MODELING THROUGH

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ABSTRACT

Theorists of justice have long imagined a decision-maker capable of acting wisely in every circumstance. Policymakers seldom live up to this ideal. They face well-understood limits, including an inability to anticipate the societal impacts of state intervention along a range of dimensions and values. Policymakers see around corners or address societal problems at their roots. When it comes to regulation and policy-setting, policymakers are often forced, in the memorable words of political economist Charles Lindblom, to "muddle through" as best they can.

Powerful new affordances, from supercomputing to artificial intelligence, have arisen in the decades since Lindblom's 1959 article that stand to enhance policymaking. Computer-aided modeling holds promise in delivering on the broader goals of forecasting and systems analysis developed in the 1970s, arming policymakers with the means to anticipate the impacts of state intervention along several lines—to model, instead of muddle. A few policymakers have already dipped a toe into these waters, others are being told that the water is warm.

The prospect that economic, physical, and even social forces could be modeled by machines confronts policymakers with a paradox. Society may expect policymakers to avail themselves of techniques already usefully deployed in other sectors, especially where statutes or executive orders require the agency to anticipate the impact of new rules on particular values. At the same time, "modeling through" holds novel perils that policymakers may be ill equipped to address. Concerns include privacy, brittleness, and automation bias, all of which law and technology scholars are keenly aware. They also include the extension and deepening of the quantifying turn in governance, a process that obscures normative judgments and recognizes only that which the machines can see. The water may be warm, but there are sharks in it.

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These tensions are not new. And there is danger in hewing to the status quo. As modeling through gains traction, however, policymakers, constituents, and academic critics must remain vigilant. This being early days, American society is uniquely positioned to shape the transition from muddling to modeling.

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INTRODUCTION

Policymakers are limited. They are limited in the facts they know, in their expertise, in their time. Like everyone else, policymakers are imperfectly objective. They cannot, and seldom claim to, precisely weigh competing values or anticipate all potential outcomes when coming to a consequential decision.

Our system of government is built around these limitations. Though safeguarding against tyranny often takes center stage, the structure of the Constitution assumes official error and a diversity of competencies. That legislators are limited is the very insight that justified the extra-constitutional rise of the administrative state during the Progressive Era, the New Deal, and the Great Society.[1] In a complex republic such as our own, members of Congress cannot become experts in every subject nor respond nimbly to unfolding conditions.[2] Guided by Congress and overseen by the courts, responsibility for policymaking across our vast and varied society has come to reside largely in expert agencies.

These institutions have their limits too. Even agencies with domain knowledge and engaged stakeholders face a dearth of information, expertise, time, objectivity, and moral wisdom. As

1. *See* Mistretta v. United States, 488 U.S. 361, 372 (1989) ("[I]n our increasingly complex society, replete with ever-changing and more technical problems, Congress simply cannot do its job absent an ability to delegate power under broad general directives."); *see also* Ryan Calo & Danielle Keats Citron, *The Automated Administrative State: A Crisis of Legitimacy*, 70 EMORY L.J. 797, 803–04 (2021).

2. *See* Calo & Citron, *supra* note 1, at 832.

political economist Charles Lindblom argues in his classic 1959 article on the limits of policymaking, "The Science of 'Muddling Through,'" a public administrator is never in a position to fully maximize public and private values in a single intervention.[3] As much as they may wish to employ the "root" method of calibrating optimal policy by taking into account all relevant parameters, instead they must settle for the "branch" method of setting a specific goal and adjusting policy iteratively to address unintended consequences one issue at a time.[4] Although the root method can be followed in "relatively simple problems," writes Lindblom, "[i]t assumes intellectual capacities and sources of information that men simply do not possess."[5]

Lindblom's insight echoes that of economist and philosopher F.A. Hayek in "The Use of Knowledge in Society" with respect to economic planning.[6] Hayek readily concedes that "so far as scientific knowledge is concerned, a body of suitably chosen experts may be in the best position to command all the best knowledge available."[7] But he observes that nothing even approaching complete or sufficient knowledge is likely to occur in practice.[8] No central administrator, however masterful their grasp of economic policy, is capable of keeping up with facts on the ground, let alone the preferences of economic participants. The mistake of proponents of central economic planning is to overlook the "unavoidable imperfection of man's knowledge."[9]

Policymaking has never been a perfect art. And yet, big thinkers have long imagined an idealized decisionmaker armed with perfect knowledge and wisdom. Plato depicts Kallipolis, a utopian society ruled over by enlightened philosopher kings.[10] John Rawls imagines unbiased, powerfully rational policymakers making ideal moral decisions behind a "veil of ignorance."[11] Ronald Dworkin invokes Hercules—a supernatural judge with such exquisite knowledge of legal

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3. Charles E. Lindblom, *The Science of "Muddling Through*,*"* 19 PUB. ADMIN. REV. 79, 80 (1959).

4. *Id.* at 81.

5. *Id.* at 80.

6. *See* F. A. Hayek, *The Use of Knowledge in Society*, 35 AM. ECON. REV. 519, 520 (1945).

7. *Id.* at 521.

8. *Id.* at 530.

9. *Id.*

10. PLATO, REPUBLIC: BOOKS 1–5, at 539 (Chris Emlyn-Jones & William Preddy eds. trans., Harvard Univ. Press 2013) (c. 375 B.C.E.).

11. JOHN RAWLS, A THEORY OF JUSTICE 118 (Harvard Univ. Press rev. ed. 1999) (1971).

and moral principles that he was able to arrive at the "right" interpretation of every legal question—to illustrate his notions of justice as a form of integrity between prior precedent and moral structure.[12]

Aspiration or foil, the perfect policymaker is the stuff of fiction and theory. No person or institution feels capable of harnessing the kind of knowledge, imagination, or objectivity necessary to design an intervention into human affairs that improves society from the roots up. Society is simply too complicated, policymakers too limited in their knowledge and capabilities. Whatever the stakes, there can be no perfect policymaking any more than there could be a perfect game of chess.

And yet, millennia after Plato, and a half-century after Lindblom, along comes a set of techniques that appear vastly superior to people at making complex assessments. Particularly noteworthy is the development of artificial intelligence ("AI"), "a set of techniques aimed at approximating some aspect of human or animal cognition using machines."[13] Some of the machines among us are capable of processing an unfathomable array of variables, thereby dramatically outperforming people in certain contexts. In domains such as chess, where the rules and objectives are clear, machine decision-making indeed approaches the Herculean. No unaided human being will ever again come close to the capacity of contemporary computers to marshal chess knowledge into an unerring decision engine.[14] To witness a machine play chess—or to watch as text in one language is

12. RONALD DWORKIN, LAW'S EMPIRE 239 (1986).

13. Ryan Calo, *Artificial Intelligence Policy: A Primer and Roadmap*, 51 U.C. DAVIS L. REV. 399, 404 (2017) (defining artificial intelligence). The term "artificial intelligence" predated Lindblom's article by several years. *See* JOHN MARKOFF, MACHINES OF LOVE AND GRACE: THE QUEST FOR COMMON GROUND BETWEEN HUMANS AND ROBOTS xii (2015). Only in recent years, however, has AI advanced to the point where nonspecialists are aware of—and, indeed, often overstate—the technology's potential to enhance decision-making in an almost arbitrary set of domains. Eric Colson, *What AI-Driven Decision Making Looks Like*, HARV. BUS. REV. (July 8, 2019), https://hbr.org/2019/07/what-ai-driven-decision-making-looks-like [https://perma.cc/MB3V-WGF3].

14. Garry Kasparov, *The Chess Master and the Computer*, N.Y. REV. BOOKS (Feb. 11, 2010), https://www.nybooks.com/articles/2010/02/11/the-chess-master-and-the-computer [https://perma.cc/Q695-NWLR] (reviewing DIEGO RASSKIN-GUTMAN, CHESS METAPHORS: ARTIFICIAL INTELLIGENCE AND THE HUMAN MIND (Deborah Klosky trans. 2009)). The observation that people-machine teams outperform machines alone is now the stuff of technological nostalgia. KEVIN ROOSE, FUTUREPROOF: 9 RULES FOR HUMANS IN THE AGE OF AUTOMATION 19–20 (2021).

instantaneously translated into almost any other—is to experience an uneasy sense of wonder.

This Article explores the specific capacity of machines to model the world in service of better policymaking, a process this Article calls "modeling through."[15] It is no longer always necessary to muddle, as the intelligence, military, and industrial sectors broadly acknowledge.[16] Contemporary techniques of computation, including AI, can help policymakers build more complex models of the world to anticipate the impacts of proposed interventions on a range of values. At the same time, this Article argues that the anticipated world of modeling through has its own perils, perils that have largely escaped notice in a literature focused on the intransparency of algorithmic decision-making. Some perils are specific to information technology; others echo longstanding critiques of the cost-benefit analysis framework from which machine analysis arises.

The capacity of machines to improve the world through superior decision-making has captured the public imagination.[17] Law professors are no exception.[18] Although these techniques exist on a continuum with prior statistical methods—and while they reproduce logics and biases that are centuries in the making—there is a growing sense in law and policy circles that technology generally, and AI in particular, is positioned to enhance human decision-making at all levels.

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15. The term appears in previous work with Danielle Keats Citron. Calo & Citron, *supra* note 1, at 842. The views expressed in this Article are those of the author and should not necessarily be attributed to Professor Citron.

16. *See* TAMZY J. HOUSE, JAMES B. NEAR, JR., WILLIAM B. SHIELDS, RONALD J. CELENTANO, DAVID M. HUSBAND, ANN E. MERCER & JAMES E. PUGH, WEATHER AS A FORCE MULTIPLIER: OWNING THE WEATHER IN 2025, at vi (1996) (discussing intelligence and military uses); Louise Wright & Stuart Davidson, *How To Tell the Difference Between a Model and a Digital Twin*, ADVANCED MODELING & SIMULATION ENG. SCI., Dec. 2020, at 1, 7 (discussing industrial uses).

17. Helen Margetts & Cosmina Dorobantu, *Rethink Government with AI*, NATURE, Apr. 11, 2019, at 163, 163–64.

18. *See, e.g.*, JOHN O. MCGINNIS, ACCELERATING DEMOCRACY: TRANSFORMING GOVERNANCE THROUGH TECHNOLOGICAL CHANGE 1 (2012); Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 GEO. L.J. 1147, 1153 (2017); Eugene Volokh, *Chief Justice Robots*, 68 DUKE L.J. 1135, 1137 (2019); Mariano-Florentino Cuéllar, *A Simpler World: On Pruning Risks and Harvesting Fruits in an Orchard of Whispering Algorithms*, 51 U.C. DAVIS L. REV. 27, 29 (2017); Richard M. Re & Alicia Solow-Niederman, *Developing Artificial Intelligent Justice*, 22 STAN. TECH. L. REV. 242, 255–58 (2019).

Yet, the government's use of machines to make decisions about people has a poor history. Designed for efficiency, automated decision-making systems deployed by state administrative agencies have instead delivered ill will and costly litigation.[19] These roughly hewn software systems are responsible for multiple "algorithmic absurdities," such as reducing the in-home care available to a disabled foot amputee on the basis that he no longer had foot problems.[20] They have been criticized for their disparate impact on the vulnerable and the marginalized.[21] They have been challenged for denying due process under the Constitution,[22] for dehumanizing government-citizen interactions,[23] for thwarting public participation under the Administrative Procedure Act.[24] The systems have even been accused (by Professor Danielle Keats Citron and the author) of undermining the legitimacy of the administrative state by throwing away the very expertise and discretion that justify lawmaker delegation to agencies.[25]

Of course, all machines are different machines.[26] The automated software making headlines and court dockets across the country should not be conflated with the sophisticated systems that drive vehicles or defeat grandmasters. More fundamentally, a central problem with so-called automated decision-making systems is the fact that they are automated. People design such systems, but no person reviews the decision before its impacts are felt. It is tempting and fair to draw a distinction between decisions made automatically by simplistic

19. Calo & Citron, *supra* note 1, at 818–32.

20. *Id.* at 821 (quoting Memorandum from Kevin De Liban, Att'y, Legal Aid of Ark., Legal Aid of Arkansas Algorithm Absurdities—RUGs as Implemented in Arkansas 2 (n.d.) (on file with authors)).

21. *See, e.g.*, SAFIYA UMOJA NOBLE, ALGORITHMS OF OPPRESSION: HOW SEARCH ENGINES REINFORCE RACISM 1 (2018); RUHA BENJAMIN, RACE AFTER TECHNOLOGY: ABOLITIONIST TOOLS FOR THE NEW JIM CODE 1 (2019); VIRGINIA EUBANKS, AUTOMATING INEQUALITY: HOW HIGH-TECH TOOLS PROFILE, POLICE, AND PUNISH THE POOR 6–7 (2017).

22. *See generally* Kate Crawford & Jason Schultz, *Big Data and Due Process: Toward a Framework To Redress Predictive Privacy Harms*, 55 B.C. L. REV. 93 (2014) (arguing for procedural due process over big data).

23. *See* Paul Schwartz, *Data Processing and Government Administration: The Failure of the American Legal Response to the Computer*, 43 HASTINGS L.J. 1321, 1342 (1992).

24. Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1288 (2008).

25. Calo & Citron, *supra* note 1, at 818.

26. The reference is to the 2021 television show Ted Lasso, wherein a character reminds another that "all people are different people." *Ted Lasso: Goodbye Earl* (Warner Bros. Ent. streaming release July 23, 2021).

software and human decisions informed by sophisticated machine learning models. The former substitutes algorithmic for human judgment, the latter enhances human judgment with the power of AI.

As imprudent as it may be to turn over official judgment to software, one wonders how long policymakers can ignore the extraordinary new affordances at their fingertips. The government helps forecast the weather with steadily increasing accuracy and lifesaving consequences.[27] Games like SimCity inspired a generation of urban planners by showing them the complex effects of small decisions.[28] Why not apply the same principles to policy interventions? Attacking problems at the branch instead of the root has its costs, after all. Waiting for unintended consequences to surface before addressing them invites suffering and makes guinea pigs out of our citizenry. The government also faces formal requirements in certain settings to assess the impact of new rules on particular communities and values in accordance with best practice.[29] "[W]e cannot put up with a government that inaccurately assesses policy results with outdated methods," writes Professor John McGinnis, "when new smarter mechanisms are within its reach."[30]

At the urging of successive presidents,[31] federal policymakers are indeed beginning to experiment with machine learning and other techniques of AI in order to shape enforcement discretion, manage and analyze government information, communicate with the public, and perform other administrative functions.[32] The emerging pictures show that AI may increase efficiency in particular domains. But the government's task-based approach—wherein present-day government functions are simply sped up or sharpened by pattern recognition—has

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27. *See* Peter Bauer, Alan Thorpe & Gilbert Brunet, *The Quiet Revolution of Numerical Weather Prediction*, NATURE, Sept. 3, 2015, at 47, 47.

28. Jessica Roy, *Must Reads: From Video Game to Day Job: How 'Sim City' Inspired a Generation of City Planners*, L.A. TIMES (Mar. 5, 2019, 5:00 AM), https://www.latimes.com/business/technology/la-fi-tn-simcity-inspired-urban-planners-20190305-story.html [https://perma.cc/T42N-GXFZ].

29. *See* 44 U.S.C. § 3501; 42 U.S.C. § 4332.

30. MCGINNIS, *supra* note 18, at 2.

31. *See, e.g.*, NAT'L SCI. & TECH. COUNCIL, PREPARING FOR THE FUTURE OF ARTIFICIAL INTELLIGENCE 5 (2016); Exec. Order No. 13,859, 3 C.F.R. § 13859 (2019).

32. DAVID FREEMAN ENGSTROM, DANIEL E. HO, CATHERINE M. SHARKEY & MARIANO-FLORENTINO CUÉLLAR, GOVERNMENT BY ALGORITHM: ARTIFICIAL INTELLIGENCE IN FEDERAL ADMINISTRATIVE AGENCIES 6–7 (2020); *see also* HM TREASURY, REVIEW OF QUALITY ASSURANCE OF GOVERNMENT ANALYTICAL MODELS: FINAL REPORT 7 (2013) (defining seven areas where the U.K. Government routinely uses models and exposing the current extent and nature of their use).

yet to tap into the full potential of computational modeling. It seems rather that governments are still muddling through, just with greater speed and efficiency. The very places where one might expect computational modeling to be of use—cost-benefit analysis and impact assessment, for example, both of which are often required by statute—do not appear to leverage contemporary information technology beyond the spreadsheet.

Modeling through ultimately presents a paradox for policymakers. On the one hand, the introduction of powerful new affordances to policymaking such as computational modeling ought to raise societal expectations of how policy formulation occurs, especially where cost-benefit analysis and impact assessment are written into the law itself. Muddling isn't good enough anymore when you can model, as other sectors such as industry and academia appear to recognize. On the other, the logical endpoint of modeling through by government may be a society misdirected by technology and inexorably reduced to the measurable. This tension is an old one, poised to play out further in the years and decades to come.

This Article proceeds as follows. Part I describes at a high level the capacity of existing and emerging technology to construct elaborate, multivariable models of the world. It describes what models are, how technology improves them, and how models are used across society. Part II examines whether the U.S. government, which has been experimenting with machine learning in recent years, is modeling through in practice. Not quite yet: federal agencies are using AI largely to *muddle through* more efficiently, with a few telling exceptions. But these are early days. Part III identifies the physical, theoretical, and moral limits of modeling through, drawing in part from discussions of government modeling over the past decade. These include, inter alia, privacy harms, discrimination, and automation bias that are familiar to students of algorithmic law, alongside dangers such as the sublimation of value judgments in world simulation better known to longstanding critics of cost-benefit. Modeling through, and its tradeoffs, may both prove inevitable.

I. MODELING 101

Machines have improved our ability to model the world, with important consequences to human wellbeing. A deceptively simple example is weather prediction. The U.S. government—specifically, the National Weather Service within the National Oceanic and

Atmospheric Administration—helps generate a model of the weather and shares it with the world so that people and institutions can plan accordingly.[33] Most weather modeling today uses the same techniques as a century ago—so-called numerical weather prediction.[34] The fundamentals of numerical weather prediction date back to the turn of the twentieth century when physicists in the United States and Germany independently worked out many of the equations underlying the behavior of weather.[35] The difference is that today's weather models integrate billions of data points from thousands of terrestrial sensors, weather balloons, airplanes, satellites, and other sources—a feat that would not be possible without digital connectivity and powerful computers.[36]

As of this writing, weather modeling is not heavily reliant upon AI. The field has slowly begun to introduce machine learning and other techniques to enhance predictions or approximate a similar efficacy as numerical methods using fewer computer resources.[37] Other fields have embraced AI with aplomb, from optimizing energy consumption within a server farm to mapping the structure of proteins.[38] This modeling is subtly different and easy to oversimplify. Roughly speaking, machine learning involves extracting a set of features from large bodies of data in order to draw inferences.[39] The process is divided into a training phase, wherein a model is trained and refined on the basis of a large body of data, and an inference phase, wherein the trained model is deployed to classify or predict yet unseen data.[40] Integrated into systems, machine learning can help model

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33. *See About*, NAT'L WEATHER SERV., https://www.weather.gov/about [https://perma.cc/UW5K-UAC8].

34. *See* Bauer, Thorpe & Brunet, *supra* note 27.

35. *See id.*

36. *See id.* at 51.

37. *See, e.g.*, Hannah Hickey, *A.I. Model Shows Promise To Generate Faster, More Accurate Weather Forecasts*, U. WASH. NEWS (Dec. 15, 2020), https://www.washington.edu/news/2020/12/15/a-i-model-shows-promise-to-generate-faster-more-accurate-weather-forecasts [https://perma.cc/4JY5-MUCH].

38. *See, e.g.*, Richard Evans & Jim Gao, *DeepMind AI Reduces Google Data Centre Cooling Bill by 40%*, DEEPMIND (July 20, 2016), https://deepmind.com/blog/article/deepmind-ai-reduces-google-data-centre-cooling-bill-40 [https://perma.cc/AW2P-XCE7]; Ewen Callaway, *DeepMind's AI Predicts Structures for a Vast Trove of Proteins*, NATURE, July 22, 2021, at 635, 635.

39. Ivan Evtimov, David O'Hair, Earlence Fernandes, Ryan Calo & Tadayoshi Kohno, *Is Tricking a Robot Hacking?*, 34 BERKELEY TECH. L.J. 891, 895 (2019); Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87, 89 (2014).

40. Evtimov et al., *supra* note 39.

environments well enough to drive cars, recognize faces and voices, translate text into hundreds of languages, and defeat grandmasters at chess.

With the introduction of supercomputers in the 1970s, weather prediction became much more accurate.[41] And it is getting more accurate year by year.[42] This improvement really matters to human activity. It is not just a question of whether people will leave their homes with an umbrella. Military operations, space launches, commercial aviation, firefighting, farming, and many other activities rely upon a working sense of upcoming weather patterns.[43] Of particular importance is the lead-time modern meteorology gives government officials of impending disaster. Better weather modeling literally saves lives. The same is true of earthquake and tsunami prediction. By extension, climate modeling improves human well-being by helping people and institutions adapt to likely system-wide changes in weather due to climate change—a point to which I return below.

Modeling has become indispensable to many other areas of human industry. One example is industrial design.[44] No major structure will be built, no spacecraft launched, no wind turbine shipped, without extensive modeling. Modeling can help with the difficult task of optimizing design across multiple variables. Imagine you are building a bridge that you want to be safe, durable, sightly, and low cost. Each of these variables is important and yet often must be traded off against another. The result is a multi-objective optimization problem that can be very difficult for humans to approach unaided. Modeling can assist the designer of an artifact or system to arrive at Pareto optimality, that is, the set of designs wherein no variable can be improved without sacrificing another.[45] Human input is still needed. And the designer will ultimately need to select from a range of Pareto equivalent options, therefore privileging one value over another. But to the extent multi-

41. Bauer, Thorpe & Brunet, *supra* note 27, at 48.

42. *See id.*

43. Air Force officials have expressed a desire not only to anticipate the weather but to also alter and even weaponize it. HOUSE ET AL., *supra* note 16.

44. *See* Wright & Davidson, *supra* note 16, at 8, 11.

45. *See, e.g.*, Haris Aziz, Hervé Moulin & Fedor Sandomirskiy, *A Polynomial-time Algorithm for Computing a Pareto Optimal and Almost Proportional Allocation*, 48 OPERATIONS RSCH. LETTERS 573, 573 (2020); R. Murat Demirer & Oya Demirer, *Early Prediction of Sepsis from Clinical Data Using Artificial Intelligence*, 2019 SCI. MEETING ON ELECTRICAL-ELECTRONICS & BIOMEDICAL ENG'G & COMPUT. SCI (EBBT), June 20, 2019, at 1, 3.

objective optimization is a mathematical problem, machines can be brought fruitfully to bear.

A model constitutes an alternate version of an object or environment, one that can be manipulated in time and space. Models permit designers to ask "what if" questions about alternative designs or circumstances without the expenditure or risk associated with a physical process or prototype. Introducing processes such as torsion and sheer to a model of an airplane can help establish when the plane will become unsafe and need repair without waiting for an actual plane undercarriage to buckle. As with weather prediction, the consequences to society are real: engineers apply insights from inside models to improve real airplane design and anticipate maintenance needs. Meanwhile, the pilots who will fly those planes train inside a modeled environment called a flight simulator before practicing in the air.

Models can be more or less accurate, of course, depending on several conditions. Weather models include quite a bit of information relevant to predicting weather patterns, but not everything. Flight simulators model the cockpit, ground, and airspace well enough for a pilot to get a sense of flight, but not so well that they may fly a plane without practicing in the air with an instructor. Meanwhile, the more parameters a model needs to account for, the greater the need for computational power. A static model representing shape and color needs next to no computation, as most sculptors will attest. A dynamic model aimed at predicting earthquakes on the basis of far-flung sensory data and plate tectonics requires a great deal more.[46]

Objects and environments behave in accordance with the laws of physics and chemistry. Policymakers must deal with an unruly set of actors called people. Modeling may have far less utility in anticipating the effects of rules on heterogeneous human populations equipped with free will and complex influences. Yet several innovations in modeling hold promise even with respect to anticipating human behavior. The field of study and practice known as agent-based modeling (sometimes individual-based) attempts to represent the world on the basis of the individual actions of artificial agents

46. *See generally* Paul A. Johnson et al., *Laboratory Earthquake Forecasting: A Machine Learning Competition*, PROC. NAT'L ACAD. SCI., Feb. 2021, at 1 (providing an overview of a machine learning competition where more than 4,500 teams designed an earthquake forecasting model using laboratory seismic data).

interacting with both an environment and one another.[47] For now, these agents remain relatively simplistic, but even following simple rules and objectives, agent-based modeling can reveal complex emergent behaviors and dynamics that would be hard to anticipate in advance.[48]

Agent-based modeling might interest Hayek. The technique arose to address contexts in which central planning is infeasible due to the distribution of relevant information and behaviors across many participants.[49] A traffic jam is a core example. Traffic jams consist of many vehicles following the same basic rules, and yet whether or when a traffic jam will form or dissolve resists human intuition. It may nevertheless be possible to model the myriad forces that contribute to traffic jams.[50] Agent-based modeling holds potential in modeling people when constrained by rules—for example, pedestrian and vehicle traffic in a city.[51] The technique is already of some utility to urban planners trying to set parking fees and time traffic lights.[52] As the field of agent-based modeling progresses, it should be possible to model more sophisticated behaviors.

Agent-based modeling and related techniques have been used by academics to anticipate dynamic effects in a range of contexts, from viral misinformation to the impacts of climate change. Researchers at the Center for an Informed Public—an interdisciplinary center at the University of Washington devoted to the study and resistance of strategic misinformation—use computational modeling to evaluate the

47. NIGEL GILBERT, AGENT-BASED MODELS 2–18 (2d ed. 2020); *see also* Coglianese & Lehr, *supra* note 18, at 1173–74 (discussing the utility of agent-based models to policymakers).

48. GILBERT, *supra* note 47.

49. Julia Kasmire, *Introduction to Agent-based Modelling for Social Scientists*, U.K. DATA SERV. (Jan. 16, 2020), https://dam.ukdataservice.ac.uk/media/622577/introabm.pdf [https://perma.cc/2NU6-SHJ9].

50. I owe this example to a very helpful explainer on agent-based modeling in the social sciences by Dr. Julia Kasmire of the UK Data Service. *Id.*

51. The use of the word "agent" in this context is not limited to people or even living things. A scallop or a wave can be an agent in an agent-based model—much like an object can be an actant in actor network theory. Michal Callon, *Some Elements of a Sociology of Translation: Domestication of the Scallops and the Fishermen of St Brieuc Bay*, 32 SOC. REV. 196, 204 (1984).

52. Wenwen Zhang & Kaidi Wang, *Parking Futures: Shared Automated Vehicles and Parking Demand Reduction Trajectories in Atlanta*, LAND USE POL'Y, Feb. 2020, at 1, 4; Tong Pham, Aly Tawfik & Matthew E. Taylor, *A Simple, Naïve Agent-based Model for the Optimization of a System of Traffic Lights: Insights from an Exploratory Experiment*, PROCEDIA, 2013, at 1, 1.

efficacy of interventions into misleading viral content.[53] Inspired by infectious disease research, the researchers modeled the spread of misinformation on the social network Twitter and then introduced commonly proposed interventions—for example, content removal, virality circuit breakers, nudges, and account banning—to assess their impact on the model.[54] They found that few interventions were likely to have a significant impact in isolation, but that a combined approach reduced misinformation virality by as much as 50 percent.[55]

Other researchers combine computational modeling with qualitative or other scientific methods to design models of climate change that account for human dynamics. The Potsdam Institute for Climate Impact Research brings together experts in game theory and agent-based modeling with those who study earth resilience and climate change, with the goal of "identifying emergent behaviour [sic], scenarios, risks, and suitable management options and rules such as sustainability paradigms."[56] Their aim is to build compelling models of human behavior interacting with the earth's environment so as to anticipate changes to the planet under various behavioral conditions. A recent paper by this group and collaborators identifies "social tipping elements" for climate change mitigation as a prelude to larger-scale modeling efforts hoping to test the efficacy of policy interventions on heading off crisis.[57]

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53. Joseph B. Bak-Coleman, Ian Kennedy, Morgan Wack, Andrew Beers, Joseph S Schafer, Emma Spiro, Kate Starbird & Jevin West, Combining Interventions To Reduce the Spread of Viral Misinformation 1–2 (May 23, 2021) (unpublished manuscript), https://osf.io/preprints/socarxiv/4jtvm [https://perma.cc/X6AF-UC2X]. The researchers modeled the spread of misinformation on Twitter by applying statistical and computational methods to a large corpus of tweets collected during the 2020 U.S. presidential election. *Id.* at 6. Relying on a set of plausible assumptions—such as the assumption that tweets from accounts with larger follower numbers have greater reach, and that new topics are more salient than old ones—the team then simulated the impact of various common interventions on the spread of misinformation. *Id.* at 2, 5.

54. *Id.* at 1.

55. *Id.*

56. *See Copan — Coevolution of Human-environment Systems in the Anthropocene*, POTSDAM INST. FOR CLIMATE IMPACT RSCH., https://www.pik-potsdam.de/en/institute/departments/activities/copan [https://perma.cc/X8ZS-78G6]; Jonathan F Donges, Ricarda Winkelmann, Wolfgang Lucht, Sarah E Cornell, James G Dyke, Johan Rockström, Jobst Heitzig & Hans Joachim Schellnhuber, *Closing the Loop: Reconnecting Human Dynamics to Earth System Science*, 4 ANTHROPOCENE REV. 151, 155–56 (2017).

57. Ilona M. Otto et al., *Social Tipping Dynamics for Stabilizing Earth's Climate by 2050*, 117 PROC. NAT'L ACAD. SCI. 2354, 2354 (2020). I owe these examples to computational biologist Joe Bak-Coleman.

Modeling behavior is also at the heart of online advertising and other, sometimes extractive, practices by internet and technology companies. Online advertising exchanges parse billions of data points to match advertising content with consumers upon whom it will have the greatest impact.[58] Google, Facebook, Uber, and Twitter structure their platforms in ways that maximize profit. Indeed, these companies and others have been criticized for many years for collecting, processing, and analyzing data for the purpose of manipulating consumers, cornering human attention, and ultimately optimizing advertising revenues.[59] Although there is evidence that these capabilities are overstated, the technology sector is among the most lucrative industries in the history of human business.[60]

The full range of possibilities for modeling people is perhaps best showcased in entertainment. Contemporary videogames represent entire cities—entire worlds—complete with physical properties like gravity and atmosphere but also complex social behaviors and dynamics. Until at least 2014, when Electronic Arts shipped the latest and last version of the game, SimCity represented the vanguard of social simulation.[61] A spinoff called The Sims remains among the most popular videogames of all time.[62] Neither SimCity nor The Sims has a defined goal. Play is open ended, allowing a player to model a world through a series of actions. The allure of SimCity and The Sims is witnessing complex social ramifications from simple decisions—albeit in accordance with constraints that are not always visible to the

58. Patrali Chatterjee, Donna L. Hoffman & Thomas P. Novak, *Modeling the Clickstream: Implications for Web-Based Advertising Efforts*, 22 MKTG. SCI. 520, 521 (2003).

59. *See* Salomé Viljoen, Jake Goldenfein & Lee McGuigan, *Design Choices: Mechanism Design and Platform Capitalism*, BIG DATA & SOC'Y, Aug. 4, 2021, at 1, 2; Ryan Calo, *Digital Market Manipulation*, 82 GEO. WASH. L. REV. 995, 1003 (2014) [hereinafter Calo, *Digital Market Manipulation*].

60. Technology companies make up four of the five largest public corporations by market cap as of this writing and have for several years now. *See List of Public Corporations by Market Capitalization*, WIKIPEDIA, https://en.wikipedia.org/wiki/List_of_public_corporations_by_market_capitalization#2011 [https://perma.cc/769U-3VEB].

61. *See* Liam Martin, *The Sims 4 Becomes the First PC Game To Top All-Format Chart in Two Years*, DIGIT. SPY (Aug. 9, 2014), https://www.digitalspy.com/videogames/weekly-charts/a595181/the-sims-4-becomes-first-pc-game-to-top-all-format-chart-in-two-years [https://perma.cc/3JMM-4242].

62. Elise Favis, *How The Sims Navigated 20 years of Change To Become One of the Most Successful Franchises Ever*, WASH. POST (Feb. 4, 2020), https://www.washingtonpost.com/video-games/2020/02/04/how-sims-navigated-20-years-change-become-one-most-successful-franchises-ever [https://perma.cc/4QJ6-X5BY].

player.[63] SimCity inspired a generation of urban designers, enamored with the ways a single change can alter the patterns of an entire city.[64]

This brief discussion of modeling has implied a dichotomy between the real world and its virtual representation. Models are partial replicas, almost by definition. It is important to note, however, that models can be dynamically updated to reflect the latest facts. Weather prediction becomes more accurate the nearer the event because weather models are constantly being updated to reflect the latest sensor data.[65] Moreover, the efficacy of predictive models can be tested against what actually happens, which in turn improves the model.[66] Modeling has become an ongoing, dynamic process that (hopefully) gets better the more it's done. Nevertheless, a model is just that. There are no means technically available to perfectly model an environment in all its complexity. The modeler must select the parameters they wish to include—a point that will weigh heavily in the analysis in Part III.

II. MODELING'S PROMISE

Few issues of concern to policymakers—politics, morality, economy, self-interest—can be resolved by reference to technology. This Part explores the intuition that technology could nevertheless assist policymakers in specific but important ways: by helping officials anticipate regulatory impacts on a wider array of values. Federal agencies are expected to conduct cost-benefit analysis of new regulation and sometimes are required by statute to assess the impact of interventions on specific values or communities, such as privacy or small businesses. This Part explores how models can help anticipate the likely impact of government intervention on a particular value, community, or society as a whole.

Nearly all policymaking involves discernable tradeoffs among stakeholders, whether in the dedication of resources or the limitation

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63. *See* Kevin T. Baker, *Model Metropolis*, LOGIC (Jan. 1, 2019), https://logicmag.io/play/model-metropolis [https://perma.cc/7G5Y-BXED].

64. Roy, *supra* note 28.

65. *See Data Assimilation*, EUROPEAN CTR. FOR MEDIUM-RANGE WEATHER FORECASTS, https://www.ecmwf.int/en/research/data-assimilation [https://perma.cc/9RGD-KS9G].

66. *See id.*

of behavior.[67] Military spending means less spending on public schools. A ban on selling cigarettes to minors, however wise, curtails the activity of an industry and limits the options of people under the age of eighteen. Even assuming policymakers have in mind an optimal allocation or balance, they can never be certain that a specific intervention will achieve their goals. Examples of failed legislation or unintended consequences abound, requiring subsequent correction—hence the muddling through.[68] The prospect that state intervention will be ineffective, or do more harm than good, haunts policymakers and arms their critics.[69] Were policymakers able to model the impact a new statute or regulation would have, they could, in theory, devise stronger policy.

The idea that policymakers should bring greater rigor to assessing objectives and modeling impact is not new. Cost-benefit analysis, the dominant mode of governance in most corners of the United States' government administration, grew out of the "science" of systems analysis at the height of the Cold War.[70] As Professor Bernard Harcourt describes in his genealogy, systems analysis undertakes to analyze the objectives of a given system—whether military, postal, or healthcare—and methodically select policy from multiple alternatives most likely to realize those objectives.[71] Originating at the RAND Corporation, systems analysis dominated 1960s U.S. military strategy and came to permeate federal policymaking and ultimately to "shape[] the American administrative state."[72]

Closely related to systems analysis is the set of techniques known as forecasting, that is, the use of qualitative and quantitative methods

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67. I do not intend to endorse the dominant view of governance as welfare maximization, nor embrace the liberal conception of the self at the heart of cost-benefit analysis. I have my doubts about each, as will become clearer as the Article unfolds. Regardless, the influence of cost-benefit analysis on U.S. policymaking is hard to gainsay. *See generally* FRANK ACKERMAN & LISA HEINZERLING, PRICELESS: ON KNOWING THE PRICE OF EVERYTHING AND THE VALUE OF NOTHING (2004) (critiquing the ubiquity of cost-benefit analysis in U.S. governance); Bernard E. Harcourt, *The Systems Fallacy: A Genealogy and Critique of Public Policy and Cost-Benefit Analysis*, 47 J. LEGAL STUD. 419 (2018) (identifying the "systems fallacy: the mistaken belief that systems-analytic decision-making techniques . . . are neutral and objective, when in fact they normatively shape political outcomes").

68. *See* Lindblom, *supra* note 3.

69. *Death of Common Sense*, Philip Howard's 1994 excoriation of government regulation amidst the Gingrich revolution, is a prominent example.

70. Harcourt, *supra* note 67, at 419.

71. *Id.* at 420.

72. *Id.*

to develop potential future scenarios in an effort to navigate changing conditions.[73] Forecasting purports to bring methodological rigor to the anticipation of future events based on present-day knowledge. Given Yogi Berra's adage that "[i]t's tough to make predictions, especially about the future,"[74] forecasting will typically generate multiple potential scenarios, allowing an institution to develop responses to each should they happen to unfold. For example, Shell Oil credits scenario planning with the company's successful navigation of the 1970s energy crisis and continues to use the technique today.[75]

Technological affordances have changed a great deal since the 1960s and 70s. The impact of technological change on forecasting and systems analysis is uneven. Qualitative methods in this field are little changed. Neither longstanding techniques such as scenario planning or Delphi expert surveys,[76] nor more recent methods such as design fiction,[77] are much altered by greater computational power or the ascendance of AI. These techniques ask groups of people to describe what they know or imagine. Quantitative methods, on the other hand, which rely upon statistical analysis, and hybrid approaches such as trend impact analysis that integrate expert insights into statistical forecasts using historical data,[78] tend to advance alongside computer processing power. More powerful computing translates into the capacity to perform more calculations, more quickly, on a greater number of variables.

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73. *See generally* JEROME C. GLENN & THEODORE J. GORDON, FUTURES RESEARCH METHODOLOGY 3.0 (2009) (surveying a variety of forecasting methods and assessing their relative strengths and weaknesses).

74. *The Perils of Prediction*, ECONOMIST (July 15, 2007), https://www.economist.com/letters-to-the-editor-the-inbox/2007/07/15/the-perils-of-prediction-june-2nd [https://perma.cc/3YR7-3K6Q].

75. *See* Angela Wilkinson & Roland Kupers, *Living in the Futures*, HARV. BUS. REV. (May 2013), https://hbr.org/2013/05/living-in-the-futures [https://perma.cc/E452-EFJF].

76. *See Delphi Method*, RAND, https://www.rand.org/topics/delphi-method.html [https://perma.cc/FR9N-SK7M].

77. *See*, *e.g.*, Eric P.S. Baumer, Timothy Berrill, Sarah C. Botwinick, Jonathan L. Gonzales, Kevin Ho, Allison Kundrik, Luke Kwon, Tim LaRowe, Chanh P. "Sam" Nguyen, Fredy Ramirez, Peter Schaedler, William Ulrich, Amber Wallace, Yuchen Wan &Benjamin Weinfeld, *What Would You Do?: Design Fiction and Ethics*, PROC. 2018 ASS'N FOR COMPUTING MACH. CONF. ON SUPPORTING GROUPWORK, Jan. 7–10, 2018, at 244, 244, https://dl.acm.org/doi/abs/10.1145/3148330.3149405 [https://perma.cc/PGR9-JK9N]; Jason Shun Wong, *Design and Fiction: Imagining Civic AI*, INTERACTIONS, Nov.–Dec. 2018, at 42, 42.

78. Nedaa Mohamed Ezzat Agami, Ahmed Mohamed Ahmed Omran, Mohamed Mostafa Saleh & Hisham Emad El-Din El-Shishiny, *An Enhanced Approach for Trend Impact Analysis*, 75 TECH. FORECASTING & SOC. CHANGE 1439, 1439 (2008).

The techniques and technologies behind modeling discussed above arguably provide policymakers with a powerful set of affordances.[79] A policymaker could, in theory, leverage computational modeling to conduct cost-benefit analyses that better optimize across multiple variables, as well as to generate and select among feasible regulatory alternatives. Such analyses are required by statute in some contexts[80] and are a facet of most regulatory review expected by the modern White House.[81] Present-day cost-benefit analyses, however, range from back-of-napkin calculations and checklists to elaborate mathematical tables.[82] Nothing like the sort of modeling capability of the National Weather Service has been brought to bear, unless it is by intelligence agencies behind closed doors.

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79. The term "affordance" originates in the work of perceptual psychologist James Gibson and refers to the capacity of an organism to perceive and take advantage of different facets of their environment, including through the use of technology. JAMES J. GIBSON, THE ECOLOGICAL APPROACH TO VISUAL PERCEPTION 127 (2014). For a discussion of affordances and their relevance for law and technology, see Ryan Calo, *Privacy, Vulnerability, and Affordance*, 66 DEPAUL L. REV. 591, 601 (2017); Ryan Calo, *Can Americans Resist Surveillance?*, 83 U. CHI. L. REV. 23, 25 (2016).

80. 15 U.S.C. § 45(n).

81. MAEVE P. CAREY, CONG. RSCH. SERV., R41974, COST-BENEFIT AND OTHER ANALYSIS REQUIREMENTS IN THE RULEMAKING PROCESS, at i (2014); Lisa Heinzerling, *Quality Control: A Reply to Professor Sunstein*, 102 CALIF. L. REV. 1457, 1458 (2014). A 2019 Office of Management and Budget ("OMB") memo purported to obligate independent federal agencies to run "major" legislation by the OMB's Office of Information and Regulatory Affairs for a thorough cost-benefit analysis. Memorandum from Russell T. Vought, Acting Dir., Off. of Mgmt. & Budget, to the Heads of Exec. Dep'ts & Agencies 6–7 (Apr. 11, 2019), https://www.whitehouse.gov/wp-content/uploads/2019/04/M-19-14.pdf [https://perma.cc/KK8D-FNUC]. The basis for the memo, however, appears to be the Congressional Review Act, which requires only that OMB's Office of Information and Regulatory Affairs determine if the rule is "major" and hence subject to a review period by Congress before entering into effect. *Id.* at 3–4. Subsequent guidance from the Biden Administration in January of 2021 entitled "Modernizing Regulatory Review" directed OMB to broaden its review to encompass, inter alia, "regulatory benefits that are difficult or impossible to quantify," which may signal backing away from, or at any rate revisiting, cost-benefit analysis to the extent it stands in the way of government intervention. Joseph R. Biden Jr., *Modernizing Regulatory Review*, WHITE HOUSE (Jan. 20, 2021), https://www.whitehouse.gov/briefing-room/presidential-actions/2021/01/20/modernizing-regulatory-review [https://perma.cc/R37Y-FWGH].

82. *Compare* Tim Stobierski, *How To Do a Cost-Benefit Analysis & Why It's Important*, HARV. BUS. SCH. BUS. INSIGHTS (Sept. 5, 2019), https://online.hbs.edu/blog/post/cost-benefit-analysis [https://perma.cc/3J8Z-QNTS] ("Generally speaking, cost-benefit analysis involves tallying up all costs of a project or decision and subtracting that amount from the total projected benefits of the project or decision."), *with* David K. Miles, Michael Stedman & Adrian H. Heald, *"Stay at Home, Protect the National Health Service, Save Lives": A Cost-Benefit Analysis of the Lockdown in the United Kingdom*, INT'L J. CLINICAL PRAC., Aug. 10, 2020, at 1, 8 (displaying complex tables used in the calculation of a cost-benefit analysis).

Sophisticated models could help agencies conduct impact assessments required by statute—for example, the privacy impact assessments required by Section 208 of the E-Government Act of 2002 or the longstanding requirement under the National Environmental Policy Act that federal agencies assess the environmental effects of proposed actions.[83] Especially as agent-based modeling improves, local, state, and federal governments could build computer simulations to help anticipate the likely impact of new economic, traffic, health, or other rules to the extent they are amenable to quantification. Impact assessment as presently envisioned is also siloed. Regulatory impacts on budget, privacy, paperwork, small businesses, and the environment are all treated separately. There could be one model to bring them all, and in the Beltway bind them.

These claims may seem at once fanciful and familiar. The prospect that technology could enhance policymaking has led to louder and louder calls for the government to embrace contemporary information technology like AI, which some officials have taken to heart.[84] Federal regulators in particular have been experimenting with the pattern recognition potential of machine learning—as successive executive orders from both Democratic and Republican administrations have urged.[85]

In theory, a sustained examination of how government is using emerging information technologies such as AI could serve as a window into the government's appetite for modeling. The Administrative Conference of the United States, the mission of which is to "study the efficacy, adequacy, and fairness of . . . administrative procedure," recently published a report it commissioned on the use of AI by federal agencies.[86] Research teams from Stanford and New York Universities canvassed 142 federal departments and agencies, finding that 45

83. 44 U.S.C. § 3501 note; 42 U.S.C. § 4332.

84. *E.g.*, Margetts & Dorobantu, *supra* note 17, at 163–65. U.S. monetary policy already relies on large-scale, multi-factor modeling, as does housing policy. *See* Flint Brayton, Thomas Laubach & David L. Reifschneider, *The FRB/US Model: A Tool for Macroeconomic Policy Analysis*, FEDS NOTES (Apr. 3, 2014), https://www.federalreserve.gov/econresdata/notes/feds-notes/2014/a-tool-for-macroeconomic-policy-analysis.html [https://perma.cc/39Z6-S53A]; Hess T. Chung, Michael T. Kiley & Jean-Philippe Laforte, *Documentation of the Estimated, Dynamic, Optimization-based (EDO) Model of the U.S. Economy* 2–3 (Fed. Rsrv. Bd., Working Paper No. 2010-29, 2010); KEN LAM, FED. HOUS. FIN. AGENCY, THE SIZE OF THE AFFORDABLE MORTGAGE MARKET: 2022-2024 ENTERPRISE SINGLE-FAMILY HOUSING GOALS 3 (2021).

85. *See* NAT'L SCI. & TECH. COUNCIL, *supra* note 31.

86. ENGSTROM et al., *supra* note 32, at 2.

percent have experimented with "AI and related machine learning (ML) tools."[87] But modeling through, as such, was largely absent.

Primary use cases for AI by the federal government include (1) enforcing regulatory mandates, (2) adjudicating government benefits and privileges, (3) monitoring and analyzing risks to the public, (4) extracting usable information from government data, and (5) communicating with the public.[88] Agencies such as the Securities and Exchange Commission and Internal Revenue Service leverage machine learning to attempt to identify likely candidates for enforcement by spotting behavior patterns associated with fraud and evasion.[89] Agencies such as the Food and Drug Administration use AI to analyze reports of adverse drug events to identify emerging safety risks to the public, whereas the U.S. Patent and Trademark Office is experimenting with using AI to parse through patent and trademark applications looking for indicators of originality (or their absence).[90] Some agencies are using software tools to assist with procurement decisions or vet government vendors for compliance with regulatory requirements.[91] Still others are using low level systems as chatbots—software designed to interact with people as naturally as they can—to answer questions for the public by phone or online.[92]

It is worth noting that few of the administrative use cases involve the sorts of automatic denial of benefits or rejection of claims that have motivated algorithmic accountability lawsuits and fueled public outrage. Federal agencies are mostly using AI to spot useful patterns in their data. It is also worth noting that the government's use of AI can hardly be described as cutting edge. The study authors ran the techniques they surfaced by Stanford computer scientists who purported to group use cases by sophistication.[93] The report concluded that only 12 percent of use cases were "highly sophisticated."[94] While the methodology was not terribly clear—61 percent of the time the team could not tell what technique was being used, and the

87. *Id.* at 6.
88. *Id.*
89. *Id.* at 22.
90. *Id.* at 46, 53.
91. *Id.* at 10.
92. *Id.* at 59.
93. *Id.* at 19.
94. *Id.* at 20.

sophistication scalewas comprised of only three techniques of many[95]—a fair takeaway is that the overwhelming use cases do not approach the full potential of the technology as deployed in other sectors.

The federal government is using AI mostly to muddle better. There are, however, glimmers of modeling to be seen in the United States and elsewhere. Some state and local governments are turning to AI to model municipal data to better allocate scarce resources.[96] In 2013, the City of Los Angeles adjusted traffic signals—and hence the rules of the road—on the basis of elaborate and dynamic models of vehicle and foot traffic.[97] The U.S. military, intelligence sector, and Department of Homeland Security deploy modeling to assess the potential impact of attacks on U.S. populations or infrastructure.[98] The Bank of England is modeling the British housing market in order to simulate the effects of policy interventions aimed at mitigating financial risk.[99] The French National Assembly has recently turned to a tool called LexImpact to calculate the fiscal impacts of proposed legislation on people and the economy as a whole.[100]

Calls for broader use of AI by government are mounting. Writing in *Nature*, Helen Margetts and Cosmina Dorobantu of the Allen Turing Institute in London note that "governments have been slow to apply AI to hone their policies and services."[101] They urge governments to consider the use of "state-of-the-art modeling" to improve policymaking:

> [G]overnments could simulate complex systems, from military operations to the private sectors of entire countries. This would enable governments to experiment with different policy options and to spot unintended consequences before committing to a measure.[102]

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95. Their interesting scale placed "logistic regression using structured data" on one end of sophistication and deep learning on the other, with "a random forest with attention to hyperparameter tuning" in between. *Id.* at 19. These are only three of many techniques of AI, and it is not clear from the text why they were particularly selected. *Id.* Ultimately the team found "insufficient publicly available technical documentation to determine with precision what methods are deployed" in 61 percent of the cases. *Id.*

96. Coglianese & Lehr, *supra* note 18, at 1161–62.

97. *Id.* at 1171.

98. *See* Margetts & Dorobantu, *supra* note 17, at 164.

99. *Id.*

100. I owe this example to Caroline Lequesne-Roth.

101. Margetts & Dorobantu, *supra* note 17, at 163.

102. *Id.* at 164 (emphasis added).

Similar calls emanate from other quarters. The Humans and Artificial Intelligence initiative at Stanford University and the Allen Institute for Artificial Intelligence in Seattle call for more computation in government.[103] Legal scholars Cary Coglianese and David Lehr imagine a range of applications of agent-based modeling to federal rulemaking, including more responsive financial and workplace safety regulation.[104] Professor McGinnis hopes that AI will help "accelerate democracy," in part by helping policymakers ascertain and reconcile values and test policy hypotheses.[105] "The technological revolution," McGinnis argues, "is giving us progressively better hardware to gather the information in the world to improve policy outcomes. But government structures and rules provide the essential social software to make that hardware work effectively on behalf of society."[106]

Federal agencies are experimenting with AI, if not modeling through. The uses to which agencies seem to be putting machine learning do not suggest that they are using computation to maximize welfare in the course of cost-benefit or building models of the world to study the potential impact of regulation. Rather, the government seems to be using AI largely to *muddle through* with greater speed and efficacy. But the growing awareness of information technology, coupled with longstanding expectations of cost-benefit and impact assessment, suggest that modeling through may be waiting around the corner. And as the capacity to model through develops in the policy domain, it is fair to ask whether policymakers can continue to muddle. Anyone who transfers money or pays for groceries with a few taps of their mobile phone must wonder why departments of motor vehicles still only take traveler's checks.[107]

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103. "The Intelligence Community (IC) faces a moment of reckoning. If the IC cannot adopt AI and other emerging technologies successfully, it risks failure." Amy Zegart, *Policy Brief: The Moment of Reckoning: AI and the Future of U.S. Intelligence*, STAN. UNIV. HUM.-CENTERED A.I. (2021), https://hai.stanford.edu/sites/default/files/2021-05/Policy-Brief_The-Moment-of-Reckoning-AI-and-the-Future-of-U.S.-Intelligence.pdf [https://perma.cc/7YJH-4A6A]. One of the Allen Institute for Artificial Intelligence's teams is focused on the development of Skylight, a tool for surfacing suspicious events in the maritime domain that can be leveraged by governments, nongovernmental organizations, and partners to address illegal, unreported, and unregulated ("IUU") fishing. SKYLIGHT, https://skylight.global [https://perma.cc/J9Z8-5TD8].

104. *See* Coglianese & Lehr, *supra* note 18, at 1166, 1174.

105. *See* MCGINNIS, *supra* note 18, at 2.

106. *Id.*

107. The author owes this example to Erika Douglas. *But see generally* Daniel Antony Kolkman, Paolo Campo, Tina Balke-Visser & Nigel Gilbert, *How To Build Models for Government: Criteria Driving Model Acceptance in Policymaking*, 49 POL'Y SCI. 489 (2016)

III. MODELING'S PERILS

To summarize the argument so far: policymakers face limitations and hurdles, leading them to muddle through policy problems as best they can. The challenge of predicting the impacts of intervention on a wider variety of values may benefit from modeling techniques widely deployed in other sectors. These powerful techniques permit designers to craft environments they can age or change at will, and which bear a close enough resemblance to the real world as to yield consequential insights. Advances in computing, particularly AI, are bringing these techniques to new heights. Modeling and model-based analysis have become indispensable to many sectors of society and are being explored by policymakers, albeit in tentative and narrow ways.

Law and technology can be a reactive field, always looking for ways to restore the status quo ex ante in the face of technological disruption.[108] Yet new technologies also present the opportunity to inventory our values and standards.[109] The widespread availability of modeling in other sectors, along with the improvement to design and decision-making modeling, suggest that society should expect more of policymakers than Lindblom allows.[110] Policymaking will continue to be imperfect, but the prospect of modeling through should be taken seriously and even expected. Formal cost-benefit and impact assessments imposed by Congress only bolster this expectation.

It is in many ways felicitous that modeling through remains in its infancy. We are positioned, as rarely, to inject a note of caution almost at the outset. Modeling as a set of practices implicates different values, and risks different harms, than muddling. Some of these harms are well-known to the community studying privacy, bias, and other societal impacts of AI. Others are better known to long-standing critics of systems or cost-benefit analyses, which government reliance upon computational modeling has the potential to extend and deepen. This Part raises six specific concerns around modeling through: (1) privacy, (2) brittleness, (3) human bias, (4) automation bias, (5) hidden normativity, and (6) dehumanization. Some of the concerns can be

(identifying eleven criteria that can influence an agency's acceptance of models in policymaking, besides their technical aspects).

108. *See* Calo & Citron, *supra* note 1, at 805, 811.

109. *See id.* at 811.

110. *See* Lindblom, *supra* note 3.

mitigated through law or technology;[111] others appear endemic. Each area of concern urges caution and humility in modeling through.

Modeling implicates privacy. The world Hayek doubts to be possible—wherein central administrators have access to everyone's preferences and conditions—also holds dangers for privacy. As I have argued elsewhere, the idea of the state giving "to each according to his needs" requires extensive and invasive knowledge on the part of the government.[112] That is why markets can be strangely privacy protective, even as information capitalism creates incentives for firms to extract data from participants.[113]

The most vulnerable often must yield the most privacy, as scholars from Khiara Bridges to Scott Skinner-Thompson elegantly show.[114] The private sector requires relatively little disclosure of those with the means to pay for services rather than ask them of the state. Bridges compares the experience of a pregnant person with health insurance asking for prenatal care, of whom the private doctor asks little, versus the recipient of state services, who is asked invasive questions about how they became pregnant and with whom they live.[115] State services come with invasive demands for information. In contrast, goods and services distributed across society by a market mechanism such as price requires relatively little information to be centralized in government.[116]

111. *See, e.g.*, PBL NETH. ENV'T ASSESSMENT AGENCY, GUIDANCE FOR UNCERTAINTY ASSESSMENT AND COMMUNICATION 8–9 (2d ed. 2013) (proposing tools for managing uncertainties in policy-oriented scientific research and advice on how to communicate them, thus addressing aspects of automation bias and hidden normativity); HM TREASURY, *supra* note 32, at 11 (providing a set of best practices in quality assurance ("QA") of analytical models that inform policy across the U.K. Government, to ensure models are robust and their "outputs . . . [can] be used with genuine understanding and confidence"); *see also* Andrea Saltelli et al., *Five Ways To Ensure That Models Serve Society: A Manifesto*, NATURE (June 24, 2020), https://www.nature.com/articles/d41586-020-01812-9 [https://perma.cc/ULA9-7Z79] (proposing a set of "best practices for responsible mathematical modelling" to prevent hidden normativity, including political leaning).

112. Ryan Calo, *Privacy and Markets: A Love Story*, 91 NOTRE DAME L. REV. 649, 679 (2015) (quoting Karl Marx, *Critique of the Gotha Programme*, *in* 3 KARL MARX & FREDERICK ENGELS: SELECTED WORKS 8 (1973)).

113. *See* Calo, *Digital Market Manipulation*, *supra* note 59, at 1001.

114. KHIARA M. BRIDGES, THE POVERTY OF PRIVACY RIGHTS 5 (2017); SCOTT SKINNER-THOMPSON, PRIVACY AT THE MARGINS 8–9 (2021).

115. *See* BRIDGES, *supra* note 114, at 1–5.

116. Calo, *supra* note 112, at 650. The predatory practices of companies around consumer data presents a distinct set of problems. Firms have incentives to leverage what they know about consumers—quite a lot—to manipulate them and extract commercial advantage. Calo, *Digital Market Manipulation*, *supra* note 59, at 999.

Insofar as building a useful and accurate model of society requires extensive, real-time information about individuals or groups, then modeling through will come at a cost to privacy.[117]

Models will be brittle. In E.M. Forster's classic short story "The Machine Stops," a society that relies upon machines to take care of every individual and collective need grinds to a halt after the machine inexplicably stops.[118] However carefully constructed, predictive models based on machine learning can work for a time only inexplicably to breakdown. Such models are based on features extracted from data or dynamics that can become outdated as conditions change on the ground.

An infamous example of the government relying on outdated models involves the use of Google Flu Trends by the Centers for Disease Control and Prevention to allocate resources during flu season.[119] Google Flu Trends anticipated flu outbreaks very well for a time but then declined in performance until it was quietly shuttered.[120] Another example comes from outside government in the high-stakes world of investment. For a period of time, algorithmically driven investment outperformed the market, only to inexplicably plateau and decline.[121] Although continuously updating data could lessen this danger, and while advances in machine learning may come to address problems of brittleness, the prospect that models will breakdown urges caution on the part of policymakers.[122]

Modeling will be biased. Some see machine decision-making as a more objective substitute for the biased decisional processes of

117. For an early and wise discussion of the perils of data processing in government administration, see Schwartz, *supra* note 23, at 1343. Some of the privacy costs associated with modeling can be mitigated by techniques such as differential privacy that permit insights to be gleaned from data that cannot be traced back to an individual or group. Cynthia Dwork, Frank McSherry, Kobbi Nissim & Adam Smith, *Calibrating Noise to Sensitivity in Private Data Analysis*, 7 J. PRIV. CONFIDENTIALITY 17, 18 (2016). But privacy will never cease to be a concern.

118. E. M. FORSTER, THE ETERNAL MOMENT AND OTHER STORIES 3–38 (1928).

119. David Lazer, Ryan Kennedy, Gary King & Alessandro Vespignani, *The Parable of Google Flu: Traps in Big Data Analysis*, 343 SCIENCE 1203, 1203 (2014).

120. *Id.*

121. *See* Silvia Amaro, *The 'Ferocious' Market Sell-Off Was Driven by Algorithms, Strategist Says*, CNBC (Feb. 6, 2018), https://www.cnbc.com/2018/02/06/market-sell-off-driven-by-algorithms-strategist-says.html [https://perma.cc/D3YD-RPVW].

122. *Cf.* Andrew G. Haldane & Vasileios Madouros, *The Dog and the Frisbee*, THE CHANGING POLICY LANDSCAPE – JACKSON HOLE ECONOMIC POLICY SYMPOSIUM, Aug. 30–Sep. 1, 2012, at 109, 115 ("Applying complex decision rules in a complex environment may be a recipe not just for a mere blunder but catastrophe.").

people.[123] Since Professors Batya Friedman and Helen Nissenbaum published "Bias in Computer Systems" in 1996, however, an extensive literature has arisen to document and critique the ways computing reproduces and entrenches racial, gender, and other biases. Different scholars and communities hold different views about how curable such biases may be.[124] Some scholars see flaws in antidiscriminatory discourse itself, which largely focuses on achieving fairness by combatting discrimination, thereby obscuring "the very hierarchical logic that produces advantaged and disadvantaged subjects in the first place."[125] But there seems to be consensus today around the prospect that models based on people will tend to replicate peoples' biases.[126]

Real-world examples of the government using biased data abound. Predictive policing—the practice of attempting to use historical data to predict perpetrators and victims of harm—is replete with bias, due to its model's basis in data riddled with preconceptions and civil rights violations.[127] A data set into which people of color have been disproportionately selected due to biases of officers and the criminal justice system, tends to generate a model that categorizes people of color as disproportionately dangerous or lawless. A 2016 RAND Corporation study concluded that Chicago's "heat map" of anticipated violent crime failed to reduce gun violence but did lead to a greater prevalence of arrests in low-income or diverse

123. *See generally* Batya Friedman & Helen Nissenbaum, *Bias in Computer Systems*, 14 ACM TRANSACTIONS ON INFO. SYS. 330 (1996) (analyzing bias in computer systems and proposing remedies to minimize bias).

124. *Compare* Ziad Obermeyer, Brian Powers, Christine Vogeli & Sendhil Mullainathan, *Dissecting Racial Bias in an Algorithm Used To Manage the Health of Populations*, 366 SCIENCE 447, 453 (2019) (arguing that "label biases are fixable"), *with* Veronica Barassi, *Algorithmic Bias Cannot Be Fixed*, HUMAN ERROR PROJECT (Nov. 20, 2020), https://thehumanerrorproject.ch/ai-cultural-bias-and-the-human-error [https://perma.cc/9BG7-AQRV] (arguing there is nothing we can do to combat our bias because it will always be there).

125. Anna Lauren Hoffmann, *Where Fairness Fails: Data, Algorithms, and the Limits of Antidiscrimination Discourse*, 22 INFO. COMMC'N & SOC'Y 900, 901 (2019).

126. *See* Amanda Levendowski, *How Copyright Law Can Fix Artificial Intelligence's Implicit Bias Problem*, 93 WASH. L. REV. 579, 582, 585 (2018). *See generally* Sandra G. Mayson, *Bias In, Bias Out*, 128 YALE L.J. 2218 (2019) ("[A]ny method of prediction will project the inequalities of the past into the future.").

127. *See generally* Rashida Richardson, Jason M. Schultz & Kate Crawford, *Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice*, 94 N.Y.U. L. REV. ONLINE 15 (2019) (finding that "[d]eploying predictive policing systems in jurisdictions with extensive histories of unlawful police practices presents elevated risks that dirty data will lead to flawed or unlawful predictions, which in turn risk perpetuating additional harm via feedback loops throughout the criminal justice system").

neighborhoods.[128] A ground-breaking investigation by ProPublica found that algorithmic pre-trial risk assessment tended to overestimate the risk of Black defendants and, by roughly the same margin, underestimate the risk of white ones.[129]

Modeling will invite automation bias. The prospect that a model will lull the official into unwarranted complacency or reproduce societal bias is compounded by a bias of another kind: a bias in favor of automated results. Ostensibly a subordinate partner, people tend to assume that insights generated by computers are accurate. Researchers and designers are aware of so-called automation bias;[130] corporations go so far as to exploit it. The ridesharing company Uber, for instance, introduced a false algorithmic specificity to its pricing when demand outstrips supply (so-called surge pricing) after the company realized that consumers viewed doubling or tripling prices as price gouging.[131] Now the Uber app displays prices such as "x2.2" that convey a false objectivity people take to be computer generated.[132] In other contexts, such as the theatre of war, automation bias has had deadly consequences: in 1988, an anti-aircraft system incorrectly identified a commercial jet as an enemy fighter, leading a soldier to fire upon and kill innocent civilians.[133] Policymakers interested in modeling through must be sober-eyed about the allure of automation bias: models are an aid to decision-making, not a substitute for expert judgment.

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128. Jessica Saunders, *Pitfalls of Predictive Policing*, RAND BLOG (Oct. 11, 2016), https://www.rand.org/blog/2016/10/pitfalls-of-predictive-policing.html [https://perma.cc/4XUL-5U5H].

129. 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/8UGC-GWLS].

130. *See, e.g.*, M.L. CUMMINGS, AUTOMATION BIAS IN INTELLIGENT TIME CRITICAL DECISION SUPPORT SYSTEMS 2 (2004), https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.91.2634&rep=rep1&type=pdf [https://perma.cc/LRU2-SMLG]; E. Alberdi, P. Ayton, A.A. Povyakalo & L. Strigini, *Automation Bias and System Design: A Case Study in a Medical Application*, IEEE & MOD HFI DTC SYMP. ON PEOPLE & SYS. – WHO ARE WE DESIGNING FOR, 2005, at 53, 54; Andrea Saltelli & Silvio Funtowicz, *When All Models Are Wrong*, 30 ISSUES SCI & TECH. 79, 81 (2014) ("[T]he beliefs of the public and policymakers about what should be done on climate . . . are relying on what models are forecasting about the future, with little if any sensitivity to the limits on what the models are actually capable of forecasting with any accuracy.").

131. Ryan Calo & Alex Rosenblat, *The Taking Economy: Uber, Information, and Power*, 117 COLUM. L. REV. 1623, 1657–58 (2017).

132. *Id.* at 1658.

133. P.W. SINGER, WIRED FOR WAR: THE ROBOTICS REVOLUTION AND CONFLICT IN THE 21ST CENTURY 125 (2009).

Modeling obscures normative dimensions to policymaking. Modeling improves on muddling by bringing to bear computational methods to anticipate the impact of regulatory interventions with greater accuracy across a wider array of stakeholder values. Just like systems and cost-benefit analyses, however, the process of value optimization through modeling requires ex ante normative assessments that can escape political scrutiny. Modeling, like cost-benefit, requires a determination of what counts as a valid input and what exactly the system is optimizing toward.[134] Little about modeling or technology addresses this long-standing problem around cost-benefit—if anything, technology stands to deepen it.

The predecessors to modeling through are, again, systems analysis, forecasting, and cost-benefit.[135] As Harcourt argues, although "systems-analytic methods are portrayed as scientific, objective, and neutral tools," in actuality they "entail normative choices about political values at every key step."[136] Systems analysis maximizes welfare only partially. In selecting the scope of the analysis—to include, for instance, the criminal justice system but not healthcare—the policymaker is already making value-laden choices about the contours of welfare analysis. The very metaphor of the "criminal justice system" directs attention and reform efforts to one area, such as crime prevention, at the expense of another, such as education or cancer research.[137]

Ideally, modeling would ameliorate this concern by giving policymakers more tools to optimize welfare across many variables. After all, "decision theorists turned to systems-analytic methods in large part because total welfare analysis was viewed as too unwieldy for policy making."[138] Yet until such a time as modeling advances to the

134. *See, e.g.*, Saltelli & Funtowicz, *supra* note 130, at 82 ("Detailed case studies of modeling activity in policy-relevant problems as diverse as climate change, nuclear waste disposal, and beach-erosion assessment show that many model assumptions are themselves the result of a negotiation process among scientists with different perspectives on the problem; that is, the assumptions are value-laden."); *see also* Saltelli et al., *supra* note 111 ("Examples of terms that promise uncontested precision include: 'cost–benefit', 'expected utility', 'decision theory', 'life-cycle assessment', 'ecosystem services', and 'evidence-based policy'. Yet all presuppose a set of values about what matters — sustainability for some, productivity or profitability for others. Modellers should not hide the normative values of their choices.").

135. *See* Harcourt, *supra* note 67, at 420; *see generally* GLENN & GORDON, *supra* note 73.

136. Harcourt, *supra* note 67, at 421.

137. *See id.*

138. *Id.* at 442.

point of being capable of total welfare analysis—a grand feat indeed—the danger remains that modeling through will only reproduce the tendency of prior methods to obscure normative choices as to scope.[139]

The work of technology historian Kevin Baker helps illustrate this concern for modeling through. In "Model Metropolis," Baker tells the story of how the game SimCity—discussed in Part II—came to be.[140] Apparently, the game designer, Will Wright, read a book on urban planning by Jay Forrester called *Urban Dynamics*.[141] Forrester was himself an electrical engineer who also worked on computer modeling and used simulation to develop a theory of how cities grow and decline.[142] Wright deployed the theory's principles in developing SimCity.[143]

It turns out, however, that Forrester's theory of the city was problematic and controversial. Forrester decried government intervention and, like Professor Phillip Howard and former speaker of the U.S. House Newt Gingrich would decades later, assumed that government assistance to the poor would backfire.[144] His model, and therefore that of Wright's SimCity, privileged revitalization efforts that focused on incentivizing business and stemming migration of the professional class.[145] His posture was clear to readers of the book *Urban Dynamics* but highly obscured by gameplay in SimCity. Rather, the player was tacitly rewarded for making Forrester-like changes to urban landscape without necessarily appreciating the normative assumptions behind the computer model.

Modeling may dehumanize. Assume that the preceding concerns can be mitigated—privacy, bias, normative intransparency, all somehow addressed. Imagine modeling works as advertised, that is, provides the computational means by which to optimize welfare and

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139. Unless a different approach is adopted. *See, e.g.*, Arthur C. Petersen, Albert Cath, Maria Hage, Eva Kunseler & Jeroen P. van der Sluijs, *Post-Normal Science in Practice at the Netherlands Environmental Assessment Agency*, 36 SCI. TECH. & HUM. VALUES 362, 365–66 (2011) (exploring the Post-Normal Science paradigm as an alternative style of science advising, which looks to openly recognize the uncertainties and plurality of normative perspectives present in knowledge production).

140. *See* Baker, *supra* note 63.

141. *Id.*

142. *Id.*

143. *See id.*

144. *See id. See generally* Paul Starr, *Seductions of Sim: Policy as a Simulation Game*, AM. PROSPECT, Spring 1994, at 19 (discussing the limitations and unsurfaced assumptions of SimCity).

145. *See* Baker, *supra* note 63.

generate a model of the world accurate enough to assess the impacts of proposed policy alternatives. Is this an unambiguous good? Perhaps, but perhaps not. Modeling, especially as supported by AI, still holds the potential to dehumanize public administration along several lines.

In her work on the social impacts of AI, researcher Kate Crawford traces the origins of AI—especially machine learning—to a troubled Western tradition of classification. "The politics of classification," writes Crawford, "is a core practice in artificial intelligence."[146] Classification is a reductive practice, elevating certain characteristics and repressing others. In machine learning, a trained model is often called a "classifier," because its goal is to classify new inputs in light of the features of its training data.[147] But, as Crawford observes, every act of classification reduces its object to a politically derived set of characteristics.[148]

Models are reductive in the same way. A model is a replica of the world but only along selected lines. Just as no sculptor short of Pygmalion, or no woodcutter short of Geppetto, is able to capture the internal state of their subject, no computational model is capable of modeling every social, cultural, or spiritual aspect of the individuals and society. It may be possible to leverage AI to improve traffic flow in New Orleans or stave off hurricane damage but not to preserve the distinctive character of that city or its inhabitants.

Modeling only accelerates a problematic tendency of government to look at everything through the lens of quantification, what political scientist James Scott famously calls "seeing like a state."[149] Scott's case studies—from Russia to Tanzania—showcase how various governments with good intentions manage to undermine human welfare rather than promote it by managing only what the government could measure.[150] Across a variety of contexts—from farming to urban planning—Scott demonstrates how officials tend to reduce populations and the environment to a set of data points capable of being committed to a ledger.[151] To see like a state is to reduce the world to the

146. KATE CRAWFORD, ATLAS OF AI: POWER, POLITICS, AND THE PLANETARY COSTS OF ARTIFICIAL INTELLIGENCE 127 (2021).

147. *See id.* at 135–36.

148. *Id.* at 146–47.

149. *See* JAMES C. SCOTT, SEEING LIKE A STATE: HOW CERTAIN SCHEMES TO IMPROVE THE HUMAN CONDITION HAVE FAILED 2 (1999).

150. *See id.* at 6–7.

151. *See id.* at 103–46, 262–306.

quantifiable. Modeling through, with its reliance on rendering human affairs computable, risks deepening and extending this concern.[152]

As Professor Lisa Heinzerling convincingly argues, with economist Frank Ackerman and elsewhere, the problem of quantification inures to cost-benefit analysis.[153] Attempts to expand cost-benefit to a broader set of values only serves to distort those values beyond recognition. In one of her examples, the Department of Justice struggles to conduct a cost-benefit analysis of a policy requiring bathroom accommodations for people living with disabilities.[154] The costs of retrofitting bathrooms for wheelchairs are clear enough, but the very act of quantifying the indignity experienced by people in wheelchairs having to ask for assistance to use the bathroom undermines the very concept of dignity: "[T]reating someone with dignity does not typically involve asking her how much she is willing to pay for the privilege."[155] In another, Heinzerling remarks upon the incoherence of attempting to quantify the harm of prison rape on the basis of inmates' willingness to avoid it. "To ask how much victims of rape would be willing to accept in order to accept rape," she observes, "is to misunderstand the very nature of the crime in question."[156]

Modeling relies upon reducing our world to a set of features that can be modeled. There are other, deeper costs. As early as 1991, Professor Paul Schwartz recognized the degree to which a reliance on computation undermines the human element of governance.[157] The computer becomes a mediating barrier between officials and citizens, a reason for action that defies everyday common sense and experience. As Professors Brett Frischmann and Evan Selinger elegantly argue in *Re-Engineering Humanity*, AI represents a kind of culmination of Taylorism—the application of scientific principles of management championed by engineer Frederick Taylor at the turn of the twentieth century.[158] These scholars and others warn that a society managed by models may be impoverished spiritually. And individuals living in such

152. It is perhaps telling that Scott cited "The Science of 'Muddling Through'" with approval. *Id.* at 328 (noting that Lindblom's and similar positions "amount to a well-reasoned strategic retreat from the ambition to comprehensive, rational planning").

153. *See* Heinzerling, *supra* note 81; ACKERMAN & HEINZERLING, *supra* note 67, at 42.

154. Heinzerling, *supra* note 81, at 1464.

155. *Id.*

156. *Id.* at 1466.

157. *See* Schwartz, *supra* note 23, at 1349.

158. BRETT FRISCHMANN & EVAN SELINGER, RE-ENGINEERING HUMANITY 72 (2018).

a society may lack opportunities for experimentation and self-development.[159]

Modeling through, even (and especially) if perfected, holds the potential to dehumanize in other ways. I will end by noting that as imperfect as human policymakers are—as much as they muddle through to sometimes unfortunate consequences—there will be many in society that bemoan a technocratic government designing an ostensibly optimal world.

CONCLUSION

Theorists have long imagined an ideal decision-maker capable of acting wisely in all circumstances. Policymakers have never lived up to this ideal. They face well-understood limits, including an inability to maximize welfare or anticipate the societal impacts of state intervention. Modeling holds promise in delivering on the broader goals of forecasting and systems analysis, arming policymakers with a powerful set of affordances to venture away from the branch method and into the roots—to model instead of muddle. A few policymakers have already dipped a toe into these deep waters and are being told that the water is warm.

The prospect that economic, physical, and even social forces could be modeled by machines confronts policymakers with a paradox. Society should expect more of a policymaker who can avail themselves of techniques already usefully deployed in other sectors. In some cases, formal requirements obligate policymakers to anticipate the impact of new rules on particular communities or values. At the same time, such techniques hold novel perils that policymakers may be ill equipped to address. These concerns include privacy, brittleness, and automation bias, of which law and technology scholars are keenly aware. They also include the extension and deepening of the quantifying turn in governance, a process that obscures normative judgments and recognizes only that which the machines can see. The water may be warm, but there are sharks in it.

These tensions are not new. And there is danger in hewing to the status quo. We cannot deny the government every tool of the twenty-first century merely because there are risks that inhere in their use. As modeling through gains traction, however, policymakers, constituents,

159. JULIE E. COHEN, CONFIGURING THE NETWORKED SELF: LAW, CODE, AND THE PLAY OF EVERYDAY PRACTICE 227–29 (2012).

and academic critics must remain vigilant. This being the early days, U.S. society is uniquely positioned to shape the transition from muddling to modeling. This Article means, at minimum, no one can say they were not warned.