE LEGAL ANALYST: A TOOLKIT FOR THINKING ABOUT THE LAW* 64, 71, 164-68, 171 (2007); Ehrlich & Posner, *supra* note 43, at 260, 262, 267; Louis Kaplow, *Rules Versus Standards: An Economic Analysis*, 42 DUKE L.J. 557, 572-75 (1992); Cass R. Sunstein, *Problems with Rules*, 83 CALIF. L. REV. 953, 969, 972, 980-81 (1995); Frederick Schauer, *The Convergence of Rules and Standards*, 2003 N.Z. L. REV. 303, 308-10.

45. See, e.g., Kaplow, *supra* note 44, at 564, 577.

46. See *State v. Stanko*, 974 P.2d 1132, 1134-35 (Mont. 1998). The court overturned Stanko’s conviction for speeding and held that section 81-8-303 of the Montana Code Annotated was unconstitutionally vague. *Id.* at 1136.

47. See, e.g., Jeremy Waldron, *The Rule of Law*, STAN. ENCYC. PHIL. (June 22, 2016), <https://plato.stanford.edu/entries/rule-of-law/> [<https://perma.cc/MB9Q-MVYA>]. Open-ended standards also give more discretion to government decisionmakers, who may then enforce laws on a discriminatory or corrupt basis. See Sunstein, *supra* note 44, at 1012.

48. See Casey & Niblett, *supra* note 1, at 1412.

49. See *id.* at 1416-17.

50. See *id.* at 1412-13.

51. To be sure, there are other arguments against more finely tailored laws as well. See, e.g., Seana Valentine Shiffrin, *Inducing Moral Deliberation: On the Occasional Virtues of Fog*, 123 HARV. L. REV. 1214, 1217-20 (2010) (arguing that open-ended standards can deliver justice and fairness).

incorporates weather conditions, the quality of the car's braking system, the time of day, the driver's reaction times, the density of animals in the area, and other factors. Such a law could produce a speed limit that is well calibrated to the conditions present at any given moment. And, in theory, such a law would tell drivers exactly how fast they are allowed to drive. In practice, however, drivers would likely find the law impenetrably difficult to apply, and the result would be complexity without clarity.⁵²

Recent technological developments suggest new ways for the law to calibrate outcomes to extremely specific circumstances while still providing citizens with clear, accessible legal guidance.⁵³ The Internet of Things promises the ability to rapidly disseminate, process, and use information.⁵⁴ At the same time, advances in data science have made it easier to gather large amounts of data and find patterns within it, allowing lawmakers to better understand the consequences of applying a given legal rule to particular circumstances.⁵⁵

This is the heart of “personalized law”—optimizing legal rules to fit the specific circumstances of each regulated party in order to produce the best possible outcomes.⁵⁶ Commentators envision a time when machines can make real-time decisions about whether certain types of behaviors are permissible and clearly communicate the answer in a way that people can understand.⁵⁷ Consider again the hypothetical seventeen-variable speed limit, but now imagine that every car accesses all seventeen variables, performs the relevant calculations, and displays the resulting speed limit to the driver at all times. The speed limit is now perfectly clear and, from the driver's perspective, simple.

52. There are other concerns as well. Drafting such rules is challenging for policymakers. In addition, complicated and interrelated rules frequently produce unexpected and undesired consequences. *See, e.g.*, Jordan M. Barry, *On Regulatory Arbitrage*, 89 TEX. L. REV. *SEE ALSO* 69, 73 (2011).

53. Casey & Niblett, *supra* note 1, at 1405 (stating that personalized law “provides the certainty of a rule and the calibration of a standard, with none of the decision costs associated with either”).

54. *Id.* at 1431-33.

55. *See id.* at 1424-26.

56. *Id. passim.*

57. *See, e.g., id.* at 1423-33.

Personalized law allows policymakers to carve up the universe of possible circumstances and assign clear, predictable legal outcomes in ways that have not been possible historically.⁵⁸ It enables regulators “to choose very specific rules that are highly calibrated to legislative objectives without introducing compliance costs that would otherwise be associated with such complexity.”⁵⁹ Without personalized law, the hypothetical seventeen-variable speed limit was effectively unavailable; with personalized law, it may be a tempting option.

To be sure, personalized law does not say what the “best” outcome is in a given situation.⁶⁰ Lawmaking entails trade-offs between competing values, and reasonable people will disagree on how those trade-offs should be managed.⁶¹ Advancements in data science provide greater clarity on the nature of some of these trade-offs, but they do not resolve the underlying disagreements about values that lead different people to prefer particular trade-offs over others. Data science can provide insight on how raising the speed limit from 65 mph to 70 mph will affect traffic patterns, fuel consumption, and driver safety. However, it cannot tell you whether it is unfair to accord some people a higher speed limit than others.⁶² It cannot tell you how much weight to give shorter travel times compared to

58. *See id.* at 1422-23.

59. *Id.* at 1419.

60. Casey & Niblett, *supra* note 25, at 336 (“[P]ersonalization technology, for all its promise, cannot provide [law’s underlying] objective.”); Casey & Niblett, *supra* note 1, at 1440 (“[L]awmakers of the future must be able to translate society’s values into programmable objectives for the machines. The task of identifying those values, it seems to us, will remain a human one.”).

61. *See, e.g.*, Casey & Niblett, *supra* note 1, at 1437, 1439-40, 1442-43.

62. This question can be thornier than it might initially appear. Richer people will tend to have higher-quality cars with higher-quality brake systems and other safety features. If personalized law considers a car’s brakes or other safety features in determining how fast it should be allowed to travel, the wealthy will have higher effective speed limits on public roads than the poor. Many might find this objectionable. One could also imagine that drivers might be accorded a higher speed limit for engaging in (possibly unrelated) meritorious behavior—people who volunteer their time or eat healthy could get a higher speed limit as a reward and inducement. This raises concerns about how closely we want human behavior to be regulated and the potential perils of attaching too many consequences to a regulator’s determination of merit. *See, e.g.*, Shiffrin, *supra* note 51, at 1228, 1238; Alexandra Ma, *China Has Started Ranking Citizens with a Creepy ‘Social Credit’ System—Here’s What You Can Do Wrong, and the Embarrassing, Demeaning Ways They Can Punish You*, BUS. INSIDER (Oct. 29, 2018, 12:06 PM), <https://www.businessinsider.com/china-social-credit-system-punishments-and-rewards-explained-2018-4> [<https://perma.cc/DZ43-FA6V>].

reduced automotive fatalities.⁶³ It cannot even tell you whether shorter travel times are a good thing.⁶⁴

Thus, personalized law is not a new way of resolving long-standing debates about what our values should be. By contrast, the potential of personalized law is that it can enable society to achieve outcomes that it previously could not; it transforms a seventeen-variable speed limit into a legitimately viable option. Accordingly, throughout this Article, we will generally put aside the question of what legal outcomes society should prefer in different situations or how society should make that decision.⁶⁵ Instead, we will generally take society's ranking of possible outcomes as a given and will consider how close society can get to its preferred outcome under a system of personalized law. This is a vital inquiry: gaps between society's goals and its legal prescriptions damage millions of people; conversely, a better fit between social goals and the law could dramatically improve millions of lives.

To see the transformative potential of personalized law, imagine that a new diagnostic machine (the "Medical Machine") appears in doctors' offices.⁶⁶ The Medical Machine takes into account relevant facts about Medicare patients—their medical history, test results, symptoms, and so on—as well as all published medical scholarship. It then uses this information to determine which medical procedures should be available to each Medicare patient.⁶⁷ The Medical Machine makes superior decisions, does so rapidly, and communicates them to the doctor in an easy-to-understand way. The Medical Machine is so accurate that a doctor who fails to offer its prescribed treatments to the patient, or who offers a course of treatment that

63. Cf. FED. HIGHWAY ADMIN., U.S. DEP'T OF TRANSP., CRASH COSTS FOR HIGHWAY SAFETY ANALYSIS (2018), <https://safety.fhwa.dot.gov/hsip/docs/fhwasa17071.pdf> [<https://perma.cc/B98R-6DTJ>].

64. For example, a hypothetical society might want to discourage driving—perhaps to reduce pollution, to increase density and reduce sprawl, or to encourage people to get more exercise by walking or biking. It might therefore prefer that car trips take longer as a way of raising the time cost of driving, thus discouraging it.

65. Cf. Kenneth J. Arrow, *A Difficulty in the Concept of Social Welfare*, 58 J. POL. ECON. 328, 328-34 (1950) (discussing the difficulties and indeterminacies of democratic decision-making).

66. Cf. Casey & Niblett, *supra* note 1, at 1412-16 (discussing a similar example).

67. We assume that patients still get to choose whether they want a particular procedure that is available to them.

is not recommended, exposes herself to liability for malpractice.⁶⁸ Moreover, the government will not pay for any treatment the Medical Machine does not recommend, on the grounds that the costs exceed the benefits. The Medical Machine would have effectively replaced all of the rules and standards that currently govern medical malpractice and Medicare benefits with a system of personalized law.⁶⁹

It is easy to see the theoretical advantages of such a system. Unlike our current system, the Medical Machine always produces clear answers as to what the doctor should do. Moreover, those answers can be as finely tailored as one might want: The only entity that must understand the rules assigning medical care is the Medical Machine. No specific individual—neither the doctor, nor the patient, nor even a court reviewing what the doctor did—needs to understand the underlying process that determines medical care. That process can therefore be as complicated, and outcomes can be as personalized, as policymakers desire.

Some commentators have suggested that personalized law will indeed be able to match almost all factual circumstances to the best possible legal outcomes.⁷⁰ For example, Professors Casey and Niblett, who have become prominent scholars of personalized law, have stated that personalized law will cover “all possible contexts”

68. Cf. Casey & Niblett, *supra* note 1, at 1405 (“[F]ailure to use the technology will become a per se violation of a legal standard.”).

69. One could similarly imagine that the Medical Machine would be programmed with the coverage information contained within private insurance contracts or that private insurance contracts would base coverage decisions on the Medical Machine’s determinations as well. Thus, the Medical Machine might subsume additional areas of health law. Cf. *id.* at 1446-47 (describing how technological revolutions can impact “all spheres of law”).

70. See Brett Frischmann, *Algorithm and Blues: The Tyranny of the Coming Smart-Tech Utopia*, SCI. AM. BLOG NETWORK (July 30, 2018), <https://blogs.scientificamerican.com/observations/algorithm-and-blues-the-tyranny-of-the-coming-smart-tech-utopia/> [<https://perma.cc/G7ZN-KX9F>] (“These claims [about personalized law] are rooted deeply in a smart-tech utopian vision that builds from prior techno-utopian visions ... as well as from economic-utopian visions.... Smart-tech utopianism is driving social and technological progress in the 21st century, yet it seems doomed to end in tyranny.”); cf. Lloyd Hitoshi Mayer, *The Promises and Perils of Using Big Data to Regulate Nonprofits*, 94 WASH. L. REV. 1281, 1281 (2019) (“For the optimist, government use of ‘Big Data’ involves the careful collection of information from numerous sources.... [And] expert analysis of those data to reveal previously undiscovered patterns ... [, which] revolutionizes the regulation of criminal behavior, education, health care, and many other areas.”); Porat & Strahilevitz, *supra* note 3, at 1422 (“The ills of personalization, it turns out, may be countered by even more personalization.”).

via “a vast catalog of legal rules—each of which is tailored to best achieve the objective in a specific scenario.”⁷¹ Personalized laws “will be highly calibrated to policy objectives with no chance of judges introducing bias or incompetence.”⁷² These “laws will automatically and rapidly adapt to the circumstances, optimizing according to the objective of the law.”⁷³ They will “be able to take into account” laws’ effects across many dimensions and design the legal regime that produces “a global optimum,” as defined by policymakers.⁷⁴ Casey and Niblett worry that personalized law’s purportedly near-perfect power to tailor legal outcomes to factual scenarios will be so alluring that it will override any and all countervailing concerns about the technology:

One might think that if the ... concerns [raised by personalized law] are great enough, lawmakers will reject the move to [personalized law]. We do not see this happening. The growth of predictive technology is robust. The lure of accuracy (“getting things right”) and the regulated actors’ desire for certainty are powerful forces that will dominate political and legal debates.⁷⁵

Some other scholars have taken a similarly rosy view of the future of personalized law. Professor Cass Sunstein has dubbed it “the wave of the future,”⁷⁶ and several other prominent scholars have predicted that personalized law “will only increase” over time.⁷⁷ By moving decisions from inscrutable human judgment to objective algorithms and calculations, personalized law will provide “ultimate transparency.”⁷⁸ In addition, personalized law will “mitigat[e] ... economic and legal inequality.”⁷⁹ In the views of some

71. Casey & Niblett, *supra* note 1, at 1411-12. *But cf. id.* at 1410 (“[T]he calibration [of personalized law] need not be perfect, it only needs to be better than the calibration associated with the alternatives of legislated rules and adjudicated standards.”).

72. *Id.* at 1410.

73. *Id.* at 1437.

74. *Id.* at 1437-38.

75. *Id.* at 1445. Casey and Niblett worry that, as a result, “[t]he more nuanced considerations” that they discuss in their work will “be sidelined.” *Id.*

76. Sunstein, *supra* note 3, at 57.

77. Devins et al., *supra* note 3, at 368; *see also* Kaeseberg, *supra* note 10, at 235.

78. Verstein, *supra* note 9, at 567.

79. Hacker & Petkova, *supra* note 8, at 2.

commentators, even “[t]he ills of personalization ... may be countered by even more personalization.”⁸⁰

Yet even in the idealized world of our Medical Machine, there are limits on how well society can match factual circumstances to legal outcomes. Governance—by public or private parties—is a dynamic process: policymakers issue rules, and regulated parties change their behavior in response.⁸¹ Personalizing law does not eliminate that core dynamic; to the contrary, it will likely intensify it.⁸² Thus, gamesmanship by regulated parties will impose limits on personalized law. That is the focus of this Article, to which we now turn.

II. INDIVIDUAL RESPONSES TO PERSONALIZED LAW

Consider again our hypothetical Medical Machine. In a world in which people simply accept its decisions, a carefully programmed Medical Machine could produce socially optimal results: Policymakers could encode any desired decision-making rule into the Medical Machine. The healthcare system, guided by the Medical Machine, would then supply each patient with the exact medical care that society deems appropriate.

In practice, people have strong incentives to alter their treatment under the Medical Machine. These incentives underlie three broad classes of problems that have been well explored in the economics literature: elicitation, signaling, and moral hazard. We consider each in turn.

A. *Elicitation*

To tailor responses to different circumstances, one must ascertain what those circumstances are. One way to do this is to simply ask people to identify their characteristics.⁸³ Self-identification can

80. Porat & Strahilevitz, *supra* note 3, at 1422.

81. See, e.g., Jordan M. Barry & Paul L. Caron, *Tax Regulation, Transportation Innovation, and the Sharing Economy*, 82 U. CHI. L. REV. DIALOGUE 69, 72-74 (2015).

82. See *infra* Part II.

83. One might argue that the rise of big data has made this information gathering strategy somewhat less important. However, much of the “big data” that companies use now, and that regulations would presumably use in the future, is self-reported data. For example, consider COMPAS, a widely used software program that uses a wide range of data to predict

work well when a characteristic is both easily verifiable and positively associated with outcomes.

For example, if an employer wants to hire students with high grades, it is sufficient to allow students to provide their transcripts. Students with high grades will happily do so⁸⁴: These students wish to make themselves appear as attractive to employers as possible. They know that employers value high grades and want employers to know that they possess them. Similarly, if the government wants to provide tax credits to taxpayers with minor children, such taxpayers will be happy to identify themselves, as they reap a direct monetary benefit from doing so.⁸⁵

Voluntary disclosures can work in certain applications of the Medical Machine as well. For example, if asked, people might be willing to share whether a particular disease runs in their family, if doing so enables the Medical Machine to make more accurate diagnoses. Similarly, asking patients whether they would like to receive medications that are unpleasant to ingest and only offer benefits if a patient is truly sick—such as chemotherapy drugs or syrup of ipecac—is likely to elicit an honest response.

But in many cases, patients will have incentives to misreport their circumstances. One way in which this could arise is with respect to health conditions that, if present, will reduce the level of care that a patient will receive now. For example, there is a chronic

criminal defendants' likelihood of committing crimes in the future. COMPAS relies, in part, on defendants' responses to survey questions. *See, e.g.*, Julia Angwin, Jeff Larson, Surya Mattu & Lauren Kirchner, *Machine Bias*, PROPUBLICA (May 23, 2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing> [<https://perma.cc/CXN8-272F>] (listing a number of such questions, including: "Was one of your parents ever sent to jail or prison?", "How many of your friends/acquaintances are taking drugs illegally?", "How often did you get in fights while at school?", "[Does] a hungry person ha[ve] a right to steal[?]" and "If people make [you] angry or lose [your] temper, [can you] be dangerous?").

84. The dynamics may be such that the market unravels and all students disclose. For example, if only the top 10 percent of students disclose their grades, rational employers will assume that a nondisclosing student is in the middle of the nondisclosing group. A student near the top GPA of the nondisclosing group (for example, at the 80th percentile) will thus find it in her interest to disclose. As additional relatively high-performing students disclose, the average GPA of the nondisclosing students drops. This encourages the highest-performing remaining nondisclosers to disclose, repeating the cycle. Ultimately, all students may be forced to disclose their grades, lest employers infer that their grades are worse than they actually are. But for purposes of this example, it suffices that students with high grades disclose.

85. *See* I.R.C. § 24.

shortage of kidneys available for transplant in the United States.⁸⁶ Thousands of people on the waiting list for kidneys die each year, waiting for one to become available.⁸⁷ In an attempt to mitigate the human cost of this shortage, assume that policymakers program the Medical Machine to consider potential kidney recipients' expected post-transplant longevity when allocating kidneys. Knowing this, a candidate for a transplant might not disclose a family history of any serious illness—diabetes, lung cancer, Huntington's disease—that might reduce her chances of receiving a kidney transplant now. This would limit the information available to the Medical Machine, reducing its ability to distinguish between circumstances.

One might protest that this example is unrealistic because the Medical Machine would have other ways of getting that information. Perhaps it could access the medical files of a patient's parents or other relatives to directly check the incidence of disease in the family.⁸⁸

However, there are other types of information that cannot be gleaned in this manner. For instance, it is difficult for an outside observer to tell whether a soft-tissue injury is painful.⁸⁹ Of course, the patient will know, but because patients who are not in pain may still desire medications (such as oxycodone, morphine, or fentanyl), relying on patients' assertions alone is problematic.⁹⁰

86. See, e.g., Benny Evangelista, *Facebook Hopes to Expand Organ Donation Awareness*, SFGATE (Aug. 6, 2012, 2:47 PM), <https://www.sfgate.com/business/article/Facebook-hopes-to-expand-organ-donation-awareness-3525917.php> [<https://perma.cc/P4B4-TUVU>].

87. See, e.g., *Organ Donation and Transplantation Statistics*, NAT'L KIDNEY FOUND., <https://www.kidney.org/news/newsroom/factsheets/Organ-Donation-and-Transplantation-Stats> [<https://perma.cc/76EL-DXDK>].

88. Alternatively, perhaps the Medical Machine could glean the required information from the patient's DNA, assuming it is available to the machine.

89. See, e.g., Ephrat Livni, *How Do You Prove Soft Tissue Injury?*, FINDLAW (May 25, 2016, 6:59 AM), <https://blogs.findlaw.com/injured/2016/05/how-do-you-prove-soft-tissue-injury.html> [<https://perma.cc/9AKN-ZZKL>] ("Soft tissue injuries are like feelings—they're real and they hurt but they can be invisible and not everyone believes in them. For these reasons, proving this kind of injury can be difficult.")

90. See, e.g., Pamela L. Pentin, *Commentary, Drug Seeking or Pain Crisis? Responsible Prescribing of Opioids in the Emergency Department*, 15 *AMA J. ETHICS* 410, 411-12 (2013); Harrison Cook, *48% of Hospitals See Patients with Drug-Seeking Behavior Daily, Survey Finds*, BECKER'S HOSP. REV. (Oct. 17, 2018), <https://www.beckershospitalreview.com/opioids/48-of-hospitals-see-patients-with-drug-seeking-behavior-daily-survey-finds.html> [<https://perma.cc/B8US-9WB4>].

Similar concerns about how accurately individuals report their circumstances arise in many other contexts. Consider securities law, which distinguishes between investors who are deemed to be sophisticated enough to fend for themselves (“accredited investors”) and those who require more protection.⁹¹ To simplify, companies are allowed to sell certain securities to accredited investors that they are not allowed to sell to other members of the public.⁹² In January 2020, the SEC issued a proposed rule that would expand the definition of accredited investor.⁹³ In doing so, it specifically called for comment on whether individuals should be able to qualify as accredited investors simply by “self-certify[ing] that they have the requisite financial sophistication.”⁹⁴

However, simply asking an investor whether he is sophisticated, or whether he appreciates the risks of an investment, is unlikely to elicit truthful and accurate responses. First, people who know that they are not sophisticated have incentives to falsely report that they are: would-be investors want to purchase the securities in question, and disclosing their lack of sophistication would prevent them from doing so.⁹⁵

Second, many people may incorrectly believe that they are sophisticated investors.⁹⁶ Robert Citron, the former treasurer of Orange County, provides a famous example.⁹⁷ He invested the county’s funds in derivatives with risks that he did not fully

91. See 17 C.F.R. §§ 230.501, 230.506 (2019); see also 15 U.S.C. § 80a-3(c)(7) (adding the similar concept of “qualified” investors).

92. For a more fulsome explanation, see SEC, UPDATED INVESTOR BULLETIN: ACCREDITED INVESTORS, INVESTOR.GOV (Jan. 31, 2019), <https://www.investor.gov/introduction-investing/general-resources/news-alerts/alerts-bulletins/investor-bulletins/updated-3> [<https://perma.cc/L7VQ-95QC>].

93. See Amending the “Accredited Investor” Definition, 85 Fed. Reg. 2574, 2574 (Jan. 15, 2020) (to be codified at 17 C.F.R. pts. 230, 240).

94. *Id.* at 2584.

95. *Cf.* BETHANY MCLEAN & JOE NOCERA, ALL THE DEVILS ARE HERE: THE HIDDEN HISTORY OF THE FINANCIAL CRISIS 111-18 (2010) (describing how investors with regulatory incentives to hold investments with high credit ratings engaged in “rating shopping” to pressure ratings agencies to rate assets they wanted to buy more highly).

96. See generally Justin Kruger & David Dunning, *Unskilled and Unaware of It: How Difficulties in Recognizing One’s Own Incompetence Lead to Inflated Self-Assessments*, 77 J. PERSONALITY & SOC. PSYCH. 1121 (1999).

97. FRANK PARTNOY, INFECTIOUS GREED: HOW DECEIT AND RISK CORRUPTED THE FINANCIAL MARKETS 112-16 (2009).

appreciate.⁹⁸ When warned (repeatedly) that he was taking on great risks, he argued that critics simply did not understand the county's investment strategy.⁹⁹ His bets paid off for years before luck turned against him and the county, resulting in the largest municipal bankruptcy in U.S. history to that point.¹⁰⁰

Testimony later revealed how out of his depth Citron was.¹⁰¹ Witnesses "testified that Citron, the 'financial wizard,' had only seventh-grade-level math ability and performed so poorly on tests that he 'bordered on brain damaged.'"¹⁰² There was also testimony "that he suffered from a form of dementia and often relied on a mail-order astrologer and a psychic for his interest rate forecasts."¹⁰³

B. Signaling

Another way of identifying individuals' characteristics is to infer them from their behaviors.¹⁰⁴ This inferential method looms particularly large in current thinking around personalized law.¹⁰⁵ The basic logic is that examining regulated parties' behavior can give regulators a more accurate picture than directly elicited answers provide.¹⁰⁶ This argument has some force; it is one thing to

98. *Id.* at 116.

99. *Id.*

100. See JOHN E. MARTHINSEN, *RISK TAKERS: USES AND ABUSES OF FINANCIAL DERIVATIVES* 109-14 (3d ed. 2018).

101. *Id.* at 136.

102. *Id.*

103. *Id.*; see also *id.* at 136 n.34 ("For the record, Citron's psychic told him that December 1994 would be a bad month. The psychic was correct."). In another, more recent example, Taylor Caudle joined a group called "Big Pump," devoted to cryptocurrency "pump-and-dump" operations—that is, organized efforts to raise the price of an asset temporarily and then sell the asset before its price drops. Shane Shifflett & Paul Vigna, *Some Traders Are Talking Up Cryptocurrencies, Then Dumping Them, Costing Others Millions*, WALL ST. J. (Aug. 5, 2018, 9:00 AM), <https://www.wsj.com/graphics/cryptocurrency-schemes-generate-big-coin/> [<https://perma.cc/9DN8-HGMT>]. Caudle participated in an attempt but failed to sell in time and "lost \$5,000 in about 30 seconds." *Id.* He had maxed out his credit card to acquire the \$5,000. *Id.*; Matt Levine, *Crypto Pumps Are Just for Fun*, BLOOMBERG (Aug. 6, 2018, 7:45 AM), <https://www.bloomberg.com/opinion/articles/2018-08-06/crypto-pumps-are-just-for-fun> [<https://perma.cc/7VND-Y2LH>].

104. See, e.g., Charles Duhigg, *What Does Your Credit-Card Company Know About You?*, N.Y. TIMES MAG. (May 12, 2009), <http://www.nytimes.com/2009/05/17/magazine/17credit-t.html> [<https://perma.cc/UE7S-S7MF>].

105. See generally Casey & Niblett, *Self-Driving Laws*, *supra* note 3.

106. See *id.* at 431-32. It would also avoid the transaction costs involved in asking people

claim you are politically engaged and another to keep your television tuned to C-SPAN for two hours a day.¹⁰⁷

But here, too, regulated parties' responses to personalized law create problems. The same incentives that motivate people to falsely report their characteristics will also motivate them to change their behavior in order to disguise their true characteristics.

In economics, taking costly actions in order to convince others that you possess certain characteristics is known as "signaling."¹⁰⁸ Under a system of personalized law, regulated parties will have tremendous incentives to send signals—including false ones—to improve their regulatory treatment.

The false signaling problem is not new to personalized law; whenever the law gives different treatment to different groups, members of one group may try to disguise themselves as the other. However, personalized law can exacerbate this problem. The premise and promise of personalized law is that it can create more varied outcomes based on finer distinctions across people and scenarios.¹⁰⁹ This means that the range of available legal rules is larger, and hence the potential benefits of false signals are larger too. And because fine changes in perceived individual characteristics can produce different legal rules is larger, the potential payoff from a small shift in how an individual is perceived is likely to be larger as well.¹¹⁰

Returning to our Medical Machine example, suppose that there are two types of artificial joints for knee and hip replacements, Acme and Beta. Assume that Acme joints function better than Beta joints but that they are also more expensive. Suppose that the

about their preferences.

107. Cf. Porat & Strahilevitz, *supra* note 3, at 1437-38 (discussing how private firms often have greater confidence in big data based on purchasing behavior rather than on survey data, on the ground that the subjects of the data are less likely to manipulate the former).

108. MAS-COLELL ET AL., *supra* note 26, at 450-51.

109. Casey & Niblett, *supra* note 25, at 335 ("As technologies ... reduce the costs of discovering and communicating the relevant personal context for a law to achieve its purpose, the goal of a well-tailored, accurate, and highly contextualized law is becoming more achievable. And that is the 'new' personalization of law.").

110. However, it may be more difficult (or costly) to send a false signal under a personalized legal system than a depersonalized one (for example, a technologically advanced implementation of personalized law might be better at detecting false signals). Thus, a shift from a depersonalized legal rule to a personalized one could either increase or decrease the amount and cost of false signaling overall, depending on the specific circumstances.

Medical Machine judges that the additional cost of an Acme joint is merited only for those patients with active lifestyles; avid joggers and hikers are eligible to receive Acme joints, while other patients are eligible only for Beta joints.¹¹¹ Individuals experiencing joint pain may then try to create a data record suggesting that they love jogging and hiking—trekking up mountains and posting pictures on Facebook, buying a Fitbit and challenging their friends, jogging past the local hospital each morning—in order to qualify for the better and more expensive treatment.¹¹²

These same dynamics apply in many other legal contexts as well. Students with certain disabilities are entitled to longer amounts of time to take tests,¹¹³ including standardized tests,¹¹⁴ college exams,¹¹⁵ and bar exams.¹¹⁶ But having more time to take

111. Doctors currently select among different joints based on patients' anticipated activities post-replacement. *See, e.g.*, Lesley Alderman, *Getting a New Knee or Hip? Do It Right the First Time*, N.Y. TIMES (July 2, 2010), <https://www.nytimes.com/2010/07/03/health/03patient.html> [<https://perma.cc/A67V-SZAA>]. The same concept extends easily to many possible medical interventions. For example, patients with joint problems might be eligible for costly surgery or less costly but less effective medications or physical therapies. *Cf.* Casey & Niblett, *supra* note 1, at 1412-16 (discussing the use of predictive technology in medical diagnoses).

112. They could also create false signals through fraud—for example, hiring someone to hike while wearing the patient's Fitbit, or hacking into Fitbit's database and changing their records. *See* Sean O'Toole, *How to Cheat on Fitbit Convincingly. Spoiler: It Involves String.*, GROUPON (Dec. 27, 2018), <https://www.groupon.com/articles/how-to-cheat-on-fitbit> [<https://perma.cc/GYC8-DVL6>]; Jen Wieczner, *Fitbit Users Are Finding Creative Ways to Cheat*, FORTUNE (June 10, 2016, 1:40 PM), <https://fortune.com/2016/06/10/fitbit-hack-cheat/> [<https://perma.cc/SK3D-EH4K>]. However, this can be combatted by laws against fraud. *Cf., e.g.*, CAL. UNEMP. INS. CODE §§ 2116, 2122 (West 2004) (making the filing of false claims for disability insurance, or helping others file such claims, a criminal offense punishable by fine or imprisonment).

113. *See* 42 U.S.C. § 12189 (requiring examinations be offered “in a place or manner accessible to persons with disabilities”); 28 C.F.R. § 35.130 (2018) (discussing prohibitions against discrimination toward individuals with disabilities).

114. *See, e.g.*, *National Extended Time/Timing Code 6 Frequently Asked Questions*, ACT, <https://www.act.org/content/dam/act/unsecured/documents/FAQ-TAA-Changes.pdf> [<https://perma.cc/V58T-ENEP>]; *Extended Time Accommodation*, COLL. BD., <https://accommodations.collegeboard.org/typical-accommodations/time> [<https://perma.cc/AGJ7-U4L9>]; *LSAC Policy on Accommodations for Test Takers with Disabilities*, LAW SCH. ADMISSION COUNCIL, <https://www.lsat.org/lsat/lsac-policy-accommodations-test-takers-disabilities> [<https://perma.cc/T598-YC4A>].

115. *See, e.g.*, *Exam Accommodations*, HARV. UNIV., <https://aeo.fas.harvard.edu/accommodations-services/academic/exam-accommodations> [<https://perma.cc/SQD5-3UMG>]; *Receiving Test Accommodations*, UNIV. OF MICH., <https://lsa.umich.edu/tac/students/steps-to-using-the-tac.html> [<https://perma.cc/HG8Y-MZQQ>].

116. *See, e.g.*, *Test Accommodations for the New York Bar Exam and the New York Law*

tests is also beneficial to students without disabilities,¹¹⁷ and some students falsely present themselves as having a disability in order to secure extra time.¹¹⁸ In this context, false signaling can include spending time and money on medically unnecessary doctor's visits, as well as changing one's behavior during such visits to mislead doctors.¹¹⁹ Likewise, workers who become disabled are entitled to payments from the federal government.¹²⁰ Some individuals falsely present themselves as disabled in order to collect these benefits.¹²¹ Similarly, sincerely held religious beliefs must be accommodated in

Exam, N.Y. STATE BD. L. EXAM'RS, <https://www.nybarexam.org/ADA/ADA.htm> [<https://perma.cc/P4ZQ-WLJC>]; *Requesting Testing Accommodations*, STATE BAR OF CAL., <http://www.calbar.ca.gov/Admissions/Examinations/Requesting-Testing-Accommodations> [<https://perma.cc/EMT2-FMUQ>].

117. See, e.g., William D. Henderson, *The LSAT, Law School Exams, and Meritocracy: The Surprising and Undertheorized Role of Test-Taking Speed*, 82 TEX. L. REV. 975, 985 & nn.49-50 (2004) (collecting sources discussing "speediness" as a factor in the LSAT; that is, that the test is designed so that many test-takers do not finish each section).

118. This practice featured prominently in the recent college admissions scandal. See Associated Press, *College Admissions Scandal Shows How People Exploited Rules for Disabled Students*, MARKETWATCH (Mar. 13, 2019, 2:55 PM), <https://www.marketwatch.com/story/exam-rules-for-disabled-students-were-abused-in-admissions-scandal-2019-03-13> [<https://perma.cc/S4R5-ZWJC>]; Doree Lewak, *Rich Parents Are Using Doctor's Notes to Help Kids Cheat the SATs*, N.Y. POST (May 2, 2018, 8:37 PM), <https://nypost.com/2018/05/02/rich-parents-are-using-doctors-notes-to-help-kids-cheat-the-sats/> [<https://perma.cc/XB5U-TKX3>]; Eliza Shapiro & Dana Goldstein, *Is the College Cheating Scandal the 'Final Straw' for Standardized Tests?*, N.Y. TIMES (Mar. 14, 2019), <https://www.nytimes.com/2019/03/14/us/sat-act-cheating-college-admissions.html> [<https://perma.cc/A8SM-D9V9>].

119. See, e.g., Dana Goldstein & Jugal K. Patel, *Need Extra Time on Tests? It Helps to Have Cash*, N.Y. TIMES (July 30, 2019), <https://www.nytimes.com/2019/07/30/us/extra-time-504-sat-act.html> [<https://perma.cc/KGL2-S9C7>] (describing charges of \$3,000-\$10,000 for these services, which can take as long as ten hours, and how a student was advised to "be stupid" during the psychologist's evaluation"); Lewak, *supra* note 118; Jake Tapper, Dan Morris & Lara Setrakian, *Does Loophole Give Rich Kids More Time on SAT?*, ABC NEWS (Mar. 30, 2006, 5:10 PM), <https://abcnews.go.com/Nightline/loophole-give-rich-kids-time-sat/story?id=1787712> [<https://perma.cc/B926-U2CV>].

120. See SOC. SEC. ADMIN., PUB. NO. 05-10029, DISABILITY BENEFITS (2019), <https://www.ssa.gov/pubs/EN-05-10029.pdf> [<https://perma.cc/MK4U-MEAV>].

121. See, e.g., SOC. SEC. ADMIN., PUB. NO. 31-231, AGENCY FINANCIAL REPORT: FISCAL YEAR 2017, at 125, 152 (2017) (estimating \$4.3 billion in disability benefit overpayments in 2016); OFF. OF THE INSPECTOR GEN., "20/20" and Disability Fraud: *Seeing Is Believing*, SSA BLOG (Jan. 27, 2015), <https://oig.ssa.gov/newsroom/blog/jan27-disability-fraud> [<https://perma.cc/F99R-H9E4>] (discussing cases, including one in which a worker claimed to be blind and unable to work, but actually "could see well enough to work, drive," operate a water-ski boat, and run two businesses); *Man Claiming To Be Too Blind to Drive Seen Behind the Wheel*, ABC NEWS (May 22, 2015), <https://abcnews.go.com/2020/video/man-claiming-blind-drive-wheel-28132362> [<https://perma.cc/3N58-72HL>].

school,¹²² in the workplace,¹²³ or even in prison.¹²⁴ Some people misrepresent their religious beliefs as a result.¹²⁵ Other examples abound.¹²⁶

A personalized disability benefits regime might well do a better job of matching outcomes to facts than our current system does, and we note that the government has been making some modest moves in this direction.¹²⁷ But so long as disability benefits are attractive to those without disabilities, there will be incentives to send false signals, and personalized law will not be able to catch them all.

More disturbingly, there are other arenas in which personalizing law may make outcomes affirmatively worse. For example, consider income taxes. One of the chief arguments for low tax rates is that taxes can distort economic behavior and create deadweight loss¹²⁸: Suppose people will pay fifty dollars for a piano lesson from Jane, and that Jane is willing to teach if she nets at least thirty-five dollars per lesson.¹²⁹ If Jane is subject to a 40 percent tax on her

122. See, e.g., *A.A. ex rel. Betenbaugh v. Needville Indep. Sch. Dist.*, 701 F. Supp. 2d 863 (S.D. Tex. 2009), *aff'd*, 611 F.3d 248 (5th Cir. 2010).

123. See, e.g., *Davis v. Fort Bend County*, 765 F.3d 480, 485-86 (5th Cir. 2014); *Adeyeye v. Heartland Sweeteners, LLC*, 721 F.3d 444, 448-49 (7th Cir. 2013).

124. See, e.g., *Andreola v. Doyle*, 260 F. App'x 935, 935 (7th Cir. 2008); *Ford v. McGinnis*, 352 F.3d 582, 588 (2d Cir. 2003).

125. See generally Nathan S. Chapman, *Adjudicating Religious Sincerity*, 92 WASH. L. REV. 1185 (2017); Steven D. Smith, *The Case of the Exemption Claimants: Religion, Conscience, and Identity*, 2019 BYU L. REV. 339.

126. See generally Martha A. Field, *Problems of Proof in Conscientious Objector Cases*, 120 U. PA. L. REV. 870 (1972) (describing false claims of conscientious objection).

127. See, e.g., Robert Pear, *On Disability and on Facebook? Uncle Sam Wants to Watch What You Post*, N.Y. TIMES (Mar. 10, 2019), <https://www.nytimes.com/2019/03/10/us/politics/social-security-disability-trump-facebook.html> [<https://perma.cc/E9WN-2KHS>]; Denise Brodey, *Disability Advocates Poke Holes in White House Plan to Snoop on Facebook Pages for Disability Fraud*, FORBES (Mar. 11, 2019, 4:29 PM), <https://www.forbes.com/sites/denisebrodey/2019/03/11/disability-advocates-poke-holes-in-white-house-plan-to-snoop-on-facebook-pages-for-disability-fraud/#107c0a535880> [<https://perma.cc/7AFR-Z78Y>].

128. See, e.g., RICHARD A. POSNER, *ECONOMIC ANALYSIS OF LAW* 653-55 (8th ed. 2011); HAL R. VARIAN, *INTERMEDIATE MICROECONOMICS: A MODERN APPROACH* 304 (Jack Repcheck ed., 8th ed. 2010) (“[F]rom the economist’s viewpoint, the real cost of the tax is that the output has been reduced.”); cf. Jordan M. Barry, *The Emerging Consensus for Cutting the Corporate Income Tax Rate*, 18 CHAP. L. REV. 19, 22-24 (2014) (discussing the economic effects of a reduced corporate income tax rate).

129. Equivalently, her reservation price is thirty-five dollars. See VARIAN, *supra* note 128, at 4. For simplicity, we assume Jane has no direct costs, such as materials. The example can easily be modified to address such issues, however.

income, she will net only thirty dollars per lesson after taxes.¹³⁰ Knowing this, she will not give lessons. This is bad for Jane and her would-be piano students, as they cannot complete a transaction that would make each of them better off. Crucially, it is also bad for the government; because Jane earns no income, the government collects no tax. Subjecting Jane to the 40 percent income tax has thus made everyone, including the government, worse off.

One could imagine a personalized tax regime that calibrates individuals' tax rates based on how responsive their behavior is to taxation. If the law could determine Jane's after-tax reservation price for giving piano lessons, it could subject her to a 20 percent tax rate instead of the 40 percent tax rate to which other taxpayers are subject.¹³¹ Jane would then give lessons for fifty dollars, keeping forty dollars for herself and paying ten dollars in taxes.¹³² Jane, her student, and the government would all be better off.¹³³ One could extend this same idea beyond the income tax; estate taxes, gift taxes, sales taxes, payroll taxes, excise taxes, and property taxes all jump to mind.¹³⁴

However, such personalized tax laws would give taxpayers tremendous incentives to convince the government that they are

130. Jane is paid fifty dollars for teaching, then pays twenty dollars in taxes ($40\% \times \$50 = \20), leaving her with thirty dollars ($\$50 - \$20 = \$30$).

131. There are other arguments against doing this, such as horizontal equity-based arguments, and we will return to them in Part III.

132. Any tax rate below 30 percent will also induce Jane to give piano lessons. From a social planner's perspective, a 29 percent tax rate would likely be preferable to the 20 percent posited in the text, as it would raise more revenue and raise fewer horizontal equity concerns.

133. Jane would be better off because she would receive forty dollars, which is more than her thirty-five dollar reservation price, leaving her with five dollars of surplus. Previously, she gave no lessons and received no surplus. Her student is better off because he gets piano lessons, which he values more than the fifty dollars he pays for them; previously, he did not receive lessons. The government is better off because it gets ten dollars of tax revenue; previously, it got zero. To the extent that the government cares about the welfare of Jane and her student, it benefits in that way as well.

134. See, e.g., Richard Arnott & Petia Petrova, *The Property Tax as a Tax on Value: Deadweight Loss*, 13 INT'L TAX & PUB. FIN. 241, 255, 262 (2006) (applying similar theories to property taxes); Wojciech Kopczuk & Joel Slemrod, *The Impact of the Estate Tax on Wealth Accumulation and Avoidance Behavior*, in RETHINKING ESTATE AND GIFT TAXATION 299-300 (William G. Gale, James R. Hines, Jr. & Joel Slemrod eds., 2001) (noting the impact of estate taxes on wealth accumulation); see also Matthew A. Seligman, *Personalized Choice of Private Law* 38-39 (Cardozo Legal Stud., Rsch. Paper No. 596, 2020), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3493093 [<https://perma.cc/XXZ6-QFZV>] (suggesting a personalized carbon tax).

extremely tax-sensitive, even if they are not.¹³⁵ Taxpayers might falsely signal this by buying books on tax planning, buying tax-favored investments such as state and municipal bonds,¹³⁶ joining anti-tax groups, or simply adjusting the amount they work as their tax rates change.¹³⁷ To the extent that these efforts succeed at convincing the government to lower one's tax rate, they move reality away from the optimal outcome contemplated by the personalized law system.¹³⁸

Even if the law consistently sees through false signals, false signaling behavior remains problematic. Signaling efforts are likely to be costly for the individual engaging in them and for society at large.¹³⁹ Thus, encouraging such behavior is still a concern in and of itself.¹⁴⁰ Society may well be better off under a system that lacks personalization.

For instance, in our income tax example, if Jane purposefully lowers her work efforts in an attempt to convey that she is sensitive to tax, that means Jane is turning down work that others are happy to pay for and that she is truly willing to perform, net of taxes.¹⁴¹

135. An analogous problem arises when governments (often state and local ones) use tax incentives to attract businesses. Businesses will want to make their relocation plans appear highly sensitive to their tax treatment, even if they are not, in order to secure the greatest possible tax benefits. *See, e.g.*, Alexander Klemm, *Causes, Benefits, and Risks of Business Tax Incentives* (IMF Working Paper WP/09/21, 2009), <https://www.imf.org/external/pubs/ft/wp/2009/wp0921.pdf> [<https://perma.cc/YF5M-ACDN>]; Peter D. Enrich, *Saving the States from Themselves: Commerce Clause Constraints on State Tax Incentives for Business*, 110 HARV. L. REV. 377, 383-85 (1996); *cf.* Andrew Hanson & Shawn Rohlin, *Do Location-Based Tax Incentives Attract New Business Establishments?*, 51 J. REG'L SCI. 427, 428 (2011) (analyzing the effect of tax credits on growth in business establishments in particular areas).

136. *See* I.R.C. § 103(a) (exempting state and municipal bonds from gross income).

137. This essentially parallels companies' price discrimination efforts and consumers' responses. *See infra* Part III.A.

138. A sense that taxes are fair and that everyone pays taxes has been found to contribute to tax compliance. *See, e.g.*, Marjorie E. Kornhauser, *Normative and Cognitive Aspects of Tax Compliance: Literature Review and Recommendations for the IRS Regarding Individual Taxpayers*, in 2 NATIONAL TAXPAYER ADVOCATE: 2007 ANNUAL REPORT TO CONGRESS 138, 149-50 (2007); Leandra Lederman, *Does Enforcement Reduce Voluntary Tax Compliance?*, 2018 BYU L. REV. 623, 653-54 (collecting sources about tax compliance); Yair Listokin & David M. Schizer, *I Like to Pay Taxes: Taxpayer Support for Government Spending and the Efficiency of the Tax System*, 66 TAX L. REV. 179, 185 (2013). To the extent that a personalized tax system undermines those perceptions, it could reduce tax compliance and thus revenue.

139. *See, e.g.*, VARIAN, *supra* note 128, at 726-29.

140. *See id.* at 729.

141. *See supra* text accompanying notes 128-33. For example, suppose Jane's reservation price for piano lessons is twenty dollars. In an effort to persuade the government that she is

Meanwhile, the government collects no tax revenue. Therefore, Jane, her would-be student, and the government are all harmed by Jane's false signaling behavior.¹⁴² Similarly, recall our Medical Machine example, in which personalized law induced people—more specifically, people with joint pain who do not enjoy hiking—to drag themselves up mountains in an attempt to get higher-quality hip replacements.¹⁴³ These activities are clearly wasteful, even if they do not affect how the Medical Machine distributes joint replacements.¹⁴⁴ Further, these induced exertions could potentially accelerate patients' joint deterioration, resulting in more numerous and more expensive surgeries over time.¹⁴⁵

1. Counterargument: High Individual Cost of False Signaling

One response to this line of argument is to observe that personalized law may take into account a large amount of data. This raises the cost of misrepresenting oneself, especially over a long period of time.¹⁴⁶

Two points about this counterargument merit emphasis. First, a high cost of sending false signals is a double-edged sword: high costs may deter some individuals from changing their behavior, but they will not deter everyone, and those individuals who are not deterred

strongly tax-sensitive, she turns down a fifty dollar lesson (which would let her keep thirty dollars after paying 40 percent taxes). Jane has given up ten dollars in surplus now in her attempts to secure more surplus later (at the government's expense). Her would-be student loses surplus as well because he does not get a lesson he was willing to pay for.

142. Jane's other false signaling behaviors have similar implications. For example, if Jane shifts her investments from corporate bonds to municipal bonds, the federal government will collect less tax from her. See, e.g., JOSEPH BANKMAN, DANIEL N. SHAVIRO, KIRK J. STARK & EDWARD D. KLEINBARD, *FEDERAL INCOME TAXATION* 368 (18th ed. 2019). Unless Jane is in a high tax bracket, investing in municipal bonds will likely provide her with lower net returns, given the "implicit tax" imposed on such investments. See, e.g., *id.* at 368-70.

143. See *supra* text accompanying notes 111-12.

144. See, e.g., Michael Spence, *Job Market Signaling*, 87 Q.J. ECONOMICS 355, 368 (1973) (noting the costs associated with signaling); VARIAN, *supra* note 128, at 727-29 (discussing the inefficiency of education signaling in the job market).

145. See, e.g., *Osteoarthritis*, ARTHRITIS FOUND., <https://www.arthritis.org/diseases/osteoarthritis> [https://perma.cc/6CQQ-LHJ2].

146. Cf. Porat & Strahilevitz, *supra* note 3, at 1455 ("[M]aintaining a charade may be easy for a short period of time, [but] it gets harder ... (and easier ... to detect) with every passing day.").

will incur large costs.¹⁴⁷ These costs are intrinsic to a personalized law system.¹⁴⁸

Second, regulated individuals may not be the only ones who want to manipulate personalized law. Data providers, gatekeepers, and other interested parties may have strong incentives to alter data or disguise individuals' statuses. These actors may have the ability to affect a large number of data points. Thus, their cost of intervention may be relatively low, and countering the effects of their manipulations (that is, weeding out all that bad data) may be quite difficult.

We have already discussed how patients in our Medical Machine example might attempt to disguise themselves to change their medical treatment. Patients are not the only ones who may wish to deceive the Medical Machine; doctors may have a range of reasons to game the system as well. For example, a doctor might conclude that all patients deserve the higher-quality Acme brand joints. She may then manipulate data—choosing tests that will color the Medical Machine's assessment of her patients,¹⁴⁹ using testing equipment that is improperly calibrated,¹⁵⁰ organizing hikes for all of her patients—to convince the Medical Machine that it is cost-effective to give everyone Acme joints. She could also record outcomes for patients who receive Acme joints as more positive than they actually were, while doing the reverse for patients who receive Beta joints. A doctor could also have the opposite conviction—that Acme joints are overpriced and overrated and that patients get too much free care on the taxpayer dollar—or any number of other

147. *See, e.g., id.* (“[E]mploying smoke screens is costly. If people regularly purchase products they do not need, become Facebook friends with people they do not like, or develop hobbies they do not enjoy in order to enhance the quality of their personalized ... [legal outcome], they [are bearing real costs.] Changing one's behavior is a costly signal; it is not cheap talk.”).

148. On the one hand, it is good that false signaling behaviors are costly. False signaling is socially undesirable behavior that is both inefficient and inequitable; we should want such behavior to be costly in order to discourage people from engaging in it. However, the costs created by these behaviors are real. In an ideal world, people would not engage in these behaviors at all.

149. For example, a doctor could screen horror films (or Bob Ross) to patients while testing their blood pressure in order to raise (or lower) the observed results.

150. For example, if a doctor has one thermometer that works correctly and a second that regularly overestimates (or underestimates) temperatures by two degrees, she can make patients appear healthier or sicker depending on which thermometer she uses.

preferences that differ from those of the Medical Machine's creators, and manipulate the data to achieve her preferred result.¹⁵¹

Nor are patients and doctors the only actors who might wish to deceive or manipulate the Medical Machine. Hospitals, insurers, manufacturers of medical equipment, and even politicians may wish to influence care decisions, and they all have levers they can pull to further their ends.¹⁵²

To be clear, all of these problems can arise in various forms under depersonalized legal systems as well. In many cases, personalized law may make these problems better;¹⁵³ in some cases, it may make them worse. But either way, these problems will persist.

151. For example, one could imagine a doctor motivated by more venal concerns seeking to maximize the profit that the hospital receives from treatments, or even the amount of compensation that the doctor receives from Acme or Beta. Cf. Dhruv Khullar & Anupam B. Jena, *Do Incentives Nudge Physicians to Prescribe Opioids for Pain?*, STAT NEWS (Aug. 18, 2016), <https://www.statnews.com/2016/08/18/opioids-pain-prescribing-physicians/> [<https://perma.cc/Z9BP-T95Q>]; Charles Ornstein, Ryann Grochowski Jones & Mike Tigas, *Drug-Company Payments Mirror Doctors' Brand-Name Prescribing*, NPR (Mar. 17, 2016, 5:00 AM), <https://www.npr.org/sections/health-shots/2016/03/17/470679452/drug-company-payments-mirror-doctors-brand-name-prescribing> [<https://perma.cc/2BJM-B9MX>]; Aaron Kessler, Elizabeth Cohen & Katherine Grise, *The More Opioids Doctors Prescribe, the More Money They Make*, CNN (Mar. 12, 2018, 8:45 AM), <https://www.cnn.com/2018/03/11/health/prescription-opioid-payments-eprise/index.html> [<https://perma.cc/MK6Z-FM2Q>]. Doctors might also have a variety of other socially problematic preferences, such as animus toward, or subconscious biases against, a particular group of people. See, e.g., Andrea M. Elliott, Stewart C. Alexander, Craig A. Mescher, Deepika Mohan & Amber E. Barnato, *Differences in Physicians' Verbal and Nonverbal Communication with Black and White Patients at the End of Life*, 51 J. PAIN & SYMPTOM MGMT. 1, 4 (2016); Monique Tello, *Racism and Discrimination in Health Care: Providers and Patients*, HARV. HEALTH BLOG (July 9, 2020, 12:34 PM), <https://www.health.harvard.edu/blog/racism-discrimination-health-care-providers-patients-2017-011611015> [<https://perma.cc/T8D3-DHN8>]; Michael O. Schroeder, *Racial Bias in Medicine Leads to Worse Care for Minorities*, U.S. NEWS (Feb. 11, 2016, 10:13 AM), <https://health.usnews.com/health-news/patient-advice/articles/2016-02-11/racial-bias-in-medicine-leads-to-worse-care-for-minorities> [<https://perma.cc/W43L-TK5V>].

152. Disability fraud cases provide a useful, if stark, example. To date, the biggest prosecutions involved misconduct by gatekeepers and service providers. See, e.g., *Top 5 Most Outrageous Social Security Fraud Cases*, RITACCO DISABILITY L. (June 8, 2017), [<https://perma.cc/6DVN-2HC8>]; Timothy Williams, *70 Are Indicted in Puerto Rico in Social Security Fraud*, N.Y. TIMES (Aug. 21, 2013), <https://www.nytimes.com/2013/08/22/us/70-are-indicated-in-puerto-rico-in-social-security-fraud.html> [<https://perma.cc/C87Y-CJ8T>].

153. Cf. Casey & Niblett, *supra* note 25, at 357-58 (tying personalized law's benefits to how lawmakers define "better" legal outcomes).

2. Counterargument: Impenetrability of Personalized Law

One might also argue that people will not engage in false signaling because they will not know which false signals to send to achieve their goals. Under this argument, the “black box” nature of personalized law renders its inner workings impenetrable, thereby rendering gamesmanship impossible.¹⁵⁴ For example, suppose that personalized law relies on complicated machine learning algorithms. People may not know how these algorithms work, and thus will not know how to manipulate them.¹⁵⁵ Because sending false signals is costly, and because people cannot predict how sending a false signal will affect their legal treatment,¹⁵⁶ they may give up the attempt altogether.

As a preliminary matter, personalized law’s algorithms may or may not be impenetrable in practice. Assuming *arguendo* that society intends the algorithms to be opaque,¹⁵⁷ one can imagine an arms race between regulators striving to hide how their algorithms work and private parties working to crack the algorithms and take advantage of their flaws. It is not obvious that regulators would have the upper hand in such a battle.¹⁵⁸ Regardless of who wins, the arms race itself is socially wasteful, as regulators and regulated parties spend valuable resources trying to outmaneuver each other.

We see similar dynamics playing out currently with respect to privately maintained algorithms. Website owners use search engine

154. See, e.g., Porat & Strahilevitz, *supra* note 3, at 1455 (“[A] great deal of predictive analytics is and will remain proprietary. Guessing [how to manipulate the system] will not be easy.”).

155. See *id.*

156. See *id.*

157. Cf. *infra* Part III.D.

158. For instance, regulators may have difficulties hiding the workings of their algorithm given formal and informal pressures favoring government transparency. Regulated parties presumably would have access to the personalized law—for example, doctors would have access to the Medical Machine, and could ask it questions—so they may also be able to reverse-engineer the algorithm, or at least hunt for misclassifications, simply by asking the regulators to classify large numbers of (hypothetical) inputs. See *infra* Part III.D; cf. Casey & Niblett, *supra* note 1, at 1419-20 (contemplating a world in which tax authorities would allow taxpayers to enter facts into a website or app and get an immediate ruling on the applicable tax consequences). Moreover, private firms may be willing to commit more resources to the project of gaming regulations than governments will expend on enforcing them, allowing the avoiders to devote more human and computational power to the competition.

optimization (SEO) to lift their sites toward the top of Google's search results for particular terms.¹⁵⁹ Sellers boost their products toward the top of Amazon's search results.¹⁶⁰ Companies and other organizations game Facebook's algorithms to disseminate particular messages as widely as possible.¹⁶¹ These efforts cost tens of billions of dollars each year.¹⁶²

Google, Amazon, Facebook, and their ilk do not passively accept such conduct. They are all large companies whose business models depend on the quality and accuracy of their algorithms, and they deploy their considerable technical expertise against those who would manipulate them.¹⁶³ Even so, they have a mixed record against these machinations,¹⁶⁴ in one infamous example, a backyard

159. See TJ McCue, *SEO Industry Approaching \$80 Billion but All You Want Is More Web Traffic*, FORBES (July 30, 2018, 3:41 AM), <https://www.forbes.com/sites/tjmccue/2018/07/30/seo-industry-approaching-80-billion-but-all-you-want-is-more-web-traffic/#54136d9c7337> [<https://perma.cc/HZ5V-G9BV>].

160. See, e.g., Jon Emont & Clément Bürge, *How Scammers in China Manipulate Amazon*, WALL ST. J. (Dec. 17, 2018, 6:00 AM), <https://www.wsj.com/articles/how-scammers-in-china-manipulate-amazon-11545044402> [<https://perma.cc/7NGP-Y6W3>]; Leticia Miranda, *Some Amazon Sellers Are Paying \$10,000 a Month to Trick Their Way to the Top*, BUZZFEED NEWS (Apr. 24, 2019, 4:47 PM), <https://www.buzzfeednews.com/article/leticiamiranda/amazon-marketplace-sellers-black-hat-scams-search-rankings> [<https://perma.cc/RJ2H-7B6J>]; Laura Stevens & Jon Emont, *How Sellers Trick Amazon to Boost Sales*, WALL ST. J. (July 28, 2018, 8:18 AM), <https://www.wsj.com/articles/how-sellers-trick-amazon-to-boost-sales-1532750493> [<https://perma.cc/7ZEU-YYHN>].

161. See, e.g., Hunt Allcott & Matthew Gentzkow, *Social Media and Fake News in the 2016 Election*, 31 J. ECON. PERSPS. 211, 212-13, 226 (2017) (finding that, in the run-up to the 2016 election, social media was the "most important" news source for 14 percent of Americans, that 115 pro-Trump fake stories "were shared on Facebook a total of 30 million times, and 41 pro-Clinton fake stories [were] shared a total of 7.6 million times," and that the average American adult "saw 1.14 fake stories"); Jessica Guynn & Elizabeth Weise, *Thousands of Facebook Ads Bought by Russians to Fool U.S. Voters Released by Congress*, USA TODAY (May 10, 2018, 7:19 PM), <https://www.usatoday.com/story/tech/2018/05/10/thousands-russian-bought-facebook-social-media-ads-released-congress/849959001/> [<https://perma.cc/Y9EP-4K7G>]; see also Samuel C. Woolley & Douglas R. Guilbeault, *Computational Propaganda in the United States of America: Manufacturing Consensus Online* 9-10 (Computational Propaganda Rsch. Project, Working Paper No. 2017.5), <http://comprop.oii.ox.ac.uk/wp-content/uploads/sites/89/2017/06/Comprop-USA.pdf> [<https://perma.cc/B2FF-82GH>].

162. See, e.g., McCue, *supra* note 159.

163. See, e.g., Stevens & Emont, *supra* note 160.

164. See, e.g., Rob Copeland & Katherine Bindley, *Millions of Business Listings on Google Maps Are Fake—and Google Profits*, WALL ST. J. (June 20, 2019, 7:44 PM), <https://www.wsj.com/articles/google-maps-littered-with-fake-business-listings-harming-consumers-and-competitors-11561042283> [<https://perma.cc/TQ8M-GZWR>]; Oobah Butler, *I Made My Shed the Top-Rated Restaurant on TripAdvisor*, VICE (Dec. 6, 2017, 12:20 PM), <https://www.vice.com/en-us/article/2017/12/6/i-made-my-shed-the-top-rated-restaurant-on-tripadvisor>.

shed that had never served a customer got itself ranked as TripAdvisor's number one restaurant in London.¹⁶⁵ It is not clear that government regulators would do better at combatting gamesmanship than these companies have.¹⁶⁶

Even assuming that regulators' algorithms are impenetrable, that still will not eliminate the problem of false signaling; regulated parties' lack of information may deter some strategic behavior but can also spawn additional wasteful conduct.¹⁶⁷ People will have strong incentives to change the legal rules that apply to them.¹⁶⁸ Even if an individual only has weak guesses about how an algorithm works, acting on those guesses will still be worthwhile if the gains from changing her classification are large enough; a low probability of a high payoff can induce action.¹⁶⁹

Impenetrable algorithms can produce even larger costs when regulated parties misunderstand them. Many people currently hold—and act on—incorrect beliefs about the law.¹⁷⁰ For example, many people believe that undercover police officers must identify themselves as police when asked; this is not the case.¹⁷¹ Perhaps

com/en_us/article/434gqw/i-made-my-shed-the-top-rated-restaurant-on-tripadvisor [https://perma.cc/DG2U-SAZS] (describing the author's experience at a previous job where restaurants he had never visited would pay him thirteen dollars to write a positive review on TripAdvisor and his observation from "monitoring the ratings of these businesses ... [that their] fortunes would genuinely turn").

165. Butler, *supra* note 164.

166. Private companies, driven by profit motive, may have better incentives to address these problems than the government does. Because private companies often pay more than government does, they seem likely to attract more top-flight computer programmers. On the other hand, government does have greater coercive powers at its disposal to deploy against misbehavior.

167. See, e.g., Porat & Strahilevitz, *supra* note 3, at 1454-55.

168. See, e.g., *id.* at 1455.

169. See generally Manfred Borovcnik, *Risk and Decision Making: The "Logic" of Probability*, 12 MATHEMATICS ENTHUSIAST 113 (2015) (defining risk and analyzing its interaction with probability and utility). This point is readily apparent in many everyday behaviors, such as buying a lottery ticket, insuring one's home or car, or wearing a seatbelt.

170. See, e.g., Andrew Lu, *Do You Have a 'Right' to Phone Calls After Arrest?*, FINDLAW (May 1, 2013, 10:08 AM), <http://blogs.findlaw.com/blotter/2013/05/do-you-have-a-right-to-phone-calls-after-arrest.html> [https://perma.cc/8TB4-KHPY] (describing the common misconception that individuals are entitled to one phone call after arrest); Karl Smallwood, *Are You Really Entitled to a Phone Call When Arrested?*, TODAYIFOUNDOUT (May 9, 2014), <http://www.todayifoundout.com/index.php/2014/05/really-entitled-phoncall-arrested/> [https://perma.cc/BT9U-FNMS] (explaining that the number of phone calls an individual may make varies depending on a range of factors).

171. See, e.g., *Common Myths About Police Encounters*, ACLU OF NEV., <https://www.aclunv>.

more disturbingly, large swaths of the public hold mistaken beliefs about major facets of contract law¹⁷²—a body of law with which most people interact daily and which many commentators defend as intuitive and in line with people’s expectations. An opaque algorithm seems likely to spawn more confusion and misconceptions than publicly posted laws do. People acting on false beliefs will incur real costs.¹⁷³

A related problem is that if people do not understand how the personalized law program works, they may not trust it to do its job. Thus, they may feel the need to engage in costly signaling to ensure that the system characterizes them *correctly*. This signaling can result in regulated parties incurring costs, even when they are not necessary.¹⁷⁴

For example, assume Alex is an avid rock climber who will reap substantial benefits from an Acme joint. Further, assume that the Medical Machine can deduce these facts about Alex and will assign her an Acme joint, but that Alex does not know this.¹⁷⁵ Alex may decide that she should buy a Fitbit, join Crossfit, and register for a marathon to ensure that the Medical Machine knows she is the type of person who should receive an Acme joint. In fact, these costly expenditures of time and effort are totally unnecessary, as the Medical Machine was already going to assign Alex an Acme joint.¹⁷⁶

Perhaps more troublingly, this problem can also manifest itself at the provider level. Suppose a doctor comes to believe—rightly or

org/sites/default/files/sex_workers_myths_0.pdf [https://perma.cc/DT97-SECN].

172. See, e.g., Meirav Furth-Matzkin & Roseanna Sommers, *Consumer Psychology and the Problem of Fine-Print Fraud*, 72 STAN. L. REV. 503, 541-42 (2020) (finding that consumers believe that fine print is enforceable even when a contract is secured through misrepresentation); Matthew A. Seligman, *The Error Theory of Contract*, 78 MD. L. REV. 147, 169 (2018) (finding that 31 percent of survey respondents believe specific performance is the typical remedy for breach of contract); Roseanna Sommers, *Commonsense Consent*, 129 YALE L.J. 2232, 2236 (2020) (reporting that laypeople often believe that contracts obtained via deception are legally enforceable even when they are not); Tess Wilkinson-Ryan & David A. Hoffman, *The Common Sense of Contract Formation*, 67 STAN. L. REV. 1269, 1297 (2015) (finding that people believe that formalities are key to contract formation, rather than assent).

173. See, e.g., Porat & Strahilevitz, *supra* note 3, at 1455 (describing the costs of fake signaling).

174. Cf. *id.* (arguing that false signaling by consumers will often harm them).

175. Cf. DREW FUDENBERG & JEAN TIROLE, *GAME THEORY* 541-71 (1991) (discussing the effects of knowledge on equilibrium behavior).

176. Moreover, these activities may have damaged her knee further, increasing the cost and frequency of her surgery. See *supra* note 148 and accompanying text.

not—that her colleagues report overly rosy assessments of patients’ health after they receive Acme joints. She might then feel obligated to report similarly rosy assessments of her own patients to make sure that the Medical Machine classifies her patients correctly and gives them appropriate joints. If she begins coloring her reporting, that further increases the pressure on other doctors to do the same. As more doctors change their reporting practices, the data becomes less accurate, reducing the Medical Machine’s ability to match outcomes to circumstances as originally contemplated. Once doctors report inaccurately—or are perceived to—it becomes very difficult for any individual doctor to push back against the practice, lest her patients be given worse joints.¹⁷⁷

In summary, it is questionable whether personalized law would truly be an impenetrable black box. Even if it were, that would not eliminate costly gamesmanship. Thus, the opacity of personalized law offers at most a partial counterargument against the signaling problems identified above.

C. Moral Hazard

Rational actors consider the future consequences of their actions when they make decisions. Altering the possible outcomes that an individual faces in the future can cause her to change her present conduct for the worse.¹⁷⁸ For example, if Dana is uninsured, she bears the full cost of having her car stolen and will have good incentives to protect her car against theft.¹⁷⁹ On the other hand, if insurance will fully compensate Dana if her car is stolen, she has little incentive to keep her car secure.¹⁸⁰

177. The doctor might also be subject to direct negative consequences. For example, the government might see that her patients have worse outcomes than other doctors’ patients do and decide that Medicare will not pay for any joint replacements that she performs.

178. Such alterations can also induce people to change their conduct for the better, and many laws are written with this intent in mind. *See generally* Uri Gneezy, Stephan Meier & Pedro Rey-Biel, *When and Why Incentives (Don’t) Work to Modify Behavior*, 25 J. ECON. PERSPS. 191 (2011) (analyzing when incentives can generate positive behavior). For example, the tax law accords a deduction for those who donate to charity as a way of encouraging charitable donations. *See* 26 I.R.C. § 170(a)(1).

179. *See* VARIAN, *supra* note 128, at 724.

180. *See, e.g., id.* An overinsured person may intentionally court disaster. *See, e.g., “Nub City”—the Florida Town Where People Cut Off Their Appendages for Insurance Money*, VA

Economists refer to this phenomenon as moral hazard.¹⁸¹ Moral hazard differs from signaling because signaling is about actions that convey (or disguise) characteristics without changing them, whereas moral hazard entails actually changing the characteristics themselves.¹⁸² Like signaling, moral hazard is an old and well-known problem¹⁸³ that personalized law can exacerbate. In particular, when personalized regulation affords better treatment to those who find themselves in worse positions, people will have fewer incentives to avoid being in bad positions.¹⁸⁴

For example, returning to the Medical Machine, suppose that Pat has recurring hip pain, but that her condition is not deemed severe enough to merit immediate replacement; Pat is placed down the queue. If Pat would prefer to get her hip replaced now, she would have incentives to exacerbate her condition in order to qualify for a new joint more quickly; she might book a ski trip or a day at the trampoline park.

Similar self-destructive and socially undesirable behaviors can arise in many other contexts. For instance, imagine a personalized environmental law regime that considers how costly it is for each factory to reduce its emissions; factories with a high cost of reducing pollution (“hard-to-green” factories) are allowed to emit more pollution than those that can reduce pollution more cheaply. This approach may work well if the factories are already built.¹⁸⁵ But, if companies know that hard-to-green factories will receive better regulatory treatment, they will have incentives to build hard-to-green factories.¹⁸⁶ This can produce much worse results than a

VIPER (Mar. 15, 2018), <http://vaviper.blogspot.com/2018/03/nub-city-florida-town-where-people-cut.html> [<https://perma.cc/AT89-22K7>].

181. VARIAN, *supra* note 128, at 724.

182. *See id.* at 724-26.

183. *See id.* at 724.

184. *See* Omri Ben-Shahar & Ariel Porat, *Personalizing Mandatory Rules in Contract Law*, 86 U. CHI. L. REV. 255, 270 (2019).

185. In this case, the legal rule will not affect the design of the factories. Thus, the only efficiency concern is how to reduce pollution at the least cost, given the factories that already exist.

186. For example, suppose that there are two factory designs. Each emits the same amount of pollution, each can be modified to produce a lesser amount of pollution, and reducing a factory’s pollution level creates \$500,000 in social benefits. The “easy-to-green” factory costs \$1 million to build and can be modified to reduce pollution at a cost of \$300,000. The hard-to-green factory costs \$1.1 million, and its pollution can be reduced at a cost of \$900,000. Assume

depersonalized system that requires all companies to reduce pollution by a fixed amount or a fixed percentage, or that taxes factories on each ton of pollution they emit.¹⁸⁷ Companies would have similar incentives with respect to many other personalized legal regimes, including worker safety, animal testing laws, computer security, and privacy protections.

To provide another example, assume a personalized system of traffic laws, administered via self-driving cars.¹⁸⁸ People who urgently need to be somewhere at a particular time get priority treatment and are shuttled through traffic to arrive promptly at their destinations, while others who are less time-sensitive face delays. Dr. Garcia, who is set to perform surgery in a short time, would be shunted rapidly to the hospital.¹⁸⁹ However, if she were to leave her house earlier, there would be comparatively little rush to get her to work; therefore, the traffic system would give her a lower priority and a longer ride. Knowing this, and preferring to spend time at home rather than in traffic, Dr. Garcia would have incentives to leave for work later, even though this imposes costs on other commuters and raises the chance that she will be late for her surgery.

In a depersonalized system in which all cars must navigate the same traffic, Dr. Garcia has better incentives to leave early to beat the traffic and ensure that she is on time for her surgery. Thus,

the law requires easy-to-green factories to reduce their pollution output, as the social benefits of doing so exceed the costs. Suppose further that hard-to-green factories need not reduce their pollution, as the costs exceed the social benefits. If companies anticipate the legal rule, they will find hard-to-green factories more profitable (total cost \$1.1 million) than easy-to-green factories (total cost \$1.3 million). The incentive stems entirely from the difference in legal treatment.

187. For instance, continuing the example above, if all factories must reduce pollution, easy-to-green factories (total cost \$1.3 million) are more profitable than hard-to-green ones (total cost \$2 million). Easy-to-green factories are similarly more profitable if there is a fixed tax on pollutants emitted.

188. One could also achieve the same result via a sufficiently sophisticated congestion pricing system.

189. *Cf.* Casey & Niblett, *supra* note 1, at 1417 (“[T]raffic lights in some jurisdictions already contain sensors ... and adjust the timing of red and green lights accordingly. Some traffic lights contain detectors allowing emergency service vehicles to ‘preempt’ the signal and expedite their journey.... In the not-so-distant future, a traffic-light system may know that a passenger in a regular vehicle requires medical attention and give the rushing driver a series of green lights all the way to the hospital.” (footnotes omitted)).

moral hazard can lead personalized law to produce worse outcomes than a depersonalized system.

III. REGULATORY RESPONSES AND THEIR LIMITS

We now shift our focus of analysis from the regulated parties to the regulators themselves. When designing personalized legal systems, regulators must take into account how people will respond to the system they are creating.¹⁹⁰ A regulatory regime that properly accounts for these machinations—one that does not afford regulated parties attractive opportunities to manipulate it in ways that regulators do not want—is termed “incentive compatible.”¹⁹¹

However, incentive compatibility is a high standard.¹⁹² It is unlikely that a personalized legal regime can both impose the optimal rule in all situations *and* be incentive compatible.¹⁹³

If regulators impose personalized laws that match optimal outcomes to all situations but that are not incentive compatible, regulated parties will thwart the system. As a result, personalized law will not work as regulators intended and will not optimally match situations to outcomes. Alternatively, regulators can prioritize creating an incentive-compatible system at the cost of a poorer matching of circumstances to legal outcomes.¹⁹⁴ Such a system is likely to operate as regulators intended but will not produce the optimal result in all cases. Whichever option regulators choose, personalized law will not create optimal results in all circumstances.

190. Victor Fleischer, *Regulatory Arbitrage*, 89 TEX. L. REV. 227, 253, 288 (2010); see Barry, *supra* note 52, at 73 (“[R]egulatory arbitrage can be eliminated by crafting legal rules that ... take economic reality into account.”).

191. See MAS-COLELL ET AL., *supra* note 26, at 493-94.

192. See Jerry Green & Jean-Jacques Laffont, *Characterization of Satisfactory Mechanisms for the Revelation of Preferences for Public Goods*, 45 ECONOMETRICA 427, 427 (1977).

193. For possible counterexamples, see Porat & Strahilevitz, *supra* note 3, at 1475, for an argument that personalized disclosure rules will provide individuals with little incentive to engage in strategic behavior to change the disclosures they receive, and Seligman, *supra* note 134, at 3, for the proposal that individuals have a choice between certain private law regimes.

194. See Fleischer, *supra* note 190, at 289 (stating that “enhancing legal antiavoidance constraints, while imperfect, is likely to be a more fruitful line of attack for policy makers” to the attractiveness of opportunities to manipulate the system).

We now turn to the technological, social, and political reasons why it is so difficult to craft an incentive-compatible legal regime. In particular, regulators will encounter problems of information, authority, and transparency. These issues interrelate and feed off each other and are likely to foster conservatism on the part of regulators, which will itself be a constraint.¹⁹⁵

A. Information Problems 1: Muddling

Consider the criteria that a personalized law regime must satisfy to be incentive compatible: No regulated party can have any incentive to falsely identify itself when asked.¹⁹⁶ No regulated party can have any incentive to engage in false signaling.¹⁹⁷ No regulated party can be tempted by moral hazard.¹⁹⁸ An optimal Medical Machine must allocate medical resources—and must render ineffectual the false-signaling efforts of patients looking to improve their medical treatment. An optimal system of personalized environmental regulation must allocate pollution rights across existing factories and defeat the moral hazard problems described above, which encourage companies to build hard-to-green factories.

One way to eliminate parties' incentive to engage in problematic behaviors is to detect such behaviors and punish them.¹⁹⁹ If the environmental agency has a crack team of inspectors who can always determine whether a company built a hard-to-green factory to achieve better regulatory treatment, the agency can treat the factory as if it were not a hard-to-green factory.²⁰⁰ Such measures will eliminate companies' regulatory incentives to build hard-to-green factories and thus the moral hazard problem.²⁰¹

195. See *infra* Part III.E.

196. See Green & Laffont, *supra* note 192, at 431.

197. See *id.*

198. See *id.* at 430.

199. See VARIAN, *supra* note 128, at 726.

200. For instance, returning to the facts of note 186, if a company would have built an easy-to-green factory if not for the hard-to-green factory's regulatory advantages, the regulator can require the company to reduce the pollution of its factory. This makes the total cost of the hard-to-green factory \$2 million and the total cost of an easy-to-green factory \$1.3 million, eliminating the regulatory incentive to construct hard-to-green factories.

201. Continuing the example above, if the company knows that moral hazard behavior will be detected and will create no regulatory benefits, it will prefer to build an easy-to-green

However, this type of detection is generally costly, difficult, and imperfect.²⁰² The environmental agency may not have enough information to unravel the process of how the factory's design evolved. This information problem may be even more severe in other contexts. How are regulators to tell whether Bob drank champagne to aggravate his liver problems, or why Dr. Garcia is running late for work?²⁰³

Regulated parties will purposefully exacerbate regulators' information problems. If a company building a factory anticipates an investigation into its intentions during construction, it will attempt to make its intentions appear as positive as possible.²⁰⁴ The basic dynamic—regulated individuals will change their behavior to improve their legal treatment—continues to apply. Data muddling by regulated parties will complicate big data analytics, limiting regulators' ability to optimally match circumstances to outcomes.

We have already seen this dynamic play out in the private sphere.²⁰⁵ Companies' most successful big data efforts seem to have been those that consumers had no desire to thwart. Consider retailer Target, which has received accolades for its use of big data to identify and target shoppers.²⁰⁶ Target identified pregnancy as a time when shoppers tend to forge long-lived purchasing patterns. Accordingly, it was particularly important to identify pregnant

factory (total cost \$1.3 million) rather than a hard-to-green factory (total cost \$2 million).

202. See VARIAN, *supra* note 128, at 654.

203. Regulators can offset gaps in detection with increases in punishment for those who are caught. However, there are limitations on how far this strategy can go, and how much we should expect it to be politically feasible. See *infra* Parts III.B-C.

204. To quote Matt Levine:

[The] First Law of Bribes ... is that when you are talking about bribes, particularly in writing, you should not refer to them as "bribes," and you should certainly not refer to them as "chickens" or "sugar" or some other clever euphemism; you should refer to them by boring but technically accurate terms.... [U]sing boring business terms gives you a fighting chance of not getting caught, and even if you do get caught you've got a fighting chance to persuade a jury that it was all fine, and even if you do get convicted it is just, I mean, it is aesthetically a bit less embarrassing than if you'd used the dumb euphemisms.

Matt Levine, *The Dogs Ate SoftBank's Money*, BLOOMBERG (Dec. 10, 2019, 11:59 AM), <https://www.bloomberg.com/opinion/articles/2019-12-10/the-dogs-ate-softbank-s-money> [<https://perma.cc/3YQ3-9ADD>].

205. See, e.g., *supra* notes 159-62 and accompanying text.

206. See generally Duhigg, *supra* note 15 (describing Target's successful big data collection efforts).

shoppers and get them to purchase items from Target.²⁰⁷ Some pregnant shoppers self-identified by opening baby registries with Target.²⁰⁸ To spot other pregnant shoppers, Target used big data techniques to find shoppers who had not opened a baby registry with Target but whose behavior changed in the same ways that Target's baby-registering shoppers' behavior did.²⁰⁹ Presumably, some of these changes were straightforward—purchasing maternity clothes, breastfeeding paraphernalia, baby items—but others were more subtle. For instance, one key indicator was that pregnant shoppers tended to switch from scented to unscented lotions, perhaps because their sense of smell sharpened and they experienced increased nausea.²¹⁰

Target's shopper identification is impressive and has proven profitable for the retailer.²¹¹ However, it bears emphasis that Target shoppers were not actively trying to game their pregnancy status.²¹² It does not appear that pregnant women were trying to falsely signal to Target that they were not pregnant,²¹³ and it is hard to imagine anyone seeking to become pregnant in order to open a Target baby registry.²¹⁴

Regulated parties, by contrast, often care quite a bit about their legal treatment and may want to hide or disguise some of their characteristics from regulators. Thus, companies' experiences with personalized advertising and product offerings will not fully translate to the regulatory context. For a closer private sector analog, consider companies' efforts to price discriminate: If a company can tell how much consumers are willing to pay for

207. *Id.*

208. *Id.*

209. *Id.*; see also Kashmir Hill, *How Target Figured Out a Teen Girl Was Pregnant Before Her Father Did*, FORBES (Feb. 16, 2012, 11:02 AM), <https://www.forbes.com/sites/kashmirhill/2012/02/16/how-target-figured-out-a-teen-girl-was-pregnant-before-her-father-did/?sh=2fcfe2066686> [<https://perma.cc/SBW9-XX57>] (“Target, for example, has figured out how to data-mine its way into your womb, to figure out whether you have a baby on the way long before you need to start buying diapers.”).

210. Duhigg, *supra* note 15. They also bought certain vitamins and supplements. *Id.*

211. *Id.*

212. *See id.*

213. *See id.*

214. On the other hand, if pregnant women received valuable discounts, nonpregnant women would have an incentive to falsely signal that they were pregnant. This may have happened; or customers may not have known about the opportunity.

products, it can profit by charging higher prices to less price-sensitive customers and lower prices to more price-sensitive customers.²¹⁵ In this instance, consumers all wish to be perceived as strongly price-sensitive, even if they are not, in order to receive better deals.²¹⁶

Price discrimination is a potentially attractive strategy for companies such as Uber or Amazon; both companies have large amounts of information about their customers, have sophisticated data analytics professionals, and employ interfaces that allow them to offer different prices to different customers simultaneously.²¹⁷ For example, Uber could charge higher prices to customers who are traveling on expense accounts,²¹⁸ heading to luxury destinations,²¹⁹ or whose phones are running out of power.²²⁰ Yet both Uber and Amazon have encountered obstacles when they attempted to put price discrimination strategies into practice.²²¹

One major obstacle these companies encountered is that customers began injecting false data points into the system to manipulate the companies' predictive algorithms. Amazon shoppers intentionally browsed through items without buying them, suggesting to Amazon's algorithm that they were price-sensitive.²²² Uber users produced the same effect by requesting rides and then canceling

215. VARIAN, *supra* note 128, at 467-68.

216. *Id.* at 465.

217. *See, e.g.*, Bar-Gill, *supra* note 13, at 225-26; Elizabeth Pollman & Jordan M. Barry, *Regulatory Entrepreneurship*, 90 S. CAL. L. REV. 383, 387-88 (2017).

218. *Separate Your Work and Personal Trips by Creating an Uber Business Profile*, UBER BLOG (Aug. 30, 2016), <https://www.uber.com/en-AU/blog/business-profile/> [<https://perma.cc/SJF8-38PY>]; Will Preston, *Uber Is Ripping Off Frequent Riders and Here's How to Avoid It*, RIDE SHARE GUY (Mar. 21, 2018), <https://therideshareguy.com/uber-is-ripping-off-frequent-riders-and-heres-how-to-avoid-it/> [<https://perma.cc/VX37-64MK>].

219. *See* Eric Newcomer, *Uber Starts Charging What It Thinks You're Willing to Pay*, BLOOMBERG (May 19, 2017, 3:19 PM), <https://www.bloomberg.com/news/articles/2017-05-19/uber-s-future-may-rely-on-predicting-how-much-you-re-willing-to-pay> [<https://perma.cc/EA94-6YTQ>] (describing Uber's experimenting with "route-based pricing").

220. Amit Chowdhry, *Uber: Users Are More Likely to Pay Surge Pricing If Their Phone Battery Is Low*, FORBES (May 25, 2016, 6:30 AM), <https://www.forbes.com/sites/amitchowdhry/2016/05/25/uber-low-battery/#4da9c46974b3> [<https://perma.cc/QAW5-R3B9>].

221. Newcomer, *supra* note 219; Jennifer Abel, *Lawsuit Alleges Amazon Charges Prime Members for "Free" Shipping*, CONSUMERAFFS. (Mar. 14, 2014), <https://www.consumeraffairs.com/news/lawsuit-alleges-amazon-charges-prime-members-for-free-shipping-031414.html> [<https://perma.cc/9BYD-FUBA>].

222. Abel, *supra* note 221.

when they saw those rides' prices.²²³ Uber users have also thwarted Uber's algorithms by changing their destination mid-ride.²²⁴

Since its initial foray into price discrimination, Uber has denied that it offers different prices to individual riders.²²⁵ It has also begun offering its own credit card.²²⁶ That card's benefits program and privacy policy suggest that one of Uber's motivations for the venture may be the data it will generate on each individual customer's spending.²²⁷ This data would be more difficult for consumers to muddle, potentially enabling Uber to price discriminate better.²²⁸

Regulators implementing personalized laws can expect to face similar challenges. However, as Section B explains, regulators may not be able to follow Uber's hypothesized approach.

B. Information Problems 2: Privacy

Regulators can overcome the problems described in Section A if they have access to information that is both tightly tied to the behaviors of interest and difficult for regulated parties to muddle.²²⁹ But even if such information is technologically available, privacy concerns may lead society to limit regulators' ability to access or use it.²³⁰

223. See Kominers, *supra* note 18.

224. Aaron Mak, *Is Uber Really Charging Frequent Users Higher Fares?*, SLATE (Mar. 30, 2018, 2:40 PM), <https://slate.com/technology/2018/03/is-uber-really-charging-frequent-users-more.html> [<https://perma.cc/WN84-HYNW>]; Preston, *supra* note 218.

225. See, e.g., Arwa Mahdawi, *Is Your Friend Getting a Cheaper Uber Fare Than You Are?*, GUARDIAN (Apr. 13, 2018, 12:39 PM), <https://www.theguardian.com/commentisfree/2018/apr/13/uber-lyft-prices-personalized-data> [<https://perma.cc/YV53-A5M5>].

226. Scott Duke Kominers, *Uber Really Wants You to Use Its Credit Card*, BLOOMBERG (Dec. 6, 2017, 5:00 AM), <https://www.bloomberg.com/opinion/articles/2017-12-06/uber-really-wants-you-to-use-its-credit-card> [<https://perma.cc/V9QE-QCTJ>].

227. *Id.* If so, Uber would not be the first big company to launch a line of business for the purpose of gathering data. Cf. Porat & Strahilevitz, *supra* note 3, at 1439 (suggesting that getting access to data on individuals' preferences, and hence their personalities, motivated Google to enter the smartphone business).

228. Kominers, *supra* note 226; see Porat & Strahilevitz, *supra* note 3, at 1437-38 (discussing how private firms often have greater confidence in big data based on consumers' purchasing behavior because it is less likely to be manipulated by consumers).

229. See, e.g., Porat & Strahilevitz, *supra* note 3, at 1454 ("[P]ersonalized ... rules tied to an individual's immutable characteristics, such as sex or age, alleviate significant concerns about strategic behavior.").

230. See, e.g., Alessandro Acquisti, *The Economics and Behavioral Economics of Privacy*, in *PRIVACY, BIG DATA, AND THE PUBLIC GOOD: FRAMEWORKS FOR ENGAGEMENT* 76, 78-91 (Julia

Personalized law raises fundamental questions about how closely—some might say intrusively—we want human behavior to be regulated.²³¹ For many, the idea of a regulator that knows enough to draw fine distinctions among its citizens evokes the image of a dystopic police state.²³² For some, the closest analogy may be China’s “social credit system,” which assigns each Chinese citizen a social credit score based on her behavior.²³³ A wide variety of behaviors affect that score: “bad driving, smoking in non-smoking zones, [or] buying too many video games” can all lower one’s score.²³⁴ Paying bills on time, buying Chinese products, and performing community service can raise one’s score.²³⁵ Citizens with high social credit scores get rewards such as reduced energy bills, better rental terms, better interest rates on loans, and more matches on dating websites.²³⁶ Those with low social credit scores can be subjected to a variety of punishments, including not being permitted to purchase airline or train tickets; lower internet speeds; exclusion from schools, jobs, or hotels; public shaming; and having their pets

Lane et al. eds., 2014); Niva Elkin-Koren & Michal S. Gal, *The Chilling Effect of Governance-by-Data on Data Markets*, 86 U. CHI. L. REV. 403, 403 (2019) (“The sharing of data for the purpose of law enforcement raises obvious concerns for civil liberties.”); Paul Ohm, *Broken Promises of Privacy: Responding to the Surprising Failure of Anonymization*, 57 UCLA L. REV. 1701, 1704, 1733 (2010); Daniel J. Solove, *Data Mining and the Security-Liberty Debate*, 75 U. CHI. L. REV. 343, 345 (2008); Omer Tene & Jules Polonetsky, *Privacy in the Age of Big Data: A Time for Big Decisions*, 64 STAN. L. REV. ONLINE 63, 63 (2012).

231. See, e.g., Shiffrin, *supra* note 51, at 1223, 1244 (arguing that standards require people to engage in ethical decision-making that is important to moral health, and that too many clear directives could erode moral health); Thomas A. Smith, *From Law to Automation*, 1 CRITERION J. ON INNOVATION 535, 536 (2016).

232. See Ma, *supra* note 62.

233. *Id.* The system has been piloted on millions of citizens to date and was scheduled to become compulsory for all citizens in 2020. *Id.*; see, e.g., Sophie Perryer, *China’s Social Credit System Awards Points to Citizens Who Conform*, NEW ECON. (May 22, 2019), <https://www.theneweconomy.com/strategy/116498> [<https://perma.cc/NTU7-RQYC>].

234. Ma, *supra* note 62; see Perryer, *supra* note 233.

235. *How Can Chinese Citizens Increase Their ‘Social Credit Score’?*, DAILY MAIL (Aug. 21, 2018, 12:50 PM), <https://www.dailymail.co.uk/sciencetech/fb-6083597/HOW-CHINESE-CITIZENS-INCREASE-SOCIAL-CREDIT-SCORE.html> [<https://perma.cc/E62A-QRY4>].

236. Ma, *supra* note 62; Simina Mistreanu, *Life Inside China’s Social Credit Laboratory*, FOREIGN POL’Y (Apr. 3, 2018), <https://foreignpolicy.com/2018/04/03/life-inside-chinas-social-credit-laboratory/> [<https://perma.cc/28D5-YB7Z>].

confiscated.²³⁷ Western commentators have generally taken an unfavorable view of this system.²³⁸

In many instances, our society has tried to prevent overreach by restricting access to personal information.²³⁹ Sometimes these restrictions take the form of outright prohibitions on the use of certain data by public or private actors. For example, Congress has restricted the government's use of emails, financial information, and similar information that was gathered for foreign intelligence purposes.²⁴⁰ The Equal Credit Opportunity Act prohibits lenders from inquiring about a borrower's public assistance status, marital status, or birth control practices, among other topics.²⁴¹

In other instances, the law requires public or private actors to clear procedural hurdles before accessing particular data.²⁴² The Fourth Amendment famously requires law enforcement officers to obtain a warrant prior to conducting searches or seizures.²⁴³ The Fair Credit Reporting Act (FCRA) limits access to consumers' credit history: credit reporting agencies can only allow potential lenders and others with a similar "valid need" to access a consumer's file.²⁴⁴

237. Ma, *supra* note 62.

238. *See, e.g., id.* (calling it "creepy"); Maya Wang, *China's Chilling 'Social Credit' Blacklist*, WALL ST. J. (Dec. 11, 2017, 6:47 PM), <https://www.wsj.com/articles/chinas-chilling-social-credit-blacklist-1513036054> [<https://perma.cc/G6BV-2W5W>]; Rachel Botsman, *Big Data Meets Big Brother as China Moves to Rate Its Citizens*, WIRED UK (Oct. 21, 2017), <https://www.wired.co.uk/article/chinese-government-social-credit-score-privacy-invasion> [<https://perma.cc/C4M7-VRDE>].

239. *See* Elkin-Koren & Gal, *supra* note 230, at 415-16 (noting that using data for regulatory purposes can change the incentives to collect data and thus can reduce the amount of data available).

240. Electronic Communications Privacy Act of 1986, 18 U.S.C. § 2703 (restricting the government's access to electronic communications); Right to Financial Privacy Act of 1978, 12 U.S.C. § 3402 (limiting the government's access to financial information); Foreign Intelligence Surveillance Act of 1978, 50 U.S.C. § 1801 (codifying minimization procedures the government must follow to protect private parties' information); USA FREEDOM Act of 2015 §§ 201-02, 50 U.S.C. §§ 1841(4)(B), 1842(h)(1) (providing privacy safeguards for information gathered by pen registers, and trap and trace devices).

241. *See* 12 C.F.R. § 202.6 (2019); *Your Equal Credit Opportunity Rights*, FTC CONSUMER INFO. (Jan. 2013), <https://www.consumer.ftc.gov/articles/0347-your-equal-credit-opportunity-rights> [<https://perma.cc/NV9Z-KGX3>]. *But see* 12 C.F.R. § 202.5 (2019) (allowing creditors to inquire into marital status in certain ways under specific circumstances).

242. *See, e.g.,* I.R.C. §§ 6103, 7213 (noting procedural hurdles that must be cleared before certain consumer tax information can be disclosed).

243. U.S. CONST. amend. IV.

244. FTC, A SUMMARY OF YOUR RIGHTS UNDER THE FAIR CREDIT REPORTING ACT 2, <https://www.consumer.ftc.gov/articles/pdf-0096-fair-credit-reporting-act.pdf> [<https://perma.cc/>].

A consumer who is denied credit, insurance, or employment because of her credit report must be informed and given the contact information of the agency that provided the report.²⁴⁵ Furthermore, FCRA requires credit reporting agencies to adhere to various procedures while maintaining credit files.²⁴⁶ Among other requirements, credit reporting agencies must give consumers access to all of the information in their files, provide consumers their credit score upon request, investigate claims that information in the file is inaccurate, and delete or correct inaccurate, incomplete, or unverifiable information.²⁴⁷

From the perspective of personalized lawmaking, the two approaches described above—taking information off the table or placing it behind procedural barriers—constitute differences in degree, but not in kind. Both reduce the amount of data that policymakers can bring to bear and the ways in which they can deploy it.²⁴⁸ Accordingly, both limit regulators' ability to personalize law.²⁴⁹

Even if regulators are legally permitted to use certain data, privacy concerns may still shape and limit the personalization of law. First, regulators may need to take efforts to maintain the security of certain information entrusted to their care.²⁵⁰ Such security measures may make it more difficult to use that data. For example, the gold standard for safeguarding data is to only keep it on computers that are not connected to the internet, sometimes

cc/VT2L-BHVW]. FCRA uses the term “consumer reporting agency.” *Id.* at 1. For the benefit of readers who are unfamiliar with FCRA’s statutory framework, we use the (hopefully more intuitive) phrase “credit reporting agency.” *See* 15 U.S.C. §§ 1681(a)(4), 1681(b).

245. FTC, *supra* note 244, at 1.

246. *Id.* at 1-2.

247. *Id.* Some of FCRA’s other requirements are that credit reporting agencies may not report negative information that happened sufficiently far in the past, they may not give access to an employer or potential employer without the consumer’s written consent, and they must allow consumers to implement a “security freeze” that prohibits the release of any information without the consumer’s express authorization. *Id.* at 2.

248. *See* Porat & Strahilevitz, *supra* note 3, at 1467-68 (noting the trade-offs between protecting privacy and the degree of legal personalization).

249. *Id.* at 1467.

250. *See, e.g.*, U.S. DEP’T OF EDUC., SAFEGUARDING STUDENT PRIVACY 1, <https://www2.ed.gov/policy/gen/guid/fpco/ferpa/safeguarding-student-privacy.pdf> [<https://perma.cc/S9KE-A64Y>]; U.S. DEP’T OF HEALTH & HUM. SERVS., SUMMARY OF THE HIPAA SECURITY RULE (July 26, 2013), <https://www.hhs.gov/hipaa/for-professionals/security/laws-regulations/index.html> [<https://perma.cc/CV7R-QF3C>].

known as “air-gapping.”²⁵¹ Air-gapping makes data more secure by making it much harder for would-be hackers to access it—but it also makes it much harder for workers within an organization to access that data.²⁵² Less draconian security measures also create access problems. For instance, Veterans Administration doctors have complained that security measures designed to protect service members’ medical information make it difficult for doctors to access patient records and to provide care.²⁵³

Second, an extremely well-tailored rule may tell regulated parties that the regulator knows a great deal about them. Regulators may not wish to make this fact so salient—for altruistic reasons, self-serving reasons, or a combination of the two.

For example, avid runner Alex may be grateful when the Medical Machine assigns her an Acme joint, but she may also be disturbed that the government knew enough about her habits and lifestyle to make that decision.²⁵⁴ A purely altruistic regulator should take into account the discomfort that Alex experiences from her loss of privacy, as revealed to her through overly specific rules, when designing personalized laws. A self-interested regulator should also include Alex’s discomfort in its calculations, albeit for different reasons: citizens’ unease may lead to political consequences that the regulator does not want; that unease may cause Alex (and others) to support legislation that increases privacy protections or curbs personalized rulemaking.²⁵⁵ These concerns are not mutually

251. The term arose “because prior to wireless networking it literally meant making sure there was no cable physically connecting a computer to the public Internet.” Josephine Wolff, *Great, Now Malware Can Jump the “Air Gap” Between Computers*, SLATE (Dec. 3, 2013, 5:08 PM), <https://slate.com/technology/2013/12/researchers-michael-hanspach-michael-goetz-prove-malware-can-jump-air-gap-between-computers.html> [<https://perma.cc/Q9PL-Q9YR>].

252. *See id.* (“[Air gapping] is one of the most drastic, inconvenient, and difficult-to-maintain computer security measures out there. It’s usually reserved for systems that require the very highest levels of security, because it leaves you with a computer system that may be limited in what it can do.”); *see also* Samuel Joseph O’Malley & Kim-Kwang Raymond Choo, *Bridging the Air Gap: Inaudible Data Exfiltration by Insiders* 1, (20th Ams. Conf. on Info. Sys., 2014), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2431593 [<https://perma.cc/XV25-7DLB>].

253. *See, e.g.*, Arthur Allen, *‘We Took a Broken System and Just Broke It Completely,’ POLITICO* (Mar. 8, 2018, 5:05 AM), <https://www.politico.com/story/2018/03/08/veterans-military-health-system-trump-386232> [<https://perma.cc/B76G-DRV9>].

254. *Cf.* Seligman, *supra* note 134, at 13-14.

255. *Cf.* European Parliament and Council Regulation 2016/679, 2016 O.J. (L 119) 1, 1-2 (providing an example of regulations designed to increase privacy protection for personal

exclusive. Taken together, they suggest that regulators themselves may not wish to target rules as specifically as they could.

Corporations have encountered a variant of this problem. As noted earlier, Target uses big data techniques to identify shoppers, such as pregnant women, who are likely to buy specific items.²⁵⁶ It then sends customers coupon books showcasing products that are likely to be of particular interest.²⁵⁷ Target found that people did not like receiving hyper-targeted coupon books.²⁵⁸ People were uncomfortable that Target knew such personal things about them—that they recently became pregnant, for example—without being told.²⁵⁹ Target responded by making its coupon books less personalized; it intentionally added coupons for items that recipients would not want to purchase.²⁶⁰ This made the recipients feel as if the coupons for items they *did* want to purchase—the crib pictured next to the bar stool or bocce ball set—were fortuitous coincidences and not the result of intrusive data gathering.²⁶¹ As one Target executive put it:

[W]e started mixing in all these ads for things we knew pregnant women would never buy, so the baby ads looked random. We'd put an ad for a lawn mower next to diapers. We'd put a coupon for wineglasses next to infant clothes. That way, it looked like all the products were chosen by chance.

And we found out that as long as a pregnant woman thinks she hasn't been spied on, she'll use the coupons. She just assumes that everyone else on her block got the same mailer for diapers and cribs. As long as we don't spook her, it works.²⁶²

Other companies have had similar experiences. Credit card companies have identified a wide range of purchasing behaviors that indicate that a customer has become more or less likely to pay her

data).

256. Duhigg, *supra* note 15.

257. *Id.*

258. *Id.*

259. *Id.*

260. *Id.*

261. *Id.*

262. *Id.*

debts.²⁶³ For instance, buying carbon-monoxide detectors, name-brand automotive oil, or “those little felt pads that stop chair legs from scratching the floor” were associated with strong creditworthiness.²⁶⁴ Charges at pawn shops, for marital therapy, or even at specific bars were associated with decreased creditworthiness.²⁶⁵ However, companies generally made little use of this information because executives were “scared that people will resent companies for knowing too much” and “because they worried that customers would revolt if they found out they were being studied so closely.”²⁶⁶

These experiences suggest that regulators may also prefer to employ incompletely personalized laws, even if it results in a poorer matching of circumstances to legal outcomes.

C. Regulatory Authority

Even making the heroic assumption that regulators can access all of the necessary information, they may lack the legal authority or the political will to thwart gamesmanship. Suppose that the transportation authority knows that Dr. Garcia is running late because she tried to game the system and shorten her commute. What will it do with that information? If it fails to prioritize her commute, Dr. Garcia will suffer—and so will her patient.²⁶⁷ Faced

263. Duhigg, *supra* note 104.

264. *Id.* Buying “premium birdseed and a device called a ‘snow roof rake’ that homeowners use to remove high-up snowdrifts so they don’t fall on pedestrians” were also strong positive indicators of creditworthiness. *Id.*

265. *Id.* (“[D]ata indicated those [charges] were signs of desperation or depression that might lead to job loss.” Researchers identified “the ‘riskiest’ drinking establishment in Canada [was] Sharx Pool Bar in Montreal, where 47 percent of the patrons who used their Canadian Tire card missed four payments over 12 months.”). Buying a “chrome-skull car accessory or a ‘Mega Thruster Exhaust System’” was also a bad sign. *Id.*

266. *Id.* The FTC successfully challenged a credit provider that based credit restrictions on an undisclosed behavioral scoring model that penalized customers for using their credit cards for certain transactions, such as marriage counseling, therapy, or tire repair services. See Complaint for Permanent Injunction & Other Equitable Relief at 34-35, *FTC v. CompuCredit Corp.*, No. 1:08-CV-1976 (N.D. Ga. June 10, 2008), <https://www.ftc.gov/sites/default/files/documents/cases/2008/06/080610compucreditcmptsigned.pdf> [<https://perma.cc/4WPL-CMZT>]; Stipulated Order for Permanent Injunction & Other Equitable Relief Against Defendant CompuCredit Corp. at 3, *FTC v. CompuCredit Corp.*, No. 1:08-CV-1976 (N.D. Ga. Dec. 19, 2008), <https://www.ftc.gov/sites/default/files/documents/cases/2008/12/081219compucreditstiporder.pdf> [<https://perma.cc/338X-ULPJ>].

267. See *supra* text accompanying notes 191-93.

with this choice, it would be very difficult for the regulator not to give Dr. Garcia beneficial treatment and speed her off to work.²⁶⁸

Giving the regulator a wider set of responsive options can ameliorate this problem. Perhaps the transportation authority could speed Dr. Garcia to work but then slow her commute home by a comparable amount. Alternatively, perhaps it could impose a fine on Dr. Garcia. If the regulator is a state actor, there are potentially a wide range of options available to it.²⁶⁹ But if the creators and enforcers of personalized law are predominantly private actors, as some have predicted, then the regulator's powers may be restricted to a more narrowly circumscribed domain.²⁷⁰

A private transportation authority may have sufficient options to deal with the delinquent doctor. But what to do with Bob and his damaged liver? Even if regulators know for certain that he drank champagne with the intent of damaging his liver, ignoring his new state could be a death sentence. The medical authority could punish him by providing him worse medical care, but this also seems ghoulish. Perhaps the medical authority could impose fines, but it might take a very high fine to dissuade Bob from moving himself up the queue. And what if Bob cannot pay? Would the medical authority have the ability to subject Bob to criminal punishment?

These kinds of heavy-handed responses could be extremely unpopular, which raises two related problems. First, it may reduce the likelihood that regulators will be granted the authority to take these actions. Second, even if regulators are authorized to take

268. This dilemma matches a game theory concept known as subgame perfection. Essentially, for a particular strategy combination to be sustainable, every actor in the sequence must be willing to act according to its stated strategy in every possible outcome. See FUDENBERG & TIROLE, *supra* note 175, at 69-74. The transportation authority can try to discourage the doctor from waiting to leave for work by threatening not to prioritize her travel if she does. But if, when it comes down to it, the transportation authority is not willing to delay the doctor on her way to work, the doctor can essentially call their bluff by delaying her trip and forcing the transportation authority to either speed her to work or suffer the consequences of her being late. This renders the transportation authority's threat ineffective.

269. See Verstein, *supra* note 9, at 578 ("When optimal personalization turns on global knowledge and this information cannot be shared with private actors, the government may be the appropriate personalizing body.")

270. See *id.* at 579 (noting that private regulators may confront "legitimacy objections" when issuing personalized law).

these actions, political concerns may make regulators reticent to use that power.²⁷¹

Personalized law could also be politically unpopular for a different reason: individuals will vary in their ability to circumvent personalized law. For example, sophisticated parties will generally have a greater ability to manipulate a complicated regulatory system than less sophisticated parties.²⁷² Accordingly, the gaming of personalized law can raise issues of equity—on top of the underlying issues of equity already inherent to personalized law.²⁷³ Regulators may worry that popular concerns about equity will make personalized law politically unpopular and thus infeasible.²⁷⁴ This popularity concern will push regulators toward a lower level of legal personalization.

Regulators can limit regulated parties' ability to circumvent personalized law by focusing on characteristics that regulated parties cannot easily change.²⁷⁵ However, regulating based on immutable (or quasi-immutable) characteristics raises a number of concerns.²⁷⁶ The political process often translates those concerns into legal limitations on the consideration of such characteristics.

First, many immutable or quasi-immutable characteristics—race, ethnicity, gender, sexual orientation, national origin, religious identity, medical status, and disability, to name a few—are social and political flashpoints.²⁷⁷ Regulating on any of these bases is at

271. See, e.g., Paula Mejia, *IRS Under Microscope After John Oliver Televangelism Segment*, NEWSWEEK (Aug. 23, 2015, 1:28 PM), <https://www.newsweek.com/irs-under-microscope-after-john-oliver-televangelism-segment-365291> [<https://perma.cc/UX6S-LMSK>] (“The IRS conducted a mere three audits of churches in 2013-2014, and had suspended them entirely between 2009 and 2013.”); *Our Lady of Perpetual Exemption*, WIKIPEDIA, https://en.wikipedia.org/wiki/Our_Lady_of_Perpetual_Exemption [<https://perma.cc/5J24-YA76>] (describing John Oliver’s stunt church, created to highlight the lax IRS regulation of churches).

272. Depersonalized laws often exhibit the same dynamic. See, e.g., Parag A. Pathak & Tayfun Sönmez, *Leveling the Playing Field: Sincere and Sophisticated Players in the Boston Mechanism*, 98 AM. ECON. REV. 1636, 1637-38 (2008) (finding that sophisticated students could better manipulate a public school admissions system). Thus, whether personalized law improves upon or exacerbates this issue will depend on the specific circumstances. See *id.*

273. See Fleischer, *supra* note 190, at 229-30 (noting the ethical problems associated with regulatory gamesmanship).

274. Of course, regulators may also be concerned about these issues of equity directly. That would further push regulators toward a lesser degree of personalization.

275. See Porat & Strahilevitz, *supra* note 3, at 1454.

276. See, e.g., Seligman, *supra* note 134, at 14.

277. Distinguishing based on immutable characteristics, directly or indirectly, raises deep

best controversial and, in many instances, deeply and fundamentally objectionable.²⁷⁸ Not surprisingly, a plethora of statutes and several constitutional provisions forbid various decision makers from taking these items into account.²⁷⁹

One might think that this would be an easy problem to address: machines would presumably work out personalized laws by applying algorithms to data and “machines can be instructed to ignore factors that we do not want the law to consider. Thus a machine can be told to ignore race, gender, religion and the like even if they are relevant to an outcome objective.”²⁸⁰

However, in reality, the problem is much thornier. Even if machines are not given data on disfavored characteristics, they are likely to receive other data that can function as proxies.²⁸¹ Many neighborhoods exhibit a low degree of racial diversity; an individual’s address can thus serve as a close proxy for race.²⁸² Knowing that a person attended a women’s college is a good indicator that the individual is female. Knowing that a person buys a pine tree each December is a good indicator that he may be Christian. If

questions of equity and social values. *See, e.g.*, Talia B. Gillis & Jann L. Spiess, *Big Data and Discrimination*, 86 U. CHI. L. REV. 459, 485-86 (2019); Dawinder S. Sidhu, *Moneyball Sentencing*, 56 B.C. L. REV. 671, 709 (2015); Sonja B. Starr, *Evidence-Based Sentencing and the Scientific Rationalization of Discrimination*, 66 STAN. L. REV. 803, 806 (2014). Beyond these important policy questions, distinguishing on certain immutable characteristics is unconstitutional. *See, e.g.*, *Brown v. Bd. of Educ.*, 347 U.S. 483, 495 (1954) (holding that racial segregation in public schools violates the Equal Protection Clause), *supplemented by*, 349 U.S. 294 (1955); *Craig v. Boren*, 429 U.S. 190, 210 (1976) (striking down a statute that adopted different legal drinking ages for men and women for violating the Equal Protection Clause).

278. *See, e.g.*, Seligman, *supra* note 134, at 14-15; Starr, *supra* note 277, at 803.

279. *See, e.g.*, U.S. CONST. amends. XIV, XV, XIX, XXVI; 42 U.S.C. §§ 1981, 2000a, 3604, 3605(a); 15 U.S.C. § 1691(a)(1)-(3). Private organizations sometimes create their own nondiscriminatory policies as well. *See, e.g.*, *Code of Ethics and Business Conduct*, SOC’Y FOR HUM. RES. MGMT., <https://www.shrm.org/resourcesandtools/tools-and-samples/policies/pages/code-of-ethics-conduct-policy.aspx> [<https://perma.cc/G9CL-RCFX>].

280. Casey & Niblett, *supra* note 1, at 1428.

281. *See, e.g.*, Gillis & Spiess, *supra* note 277, at 468-71; Talia Gillis, *False Dreams of Algorithmic Fairness: The Case of Credit Pricing* 48-53 (Nov. 1, 2019) (unpublished manuscript), https://scholar.harvard.edu/files/gillis/files/gillis_jmp_191101.pdf [<https://perma.cc/8A5V-QRR4>].

282. *See, e.g.*, MARGERY AUSTIN TURNER & JULIE FENDERSON, *URB. INST., UNDERSTANDING DIVERSE NEIGHBORHOODS IN AN ERA OF DEMOGRAPHIC CHANGE 2* (2006), <https://www.urban.org/sites/default/files/publication/50906/411358-Understanding-Diverse-Neighborhoods-in-an-Era-of-Demographic-Change.PDF> [<https://perma.cc/76DX-RPFW>] (“[A]lmost a quarter of all tracts in the 100 largest metro areas (23.8 percent) are racially and ethnically exclusive (more than 90 percent white).”).

religion is relevant to an outcome of interest,²⁸³ then pine tree-purchasing behavior will also appear relevant to that outcome, even if it is not, because it is highly correlated with religion—which, by assumption, is both unobserved and relevant.²⁸⁴ The machines will effectively use pine tree-purchasing behavior as a proxy for religion when crafting personalized law.²⁸⁵ In other words, denying the machines access to specific characteristics that we do not want them to consider will not prevent the machines from finding indirect ways to deduce those characteristics.²⁸⁶

283. Any such relevance may itself represent a social problem. For example, race may be associated with a higher likelihood of arrest if members of some races are more likely to be stopped and questioned by law enforcement, and thus are more likely to be caught when they engage in illegal behavior, than members of other races. Indeed, this result could obtain even when individuals of an over-arrested race engage in illegal behavior less frequently than other individuals. *See, e.g.*, Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671, 687 (2016); Anupam Chander, *The Racist Algorithm?*, 115 MICH. L. REV. 1023, 1036-39 (2017).

284. *See, e.g.*, Kevin A. Clarke, *The Phantom Menace: Omitted Variable Bias in Econometric Research*, 22 CONFLICT MGMT. & PEACE SCI. 341, 343 (2005); Bernard E. Harcourt, *Risk as a Proxy for Race*, CRIMINOLOGY & PUB. POL'Y 2 (Univ. Chi., Olin L. & Econ. Working Paper, Paper No. 535, Pub. L. & Legal Theory Working Paper No. 323, 2010), http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1677654 [<https://perma.cc/DV4M-U6W3>].

285. Of course, the machines will not know that they are doing this, but that is presumably little consolation. Moreover, it may be difficult to tell whether and to what extent the machines are using a particular piece of data for its own sake or as a proxy for prohibited considerations. *See, e.g.*, Chander, *supra* note 283, at 1036-39. For example, knowing someone's address gives you information not only about her race but also about the weather, air and water pollution, crime, and noise to which she is exposed. This complicates the data oversight problem.

286. *See* Gillis, *supra* note 281, at 52-62. Antidiscrimination laws generally prohibit discrimination based on indirect proxies for prohibited considerations, and many allow claims based on disparate impact, that is, facially neutral conduct that has discriminatory effects. *See, e.g.*, *Tex. Dep't of Hous. & Cmty. Affs. v. Inclusive Cmty. Project, Inc.*, 576 U.S. 519, 525 (2015) (confirming that disparate impact claims can be made under the Fair Housing Act); *Ramirez v. GreenPoint Mortg. Funding, Inc.*, 633 F. Supp. 2d 922, 926-27 (N.D. Cal. 2008) (allowing a disparate impact claim under the Equal Credit Opportunity Act). Even if indirect algorithmic consideration of such characteristics were legal, that legality would not address many of the moral or philosophical objections to taking such considerations into account.

It is worth noting that personalized law, with its increased use of algorithmic decision-making, could make it easier to root out discrimination; unlike with a human decision maker, one can often see exactly what an algorithm considered when making its decision and how changes in circumstances would change that decision. *See, e.g.*, Jon Kleinberg, Jens Ludwig, Sendhil Mullainathan & Cass R. Sunstein, *Discrimination in the Age of Algorithms*, 10 J. LEGAL ANALYSIS 113, 114 (2018) ("Crucially, these benefits will only be realized if policy changes are adopted.... [W]ithout the appropriate safeguards, the prospects for detecting discrimination in a world of unregulated algorithm design could become even more serious

Moreover, regulating based on immutable characteristics raises concerns even when it does not touch on prominent social fault lines. For example, consider one source of data that could be useful for personalized law: DNA, our genetic code. One's DNA is difficult to alter, and genes may be associated with a number of items of interest, including predisposition to diseases,²⁸⁷ physical traits,²⁸⁸ and behaviors.²⁸⁹ Some of the information contained in DNA implicates the flashpoints described above,²⁹⁰ but much of it does not.²⁹¹ DNA might therefore constitute useful data that decision makers could take into account, provided they meet appropriate safeguards. However, concerns over the use of genetic data led Congress to enact the Genetic Information Nondiscrimination Act of 2008 (GINA).²⁹² GINA prohibits health insurance companies from using genetic test results to determine coverage costs, and employers from using

than they currently are.”). In any event, personalized law will not eliminate all objectionable discrimination, and thus this issue will persist to some degree.

287. See, e.g., Laura J. van't Veer, Hongyue Dai, Marc J. van de Vijver, Yudong D. He, Augustinus A. M. Hart, Mao Mao, Hans L. Peterse, Karin van der Kooy, Matthew J. Marton, Anke T. Witteveen, George J. Schreiber, Ron M. Kerkhoven, Chris Roberts, Peter S. Linsley, René Bernards & Stephen H. Friend, *Gene Expression Profiling Predicts Clinical Outcome of Breast Cancer*, 415 NATURE 530, 532 (2002).

288. See, e.g., Hana Lango Allen et al., Letter, *Hundreds of Variants Clustered in Genomic Loci and Biological Pathways Affect Human Height*, 467 NATURE 832, 832 (2010); S. Craig Roberts, Anthony C. Little, L. Morris Gosling, David I. Perrett, Vaughan Carter, Benedict C. Jones, Ian Penton-Voak & Marion Petrie, *MHC-Heterozygosity and Human Facial Attractiveness*, 26 EVOLUTION & HUM. BEHAV. 213, 213 (2005); cf. Irene Hanson Frieze, Josephine E. Olson & June Russell, *Attractiveness and Income for Men and Women in Management*, 21 J. APPLIED SOC. PSYCH. 1039, 1052 (1991); Timothy A. Judge & Daniel M. Cable, *The Effect of Physical Height on Workplace Success and Income: Preliminary Test of a Theoretical Model*, 89 J. APPLIED PSYCH. 428, 437-38 (2004).

289. See, e.g., Justin R. Garcia, James MacKillop, Edward L. Aller, Ann M. Merriwether, David Sloan Wilson & J. Koji Lum, *Associations Between Dopamine D4 Receptor Gene Variation with Both Infidelity and Sexual Promiscuity*, 5 PLOS ONE 1, 4 (2010); Kerry L. Jang, W. John Livesley & Philip A. Vernon, *Heritability of the Big Five Personality Dimensions and Their Facets: A Twin Study*, 64 J. PERSONALITY 577, 577 (1996); Porat & Strahilevitz, *supra* note 3, at 1469-70 (“Personality seems to have a strong genetic component and be heritable.”).

290. For example, the presence of “XX” or “XY” chromosome pairs would tell one a lot about a person's gender.

291. See, e.g., *Scientists Identify Genes Associated with Violent Crime*, IFLSCIENCE, <https://www.iflscience.com/brain/genes-associated-violent-crimes-identified/> [<https://perma.cc/4USR-RM5F>]; *Gene Linked to Needing Less Sleep Identified*, SCI. DAILY (Aug. 28, 2019), <https://www.sciencedaily.com/releases/2019/08/190828111247.htm> [<https://perma.cc/43X2-AFVX>].

292. Pub. L. No. 110-233, 122 Stat. 881.

genetic information to make hiring, firing, and promotion decisions.²⁹³ This precedent illustrates how popular concerns may limit regulatory regimes based on characteristics that are difficult for regulated parties to manipulate.

Unpopularity has already constrained private actors' use of big data. For instance, customers have generally reacted very negatively to the use of big data to price discriminate.²⁹⁴ To take one example, in 2000, a customer appeared to catch Amazon personalizing the price of a DVD, offering him a price that was four dollars more than that offered to other potential buyers.²⁹⁵ Amazon CEO Jeff Bezos apologized personally, and Amazon gave refunds to thousands of customers.²⁹⁶ Some commentators have speculated that, in the age of social media, a similar incident today could lead to a boycott.²⁹⁷ Amazon now claims that it does not use much of the data to which it has access—such as where a customer lives, her browsing history, and what she has previously bought on Amazon—when setting prices.²⁹⁸

Other companies have been caught engaging in price discrimination and found themselves pilloried in major news outlets. The *Wall Street Journal* found that Staples engaged in price discrimination,

293. *Id.* at 883, 896, 907.

294. See Kominers, *supra* note 18; Adam Tanner, *Different Customers, Different Prices, Thanks to Big Data*, FORBES (Mar. 26, 2014, 6:00 AM), <https://www.forbes.com/sites/adam-tanner/2014/03/26/different-customers-different-prices-thanks-to-big-data/?sh=5c3b100346bd> [<https://perma.cc/T8TV-D99L>]. See generally Eric T. Anderson & Duncan I. Simester, *Price Stickiness and Customer Antagonism*, 125 Q.J. ECONOMICS 729 (2010) (investigating how price stickiness affects consumer behavior); Daniel Kahneman, Jack L. Knetsch & Richard Thaler, *Fairness as a Constraint on Profit Seeking: Entitlements in the Market*, 76 AM. ECON. REV. 728 (1986) (analyzing how fairness concerns, including customer reactions to price setting, constrain firms' behavior).

295. Brian Wallheimer, *Are You Ready for Personalized Pricing?*, CHI. BOOTH REV. (Feb. 26, 2018), <https://review.chicagobooth.edu/marketing/2018/article/are-you-ready-personalized-pricing> [<https://perma.cc/QG98-EH84>]. Amazon claimed that the company was not price discriminating, but was instead offering random prices to determine how to optimally price products. *Id.*

296. *Id.*

297. See *id.* Amazon's customers have also brought several lawsuits against the company challenging its discriminatory pricing. See, e.g., Abel, *supra* note 221 (discussing lawsuits alleging that the interaction of Amazon's personalized pricing and its Amazon Prime memberships created unlawful results).

298. See Michael J. Martinez, *Amazon Error May End 'Dynamic Pricing'*, ABC NEWS (Jan. 7, 2006, 7:29 AM), <https://abcnews.go.com/Technology/story?id=119399&page=1> [<https://perma.cc/U3TP-XV3F>].

offering lower prices to customers who lived close to rivals such as OfficeMax or Office Depot.²⁹⁹ Commentators then criticized Staples for charging higher prices to poorer and rural customers.³⁰⁰ Orbitz “charged Mac users as much as 30% more than PC users” for lodging, then discontinued the practice after the conduct was publicized.³⁰¹ Travelocity, Home Depot, Rosetta Stone, and other companies allegedly engaged in similar behaviors as well.³⁰² Companies’ responses to these stories demonstrate just how concerned they are about bad press and popular backlash.³⁰³

Popular outrage and opprobrium may be at least as big a problem for a regulator, which is at the mercy of the political process, as it is for private companies. Political roadblocks may thus limit regulators’ ability to implement personalized laws, especially personalized laws that draw fine distinctions. And, as noted above, fine distinctions may be impossible in any event due to the data muddling or privacy concerns of regulated parties.³⁰⁴

D. Transparency

People’s reactions to personalized laws will depend on their level of trust in the relevant regulatory body. In a democracy, transparency is a key determinant of people’s comfort levels. If regulators are shielded from oversight, citizens may worry about corruption,

299. Jennifer Valentino-DeVries, Jeremy Singer-Vine & Ashkan Soltani, *Websites Vary Prices, Deals Based on Users’ Information*, WALL ST. J. (Dec. 24, 2012), <https://www.wsj.com/articles/SB10001424127887323777204578189391813881534> [<https://perma.cc/6NBF-7M3V>].

300. See, e.g., Devindra Hardawar, *Staples, Home Depot, and Other Online Stores Change Prices Based on Your Location*, VENTURE BEAT (Dec. 24, 2012, 6:48 AM), <https://venturebeat.com/2012/12/24/staples-online-stores-price-changes/> [<https://perma.cc/8WUZ-ANBP>]; Cathy O’Neil, *Staples.com Rips Off Poor People; Let’s Take Control of Our Online Personas*, MATHBABE (Aug. 22, 2013), <https://mathbabe.org/2013/08/22/staples-com-rips-off-poor-people-lets-take-control-of-our-online-personas/> [<https://perma.cc/823A-QNDT>].

301. Elizabeth Dwoskin, *Why You Can’t Trust You’re Getting the Best Deal Online*, WALL ST. J. (Oct. 23, 2014, 12:01 AM), <https://www.wsj.com/articles/why-you-cant-trust-youre-getting-the-best-deal-online-1414036862> [<https://perma.cc/S9F4-XVTA>]; see Valentino-DeVries et al., *supra* note 299.

302. Dwoskin, *supra* note 301; Valentino-DeVries et al., *supra* note 299.

303. See, e.g., Dwoskin, *supra* note 301; Valentino-DeVries et al., *supra* note 299; cf. Victoria L. Schwartz, *Corporate Privacy Failures Start at the Top*, 57 B.C. L. REV. 1693, 1693 (2016) (arguing that corporate executives are selected not to value privacy, and that this makes it harder for them to anticipate when others will be upset by privacy intrusions).

304. See *supra* Parts III.A-B.

improper use of data, and other bad behavior.³⁰⁵ By contrast, if it is easy to see what regulators are doing, there will be less opportunity for regulatory malfeasance, and people will be more willing to empower regulators.³⁰⁶

At the same time, the more that regulators disclose about how their algorithms work, the easier it will be for regulated parties to manipulate those algorithms.³⁰⁷ The transparency required for appropriate oversight thus makes it harder to create an incentive-compatible system. Accommodating these constraints may mean accepting a system that matches circumstances to results in a suboptimal way.

A number of constraints may further complicate society's attempts to strike the right balance on transparency. First, people are anxious about machines taking on tasks, including decision-making, that have traditionally been left to humans.³⁰⁸ As a result, they tend to hold machines to a higher standard, demanding more accuracy from a machine than they would from a human performing the same task.³⁰⁹ The news cycle can reinforce this dynamic; in these contexts, human error may be routine and thus not newsworthy in a way that machine errors are. For example, many experts believe that self-driving cars are safer than human-driven cars, but the public disagrees and many states do not permit autonomous vehicles on public roads.³¹⁰ A human-driven car kills a pedestrian in

305. See B. Peter Rosendorff & John A. Doces, *Transparency and Unfair Eviction in Democracies and Autocracies*, 12 SWISS POL. SCI. REV. 99, 102 (2011).

306. *Id.* at 102, 111.

307. Cf. Porat & Strahilevitz, *supra* note 3, at 1455 (stating that confidential algorithms are harder to manipulate).

308. See, e.g., Casey & Niblett, *supra* note 1, at 1444 (“[P]eople are generally uncomfortable with allowing machines to make important ethical decisions.”); Olivia Solon, *More Than 70% of U.S. Fears Robots Taking Over Our Lives, Survey Finds*, GUARDIAN (Oct. 4, 2017, 1:15 PM), <https://www.theguardian.com/technology/2017/oct/04/robots-artificial-intelligence-machines-us-survey> [https://perma.cc/FB6K-PV7M].

309. See Paul Slovic, *Perception of Risk*, 236 SCIENCE 280, 280 (1987). Of course, this may change over time as people become increasingly comfortable with machines operating in this sphere. The reverse could also be true. Either way, this dynamic is likely to apply in the short term. Cf. Casey & Niblett, *supra* note 1, at 1427 (“[H]umans increasingly place their trust in machines and discover that outcomes predicted by big data are systematically better than human intuition.”).

310. See, e.g., Solon, *supra* note 308 (“Fifty-six [percent of Americans] said they would not want to ride in [a self-driving car] if given the opportunity, citing a lack of trust in the technology or an unwillingness to cede control to a machine in a potentially life-or-death

the United States roughly every ninety minutes; each of these deaths, though tragic, gets little public attention.³¹¹ However, when a self-driving car killed a pedestrian in March 2018, it was major national news.³¹² Popular concerns about automated decision-making may require regulators to provide a great deal of transparency when they use the automated tools that personalized law envisions.³¹³

Second, private parties will likely develop much of the machinery underlying personalized law.³¹⁴ These private parties will generally push to keep the details of their algorithms secret to hide them from

situation.”); *Autonomous Vehicles | Self-Driving Vehicles Enacted Legislation*, NAT’L CONF. OF STATE LEGISLATURES (Feb. 18, 2020), <http://www.ncsl.org/research/transportation/autonomous-vehicles-self-driving-vehicles-enacted-legislation.aspx> [https://perma.cc/SK3Z-THBY]; cf. Peter Hancock, *Are Autonomous Cars Really Safer Than Human Drivers?*, SCI. AM. (Feb. 3, 2018), <https://www.scientificamerican.com/article/are-autonomous-cars-really-safer-than-human-drivers/> [https://perma.cc/EER2-DRRS] (questioning whether self-driving cars are preferable to human-driven cars).

311. See, e.g., Chris Isidore, *Self-Driving Cars Are Already Really Safe*, CNN (Mar. 21, 2018, 12:07 PM), <https://money.cnn.com/2018/03/21/technology/self-driving-car-safety/> [https://perma.cc/EFX3-N87F].

312. See, e.g., Daisuke Wakabayashi, *Self-Driving Uber Car Kills Pedestrian in Arizona, Where Robots Roam*, N.Y. TIMES (Mar. 19, 2018), <https://www.nytimes.com/2018/03/19/technology/uber-driverless-fatality.html> [https://perma.cc/9THX-8LQT]; Isidore, *supra* note 311; Russ Mitchell, *Self-Driving Cars May Ultimately Be Safer than Human Drivers. But After a Pedestrian’s Death, Will the Public Buy It?*, L.A. TIMES (Mar. 21, 2018, 5:00 AM), <https://www.latimes.com/business/autos/la-fi-hy-robot-car-safety-pr-20180321-story.html> [https://perma.cc/6S6G-WQ6X].

313. These concerns may fade over time as people become more used to, and thus more comfortable with, machines acting in this capacity. See, e.g., Casey & Niblett, *Self-Driving Laws*, *supra* note 3, at 436 (discussing lasting but now-faded concern over automatic elevators). People might also have the opposite reaction, becoming more concerned if bad outcomes receive widespread news coverage. See, e.g., Thomas Germain, *How to Use Facebook Privacy Settings*, CONSUMER REPS. (Oct. 7, 2020), <https://www.consumerreports.org/privacy/facebook-privacy-settings/#:~:text=On%20a%20computer%3A%20Go%20to,%22%20and%20%22Social%20Interactions.%22> [https://perma.cc/4HWZ-7X5H] (describing consumers’ privacy concerns stemming from scandals surrounding Facebook’s data collection, including its use of automated facial recognition technology on users’ accounts); Doug Gross, *Survey: 1 in 4 Users Lie on Facebook*, CNN (May 4, 2012, 2:11 PM), <https://www.cnn.com/2012/05/04/tech/social-media/facebook-lies-privacy/index.html> [https://perma.cc/JHU8-M44F] (“25% of users said they falsified information in their profiles to protect their identity ... up from 10% ... two years ago.”). In any event, this concern is likely to be an issue initially.

314. See, e.g., Jason Tasha, *Courts Are Using AI to Sentence Criminals. That Must Stop Now*, WIRED (Apr. 17, 2017, 7:00 AM), <https://www.wired.com/2017/04/courts-using-ai-sentence-criminals-must-stop-now/> [https://perma.cc/4TDF-HK8D] (“Typically, government agencies do not write their own algorithms; they buy them from private businesses.”); Angwin et al., *supra* note 83 (discussing COMPAS and other privately developed predictive software).

competitors.³¹⁵ Private developers' desire for secrecy may make it difficult for the government to provide transparency to citizens.³¹⁶ This problem is complicated by regulated parties' constitutional and statutory information rights.³¹⁷

For example, consider the COMPAS software program.³¹⁸ COMPAS evaluates a wide range of data and assesses how likely a criminal defendant is to commit additional crimes.³¹⁹ It also predicts how various interventions (such as drug treatment programs, counseling services, or housing assistance) will affect a defendant's chances of reoffending.³²⁰ State and local authorities in many states use COMPAS scores when making bail decisions, sentencing determinations, and parole decisions.³²¹ Defendants and their counsel generally receive their COMPAS scores but are not told the details of how those scores were calculated.³²²

315. See, e.g., Simson L. Garfinkel, *A Peek at Proprietary Algorithms*, 105 AM. SCIENTIST 326 (2017), <https://www.americanscientist.org/article/a-peek-at-proprietary-algorithms> [<https://perma.cc/J6JN-T5DB>]; Rebecca Wexler, *Life, Liberty, and Trade Secrets: Intellectual Property in the Criminal Justice System*, 70 STAN. L. REV. 1343, 1343 (2018) (arguing that trade secrets should not be privileged in criminal proceedings).

316. See, e.g., Wexler, *supra* note 315, at 1349-50.

317. See, e.g., FRANK PASQUALE, *THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION* 165-66, 193 (2015); Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 17 (2014). Much of the outside knowledge of Target's use of big data comes from a *New York Times Magazine* article in which a Target statistician spoke to a reporter. See Duhigg, *supra* note 15. After Target learned that the statistician was speaking to the journalist, it asked him to stop, and he did. *Id.*

318. COMPAS is an acronym for Correctional Offender Management Profiling for Alternative Sanctions. Angwin et al., *supra* note 83.

319. *Id.* Technically, COMPAS predicts how likely similarly situated defendants are to commit crimes, as compared to the specific defendant at issue. *State v. Loomis*, 881 N.W.2d 749, 754 (Wis. 2016).

320. See Angwin et al., *supra* note 83.

321. *Id.* (identifying Florida and Wisconsin jurisdictions as using COMPAS scores to make bail decisions; Arizona, Colorado, Delaware, Kentucky, Louisiana, Oklahoma, Virginia, Washington, and Wisconsin as states in which judges receive risk assessment scores from COMPAS or a competitor program at the time of sentencing; Wisconsin as using COMPAS scores to make parole decisions); see also Cecelia Klingele, *The Promises and Perils of Evidence-Based Corrections*, 91 NOTRE DAME L. REV. 537, 551-52, 582-83 n.202 (2015).

322. Angwin et al., *supra* note 83; see also *State v. Walls*, No. 116,027, 2017 WL 2709819, at *1, *4 (Kan. Ct. App. June 23, 2017) (vacating the sentence of a defendant who received only the cover page of a report prepared by another algorithmic assessment tool (the Level of Service Inventory-Revised, or "LSI-R"), instead of the whole report, on the ground that he was denied his rights under section 21-6704(a)(1) of the Kansas Code and his constitutional right to due process of law).

This was the experience of Eric Loomis.³²³ In 2013, he was arrested driving a car that had been used recently in a drive-by shooting.³²⁴ He pled guilty to attempting to flee an officer and no contest to operating a vehicle without the owner's consent; he hoped to receive probation.³²⁵ Instead, he was sentenced to six years in prison, in part because he was "identified, through the COMPAS assessment, as an individual who is at high risk to the community."³²⁶ Loomis was given the COMPAS score, but he was not given access to the details of how the score was calculated.³²⁷ He challenged his sentence as violating his constitutional right to due process, both "because the proprietary nature of COMPAS prevent[ed him] from challenging the COMPAS assessment's scientific validity" and because COMPAS assessments consider a defendant's gender.³²⁸

The Wisconsin Supreme Court ruled against Loomis, affirming his sentence.³²⁹ Nonetheless, the ruling calls into question what role COMPAS and similar software can play going forward absent increased transparency regarding their algorithms. The court held that judges can "consider a COMPAS risk assessment at sentencing" but may not use the score "(1) to determine whether an offender is incarcerated; or (2) to determine the severity of the sentence."³³⁰ In addition, "risk scores may not be used as the determinative factor in deciding whether an offender can be supervised safely and effectively in the community."³³¹ Commentators have called into question exactly what courts *can* use COMPAS for in sentencing.³³²

323. *Loomis*, 881 N.W.2d at 754-56.

324. *Id.* at 754.

325. *Id.*

326. *Id.* at 755, 756 n.18. He was also sentenced to five years of extended supervision. *Id.* at 756 n.18.

327. *Id.* at 761.

328. *Id.* at 753.

329. *Id.* at 753-54.

330. *Id.* at 769.

331. *Id.*

332. As two commentators put it:

For Loomis, the COMPAS output was purportedly used only to "reinforce" the "assessment of the other factors" considered. The Wisconsin Supreme Court stated that the sentencing court "would have imposed the exact same sentence without it. Accordingly, we determine that the circuit court's consideration of COMPAS in this case did not violate Loomis's due process rights."

The court also required that judges receiving COMPAS assessments be advised in writing of the assessments' limitations and of concerns that have been raised about them.³³³ The opinion explicitly leaves open additional lines of attack that Loomis did not raise.³³⁴ While the case was pending, Wisconsin stopped including COMPAS assessments in presentencing reports.³³⁵ Three years passed between Loomis's initial sentencing and the Wisconsin Supreme Court's ruling in the case.³³⁶ If other defendants challenge the use of COMPAS in sentencing in the future, the state may again forbear from using COMPAS while those cases are pending. That could translate into significant stretches of time during which the state does not use COMPAS. Combined, these restrictions and limitations may render greater algorithmic transparency a necessity as a practical matter.³³⁷

This logic leads to a troubling paradox. On the one hand, if the use of a proprietary risk assessment tool at sentencing is only appropriate when the same sentencing decision would be reached without it, this suggests that the risk assessment plays absolutely no role in probation or sentencing decisions. If that is the case, then why use it at all? If, on the other hand, it may have a potential impact—despite the Wisconsin court's assertion to the contrary—then the due process question can't be pushed aside.

John Villasenor & Virginia Foggo, *Algorithms and Sentencing: What Does Due Process Require?*, BROOKINGS (Mar. 21, 2019), <https://www.brookings.edu/blog/techtank/2019/03/21/algorithms-and-sentencing-what-does-due-process-require/> [<https://perma.cc/EV89-HN6W>].

333. *Loomis*, 881 N.W.2d at 769-70.

334. Notably, the court discussed *Craig v. Boren*, 429 U.S. 190 (1976):

[*Boren* was] a case where the United States Supreme Court concluded that an Oklahoma law that prohibited the sale of 3.2% beer to men under the age 21 and to women under the age of 18 violated the [E]qual [P]rotection [C]lause of the Fourteenth Amendment. The Court explained that although state officials offered sociological or empirical justifications for the gender-based difference in the law, “the principles embodied in the Equal Protection Clause are not to be rendered inapplicable by statistically measured but loose-fitting generalities concerning the drinking tendencies of aggregate groups.”

Id. at 766. The court then noted that because Loomis had raised a due process argument instead of an equal protection argument, the court need not decide the equal protection question. *Id.*; see also Starr, *supra* note 277, at 803 (arguing that the use of certain actuarial recidivism risk prediction instruments violates the Equal Protection Clause).

335. Angwin et al., *supra* note 83.

336. Loomis was sentenced on August 12, 2013, and the Wisconsin Supreme Court ruled on July 13, 2016. See *Loomis*, 881 N.W.2d at 749; Brief of Defendant-Appellant, at 2, *Loomis*, 881 N.W.2d 749 (No. 2015AP000157).

337. See generally Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249 (2008) (discussing the procedural defects associated with automation and calling for transparency in algorithmic decision-making).

There are many other examples of regulated parties' information rights colliding with private parties' desires for secrecy regarding their proprietary algorithms. For instance, criminal defendants have challenged the admissibility of DNA identifications on the ground that the government did not provide the source code of the software that made the DNA match.³³⁸ Such arguments have sometimes proven successful.³³⁹ In another instance, the Arkansas Department of Human Services attempted to start allocating care to beneficiaries based on algorithmic assessments.³⁴⁰ Beneficiaries who were losing care sued the state, alleging that their right to due process had been violated ("Arkansas DHS Litigation"), and won.³⁴¹ A similar story played out in Idaho.³⁴²

But even the concept of transparency is tricky when it comes to algorithms.³⁴³ Most citizens understand neither the advanced mathematical techniques underlying machine learning algorithms, nor the source code implementing them.³⁴⁴ Thus, most people will have a difficult time grasping the mechanics of how an algorithm operates, even if the underlying source code is disclosed.³⁴⁵ The Arkansas DHS Litigation provides a stark and almost comic example: The software Arkansas used to assign care was designed

338. See, e.g., *People v. Wakefield*, 107 N.Y.S.3d 487, 492-93 (App. Div. 2019); Christian Chessman, Note, A "Source" of Error: Computer Code, Criminal Defendants, and the Constitution, 105 CALIF. L. REV. 179, 205-14 (2017) (explaining reasons why courts deny defendants access to source code).

339. See, e.g., Matthew Shaer, *The False Promise of DNA Testing*, ATLANTIC (June 2016), <https://www.theatlantic.com/magazine/archive/2016/06/a-reasonable-doubt/480747/> [<https://perma.cc/LHA6-4YVX>] (describing one judge's ruling that particular DNA profiling evidence was inadmissible).

340. See Colin Lecher, *What Happens When an Algorithm Cuts Your Health Care*, VERGE (Mar. 21, 2018, 9:00 AM), <https://www.theverge.com/2018/3/21/17144260/healthcare-medicaid-algorithm-arkansas-cerebral-palsy> [<https://perma.cc/R9JG-PDZK>].

341. See MEREDITH WHITTAKER, KATE CRAWFORD, ROEL DOBBE, GENEVIEVE FRIED, ELIZABETH KAZIUNAS, VAROON MATHUR, SARAH MYERS WEST, RASHIDA RICHARDSON, JASON SCHULTZ & OSCAR SCHWARTZ, AI NOW INST., AI NOW REPORT 2018, at 18 (2018), https://ainowinstitute.org/AI_Now_2018_Report.pdf [<https://perma.cc/9GRK-XX8N>].

342. Lecher, *supra* note 340.

343. See generally Robert H. Sloan & Richard Warner, *When Is an Algorithm Transparent?: Predictive Analytics, Privacy, and Public Policy*, IEEE: SEC. & PRIV., May 2018 (discussing algorithmic transparency concerns in the context of consumer transactions).

344. Cf. Casey & Niblett, *supra* note 25, at 355.

345. See Joshua A. Kroll, Joanna Huey, Solon Barocas, Edward W. Felten, Joel R. Reidenberg, David G. Robinson & Harlan Yu, *Accountable Algorithms*, 165 U. PA. L. REV. 633, 638 (2017).

by a nonprofit coalition called InterRAI.³⁴⁶ At one point, plaintiffs called in Brant Fries, president of InterRAI, to testify about how the algorithm worked.³⁴⁷ Plaintiffs' counsel asked Fries to apply the algorithm to one of the plaintiffs to demonstrate how it worked.³⁴⁸ At that point, Fries realized that the wrong calculation had been conducted, and the state agreed to restore that plaintiff's pre-algorithm level of care.³⁴⁹ As plaintiffs' counsel summarized the situation:

Of course we're gratified that DHS has reported the error and certainly happy that it's been found, but that almost proves the point of the case.... There's this immensely complex system around which no standards have been published, so that no one in their agency caught it until we initiated federal litigation and spent hundreds of hours and thousands of dollars to get here today.³⁵⁰

As challenging as it can be to understand a complicated algorithm's nuts and bolts, understanding its full implications is even harder.³⁵¹ For example, COMPAS does not consider a defendant's race directly, but it does consider factors that correlate with race.³⁵²

346. Lecher, *supra* note 340.

347. *Id.*

348. *Id.*

349. *Id.*

350. *Id.*

351. See, e.g., Ruha Benjamin, *Assessing Risk, Automating Racism*, 366 SCIENCE 421, 421 (2019); Ziad Obermeyer, Brian Powers, Christine Vogeli & Sendhil Mullainathan, *Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations*, 366 SCIENCE 447, 447 (2019) (finding that a commonly used commercial algorithm discriminates against Black patients because it uses patient care costs as a proxy for health needs; because less money is spent on Black patients' healthcare than on white patients with comparable health needs, reliance on spending as a proxy "reduces the number of Black patients identified for extra care" from 46.5 percent to 17.7 percent); Kleinberg et al., *supra* note 286, at 114 ("[A]lgorithms are not decipherable—one cannot determine what an algorithm will do by reading the underlying code. This is more than a cognitive limitation; it is a mathematical impossibility. To know what an algorithm will do, one must run it.").

352. See, e.g., Sam Corbett-Davies, Emma Pierson, Avi Feller & Sharad Goel, *A Computer Program Used for Bail and Sentencing Decisions Was Labeled Biased Against Blacks. It's Actually Not That Clear.*, WASH. POST (Oct. 17, 2016, 5:00 AM), <https://www.washingtonpost.com/news/monkey-cage/wp/2016/10/17/can-an-algorithm-be-racist-our-analysis-is-more-cautious-than-propublicas/> [<https://perma.cc/GGM3-BDHC>] ("While Northpointe's algorithm does not use race directly, many attributes that predict reoffending nonetheless vary by race. For example, black defendants are more likely to have prior arrests, and because prior arrests

One might therefore wonder whether the software discriminates against certain defendants based on their race. ProPublica judged that it does: it analyzed the COMPAS risk assessment scores for over seven thousand people arrested in Broward County, Florida, and concluded that COMPAS discriminates against Black defendants.³⁵³ Northpointe, Inc., the company that owns COMPAS, disputes ProPublica's findings,³⁵⁴ and other researchers have

predict reoffending, the algorithm flags more black defendants as high risk even though it does not use race in the classification.”).

353. See Angwin et al., *supra* note 83. ProPublica found that Black defendants were more likely to be mischaracterized as having a high risk of re-offending, while white defendants were more likely to be mischaracterized as having a low risk of reoffending. *Id.*; Jeff Larson, Surya Mattu, Lauren Kirchner & Julia Angwin, *How We Analyzed the COMPAS Recidivism Algorithm*, PROPUBLICA (May 23, 2016), <https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm> [<https://perma.cc/AQ4W-Q2GQ>].

354. WILLIAM DIETERICH, CHRISTINA MENDOZA & TIM BRENNAN, NORTHPOINTE INC. RSCH. DEP'T, COMPAS RISK SCALES: DEMONSTRATING ACCURACY EQUITY AND PREDICTIVE PARITY (2016), http://go.volarisgroup.com/rs/430-MBX989/images/ProPublica_Commentary_Final_070616.pdf [<https://perma.cc/Y8EH-CFND>] (“present[ing] evidence that refutes the claim that the COMPAS risk scales [are] biased against black defendants ... in Broward County, Florida”); see also Julia Angwin & Jeff Larson, *ProPublica Responds to Company's Critique of Machine Bias Story*, PROPUBLICA (July 29, 2016, 11:56 AM), <https://www.propublica.org/article/propublica-responds-to-companys-critique-of-machine-bias-story> [<https://perma.cc/Y3VD-2BQ5>]; Jeff Larson & Julia Angwin, *Technical Response to Northpointe*, PROPUBLICA (July 29, 2016, 11:55 AM), <https://www.propublica.org/article/technical-response-to-north-pointe> [<https://perma.cc/6N7J-JUWL>] (responding to Northpointe's criticisms and standing by ProPublica's findings).

weighed in on the topic.³⁵⁵ COMPAS continues to be widely used, but its use remains controversial.³⁵⁶

E. Regulatory Conservatism

The problems of information, regulatory authority, and transparency all feed into each other: If the transportation authority's inscrutable algorithm can levy fines or impose arbitrary delays based on its assessment of travel patterns, regulated parties will likely want to limit the information that the algorithm can access. Similarly, if the transportation authority can access vast amounts of personal information, people are likely to want strong restrictions on the purposes for which it can use that information and the actions it can take. These effects limit regulators' ability to create incentive-compatible systems and thus personalized law's ability to match factual scenarios to legal outcomes.

The complicated sociopolitical landscape surrounding personalized law may make officials wary about taking actions that may prove unpopular.³⁵⁷ Because power in the United States is

355. See, e.g., Alexandra Chouldechova, Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments 1 (Feb. 28, 2017) (unpublished manuscript) (on file with Cornell University), <https://arxiv.org/pdf/1703.00056.pdf> [<https://perma.cc/6KB9-VB8D>]; Corbett-Davies et al., *supra* note 352; Anthony W. Flores, Kristin Bechtel & Christopher T. Lowenkamp, *False Positives, False Negatives, and False Analyses: A Rejoinder to "Machine Bias: There's Software Used Across the Country to Predict Future Criminals. And It's Biased Against Blacks."*, 80 FED. PROB. 38, 38 (2016); Jon Kleinberg, Sendhil Mullainathan & Manish Raghavon, Inherent Trade-Offs in the Fair Determination of Risk Scores 1 (Nov. 17, 2016) (unpublished manuscript) (on file with Cornell University), <https://arxiv.org/pdf/1609.05807.pdf> [<https://perma.cc/B4XZ-THEJ>]; see also Julia Angwin, ProPublica's Annotations in Response to Flores Et Al., (Dec. 30, 2016), <https://www.documentcloud.org/documents/3248777-Lowenkamp-Fedprobation-sept2016-0.html> [<https://perma.cc/F8WF-BLKK>]; Julia Angwin & Jeff Larson, *Bias in Criminal Risk Scores Is Mathematically Inevitable, Researchers Say*, PROPUBLICA (Dec. 30, 2016, 4:44 PM), <https://www.propublica.org/article/bias-in-criminal-risk-scores-is-mathematically-inevitable-researchers-say> [<https://perma.cc/H393-DKT2>]; Ziyuan Zhong, *A Tutorial on Fairness in Machine Learning*, TOWARDS DATA SCI. (Oct. 21, 2018), <https://towardsdatascience.com/a-tutorial-on-fairness-in-machine-learning-3ff8ba1040cb> [<https://perma.cc/26ZD-Y5TK>]; Moritz Hardt, Eric Rice & Nathan Srebro, Equality of Opportunity in Supervised Learning 1 (Oct. 7, 2016) (unpublished manuscript) (on file with University of Chicago), <https://ttic.uchicago.edu/~nati/Publications/HardtPriceSrebro2016.pdf> [<https://perma.cc/4K7U-W539>].

356. See, e.g., Tashea, *supra* note 314; Julia Dressel & Hany Farid, *The Accuracy, Fairness, and Limits of Predicting Recidivism*, 4 SCI. ADVANCES 1, 1 (2018).

357. One additional complication is that this landscape may shift over time, further

disseminated and exercised through a multilayered structure, concerns at each layer about staying within socially approved boundaries can compound: Elected officials may limit agencies' power, or grant agencies power using vague, qualified language.³⁵⁸ Regulatory agencies may be wary of testing the vague boundaries of their powers and may confine their actions to what they consider safer legal and political ground.³⁵⁹ This dynamic can also play out within the hierarchy of an agency.³⁶⁰ These repeated iterations of caution in the face of uncertainty can significantly reduce the sphere in which regulators ultimately operate.

Regulators know that if they do overstep, they run the risk of provoking a backlash. A backlash can take many forms and may manifest on a different front than the one on which regulators overstepped. For example, suppose a regulator is considering whether to make law more personalized by incorporating new data into a legal rule. If that action proves unpopular, how might society respond? It might eliminate the regulator's access to that type of data entirely. It might take a particular enforcement tool out of the regulator's hands; it might prohibit the regulator from issuing fines above a certain level or from garnishing wages.³⁶¹ It might require the regulator to meet higher procedural or transparency hurdles before taking enforcement action.³⁶² It could impose many other measures as well, alone or in combination. The wide range of possible societal responses increases regulators' uncertainty about the consequences of potentially controversial actions. This uncertainty can encourage regulators to be conservative when designing

complicating regulators' efforts to stay on safe footing.

358. See, e.g., 15 U.S.C. § 45(a)(2) (“[e]mpower[ing] and direct[ing] the FTC to prevent ... [the use of] unfair methods of competition ... and unfair or deceptive acts or practices in or affecting commerce”); I.R.C. § 7611 (imposing limitations on the IRS's ability to audit churches, including requiring the approval of an IRS regional commissioner or higher to begin an inquiry); I.R.C. § 5000A(g) (limiting the tools available to the IRS to enforce the Patient Protection and Affordable Care Act's requirement that individuals carry insurance); see also Jordan M. Barry & Bryan T. Camp, *Is the Individual Mandate Really Mandatory?*, 135 TAX NOTES 1633, 1633, 1642 (2012) (arguing that restrictions on the IRS's ability to collect the penalty make the individual mandate nonmandatory for many taxpayers).

359. Cf. Pollman & Barry, *supra* note 217, at 410-24 (discussing how businesses can take the opposite approach).

360. See Jennifer Nou, *Intra-Agency Coordination*, 129 HARV. L. REV. 421, 429-30 (2015).

361. See, e.g., I.R.C. § 5000A(g).

362. See, e.g., *id.* § 7611 (imposing new procedural requirements on audits of churches).

personalized laws or policing gamesmanship, thereby limiting how personalized the law will be.

Finally, regulators will face uncertainty regarding how regulated parties will react to personalized laws.³⁶³ Regulated parties have frequently used rules in ways that policymakers did not anticipate or desire.³⁶⁴ This history may push regulators toward caution and incrementalism.³⁶⁵ Regulators may feel even more cautious when legal rules are the result of a multidimensional, big data modeling algorithm that no single individual may fully understand. This may encourage regulators to be more conservative when designing personalized laws, making the laws less personalized and more like conventional legal systems.

CONCLUSION

When a regulator issues a rule, it can be tempting to see that as the end of the story. But it is not. It is just one piece of a continuing interaction. Regulated parties react to the rule, changing their behavior. Some of those changes will be the ones regulators desired. Others may be unexpected, and may necessitate further responses from the regulator, continuing the back-and-forth cycle. Desired or not, expected or not, these changes constitute a significant part of the rule's real-world effects.

This dynamic between regulators and regulated parties applies with respect to personalized laws, just as it does in more conventional regulatory settings. In fact, with more varied legal rules tailored to more finely classified circumstances, regulated parties' responses may become much *more* important in the context of personalized law.

363. Modern data science techniques may give additional insight into this question. Still, even when regulators think they know how regulated parties will react to personalized laws, it will be difficult to know for sure.

364. See, e.g., Martin D. Ginsburg, *Making Tax Law Through the Judicial Process*, 70 A.B.A. J. 74, 76 (1984) (“[E]very stick crafted to beat on the head of a taxpayer will metamorphose sooner or later into a large green snake and bite the commissioner on the hind part.”); Jordan M. Barry, *Taxation and Innovation: The Sharing Economy as a Case Study*, in THE CAMBRIDGE HANDBOOK OF THE LAW OF THE SHARING ECONOMY 381, 383 (Nestor M. Davidson, Michèle Finck & John J. Infranca eds., 2018).

365. See Barry & Caron, *supra* note 81, at 73-74.

The fact that regulated parties will react to regulation does not mean that regulators cannot implement personalized laws or that doing so will produce no benefits. To the contrary, personalized law holds substantial promise and may mark a major step forward in law's long evolution.

But regulated parties' reactions to regulation—in particular, muddling data, signaling, and moral hazard—will complicate and limit personalized law. Concerns about misjudging regulated parties' reactions, and about increasing regulated parties' incentives to change their legal treatment, will push regulators toward adopting a lesser degree of personalization.

All of the issues described in this Article can be managed to varying degrees, but they cannot be fully overcome. No matter how good technology gets, we should never expect law to perfectly match outcomes to circumstances. Regulated parties' responses to laws—even personalized ones—will always prevent regulators from achieving the utopia that some envision. Personalized law may be “the future of law,”³⁶⁶ but it is no panacea.

366. Casey & Niblett, *supra* note 1, at 1402.