Notes

Preface

1. The idea of cognitive biases has of course been subject to many questions. For example, *see* Gerd Gigerenzer, *The Intelligence of Intuitions* (2023). There is much to admire and to learn from in Gigerenzer's work, but his claims about the accuracy of heuristics seem to me to be overstated. For a detailed explanation, *see* Sanjit Dhami & Cass R. Sunstein, *Bounded Rationality* (2022). Among other things, we shall see that in situations of uncertainty, where probabilities cannot be assigned to outcomes, it is very challenging to figure out what to do.

2. *See* Gigerenzer, *supra* note 1.

3. *See* Friedrich Hayek, *The Theory of Complex Phenomena: In Honor of Karl R. Popper*, *in* The Market and Other Orders 257–87 (Bruce Caldwell ed., 2014).

4. *Id.* at 268.

5. *Id.*

6. *Id.* at 269.

7. *Id.* at 275.

Chapter 1

1. *See* David Freeman Engstrom, Daniel E. Ho, Catherine M. Sharkey & Mariano-Florentino Cuéllar, *Government by Algorithm: AI in Federal Administrative Agencies* 6–8 (2020).

2. Ziad Obermeyer, Brian Powers, Christine Vogeli & Sendhil Mullainathan, *Dissecting Racial Bias in an Algorithm Used To Manage the Health of Populations*, 366 Sci. 447, 447 (2019).

3. This is a central theme of Daniel Kahneman, Olivier Sibony & Cass R. Sunstein, *Noise* (2021).

4. For an overview, *see generally* R. F. Pohl, *Cognitive Illusions* (2016).

5. There is a large literature here. A defining treatment is Nicola Gennaioli & Andrei Shleifer, *A Crisis of Beliefs* (2018).

6. *See* Tali Sharot, *The Optimism Bias* 40 (2011).

7. The planning fallacy is the tendency to think that projects will take less time than they actually do. *See, e.g.*, Daniel Kahneman, *Thinking, Fast and Slow* 245–47 (2011) (describing the planning fallacy); *see also* Roger Buehler, Dale Griffin & Michael Ross, *Exploring the "Planning Fallacy": Why People Underestimate Their Task Completion Times*, 67 J. Personality & Soc. Psych. 366, 366 (1994) (defining the planning fallacy). *See generally* Markus K. Brunnermeier, Filippos Papakonstantinou & Jonathan A. Parker, *An Economic Model of the Planning Fallacy* (Nat'l Bureau Econ. Rsch., Working Paper No. 14228, 2008) (exploring the planning fallacy in both theory and practice).

8. Amos Tversky & Daniel Kahneman, *Judgment Under Uncertainty: Heuristics and Biases*, *in* Judgment Under Uncertainty: Heuristics and Biases 3, 11 (Daniel Kahneman, Paul Slovic & Amos Tversky eds., 1982) [hereinafter Tversky & Kahneman, *Judgment Under Uncertainty*].

9. *See generally* Ted O'Donoghue & Matthew Rabin, *Present Bias: Lessons Learned and To Be Learned*, 105 Am. Econ. Rev. 273 (2015) (describing lessons learned through the study of present bias and the open questions that remain).

10. An "anchor" is often understood as some numerical value, possibly provided at random, that affects numerical estimates. *See* Karen E. Jacowitz & Daniel Kahneman, *Measures of Anchoring in Estimation Tasks*, 21 Personality & Soc. Psych. Bull. 1161, 1161 (1995) (discussing how people who are presented with an arbitrary value are more likely to make an estimate close to that number).

11. *See* Mahzarin R. Banaji & Anthony G. Greenwald, *Blindspot: Hidden Biases of Good People* xii (2013).

12. *See* Paul Slovic, Melissa L. Finucane, Ellen Peters & Donald G. MacGregor, *The Affect Heuristic*, 177 Eur. J. Operational Rsch. 1333, 1334 (2007).

13. *See id.*

14. *See* Kahneman et al., *supra* note 3, at 6–7.

15. *See* Daniel Chen, Tobias J. Moskowitz & Kelly Shue, *Decision-Making Under the Gambler's Fallacy: Evidence from Asylum Judges, Loan Officers, and Baseball Umpires* 1–2 (Nat'l Bureau Econ. Rsch., Working Paper No. 22026, 2016); Kahneman et al., *supra* note 3, at 6–7.

16. *See generally* Cass R. Sunstein, *Cognition and Cost-Benefit Analysis*, 29 J. Legal Stud. 1059 (2000) (urging that cost-benefit analysis can correct for cognitive biases).

17. *See* Cass R. Sunstein, *The Value of a Statistical Life: Some Clarifications and Puzzles*, 4 J. Benefit-Cost Analysis 237, 237–41 (2013) (discussing the use of the value of statistical life and its foundations).

18. *See* Gerd Gigerenzer, *The Intelligence of Intuitions* (2023).

19. *See* Kahneman et al., *supra* note 3.

20. For a classic study, *see generally* Jerry Mashaw, *Bureaucratic Justice* (1983), which emphasizes the role and value of rules in administrative adjudication.

21. *See, e.g.*, Jaya Ramji-Nogales, Andrew I. Schoenholtz & Philip G. Schrag, *Refugee Roulette: Disparities in Asylum Adjudication*, 60 Stan. L. Rev. 295, 301–2 (2007) [hereinafter Ramji-Nogales et al., *Refugee Roulette*]; Alafair S. Burke, *Improving Prosecutorial Decision Making: Some Lessons of Cognitive Science*, 47 Wm. & Mary L. Rev. 1587, 1590–92 (2006); Sjoerd Stolwijk & Barbara Vis, *Politicians, the Representativeness Heuristic and Decision-Making Biases*, 43 Pol. Behav. 1411, 1427–29 (2020).

22. 8 U.S.C. § 1101(a)(42).

23. For evidence to this effect in the federal courts, *see* Kenny Mok & Eric A. Posner, Constitutional Challenges to Public Health Orders in Federal Courts During the COVID-19 Pandemic 3–4 (Aug. 1, 2021) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3897441 [https://perma.cc/GU63-24WK]. *See generally* Fatma E. Marouf, *Implicit Bias and Immigration Courts*, 45 New Eng. L. Rev. 417 (2011) (showing how implicit bias, with few safeguards to prevent it, unduly influences immigration decisions).

24. *Cf.* Dan P. Ly, *The Influence of the Availability Heuristic on Physicians in the Emergency Department*, 78 Annals Emergency Med. 650, 650–53 (2021) (discussing how use of the availability heuristic by doctors leads some doctors to test more for conditions they have diagnosed recently compared to other doctors).

25. As Kleinberg, Lakkaraju, Leskovec, Ludwig, and Mullainathan explain, "The superior performance of the predicted judge suggests that, on net, the costs of inconsistency outweigh the gains from private information in our

context. Whether these unobserved variables are internal states, such as mood, or specific features of the case that are salient and overweighted, such as the defendant's appearance, the net result is to create noise, not signal." Jon Kleinberg, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig & Sendhil Mullainathan, *Human Decisions and Machine Predictions*, 133 Q. J. Econ. 237, 242 (2018) [hereinafter Kleinberg et al., *Human Decisions*].

26. *See* Ramji-Nogales et al., *Refugee Roulette*, *supra* note 21, at 295, 301–2.

27. *Id.* at 301. Refugee roulette can be found many places. *See, e.g.*, Andrew Burridge & Nick Gill, *Conveyor-Belt Justice: Precarity, Access to Justice, and Uneven Geographies of Legal Aid in UK Asylum Appeals*, 49 Antipode 23, 23–30 (2017) (describing how the U.K. asylum appeal success rate is affected by the location of the asylum seeker and corresponding access to legal representation).

28. *See, e.g.*, Chen et al., *supra* note 15, at 1–3.

29. *See, e.g.*, David M. Uhlmann, *Prosecutorial Discretion and Environmental Crime*, 38 Harv. Env't L. Rev. 159, 164 (2014) (discussing how prosecutors exercise discretion in choosing which environmental crimes to prosecute). *See generally* Angela J. Davis, *Arbitrary Justice: The Power of the American Prosecutor* (2007) (discussing how prosecutorial discretion, without sufficient public scrutiny and oversight to ensure fairness, has led to wide disparities in how prosecutors treat different cases).

30. This is the central theme of Kahneman et al., *supra* note 3.

31. *Id.* at 366–67.

32. *See id.* at 367.

33. *See, e.g.*, *id.*

34. For evidence that it might well be significant, *see* Chen et al., *supra* note 15, at 1–2, finding that, in asylum cases, up to "two percent of decisions [are] reversed purely due to the sequencing of past decisions, all else equal."

35. *See* Kahneman et al., *supra* note 3, at 73–74 (discussing how judges impose sentences with different levels of severity, which may be based on factors such as their opinions about the goals of sentencing, their geographic locations, and their political ideologies).

Chapter 2

1. *See* Jon Kleinberg, Jens Ludwig, Sendhil Mullainathan & Ziad Obermeyer, *Prediction Policy Problems*, 105 Am. Econ. Rev. 491 (2015).

2. *Id.*

3. *See* Ajay Agrawal, Joshua Gans, & Avi Goldfarb, *Prediction Machines* 27 (2022).

4. For relevant discussion, *see generally* Jens Ludwig & Sendhil Mullainathan, *Fragile AI Algorithms and Fallible Decision-Makers: Lessons from the Justice System*, 34 J. Econ. Persps. 71 (2021).

5. For valuable discussions on how algorithmic predictions help understand and reduce physicians' over- and underuse of testing in the medical field, *see generally* Sendhil Mullainathan & Ziad Obermeyer, *Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care* 4–5 (Nat'l Bureau Econ. Rsch., Working Paper No. 26168, 2021); David Arnold, Will S. Dobbie & Peter Hull, *Measuring Racial Discrimination in AI Algorithms* 2 (Nat'l Bureau Econ. Rsch., Working Paper No. 28222, 2021); Kleinberg et al., *supra* note 1, 491. On availability bias in medicine, *see* Ping Li, Zi yan Cheng & Gui lin Liu, *Availability Bias Causes Misdiagnoses by Physicians: Direct Evidence from a Randomized Controlled Trial*, 59 Internal Med. 3141, 3141 (2020), which found a significant role for availability bias among doctors.

6. *See generally* Paul E. Meehl, *Clinical Versus Statistical Prediction: A Theoretical Analysis and a Review of the Evidence* (1954) (comparing clinical prediction to statistical prediction and finding that the latter is usually better).

7. *See* Alaina N. Tallboy & Elizabeth Fuller, *Challenging the Appearance of Machine Intelligence: Cognitive Bias in LLMs and Best Practices for Workplace Adoption* (2023), https://arxiv.org/abs/2304.01358; Erik Jones & Jacob Steinhardt, *Capturing Failures of Large Language Models via Human Cognitive Biases, in* Advances in Neural Information Processing Systems Proceedings (Sanmi Koyego et al. eds., 2022), https://proceedings.neurips.cc/paper_files/paper/2022/hash/4d13b2d99519c5415661dad44ab7edcd-Abstract-Conference.html.

8. *See* Jeremy K. Nguyen, *Human Bias in AI Models? Anchoring Effects and Mitigation Strategies in Large Language Models*, 43 J. Behav. & Experimental Fin. (2024).

9. *See* Pengda Wang, Zilin Xiao, Hanjie Chen & Frederick L. Oswald, *Will the Real Linda Please Stand Up . . . to Large Language Models? Examining the Representativeness Heuristic in LLMs* (COLM 2024 conference paper, 2024), https://arxiv.org/abs/2404.01461.

10. *See* Jens Ludwig, Sendhil Mullainathan & Ashesh Rambachen, *Large Language Models: An Applied Econometric Framework* (Nat'l Bureau Econ. Rsch., Working Paper No. 33344, 2025), https://www.nber.org/papers/w33344.

11. The latter question is explored in Jon Kleinberg, Jens Ludwig, Sendhil Mullainathan & Cass R. Sunstein, *Discrimination in the Age of AI Algorithms*, 10 J. Legal Analysis 113 (2018) (urging that AI algorithms can be more transparent than human beings and thus serve to reduce discrimination).

Chapter 3

1. *See generally* David A. Strauss, *Discriminatory Intent and the Taming of* Brown, 56 U. Chi. L. Rev. 935 (1989) (exploring different possible meanings of discrimination and discriminatory intent).

2. Jon Kleinberg, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig & Sendhil Mullainathan, *Human Decisions and Machine Predictions*, 133 Q. J. Econ. 239 (2018).

3. *See id.* at 273–75; *see also* John Logan Koepke & David G. Robinson, *Danger Ahead: Risk Assessment and the Future of Bail Reform*, 93 Wash. L. Rev. 1725, 1733–34 (2018) (discussing the history of bail and that in addition to its accepted flight risk rationale, bail was controversially used as a way to prevent people from committing further crimes). *But see* Lauryn P. Gouldin, *Disentangling Flight Risk from Dangerousness*, 2016 BYU L. Rev. 837, 843 (making "constitutional, statutory, and policy-based arguments to illustrate why . . . disentangling [flight risk from dangerousness] is integral to [bail] reform efforts").

4. Kleinberg et al., *Human Decisions*, *supra* note 2, at 241.

5. *Id.* (citations omitted).

6. *See* Jens Ludwig & Sendhil Mullainathan, *Machine Learning as a Tool for Hypothesis Generation* (Nat'l Bureau Econ. Rsch., Working Paper No. 31017, 2023).

7. *See also* Sendhil Mullainathan & Ziad Obermeyer, *Diagnosing Physician Error: A Machine Learning Approach to Low-Value Health Care* (Nat'l Bureau Econ. Rsch., Working Paper No. 26168, 2021), 4, 22, 38–39 (noting AI algorithms can help correct both over- and undertesting for blockages that can lead to heart attacks); Kleinberg et al., *Human Decisions*, *supra* note 2, at 240–42.

8. Mullainathan & Obermeyer, *supra* note 7, at 4–5.

9. *Id.* at 5, 34.

10. *See id.* at 4–5, 32–33.

11. *See* Amos Tversky & Daniel Kahneman, *Availability: A Heuristic for Judging Frequency and Probability*, *in* Judgment Under Uncertainty: Heuristics and Biases 3, 11 (Daniel Kahneman, Paul Slovic & Amos Tversky eds.,

1982) at 163 [hereinafter Tversky & Kahneman, *Availability*] (describing the availability bias).

12. *See* Daniel Kahneman & Shane Frederick, *Representativeness Revisited: Attribute Substitution in Intuitive Judgment*, *in* Heuristics and Biases: The Psychology of Intuitive Judgment 49, 53 (Thomas Gilovich, Dale Griffin & Daniel Kahneman eds., 2002) (describing attribute substitution as "when an individual assesses a specified target attribute of a judgment object by substituting another property of that object—the heuristic attribute—which comes more readily to mind" (emphasis omitted)); *see also* Daniel Kahneman, *Thinking, Fast and Slow* 245–47 (2011) (distinguishing between rapid, intuitive thinking and deliberative thinking).

13. *See id.* at 166–68.

14. Tversky & Kahneman, *Judgment Under Certainty*, *supra* note 11 (Ch. 1), at 11.

15. *Id.*

16. *Id. See generally* Drew Fudenberg & David K. Levine, *Learning with Recency Bias*, 111 Proc. Nat'l Acad. Scis. (2014) (demonstrating the validity of recency bias).

17. Tversky & Kahneman, *Judgment Under Certainty*, *supra* note 11 (Ch. 1), at 11.

18. Fudenberg & Levine, *supra* note 16, at 1.

19. *See* Robert H. Ashton & Jane Kennedy, *Eliminating Recency with Self-Review: The Case of Auditors' 'Going Concern' Judgments*, 15 J. Behav. Decision Making 221, 222 (2002) (describing how recency bias's impacts can be compounded by limited access to information).

20. *See* Paul Slovic, *The Perception of Risk* 40 (Ragnar E. Löfstedt ed., 2000).

21. *See, e.g.*, Howard Kunreuther, *The Role of Insurance in Reducing Losses from Extreme Events: The Need for Public-Private Partnerships*, 40 Geneva Papers 741, 745 (2015) (discussing earthquake insurance coverage in California after the 1994 Northridge earthquake).

22. *See generally* Timur Kuran & Cass R. Sunstein, *Availability Cascades and Risk Regulation*, 51 Stan. L. Rev. 683 (1999) (analyzing availability cascades, "collective belief formation [processes] by which an expressed perception triggers a chain reaction that gives the perception of increasing plausibility through its rising availability in public discourse," and suggesting reforms to address their hazards, "includ[ing] new governmental structures designed to [insulate] civil servants" from these pressures).

23. *See* Cass R. Sunstein, *The Availability Heuristic, Intuitive Cost-Benefit Analysis, and Climate Change*, 77 Climate Change 195, 196–97 (2006).

24. *See, e.g.*, Anupam Chander, *The Racist Algorithm?*, 115 Mich. L. Rev. 1023, 1024–25 (2017); 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/6JT5-UQH9].

25. *See, e.g.*, David Arnold, Will Dobbie & Crystal S. Yang, *Racial Bias in Bail Decisions*, 133 Q. J. Econ. 1885, 1886 (2018); *see also* Ziad Obermeyer, Brian Powers, Christine Vogeli & Sendhil Mullainathan, *Dissecting Racial Bias in an Algorithm Used To Manage the Health of Populations*, 366 Sci. 447 (2019) (describing how a widely used health system algorithm exhibits racial discrimination). A terrific, clarifying discussion can be found in Ludwig & Mullainathan, *supra* note 6, at 82–88.

26. For an overview, *see* Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 Calif. L. Rev. 671, 694 (2016).

27. *See, e.g.*, *Washington v. Davis*, 426 U.S. 229, 239 (1976); *Pers. Adm'r of Mass. v. Feeney*, 442 U.S. 256, 272 (1979).

28. *See Washington*, 426 U.S. at 239.

29. *See Griggs v. Duke Power Co.*, 401 U.S. 424, 434–36 (1971) (interpreting Title VII of the 1964 Civil Rights Act).

30. *See generally* Susannah W. Pollvogt, *Unconstitutional Animus*, 81 Fordham L. Rev. 887 (2012) (proposing a doctrinal definition of "animus" based on existing case law).

31. *See* Samuel R. Bagenstos, *Implicit Bias, "Science," and Antidiscrimination Law*, 1 Harv. L. & Pol'y Rev. 477, 477 (2007).

32. *See Griggs*, 401 U.S. at 436; *Feeney*, 442 U.S. at 273.

33. 42 U.S.C. § 2000e-2(k)(1)(A)–(B).

34. *See, e.g.*, Reva B. Siegel, *Foreword: Equality Divided*, 127 Harv. L. Rev. 1, 2–4 (2013) (describing and critiquing the development of equal protection doctrine); Girardeau A. Spann, *Disparate Impact*, 98 Geo. L. J. 1133, 1135–37 (2010) (criticizing the Court's narrowing of the disparate impact doctrine); Michael Selmi, *Was the Disparate Impact Theory a Mistake?*, 53 UCLA L. Rev. 701, 706–7 (2006) (arguing that disparate impact theory is not correct).

35. *See Feeney*, 442 U.S. at 279.

36. *See* Strauss, *supra* note 1, at 956–57.

37. *See generally* Cass R. Sunstein, *The Anticaste Principle*, 92 Mich. L. Rev. 2410 (1994) (suggesting that the Constitution's Equal Protection Clause might be understood as an attack on a caste system).

38. *See* Arnold et al., *Racial Bias in Bail Decisions*, *supra* note 25.

39. *See* Kleinberg et al., *Human Decisions*, *supra* note 2, at 277.

40. *Id.*
41. *Id.*
42. *Id.*
43. *See* Elizabeth Hinton, LeShae Henderson & Cindy Reed, *An Unjust Burden: The Disparate Treatment of Black Americans in the Criminal Justice System* 2 (2018) (summarizing decades of racial discrimination within the U.S. criminal justice system).
44. *See id.* at 82.
45. Obermeyer et al., *Dissecting Racial Bias, supra* note 25, at 447 (describing how a widely used health system algorithm exhibits racial discrimination).
46. *Id.* at 453.
47. *See, e.g., Parents Involved in Cmty. Schs. v. Seattle Sch. Dist. No. 1*, 551 U.S. 701, 726 (2007).

Chapter 4

1. *See generally* Richard Thaler & Cass R. Sunstein, *Nudge: The Final Edition* (2021). A brisk, preliminary account, much developed and expanded on here, can be found in Cass R. Sunstein, *Choice Engines and Paternalistic AI*, 11 Humanities & Soc. Scis. Commc'ns, article number 888 (2024); at times I draw on that account, which was meant as a forerunner of this far more elaborate one.
2. Linda Thunström, *Welfare Effects of Nudges: The Emotional Tax of Calorie Menu Labeling*, 14 Judgment & Decision Making 11, 18–19 (2019) (finding that a substantial number of study participants favored calorie labels because "calorie content would matter to my meal choice," *id.* at 19).
3. Hunt Allcott & Judd Kessler, *The Welfare Effects of Nudges*, 11 Am. Econ. J.: Applied Econ. 236, 257 (2019).
4. Hunt Allcott, Daniel Cohen, William Morrison & Dmitry Taubinsky, *When Do "Nudges" Increase Welfare?* 4 (Nat'l Bureau Econ. Rsch., Working Paper No. 30740, 2022), https://www.nber.org/system/files/working_papers/w30740/w30740.pdf.
5. *See id.* at 29 ("While much of the empirical literature has focused on whether nudges have average effects in the 'right' direction, we show that welfare also depends on how nudges affect the variance of distortions."). For the final version of this paper, *see* Hunt Allcott, Daniel Cohen, William Morrison & Dmitry Taubinsky, *When Do "Nudges" Increase Welfare?*, Am. Econ. Review (forthcoming, 2025).

6. The term is not in general use, but something like it can be found in various places, with variations. *See* Michael Yeomans, Anuj Shah, Sendhil Mullainathan & Jon Kleinberg, *Making Sense of Recommendations*, 32 J. Behav. Decision Making 403, 403 (2019); Guy Champnis, *The Rise of the Choice Engine*, Enervee (Mar. 6, 2018), https://www.enervee.com/blog/the-rise-of-the-choice-engine; *Why Getting Help Matters*, Edelman Financial Engines (last visited July 22, 2024), http://corp.financialengines.com/individuals/why-getting-help-matters.html. Compare choice engines to the following, which is regrettably complicated: *Buying a Refrigerator Guide: How to Choose a New Fridge in 2024*, Whirlpool (last visited July 22, 2024), https://www.whirlpool.com/blog/kitchen/buying-guide-refrigerator.html.

7. *See Welcome to the Purina Dog Breed Selector*, Purina (last visited July 22, 2024), https://www.purina.co.uk/find-a-pet/dog-breeds/breed-selector.

8. This is consistent with Ian Ayres & Quinn Curtis, *Retirement Guardrails* 159–61 (2023).

9. *See id.* at 160.

10. An episode of *Black Mirror* (Netflix) could easily be based on such scenarios.

11. *See* Mohammad Zahid Hasan, Daicy Vaz, Vidya Athota, Sop Sop Maturin Desire & Vijay Pereira, *Can Artificial Intelligence (AI) Manage Behavioural Biases Among Financial Planners?*, 31 J. Glob. Info. Mgmt. 1, 7–9 (2023). For a disturbing set of findings, *see* Yang Chen, Samuel Kirshner, Anton Ovchinnikov, Meena Andiappan & Tracy Jenkin, *A Manager and an AI Walk into a Bar: Does ChatGPT Make Biased Decisions Like We Do?* (2023), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4380365.

12. *See generally* Jamie Luguri & Lior Strahilevitz, *Shining a Light on Dark Patterns*, 13 J. Legal Analysis 43 (2021).

Chapter 5

1. *See, e.g.*, Joachim Schleich, Xavier Gassmann, Thomas Meissner & Corinne Faure, *A Large-Scale Test of the Effects of Time Discounting*, 80 Energy Econ. 377 (2019); Madeline Werthschulte & Andreas Loschel, *On the Role of Present Bias and Biased Price Beliefs in Household Energy Consumption*, 109 J. Env't Econ. & Mgmt. (2021); Theresa Kuchler & Michaela Pagel, *Sticking to Your Plan: The Role of Present Bias for Credit Card Paydown*, 139 J. Fin. Econ. 359 (2021), https://www.nber.org/system/files/working_papers/w24881

/w24881.pdf; Ted O'Donoghue & Matthew Rabin, *Present Bias: Lessons Learned and To Be Learned*, 105 Am. Econ. Rev. 273 (2015); Jess Benhabib, Alberto Bisin & Andrew Schotter, *Present Bias, Quasi-Hyperbolic Discounting, and Fixed Costs*, 69 Games Econ. Behav. 205 (2010); Yang Wang & Frank Sloan, *Present Bias and Health*, J. Risk Uncertainty 177 (2018). Importantly, Wang and Sloan find strong evidence of present bias in connection with health-related decisions.

2. *See* Carey Morewedge, Sendhil Mullainathan, Haaya F. Naushan, Cass R. Sunstein, Jon Kleinberg, Manish Raghavan & Jens O. Ludwig, *Human Bias in Algorithm Design*, 7 Nature Hum. Behav. 1822 (2023). I am briefly summarizing here the central argument in that essay.

3. *See* Hunt Allcott, Benjamin Lockwood & Dmitry Taubinsky, *Regressive Sin Taxes, with an Application to the Optimal Soda Tax*, 135 Q. J. Econ. 1557, 1557 (2019).

4. *See* Yang Chen et al., *A Manager and an AI Walk Into a Bar: Does ChatGPT Make Biased Decisions Like We Do?* (2023 Manuscript at 10), available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4380365.

5. On the general problem, *see* Cass R. Sunstein, Manipulation (2025); Cass R. Sunstein, *Manipulation as Theft*, 29 J. Eur. Pub. Pol'y 1959 (2022).

6. *See* Saurabh Bhargava, George Loewenstein & Justin Sydnor, *Choose to Lose: Health Plan Choices from a Menu with Dominated Option*, 132 Q. J. Econ. 1319, 1319 (2017).

7. *See* Ian Ayres & Quinn Curtis, *Retirement Guardrails* (2023).

Chapter 6

1. John Stuart Mill, *The Subjection of Women*, 10 (1869).

2. *Id.* at 29.

3. *Id.*

4. Friedrich Hayek, *The Use of Knowledge in Society*, 35 Am. Econ. Rev. 519, 519 (1945) (italics taken from original).

5. *Id.* at 521.

6. Matthew Salganik et al., *Measuring the Predictability of Life Outcomes with a Scientific Mass Collaboration*, 117 PNAS (2020), https://www.pnas.org/cgi/doi/10.1073/pnas.1915006117.

7. *Id.* at 8402.

8. *Id.*

9. *Id.*

10. Samantha Joel, Paul W. Eastwick & Eli J. Finkel, *Is Romantic Desire Predictable? Machine Learning Applied to Initial Romantic Attraction*, 28 Psych. Sci. 1478, 1478 (2017).

11. *Id.* at 1487.

12. *See* Gerd Gigerenzer, *How to Stay Smart in a Smart World* (2022). The treatment in this book is valuable in important ways, not least in its emphasis on the limitations of algorithms in predicting outcomes. But it is too upbeat, I think, on people's ability to make accurate predictions through the use of heuristics in circumstances of genuine uncertainty. In the areas I am exploring, heuristics, used by human beings, do not do very well, either. The Socialist Calculation Debate, the AI Calculation Debate, and the Heuristics Under Uncertainty Debate should all be resolved in favor of taking ignorance really seriously. Daniel Kahneman et al., *Noise* (2021), has relevant discussion, above all in Chapters 11 and 12.

13. *See* Timur Kuran, *Private Truths, Public Lies* (1995).

14. *See* Matthew Salganik, Peter Sheridan Dodds & Duncan J. Watts, *Experimental Study of Inequality and Unpredictability*, 311 Sci. 854 (2006).

15. Ziv Epstein, Matthew Groh, Abhimanyu Dubey & Alex Pentland, *Social Influence Leads to the Formation of Diverse Local Trends*, 5 Proc. ACM on Hum.-Comput. Interaction 409 (2021).

16. I discuss these issues in Cass R. Sunstein, *How to Become Famous* (2024), and draw on some passages from that book here and elsewhere in this chapter.

17. Frank H. Knight, *Risk, Uncertainty, and Profit* 19–20 (1933).

18. *See* Jon Elster, *Explaining Technical Change: A Case Study in the Philosophy of Science* 199 (1983). *See also* Jon Elster, *Risk, Uncertainty, and Nuclear Power*, 18 Soc. Sci. Info. 371 (1979).

19. *See id.*; Truman Bewley, *Knightian Uncertainty*, *in* Frontiers of Research in Economic Theory 71 (Donald P. Jacobs, Ehud Kalai & Morton I. Kamien eds., 1988); Paul Davidson, *Is Probability Theory Relevant for Uncertainty? A Post-Keynesian Perspective*, 5 J. Econ. Persp. 129 (1991). Knightian uncertainty is sometimes described as "radical uncertainty" or "deep uncertainty"; I bracket possible differences here. *See* Decision Making Under Deep Uncertainty (Vincent Marchau, Warren Walker, Pieter Bloemen & Steven Popper eds., 2019). It is also important to note that Keynes and Knight had different concerns; their differences are not relevant for my purposes here. See Robert Dimond, *Keynes, Knight, and Fundamental Uncertainty: A Double Centenary 1921–2021*, 33 Rev. Pol. Econ. 570 (2022), https://www.tandfonline.com/doi/full/10.1080/09538259.2021.1924470?src=recsys; Bill Gerrard, *The Road Less Travelled: Keynes and Knight on Probability and Un-*

certainty, 33 Rev. Pol. Econ. (2022), https://www.tandfonline.com/doi/full/10.1080/09538259.2022.2114291, and in particular this:

> Keynes and Knight both grasped the essential difference between probability-as-risk and probability-as-uncertainty, but they travelled along vastly different roads to get there. Knight contextualised risk and uncertainty in the economic theory of profit as the reward for successful entrepreneurial action under uncertainty. The consequence of Knight's emphasis on context is that the philosophical foundations of his approach are less developed. Keynes's road was much longer, more circuitous and initially primarily concerned with the philosophical foundations, culminating in *A Treatise on Probability* before more fully contextualising his logical theory of probability in the behaviour of the economic system as a whole. The different roads followed by Keynes and Knight have had one crucial consequence. Keynes's greater emphasis on the philosophical issues led him ultimately to treat uncertainty as relating to the weight of argument (i.e., the evidential base), not probability *per se*, whereas Knight defined uncertainty in terms of probability (i.e., the degree of belief), not the evidential base that determined the degree of belief.

20. *See Statement on AI Risk*, Center for AI Safety (2024), https://www.safe.ai/work/statement-on-ai-risk.

21. John Maynard Keynes, *The General Theory of Employment,* 51 Q.J. Econ 2019, 213–14 (1921).

22. On some similarities and differences, *see* Mark D. Packard, Per L. Bylund & Brent Clark, *Keynes and Knight on Uncertainty: Peas in a Pod or Chalk and Cheese?*, 45 Cambridge J. Econ. 1099 (2021).

23. Keynes, *supra* note 21, at 214.

24. *Id.*

25. *Id.* at 215.

26. On ignorance and precaution, *see* Poul Harremoes, *Ethical Aspects of Scientific Incertitude in Environmental Analysis and Decision Making*, 11 J. Cleaner Prod. 705 (2003). For general accounts, *see* Michael Smithson, *Ignorance and Uncertainty* (1989); T. Aven & R. Steen, *The Concept of Ignorance in a Risk Assessment and Risk Management Context*, 95 Reliability Eng'g & Sys. Safety 1117 (2010); Phan H. Giang, *Decision Making Under Uncertainty Comprising Complete Ignorance and Probability*, 62 Int'l J. Approximate Reasoning 27 (2015). An invaluable resource is Kenneth Arrow, *Individual Choice Under Certainty and Uncertainty* (1984).

27. Jill Lepore, *Poor Jane's Almanac*, N.Y. Times (Apr. 23, 2011), https://www.nytimes.com/2011/04/24/opinion/24lepore.html.

28. Alex Bell, Raj Chetty, Xavier Jaravel, Neviana Petkova & John Van Reenen, *Who Becomes an Inventor in America? The Importance of Exposure to Innovation*, 134 Q. J. Econ. 647 (2019).

Chapter 7

1. The Brainwaves Video Anthology, *Daniel Kahneman—On Amos Tversky*, YouTube (Jan. 10, 2017), https://youtube.com.

2. Amos Tversky & Daniel Kahneman, *Belief in the Law of Small Numbers*, 76 Psych. Bull. 105, 105 (1971).

3. *Id.* at 109.

4. *Id.*

5. The core of a central argument in Daniel Kahneman et al., *Noise* (2021), can be found there.

6. See Tversky & Kahneman, *supra* note 2, at 105.

7. *Id.* at 105.

8. Eli R. Sugerman, Ye Li & Eric J. Johnson, *Local Warming Is Real: A Meta-analysis of the Effect of Recent Temperature on Climate Change Beliefs*, 42 Current Op. in Behav. Sci. (2021); Lawrence C. Hamilton & Mary D. Stampone, *Blowin' in the Wind: Short-Term Weather and Belief in Anthropogenic Climate Change*, 5 Weather, Climate, & Soc'y 112 (2013).

9. Daniel Chen, Tobias J. Moskowitz & Kelly Shue, *Decision-Making Under the Gambler's Fallacy: Evidence from Asylum Judges, Loan Officers, and Baseball Umpires* 1–2 (Nat'l Bureau Econ. Rsch., Working Paper No. 22026, 2016).

10. Matthew Rabin, *Inference by Believers in the Law of Small Numbers*, 117 Q. J. Econ. 775 (2002). For an interesting application, *see* Mark Simon, Susan M. Houghton & Karl Aquino, *Cognitive Biases, Risk Perception, and Venture Formation: How Individuals Decide To Start Companies*, 15 J. Bus. Venturing 113 (2000).

11. Tversky & Kahneman, *supra* note 2, at 109.

12. *Id.* at 110.

13. *Id.*

14. *Id.*

15. For relevant discussion, *see* Ziad Obermeyer, Brian Powers, Christine Vogeli & Sendhil Mullainathan, *Dissecting Racial Bias in an Algorithm Used To Manage the Health of Populations*, 366 Sci. 447, 447 (2019).

16. Daniel Kahneman, *Thinking, Fast and Slow* (2011).

17. *See* Paul E. Meehl, *Clinical Versus Statistical Prediction: A Theoretical Analysis and a Review of the Evidence* (1954).

18. Kahneman, *supra* note 16, at 118.

19. *Id.* at 119.

20. *Id.*

21. *Id.*

22. *Id.* at 121.

23. *Id.*

24. *Id.*

Chapter 8

1. *See generally* Niamh Kinchin, *Technology, Displaced? The Risks and Potential of AI for Fair, Effective, and Efficient Refugee Status Determination*, 37 Law in Context 45 (2021).

2. Jens Ludwig, Sendhil Mullainathan, & Ashesh Rambachen, *The Unreasonable Effectiveness of Algorithms* (Nat'l Bureau Econ. Rsch., Working Paper No. 32125, 2024), https://www.nber.org/papers/w32125. I say "appears to be" because there might be a specific (good) reason to favor a human judge in the particular case.

3. *See e.g.*, U.S. Department of Homeland Security, *HIVE: A Novel Algorithmic Framework for Standoff Concealed Threat Detection* (2022), https://www.dhs.gov/sites/default/files/2022-09/22_0921_st_NovelAlgorithmicFrameworkStandoffConcealedThreatDetection_September%202022.pdf; Robert J. Kovacev, *Rise of the Tax Machines: IRS AI Algorithms Are Coming for You*, The Hill (Feb. 19, 2023), https://thehill.com/opinion/finance/3864905-rise-of-the-tax-machines-irs-algorithms-are-coming-for-you/; Storm Prediction Center, National Oceanic and Atmospheric Administration / National Weather Service (last visited Sep. 10, 2024), https://www.spc.noaa.gov/; Social Security Administration, *The Social Security Administration's Use of Insight Software to Identify Potential Anomalies in Hearing Decisions* (Apr. 2019), https://oig-files.ssa.gov/audits/summary/A-12-18-50353Summary.pdf; Engstrom et al., *Government by Algorithm*, *supra* note; Cary Coglianese & Lavi Ben Dor, *AI in Adjudication and Administration*, 86 Brook. L. Rev. 791 (2021); David F. Engstrom & Daniel E. Ho, *Artificially Intelligent Government: A Review and Agenda*, *in* Research Handbook on Big Data Law (Roland Vogl ed., 2020); Cary Coglianese & David Lehr, *Regulating by Robot: Administrative Decision Making in the Machine-Learning Era*, 105 Geo. L. J. 1147 (2017).