
RESPONSE

TECHNOLOGY EXPERTISE AND PREDICTION-PROOF POLICYMAKING[†]

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[†] An invited Response to Ari Ezra Waldman, *Challenging Technological Expertise*, 106 B.U. L. REV. 451 (2026).

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INTRODUCTION

In *Challenging Technological Expertise*, Professor Ari Waldman challenges the assumption that technology policymaking must rely on technical expertise.¹ Professor Waldman interrogates the easy refrain that the problem with tech policy is an expertise deficiency on the part of policymakers and that the road to sound policy requires reliance on technical know-how.² He documents what he terms the “expert turn” in tech policy, whereby regulators and scholars tout the advantages of integrating technical forms of knowledge into our policy institutions and decision-making processes;³ traces the common justifications for this move, which typically depend on the complexity of emerging technologies, the advantages of technical expertise for accountability and oversight, or alignment between the values inherent in technical ways of knowing and policy goals;⁴ and demonstrates that the arguments for the primacy of technical expertise do not always obtain the best results and can lead to negative consequences.⁵ Professor Waldman offers us a path forward for a more thoughtful examination of the conditions under which technical expertise *is* important to policymaking, suggesting that we should be more attentive to whether technical expertise is necessary and helpful for reaching desired outcomes.

Professor Waldman’s entreaty to consider this question is both important and timely, as policymakers confront imperatives around artificial intelligence (“AI”) governance and as the internal capacities of federal agencies and other policymaking bodies are reshaped.⁶ Many of the concerns Professor Waldman raises are particularly salient in light of heightening concerns around Big Tech’s deference to the Trump Administration, coupled with the industry’s own oligarchic power and its capture of political and regulatory processes.⁷

The part of Professor Waldman’s argument that I find most provocative, and to which I would like to address this Response, are his efforts to delineate *when and how* technological expertise is warranted in policymaking.⁸ In particular, I read Professor Waldman as offering a set of conditions under which we can

¹ Ari Ezra Waldman, *Challenging Technological Expertise*, 106 B.U. L. REV. 451, 456 (2026) (“Legal scholarship, including my own, has insufficiently surfaced the rationales for bringing technical expertise into tech policymaking. This is not just a problem of theory; it has profound practical implications.” (footnote omitted)).

² *Id.* at 456-59.

³ *Id.* Part I (explaining view that regulators must have technical expertise to be effective and discussing attempts to staff agencies with experts).

⁴ *Id.* Part II (outlining common justifications for deference to technical experts in policymaking).

⁵ *Id.* Part III (scrutinizing and dismissing common rationales for categorical deference to technical experts).

⁶ *Id.* at 454-55.

⁷ See generally Julie E. Cohen, *Oligarchy, State, and Cryptopia*, 94 FORDHAM L. REV. 563 (2025).

⁸ Waldman, *supra* note 1, Part IV.

benefit from integrating technical expertise *in alignment with* additional forms of expertise, rather than displacing other ways of knowing or artificially constraining the scope of our policy ambitions.

I take up Professor Waldman's provocations by describing what I see as three useful guideposts for recognizing when and how we might want to draw upon technical expertise in our policy processes. First, we might think about the functional *roles* for technological expertise in policy conversations, and ought to deploy it when it serves one of these functions. Second, we should match expertise thoughtfully to the problems we are trying to solve, drawing on tenets of social research design in doing so. And finally, we should recognize that generalist technology policies obviate the need for reliance on specialized expertise.

I. ROLES FOR TECHNOLOGY EXPERTISE

Professor Waldman urges us not to make "[t]he simplistic assumption that technical expertise is necessary for effective policymaking," lest "we run the risk of seeing every problem, from climate change to mass incarceration, as a technical one."⁹ But he allows that technical expertise *can* be a useful resource for policymaking in certain contexts: For example, when technical expertise helps us to evaluate the claims of regulated parties and subject them to oversight, or "when the interests of the technical experts align with the public's."¹⁰ The question of when and how technical expertise can inform policymaking is a critical one. In some of my own collaborative work with computer scientists, we have sought to offer some guidance on how computational expertise can best ally and integrate with other forms of knowledge to further meaningful social change.¹¹ I offer some of those insights here, which I believe align with the recommendations developed by Professor Waldman.

Like Professor Waldman, we conceive of technical expertise as most useful when it fulfills particular functional roles in social change processes, including policymaking.¹² For example, we describe how technical expertise can serve as a *diagnostic* when it helps us to measure and specify how social problems manifest in computing systems.¹³ For instance, Professor Latanya Sweeney's now-classic study of how arrest-related ads were more likely to appear in response to Google searches for characteristically Black first names (also cited by Professor Waldman)¹⁴ required technical expertise to understand how and why search engines ranked certain ads above others, in part in response to users'

⁹ *Id.* at 460.

¹⁰ *Id.* at 516-17, 518 (emphasis omitted).

¹¹ See Rediet Abebe et al., *Roles for Computing in Social Change*, FAT* '20: PROC. 2020 CONF. ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY, Jan. 2020, at 252, 253-59.

¹² *Id.* at 253 ("Meaningful advancement toward social change is always the work of many hands. We explore where and how technical approaches might be *part* of the solution . . .").

¹³ *Id.* at 253-54.

¹⁴ Waldman, *supra* note 1, at 476 n.127.

patterns of behavior.¹⁵ Efforts by both legal scholars and computer scientists to inform the Supreme Court about how recommendation algorithms work aim to ensure that the Court's rulings reflect accurate understandings of the technology, which is critical for determining whether a firm ought to incur liability for harm under current legal frameworks.¹⁶ In other cases, as Professor Waldman also notes, technical expertise can provide information that aids in the auditing of technical systems to assess compliance with regulatory mandates.¹⁷ The diagnostic function for technical expertise is an evidentiary one: Its goal is not to propose solutions, but to provide information to policymakers to help ensure that they have necessary knowledge of how systems work in order to govern them.

A different role for technical expertise can be to function as a *rebuttal*, offering policymakers a better understanding of the *limitations* of technical interventions for social change.¹⁸ Technical experts are often well-placed to “recognize and declare th[e] limits”¹⁹ of what technology can do when policymakers rely on it as a solution to social problems. Probably the best known example of this, also discussed by Professor Waldman,²⁰ is the 2015 effort by a group of high-profile academic cryptographers to authoritatively dispel the notion that secure encryption technologies can be developed with “backdoors” for government access to data.²¹ In other cases, computer scientists have brought technical expertise to bear to demonstrate the mathematical impossibility of simultaneously meeting multiple commonly used definitions of fairness in criminal risk assessment—demonstrating that the decision about how fairness ought to be instantiated in such tools is ultimately a political and normative one.²² Mathematicians like Moon Duchin have similarly provided technical expertise to demonstrate to courts that certain electoral maps are the product of

¹⁵ See Latanya Sweeney, *Discrimination in Online Ad Delivery: Google Ads, Black Names and White Names, Racial Discrimination, and Click Advertising*, ASS'N FOR COMPUTING MACH. QUEUE, Mar. 2013, at 1, 15-18. For other examples of technical expertise being marshaled to understand harms arising from technical systems, see Abebe et al., *supra* note 11, at 253-54.

¹⁶ See, e.g., Brief for Info. Sci. Scholars as Amici Curiae in Support of Respondent at 5-8, *Gonzalez v. Google LLC*, 598 U.S. 617 (2023) (No. 21-1333).

¹⁷ Waldman, *supra* note 1, Section II.C.4.

¹⁸ See Abebe et al., *supra* note 11, at 256-57.

¹⁹ *Id.* at 256.

²⁰ Waldman, *supra* note 1, at 515-16 nn.382-83.

²¹ See Harold Abelson et al., *Keys Under Doormats: Mandating Insecurity by Requiring Government Access to All Data and Communications*, 1 J. CYBERSECURITY 69, 70-71 (2015); see also Harold Abelson et al., *Bugs in Our Pockets: The Risks of Client-Side Scanning*, 10 J. CYBERSECURITY 1, 2 (2024) (bringing together similar group of cybersecurity experts to make similar rebuttal detailing security and privacy risks of client-side scanning technology).

²² See Jon Kleinberg, Sendil Mullainathan & Manish Raghavan, *Inherent Trade-Offs in the Fair Determination of Risk Scores*, ARXIV (Nov. 17, 2016), <https://arxiv.org/abs/1609.05807> [<https://perma.cc/KD7T-DAYE>].

partisan gerrymandering, rebutting claims that such maps are merely the result of unmotivated construction.²³

Technical expertise can therefore serve certain functional roles in the service of informed policymaking, though each of these carries its own potential risks.²⁴ Even when technical expertise is marshaled in the service of these roles, I maintain that it should do so in a way that supports, rather than supplants, other forms of expertise. This observation aligns with Professor Waldman’s warning against technological solutionism.

II. MATCHING EXPERTISE TO PROBLEMS

A fundamental tenet of research design is that the research question should determine what method is used to answer it—not the other way around. In other words, to avoid the “hammer looking for a nail” problem, we should first determine what we want to know, and then determine how best to learn about that thing.²⁵ If we want to understand the causal relationship between a policy and an economic outcome, we might use a large-scale controlled experiment to answer our question; if we want to understand the mechanisms through which people understand and make meaning of some phenomenon, we might be better placed to use qualitative interviews or ethnographic methods; and so on. This general tenet applies with equal force to the context of understanding technology and its effects on the world for purposes of guiding policy. Depending on *what it is we want to know*, we might endeavor to use the tools of design research,²⁶

²³ See MOON DUCHIN, OUTLIER ANALYSIS FOR PENNSYLVANIA CONGRESSIONAL REDISTRICTING 1 (2018), <https://mggg.org/publications/md-report.pdf>.

²⁴ See Abebe et al., *supra* note 11, at 253-59 (describing additional roles for computing in social change and offering analysis of potential risks surrounding each).

²⁵ See GLENN FIREBAUGH, SEVEN RULES FOR SOCIAL RESEARCH 207 (2008) (“[M]ethods should serve as the handmaiden to theory and research design, not the other way around. . . . While we all agree to this rule in principle, in practice method can become master because we become so enamored with a particular method that our research is designed around the method rather than the method designed to fit the research.”).

²⁶ See, e.g., Franchesca Spektor et al., *Designing for Wellbeing: Worker-Generated Ideas on Adapting Algorithmic Management in the Hospitality Industry*, DIS ‘23: DESIGNING INTERACTIVE SYS. CONF., July 2023, at 623, 623-24 (using worker-generated design ideas to adapt automation toward more worker-friendly solutions in the hospitality industry).

of qualitative social science,²⁷ of experiments,²⁸ of econometrics,²⁹ or of theoretical computer science³⁰—among many other possible approaches.

In fact, Professor Waldman's own scholarship provides ample evidence of the utility of bringing different forms of expertise to bear depending on the problem one is seeking to elucidate. Professor Waldman's graduate training in sociology equips him to bring diverse empirical data and analytic methods to bear in order to address critical questions about how privacy law is created³¹ and operationalized,³² how bureaucratic data recording practices lead to legibility dilemmas for transgender and gender-nonconforming people,³³ what leads algorithmic decision-making processes to be perceived as legitimate,³⁴ and many other questions of socio-legal import. Professor Waldman marshals his own multi-method scientific expertise in the service of addressing these

²⁷ See, e.g., Angèle Christin, *Counting Clicks: Quantification and Variation in Web Journalism in the United States and France*, 123 AM. J. SOCIO. 1382, 1383-85 (2018) (drawing on ethnographic observation in two news organizations to understand the meanings newsrooms assign to audience metrics).

²⁸ See, e.g., Kowe Kadoma, Danaë Metaxa & Mor Naaman, *Generative AI and Perceptual Harms: Who's Suspected of Using LLMs?*, CHI 2025: CONF. ON HUM. FACTORS COMPUTING SYS., Apr. 2025, at 1, 1-2 (designing online experiments to study whether members of marginalized groups are more frequently suspected of using generative AI in writing tasks).

²⁹ See, e.g., Cristobal Cheyre, Steven Klepper & Francisco Veloso, *Spinoffs and the Mobility of U.S. Merchant Semiconductor Inventors*, 61 MGMT. SCI. 487, 487-88 (2015) (analyzing patent and sales data to determine mobility of semiconductor inventors in Silicon Valley).

³⁰ See, e.g., Kleinberg et al., *supra* note 22 (using mathematical modeling to demonstrate incompatibility between different commonly used definitions of fairness in predictive systems).

³¹ See Ari Ezra Waldman, *Civil Society and the Crisis of Privacy Law*, 74 EMORY L.J. 1079, 1084 (2025) (using interviews and archival data to support claims about how law constrains civil society expertise in privacy policymaking).

³² See Ari Ezra Waldman, *Privacy Law's False Promise*, 97 WASH. U. L. REV. 773, 776 (2020) (analyzing interviews, surveys, observations at industry conferences, and documentary sources to understand how processes of legal endogeneity can be understood as undermining potential of privacy law); ARI EZRA WALDMAN, *INDUSTRY UNBOUND: THE INSIDE STORY OF PRIVACY, DATA, AND CORPORATE POWER* 4-5 (2021) (drawing on similar sources to demonstrate how corporate surveillant interests inculcate practices and norms within the information industry).

³³ See Ari Ezra Waldman, *Opening the Gender Box: Legibility Dilemmas and Gender Data Collection on U.S. State Government Forms*, 49 L. & SOC. INQUIRY 2021, 2022-23 (2024) (collecting extensive public records requests and interviews with civil servants in state agencies to empirically assess how sex and gender are recorded in state administrative records, and what social and political pressures lead to these practices).

³⁴ See Kirsten Martin & Ari Waldman, *Are Algorithmic Decisions Legitimate? The Effect of Process and Outcomes on Perceptions of Legitimacy of AI Decisions*, 183 J. BUS. ETHICS 653, 653-54 (2023) (using factorial vignette survey methodology and quantitative analysis to develop causal evidence of what factors lead people to perceive algorithmic decision-making as legitimate or not).

questions, matching data sources and methods as appropriate to the question at hand.

In short, the forms of expertise that matter depend on the question being asked: We should apply the tools best suited for addressing our questions of interest. Technical expertise is appropriate to bring to bear when the policy question at hand requires it—and, just as importantly, other forms of knowledge should be brought to bear when the question at hand requires *them*. This observation might seem simplistic, or even tautological, but ultimately is intended to suggest a priori reflection on our policy goals: We should not immediately assume that any particular form of expertise is required until we’ve given significant thought to what it is we aim to understand and achieve.

Of course, there are some natural counterpoints to this claim. It may seem too romantic a view of both research design and policymaking processes to assume that they proceed *seriatim* from goal articulation and problem formulation to decisions about applicable methods and forms of expertise. In practice, the boundaries between these steps are far more porous. But even when we do tend to iterate on research or policy design based on the methods and data available to us, the point of articulating the steps as I have here is, again, to invite intentional reflection on what our goals are and what values drive our policy choices, rather than to “let the tail wag the dog” by letting available expertise determine our goals and problem formulations from the outset. This, too, is easier said than done. As Professor Waldman explains, one of the more insidious ways expertise can shape the policy conversation is by subtly limiting the scope of what’s considered possible, and redirecting our efforts toward formalist and reformist paradigms that understate the possibilities for change.³⁵ Therefore, in the next Section, I will describe what I view as a promising form of technology policymaking that helps to obviate some of these concerns.

III. THE CASE FOR PREDICTION-PROOF POLICY

A perpetual point of debate in technology governance has to do with how specific we try to be in regulating or hedging against the risks of new systems. Governance that hinges on the particulars of a technological form runs the risk of being brittle and becoming quickly outdated as the technology evolves.³⁶ We run similar risks when we overindex policy not on technological form, but on

³⁵ Waldman, *supra* note 1, Section III.C; see also Ben Green & Salomé Viljoen, *Algorithmic Realism: Expanding the Boundaries of Algorithmic Thought*, FAT* ‘20: CONF. ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY, Jan. 2020, at 19, 19-21. Technical expertise is not the only type of expertise that can limit our ambition for reform. See Jocelyn Simonson & K. Sabeel Rahman, *The Part IV Problem in Legal Scholarship*, 126 COLUM. L. REV. FORUM (forthcoming 2026) (manuscript at 3-4) (on file with the Boston University Law Review) (describing how legal scholarship is constrained by norms of articulating feasible policy prescriptions within law review articles).

³⁶ See Marc Chase McAllister, *Modernizing the Video Privacy Protection Act*, 25 GEO. MASON L. REV. 102, 103-05 (2017) (discussing failure of Video Privacy Protection Act to secure consumer privacy due to regulating obsolete modes of watching videos).

our *predictions* about precisely how technologies will impact social or economic life.

To illustrate, consider some of the policy proposals being discussed to address issues related to AI, automation, and employment. There's widespread policy concern over the impacts new technologies will have on the labor market, but substantial uncertainty about the extent of the problem (How many people will lose jobs? Will enough new jobs be created to offset the effects of displacement?), the industries technological change is most likely to affect (Which people will lose jobs? Within which sectors?), the pace of change (When might people lose jobs?), and the mechanisms through which change might occur (For instance, will jobs be reorganized to account for new bundles of work tasks? Whose jobs, and how?). Predicting the answers to each of these questions relies on certain forms of specialized expertise, from knowledge about the capacities of the technology, to forecasting about economic trends, to understanding about how firms tend to deploy new technological tools and organize work. And each of these areas is marked by uncertainty and debate among experts about what the future will hold.³⁷

A number of policy proposals have been floated to potentially address the risks of AI-driven unemployment, but their prospects for success often depend on *how* the technology will develop and impact jobs. For example, some policymakers advocate for a “robot tax”—requiring companies that deploy new technologies to pay additional taxes for doing so, essentially “treat[ing] a robot the same as a person for tax purposes . . . by subjecting the income generated by a robot to income and/or payroll taxes, which are payable by the company using the robot.”³⁸ There are other formulations, but all involve versions of more or less the same idea.³⁹ But the success of such a policy depends on technological change playing out in a particular way. How do we know that a “robot” is the most useful unit of measurement for such a policy? Does it make sense to treat a robot as equivalent to a human worker for purposes of taxation? How would we measure what counts as a robot, anyway? Do we know for sure that robots will displace human jobs? What good is such a policy if automation is used not primarily to *replace* human jobs, but to reduce their quality and lessen workers' bargaining power?⁴⁰ Even if we loosen our definitions and understand

³⁷ See, e.g., David Autor, Anton Korinek & Natasha Sarin, *What if Labor Becomes Unnecessary?*, N.Y. TIMES (Feb. 4, 2026), <https://www.nytimes.com/2026/02/04/opinion/ai-jobs-employment-industry.html> (describing disagreements among economists on likely impacts of artificial intelligence (“AI”) on employment).

³⁸ Orly Mazur, *Taxing the Robots*, 46 PEPP. L. REV. 277, 280 (2019).

³⁹ See, e.g., Michael J. Ahn, *Navigating the Future of Work: A Case for a Robot Tax in the Age of AI*, BROOKINGS (May 13, 2024), <https://www.brookings.edu/articles/navigating-the-future-of-work-a-case-for-a-robot-tax-in-the-age-of-ai/> [<https://perma.cc/6GSF-EMXX>] (discussing policies which would generate legal personhood for robots for tax purposes and considering whether manufacturers or employers would pay the tax).

⁴⁰ My own research suggests that this is a common route through which technology affects workers, harming the quality rather than the quantity of jobs. See KAREN LEVY, DATA DRIVEN:

technology-responsive policies such as a robot tax less literally (say, as a general tax levied on corporations deploying high-tech automation tools), the success of such a policy remains tightly dependent on the technology affecting work and workers in very specific ways.⁴¹

Another approach often discussed is the creation of sector-specific job retraining or upskilling programs, in which workers predicted to be at high risk of displacement by AI are given subsidized training to increase their skillset and (presumably) augment their employment prospects.⁴² This, too, relies on a number of predictions about whom technological change will affect, when, and how. For instance, similar programs were launched to redevelop rural regions when coding was seen as a surefire route to employability for newly unemployed workers in certain sectors.⁴³ But coding bootcamps and other retraining programs have been moderately successful at best—and of course, basic coding is one of the skills that may be most squarely in the crosshairs of AI’s capabilities now.⁴⁴

I suggest that one way to avoid these kinds of misfires is to formulate policies that *avoid being too reliant* on the specifics of how a technology works or what particular kinds of risks and harms it will create. We might think of these as *prediction-proof policies*—policies that will help people regardless of exactly how things unfold. For example, in the context of AI and unemployment, rather than tying our policies to predictions about exactly *how* technological change will impact workers, we could instead seek to implement more general policies that will improve the lot of workers *regardless of* exactly what happens—policies that strengthen the social safety net, ensure the availability of

TRUCKERS, TECHNOLOGY, AND THE NEW WORKPLACE SURVEILLANCE 7-10 (2023) (outlining various ways increasing employer surveillance undermines autonomy and dignity of truckers); Pegah Moradi & Karen Levy, *The Future of Work in the Age of AI: Displacement or Risk-Shifting?*, in THE OXFORD HANDBOOK OF THE ETHICS OF AI 270, 276 (Marcus D. Dubber, Frank Pasquale & Sunit Das eds., 2020) (“It is not clear to what extent AI will displace existing jobs. What is more certain and more imminent is that AI will impact the conditions of work.”).

⁴¹ To be clear, these are not the only questions that arise; there are also a spate of concerns about whether a robot tax would have negative consequences that would offset any benefits to workers like hindering innovation or driving high-tech companies to other jurisdictions. See Mazur, *supra* note 38, at 299-301. I focus on questions about implementation because they are most germane to my point: that the success of the policy depends on the specifics of how the technology affects jobs.

⁴² See Julian Jacobs, *AI Labor Displacement and the Limits of Worker Training*, BROOKINGS (May 16, 2025), <https://www.brookings.edu/articles/ai-labor-displacement-and-the-limits-of-worker-retraining> [<https://perma.cc/L2NE-VTJ8>].

⁴³ See Campbell Robertson, *They Were Promised Coding Jobs in Appalachia. Now They Say It Was a Fraud*, N.Y. TIMES (May 12, 2019), <https://www.nytimes.com/2019/05/12/us/mined-minds-west-virginia-coding.html> (recounting failed efforts to attract employers to rural areas by training former coalminers to code).

⁴⁴ See Bharat Ramamurti, Zoe Jacobs & Diego Haro, *The Biggest Economic Issue No One Is Talking About*, BULLY PULPIT WITH BHARAT RAMAMURTI (July 21, 2025), <https://bharatramamurti.substack.com/p/the-biggest-economic-issue-no-one> [<https://perma.cc/N4FH-65UR>].

unemployment insurance, decouple health insurance from employment, promote access to affordable housing and childcare, and reduce the everyday cost of living.⁴⁵ This kind of policy might not seem, on its face, like “tech policy” per se—the words “artificial intelligence” need not appear in it, nor any technical specifications at all, but it is very much tech policy. As Professor Alondra Nelson reminds us, the scope of AI regulation encompasses all kinds of policies, from trade to immigration to research funding.⁴⁶

CONCLUSION

My argument for prediction-proof policy arrives at the same endpoint as Professor Waldman, but for slightly different reasons. I suggest that we might want to reduce our reliance on policies that depend on technical expertise and steer toward generalist policies because generalist policies are safer bets for improving people’s life chances in an uncertain technological and economic environment. There is a humility to generalist policymaking because it recognizes the limits of our foresight.⁴⁷ Professor Waldman makes a complementary argument that policies that depend on technical expertise run the risk of limiting our policy ambitions and allowing for capture of policy processes by entrenched corporate interests.⁴⁸ Both arguments suggest that policy responses that rely too heavily on technical expertise might foreclose opportunities for more robust positive social change.

⁴⁵ Martha Gimbel makes a related argument, suggesting that we adopt “boring” “tried-and-true” policy solutions like unemployment insurance in response to possible AI harms to employment. See Martha Gimbel, *Don’t Get Fancy With Your Labor Market Fixes for AI*, ARGUMENT (Dec. 19, 2025), <https://www.theargumentmag.com/p/dont-get-fancy-with-your-labor-market> [<https://perma.cc/B8SX-2MQQ>].

⁴⁶ See Alondra Nelson, *The Mirage of AI Regulation*, SCIENCE (Jan. 15, 2026), <https://www.science.org/doi/10.1126/science.aee4900>.

⁴⁷ Cf. Sheila Jasanoff, *Technologies of Humility: Citizen Participation in Governing Science*, 41 MINERVA 223, 227 (2003) (describing “technologies of humility” as methods which “try to come to grips with the ragged fringes of human understanding — the unknown, the uncertain, the ambiguous, and the uncontrollable”).

⁴⁸ Waldman, *supra* note 1, Section III.C.