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University of Maryland Francis King Carey School of Law
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THE SCORED SOCIETY: DUE PROCESS FOR AUTOMATED PREDICTIONS

Danielle Keats Citron* & Frank Pasquale**

Abstract: Big Data is increasingly mined to rank and rate individuals. Predictive algorithms assess whether we are good credit risks, desirable employees, reliable tenants, valuable customers—or deadbeats, shirkers, menaces, and “wastes of time.” Crucial opportunities are on the line, including the ability to obtain loans, work, housing, and insurance. Though automated scoring is pervasive and consequential, it is also opaque and lacking oversight. In one area where regulation does prevail—credit—the law focuses on credit history, not the derivation of scores from data.

Procedural regularity is essential for those stigmatized by “artificially intelligent” scoring systems. The American due process tradition should inform basic safeguards. Regulators should be able to test scoring systems to ensure their fairness and accuracy. Individuals should be granted meaningful opportunities to challenge adverse decisions based on scores miscategorizing them. Without such protections in place, systems could launder biased and arbitrary data into powerfully stigmatizing scores.

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[Jennifer is] ranked 1,396 out of 179,827 high school students in Iowa. . . . Jennifer's score is the result of comparing her test results, her class rank, her school's relative academic strength, and a number of other factors. . . .

[C]an this be compared against all the other students in the country, and maybe even the world? . . .

That's the idea

That sounds very helpful. . . . And would eliminate a lot of doubt and stress out there.

—Dave Eggers, *The Circle*¹

INTRODUCTION TO THE SCORED SOCIETY

In his novel *The Circle*, Dave Eggers imagines persistent surveillance technologies that score people in every imaginable way. Employees receive rankings for their participation in social media.² Retinal apps allow police officers to see career criminals in distinct colors—yellow for low-level offenders, orange for slightly more dangerous, but still nonviolent offenders, and red for the truly violent.³ Intelligence agencies can create a web of all of a suspect's contacts so that criminals' associates are tagged in the same color scheme as the criminals themselves.⁴

Eggers's imagination is not far from current practices. Although predictive algorithms may not yet be ranking high school students nationwide, or tagging criminals' associates with color-coded risk assessments, they are increasingly rating people in countless aspects of their lives.

Consider these examples. Job candidates are ranked by what their online activities say about their creativity and leadership.⁵ Software engineers are assessed for their contributions to open source projects,

1. DAVE EGGERS, *THE CIRCLE* 340–41 (2013) (internal quotation marks omitted).

2. *Id.* at 190.

3. *Id.* at 419–20.

4. *Id.* at 420.

5. See Don Peck, *They're Watching You at Work*, ATLANTIC MONTHLY, Dec. 2013, at 72, 76.

with points awarded when others use their code.⁶ Individuals are assessed as likely to vote for a candidate based on their cable-usage patterns.⁷ Recently released prisoners are scored on their likelihood of recidivism.⁸

How are these scores developed? Predictive algorithms mine personal information to make guesses about individuals' likely actions and risks.⁹ A person's on- and offline activities are turned into scores that rate them above or below others.¹⁰ Private and public entities rely on predictive algorithmic assessments to make important decisions about individuals.¹¹

Sometimes, individuals can score the scorers, so to speak. Landlords can report bad tenants to data brokers while tenants can check abusive landlords on sites like ApartmentRatings.com. On sites like Rate My Professors, students can score professors who can respond to critiques via video. In many online communities, commenters can in turn rank the interplay between the rated, the raters, and the raters of the rated, in an effort to make sense of it all (or at least award the most convincing or popular with points or "karma").¹²

Although mutual-scoring opportunities among formally equal subjects exist in some communities, the realm of management and business more often features powerful entities who turn individuals into ranked and rated *objects*.¹³ While scorers often characterize their work as an oasis of

6. See E. GABRIELLA COLEMAN, CODING FREEDOM 116–22 (2013) (exploring Debian open source community and assessment of community members' contributions).

7. See Alice E. Marwick, *How Your Data Are Being Deeply Mined*, N.Y. REV. BOOKS, Jan. 9, 2014, at 22, 22.

8. Danielle Keats Citron, *Data Mining for Juvenile Offenders*, CONCURRING OPINIONS (Apr. 21, 2010, 3:56 PM), <http://www.concurringopinions.com/archives/2010/04/data-mining-for-juvenile-offenders.html>.

9. Frank Pasquale, *Restoring Transparency to Automated Authority*, 9 J. ON TELECOMM. & HIGH TECH. L. 235, 235–36 (2011).

10. Hussein A. Abdou & John Pointon, *Credit Scoring, Statistical Techniques and Evaluation Criteria: A Review of the Literature*, 18 INTELLIGENT SYSTEMS ACCT. FIN. & MGMT. 59, 60–61 (2011).

11. See Marwick, *supra* note 7, at 24; see also Jack Nicas, *How Airlines Are Mining Personal Data In-Flight*, WALL ST. J., Nov. 8, 2013, at B1.

12. Oren Bracha & Frank Pasquale, *Federal Search Commission? Access, Fairness, and Accountability in the Law of Search*, 93 CORNELL L. REV. 1149, 1159 (2008) (“This structures [sic] results in a bottom-up filtration system. At the lowest level, a large number of speakers receive relatively broad exposure within local communities likely composed of individuals with high-intensity interest or expertise. Speakers who gain salience at the lower levels may gradually gain recognition in higher-order clusters and eventually reach general visibility.” (footnotes omitted)).

13. See JARON LANIER, WHO OWNS THE FUTURE? 108 (2014); JARON LANIER, YOU ARE NOT A GADGET (2010). For the distinction between management and community, see generally ROBERT

opportunity for the hardworking, the following are examples of ranking systems that are used to individuals' detriment. A credit card company uses behavioral-scoring algorithms to rate consumers' credit risk because they used their cards to pay for marriage counseling, therapy, or tire-repair services.¹⁴ Automated systems rank candidates' talents by looking at how others rate their online contributions.¹⁵ Threat assessments result in arrests or the inability to fly even though they are based on erroneous information.¹⁶ Political activists are designated as "likely" to commit crimes.¹⁷

And there is far more to come. Algorithmic predictions about health risks, based on information that individuals share with mobile apps about their caloric intake, may soon result in higher insurance premiums.¹⁸ Sites soliciting feedback on "bad drivers" may aggregate the information, and could possibly share it with insurance companies who score the risk potential of insured individuals.¹⁹

The scoring trend is often touted as good news. Advocates applaud the removal of human beings and their flaws from the assessment process. Automated systems are claimed to rate all individuals in the same way, thus averting discrimination. But this account is misleading. Because human beings program predictive algorithms, their biases and values are embedded into the software's instructions, known as the source code and predictive algorithms.²⁰ Scoring systems mine datasets containing inaccurate and biased information provided by people.²¹

POST, CONSTITUTIONAL DOMAINS: DEMOCRACY, MANAGEMENT, COMMUNITY (1995).

14. Complaint for Permanent Injunction and Other Equitable Relief at 35, *FTC v. CompuCredit Corp.*, No. 1:08-CV-1976-BBM (N.D. Ga. June 10, 2008), available at <http://www.ftc.gov/sites/default/files/documents/cases/2008/06/080610compucrditcmptsigned.pdf>.

15. Matt Rittel, *I Was Discovered by an Algorithm*, N.Y. TIMES, Apr. 28, 2013 (Sunday Business), at 1.

16. See Danielle Keats Citron & Frank Pasquale, *Network Accountability for the Domestic Intelligence Apparatus*, 62 HASTINGS L.J. 1441, 1444–45 (2011); David Gray & Danielle Keats Citron, *The Right to Quantitative Privacy*, 98 MINN. L. REV. 62, 81 (2013).

17. See S. PERMANENT SUBCOMM. ON INVESTIGATIONS, 112TH CONG., FEDERAL SUPPORT FOR AND INVOLVEMENT IN STATE AND LOCAL FUSION CENTERS 104–05 (2012), available at <https://www.hsd.org/?view&did=723145>; Danielle Keats Citron & David Gray, *Addressing the Harm of Total Surveillance: A Reply to Professor Neil Richards*, 126 HARV. L. REV. F. 262, 266 (2013).

18. See Marwick, *supra* note 7, at 24.

19. See Frank Pasquale, *Welcome to the Panopticon*, CONCURRING OPINIONS (Jan. 2, 2007), http://www.concurringopinions.com/archives/2007/01/welcome_to_the_14.html.

20. Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1260–63 (2008).

21. *Id.*; Danielle Keats Citron, *Open Code Governance*, 2008 U. CHI. LEGAL F. 355, 363–68 [hereinafter Citron, *Open Code Governance*].

There is nothing unbiased about scoring systems.

Supporters of scoring systems insist that we can trust algorithms to adjust themselves for greater accuracy. In the case of credit scoring, lenders combine the traditional three-digit credit scores with “credit analytics,” which track consumers’ transactions. Suppose credit-analytics systems predict that efforts to save money correlates with financial distress. Buying generic products instead of branded ones could then result in a hike in interest rates. But, the story goes, if consumers who bought generic brands also purchased items suggesting their financial strength, then all of their purchases would factor into their score, keeping them from being penalized from any particular purchase.

Does everything work out in a wash because information is seen in its totality? We cannot rigorously test this claim because scoring systems are shrouded in secrecy. Although some scores, such as credit, are available to the public, the scorers refuse to reveal the method and logic of their predictive systems.²² No one can challenge the process of scoring and the results because the algorithms are zealously guarded trade secrets.²³ As this Article explores, the outputs of credit-scoring systems undermine supporters’ claims. Credit scores are plagued by arbitrary results. They may also have a disparate impact on historically subordinated groups.

Just as concerns about scoring systems are more acute, their human element is diminishing. Although software engineers initially identify the correlations and inferences programmed into algorithms, Big Data promises to eliminate the human “middleman” at some point in the process.²⁴ Once data-mining programs have a range of correlations and inferences, they use them to project new forms of learning. The results of prior rounds of data mining can lead to unexpected correlations in click-through activity. If, for instance, predictive algorithms determine not only the types of behavior suggesting loan repayment, but also automate the process of learning which adjustments worked best in the past, the computing process reaches a third level of sophistication: determining *which* metrics for measuring past predictive algorithms were effective, and recommending further iterations for testing.²⁵ In

22. Tal Zarsky, *Transparent Predictions*, 2013 ILL. L. REV. 1503, 1512.

23. Evan Hendricks, *Credit Reports, Credit Checks, Credit Scores*, A.B.A. GPSOLO, July/Aug. 2011, at 32, 34.

24. Chris Anderson, *The End of Theory: The Data Deluge Makes Scientific Inquiry Obsolete*, WIRED (June 23, 2008), http://www.wired.com/science/discoveries/magazine/16-07/pb_theory.

25. A pioneer of artificial intelligence described this process in more general terms: “In order for a program to improve itself substantially it would have to have at least a rudimentary understanding

short, predictive algorithms may evolve to develop an artificial intelligence (AI) that guides their evolution.

The goals of AI are twofold. From an engineering perspective, AI is the “science of making machines do things that would require intelligence if done by” persons.²⁶ By contrast, the cognitive perspective envisions AI as designing systems that work the way the human mind does.²⁷ The distinct goals of the accounts of AI matter. The engineering perspective aims to perform a certain task (e.g., to minimize defaults, as in the credit context), regardless of *how* it does so.²⁸ This is the classic “black box,” which converts inputs to outputs without revealing how it does so. Alternatively, the cognitive perspective aspires for AI to replicate human capacities, such as emotions and self-consciousness, though often it falls short.²⁹ If scoring systems are to fulfill engineering goals and retain *human values* of fairness, we need to create backstops for human review.

Algorithmic scoring should not proceed without expert oversight. This debate is already developing in the field of “killer robots,” where military theorists have described the following distinctions in terms of potentially autonomous, AI-driven weapons:

- Human-in-the-Loop Weapons: Robots that can select targets and deliver force only with a human command;

of its own problem-solving process and some ability to recognize an improvement when it found one. There is no inherent reason why this should be impossible for a machine.” Marvin L. Minsky, *Artificial Intelligence*, SCI. AM., Sept. 1966, at 246, 260.

26. SAMIR CHOPRA & LAURENCE F. WHITE, A LEGAL THEORY OF AUTONOMOUS ARTIFICIAL AGENTS 5 (2011) (internal quotation marks omitted).

27. *Id.* Ryan Calo has been a thought leader in integrating different conceptions of AI to contemporary privacy problems and the field of robotics. See, e.g., M. Ryan Calo, *Robots and Privacy*, in ROBOT ETHICS: THE ETHICAL AND SOCIAL IMPLICATIONS OF ROBOTICS 187 (Patrick Lin et al. eds., 2012); M. Ryan Calo, *Open Robotics*, 70 MD. L. REV. 571 (2011); M. Ryan Calo, *Peeping Hals*, 175 ARTIFICIAL INTELLIGENCE 940 (2011).

28. Anderson, *supra* note 24.

29. CHOPRA & WHITE, *supra* note 26, at 5 (“There are two views of the goals of artificial intelligence. From an engineering perspective, as Marvin Minsky noted, it is the ‘science of making machines do things that would require intelligence if done by men.’ From a cognitive science perspective, it is to design and build systems that work the way the human mind does. In the former perspective, artificial intelligence is deemed successful along a performative dimension; in the latter, along a theoretical one. The latter embodies Giambattista Vico’s perspective of *verum et factum convertuntur*, ‘the true and the made are . . . convertible’; in such a view, artificial intelligence would be reckoned the laboratory that validates our best science of the human mind. This perspective sometimes shades into the claim artificial intelligence’s success lies in the replication of human capacities such as emotions, the sensations of taste, and self-consciousness. Here, artificial intelligence is conceived of as building artificial persons, not just designing systems that are ‘intelligent.’” (alteration in original) (citations omitted)).

- Human-on-the-Loop Weapons: Robots that can select targets and deliver force under the oversight of a human operator who can override the robots' actions; and
- Human-out-of-the-Loop Weapons: Robots that are capable of selecting targets and delivering force without any human input or interaction.³⁰

Human rights advocates and computer scientists contend that “Human-out-of-the-Loop Weapons” systems violate international law because AI systems cannot adequately incorporate the rules of distinction (“which requires armed forces to distinguish between combatants and noncombatants”) and proportionality.³¹ They create a “responsibility gap” between commanders and killing machines.³² Such decisions arguably are the unique responsibility of persons using holistic, non-algorithmic judgment to oversee complex and difficult situations.³³

Just as automated killing machines violate basic legal norms, stigmatizing scoring systems at the least should be viewed with caution. We should not simply accept their predictions without understanding how they came about, and assuring that some human reviewer can respond to serious concerns about their fairness or accuracy.

Scoring systems are often assessed from an engineering perspective, as a calculative risk management technology making tough but ultimately technical rankings of populations as a whole. We call for the integration of the cognitive perspective of AI. In this Article, we explore the consequences to human values of fairness and justice when scoring machines make judgments about individuals. Although algorithmic predictions harm individuals' life opportunities often in arbitrary and discriminatory ways, they remain secret.³⁴ Human oversight is needed to

30. See *Losing Humanity: The Case Against Killer Robots*, HUM. RTS. WATCH (Int'l Human Rights Clinic, Harvard Law Sch., Cambridge, Mass.), Nov. 2012, at 2, available at http://www.hrw.org/sites/default/files/reports/arms1112_ForUpload.pdf.

31. *Id.* at 30.

32. *Id.* at 42.

33. See JOSEPH WEIZENBAUM, *COMPUTER POWER AND HUMAN REASON: FROM JUDGMENT TO CALCULATION* 227 (1976) (insisting that we should not delegate to computers “tasks that demand wisdom”). This is not to overstate the analogy of a low credit score to the kind of liberty deprivation at stake in weaponry. The *stakes* of war are far greater than being sure that an individual can be charged a higher interest rate. Nonetheless, under the *Mathews v. Eldridge*, 424 U.S. 319 (1976), calculus familiar to all students of administrative and constitutional law, *id.* at 332–39, we should not reject the targeting analogy as more-and-more predictive algorithms impact more-and-more aspects of our lives.

34. On the importance of transparency and accountability in algorithms of powerful internet intermediaries, see Bracha & Pasquale, *supra* note 12; Frank Pasquale, *Beyond Innovation and*

police these problems.

This Article uses credit scoring as a case study to take a hard look at our scoring society more generally. Part II describes the development of credit scoring and explores its problems. Evidence suggests that what is supposed to be an objective aggregation and assessment of data—the credit score—is arbitrary and has a disparate impact on women and minorities. Critiques of credit scoring systems come back to the same problem: the secrecy of their workings and growing influence as a reputational metric. Scoring systems cannot be meaningfully checked because their technical building blocks are trade secrets. Part III argues that transparency of scoring systems is essential. It borrows from our due process tradition and calls for “technological due process” to introduce human values and oversight back into the picture. Scoring systems and the arbitrary and inaccurate outcomes they produce must be subject to expert review.

I. CASE STUDY OF FINANCIAL RISK SCORING

Credit scores can make or break the economic fate of millions of individuals. *New York Times* business reporter Joe Nocera observes that while a “credit score is derived after an information-gathering process that is anything but rigorous,”³⁵ it “[e]ssentially . . . has become the only thing that matters anymore to the banks and other institutions that underwrite mortgages.”³⁶ In this Part, we will provide a brief background on credit scoring systems and explore their core problems.

A. *A (Very) Brief History of Credit Scoring Systems*

Credit scoring in the United States has developed over six decades.³⁷ Initially, retail and banking staff assessed borrowers’ trustworthiness.³⁸ In time, experts were entrusted to make lending decisions.³⁹ After World

Competition: The Need for Qualified Transparency in Internet Intermediaries, 104 NW. U. L. REV. 105 (2010) [hereinafter Pasquale, *Beyond Innovation and Competition*]; Frank Pasquale, *Taking on the Known Unknowns*, CONCURRING OPINIONS (Aug. 12, 2007), http://www.concurringopinions.com/archives/2007/08/taking_on_the_k.html.

³⁵ Joe Nocera, *Credit Score is the Tyrant in Lending*, N.Y. TIMES, July 24, 2010, at B1.

³⁶ *Id.* (reporting statement of Deb Killian, Board Member, National Association of Mortgage Brokers).

³⁷ Abdou & Pointon, *supra* note 10, at 59.

³⁸ See ROBERT D. MANNING, CREDIT CARD NATION: THE CONSEQUENCES OF AMERICA’S ADDICTION TO CREDIT 83 (2000).

³⁹ EVANS CLARK, FINANCING THE CONSUMER 1–15, 114–56, 358 (1930).

War II, specialized finance companies entered the mix.⁴⁰

In 1956, the firm Fair, Isaac & Co. (now known as FICO) devised a three-digit credit score, promoting its services to banks and finance companies.⁴¹ FICO marketed its scores as predictors of whether consumers would default on their debts.⁴² FICO scores range from 300 to 850. FICO's scoring system remains powerful, though credit bureaus ("consumer reporting agencies")⁴³ have developed their own scoring systems as well.⁴⁴

Credit scores legitimated the complex securities at the heart of the recent financial crisis.⁴⁵ In the mid-2000s, the credit score was the key connecting ordinary U.S. homeowners with international capital investors eager to invest in highly rated securities.⁴⁶ When investors purchased a mortgage-backed security, they bought the right to a stream of payments.⁴⁷ The mortgagor (borrower) shifted from paying the

40. Stan Sienkiewicz, *Credit Cards and Payment Efficiency 3* (Aug. 2001) (unpublished discussion paper), available at http://www.philadelphiafed.org/consumer-credit-and-payments/payment-cards-center/publications/discussionpapers/2001/PaymentEfficiency_092001.pdf.

41. Martha Poon, *Scorecards as Market Devices for Consumer Credit: The Case of Fair, Isaac & Company Incorporated*, 55 SOC. REV. MONOGRAPH 284, 288 (2007); *Fair, Isaac and Company History*, FUNDINGUNIVERSE, <http://www.fundinguniverse.com/company-histories/Fair-Isaac-and-Company-Company-History.html> (last visited Feb. 8, 2014).

42. On predicting "derogatory events," see *The FICO Score*, THECREDITSCORINGSITE, <http://www.creditscoring.com/creditscore/fico/> (last visited Feb. 8, 2014).

43. For a definition of credit bureau, see *Elkins v. Ocwen Federal Savings Bank Experian Information Solutions, Inc.*, No. 06 CV 823, 2007 U.S. Dist. LEXIS 84556, at *36–37 (N.D. Ill. Nov. 13, 2007) (explaining that credit bureaus and consumer reporting agencies regularly receive updates on a consumer's credit relationships from their data furnishers, such as banks, mortgage companies, debt collectors, credit card issuers, department stores and others, and produce reports that contain highly sensitive and personal details about a consumer's finances, including account numbers, loan balances, credit limits, and payment history).

44. A court case describes the fight between FICO and credit bureaus over the credit bureaus' development of their own scoring systems. See *Fair Isaac Corp. v. Experian Info. Solutions, Inc.*, 645 F. Supp. 2d 734 (D. Minn. 2009), *aff'd*, 650 F.3d 1139 (8th Cir. 2011). In such cases, courts use protective orders to ensure the confidentiality of trade secrets. See, e.g., *Textured Yarn Co. v. Burkart-Schier Chem. Co.*, 41 F.R.D. 158 (E.D. Tenn. 1966).

45. Martha Poon, *From New Deal Institutions to Capital Markets: Commercial Consumer Risk Scores and the Making of Subprime Mortgage Finance*, 34 ACCT. ORGS. & SOC'Y, 654, 662 (2009). In 1995, government-sponsored entities Fannie Mae and Freddie Mac announced that borrowers needed a credit score of at least 660 (on FICO's scale of 300 to 850) for loans to qualify for the status of "prime investment." *Id.* at 663. Those below 660 were relegated to "subprime" offerings. *Id.* at 664.

46. *Id.* at 655.

47. Chris Wilson, *What Is a Mortgage-Backed Security?*, SLATE (Mar. 17, 2008, 7:09 PM), http://www.slate.com/articles/news_and_politics/explainer/2008/03/what_is_a_mortgagebacked_security.html.

original mortgagee (lender) to paying the purchaser of the mortgage-backed security, usually through a servicer.⁴⁸ Fannie Mae, Freddie Mac, and networks of investors helped promote the credit score as a “calculative risk management technolog[y].”⁴⁹

Pricing according to credit scores had a dark side. The credit score moved the mortgage industry from “control-by-screening,” which aimed to eliminate those who were unlikely to pay back their debts, to “control-by-risk characterized by a segmented accommodation of varying credit qualities.”⁵⁰ Abuses piled up. Subprime-structured finance generated enormous fees for middlemen and those with “big short” positions, while delivering financial ruin to many end-purchasers of mortgage-backed securities and millions of homebuyers.⁵¹

B. *The Problems of Credit Scoring*

Long before the financial crisis, critics have questioned the fairness of credit scoring systems. According to experts, the scores’ “black box” assessments were “inevitably subjective and value-laden,” yet seemingly “incontestable by the apparent simplicity of [a] single figure.”⁵² There are three basic problems with credit scoring systems: their opacity, arbitrary results, and disparate impact on women and minorities.

1. *Opacity*

Behind the three-digit score (whether a raw FICO score, or another commercial credit score) is a process that cannot be fully understood, challenged, or audited by the individuals scored or even by the regulators charged with protecting them. Credit bureaus routinely deny requests for details on their scoring systems.⁵³ No one outside the scoring entity can conduct an audit of the underlying predictive algorithms.⁵⁴ Algorithms, and even the median and average scores,

48. See *Mortgage-Backed Securities*, PIMCO (Feb. 2009), <http://www.pimco.com/EN/Education/Pages/MortgageBackedSecurities.aspx>.

49. Poon, *supra* note 45, at 654.

50. *Id.* at 658 (emphasis omitted).

51. See generally MICHAEL LEWIS, *THE BIG SHORT: INSIDE THE DOOMSDAY MACHINE* (2010).

52. Donncha Marron, ‘Lending by Numbers’: *Credit Scoring and the Constitution of Risk Within American Consumer Credit*, 36 *ECON. & SOC’Y* 103, 111 (2007). For another black-box analogy, see Poon, *supra* note 45, at 658.

53. See *Index of Letters*, CREDITSCORING, <http://www.creditscoring.com/letters/> (last visited Feb. 9, 2014) (documenting a series of letter requests and stonewalling responses). There have been repeated efforts by the bureaus to resist mandatory disclosure, or even filing the models with states.

54. See *Fair Isaac Corp. v. Equifax, Inc.*, No. 06-4112, 2007 U.S. Dist. LEXIS 71187 (D. Minn.

remain secret.

The lack of transparency of credit-scoring systems leaves consumers confounded by how and why their scores change.⁵⁵ FICO and the credit bureaus do not explain the extent to which individual behavior affects certain categories.⁵⁶ Consumers cannot determine optimal credit behavior or even what to do to avoid a hit on their scores.

FICO and credit bureaus do, however, announce the relative weight of certain categories in their scoring systems.⁵⁷ For example, “credit utilization” (how much of a borrower’s current credit lines are being used) may be used. But the optimal credit utilization strategy is unclear. No one knows whether, for instance, using twenty-five percent of one’s credit limit is better or worse than using fifteen percent. An ambitious consumer could try to reverse-engineer credit scores, but such efforts would be expensive and unreliable.⁵⁸

As various rankings proliferate, so do uncertainties about one’s standing.⁵⁹ Even the most conscientious borrower may end up surprised by the consequences of his actions. Responding to the confusion, books, articles, and websites offer advice on scoring systems. Amazon offers dozens of self-help books on the topic, each capitalizing on credit scoring’s simultaneously mystifying and meritocratic reputation.⁶⁰ Hucksters abound in the cottage industry of do-it-yourself credit repair.

2. *Arbitrary Assessments*

Credit-scoring systems produce arbitrary results, as demonstrated by

Sept. 25, 2007); *see also* Public Comment Letter from Greg Fisher, Creditscoring.com, to the Board of Governors of the Federal Reserve (Sept. 17, 2004), *available at* http://www.federalreserve.gov/SECRS/2004/October/20041014/OP-1209/OP-1209_106_1.pdf.

55. Yuliya Demyanyk, *Your Credit Score Is a Ranking, Not a Score*, FED. RES. BANK CLEVELAND (Nov. 16, 2010), <http://www.clevelandfed.org/research/commentary/2010/2010-16.cfm>.

56. *Credit Checks & Inquiries*, MYFICO, <http://www.myfico.com/crediteducation/creditinquiries.aspx> (last visited Feb. 9, 2014).

57. *See, e.g., What’s in My FICO Score?*, MYFICO, <http://www.myfico.com/CreditEducation/WhatsInYourScore.aspx> (last visited Feb. 9, 2014).

58. *See* Dean Foust & Aaron Pressman, *Credit Scores: Not-So-Magic Numbers*, BLOOMBERG BUSINESSWEEK (Feb. 6, 2008), <http://www.businessweek.com/stories/2008-02-06/credit-scores-not-so-magic-numbers>.

59. *See, e.g.,* Sue Kirchhoff & Sandra Block, *Alternative Credit Scores Could Open Door for Loans*, USA TODAY (May 16, 2006, 10:01 PM), http://usatoday30.usatoday.com/money/perfi/credit/2006-05-16-credit-scores-usat_x.htm.

60. *See, e.g., Owing! 5 Lessons on Surviving Your Debt Living in a Culture of Credit [Kindle Edition]*, AMAZON.COM, <http://www.amazon.com/Lessons-Surviving-Living-Culture-Credit-ebook/dp/B00C2BMN3W> (last visited Feb. 12, 2014).

the wide dispersion of credit scores set by the commercial credit bureaus.⁶¹ In a study of 500,000 files, 29% of consumers had credit scores that differed by at least 50 points between the three credit bureaus.⁶² Barring some undisclosed, divergent aims of the bureaus, these variations suggest a substantial proportion of arbitrary assessments.

Evidencing their arbitrary nature, credit-scoring systems seemingly penalize cardholders for their *responsible* behavior.⁶³ In 2010, a movement called “Show Me the Note” urged homeowners to demand that servicers prove they had legal rights to mortgage payments.⁶⁴ Given the unprecedented level of foreclosure fraud, homeowners rightfully wanted to know who owned the stream of payments due from their mortgage.⁶⁵

A sensible credit-scoring system would reward those who had taken the trouble to demand accurate information about their mortgage.⁶⁶ The opposite, however, has happened. In one reported case, a homeowner who followed all the instructions on the “Where’s the Note” website allegedly experienced a “40 point hit” on his credit score.⁶⁷ In the Kafkaesque world of credit scoring, merely trying to figure out possible effects on one’s score can reduce it.

Of course, any particular case can be dismissed as an outlier, an isolated complaint by an unfortunate person. But this example is the tip of the iceberg. Over the past twenty years, a critical mass of complaints

61. Carolyn Carter et al., *The Credit Card Market and Regulation: In Need of Repair*, 10 N.C. BANKING INST. 23, 41 (2006). Even after bureaus adopted the advanced “VantageScore” system, “70% of the dispersion remains.” Peter Coy, *Giving Credit Where Credit is Due*, BLOOMBERG BUSINESSWEEK (Mar. 14, 2006), <http://www.businessweek.com/stories/2006-03-14/giving-credit-where-credit-is-duebusinessweek-business-news-stock-market-and-financial-advice> (“It has been highly frustrating to lenders—and to borrowers—that the same person could get drastically different credit scores from different bureaus.”).

62. Carter et al., *supra* note 61, at 41.

63. See, e.g., *The Secret Score Behind Your Auto Insurance*, CONSUMER REP., Aug. 2006, at 43 (noting that “insurance scores can penalize consumers who use credit reasonably”).

64. See, e.g., Mathew Hector, *Standing, Securitization, and “Show Me the Note,”* SULAIMAN LAW GRP., <http://www.sulaimanlaw.com/Publications/Standing-Securitization-and-Show-Me-The-Note.shtml> (last visited Feb. 9, 2014).

65. For background on foreclosure fraud, see generally YVES SMITH, WHISTLEBLOWERS REVEAL HOW BANK OF AMERICA DEFRAUDED HOMEOWNERS AND PAID FOR A COVER UP—ALL WITH THE HELP OF “REGULATORS” (2013).

66. Cf. Deltafreq, Comment to *Where’s the Note? Leads BAC to Ding Credit Score*, THE BIG PICTURE (Dec. 14, 2010, 11:03 AM), <http://www.ritholtz.com/blog/2010/12/note-bac-credit-score/>.

67. Barry Ritholtz, *Where’s the Note? Leads BAC to Ding Credit Score*, THE BIG PICTURE (Dec. 14, 2010, 9:15 AM), <http://www.ritholtz.com/blog/2010/12/note-bac-credit-score/>.

about credit scoring has emerged.⁶⁸ Cassandra Jones Havard contends that scoring models may play an integral role in discriminatory lending practices.⁶⁹ Another commentator has charged that they enabled reckless securitizations that had devastating systemic impact.⁷⁰

In many accounts of the financial crisis, credit scores exerted a baleful influence, rationalizing lending practices with ersatz quantification. As Amar Bhide argued, the idea of “one best way” to rank credit applicants flattened the distributed, varying judgment of local loan officers into the nationwide credit score—a number focused on *persons* rather than *communities*.⁷¹ Like monocultural-farming technology vulnerable to one unanticipated bug, the converging methods of credit assessment failed spectacularly when macroeconomic conditions changed. The illusion of commensurability and solid valuation provided by the models that mortgage-based securities were based on helped spark a rush for what appeared to be easy returns, exacerbating both boom and bust dynamics.

3. *Disparate Impact*

Far from eliminating existing discriminatory practices, credit-scoring algorithms instead grant them an imprimatur, systematizing them in hidden ways.⁷² Credit scores are only as free from bias as the software

68. See, e.g., Kevin Simpson, *Insurers' Use of Credit Reports Rankles Many*, DENVER POST, Aug. 20, 2003, at A1 (“Credit-scoring has been one of the components responsible for an ‘alarming trend’ of increased complaints to regulators over the past three years . . .”).

69. Cassandra Jones Havard, “*On The Take*”: *The Black Box of Credit Scoring and Mortgage Discrimination*, 20 B.U. PUB. INT. L.J. 241, 247 (2011) (arguing that credit scoring if unchecked is an intrinsic, established form of discrimination very similar to redlining).

70. Brenda Reddix-Small, *Credit Scoring and Trade Secrecy: An Algorithmic Quagmire or How the Lack of Transparency in Complex Financial Models Scuttled the Finance Market*, 12 U.C. DAVIS BUS. L.J. 87 (2011).

71. See generally AMAR BHIDE, *A CALL FOR JUDGMENT: SENSIBLE FINANCE FOR A DYNAMIC ECONOMY* (2010); Meredith Schramm-Strosser, *The “Not So” Fair Credit Reporting Act: Federal Preemption, Injunctive Relief, and the Need to Return Remedies for Common Law Defamation to the States*, 14 DUQ. BUS. L.J. 165, 169 (2012) (“A consumer’s reputation and credibility is determined not by personal interactions with others in a small community, but by examining credit files in an impersonal global world.”).

72. Havard, *supra* note 69, at 247 (arguing that “credit scoring if unchecked is an intrinsic, established form of discrimination very similar to redlining”). Cf. Citron & Pasquale, *supra* note 16, at 1459 (exploring how bias against groups can be embedded in fusion centers’ data-mining algorithms and spread through the information sharing environment). The EEOC, in a lawsuit filed against Kaplan, claimed that use of credit history would have a disparate, negative impact against minority job applicants because of the lower average credit score of these groups. Press Release, Equal Emp’t Opportunity Comm’n, EEOC Files Nationwide Hiring Discrimination Lawsuit Against Kaplan Higher Education Corp. (Dec. 21, 2010), available at <http://www.eeoc.gov/eeoc/newsroom/release/12-21-10a.cfm>.

and data behind them.⁷³ Software engineers construct the datasets mined by scoring systems; they define the parameters of data-mining analyses; they create the clusters, links, and decision trees applied;⁷⁴ they generate the predictive models applied.⁷⁵ The biases and values of system developers and software programmers are embedded into each and every step of development.⁷⁶

Beyond the biases embedded into code, some automated correlations and inferences may appear objective but may reflect bias. Algorithms may place a low score on occupations like migratory work or low-paying service jobs. This correlation may have no discriminatory intent, but if a majority of those workers are racial minorities, such variables can unfairly impact consumers' loan application outcomes.⁷⁷

To know for sure, we would need access to the source code, programmers' notes, and algorithms at the heart of credit-scoring systems to test for human bias, which of course we do not have.⁷⁸ Credit bureaus may be laundering discrimination into black-boxed scores, which are immune from scrutiny.⁷⁹

We are not completely in the dark though about credit scores' impact. Evidence suggests that credit scoring does indeed have a negative, disparate impact on traditionally disadvantaged groups.⁸⁰ Concerns about disparate impact have led many states to regulate the use of credit

73. See SHAWN FREMSTAD & AMY TRAUB, DEMOS, DISCREDITING AMERICA: URGENT NEED TO REFORM THE NATION'S CREDIT REPORTING INDUSTRY 11 (2011), available at http://www.demos.org/sites/default/files/publications/Discrediting_America_Demos.pdf

("[D]isparities in the credit reporting system mirror American society's larger racial and economic inequalities. [A] large body of research indicates that Americans with low incomes, and especially African Americans and Latinos, are disproportionately likely to have low credit scores.").

74. Zarsky, *supra* note 22, at 1518.

75. *Id.* at 1519.

76. Citron, *supra* note 20, at 1271 (discussing how administrative decision-making systems can embed bias into programs that is then applied to countless cases).

77. Kenneth G. Gunter, *Computerized Credit Scoring's Effect on the Lending Industry*, 4 N.C. BANKING INST. 443, 445, 451-52 (2000).

78. Reddix-Small, *supra* note 70, at 91 ("As property, complex finance risk models often receive intellectual property proprietary protection. These proprietary protections may take the form of patents, copyrights, trade secrets, and sometimes trademarks.").

79. Cf. Robert E. Goodin, *Laundering Preferences*, in FOUNDATIONS OF SOCIAL CHOICE THEORY 75 (Jon Elster & Aanund Hylland eds., 1986).

80. BIRNY BIRNBAUM, INSURERS' USE OF CREDIT SCORING FOR HOMEOWNERS INSURANCE IN OHIO: A REPORT TO THE OHIO CIVIL RIGHTS COMMISSION 2 (2003) ("Based upon all the available information, it is our opinion that insurers' use of insurance credit scoring for underwriting, rating, marketing and/or payment plan eligibility very likely has a disparate impact on poor and minority populations in Ohio.").

scores in insurance underwriting.⁸¹ The National Fair Housing Alliance (NFHA) has criticized credit scores for disadvantaging women and minorities.⁸²

Insurers' use of credit scores has been challenged in court for their disparate impact on minorities. After years of litigation, Allstate agreed to a multi-million dollar settlement over "deficiencies in Allstate's credit scoring procedure which plaintiffs say resulted in discriminatory action against approximately five million African-American and Hispanic customers."⁸³ As part of the settlement, Allstate allowed plaintiffs' experts to critique and refine future scoring models.⁸⁴

If illegal or unethical discrimination influences credit scoring, members of disadvantaged groups will have difficulty paying their bills.⁸⁵ Their late payments could be fed into credit scoring models as neutral, objective indicia of reliability and creditworthiness.⁸⁶ The very benchmark against which discriminatory practices are measured may indeed be influenced by discriminatory practices.

The paucity of enforcement activity makes it hard to assess the effectiveness of the Equal Credit Opportunity Act (ECOA), which prohibits discrimination in lending, and Regulation B, which applies ECOA to credit scoring systems.⁸⁷ Regulation B requires that the reasons for a denial of credit/lending has to be related to—and

81. *Credit-Based Insurance Scoring: Separating Facts from Fallacies*, NAMIC POL'Y BRIEFING (Nat'l Ass'n of Mut. Ins. Cos., Indianapolis, Ind.), Feb. 2010, at 1, available at http://iiky.org/documents/NAMIC_Policy_Briefing_on_Insurance_Scoring_Feb_2010.pdf.

82. *The Future of Housing Finance: The Role of Private Mortgage Insurance: Hearing Before the Subcomm. on Capital Mkts., Ins. & Gov't Sponsored Enters. of the H. Comm. on Fin. Servs.*, 111th Cong. 16 (2010) (statement of Deborah Goldberg, Hurricane Relief Program Director, The National Fair Housing Alliance). The NFHA has expressed concern that "the use of credit scores tends to disadvantage people of color, women, and others whose scores are often lower than those of white borrowers." *Id.* at 57. The NFHA has also expressed "growing concern about how useful credit scores are for predicting loan performance and whether the financial sector is placing too much reliance on credit scores rather than other risk factors such as loan terms." *Id.*

83. *Dehoyos v. Allstate*, 240 F.R.D. 269, 275 (W.D. Tex. 2007). The parties settled after the Fifth Circuit decided that federal civil rights law was not reverse preempted by the McCarran-Ferguson Act's allocation of insurance regulatory authority to states. *See Dehoyos v. Allstate Corp.*, 345 F.3d 290, 299 (5th Cir. 2003). The Equal Credit Opportunity Act (ECOA), which regulates lending practices, does not preempt state laws that are stricter than ECOA.

84. *Dehoyos*, 240 F.R.D. at 276.

85. *See, e.g., Gunter, supra* note 77, at 451–52.

86. *See generally* BERNARD E. HARCOURT, *AGAINST PREDICTION: PROFILING, POLICING, AND PUNISHING IN AN ACTUARIAL AGE* (2007).

87. Regulation B sets forth specific data that cannot be used in a credit scoring system, such as: public assistance status, likelihood that any person will bear or rear children, telephone listing, income because of a prohibited basis, inaccurate credit histories, and different standards for married and unmarried persons, race, color, religion, national origin, and sex. 12 C.F.R. § 202.5 (2013).

accurately describe—the factors actually scored by the creditor.⁸⁸ Based on the evidence we could uncover, cases are rare.⁸⁹ This is surely because litigation costs usually exceed the discounted present value of the monetary stakes involved. Fines and penalties probably are not large enough to deter troubling practices.⁹⁰

C. *The Failure of the Current Regulatory Model*

Contemporary problems echo concerns about unreliable credit histories that prompted lawmakers to regulate the credit industry.⁹¹ In 1970, Congress passed the Fair Credit Reporting Act (FCRA)⁹² “because it was worried that growing databases [of personal information] could be used in ways that were invisible and harmful to consumers.”⁹³ As Priscilla Regan notes, the FCRA was the first information privacy legislation in the United States.⁹⁴

The FCRA obligates credit bureaus and all other “consumer reporting agencies” to ensure that credit histories are accurate and relevant.⁹⁵ Consumers have the right to inspect their credit records, to demand corrections, and to annotate their records if disputes cannot be resolved.⁹⁶ From lawmakers, however, industry extracted a major

88. 12 C.F.R. § 202.9(b)(2). Furthermore, no factor that was a principal reason for adverse action may be excluded from the disclosure. *Id.*

89. See Scott Ilgenfritz, Commentary, *The Failure of Private Actions as an ECOA Enforcement Tool: A Call for Active Governmental Enforcement and Statutory Reform*, 36 U. FLA. L. REV. 447, 449 (1984) (“Despite congressional intent and the liberal relief provisions of the ECOA, there has been a relative dearth of private actions brought under the Act.”).

90. *Id.*

91. See ROBERT ELLIS SMITH, BEN FRANKLIN’S WEB SITE: PRIVACY AND CURIOSITY FROM PLYMOUTH ROCK TO THE INTERNET 319–20 (2004).

92. 15 U.S.C. § 1681a–x (2012).

93. Edith Ramirez, Chairwoman, Fed. Trade Comm’n, Keynote Address at the Technology Policy Institute Aspen Forum: Privacy Challenges in the Era of Big Data: A View from the Lifeguard’s Chair 3 (Aug. 19, 2013), available at http://www.ftc.gov/sites/default/files/documents/public_statements/privacy-challenges-big-data-view-lifeguard’s-chair/130819bigdataaspen.pdf (transcript as prepared for delivery).

94. PRISCILLA M. REGAN, LEGISLATING PRIVACY: TECHNOLOGY, SOCIAL VALUES, AND PUBLIC POLICY 101 (1995).

95. 15 U.S.C. § 1681e(b) (“Whenever a consumer reporting agency prepares a consumer report it shall follow reasonable procedures to assure maximum possible accuracy of the information concerning the individual about whom the report relates.”); see also *id.* § 1681a(f) (defining consumer reporting agency). See generally Reddix-Small, *supra* note 70, at 108–09 (discussing the history, purpose, and substance of the FCRA); *The Fair Credit Reporting Act (FCRA) and the Privacy of Your Credit Report*, ELECTRONIC PRIVACY INFO. CTR., <http://epic.org/privacy/fcra/> (last visited Feb. 22, 2014) (same).

96. See 15 U.S.C. § 1681i (“Procedure in Case of Disputed Accuracy”).

concession: immunity from defamation law.⁹⁷ By limiting the possible penalties for reputational injuries, the FCRA opened the door to tactics of stalling, obstinacy, and obfuscation by the credit industry.⁹⁸

What about credit scores? In 2003, the Fair and Accurate Credit Transactions Act (FACTA) required credit bureaus to disclose credit scores to individuals in exchange for a fee capped by the FTC. But the FACTA does *not* “require a consumer reporting agency to disclose to a consumer any information concerning credit scores or any other risk scores or predictors relating to the consumer,”⁹⁹ except for four “key factors” involved in credit decisions.¹⁰⁰ Regrettably, those four factors do little to explain credit scores. Phrases like “type of bank accounts” and “type of credit references” are etiolated symbols, more suited for machine-to-machine interaction than personal explanation. Factors such as “too many revolving accounts” and “late payment” are commonplace even for those with high credit scores.¹⁰¹ The law does not require credit scorers to tell individuals *how much* any given factor mattered to a particular score.¹⁰² Looking forward, a consumer has no idea, for example, whether paying off a debt that is sixty days past due will raise her score. The industry remains highly opaque, with scored individuals unable to determine the exact consequences of their decisions.

Although FCRA offers individuals a chance to dispute items on their credit *history*, it does not require credit bureaus to reveal the way they convert a history into a score.¹⁰³ That is a trade secret; a designation offering powerful legal protections to companies that want to keep their business practices a secret.¹⁰⁴ Despite such secrecy, we can draw some

97. SMITH, *supra* note 91, at 320. Note, though, that the FCRA is riddled with many exceptions, exceptions to exceptions, and interactions with state law.

98. See Schramm-Strosser, *supra* note 71, at 170–71 (“What started out as an improvement over how the common law dealt with credit-reporting issues has evolved into a regulatory scheme that tends to favor the credit reporting industry One example of the FCRA’s overly broad preemptive scope is the prohibition of injunctive relief for consumers who bring common law defamation claims against CRAs.”).

99. 15 U.S.C. § 1681g(a)(1)(B).

100. *Id.* § 1681g(f)(C).

101. *Id.*

102. *Cf.* Philip Morris v. Reilly, 312 F.3d 24, 47 (1st Cir. 2002) (holding that the state could require revelation of ingredients, but not how much of each was in the cigarettes). The tobacco company in *Reilly* successfully raised a constitutional challenge, alleging the “taking” of a trade secret. *Id.*

103. Credit histories appear on “consumer reports,” as defined by the FCRA. See 15 U.S.C. § 1681a(d); Plaintiff’s Rule 26(a)(2) Expert Witness Report, *Ellis v. Grant & Weber*, 2006 WL 3338624 (C.D. Cal. July 26, 2005) (No. CV-04-2007-CAS).

104. See Hendricks, *supra* note 23, at 34 (“Like the recipe for Coca-Cola, the precise formulas

conclusions about the black box society that credit scoring is creating. We have seen evidence that credit scores produce arbitrary results that may in fact further entrench inequality.

Now, we turn to our proposals that aspire to bring procedural regularity and regulatory oversight to our scored society, while balancing the protection of other values, including the intellectual property of the developers of scoring technology.¹⁰⁵

II. PROCEDURAL SAFEGUARDS FOR AUTOMATED SCORING SYSTEMS

Predictive scoring may be an established feature of the Information Age, but it should not continue without check. Meaningful accountability is essential for predictive systems that sort people into “wheat” and “chaff,” “employable” and “unemployable,” “poor candidates” and “hire away,” and “prime” and “subprime” borrowers.

Procedural regularity is essential given the importance of predictive algorithms to people’s life opportunities—to borrow money, work, travel, obtain housing, get into college, and far more. Scores can become self-fulfilling prophecies, creating the financial distress they claim merely to indicate.¹⁰⁶ The act of designating someone as a likely credit risk (or bad hire, or reckless driver) raises the cost of future financing (or work, or insurance rates), increasing the likelihood of eventual insolvency or un-employability.¹⁰⁷ When scoring systems have the potential to take a life of their own, contributing to or creating the situation they claim merely to predict, it becomes a *normative* matter, requiring moral justification and rationale.¹⁰⁸

used to calculate various kinds of credit scores are well-guarded trade secrets.”).

105. For an in-depth exploration of the different ways private and public decisions have been hidden to our detriment, see generally FRANK PASQUALE, *THE BLACK BOX SOCIETY* (forthcoming 2014).

106. See Michael Aleo & Pablo Svirsky, *Foreclosure Fallout: The Banking Industry’s Attack on Disparate Impact Race Discrimination Claims Under the Fair Housing Act and the Equal Credit Opportunity Act*, 18 B.U. PUB. INT. L.J. 1, 5 (2008) (“Ironically, because these borrowers are more likely to default on their loans, the banks, to compensate for that increased risk, issue these borrowers loans that feature more onerous financial obligations, thus increasing the likelihood of default.”).

107. See *id.*

108. This is part of a larger critique of economic thought as a “driver,” rather than a “describer,” of financial trends. See generally DONALD MACKENZIE, *AN ENGINE, NOT A CAMERA: HOW FINANCIAL MODELS SHAPE MARKETS* (2006) (describing how economic theorists of finance helped create modern derivative markets); Joel Isaac, *Tangled Loops: Theory, History, and the Human Sciences in Modern America*, 6 MOD. INTELL. HIST. 397, 420 (2009) (“[S]cholars are rejecting the traditional notion that economics attempts to create freestanding representations of market processes

Scoring systems should be subject to fairness requirements that reflect their centrality in people's lives. Private scoring systems should be as understandable to regulators as to firms' engineers. However well an "invisible hand" coordinates economic activity generally speaking, markets depend on reliable information about the practices of firms that finance, rank, and rate consumers. Brandishing quasi-governmental authority to determine which individuals are worthy of financial backing, private scoring systems need to be held to a higher standard than the average firm.

One of the great accomplishments of the legal order was holding the sovereign accountable for decisionmaking and giving subjects basic rights, in breakthroughs stretching from Runnymede to the Glorious Revolution of 1688 to the American Revolution. New algorithmic decisionmakers are sovereign over important aspects of individual lives. If law and due process are absent from this field, we are essentially paving the way to a new feudal order of unaccountable reputational intermediaries.¹⁰⁹

How should we accomplish accountability? Protections could draw insights from what one of us has called "technological due process"—procedures ensuring that predictive algorithms live up to some standard of review and revision to ensure their fairness and accuracy.¹¹⁰ Procedural protections should apply not only to the scoring algorithms themselves (a kind of technology-driven rulemaking), but also to individual decisions based on algorithmic predictions (technology-driven adjudication).

This is not to suggest that full due process guarantees are required as a matter of current law. Given the etiolated state of "state action"

(which economic sociologists must then insist leaves out power, or cultural context, or the fullness of human agency)."). Some commentators have argued that we need to "recognize economics not as a (misguided) science of capitalism but as its technology, that is, as one of the active ingredients in the production and reproduction of the market order." Marion Fourcade, *Theories of Markets and Theories of Society*, 50 AM. BEHAV. SCI. 1015, 1025 (2007).

109. Our proposal for basic rights of citizens vis-à-vis scoring systems also finds support in the work of other scholars concerned about the extraordinary power of private companies. See, e.g., LORI ANDREWS, I KNOW WHO YOU ARE AND I SAW WHAT YOU DID: SOCIAL NETWORKS AND THE DEATH OF PRIVACY 189–91 (2012) (concluding with a proposal for a "Social Network Constitution"); REBECCA MACKINNON, CONSENT OF THE NETWORKED 240–41 (2012) (proposing ten principles of network governance); Jeffrey Rosen, *Madison's Privacy Blind Spot*, N.Y. TIMES, Jan. 19, 2014 (Sunday), at 5 ("What Americans may now need is a constitutional amendment to prohibit unreasonable searches and seizures of our persons and electronic effects, whether by the government or by private corporations like Google and AT&T. . . . [O]ur rights to enjoy liberty, and to obtain happiness and safety at the same time, are threatened as much by corporate as government surveillance.").

110. See generally Citron, *supra* note 20.

doctrine in the United States, FICO and credit bureaus are not state actors; however, much of their business's viability depends on the complex web of state supports and rules surrounding housing finance. Nonetheless, the underlying values of due process—transparency, accuracy, accountability, participation, and fairness¹¹¹—should animate the oversight of scoring systems given their profound impact on people's lives. Scholars have built on the “technological due process” model to address private and public decision-making about individuals based on the mining of Big Data.¹¹²

We offer a number of strategies in this regard. Federal regulators, notably the Federal Trade Commission (FTC), should be given full access to credit-scoring systems so that they can be reviewed to protect against unfairness. Our other proposals pertain to individual decision-making based on algorithmic scores. Although our recommendations focus on credit scoring systems, they can extend more broadly to other predictive algorithms that have an unfair impact on consumers.

A. *Regulatory Oversight over Scoring Systems*

The first step toward reform will be to clearly distinguish between steps in the scoring process, giving scored individuals different rights at different steps. These steps include:

- 1) Gathering data about scored individuals;
- 2) Calculating the gathered data into scores;
- 3) Disseminating the scores to decisionmakers, such as employers;
- 4) Employers' and others' use of the scores in decisionmaking.

We believe that the first step, data gathering, should be subject to the same strictures as FCRA—whatever the use of the data—once a firm has gathered data on more than 2,000 individuals.¹¹³ Individuals should have the right to inspect, correct, and dispute inaccurate data, and to know the sources (furnishers) of the data. Ironically, some data brokers now refuse to give out their data sources because of “confidentiality agreements”

111. Martin H. Redish & Lawrence C. Marshall, *Adjudicator, Independence, and the Values of Procedural Due Process*, 95 YALE L.J. 455, 478–89 (1986).

112. Kate Crawford & Jason Schultz, *Big Data and Due Process: Toward a Framework to Redress Predictive Privacy Harms*, 55 B.C. L. Rev. (forthcoming 2014) (relying on a “technological due process” model to address Big Data's predictive privacy harms), available at http://lsr.nellco.org/nyu_plltwp/429/; Neil M. Richards & Jonathan H. King, *Three Paradoxes of Big Data*, 66 STAN. L. REV. ONLINE 41, 43 (2013) (calling for a “technological due process” solution to governmental and corporate decision-making by Big Data predictions).

113. This number is meant to permit small businesses' consumer research to be unregulated; we are open to suggestion as to whether the number should be higher or lower.

with sources.¹¹⁴ That position (hiding behind privacy interests to violate consumer privacy) would not stand for consumer reporting agencies covered by FCRA. It should not stand for data brokers and the like.

Second, at the calculation of data stage, ideally such calculations would be public, and all processes (whether driven by AI or other computing) would be inspectable. In some cases, the trade secrets may merit protection, and only a dedicated, closed review should be available. But in general, we need to switch the default in situations like this away from an assumption of secrecy, and toward the expectation that people deserve to know how they are rated and ranked.

The third stage is more difficult, as it begins to implicate First Amendment issues. Given the Supreme Court's ruling in *Sorrell v. IMS Health Inc.*¹¹⁵ and other rulings in cases involving the regulation of ranking systems,¹¹⁶ courts may look askance at rules that limit the dissemination of data or scores.¹¹⁷ Nevertheless, scored individuals should be notified when scores or data are communicated to an entity. That notification only *increases* speech; it does not restrict or censor communication. Coerced speech can implicate the First Amendment, but like Professor Neil Richards, we do not understand *Sorrell* to lay down a blanket rule that all data is speech.¹¹⁸ Transparency requirements are consistent with First Amendment doctrine.

The fourth and final stage is the most controversial. We believe that—given the sensitivity of scoring and their disparate impact on vulnerable populations—scoring systems should be subject to licensing and audit requirements when they enter critical settings like employment,

114. Casey Johnston, *Data Brokers Won't Even Tell the Government How It Uses, Sells Your Data*, ARS TECHNICA (Dec. 21, 2013, 12:07 PM), <http://arstechnica.com/business/2013/12/data-brokers-wont-even-tell-the-government-how-it-uses-sells-your-data/>.

115. __U.S.__, 131 S. Ct. 2653 (2011).

116. See, e.g., Pasquale, *Beyond Innovation and Competition*, *supra* note 34, at 117–19 (discussing the successful First Amendment defense of the Avvo lawyer ratings site).

117. *Sorrel*, 131 S. Ct. at 2670–72 (holding that drug companies have a constitutional right to access certain types of data without undue state interference); see also NEIL M. RICHARDS, INTELLECTUAL PRIVACY: CIVIL LIBERTIES AND INFORMATION IN A DIGITAL AGE ch. 5 (forthcoming 2014) (exploring why *Sorrell* does not lay down a blanket rule that all data is speech for purposes of the First Amendment and more narrowly rested on concerns about viewpoint discrimination among other reasons). For a critical description of the stakes of *Sorrell*, see David Orentlicher, *Prescription Data Mining and the Protection of Patients' Interests*, 38 J.L. MED. & ETHICS 74, 81 (2010) (“When people develop relationships with their physicians and pharmacists, they are entitled to the assurance that information about their medical condition will be used for their benefit and not to place their health at risk or to increase their health care costs.”); Frank Pasquale, *Grand Bargains for Big Data*, 72 MD. L. REV. 682, 740 (2013); Andrew Tutt, *Software Speech*, 65 STAN. L. REV. ONLINE 73, 75 (2012).

118. See RICHARDS, *supra* note 117, at ch. 5.

insurance, and health care. Such licensing could be completed by private entities that are themselves licensed by the EEOC, OSHA, or the Department of Labor.¹¹⁹ This “licensing at one remove” has proven useful in the context of health information technology.¹²⁰

Given scoring’s sensitivity, fair, accurate, and replicable use of data is critical. We cannot rely on companies themselves to “self-regulate” toward this end—they are obligated merely to find the most *efficient* mode of processing, and not to vindicate other social values including fairness. Licensing can serve as a way of assuring that public values inform this technology.

Licensing entities could ensure that particularly sensitive data does not make it into scoring. For example, data brokers sell the names of parents whose child was killed in car crash,¹²¹ of rape victims,¹²² and of AIDS patients.¹²³ Licensors could assure that being on such a list does not influence scoring. Public hearings could be held on other, troubling categories to gather input on whether they should be used for decisionmaking. Data brokers pigeonhole individuals on the basis of who-knows-what data and inferences. Before letting such monikers become de facto scarlet letters,¹²⁴ we need to have a broader societal conversation on the power wielded by data brokers and, particularly, the level of validity of such classifications.

Many of our proposals would require legislation. We are under no illusions that Congress is presently inclined to promote them. However, as in the case of the massive health IT legislation of 2009 (HITECH), it is important to keep proposals “ready to hand” for those brief moments of opportunity when change can occur.¹²⁵

119. For a relevant case regarding the potentially discriminatory impact of a scoring system or its use, see *EEOC v. Kronos Inc.*, 620 F.3d 287, 298 n.5 (3d Cir. 2010) (“[Regarding] the low score on the Customer Service Assessment she had completed as part of the application process[, the manager] noted from the Customer Service Assessment that Charging Party potentially might be less inclined to deliver great customer service.”).

120. Frank Pasquale, *Private Certifiers and Deputies in American Health Care*, 92 N.C. L. REV. (forthcoming 2014).

121. See Kashmir Hill, *OfficeMax Blames Data Broker for ‘Daughter Killed in Car Crash’ Letter*, FORBES (Jan. 22, 2014, 12:09 PM), <http://www.forbes.com/sites/kashmirhill/2014/01/22/officemax-blames-data-broker-for-daughter-killed-in-car-crash-letter/>.

122. Amy Merrick, *A Death in the Database*, NEW YORKER (Jan. 23, 2014), <http://www.newyorker.com/online/blogs/currency/2014/01/ashley-seay-officemax-car-crash-death-in-the-database.html>.

123. *Id.*

124. Frank A. Pasquale, *Rankings, Reductionism, and Responsibility*, 54 CLEV. ST. L. REV. 115, 122 (2006).

125. This is commonly known as the “garbage can” theory of political change—rather than being

Fortunately, the Federal Trade Commission does have statutory authority to move forward on several parts of the “scored society” agenda. The FTC can oversee credit-scoring systems under its authority to combat “unfair” trade practices under Section 5 of the Federal Trade Commission Act.¹²⁶ It can use this authority to develop much more robust oversight over credit scoring, which could then be a model for legislation for other scoring entities (or for state consumer protection authorities and state attorneys general with authority to promote fair information practices).

“Unfair” commercial practices involve conduct that substantially harms consumers, or threatens to substantially harm consumers, which consumers cannot reasonably avoid, and where the harm outweighs the benefits.¹²⁷ In 2008, the FTC invoked its unfairness authority against a credit provider for basing credit reductions on an undisclosed behavioral scoring model that penalized consumers for using their credit cards for certain transactions, such as personal counseling.¹²⁸

The FTC’s concerns about predictive algorithms have escalated with their increasing use. In March 2014, the FTC is hosting a panel of experts to discuss the private sector’s use of algorithmic scores to make decisions about individuals, including individuals’ credit risk with certain transactions, likelihood to take medication, and influence over others based on networked activities.¹²⁹ The FTC has identified the following topics for discussion:

- How are companies utilizing these predictive scores?
- How accurate are these scores and the underlying data

rationally planned, most legislative efforts depend on whatever plans are at hand. J. Bendor et al., *Recycling the Garbage Can: An Assessment of the Research Program*, 95 AM. POL. SCI. REV. 95, 169 (2001).

126. See Federal Trade Commission Act § 5, 15 U.S.C. § 45 (2012). See generally *A Brief Overview of the Federal Trade Commission’s Investigative and Law Enforcement Authority*, FED. TRADE COMM’N, <http://www.ftc.gov/about-ftc/what-we-do/enforcement-authority> (last updated July 2008).

127. 15 U.S.C. § 45(n) (2012).

128. Stipulated Order for Permanent Injunction and Other Equitable Relief Against Defendant CompuCredit Corp., *FTC v. CompuCredit Corp.*, No. 1:08-CV-1976-BBM-RGV (N.D. Ga. Dec. 19, 2008), available at <http://www.ftc.gov/sites/default/files/documents/cases/2008/12/081219compucreditsstiporder.pdf>. For a compelling account of the crucial role that the FTC plays in regulating unfair consumer practices and establishing a common law of privacy, see Daniel J. Solove & Woodrow Hartzog, *The FTC and the New Common Law of Privacy*, 114 COLUM. L. REV. (forthcoming 2014), available at <http://ssrn.com/abstract=2312913> (last updated Oct. 29, 2013).

129. See *Spring Privacy Series: Alternative Scoring Products*, FED. TRADE COMM’N, <http://www.ftc.gov/news-events/events-calendar/2014/03/spring-privacy-series-alternative-scoring-products> (last visited Feb. 11, 2014).

used to create them?

- How can consumers benefit from the availability and use of these scores?
- What are the privacy concerns surrounding the use of predictive scoring?
- What consumer protections should be provided; for example, should consumers have access to these scores and the underlying data used to create them?
- Should some of these scores be considered eligibility determinations that should be scrutinized under the Fair Credit Reporting Act?¹³⁰

FTC Chairwoman Edith Ramirez has voiced her concerns about algorithms that judge individuals “not because of what they’ve done, or what they will do in the future, but because inferences or correlations drawn by algorithms suggest they may behave in ways that make them poor credit or insurance risks, unsuitable candidates for employment or admission to schools or other institutions, or unlikely to carry out certain functions.”¹³¹ In her view, predictive correlations amount to “arbitrariness-by-algorithm” for mischaracterized consumers.¹³²

Indeed, as Chairwoman Ramirez powerfully argues, decisions-by-algorithm require “transparency, meaningful oversight and procedures to remediate decisions that adversely affect individuals who have been wrongly categorized by correlation.”¹³³ Companies must “ensure that by using big data algorithms they are not accidentally classifying people based on categories that society has decided—by law or ethics—not to use, such as race, ethnic background, gender, and sexual orientation.”¹³⁴

With Chairwoman Ramirez’s goals in mind and the FTC’s unfairness authority, the FTC should move forward in challenging credit-scoring systems. The next step is figuring out the practicalities of such enforcement. How can the FTC translate these aspirations into reality given that scoring systems are black boxes even to regulators?

1. Transparency to Facilitate Testing

The FTC should be given access to credit-scoring systems and other scoring systems that unfairly harm consumers. Access could be more or

130. *Id.*

131. Ramirez, *supra* note 93, at 7.

132. *Id.* at 8.

133. *Id.*

134. *Id.*

less episodic depending on the extent of unfairness exhibited by the scoring system. Biannual audits would make sense for most scoring systems; more frequent monitoring would be necessary for those which had engaged in troubling conduct.¹³⁵

We should be particularly focused on scoring systems which rank and rate individuals who can do little or nothing to protect themselves. The FTC's expert technologists¹³⁶ could test scoring systems for bias, arbitrariness, and unfair mischaracterizations. To do so, they would need to view not only the datasets mined by scoring systems¹³⁷ but also the source code and programmers' notes describing the variables, correlations, and inferences embedded in the scoring systems' algorithms.¹³⁸

For the review to be meaningful in an era of great technological change, the FTC's technical experts must be able to meaningfully assess systems whose predictions change pursuant to AI logic. They should be permitted to test systems to detect patterns and correlations tied to classifications that are already suspect under American law, such as race, nationality, sexual orientation, and gender. Scoring systems should be run through testing suites that run expected and unexpected hypothetical scenarios designed by policy experts.¹³⁹ Testing reflects the norm of proper software development, and would help detect both programmers' potential bias and bias emerging from the AI system's evolution.¹⁴⁰

2. *Risk Assessment Reports and Recommendations*

Once the FTC evaluates credit-scoring systems to detect

135. See Helen Nissenbaum, *Accountability in a Computerized Society*, 2 SCI. & ENGINEERING ETHICS 25, 37 (1996) (describing commentators' calls for "simpler design, a modular approach to system building, meaningful quality assurance, independent auditing, built-in redundancy, and excellent documentation").

136. The FTC's Senior Technologist position has been filled by esteemed computer scientists Professor Edward Felten of Princeton University, Professor Steven Bellovin of Columbia University, and now by Professor LaTanya Sweeney of Harvard University.

137. See, e.g., Zarsky, *supra* note 22, at 1520.

138. We thank Ed Felten for suggesting that oversight of automated systems include access to programmers' notes for the purpose of assessing source code. Ed Felten, Comment to Danielle Citron, Technological Due Process Lecture at Princeton University Center on Information Technology Policy Lecture Series (Apr. 30, 2009); see also *Danielle Citron: Technological Due Process*, CTR. FOR INFO. TECH. POL'Y, <https://citp.princeton.edu/event/citron/> (last visited Feb. 11, 2014). The question we shall soon address is whether the public generally and affected individuals specifically should *also* have access to the data sets and logic behind predictive algorithms.

139. Citron, *supra* note 20, at 1310.

140. Batya Friedman & Helen Nissenbaum, *Bias in Computer Systems*, 14 ACM TRANSACTIONS ON INFO. SYSTEMS 330, 334 (1996).

“arbitrariness-by-algorithm”—as Chairwoman Ramirez astutely puts it—it should issue a Privacy and Civil Liberties Impact Assessment evaluating a scoring system’s negative, disparate impact on protected groups, arbitrary results, mischaracterizations, and privacy harms.¹⁴¹ In those assessments, the FTC could identify appropriate risk mitigation measures.

An important question is the extent to which the *public* should have access to the data sets and logic of predictive credit-scoring systems. We believe that each data subject should have access to all data pertaining to the data subject. Ideally, the logics of predictive scoring systems should be open to public inspection as well. There is little evidence that the inability to keep such systems secret would diminish innovation. The lenders who rely on such systems want to avoid default—that in itself is enough to incentivize the maintenance and improvement of such systems. There is also not adequate evidence to give credence to “gaming” concerns—i.e., the fear that once the system is public, individuals will find ways to game it. While gaming is a real concern in online contexts, where, for example, a search engine optimizer could concoct link farms to game Google or other ranking algorithms if the signals became public, the signals used in credit evaluation are far costlier to fabricate.¹⁴² Moreover, the real basis of commercial success in “big data” driven industries is likely the quantity of relevant data collected *in the aggregate*—something not necessarily revealed or shared via person-by-person disclosure of data held and scoring algorithms used.

We must also ensure that academics and other experts can comment on such scoring systems. Kenneth Bamberger and Deidre Mulligan argue that Privacy Impact Assessments required by the E-Government Act are unsuccessful in part due to the public’s inability to comment on the design of systems whose specifications and source codes remain obscured.¹⁴³

141. Zarsky, *supra* note 22, at 1529; *see also* Citron, *Open Code Governance*, *supra* note 21, at 370–71 (exploring the untapped potential of federally required Privacy Impact Assessments). For example, the Office of Civil Rights and Civil Liberties of the Department of Homeland Security is required to draft Civil Liberties Impact Assessments in response to new programs and policies impacting minorities. *Civil Rights & Civil Liberties Impact Assessments*, U.S. DEP’T OF HOMELAND SEC., <https://www.dhs.gov/civil-rights-civil-liberties-impact-assessments> (last visited Feb. 11, 2014).

142. They are, in this sense, more likely to be “honest signals,” and we should not expend a great deal of effort to assure their integrity without stronger evidence that they are likely to be compromised. *See, e.g.*, SANDY PENTLAND, *HONEST SIGNALS* (2010).

143. Kenneth A. Bamberger & Deidre K. Mulligan, *Privacy Decisionmaking in Administrative Agencies*, 75 U. CHI. L. REV. 75, 81–82, 88–89 (2008). Twelve percent of agencies do not have

As Tal Zarsky argues, the public could be informed about the datasets that predictive systems mine without generating significant social risks.¹⁴⁴ Zarsky demonstrates that—when it comes to “the collection of data and aggregation of datasets”—it is evident that “providing information regarding the kinds and forms of data and databases used in the analysis . . . generate[s] limited social risks . . . [usually only in the context of] secretive governmental datasets.”¹⁴⁵

The more difficult question concerns whether scoring systems’ source code, algorithmic predictions, and modeling should be transparent to affected individuals and ultimately the public at large. Neil Richards and Jonathan King astutely explain that “there are legitimate arguments for some level of big data secrecy,” including concerns “connected to highly sensitive intellectual property and national security assets.”¹⁴⁶ But these concerns are more than outweighed by the threats to human dignity posed by pervasive, secret, and automated scoring systems. At the very least, individuals should have a meaningful form of notice and a chance to challenge predictive scores that harm their ability to obtain credit, jobs, housing, and other important opportunities.

B. *Protections for Individuals*

In constructing strategies for technological due process in scoring contexts, it is helpful to consider the sort of notice individuals are owed when governmental systems make adverse decisions about them. Under the Due Process Clause, notice must be “reasonably calculated” to inform individuals of the government’s claims against them.¹⁴⁷ The sufficiency of notice depends upon its ability to inform affected individuals about the issues to be decided, the evidence supporting the government’s position, and the agency’s decisional process.¹⁴⁸ Clear notice decreases the likelihood that agency action will rest upon “incorrect or misleading factual premises or on the misapplication of rules.”¹⁴⁹

written processes or policies for all listed aspects of Privacy Impact Assessment (PIA) and sixteen percent of systems covered by the PIA requirement did not have a complete or current PIA. *Id.* at 81.

144. Zarsky, *supra* note 22, at 1524 (exploring the practical and normative implications of varying kinds of transparency for governmental predictive systems).

145. *Id.*

146. Richards & King, *supra* note 112, at 43.

147. *Dusenbery v. United States*, 534 U.S. 161, 168 (2002).

148. JERRY L. MASHAW, *DUE PROCESS IN THE ADMINISTRATIVE STATE* 176 (1985).

149. *Goldberg v. Kelly*, 397 U.S. 254, 268 (1970).

Notice problems have plagued agency decision-making systems. Automated systems administering public benefits programs have terminated or reduced people's benefits without any explanation.¹⁵⁰ That is largely because system developers failed to include audit trails that record the facts and law supporting every decision made by the computer.¹⁵¹ Technological due process insists that automated systems include immutable audit trails to ensure that individuals receive notice of the basis of decisions against them.¹⁵²

1. *Notice Guaranteed by Audit Trails*

Aggrieved consumers could be guaranteed reasonable notice if scoring systems included audit trails recording the correlations and inferences made algorithmically in the prediction process. With audit trails, individuals would have the means to understand their scores. They could challenge mischaracterizations and erroneous inferences that led to their scores.

Even if scorers successfully press to maintain the confidentiality of their proprietary code and algorithms vis-à-vis the public at large, it is still possible for independent third parties to review it. One possibility is that in any individual adjudication, the technical aspects of the system could be covered by a protected order requiring their confidentiality. Another possibility is to limit disclosure of the scoring system to trusted neutral experts.¹⁵³ Those experts could be entrusted to assess the inferences and correlations contained in the audit trails. They could assess if scores are based on illegitimate characteristics such as race, nationality, or gender or on mischaracterizations. This possibility would both protect scorers' intellectual property and individuals' interests.

2. *Interactive Modeling*

Another approach would be to give consumers the chance to see what happens to their score with different hypothetical alterations of their

150. Citron, *supra* note 20, at 1276–77.

151. *Id.* at 1277 (describing automated public benefits systems that failed to include audit trails and how thus the systems were “unable to generate transaction histories showing the ‘decisions with respect to each eligibility criterion for each type of assistance’ in individual cases”).

152. *Id.* at 1305. Immutable audit trails are essential so that the record-keeping function of audit trails cannot be altered. Citron & Pasquale, *supra* note 16, at 1472.

153. See Dan L. Burk & Julie E. Cohen, *Fair Use Infrastructure for Rights Management Systems*, 15 HARV. J.L. & TECH. 41, 62 (2001); Pasquale, *Beyond Innovation and Competition*, *supra* note 34, at 162.

credit histories. Imagine an interface where each aspect of a person's credit history is represented on a wiki.¹⁵⁴ To make it more concrete, picture a consumer who is facing a dilemma. She sees on her credit report that she has a bill that is thirty days overdue. She could secure a payday loan to pay the bill, but she'd face a usurious interest rate if she takes that option. She can probably earn enough money working overtime to pay the bill herself in forty days. Software could give her an idea of the relative merits of either course. If her score dropped by 100 points when a bill went unpaid for a total of sixty days, she would be much more likely to opt for the payday loan than if a mere five points were deducted for that term of delinquency.

Just as the authors of the children's series *Choose Your Own Adventure* helped pave the way to the cornucopia of interactive entertainment now offered today,¹⁵⁵ so, too, might creative customer relations demystify credit scoring. Interactive modeling, known as "feedback and control," has been successfully deployed in other technical contexts by a "values in design" movement.¹⁵⁶ It has promoted automated systems that give individuals more of a sense of how future decisions will affect their evaluation. For example, Canada's Immigration Bureau lets individuals enter various scenarios into a preliminary "test" for qualification as a permanent resident.¹⁵⁷ The digital interface allows users to estimate how different decisions will affect their potential to become a Canadian citizen. Learning French or earning a graduate degree can be a great help to those in their thirties; on the other hand, some over sixty years old can do "everything right" and still end up with too few points to apply successfully. The public scorecard does not guarantee anyone admittance, and is revised over time. Nevertheless, it provides a rough outline of what matters to the scoring process, and how much.

154. For general information on wikis, see Daniel Nations, *What is a Wiki?*, ABOUT.COM, http://webtrends.about.com/od/wiki/a/what_is_a_wiki.htm (last visited Feb. 11, 2014).

155. Grady Hendrix, *Choose Your Own Adventure*, SLATE (Feb. 18, 2011, 7:08 AM), <http://www.slate.com/id/2282786/>.

156. Comments of Deirdre K. Mulligan, Professor, Univ. of Calif. at Berkeley & Nicholas P. Doty in Response to the National Telecommunications & Information Administration's Request for Comments on the Multistakeholder Process To Develop Consumer Data Privacy Codes of Conduct, Docket No. 120214135-2135-01, at 11 (May 18, 2012), available at http://www.ntia.doc.gov/files/ntia/mulligan_doty_comments.pdf. See generally HELEN NISSENBAUM, *PRIVACY IN CONTEXT: TECHNOLOGY, POLICY, AND THE INTEGRITY OF SOCIAL LIFE* (2010); *PROFILING THE EUROPEAN CITIZEN* 67 (Mireille Hildebrandt & Serge Gutwirth eds., 2008).

157. *Determine Your Eligibility — Federal Skilled Workers*, GOV'T OF CANADA, <http://www.cic.gc.ca/english/immigrate/skilled/apply-who.asp> (last updated June 20, 2013).

Credit bureaus do need some flexibility to assess a rapidly changing financial environment. Any given score may be based on hundreds of shifting variables; a default may be much less stigmatizing in a year of mass foreclosures than in flush times. Credit bureaus may not be capable of predicting exactly how any given action will be scored in a week, a month, or a year. Nevertheless, they could easily “run the numbers” in old versions of the scoring software, letting applicants know how a given decision would have affected their scores on, for example, three different dates in the past.

We need innovative ways to regulate the scoring systems used in the finance, insurance, and real estate industries, and perhaps might even consider a “public option” in credit scoring. Even if it were first only tried in an experimental set of loans, it could do a great deal of good. If a public system could do just as well as a private one, it would seriously deflate industry claims that scoring needs to be secretive—a topic explore in more depth in the next section.

C. *Objections*

Credit bureaus will object that transparency requirements—of any stripe—would undermine the whole reason for credit scores. Individuals could “game the system” if information about scoring algorithms were made public or leaked in violation of protective orders.¹⁵⁸ Scored consumers would have ammunition to cheat, hiding risky behavior and routing around entities’ legitimate concerns such as fraud.

We concede that incidental indicators of good credit can become much less powerful predictors if everyone learns about them. If it were to become widely known that, say, the optimal number of credit accounts is four, those desperate for a loan may be most likely to alter their financial status to conform with this norm.

However, we should also ask ourselves, as a society, whether this method of judging and categorizing people—via a secretive, panoptic

158. Odysseas Papadimitriou, *Occupy Wall Street & Credit Score Reform*, WALLETBLOG (Mar. 21, 2012), <http://www.walletblog.com/2012/03/credit-score-reform/> (“[T]he Occupiers are off-base in suggesting that we centralize credit scoring and make the underlying formulas public. This would only make it easier for people to game the system, which would make existing credit scores less useful to banks and lead more of them to create their own proprietary scores that consumers would have no way of accessing.”). But bureaus may have more “economic” incentives to keep their methods hidden. See Eric Pitter, *The Law of Unintended Consequences: The Credit Scoring Implications of the Amended Bankruptcy Code—and How Bankruptcy Lawyers Can Help*, 61 CONSUMER FIN. L. Q. REP. 61, 65 (2007) (“CRAs have refused to disclose their credit scoring formula to anyone, even the Federal Reserve Board. The CRAs’ full exclusivity of their credit scoring model protects their niche and their unique role in the credit markets.”).

sort—is appropriate. It has already contributed to one of the greatest financial crises in American history, legitimizing widespread subprime lending by purporting to scientifically rank individuals' creditworthiness with extraordinary precision. Secretive credit scoring can needlessly complicate the social world, lend a patina of objectivity to dangerous investment practices, and encode discriminatory practices in impenetrable algorithms.¹⁵⁹

The benefits of secrecy are murkier than these costs. Moreover, the secrecy of credit scoring can impede incremental innovation: how can outsiders develop better scoring systems if they have no way of accessing current ones? Secret credit scoring can undermine the public good, since opaque methods of scoring make it difficult for those who feel—and quite possibly are—wronged to press their case.

If scorers can produce evidence about the bad effects of publicity, that might justify keeping the correlations, inferences, and logic of scoring algorithms from the public at large. But that logic would not apply to the FTC or third-party experts who would be bound to keep proprietary information confidential.

Another objection is that our proposal only works when the very existence of scoring systems is public knowledge, as in the case of credit scores. In non-credit contexts, entities are under no legal obligation to disclose scoring systems to the public generally and to impacted individuals specifically. Some scoring systems are not a secret because their business model is the sale of scores to private and public entities. Data brokers, for instance, rank, categorize, and score consumers on non-credit bases so they can avoid the obligations of FCRA.¹⁶⁰

To be sure, it is impossible to challenge a scoring system that consumers do not even know exists. Secret scores about people's health, employability, habits, and the like may amount to unfair practices even though they fall outside the requirements of FCRA. In that case, the FTC would have authority to require entities to disclose hidden scoring systems.

159. Amar Bhide, *The Hidden Costs of Debt Market Liquidity* 17–19 (Ctr. on Capitalism & Soc'y, Columbia Univ., Working Paper No. 79, 2013), available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2206996.

160. Pam Dixon, Exec. Dir., World Privacy Forum, Testimony Before Senate Committee on Commerce Science and Transportation: What Information Do Data Brokers Have On Consumers, and How Do They Use It? 3 (Dec. 18, 2013), available at http://www.worldprivacyforum.org/wp-content/uploads/2013/12/WPF_PamDixon_CongressionalTestimony_DataBrokers_2013_fs.pdf. For a discussion of the Fair Credit Reporting Act model, see Frank Pasquale, *Reputation Regulation: Disclosure and the Challenge of Clandestinely Commensurating Computing*, in *THE OFFENSIVE INTERNET* 107, 111–12 (Saul Levmore & Martha C. Nussbaum eds., 2010).

Of course, scoring systems that remain secret would be difficult for the FTC to identify and interrogate. Lawmakers could insist upon the transparency of scoring systems that impact important life opportunities. California, for instance, has been at the forefront of efforts to improve the transparency of businesses' use of consumer information.¹⁶¹ The FTC has called upon federal lawmakers to pass legislation giving consumers access to the information that data brokers hold about them.¹⁶² In September 2013, Senate Commerce Committee Chairman Jay Rockefeller announced his committee's investigation of the information collection and sharing practices of top data brokers.¹⁶³ We are particularly supportive of such efforts—scoring systems can only be meaningfully assessed if they are known and subject to challenge.

CONCLUSION

Imagine a young woman who failed to get a job out of college, and that failure reduced her “employability” score used by potential employers to determine her fitness for work. She found part-time work at a fast food restaurant. Her credit score fell far below 600 without her even knowing it, perhaps because of inferences associated with certain low-paying jobs. Her low credit score *caused* further bad outcomes, cascading into ever more challenging life circumstances. Talent analytics companies categorized her as a “non-innovator” and “waste.” With low scores across countless measures, the young woman was unable to get a full-time job.

To quote Wolff and De-Shalit, “without something like the type of action plan set out here, societies are destined to continue to reinforce patterns of entrenched privilege and disadvantage, widening gaps between rich and poor, and perpetuation of disadvantage.”¹⁶⁴ Michael Walzer's social theory also provides a compelling argument against the “big data's” promiscuous mashup of various data sources to deny

161. ACLU OF CAL., *LOSING THE SPOTLIGHT: A STUDY OF CALIFORNIA'S SHINE THE LIGHT LAW* 13 (2013), available at <http://www.aclunc.org/R2K>.

162. FED. TRADE COMM'N, *PROTECTING CONSUMER PRIVACY IN AN ERA OF RAPID CHANGE* 14 (2012), available at <http://www.ftc.gov/sites/default/files/documents/reports/federal-trade-commission-report-protecting-consumer-privacy-era-rapid-change-recommendations/120326privacyreport.pdf>.

163. Tom Risen, *Rockefeller Expands Investigation of Consumer Data Brokers*, U.S. NEWS & WORLD REP. (Sept. 25, 2013), <http://www.usnews.com/news/articles/2013/09/25/rockefeller-expands-investigation-on-consumer-data-brokers>.

164. JONATHAN WOLFF & AVNER DE-SHALIT, *DISADVANTAGE* 186 (2007).

opportunities.¹⁶⁵ Providing oversight over scoring systems that can cause negative spirals should be a critical aim of our legal system. Scoring systems have a powerful allure—their simplicity gives the illusion of precision and reliability. But predictive algorithms can be anything but accurate and fair. They can narrow people’s life opportunities in arbitrary and discriminatory ways.

As a society, we have made commitments to protect consumers from serious harms that they have no means to prevent. We have also aspired to provide individuals with notice about important decisions made about them and a chance to challenge them. These commitments can help us develop a model of due process for scoring systems. Transparency is a crucial first step, first to the FTC who can interrogate scoring systems under their unfairness authority. Opening up the black box scoring systems to individuals or neutral experts representing them is key to permitting them to challenge “arbitrariness by algorithm.” Our recommendations are provisional, yet, we hope the FTC and interested lawmakers move forward in bringing procedural regularity and oversight into our scored society.

165. Mike Konczal, *Demos on Credit Reporting and Employment; Surveillance, Inequalities and the Labor Market*, RORTYBOMB (June 23, 2011), <http://rortybomb.wordpress.com/2011/06/23/demos-on-credit-reporting-and-employment-surveillance-inequalities-and-the-labor-market/> (“[Walzer suggested that] nobody should be precluded a social good y because on their lack of possession of an unrelated good x. That the sloppiness of credit scores, the protection of bankruptcy against bad debts, the brute luck of bad health, etc. could all preclude someone from obtaining basic utilities and access to productive labor—that inequality in net worth, health and other spheres preclude access to the sphere of labor regardless of one’s abilities—is something to be fought tooth-and-nail.”).