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THE PROMISE AND PERILS OF ALGORITHMIC LENDERS' USE OF BIG DATA

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INTRODUCTION

Is Amazon.com racist, the headlines queried.[1] As has been well-reported, Amazon has been investing heavily in signing people up for its Prime service.[2] Half of all American households have reportedly paid the $99 membership fee.[3] In certain major metropolitan areas, Prime membership entitles customers to free same-day delivery in a bid "to eliminate one of the last advantages local retailers have over the e-commerce giant: instant gratification."[4] But same-day delivery service wasn't always available to every Prime member in those cities. A 2016 Bloomberg report found that Prime's service area excluded large swaths of "predominantly black ZIP codes" in "six major same-day delivery cities."[5] Blacks in four cities—Atlanta, Chicago, Dallas, and Washington D.C.—were only "half as likely to live in neighborhoods

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1. *See, e.g.*, Bamzi Banchiri, *Is Amazon Same-Day Delivery Service Racist?*, CHRISTIAN SCI. MONITOR (Apr. 23, 2016), https://www.csmonitor.com/Business/2016/0423/Is-Amazon-same-day-delivery-service-racist [https://perma.cc/L2LD-2P8V]; Rafi Letzter, *Amazon Just Showed Us That 'Unbiased' Algorithms Can Be Inadvertently Racist*, BUS. INSIDER (Apr. 21, 2016, 4:50 PM), http://www.businessinsider.com/how-algorithms-can-be-racist-2016-4 [http://perma.cc/MWP5-ZYFS].

2. *See, e.g.*, Kandyce Jackson, Surfing While Black 24 (Jan. 26, 2017) (unpublished manuscript) (on file with the Chicago-Kent Law Review).

3. *See* Aimee Picchi, *Amazon Prime Day: Does It Make Sense to Sign Up for Prime?*, CBS MONEYWATCH (July 11, 2017, 1:51 PM), http://www.cbsnews.com/news/amazon-prime-day-does-it-make-sense-to-sign-up-for-prime/ [https://perma.cc/P5Y9-8M7J] (reporting the estimate of L2, a digital research firm).

4. David Ingold & Spencer Soper, *Amazon Doesn't Consider the Race of Its Customers. Should It?*, BLOOMBERG (Apr. 21, 2016), https://www.bloomberg.com/graphics/2016-amazon-same-day/ [https://perma.cc/7N9S-57FL].

5. *Id*.

with access to Amazon same-day delivery as white residents."[6] And in NYC, same-day delivery included many surrounding suburbs but entirely excluded the predominantly minority borough of the "Bronx and some majority-black neighborhoods in Queens."[7]

"Prime-lining" became a public relations nightmare for Amazon.[8] The most striking example of "Prime-lining" was in Boston's Roxbury neighborhood—a primarily black area.[9] Roxbury represented a donut hole in the city's same-day delivery coverage area.[10] In other words, Roxbury was entirely surrounded by neighborhoods that were eligible for same-day delivery, but no one in Roxbury was eligible.[11] Roxbury residents were ineligible despite paying the same flat-rate Prime membership fee as every other city resident.[12]

Amazon blamed its data-driven approach for "Prime-lining" and disclaimed any discriminatory intent.[13] In apparent response to consumer pressure, Amazon—which claims to have "a 'radical sensitivity' to any suggestion that neighborhoods are being singled out by race"—has since expanded its same-day service to every zip code in every city where same-day service is offered.[14] Amazon claims that it initially offered same-day service only in those neighborhoods that had a high pre-existing concentration of Prime members, rather than singling out predominantly-minority neighborhoods for discriminatory treatment.[15] But it's not surprising that "a solely data-driven calculation that looks at numbers instead of people can reinforce long-entrenched inequality in access to retail services" given pre-existing income and wealth gaps between races and segregated residential housing patterns.[16] Whether or not Amazon deliberately intended to discriminate against

6. *Id*.

7. *Id*.

8. Hat tip to Professor Adam Levitin for suggesting this phrase. *See* @AdamLevitin, TWITTER (July 10, 2017, 10:20 AM), https://twitter.com/AdamLevitin/status/884462300316532736 [https://perma.cc/SJA6-6BEZ].

9. Ingold & Soper, *supra* note 4 ("Roxbury, with a population that's about 59 percent black and 15 percent white, is excluded.").

10. *Id.*

11. *Id.*

12. *Id.*

13. *Id.*

14. *Id.* (noting the expansion in NYC, Boston and Chicago); *see also* Chris Moran, *Amazon Now Expanding Same-Day Delivery to All ZIP Codes in 27 Cities*, CONSUMERIST (May 6, 2016, 1:58 PM), https://consumerist.com/2016/05/06/amazon-now-expanding-same-day-delivery-to-all-zip-codes-in-27-cities/ [https://perma.cc/9RDK-GAH4].

15. Ingold & Soper, *supra* note 4.

16. *Id.*

minority and low-income customers, the firm's initial failure to provide same-day delivery in every zip code had the same effect.[17]

The mainstream financial services industry has long had its own version of Prime-lining, excluding millions of Americans from taking advantage of their products and services because they lack a sufficient credit history to receive a credit score.[18] Though this discrimination is legally sanctioned, it has pernicious effects.

In the financial services sector, innovative use of Big Data[19] and creditworthiness algorithms[20] purport to eliminate the discriminatory effects of credit-score-based determinations.[21] Algorithmic lenders claim their innovations allow them to make faster, cheaper, and more predictive credit determinations, thus allowing them to lend to borrowers with lower credit

17. *Id.* (noting that Amazon's intentions did not "'make much practical difference' . . . [f]or people who live in black neighborhoods not served by Amazon").

18. A "good" credit score is the primary factor in most traditional lending decisions. EXEC. OFFICE OF THE PRESIDENT, BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS 11 (2016), https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/2016_0504_data_discrimination.pdf [https://perma.cc/4JNR-LDNS]; EVA WOLKOWITZ & SARAH PARKER, CTR. FOR FIN. SERVS. INNOVATION, BIG DATA, BIG POTENTIAL: HARNESSING DATA TECHNOLOGY FOR THE UNDERSERVED MARKET 18 (2015), http://www.morganstanley.com/sustainableinvesting/pdf/Big_Data_Big_Potential.pdf [https://perma.cc/9WY8-WZMG].

19. Big Data has been defined "as the collection and use of large data sets that can be broadly combined and distributed to identify patterns and create new data based on these insights—known as metavariables—to increase the effectiveness and efficiency of consumer finance products." WOLKOWITZ & PARKER, *supra* note 18, at 3; Kate Crawford & Jason Schultz, *Big Data and Due Process: Toward a Framework to Redress Predictive Privacy Harms*, 55 B.C. L. REV. 93, 96 (2014) (describing Big Data as "the use of large data sets in data science and predictive analytics"); *see also* Eric Bank, *How Marketplace Lenders Decide If You're a Good Risk*, CREDIBLE (Feb. 10, 2017), https://www.credible.com/blog/marketplace-lenders-decide-good-risk [https://perma.cc/R737-7EQ4]; David F. Freeman, Jr. et al., *FTC Report on Big Data Could Foreshadow Big Compliance Issues: Implications for Unfair Lending, Credit Reporting, and Unfair and Deceptive Practices Compliance*, ARNOLD & PORTER KAYE SCHOLER (Jan. 20, 2016), https://www.apks.com/en/perspectives/publications/2016/1/ftc-report-on-big-data [https://perma.cc/C5UY-M4L8] (suggesting that Big Data "can be loosely defined as the amassing and analysis of large consumer data sets and the incorporation of analytical results and conclusions into marketing and lending decisions"); *see infra* text accompanying notes 32–33.

20. *See* Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83, 84 n.1 (2017) ("Algorithms are 'procedure[s] for solving a given type of mathematical problem.'" (citing Diamond v. Diehr, 450 U.S. 175, 186 (1981))); *see also* DONALD D. SPENCER, WEBSTER'S NEW WORLD DICTIONARY OF COMPUTER TERMS 17 (5th ed. 1994) (An algorithm is "a mathematical or logical procedure for solving a problem. An algorithm is a recipe for finding the right answer to a difficult problem by breaking down the problem into simple steps."); PEDRO DOMINGOS, THE MASTER ALGORITHM: HOW THE QUEST FOR THE ULTIMATE LEARNING MACHINE WILL REMAKE OUR WORLD 1 (2015) ("An algorithm is a sequence of instructions telling a computer what to do.").

21. Chris Brummer & Yesha Yadav, *The Fintech Trilemma* 31 (Vanderbilt Law Sch., Research Paper No. 17-46, 2017), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3054770## [https://perma.cc/458S-N4A8] (describing algorithms as being "central to the fintech economy.").

scores.[22] Thus, algorithmic lenders[23] often seek to set themselves apart from mainstream providers by arguing that they can make credit available to the "Credit Invisible."[24] The credit invisible includes those non-traditional borrowers who are among the most adversely affected by the (legal) discrimination of traditional lenders.

Like many new technologies, algorithmic lenders' use of Big Data holds great promise but may also be perilous. At the most basic level, Big Data is simply a toolkit for "creating, refining, and scaling financial solutions for consumers."[25] A company's decision to use Big Data is "neither inherently good nor bad."[26] Instead—as with any other tool—it can be used to help or to harm consumers. The Janus-faced nature of emerging financial technology ("fintech") firms is particularly noteworthy, and lies at the heart of this Article.

Appropriate regulation will likely be key to delivering on Big Data's promises in the financial services sector. All financial services companies

22. NAT'L CONSUMER LAW CTR., BIG DATA: A BIG DISAPPOINTMENT FOR SCORING CONSUMER CREDIT RISK 12–13 (2014), https://www.nclc.org/images/pdf/pr-reports/report-big-data.pdf [https://perma.cc/EG78-TLY8] [hereinafter, NCLC, BIG DISAPPOINTMENT]. *But see* Michael Gordon & Vaughn Stewart, *CFPB Insights on Alternative Data Use in Credit Scoring*, LAW360 (May 3, 2017, 11:50 AM), https://www.law360.com/articles/919094/cfpb-insights-on-alternative-data-use-in-credit-scoring [https://perma.cc/F2JB-2PUZ] ("While incorporating alternative data into the underwriting process could improve risk assessments, it may be difficult, at least initially, for lenders to evaluate the predictive power of new sources of data or new credit scores based on such data.").

23. *See infra* text surrounding notes 83-86 (explaining the term algorithmic lenders by describing how one such lender operates).

24. *See* OFFICE OF RESEARCH, CONSUMER FIN. PROT. BUREAU, DATA POINT: CREDIT INVISIBLES 6 (2015), http://files.consumerfinance.gov/f/201505_cfpb_data-point-credit-invisibles.pdf [https://perma.cc/U3DU-4L3B] (using the term "credit invisibles" to describe the 26 million Americans (or about 1 in 10) that do not have a credit history, and noting that another 19 million are unscorable because their histories are too scant ("thin") or old). The reported number of unscorable Americans varies, with some estimating as many as 64 million people are affected. *See also* Mikella Hurley & Julius Adebayo, *Credit Scoring in the Era of Big Data*, 18 YALE J.L. & TECH. 148, 174 (2016); *Credit Invisibility and Alternative Data: The Devil is in the Details*, NAT'L CONSUMER LAW CTR. (June 2015), https://www.nclc.org/images/pdf/credit_reports/ib-credit-invisible-june2015.pdf [https://perma.cc/74N9-3TG4] [hereinafter NCLC, *Credit Invisibility*] (noting that the CFPB has described roughly 44 million Americans as being "credit invisible"); NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 13 (suggesting that Big Data credit scoring models attempt to address shortcomings with traditional credit scoring, and that marketplace lenders purport to use their data mining and algorithmic scoring techniques to accurately assess the creditworthiness of "thin file" or "no file" borrowers).

25. Sarah Parker, *5 Things to Remember as the Big Data Debate Heats Up*, MEDIUM (Feb. 2, 2016), https://medium.com/@CFSInnovation/5-things-to-remember-as-the-big-data-debate-heats-up-fd964185e2f0 [https://perma.cc/MTR3-PU4W].

26. *Id.* (As a financial technology tool, Big Data "is neither inherently good nor bad because its value to providers and consumers depends on the quality of its application.").

are potentially subject to a significant amount of regulation. But while regulators have paid attention to fintech's development,[27] regulations "have not kept pace with modern Big Data capabilities."[28] This presents challenges both for regulators and "for companies looking for firm legal guidelines as they build" their companies.[29] Indeed, the Consumer Financial Protection Bureau (CFPB) noted in a recent Request for Information that it needs to better understand these technologies to "encourage their responsible use and lower unnecessary barriers, including any unnecessary regulatory burden or uncertainty that impedes such use."[30] Impliedly, it will also seek to prevent fintech's irresponsible use.

The rest of this paper proceeds as follows. Part I provides a (very brief) overview of Big Data, machine learning/predicative analytics, and their use in making credit determinations. Part II discusses the promising and perilous nature of "algorithmic lending 2.0." Its major promise is to bring the so-called "credit invisibles" into the credit markets by using non-traditional credit measures. Its primary threat is the possibility that it will exacerbate financial services discrimination. Part III discusses several major pieces of the current regulatory regime, where it fails to adequately address the worst threats, and how we might improve oversight of algorithmic lenders.[31]

I. THE RISE OF BIG DATA IN CREDIT

A. What is Big Data?

"Big Data" lacks an agreed upon definition. In some ways, Big Data simply refers to any set of empirical facts. Others, however, have asserted that Big Data is like any other source of data plus "the 3Vs" (volume, variety,

27. Numerous regulators have actively sought to obtain more information about algorithmic lenders and their use of Big Data. *See, e.g.*, Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process, 82 Fed. Reg. 11,183 (Feb. 21, 2017), https://www.gpo.gov/fdsys/pkg/FR-2017-02-21/pdf/2017-03361.pdf [https://perma.cc/8NWP-9F6D] [hereinafter CFPB RFI].

28. WOLKOWITZ & PARKER, *supra* note 18, at 24 (discussing gaps and ambiguities in the current regulatory structures that may allow "data algorithms and machine-learning platforms" to use "data in an exploitive fashion to target underserved consumers with financial products that have poor quality or models designed to ensnare consumers in unhealthy relationships"); *see also* Jeremy Kidd, *Fintech: Antidote to Rent-Seeking?*, 93 CHI.-KENT. L. REV. 165, 166 (2017) (discussing how financial technology innovation will soon begin to outstrip the ability of regulators to keep pace).

29. WOLKOWITZ & PARKER, *supra* note 18, at 24.

30. CFPB RFI, *supra* note 27, at 11,183.

31. Namely, the Equal Credit Opportunity Act, the FTC's UDAP power, the CFPB's UDAAP power, and the Fair Credit Reporting Act; *see infra* Part III.

and velocity).[32] In other words, Big Data means there is a lot of data, of various types, that is capable of being rapidly processed.[33] This Article is particularly concerned with Big Data's use in the financial services sector by so-called marketplace lenders, which this article will generally call algorithmic lenders for reasons that will be made clear shortly.[34]

Companies often make sense of Big Data through the use of algorithms. An algorithm is a set of "instructions for how to solve a problem."[35] An algorithm's output is the solution to the problem the algorithm has been designed to answer. For example, one of Netflix's algorithms is designed to recommend movies to its users. Its recommendations are the algorithm's output. But it also needs inputs to make this decision. In this case, Netflix's algorithm considers similarities between movies and television shows a user has already watched and ones that user might consider watching, such as: "Were they created at roughly the same time? Do they tend to get the same ratings?"[36]

Most algorithms are simple and "extremely straightforward."[37] Their instructions are limited and the outcomes are easily determinable.[38] For example, a basic algorithm in Microsoft Excel can determine the largest number in a column of numbers. In Excel, the command is "=Max(N_x:N_y)." This algorithm searches the column of numbers "N" from row x through row y

32. Dennis D. Hirsch, *That's Unfair! Or Is It? Big Data, Discrimination and the FTC's Unfairness Authority*, 103 U. KY. L. REV. 345, 349 (2014).

33. Margaret Rouse, *3Vs (Volume, Variety, and Velocity)*, WHATIS.COM, http://whatis.techtarget.com/definition/3Vs [https://perma.cc/3UEW-JDHL].

34. Duane Pozza & Helen Wong, *FinTech Forum: A Closer Look at Marketplace Lending*, FTC (Aug. 3, 2016, 12:05 PM), https://www.ftc.gov/news-events/blogs/business-blog/2016/08/fintech-forum-closer-look-marketplace-lending [https://perma.cc/8AJ2-QXGG] ("Marketplace lenders are typically online non-bank financial companies that leverage technology to reach potential borrowers, evaluate creditworthiness, and obtain credit sources for loans.").

35. Jennifer Golbeck, *How to Teach Yourself About Algorithms*, SLATE (Feb. 9, 2016, 9:45 AM), http://www.slate.com/articles/technology/future_tense/2016/02/how_to_teach_yourself_about_algorithms.single.html [https://perma.cc/T4RB-SABM]; *see also* Tutt, *supra* note 20, at 93 (discussing simple algorithms like Google's PageRank and Deep Blue's chess playing algorithm and contrasting machine learning algorithms); Brummer & Yadav, *supra* note 21, at 31 (describing algorithms as "programmed computerized instructions").

36. Tom Vanderbilt, *The Science Behind the Netflix Algorithms That Decide What You'll Watch Next* (Aug. 7, 2013, 6:30 AM), https://www.wired.com/2013/08/qq_netflix-algorithm [https://perma.cc/EP3T-P2RS]; *see also* Golbeck, *supra* note 35 (discussing the inputs for a Google Maps algorithm).

37. Tutt, *supra* note 20, at 92.

38. A.M. Kuchling, *Background: Algorithms*, 50 EXAMPLES FOR TEACHING PYTHON, http://fiftyexamples.readthedocs.io/en/latest/algorithms.html [https://perma.cc/X2DN-F8JV].

and returns the highest number in that column. This algorithm can be executed with three instructions.[39] An algorithm like this simple example "responds to specific inputs with specific outputs that the programmer anticipated in advance."[40] If an error occurs, the simplicity of this algorithm allows the programmer to review the instructions the algorithm followed "to find out why the error occurred and correct it."[41]

Even some of the world's most "impressive algorithms are basically not much more complicated than that."[42] For example, Google rose to prominence because of its "PageRank Algorithm," which is the primary tool by which Google orders search results.[43] PageRank determines the order of search results by ranking each page based on "how many other webpages link to that page, and then it determines how much to value those links by determining how many pages link to those pages."[44] By distilling this process down to a limited set of instructions that a computer repeatedly performs, PageRank allowed Google to "rank the whole web, which was comprised of 26 million web pages at that time, 'in a few hours on a medium size workstation.'"[45]

Both previous examples were of "dumb" algorithms, but a qualitatively different type of algorithm also exists. This new breed of "learning algorithm" is not programmed by humans to complete a particular task. Instead, they are programmed to learn (on their own) how to perform a particular task.[46] Stated differently, rather than building an algorithm to create a rank order of webpages, algorithms can be developed to figure out how to best rank order webpages. These learning algorithms are referred to by various names, including machine learners, predictive analytics, or artificial intelligence.[47] But whatever you call them, these learning algorithms are a profound advance from simpler "dumb" algorithms.[48]

39. *Id*. ("1. Set max to O. 2. For each number x in the list L, compare it to max. If x is larger, set max to x. 3. max is now set to the largest number in the list.").

40. Tutt, *supra* note 20, at 93.

41. *Id*.

42. *Id.*; *see also* Sishaar Rao, *Demystifying the PageRank Algorithm*, DEV (May 13, 2017), https://dev.to/sishaarrao/demystifying-the-pagerank-algorithm [http://perma.cc/Z3HV-53WE].

43. Tutt, *supra* note 20, at 93; Rao, *supra* note 42 (describing PageRank as "arguably the most widely-utilized and influential algorithm in our modern day").

44. *Id.*; Rao, *supra* note 42 (describing the technical details of how PageRank works).

45. Tutt, *supra* note 20, at 93.

46. *Id.* at 94.

47. *Id.*; Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87, 88–89 (2014) (describing "machine learning" as "a subfield of computer science concerned with computer programs that are able to learn from experience and thus improve their performance over time").

48. *See* Tutt, *supra* note 20, at 87, 95.

Learning algorithms learn from and help make sense of Big Data.[49] Big Data involves aggregating large amounts of often-messy information, so learning algorithms can sort and analyze that information to provide novel insights and "solve problems in numerous disciplines and business arenas."[50] The paramount value of learning algorithms is "to detect patterns in data in order to automate complex tasks or make predictions."[51] For example, by analyzing their retail purchases, the New York Times reported that Target was able to accurately predict whether its female customers were pregnant.[52] Reportedly, Target assigned shoppers a "pregnancy prediction" score by studying whether and when shoppers purchased 25 particular products.[53] For example, a shopper that purchased "cocoa-butter lotion, a purse large enough to double as a diaper bag, zinc and magnesium supplements and a bright blue rug" might be judged 87 percent likely to be pregnant.[54] Of course, to determine that these 25 products were key predictors of pregnancy, Target's algorithm must have analyzed thousands of products and likely millions of product combinations.[55] Once identified, a shopper could be targeted with marketing materials and coupons to encourage her to buy more products at Target.[56]

Big Data is not a futuristic phenomenon. It is already in widespread use, pervading "all aspects of our daily lives."[57] For example, Google Search uses Big Data. Google Search collects and analyzes "hundreds of thousands of data points to arrive at the content and sequence of search results."[58] And this is just one of Big Data's many applications. Eventually "a group of enterprising companies realized that the same kind of processing [as Google Search uses] could be used in the field of consumer credit by developing new underwriting methods that went beyond FICO scores."[59] Since then the use

49. "'Big Data' is lingo used to describe computations that sift immense data sets for valuable nuggets of information." *See* Bank, *supra* note 19; *see also supra* text accompanying note 19.

50. Crawford & Schultz, *supra* note 19, at 96.

51. Surden, *supra* note 47, at 89.

52. Hirsch, *supra* note 32, at 350 (discussing this aspect of Target's Big Data usage).

53. *See* Charles Duhigg, *How Companies Learn Your Secrets*, N.Y. TIMES MAG., (Feb. 16, 2012), http://www.nytimes.com/2012/02/19/magazine/shopping-habits.html [https://perma.cc/5EEW-LQFG].

54. *Id.*

55. *Id.*

56. *See* Hirsch, *supra* note 32.

57. Bank, *supra* note 19; Sara Hajian et al., *Algorithmic Bias: From Discrimination Discovery to Fairness-aware Data Mining*, 22 ACM SIGKDD INT'L CONF. ON KNOWLEDGE DISCOVERY & DATA MINING 2125, 2125 (2016).

58. Bank, *supra* note 19.

59. *Id.* Most companies that use alternative data also continue to use traditional measures of creditworthiness. At least one company that claimed to have a "FICO-Free Zone" apparently secretly (and deceptively) continued to primarily rely on FICO scores for making credit determinations. *See* Thornton

of Big Data in the financial services sector has taken off, with a recent survey by the Economist estimating "that at least 74 percent of companies in the banking space have recently invested in new technologies to better leverage Big Data."[60]

B. Big Data in Credit Scoring

Algorithmic lending has a long history.[61] Although algorithmic lending is often thought of as being a twenty-first century phenomenon, it has been around at least since the introduction of the credit score by Fair, Isaac, and Company ("FICO") in 1989.[62] Although the exact details of the FICO score are a closely guarded secret, a FICO score is an algorithmic output.[63] In other words, a FICO score is the output of a set of instructions on how to transform various inputs, such as a history of late payments, a person's debt-to-credit-limit ratio, and other elements, into a single numerical value. A FICO score is reportedly derived from fewer than fifty data points.[64]

In recent memory, the traditional path to obtaining a long-term, unsecured consumer loan required a prospective borrower to visit a bank's physical offices. At the bank, the prospective borrower would discuss a possible

McEnery, *SoFi's "FICO-Free Zone" Loan Process Was Maybe Actually Rather Full Of FICO*, DEALBREAKER (Sept. 14, 2017, 5:06 PM), http://dealbreaker.com/2017/09/sofis-fico-free-zone-loan-process-was-actually-rather-full-of-fico/ [https://perma.cc/LX9Q-ZWTT] ("According to conversations with numerous former SoFi employees, the company's 'FICO-Free Zone' loan product actually relied quite heavily on evaluating applicants by their FICO score.").

60. Freeman, Jr. et al., *supra* note 19.

61. WOLKOWITZ & PARKER, *supra* note 19, at 4 (describing early use of "Big Data" as beginning when credit bureaus gathered "tradeline information to assign consumer repayment risk; insurance companies utilized applicant histories and demographics to set premiums; and car dealerships used information on average vehicle life expectancy to calculate blue book values." And claiming that "[t]he earliest uses of large data sets to inform financial product offerings did not differ greatly, in theory or aim, from how Big Data usage is conceived today.").

62. Ann Carns, *Is That Credit Score a FICO, or a FICO 8?*, N.Y. TIMES: BUCKS (May 10, 2012, 3:44 PM), https://bucks.blogs.nytimes.com/2012/05/10/is-that-credit-score-a-fico-or-a-fico-8/?_php=true&_type=blogs&_r=0 [https://perma.cc/7E5T-6UAV].

63. *How Credit History Impacts Your Credit Score*, MYFICO.COM, http://www.myfico.com/credit-education/whats-in-your-credit-score [https://perma.cc/N8KD-KJL4] (The most popular credit score, the FICO Score, is primarily composed of five factors: (i) payment history; (ii) amounts owed; (iii) length of credit history; (iv) new credit; and (v) types of credit used).

64. *Introducing ZAML: Zest Automated Machine Learning*, ZESTFINANCE, https://www.zestfinance.com/zaml [https://perma.cc/3V5U-TGT9] ("Most traditional underwriting systems use fewer than 50 data points for credit decisions.").

loan with the bank's loan officer[65] and fill out the necessary paperwork.[66] The bank would verify the prospective borrower's income, assets and debts, and pull the prospective borrower's credit score. The bank might also check the prospective borrower's personal and professional references, and make a subjective determination of his or her appearance.[67] If satisfied, the bank would lend to the prospective borrower. Because signature loans are unsecured and there is typically no co-signor, these loans are usually only made to people who are "very good credit risks or to people with whom the lender has a relationship."[68] As a result, prospective borrowers often fail to obtain the loan they seek.

Starting in 2006, a new type of lender appeared on the scene, threatening to disrupt the traditional method of obtaining a loan.[69] These lenders are also algorithmic lenders, but have combined algorithmic lending with Big Data. Commonly referred to as "marketplace lenders" or "fintech" companies,[70] these new algorithmic lenders are usually non-bank financial companies that operate mostly online and use financial technology to market themselves to prospective borrowers, evaluate borrower creditworthiness,

65. Hurley & Adebayo, *supra* note 24, at 155 ("Prior to the 1980s, most lending decisions were entrusted to individual loan officers and specialists who evaluated applicants on an individual basis. These underwriting processes were not only labor-intensive, but could be influenced by personal bias.").

66. *See, e.g.*, Lucy Lazarony, *How to Apply for a Personal Loan*, CREDIT.COM (Nov. 29, 2016), https://www.credit.com/loans/loan-articles/how-to-apply-for-personal-loan/ [https://perma.cc/CT7D-CA59].

67. *4 Signature Loan Application Tips: What to Tell the Lender*, LOAN.COM, http://www.loan.com/personal-loans/4-signature-loan-application-tips-what-to-tell-the-lender.html [https://perma.cc/HZ5U-TN39] (advising prospective borrowers to "[b]e neat in appearance and make sure your documentation looks professional").

68. *Id.*

69. *See* Kathryn F. Lazarev, *CFPB Steps Up Scrutiny of FinTech Companies*, GOODWIN: LENDERLAW WATCH (Mar. 10, 2016), http://www.lenderlawwatch.com/2016/03/10/cfpb-steps-up-scrutiny-of-fintech-companies/ [https://perma.cc/YD9E-J5WW] ("[M]arketplace lending is 'a relatively new kind of online model.'"); *see also* U.S. DEP'T OF THE TREASURY, OPPORTUNITIES AND CHALLENGES IN ONLINE MARKETPLACE LENDING 11 (2016), https://www.treasury.gov/connect/blog/Documents/Opportunities_and_Challenges_in_Online_Marketplace_Lending_white_paper.pdf [https://perma.cc/4KQG-2549] [hereinafter TREASURY] (describing marketplace lenders as emerging in 2006); DELOITTE, A TEMPORARY PHENOMENON? MARKETPLACE LENDING 4 (2016), https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/financial-services/deloitte-uk-fs-marketplace-lending.pdf [https://perma.cc/FV7B-TNN5] [hereinafter DELOITTE REPORT] (reporting that "[t]he world's first [marketplace lender], Zopa, was founded in the UK in 2005. The first in the US, Prosper, was founded in 2006"); Freeman, Jr. et al., *supra* note 19 (claiming that "Big Data is quickly becoming a fixture in the consumer lending industry").

70. This is a portmanteau of abbreviations for the words "financial" and "technology." *See* Christopher G. Bradley, *FinTech's Double Edge*, 93 CHI.-KENT. L. REV. 61, 61 (2017).

and to match prospective borrowers with sources of credit.[71] Examples include SoFi, Lending Club, and Prosper.[72] Another common thread with fintech lenders is the "use of non-traditional methods to determine creditworthiness."[73] In other words, these firms have increasingly embraced Big Data and learning algorithms, which allows them to exploit a market niche that traditional banks do not.

Each algorithmic lender has its own proprietary blend of data and analytics, but it remains possible to generalize somewhat about these companies.[74] Marketplace lenders are widely touted as utilizing both traditional methods of underwriting, like FICO scores, and "highly sophisticated mathematical and machine learning processes in order to ascertain the credit worthiness of a potential borrower."[75] In other words, version 2.0 algorithmic lenders use different inputs and a different process to evaluate prospective borrowers than traditional lenders, who typically focus primarily on a borrower's credit score.[76] For example, "Lenddo makes use of more than 12,000

71. Pozza & Wong, *supra* note 34; Glen P. Trudel et al., *Treasury Releases White Paper on Online Marketplace Lending*, BALLARD SPAHR (May 13, 2016), http://www.ballardspahr.com/alertspublications/legalalerts/2016-05-13-treasury-releases-white-paper-on-online-marketplace-lending.aspx [https://perma.cc/N5UV-9FJY] (citing Treasury's definition for fintech and focusing on marketplace lender's online presence and use of venture capital).

72. Lauren Gensler, *The 10 Biggest Fintech Companies in America*, FORBES (Aug. 8, 2017, 9:45 AM), https://www.forbes.com/sites/laurengensler/2017/08/08/biggest-us-fintech-companies/#7438479c59d8 [https://perma.cc/UYD4-KPRE].

73. Bank, *supra* note 19; *see also* Freeman, Jr. et al., *supra* note 19 (noting the "emerging array of new FinTech companies offering loan products or services based on the use of non-traditional methods for assessing creditworthiness, largely through the use of Big Data").

74. Mercedes Tunstall & Andrew Caplan, *When Marketplace Lending and Big Data Collide*, LAW360 (July 11, 2016, 12:18 PM), https://www.law360.com/articles/815683/when-marketplace-lending-and-big-data-collide [https://perma.cc/YQ93-JRJV] (describing marketplace lenders as "looking beyond FICO scores to nontraditional data points—such as utility bills, rental payments, cell phone and cable bills, social media sites and online search histories, and other Big Data—so that they can better assess whether individuals who have little or no credit, or who have had poor credit behavior in the past, may be willing and able to pay off loans").

75. *See* Christopher K. Odinet, *Consumer Bitcredit and Marketplace Lending*, ALA. L. REV. (forthcoming Spring 2018) (manuscript at 8) (on file with the Chicago-Kent Law Review); *see also* U.S. PUB. INTEREST RESEARCH GRP. & CTR. FOR DIG. DEMOCRACY, COMMENTS BY THE U.S. PUBLIC INTEREST RESEARCH GROUP (USPIRG) AND THE CENTER FOR DIGITAL DEMOCRACY (CDD) ON "EXPANDING ACCESS TO CREDIT THROUGH ONLINE MARKETPLACE LENDING." U.S. DEPARTMENT OF THE TREASURY RFI. [FR DOC. 2015–17644 BILLING CODE 4810–25–P4810-25-P DOCKET #RFI, TREAS-DO-2015-0007-0001.] 5 (2015), https://www.democraticmedia.org/sites/default/files/field/public/2015/uspirg_cdd_marketplacelendingrfi_final30sept2015.pdf [https://perma.cc/7VFW-VB7P] [hereinafter USPIRG & CDD] (noting that fintech companies still use traditional measures of creditworthiness, such as FICO scores).

76. USPIRG & CDD, *supra* note 75; *see* CFPB RFI, *supra* note 27, at 11,184 (defining "'[t]raditional [credit] data'" as data held by credit reporting agencies, such as "tradeline information (including certain loan or credit limit information, debt repayment history, and account status), and credit inquiries, as well as information from public records relating to civil judgments, tax liens, and bankruptcies. It also

data points gathered from social websites, such as Yahoo, Google, LinkedIn, Twitter and Facebook, to assess a consumer's potential to pay off loans."[77] Other algorithmic lenders use different proxies for creditworthiness, such as "payment and sales history, online small business customer reviews," repayment history in various contexts (e.g., rent, utilities, including telephone and cable bills, and subprime credit), "educational history, professional licensure data, and personal property ownership data."[78]

By incorporating Big Data, algorithmic lenders greatly expanded the inputs used to determine a prospective borrower's creditworthiness. But at first, these new algorithmic lenders continued to use the same sort of "dumb" algorithms used by traditional lenders. In other words, the first generation of algorithmic lenders increased the volume of data inputs, but did not fundamentally change the process of evaluating a prospective borrower's creditworthiness. That is, these algorithms were hand programmed. Human programmers had to decide which data elements were relevant to making credit determinations, and how much weight to give to each data element in making these determinations.

Algorithmic lenders—whose hand-programmed algorithms analyze the flood of additional data points—are similar to Deep Blue, the supercomputer that defeated the world's greatest human chess player, Gary Kasparov.[79] Deep Blue was able to think through millions more moves per second than Kasparov, but to defeat Kasparov, Deep Blue had to evaluate which possible move most improved its board position relative to other possible moves.[80] To do so, "Deep Blue's programmers came up with over eight thousand different parameters (known as 'features') that might be used to determine

refers to data customarily provided by consumers as part of applications for credit, such as income or length of time in residence.").

77. Bank, *supra* note 19; *see also* USPIRG & CDD, *supra* note 75 (noting that "marketplace lenders are using online data from sources such as Facebook, Google, . . . shopping trends on various websites," and Yelp).

78. TREASURY, *supra* note 69, at 5; *see also* Bank, *supra* note 19; FED. TRADE COMM'N, BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION? (2006), https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-understanding-issues/160106big-data-rpt.pdf [https://perma.cc/2XWW-ZEJK] [hereinafter FTC REPORT] (noting that "consumers who may not have access to traditional credit, but, for instance, have a professional license, pay rent on time, or own a car, may be given better access to credit than they otherwise would have"); WOLKOWITZ & PARKER, *supra* note 18, at 12 ("LendUp incorporates borrowers' repayment behavior.").

79. Tutt, *supra* note 20, at 93.

80. *Id.*

whether a particular board position was good or bad."[81] Most of these features (and the weight accorded to each feature) had to be devised by human programmers, programmed into Deep Blue and then repeatedly adjusted.[82]

C. Algorithmic Lending 2.0

But what this article refers to as "algorithmic lending 2.0"—lenders that have both expanded the volume of data inputs and turned to learning algorithms to analyze that data—have already begun to emerge.[83] A prime example of this new breed of lender is ZestFinance. ZestFinance's CEO "has proudly stated that 'all data is credit data' – that is, predictive analytics can take virtually any scrap of information about a person, analyse whether it corresponds to a characteristic of known-to-be-creditworthy people, and extrapolate accordingly."[84] In other words, these emergent, version 2.0 algorithmic lenders are expanding the world of credit data (and algorithmic inputs) even further than the original algorithmic lenders.[85] Instead of limiting their use of data to information that has a reasonably clear relationship with creditworthiness, they are embracing the unclear relationships between "Big Data" and creditworthiness. For example, "a consumer's email addresses, brand of car, Facebook friends, educational background and college major, even whether he or she sends text messages in all capital letters or in lower case."[86] In short, version 2.0 algorithmic lenders are collecting every byte of data they can to feed into their credit-scoring algorithms.

In addition, unlike the dumb algorithms used by first-generation algorithmic lenders, version 2.0 algorithmic lenders use so-called learning algorithms to make credit decisions. As a result, these version 2.0 algorithmic lenders have not only changed the volume of inputs that their algorithms

81. *Id.* at 94.

82. *Id.*

83. *Id.* at 86. It is these new version 2.0 algorithmic lenders that are the primary focus of this Article.

84. Frank Pasquale, *Digital Star Chamber*, AEON (Aug. 18, 2015), https://aeon.co/essays/judge-jury-and-executioner-the-unaccountable-algorithm [https://perma.cc/AT2Y-FS3J].

85. In this regard, their intentions are not much different than traditional lenders. *See* WOLKOWITZ & PARKER, *supra* note 18, at 4 ("The earliest uses of large data sets to inform financial product offerings did not differ greatly, in theory or aim, from how Big Data usage is conceived today. Rather, its use was limited by rudimentary computing power and the hurdles of gathering and normalizing data from incompatible or non-digitized sources, both of which made the process relatively inefficient.").

86. Gregory Roberts, *Regulator Wades into Big Data Credit Swamp*, BLOOMBERG LAW: BANKING (Apr. 20, 2017), https://www.bna.com/regulator-wades-big-n57982086887/ [https://perma.cc/T8VP-JPZR].

must consider, but have also changed how those algorithms process that data. In doing so, they may have created a "black box" problem.[87]

Learning algorithms are fundamentally different than "dumb" algorithms.[88] As noted above, the first algorithmic lenders hand-crafted their algorithms.[89] Their goal was to design a set of instructions their credit-algorithm could execute that would make better credit determinations than traditional FICO scores can.[90] Designers of the new version of credit algorithms have a different objective. They have to design a set of instructions that will create an algorithm that can learn how to make creditworthiness determinations on its own.[91] Instead of deciding which features to prioritize and how much weight to give each feature, a learning algorithm is usually given a set of data on which to train itself.[92] The algorithm (not the programmers) decides which features are relevant and how to weigh them.[93] In other words, learning algorithms are often thought of as a black box, where programmers can see what went in (vast amounts of data) and what came out (e.g., a credit-determination) but now how or why the algorithm made any particular determination.[94] As a result, if an error occurs with a learning algorithm, a programmer usually cannot review the instructions the algorithm followed "to find out why the error occurred and correct it," as they can with a dumb algorithm.[95]

To return to the Deep Blue analogy, Deep Blue was successfully programmed to be the best chess player in the world. By contrast, new chess-

87. *See* Bennie Mols, *In Black Box Algorithms We Trust (or Do We?)*, ACM NEWS (Mar. 16, 2017), https://cacm.acm.org/news/214618-in-black-box-algorithms-we-trust-or-do-we/fulltext (noting that most learning algorithms "operate like black boxes (devices that can be viewed in terms of their inputs and outputs, without any knowledge of their internal workings)").

88. Tutt, *supra* note 20, at 85.

89. *See supra* text accompanying note 82; *see also* Surden, *supra* note 47, at 93 ("Most software is developed by a manual approach in which programmers explicitly specify a series of rules for a computer to follow that will produce some desired behavior.").

90. Tutt, *supra* note 20, at 95–96.

91. *Id.* at 84 n.1.

92. Hurley & Adebayo, *supra* note 24, at 181 ("ZestFinance may rely on statistical algorithms to automatically identify the most significant metavariables."); Surden, *supra* note 47, at 93 ("[M]achine learning algorithms are able to automatically build accurate models of some phenomenon . . . without being explicitly programmed.").

93. Solon Barocas & Andrew Selbst, *Big Data's Disparate Impact*, 104 CAL. L. REV. 671, 678 (2016) ("In particular, by exposing so-called 'machine learning' algorithms to examples of the cases of interest (previously identified instances of fraud, spam, default, and poor health), the algorithm 'learns' which related attributes or activities can serve as potential proxies for those qualities or outcomes of interest."); *see also* Surden, *supra* note 47, at 93. This is not true in every case. In some cases, programmers may continue to manually curate some features of learning algorithms.

94. *See* Mols, *supra* note 87.

95. Tutt, *supra* note 20, at 93.

playing algorithms are teaching themselves to be the best chess players in the world.[96] Algorithms can learn to solve problems by being exposed to "training data."[97] For credit-scoring, an algorithm may analyze a vast data set, comprised of all the company's data about people who previously applied for credit, including whether these people received credit and, if so, whether they repaid their loans.[98] The algorithm may then mine this data to identify variables that correlate with loan repayment and assign appropriate weights to these variables.[99] If it's been programmed well and the training data is good, the variables and weights the algorithm identifies should be useful for determining the creditworthiness of prospective borrowers as well.[100] In other words, based on having reviewed a large enough sample of borrowers and the details known about them, including their repayment history, a learning algorithm can learn to predict the likelihood that future borrowers will repay their loans.

II. THE PROMISE AND PERIL OF ALGORITHMIC LENDING

A. The Promise

Algorithmic lending 2.0 may produce significant benefits relative to traditional lending. In its 2016 report on Big Data, the Obama White House declared, "Big [D]ata and associated technologies have enormous potential for positive impact in the United States."[101] There are at least three primary

96. *Id.* at 98–99 (comparing Deep Blue to Giraffe, which has taught itself to play chess at a level that is comparable "to the best expert-designed counterparts in existence today, many of which have been fine tuned over the course of decades"); *cf.* Dawn Chan, *The AI That Has Nothing to Learn from Humans*, ATLANTIC (Oct. 20, 2017), https://www.theatlantic.com/technology/archive/2017/10/alphago-zero-the-ai-that-taught-itself-go/543450/?utm_source=twb [https://perma.cc/VW2G-Z755] (describing a game-playing AI, AlphaGo Zero, which "picked up Go from scratch, without studying any human games at all" and after "a mere three days" was playing so well that it was like AlphaGo Zero was from an "alternate dimension").

97. Barocas & Selbst, *supra* note 93, at 680; *see also* Michael Feldman et al., *Certifying and Removing Disparate Impact*, 21 ACM SIGKDD INT'L CONF. ON KNOWLEDGE DISCOVERY & DATA MINING 259 (2015).

98. *Cf.* Feldman et al., *supra* note 97 (explaining how data mining works, as trying to find "the best set of decision rules among a large set of candidate rules").

99. *Cf.* W. Nicholson Price II, *Regulating Black-Box Medicine*, 116 MICH. L. REV. 421, 431 (2017) (using Google Image's image recognition learning algorithm to explain the four-step process by which some algorithms are trained. First, the algorithm is shown "a set of known images ('Here are 10,000 pictures of ducks')." Second, the algorithm "develops complex internal rules based on nonlinear processes." Third, the algorithm "tests those rules on a test set ('Which of these are ducks?')." And fourth, the algorithm adjusts its "internal rules based on the success of the test." These steps are repeated a*d infinitum* "until it can accurately and consistently classify the images.").

100. *Cf. id.*

101. EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 4; *see also* Hirsch, *supra* note 32, at 362. The new administration's position is currently unknown.

improvements that may result from using Big Data and learning algorithms in the financial services industry. First, using alternative data sources may improve the predictive accuracy of creditworthiness determinations, allowing algorithmic lenders to increase credit access for people who cannot borrow from traditional lenders.[102] Second, algorithmic lending may be less expensive, thereby making credit more affordable and accessible. And finally, proponents of version 2.0 algorithmic lending claim that it can remove human bias from the credit-granting process. Each of these will be discussed in turn.

First, algorithmic lenders may increase credit access by using non-traditional lending criteria. A "good" credit score is the primary factor in most traditional lending decisions. Yet, "tens of millions of Americans . . . do not have enough information in their credit files to receive a traditional credit score or . . . have an undeservedly low score."[103] Without a traditional credit score, these so-called "credit invisibles"[104] are unable to "access traditional forms of credit."[105] Minorities, youths, and low-income borrowers are more likely to be credit invisible than their white, older, and higher-income peers.[106] Because algorithmic lenders use non-traditional measures of creditworthiness, they may be willing to lend to the "credit invisible."[107] Using Big Data and machine learning in credit decisions also has the potential to create better predictions of which prospective borrowers will repay their loans.[108]

102. For example, Lenddo claims to increase approval rates by 15% while decreasing defaults by 12%. *Credit Scoring Solution*, LENDDO, https://www.lenddo.com/pdfs/Lenddo_FS_CreditScoring_201705.pdf [https://perma.cc/HAE2-4X6D].

103. EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 12; WOLKOWITZ & PARKER, *supra* note 18, at 8 (noting that the use of alternative data points allow lenders "to extend credit with more affordable rates and terms than small business owners could access using only their personal credit scores"). The reported number of unscorable Americans varies, with some estimating as many as 64 million people are affected. *See supra* text accompanying note 24.

104. *See* CONSUMER FIN. PROT. BUREAU, *supra* note 24, at 6 (using the term "credit invisibles").

105. Hurley & Adebayo, *supra* note 24, at 155.

106. *See* CONSUMER FIN. PROT. BUREAU, *supra* note 24, at 6; *see also* NCLC, *Credit Invisibility*, *supra* note 24.

107. NCLC, BIG DISAPPOINTMENT, *supra* note 22.

108. *Id.* at 12; Julapa Jagtiani & Catharine Lemieux, *Fintech Lending: Financial Inclusion, Risk Pricing, and Alternative Information* (Fed. Reserve Bank of Phila., Working Paper No. 17-17, 2017), https://www.philadelphiafed.org/-/media/research-and-data/publications/working-papers/2017/wp17-17.pdf?la=en [https://perma.cc/BH2J-GTAW] (presenting some of the first data on whether loans made using alternative data points perform better than loans using traditional FICO scores alone and concluding that they do).

Accordingly, providing less expensive, and therefore more accessible, financial services to tens of millions of unbanked and underbanked consumers is the most widely touted benefit of the new algorithmic lenders. For example, ZestFinance has declared its intent "to make the extension of credit to consumers fairer and more inclusive, by expanding the measures used beyond the traditional ones that may work to the disadvantage of certain kinds of borrowers. Those people might include young adults, immigrants or men or women recently divorced."[109]

Early reports on version 2.0 algorithmic lenders' potential to increase credit access are very positive. Two studies found that algorithmic lending may truly democratize credit access by considering just a few additional data points. In the first study, the Policy and Economic Research Council reviewed more than four million credit files and "found that if both positive and negative utility and telecom payments were included, over 70 percent of the unscorable files would become scorable and 64 percent of the 'thin files' (files with very little other credit history) would see improved scores."[110] Another study—this one by LexisNexis—found similar results. It determined that nearly two-thirds of credit invisibles are low-risk and "likely to be good and profitable customers for lenders and credit card issuers."[111] Such dramatic changes are possible because many credit invisibles are often denied credit because of "the absence of credit history rather than anything negative in their credit histories."[112] In other words, credit invisibles are generally either too young to have established a credit history, or have never been welcomed into the traditional banking system.[113] As such, these changes would especially benefit the young, the low-income, and minorities.[114]

109. Roberts, *supra* note 86; *see also* WOLKOWITZ & PARKER, *supra* note 18, at 9.

110. EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 12.

111. JEFFREY FEINSTEIN, LEXISNEXIS RISK SOLUTIONS, ALTERNATIVE DATA AND FAIR LENDING 8 (2013), http://www.lexisnexis.com/risk/downloads/whitepaper/fair_lending.pdf [https://perma.cc/D8T3-D2CT].

112. NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 13 (Certain groups "have very little reported credit history—often because low-income consumers are less likely to access the types of financial services that report to the traditional credit bureaus.").

113. NCLC, *Credit Invisibility*, *supra* note 24.

114. EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 12 ("The study also found that this change especially benefits low-income borrowers."); NCLC, *Credit Invisibility*, *supra* note 24 ("African American, Hispanic, and low-income consumers are more likely" to be underserved in this regard.); *see also* Robert Bartlett et al., Consumer Lending Discrimination in the FinTech Era 3 (Nov. 2, 2017) (unpublished manuscript), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3063448 [https://perma.cc/U3VK-QXZF] (finding that "African-American and Hispanic applicants are 2% more likely to be rejected for a mortgage than other applicants" and it is "small, independent mortgage originators, not large banks and not FinTech firms that impose greater discrimination").

In practice, there is some evidence that algorithmic lenders have increased credit accessibility, as these studies suggest they should.[115] For example, in response to the Treasury Department's Request for Information (RFI), some responders "suggested that online marketplace lending is expanding access to credit in some segments by providing loans to certain borrowers who might not otherwise have received capital."[116] Others have claimed that some newer entrants to the market have begun "to move down the credit spectrum and target sub-prime borrowers, . . . offering rates up to 36 percent to borrowers with FICO scores as low as 580."[117] While 36 percent is quite high for prime borrowers, it is far superior to the annualized interest rates available when a sub-prime borrower gets a loan from payday and pawn lenders.[118] In addition, "[s]ome online marketplace lenders are accepting applicants without FICO scores or with short credit histories and making credit decisions based on the applicant's college, school, and current income."[119]

Evidence that algorithmic lenders are democratizing credit access remains limited and anecdotal, however. And there is substantial evidence suggesting that "the majority of borrowers of unsecured consumer credit using online marketplace lenders are prime borrowers refinancing existing debts, not receiving new credit."[120] In other words, debt consolidation is the primary use of marketplace loans so far.[121] At a minimum, it's fair to write that

115. *See, e.g.*, WOLKOWITZ & PARKER, *supra* note 18, at 16 (discussing various marketplace lenders and how their use of Big Data has allowed them to expand lending); *see also* Jagtiani & Lemieux, *supra* note 108.

116. TREASURY, *supra* note 69, at 1 (claiming that these underserved borrowers include small business owners who are receiving loans for their "general working capital and expansion needs.").

117. *Id.*

118. *See What is a Payday Loan?*, CONSUMER FIN. PROT. BUREAU, https://www.consumerfinance.gov/ask-cfpb/what-is-a-payday-loan-en-1567/ [https://perma.cc/5FNZ-TMEF] (last updated June 2, 2017) (noting that payday loans typically have an effective annual interest rate of almost 400%, which is substantially higher than credit card interest rates).

119. TREASURY, *supra* note 69, at 12–13; *see* Christopher J. Willis, *CFPB Provides Some Clarity on Alternative-Data Models Through No-Action Letter*, CONSUMER FIN. MONITOR (Sept. 20, 2017), https://www.consumerfinancemonitor.com/2017/09/20/cfpb-provides-some-clarity-on-alternative-data-models-through-no-action-letter/ [https://perma.cc/7PZS-CVQH] (noting that Upstart, a marketplace lender, uses "the identity of the college attended by the applicant" in its underwriting process).

120. TREASURY, *supra* note 69, at 13.

121. *Id.* at 1; *see also* RYAN NASH & ERIC BEARDSLEY, GOLDMAN SACHS, THE FUTURE OF FINANCE: THE RISE OF THE NEW SHADOW BANK 14 (2015) (reporting that "77.7% of loans originated on the Lending Club platform to date (as of 3Q14) have been for either debt refinancing (56.6%) or credit card payoff (21.1%)"). *But see* WOLKOWITZ & PARKER, *supra* note 18; Jagtiani & Lemieux, *supra* note 108, at 14.

additional opportunities remain "to expand access to credit further into underserved markets."[122]

Second, algorithmic lending may be less expensive than traditional lending, which may make credit from algorithmic lenders more affordable and, therefore, more accessible.[123] This new breed of lenders has witnessed tremendous growth, despite offering loan products that are very similar to those offered by traditional lenders, suggesting that existing loan models were not the most efficient model available.[124] One of the clearest potential cost savings for algorithmic lenders is that a more accurate credit-underwriting model should decrease the incidence of loan defaults. For example, Lenddo, a version 2.0 algorithmic lender, claims to increase approval rates by 15% while decreasing defaults by 12%.[125]

And there are many other ways that version 2.0 algorithmic lenders may streamline the traditional lending process, reduce costs, and "improve operational efficiencies."[126] Automation can lower the cost of obtaining and analyzing data for lenders, making credit underwriting faster.[127] In theory, algorithmic lenders will need fewer employees in the future, though for now it may be that they've largely substituted engineers for loan officers. Algorithmic lenders—which operate almost exclusively online—can also pass along "the cost savings of forgoing a physical brick and mortar structure."[128] Algorithmic lenders may have a lower cost structure because they "engage in more targeted advertising" than traditional lenders, often advertising through "online and social media advertising channels," because they have

122. TREASURY, *supra* note 69, at 1; *see also* NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 13 (suggesting that although algorithmic lenders may "extend access to credit to traditionally underserved populations" in the future, they largely appear not to have done so to date).

123. NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 29.

124. NASH & BEARDSLEY, *supra* note 121 ("Surprisingly, the loan products offered by P2P lenders are similar to personal loans issued by banks"); *see also* TREASURY, *supra* note 69 ("The lower overhead costs associated with the use of automated platforms, online operations, and data-driven lending models has allowed online marketplace lenders to offer consumers competitive rates for debt consolidation and refinancing."); *see also* Tunstall & Caplan, *supra* note 74 ("Further, low overhead costs compared to traditional financial institutions allow marketplace lenders to provide very competitive interest rates.").

125. *Credit Scoring Solution*, LENDDO, https://lenddo.com/pdfs/Lenddo_FS_CreditScoring_201705.pdf [https://perma.cc/8LVB-UJGL].

126. TREASURY, *supra* note 69, at 8.

127. CFPB RFI, *supra* note 27, at 11,184–85; TREASURY, *supra* note 69, at 1 (suggesting that expedited credit assessments are cheaper); *see also* Lawrence D. Kaplan et al., *Addressing ECOA Risk in Marketplace Lending*, STAYCURRENT (Paul Hastings, Washington D.C.), Aug. 25, 2016, at 1 https://www.paulhastings.com/publications-items/details/?id=802eea69-2334-6428-811c-ff00004cbded [https://perma.cc/BDC5-X6EF].

128. They can operate less expensively than traditional banks because their automated online loan processes require fewer man-hours of labor and they lack retail branches. *See* Kaplan et al., *supra* note 127; *see also* TREASURY, *supra* note 69, at 5.

identified an underserved market niche.[129] Better models should also reduce incidences of fraud.[130] Finally, algorithmic lenders may have successfully "avoid[ed] dealing with many of the costly regulations" that traditional lenders must endure.[131]

Whether algorithmic lenders enjoy cost advantages over traditional lenders and, if they do, whether these savings are passed along to consumers is a hotly contested question.[132] But at least one report suggested that various firms were making more affordable loans because of their innovative use of new data sources. In a recent white paper, the Center for Financial Services Innovation reported that two algorithmic lenders—OnDeck and Kabbage—were using "sales volume, customer reviews, and shipping histories" as proxies for the health of small businesses, which allowed these firms "to extend credit with more affordable rates and terms than small business owners could access using only their personal credit scores."[133]

129. *See* Kaplan et al., *supra* note 127, at 2–3.

130. TREASURY, *supra* note 69, at 19; *see also* Jagtiani & Lemieux, *supra* note 108.

131. NASH & BEARDSLEY, *supra* note 121; *see also* Linsay Sobers, Consumer Financial Protection Courts: A Review of The True Lender Doctrine 8 (Dec. 1, 2016) (unpublished manuscript) (on file with the Chicago-Kent Law Review) (recognizing that bank-affiliated algorithmic lenders can avail themselves of a national bank's preemption powers to avoid, among other things, interest rate caps set by state usury laws).

132. *Compare* TREASURY, *supra* note 69, at 20, 22–23 (noting that, in theory, fintech firms should get "efficiency benefits of automated data sources replacing paper sources" and that "co-branded or white label partnerships with banks or CDFIs can materially reduce customer acquisition costs for online marketplace lenders, thereby increasing the potential to serve more borrowers"), *and id.* at 19 (respondents to Treasury's RFI contend that "consumers and small businesses benefit from lower costs, quicker turnaround times, and greater convenience," and that "new data sources are already expanding access to credit for small business borrowers and consumers."), *with* NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 30 (finding "that high prices remained the norm").

Even if credit is being expanded, though, at this point it's difficult to determine whether these are sound business decisions made possible by new technologies or whether they represent the grow-at-all-costs mindset of many startup firms. *See* Matt Scully, *SoFi's Loan Losses Pile Up as Even Wealthy Borrowers Default*, BLOOMBERG (Mar. 13, 2017, 2:46 PM), https://www.bloomberg.com/news/articles/2017-03-13/sofi-s-loan-losses-pile-up-as-even-wealthy-borrowers-default [https://perma.cc/S3DJ-LKTP] (describing how the "'grow at all cost' attitude" of some marketplace lenders appears to have resulted in bad credit risks and a mini industry downturn.). If the latter, these firms may be creating consumer surplus that will disappear once the industry matures and consolidates. Finally, if credit is being expanded and it's a good business decision, it's also not clear whether marketplace lenders are cherry-picking so-called HENRYs (High Earner Not Rich Yet) or whether they are beginning to reduce "the racial economic divide and wealth gap." NCLC, *Credit Invisibility*, *supra* note 24. It's well documented that "[c]ommunities of color have less income, and they have far fewer assets to cushion the blow of financial catastrophes such as job losses or sickness. These income and wealth disparities are caused by centuries of discrimination, which still have a huge impact to this day." *Id.*

133. WOLKOWITZ & PARKER, *supra* note 18, at 16.

Finally, algorithmic lending's proponents tout its ability to remove human bias from lending decisions.[134] Big Data analytics purportedly allow for the objective truth to be revealed by eliminating "the subjectivity and cognitive biases inherent in human decision-making."[135] As a result, "US regulators have often encouraged businesses to use algorithms to make decisions. Regulators want to avoid the irrational or subconscious biases of human decision-makers."[136] Among other boosters, a report by the Obama White House claimed that "[B]ig [D]ata provides opportunities for innovations that reduce discrimination and promote fairness and opportunity, including . . . removing subconscious human bias."[137]

Lending discrimination is a very important issue in which the federal government has historically been complicit.[138] For example, "redlining"[139] was a practice "invented by the Federal Housing Administration" that had the effect of depriving African Americans of "the ability to accumulate

134. "With enough data, the numbers speak for themselves," wrote Chris Anderson in Wired Magazine. Chris Anderson, *The End of Theory: The Data Deluge Makes the Scientific Method Obsolete*, WIRED (June 23, 2008, 12:00 PM), https://www.wired.com/2008/06/pb-theory/ [https://perma.cc/4F8G-N29J]; *cf.* Kate Crawford, *The Hidden Biases in Big Data*, HARV. BUS. REV. (Apr. 1, 2013), https://hbr.org/2013/04/the-hidden-biases-in-big-data [https://perma.cc/5KUH-3X3U] (describing Anderson's view as "'data fundamentalism,' the notion that correlation always indicates causation, and that massive data sets and predictive analytics always reflect objective truth"); *see also* TREASURY, *supra* note 69, at 5 (claiming that, in consumer credit markets, Big Data appears to remove human decision-making from the credit-granting process).

135. KEVIN PETRASIC ET AL., WHITE & CASE, ALGORITHMS AND BIAS: WHAT LENDERS NEED TO KNOW 2 (2017), https://www.whitecase.com/sites/whitecase/files/files/download/publications/algorithm-risk-thought-leadership.pdf [https://perma.cc/EWH6-RLQR].

136. Pasquale, *supra* note 84 (contesting the claim that algorithms are bias-free, arguing instead that "human decision-makers devised the algorithms, inflected the data, and influenced its analysis"); *see also* Danielle Keats Citron & Frank A. Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 13 (2014) (noting that "[a]dvocates applaud the removal of human beings and their flaws from the assessment process," but arguing that bias remains "[b]ecause human beings program predictive algorithms, their biases and values are embedded into the software's instructions").

137. EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 4.

138. Historically, racial discrimination was both overt and government sanctioned. *See* Jordan Pearson, *How Big Data Could Discriminate*, VICE: MOTHERBOARD (Sept. 16, 2014, 6:00 AM) (citing GEORGE LIPSITZ, THE POSSESSIVE INVESTMENT IN WHITENESS 24–33 (1998)), https://motherboard.vice.com/en_us/article/d73x7v/why-the-federal-trade-commission-thinks-big-data-could-be-discriminatory [https://perma.cc/R8T7-DA5V] (describing "how Federal Housing Administration loan policies explicitly favored whites up until 1948 (though they were allowed by the Supreme Court to continue after), effectively locking black families out of lucrative housing markets for generations").

139. "Redlining is the practice of denying or limiting financial services to certain neighborhoods based on racial or ethnic composition without regard to the residents' qualifications or creditworthiness." Rachelle Alexandre, Discriminatory Lending Practices Against African Americans 4 (Nov. 28, 2016) (unpublished manuscript) (on file with the Chicago-Kent Law Review); SHIRLEY SAGAWA & ELI SEGAL, COMMON INTEREST, COMMON GOOD: CREATING VALUE THROUGH BUSINESS AND SOCIAL SECTOR PARTNERSHIPS 30 (2000).

wealth through homeownership."[140] Although overt racial discrimination, such as redlining, is now illegal, many insidious forms of discrimination appear alive and well. In addition, the effects of scores of years of state-sponsored and state-tolerated racial discrimination continue to have a pernicious effect on the financial health of many minorities.[141] As a result, "[c]redit reports and scores reflect stunning racial disparities."[142]

While racial discrimination is now illegal in many contexts, it continues.[143] For example, in 2015, "Hudson City Savings Bank, New Jersey's largest savings bank," paid a $33 million fine (while admitting no wrongdoing) "for redlining, the practice in which banks choke off lending to minority communities."[144] Hudson allegedly "focused on marketing mortgages in predominantly white sections of suburban New Jersey and Long Island," instead of in black and Hispanic communities.[145] As a result, "[i]n 2014, Hudson approved 1,886 mortgages in the market that includes New Jersey and sections of New York and Connecticut, federal mortgage data show. Only 25 of those loans went to black borrowers."[146] Similar examples abound.[147]

In short, eliminating human bias that fosters discriminatory lending is an important goal. And Americans ought to welcome any technology that can democratize credit access and begin to reverse some of the most pernicious effects of the centuries of racism that have left various minorities, but

140. NAT'L CONSUMER LAW CTR., PAST IMPERFECT: HOW CREDIT SCORES AND OTHER ANALYTICS "BAKE IN" AND PERPETUATE PAST DISCRIMINATION 2, (2016), http://www.nclc.org/images/pdf/credit_discrimination/Past_Imperfect050616.pdf [https://perma.cc/S8ED-WTDR] [hereinafter NCLC, PAST IMPERFECT]; *see also* B. Alicia Johnson, Credit Discrimination, the Continuing Cycle, and Possible Solutions 5 (Nov. 30, 2016) (unpublished manuscript) (on file with the Chicago-Kent Law Review).

141. By no means were African Americans the only group affected by redlining. *See, e.g.*, Emily Badger, *How Redlining's Racist Effects Lasted for Decades*, N.Y. TIMES (Aug. 24, 2017), https://www.nytimes.com/2017/08/24/upshot/how-redlinings-racist-effects-lasted-for-decades.html?_r=0 [http://perma.cc/XKH6-X64M] (discussing Brooklyn's Bedford-Stuyvesant neighborhood—a predominantly black neighborhood—and noting that although approximately 30 percent of the population was not black they were nonetheless affected by redlining).

142. NCLC, PAST IMPERFECT, *supra* note 140, at 1–2 (explaining that these disparities exist, in large part because of "centuries of discrimination, redlining, and exclusion").

143. *See, e.g.*, Nathan Bomey, *JPMorgan Pays $55M to Settle Mortgage Discrimination Lawsuit*, USA TODAY (Jan. 18, 2017, 7:18 PM), www.usatoday.com/story/money/2017/01/18/us-accuses-jpmorgan-mortgage-discrimination-lawsuit/96710486/ [https://perma.cc/GJ5U-JB7W]; Rachel Swarns, *Biased Lending Evolves, and Blacks Face Trouble Getting Mortgages*, N.Y. TIMES (Oct. 30, 2015), https://www.nytimes.com/2015/10/31/nyregion/hudson-city-bank-settlement.html?_r=0. [https://perma.cc/536J-PE6C]; Bartlett et al., *supra* note 114 (finding both decreased access to mortgage loans for certain racial minorities and increased prices).

144. Swarns, *supra* note 143.

145. *Id.*

146. *Id.*

147. *See, e.g.*, Bartlett et al., *supra* note 114.

particularly African Americans, in poor financial health. But, without intentionally pursuing these ends, algorithmic lenders' use of machine-learning and Big Data is unlikely to achieve these worthwhile goals.[148] Some sort of intervention is almost surely needed. Even worse than failing to remove bias, algorithmic lending may provide a veneer of objectivity to credit determinations, systemizing discrimination in hidden ways.[149]

B. The Perils

Although algorithmic lenders and their Big Data usage may offer substantial benefits to consumers, it may also be perilous. As a result, the challenge will be, as the Obama White House declared in its Big Data report, "to support growth in the beneficial use of [B]ig [D]ata while ensuring that it does not create unintended discriminatory consequences."[150] To support algorithmic lending's promise while stifling its threats, we must first explore those potential threats. As the Obama White House report noted, there is one concern that stands above all others: illegal discrimination.

While Big Data's supporters claim that algorithmic decision-making reduces the incidence of human bias, there are several notable examples of human bias bleeding into algorithmic decision-making processes. Thus, "if these technologies are not implemented with care, they can . . . perpetuate, exacerbate, or mask harmful discrimination."[151] For example, a British hospital, St. George's, created an algorithm to help decide which students to admit for medical training at the hospital.[152] This algorithm was a learning

148. "It is often assumed that Big Data techniques are unbiased because of the scale of the data and because the techniques are implemented through algorithmic systems. However, it is a mistake to assume they are objective simply because they are data-driven." EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 6; *see also* Hajian et al., *supra* note 57 (pointing out that discriminatory algorithms show "ads for high-income jobs to men more often than to women" and "ads for arrest records are significantly more likely to show up on searches for distinctively black names."); *infra* text accompanying notes 163–167.

149. *See* Citron & Pasquale, *supra* note 136, at 13. *But see* Anderson, *supra* note 134.

150. EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 4; *see also* Hirsch, *supra* note 32, at 346.

151. EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 5. Big Data may be used to purposefully discriminate against low-income, minority and underserved populations using "legally protected characteristics in hiring, housing, lending, and other processes" as proxies for variables that could not be used. *See* Odia Kagan et al., *Use of Big Data May Violate Federal Consumer Protection Laws, FTC Report Warns*, BALLARD SPAHR (Jan. 13, 2016), http://www.ballardspahr.com/alertspublications/legalalerts/2016-01-13-use-of-big-data-may-violate-consumer-protection-laws-ftc-report-warns.aspx [https://perma.cc/5ZYH-TQBX] [hereinafter *FTC Report Warns*] (reporting that the FTC has expressed concern about "how [B]ig [D]ata could be used in the future to the disadvantage of low-income and underserved communities and adversely affect consumers" (citation omitted)); Barocas & Selbst, *supra* note 93, at 674 (noting that "because the mechanism through which data mining may disadvantage protected classes is less obvious in cases of unintentional discrimination, the injustice may be harder to identify and address").

152. Barocas & Selbst, *supra* note 93, at 682.

algorithm, trained using a data set derived from some of the school's past admissions decisions.[153] As it turned out, St. George's prior admissions decisions had been systematically unfavorable to equally qualified racial minorities and women.[154] And because St. George's used those past admissions decisions to teach its algorithm how to make future decisions, its admissions algorithm replicated the biases inherent in its training data.[155] Essentially, automating a process based on discriminatory past practices had transformed past prejudice or bias (whether conscious or unconscious) into a formalized rule that systematically and negatively affected the prospects of all future applicants.[156]

Moreover, a learning algorithm has numerous opportunities to pick up human biases and therefore create discriminatory outcomes.[157] First, the algorithm can be given biased training data, as noted in the example from St. George's Hospital above.[158] Second, an algorithm could be biased when it is initially programmed. Programming bias is particularly likely to occur when the problem to be solved does not "rely on extant, binary categories."[159] In such cases, programmers need to "translate some amorphous problem into a question that can be expressed in more formal terms that computers can parse."[160] And it is "[t]hrough this necessarily subjective process of translation," that programmers may "systematically disadvantage protected classes."[161] This is a definite worry in the credit-underwriting context.

153. *Id.*

154. *Id.*

155. *Id.*

156. *Id.*

157. PETRASIC ET AL., *supra* note 135 ("In an algorithmic system, there are three main sources of bias that could lead to biased or discriminatory outcomes: input, training and programming."); *see also* Pasquale, *supra* note 84 ("Algorithms will never offer an escape from society."); Citron & Pasquale, *supra* note 136, at 4 (arguing that a programmer's "biases and values are embedded into . . . predictive algorithms"); Hajian et al., *supra* note 57 (noting that the potential for "algorithmic bias exists even when there is no discrimination intention [sic] in the developer of the algorithm").

158. PETRASIC ET AL., *supra* note 135. Feeding an algorithm biased training data may be inadvertent or intentional. If the latter, it may be more appropriately considered programming bias. *See* Barocas & Selbst, *supra* note 93, at 680 (discussing how "biased training data leads to discriminatory models"); Crawford, *supra* note 134 (discussing how Boston used the technology in smartphones to "passively detect potholes," and noting that lower levels of "smartphone penetration" in poorer parts of town resulted in the perception that there were fewer potholes in those neighborhoods, a form of input bias).

159. Barocas & Selbst, *supra* note 93; *see also* PETRASIC ET AL., *supra* note 135 (noting that programming bias can "occur in the original design or when a smart algorithm is allowed to learn and modify itself through successive contacts with human users, the assimilation of existing data, or the introduction of new data"); Brummer & Yadav, *supra* note 21, at 34 (noting that "sophisticated algorithms operate in accordance with programming that is based on a set of assumptions and parameters, statistical models and decision-making processes – any of which may be wrong, inaccurate or insufficiently precise").

160. Barocas & Selbst, *supra* note 93.

161. *Id.*

Finally, algorithms can develop biases in ways that we don't quite understand.[162] For example, a 2012 study conducted by Professor Latanya Sweeney found that the algorithms powering Google's AdWords advertising system may be expressing racial bias by more frequently associating black-identifying names with suggestions that a person has been arrested than it does with white-identifying names.[163] This is true "regardless of whether the company placing the ad reveals an arrest record associated with the name."[164] Professor Sweeney's study concluded that Google is "25 percent more likely" to suggest that people with black-identifying names are potential criminals than people with white-identifying names.[165] Ultimately, the study simply noted that racial bias exists in this space, but was unable to explain why.[166]

Of course, the problem of using inaccurate or biased data to justify decisions that harm minorities or other protected populations is not a new one.[167] And algorithmic lenders need only do better than traditional lenders to make a difference.[168] But some are concerned that the imprimatur provided by using a supposedly bias-free algorithm will "make it more difficult for the company using such data to identify the source of discriminatory effects and address it."[169] Moreover, the notion that math somehow represents objective truth and that numbers don't lie can obfuscate "bias problems that negatively impact people's lives."[170] In reality, algorithmic lending has the potential to disparately impact certain groups (and expose lenders to fair lending violations).[171]

Not only is it false "that data doesn't lie—and therefore, that algorithms that analyze the data can't be prejudiced," but Big Data can perpetuate, or

162. The persistent shrouding of the credit-scoring process makes it difficult to understand how scores are compiled, let alone whether those scores are appropriate. Citron & Pasquale, *supra* note 136, at 10–11 (discussing efforts by FICO and others to keep their processes a secret).

163. Latanya Sweeney, *Discrimination in Online Ad Delivery*, ACM QUEUE, Apr. 2, 2013, at 11 (using a list of the top "whitest- and blackest-identifying girls' and boys' names").

164. *Id.* at 4.

165. *Id.* at 8, 13.

166. *Id.* at 14.

167. *See* FTC REPORT, *supra* note 78, at 8.

168. Early evidence suggests that algorithmic lending 2.0 may be more predictive than traditional credit underwriting models. *See* Jagtiani & Lemieux, *supra* note 108.

169. *See* FTC REPORT, *supra* note 78, at 8.

170. EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 10; *see also* Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249, 1249 (2008) (suggesting a "hearing officer's tendency to presume a computer system's infallibility").

171. TREASURY, *supra* note 69, at 1.

even exacerbate, "existing systems of racism, discrimination, and inequality."[172] Similarly, once biases are embedded in the code (or the algorithm learns to be biased based on its training data), it may draw inferences that appear objective but are actually biased.[173] For example, an algorithm may draw a negative correlation between creditworthiness and occupations that involve migratory work (like fruit harvesting) or low-paying service jobs.[174] While this correlation may not reflect intentional bias, it can have a discriminatory (and illegal) effect on certain protected groups if, for example, a majority of fruit harvesters or service workers are racial minorities or otherwise members of a protected category of persons.[175]

As noted above, algorithmic lenders' use of Big Data promises to predict the creditworthiness of those who were previously credit invisible. But the reliance on certain data points may discriminate unfairly. For example, version 2.0 algorithmic lenders often use data from a prospective borrower's social media accounts, such as the creditworthiness of the prospective borrower's peer group, when making credit determinations. But, as noted above, "African Americans tend to have lower incomes[, less wealth,] and lower credit scores than white Americans. If a borrower's application or pricing is based, in part, on the creditworthiness of her social circles, that data can lead to [unlawful] discrimination against minorities compared to white borrowers with the same credit scores."[176]

Similarly, Big Data can be used to compare a prospective borrower's shopping patterns to those of previous borrowers. But this can also have a discriminatory effect. In a commonly noted and related example, "American Express lowered a customer's credit limit from $10,800 to $3,800, not based on his payment history with the company, but because '[o]ther customers who [had] used their card at establishments where [he had] recently shopped

172. Michael Brennan, *Can Computers Be Racist? Big Data, Inequality, and Discrimination*, FORD FOUND.: EQUALS CHANGE BLOG (Nov. 18, 2015), https://www.fordfoundation.org/ideas/equals-change-blog/posts/can-computers-be-racist-big-data-inequality-and-discrimination/ [https://perma.cc/A2EW-BRPH].

173. Citron & Pasquale, *supra* note 136, at 14 (for example, "[a]lgorithms 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.").

174. *Id.*

175. *Id.*

176. Letter from Lauren Saunders, Assistant Dir., NCLC, Laura Temel, Policy Advisor, U.S. Dep't of the Treasury (Sept. 30, 2015), https://www.nclc.org/images/pdf/rulemaking/treasury-marketplace-loan-comments.pdf [https://perma.cc/6ATS-3RXC].

[had] a poor repayment history with American Express.'"[177] Historic discrimination has contributed to residential housing segregation and to the racial wealth and income gaps. Assessing a prospective borrower based on his or her social network or shopping patterns is likely to simply institutionalize and legitimize differential (and likely worse) treatment of poor and minority borrowers.[178]

Even an algorithm that has been specifically constructed to avoid considering a prospective borrower's race (because race is a protected category under most fair lending laws) might nevertheless discriminate against a prospective borrower by using proxies for race.[179] Some simple proxies for race include zip code, surname, and college attendance data.[180] As minorities have historically tended to have lower incomes and lower credit scores, an algorithm trained on past lending decisions might learn to consistently reject borrowers using proxies for race, such as having graduated from a historically black college or university.[181]

There is no simple way to avoid the problem that version 2.0 algorithmic lenders may find correlations in their data that have a discriminatory impact on members of protected categories. Without training data, algorithms generally cannot learn to make decisions. But the legacies of discrimination pervade American society and infect consumer credit data. Thus, we should assume that, absent affirmative interventions, version 2.0 credit algorithms will perpetuate bias.[182]

177. NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 27–28.

178. "Big Data can lead to decision-making based on the actions of others with whom consumers share some characteristics." FTC REPORT, *supra* note 78, at 9 (citing FTC v. CompuCredit Corp., No. 1.08-cv-1976-BBM-RGV, 2008 WL 8762850 (N.D. Ga. June 10, 2008), https://www.ftc.gov/sites/default/files/documents/cases/2008/12/081219compucreditstiporder.pdf [http://perma.cc/UX4R-PDWE]) (noting that one credit card company settled FTC allegations that it failed to disclose its practice of rating consumers as having a greater credit risk because they used their cards to pay for marriage counseling, therapy, or tire-repair services, based on its experiences with other consumers and their repayment histories"); *see also* Citron & Pasquale, *supra* note 136, at 4.

179. *See generally* CONSUMER FIN. PROT. BUREAU, USING PUBLICLY AVAILABLE INFORMATION TO PROXY FOR UNIDENTIFIED RACE AND ETHNICITY 4 (2014), files.consumerfinance.gov/f/201409_cfpb_report_proxy-methodology.pdf [https://perma.cc/8KQS-AHPC] (noting the prohibitions found in the ECOA and Regulation B).

180. *See generally id.* at 3 (describing how "geography- and surname-based information" can be combined "into a single proxy probability for race and ethnicity" using the BISG method.). *See also* Barocas & Selbst, *supra* note 93, at 682 (discussing the use of attendance at HBCUs as a proxy for race).

181. Barocas & Selbst, *supra* note 93, at 682. Nevertheless, the CFPB recently issued the startup lender, Upstart, a "no action letter" for Upstart's use of alternative data points, including college attendance data. *See* Willis, *supra* note 119.

182. Barocas & Selbst, *supra* note 93, at 671.

III. THE REGULATORY REGIME AND ITS ISSUES

The examples in this Article are meant to highlight the many reasons to be concerned about algorithmic lenders' use of Big Data, particularly the concerns about its potentially discriminatory effects on prospective borrowers. The United States has numerous anti-discrimination laws designed to cover an array of market practices, "from loan disclosures to credit reporting to privacy practices to debt collection."[183] This section will discuss some of these laws, and evaluate the likelihood that they are effective in reducing the threats and promoting the promise of algorithmic lending 2.0. It also identifies some areas where additional steps are needed to prevent version 2.0 algorithmic lenders from unlawfully discriminating against members of protected classes.[184]

Many consumer protection agencies have been paying close attention to version 2.0 algorithmic lenders, with several issuing targeted warnings.[185] For example, former "CFPB director, Richard Cordray, warned that '[a]ll lenders, from startups to large banks, must follow consumer protection laws.'"[186] The Federal Trade Commission (FTC), has been notably active. It recently held a series of forums on marketplace lending, where Equal Credit Opportunity Act (ECOA) and Fair Credit Reporting Act (FCRA) issues were repeatedly raised.[187] In this way and others, the FTC has signaled its intention to regulate Big Data practices that could violate the consumer protection laws it is charged with enforcing.[188]

183. Numerous state and federal statutes and regulations affect consumer lending in the United States, including, among others, the Fair Housing Act, the FTC Act, the Truth in Lending Act, the Electronic Fund Transfer Act, the Fair Credit Reporting Act, the Equal Credit Opportunity Act, and the Fair Debt Collection Practices Act. *See* Pozza & Wong, *supra* note 34 (detailing many other regulations that apply and providing some detail on each, including lending disclosures and advertising, use of online data, preauthorizing electronic payments, and servicing and debt collection); *see also* Freeman, Jr. et al., *supra* note 19.

184. Barocas & Selbst, *supra* note 93 at 692.

185. The Federal Trade Commission, CFPB, Federal Deposit Insurance Corporation, and the Treasury Department have all been studying the issue and trying to get a handle on the promise and risks of algorithmic lending. *See* CFPB RFI, *supra* note 27, at 11,185–86; TREASURY, *supra* note 69, at 1; Angela M. Herrboldt, *Marketplace Lending*, SUPERVISORY INSIGHTS (Fed. Deposit Ins. Corp., Washington, D.C.), Winter 2015, at 12, https://www.fdic.gov/regulations/examinations/supervisory/insights/siwin15/si_winter2015.pdf [https://perma.cc/3GF2-MUCN]; FTC REPORT, *supra* note 78.

186. Lazarev, *supra* note 69.

187. 15 U.S.C. § 1691 (2015) (ECOA); 15 U.S.C. § 1681 (2015) (FCRA); *see also* Tunstall & Caplan, *supra* note 74.

188. John K. Higgins, *FTC Issues Regulatory Warning on Big Data Use*, E-COM. TIMES (Jan. 20, 2016), http://www.ecommercetimes.com/story/83004.html [https://perma.cc/GLT2-VTBR] (highlighting a report in which the FTC indicated that it "'will continue to monitor areas where Big Data practices' could violate those laws 'and will bring enforcement actions where appropriate.'"); Barbara S. Mishkin, *FTC Sends 2016 ECOA Report to CFPB*, CONSUMER FIN. MONITOR (Feb. 13, 2017)

In the three subsections that follow, this Article will focus on the application of four laws (the ECOA, the FCRA, the FTC's Unfair and Deceptive Acts or Practices (UDAP) authority and the CFPB's Unfair, Deceptive, and Abusive Acts or Practices (UDAAP) authority) to algorithmic lending 2.0, and consider whether each of these statutes helps protect against the most perilous aspects of algorithmic lending and whether they help algorithmic lenders fulfill their promise. The ECOA and the FCRA are two of the principal statutes governing consumer loans.[189] These statutes and related regulations aim to increase transparency in the credit-granting process "by providing an applicant with a reason when a loan is not approved."[190] They also seek to prevent discrimination against certain categories of people.[191] Both the FTC and the CFPB have authority to enforce these statutes. In addition, the FTC and CFPB both have the power to prohibit unfair or deceptive acts or practices.[192] Finally, the CFPB alone may also prohibit abusive acts or practices.[193]

A. The Equal Credit Opportunity Act

The ECOA's goal is to increase credit availability for "all creditworthy applicants" without regard to certain protected statuses.[194] Thus, preventing discriminatory lending practices is the primary aim of the ECOA. Among other things, the ECOA makes it illegal for a lender, including its affiliates and assignees, to discriminate against prospective borrowers "on the basis of

https://www.cfpbmonitor.com/2017/02/13/ftc-sends-2016-ecoa-report-to-cfpb/ [https://perma.cc/43ZR-XGNT] (noting that the FTC report "discussed the potential applicability of various [consumer protection] laws, including the ECOA, to Big Data practices and provided a list of 'questions for legal compliance' for companies to consider in light of these laws."); Letter from Malini Mithal, Acting Assoc. Dir., Div. of Fin. Practices, Fed. Trade Comm'n, to Patrice Ficklin, Assistant Dir., Fair Lending & Equal Opportunity, Consumer Fin. Prot. Bureau (Feb. 3, 2017), https://www.ftc.gov/system/files/documents/reports/federal-trade-commission-enforcement-activities-under-equal-credit-opportunity-act-regulation-b/p154802_ftc_letter_to_cfpb_re_ecoa.pdf [https://perma.cc/AL34-RWXK] (same).

189. Roberts, *supra* note 86; NCLC, *Credit Invisibility*, *supra* note 24 ("'Big Data' used for credit, employment, insurance, or other purposes is covered by the Fair Credit Reporting Act, and providers must comply with that Act. If Big Data is used for credit, the Equal Credit Opportunity Act applies. Lenders must ensure that the use of Big Data does not create a disparate impact for protected groups.").

190. WOLKOWITZ & PARKER, *supra* note 18, at 24.

191. *Id.*

192. Federal Trade Commission Act, 15 U.S.C. § 45(n) (2011); CONSUMER FIN. PROT. BUREAU, CFPB BULL. 2013-07, PROHIBITION OF UNFAIR, DECEPTIVE, OR ABUSIVE ACTS OR PRACTICES IN THE COLLECTION OF CONSUMER DEBTS (2013), http://files.consumerfinance.gov/f/201307_cfpb_bulletin_unfair-deceptive-abusive-practices.pdf [https://perma.cc/MN8W-9T2S]; Dodd–Frank Wall Street Reform and Consumer Protection Act, Pub. L. No. 111-203, § 1002(12), 124 Stat. 1376 (2010) (codified at 12 U.S.C. § 5481).

193. 2 U.S.C. § 5531(d).

194. 12 C.F.R. § 1002.1(b) (2016).

race, color, religion, national origin, sex or marital status, or age (provided the applicant has the capacity to contract)."[195] The ECOA's prohibitions apply broadly to all aspects of credit transactions, including advertising, credit determinations, the "approval process, and servicing and collection activities."[196]

The ECOA is likely to apply to algorithmic lenders[197]—whether they use a direct- or bank-affiliated lending model—because they are all likely "creditors" as defined under the ECOA.[198] The ECOA defines "creditors" as "any person who regularly extends, renews, or continues credit; any person who regularly arranges for the extension, renewal, or continuation of credit; or any assignee of an original creditor who participates in the decision to extend, renew, or continue credit."[199] Direct lenders regularly extend credit themselves and are clearly covered by the ECOA.[200] Given the breadth of their involvement in credit issuances, the ECOA also applies to most bank-affiliated lenders because, at a minimum, they regularly arrange for their partner banks to extend credit. One exception would be if a bank-affiliated

195. The ECOA prohibits discrimination by "creditors," which are defined as "any person who regularly extends, renews, or continues credit; any person who regularly arranges for the extension, renewal, or continuation of credit; or any assignee of an original creditor who participates in the decision to extend, renew, or continue credit." 15 U.S.C. § 1691a(e) (2015). The ECOA also prohibits discrimination "because all or part of the applicant's income derives from any public assistance program; or (3) because the applicant has in good faith exercised any right under this chapter." § 1691(a); *see also* Paul Slattery, *Square Pegs in a Round Hole: SEC Regulation of Online Peer-to-Peer Lending and the CFPB Alternative*, 30 YALE J. ON REG. 233, 268 (2013); Roberts, *supra* note 86; Tunstall & Caplan, *supra* note 74; PETER MANBECK ET AL., CHAPMAN & CUTLER, THE REGULATION OF MARKETPLACE LENDING: A SUMMARY OF THE PRINCIPAL ISSUES 75 (2017), https://www.chapman.com/media/publication/744_Chapman_Regulation_Marketplace_Lending_0317.pdf [https://perma.cc/RJ4F-Q4DB].

196. MANBECK ET AL., *supra* note 195; *see also* Roberts, *supra* note 86.

197. There are two primary models used by algorithmic lenders "to originate and fund loans": direct lending and bank-affiliated lending. Glen P. Trudel et al., *FDIC Highlights Marketplace Lending Risks for Bank Partners*, BALLARD SPAHR (Feb. 5, 2016), http://www.ballardspahr.com/alertspublications/legalalerts/2016-02-05-fdic-highlights-marketplace-lending-risks-for-bank-partners.aspx [https://perma.cc/6A6B-HH7W]. Direct lenders are usually non-banks that lend "funds directly to the borrower and issues notes to investors who provide such funds." *Id*. Direct lenders generally act quite like traditional lenders in that they solicit borrowers, make loans and hold those loans on their own balance sheets. *See* TREASURY, *supra* note 69, at 6 (direct lenders often "hold loans on their balance sheets" instead of selling these loans to outside investors). Bank-affiliated lenders are usually a non-bank company that has partnered with a nationally-chartered bank. The bank originates the loans, and sells each loan to its affiliate algorithmic lender who "sells notes to investors who agreed to fund [each] loan." Trudel et al., *supra* note 197; *see also* Sobers, *supra* note 131, at 3 (citing Herrboldt, *supra* note 185, at 14) (contrasting "bank-affiliated" algorithmic lenders with direct lenders); Odinet, *supra* note 75, at 11; TREASURY, *supra* note 69, at 5; Kaplan et al., *supra* note 127.

198. Hurley & Adebayo, *supra* note 24, at 191–92 (explaining why the ECOA likely applies to marketplace lenders, unless they merely solicit prospective borrowers); *see also* Slattery, *supra* note 195, at 268–69.

199. 15 U.S.C. § 1691a(e) (2015).

200. MANBECK ET AL., *supra* note 195, at 76 n.168.

lender merely solicits prospective borrowers but is not otherwise involved in the credit transaction. Such lenders would not be covered by the ECOA.[201] Also worth noting is that, in some jurisdictions, courts have found that bank-affiliated lenders are the "true lender" rather than the assignee of their bank partner, at least for some regulatory purposes.[202] If the true lender doctrine were to apply for purposes of ECOA coverage, bank-affiliated lenders would be indistinguishable from direct lenders.

Assuming the ECOA applies, there are generally two ways to prove an ECOA violation.[203] The first, disparate treatment, bans intentionally different treatment of potential borrowers.[204] "Disparate treatment ranges from overt discrimination to more subtle differences in treatment."[205] An example of overt discriminatory treatment would be if a lender had a policy of offering more favorable credit terms to older applicants.[206] This policy violates the prohibition on discrimination based on age.[207] Similarly, overt discriminatory treatment would exist if an algorithmic lender steered "applicants to products with a higher-price, higher-risk or more onerous terms on a prohibited basis instead of the applicants' needs."[208]

The second way to prove an ECOA violation, disparate impact, prohibits using apparently neutral criteria that nevertheless result in disparate treatment of prospective borrowers without a "legitimate business need."[209] Disparate impact means that the policy or practice "has a disproportionately

201. Hurley & Adebayo, *supra* note 24; *see also* Slattery, *supra* note 195, at 268–69.

202. *See* Sobers, *supra* note 131.

203. *See* Kaplan et al., *supra* note 127 ("Lenders are prohibited both from engaging in disparate treatment of applicants, which occurs if a lender directly or overtly discriminates on a prohibited basis, and, more challengingly, lenders are prohibited from acting in a way that causes a disparate impact.").

204. Roberts, *supra* note 86.

205. *Side by Side: A Guide to Fair Lending*, FDIC, https://www.fdic.gov/regulations/resources/side/results.html [https://perma.cc/XRR3-W3FA] (last updated July 28, 1999).

206. AM. BANKERS ASSOC., ABA TOOLBOX ON FAIR LENDING, TOOL 2: FAIR LENDING LEGAL FOUNDATIONS 7 (2012), https://www.aba.com/aba/toolbox/FairLending/FairLending_Tool2r.pdf [https://perma.cc/2GSA-VPE2] [hereinafter ABA TOOLBOX] ("Or, if a lender has a specific underwriting policy that treats married joint applicants differently than unmarried joint applicants, that policy would constitute overt discrimination on the basis of marital status.").

207. 15 U.S.C. § 1691(a); *see also* ABA TOOLBOX, *supra* note 206.

208. ABA TOOLBOX, *supra* note 206, at 8; *see also* Freeman, Jr. et al., *supra* note 19 (noting the potential for ECOA liability "should a company decide to lend only to women or only to married people" or any other protected class).

209. *See* Kaplan et al., *supra* note 127; *see also* Roberts, *supra* note 86; Freeman, Jr. et al., *supra* note 19 ("[A] lender may find itself facing regulatory actions and/or civil litigation if the metrics it uses to make credit decisions have a disproportionate impact on a protected group, even if no discriminatory intent is present."); Policy Statement on Discrimination in Lending, 59 Fed. Reg. 18,267 (Apr. 15, 1994), https://www.fdic.gov/regulations/laws/rules/5000-3860.html [https://perma.cc/96AZ-77T3] ("Evidence of 'disparate impact,' [exists] when a lender applies a practice uniformly to all applicants but the practice has a discriminatory effect on a prohibited basis and is not justified by business necessity.").

negative impact on qualified applicants from a prohibited basis group."[210] For example, a lender may adopt the seemingly neutral policy of not making mortgage loans of less than $500,000 to any prospective borrower.[211] If establishing a minimum loan amount can be shown "to disproportionately exclude potential minority applicants from consideration because of their income levels or the value of the houses in certain areas in which they live, the lender will be required to justify the 'business necessity' for the policy," or be found to have disparately impacted such borrowers.[212] Since "the very point of data mining is to provide a rational basis upon which to distinguish between individuals and to reliably confer to the individual the qualities possessed by those who seem statistically similar," algorithmic lenders ought to be seriously concerned about potential disparate impact claims under the ECOA.[213]

But some commentators have argued that algorithmic lenders are less likely to face successful disparate impact or disparate treatment claims than traditional lenders for several reasons.[214] Algorithms are meant to reduce "the influence of individual loan-officer discretion on lending decisions," thus decreasing the likelihood that a loan officer's individual bias will result

210. ABA TOOLBOX, *supra* note 206, at 9; *see also* Kaplan et al., *supra* note 127 ("A lender may unknowingly cause a disparate impact if it engages in a facially neutral practice, but that practice has an adverse impact on members of a protected class and the lender is unable to demonstrate that the practice is justified by a legitimate business need and cannot reasonably be achieved by other less discriminatory means.").

211. *Side by Side: A Guide to Fair Lending*, *supra* note 205.

212. *See id.*; *see also* FTC REPORT, *supra* note 78, at iii; Hurley & Adebayo, *supra* note 24, at 194 (describing the test for establishing a prima facie disparate impact claim as requiring "three things: 1) a specifically identifiable practice or policy; 2) a statistically significant disparity in treatment between a protected group and other groups; and, 3) a causal link between the disparity and the practice or policy"); Roberts, *supra* note 86 (providing two additional examples: "For example, if research showed that graduates of certain selective universities made for better credit risks, and a lender based its decisions on that criterion, the process might result in a disparate impact if the admissions procedures for the universities discriminated against a protected group. A lender could run into disparate-impact problems if it evaluated applicants on whether they shopped online for wedding anniversary gifts, even if that correlated with creditworthiness, because that behavior could be a proxy for marital status.").

213. Barocas & Selbst, *supra* note 93, at 677.

214. Hurley & Adebayo, *supra* note 24, at 193. It's not even certain that disparate-impact claims are available under the ECOA, as the statutory text "makes no mention of disparate impact analysis." *Id.* Although the Supreme Court has allowed disparate impact claims under the Fair Housing Act, it has not considered the availability of such claims under the ECOA. *Id.* (noting that the "circuit courts have consistently held that such claims are available"). Finally, in *Inclusive Communities Project, Inc*., the Court suggested that where a lender can cite "multiple factors" for its decision, it may be more difficult to establish a disparate impact violation. Tex. Dep't of Hous. & Cmty. Affairs v. Inclusive Cmtys. Project, Inc., 135 S. Ct. 2507, 2523–24 (2015); *see also* Hurley & Adebayo, *supra* note 24, at 193–94.

in liability for an algorithmic lender.[215] In addition, Mikella Hurley and Julius Adebayo claim that lenders with a taste for discrimination could engage in subterfuge by singling out members of protected classes using "facially-neutral proxy variables in its scoring model as stand-ins for characteristics like race" instead of adopting facially discriminatory policies.[216] While the latter assertion is likely true, it's not clear that the former is. It's not clear that programmers are less biased than loan-officers and so increasing the influence of the former to decrease the influence of the latter seems unlikely to make an appreciable difference in the success of disparate treatment claims.[217]

1. The Business Necessity Defense to Disparate Impact Liability

Version 2.0 algorithmic lenders' use of Big Data and machine learning may allow them to more successfully defend against disparate impact liability than traditional lenders. Despite otherwise unlawful discrimination, lenders may avoid disparate impact liability if they can establish that such discrimination has a valid purpose and is not an "artificial, arbitrary, and unnecessary" barrier to obtaining a loan.[218] To avoid disparate impact liability, the lender must prove there is a "'demonstrable relationship between' the challenged policy and 'creditworthiness.'"[219] Maximizing profit is not a valid purpose.[220] Hurley & Adebayo argue that algorithmic lenders are likely to successfully establish a business necessity defense to disparate impact liability by arguing that their credit algorithms—even if discriminatory—serve a valid purpose because they accurately predict the chances a borrower

215. Hurley & Adebayo, *supra* note 24, at 192–93; *accord* Bartlett et al., *supra* note 114 (finding less bias by algorithmic lenders than by small banks).

216. *Id*. at 191; *see also* GARY BECKER, THE ECONOMICS OF DISCRIMINATION 2–5 (1957).

217. *But see* Bartlett et al., *supra* note 114. However, it may be easier to hide discrimination beneath the veneer of objectivity offered by algorithmic lending 2.0. For example, Synchrony Bank recently entered into a consent decree to settle claims that it had violated the ECOA by "discriminat[ing] on the basis of national origin by excluding Borrowers who had 'Spanish preferred' indicators on their accounts or Borrowers with mailing addresses in Puerto Rico . . . from two direct-mail debt-repayment programs." *See* Consent Order, United States v. Synchrony Bank, No. 2:14-cv-00454-DS (D. Utah June 27, 2014). Synchrony might have been able to more effectively discriminate against certain "Spanish preferred" borrowers by using neutral proxies for national origin programmed into a credit algorithm instead of the more obvious proxies that it did use.

218. *Inclusive Cmtys. Project, Inc.*, 135 S. Ct. at 2524 (quoting Griggs v. Duke Power Co., 91 S. Ct. 849, 853 (1971)); *see also* Ballard J. Yelton, *The Direct Impact of Disparate Impact Claims on Banks*, 20 N.C. BANKING INST. 167, 179 (2016).

219. NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 29 (citing 12 C.F.R. pt. 202 supp. I § 202.6(a)-2 (2013) (Official Staff Interpretations)).

220. *Id.*

will repay them.[221] As such, charging certain borrowers higher rates of interest (or declining to lend to some borrowers all together) is not an "artificial, arbitrary, and unnecessary" barrier but a business necessity.

By contrast, the National Consumer Law Center (NCLC) has argued that algorithmic lenders will have a more difficult time than traditional lenders establishing the necessary "demonstrable relationship."[222] This is because traditional models use data elements that have "an understandable connection between timely repayment of past obligations and the likelihood of timely repayment of future obligations."[223] However, the correlations "between web searches, IP address, or social media posts and the likelihood of repayment" will be harder to establish because "there has been no definitive understandable reason provided as to why those data points are a good measure of creditworthiness."[224] While this is currently true, one imagines that time will either demonstrate some relationship between the data used by algorithmic lenders and creditworthiness, or that algorithmic lenders will go out of business because they'll have made a heap of bad loans. In the interim, regulators are giving algorithmic lenders the space to tinker with their business models and consider alternative data points without imposing ECOA liability.[225]

Both arguments depend on whether algorithmic lending models are predictive of creditworthiness. Although time will tell, this Author believes that it's likely that algorithmic credit-underwriting is, or will soon be, superior to traditional credit-underwriting. Thus, algorithmic lenders will be able to establish the demonstrable relationship between their algorithms and creditworthiness. But that doesn't mean Hurley & Adebayo have it quite right either.

Assuming that a lender can establish that their models are predictive of a borrower's likelihood of repayment, it may still face liability. The lender may still have liability under a disparate impact theory of liability if the plaintiff can establish that there is a less discriminatory alternative. And lenders that do not cleanse their data of its proxies for protected classes may risk such liability, as there are now techniques available that can, in some instances, "repair" data sets to eliminate discriminatory impact without losing

221. Hurley & Adebayo, *supra* note 24, at 194 ("In order to prove 'business necessity,' the defendant need not show that the challenged policy or practice was indispensable to its objective, but only that the policy was 'related' to its objective or business goals."). *See supra* text accompanying note 108.

222. NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 29.

223. *Id.*

224. *Id.*

225. *See* Willis, *supra* note 181.

substantial predictive accuracy.[226] If plaintiffs bringing a disparate impact claim under the ECOA can demonstrate that a less discriminatory but equally effective model existed, defendant's business necessity defense must fail.[227]

Whether a lender's failure to repair its data will establish disparate impact liability, it's also important that regulators do not hold algorithmic lenders to a higher standard than traditional lenders.[228] Whereas version 2.0 algorithmic lenders are trying to innovate, most traditional lenders use credit-scoring models that are generally considered outdated and therefore generally do not represent the least discriminatory options available to them. For example, although it's widely known that FICO scores exist, it's less well-known that FICO has nine different versions of its credit scoring system. Each new version reflects the most up-to-date and sophisticated credit scoring model then in existence. For example, in the ninth iteration, FICO largely disregards the existence of medical debt when evaluating a borrower's creditworthiness because FICO "recognizes that medical debt is not a good predictor of other forms of non-repayment."[229] But "most mainstream providers have not switched to using the new FICO model."[230] As a result, consumers saddled with medical debt continue to struggle to obtain credit.[231] Arguably, therefore, most mainstream lenders are using credit scoring models that are known to include elements that are not predictive of creditworthiness and do

226. *See* Feldman et al., *supra* note 97 (arguing that the legitimate business purpose defense is not satisfied where such credit data can be repaired); *see also* Hajian et al., *supra* note 57 (discussing how to reduce the incidence of discrimination in data); *accord* Cynthia Dwork et al., *Fairness Through Awareness*, 3 INNOVATIONS THEORETICAL COMPUTER SCI. 214 (2012); Bryce W. Goodman, *A Step Towards Accountable Algorithms?: Algorithmic Discrimination and the European Union General Data Protection*, 29 CONF. ON NEURAL INFO. PROCESSING SYS. (2016).

227. Hurley & Adebayo, *supra* note 24, at 194–95 ("[I]f the defendant shows business necessity, the burden shifts back to the plaintiff to offer a policy or practice that would be equally effective in meeting the defendant's goals, but that would not produce a disparate impact.").

228. To be clear, plaintiffs seeking to establish a lender's disparate-impact liability have a substantial burden to carry. *See* Tex. Dep't of Hous. & Cmty. Affairs v. Inclusive Cmtys. Project, Inc., 135 S. Ct. 2507, 2523–24 (2015). Plaintiffs must marshal empirical evidence showing a statistically significant disparity in treatment, establish that the disparity is caused by the lender (instead of related to a pre-existing disparity), and demonstrate a causal relationship between the disparity and the challenged practice. *See, e.g.*, City of Miami v. Bank of Am. Corp., 171 F. Supp. 3d. 1314, 1320 (S.D. Fla. 2016) (holding that "Inclusive Communities requires that an FHA disparate impact complaint (1) show statistically-imbalanced lending patterns which adversely impact a minority group; (2) identify a facially-neutral policy used by Defendants; (3) allege that such policy was 'artificial, arbitrary, and unnecessary;' and (4) provide factual allegations that meet the 'robust causality requirement' linking the challenged neutral policy to a specific adverse racial or ethnic disparity" (citing *Inclusive Cmtys. Project, Inc.*, 135 S. Ct. at 2522–24)).

229. WOLKOWITZ & PARKER, *supra* note 18, at 19.

230. *Id*. ("In fact, the majority of lenders nationwide are still using FICO Score 4, and only a relative handful has gotten so far as FICO Score 8, released six years ago.")

231. *Id*.

so without sanction. Thus, it seems hard to argue against allowing algorithmic lenders to use new models that reflect up-to-date thinking and that are (hopefully) more predictive but are, as of yet, unproven.

To promote the promise of algorithmic lending, regulators must allow algorithmic lenders the space to innovate. If regulators and courts subject algorithmic lenders to disparate impact liability because they cannot prove their models are predictive of creditworthiness, these lenders will not be able to operate. And unless algorithmic lenders are allowed to use these new models and prove they are predictive of creditworthiness, it's unclear how the financial services sector will ever innovate. Thus, so long as the FTC and CFPB continue to give algorithmic lenders the freedom to iterate and innovate, they may appropriately encourage the promise of algorithmic lending.

2. Adverse Impact Notices

An important objective of the ECOA is to increase transparency in lending decisions. The ECOA's drafters sought to increase transparency by, among other things, requiring that lenders provide so-called adverse impact notices. These notices are meant to explain to applicants why they've been denied credit.[232] Regulation B, which implements the FCRA and the ECOA, provides a template adverse action notice that requires, among other things, "that applicants who are turned down for a loan in the U.S. must be given a standard notice that states a legal, nondiscriminatory reason for the rejection along with the sources of information used."[233] The idea is rejected appli-

232. Adverse action notices must be sent within 30 days of the "creditor's approval of, counteroffer to, or adverse action" on a borrower's credit application. 12 C.F.R. § 1002.9(a)(1)(i) (2017). An "adverse action" is any "refusal to grant credit in substantially the amount or on substantially the terms requested in an application unless the creditor makes a counteroffer (to grant credit in a different amount or on other terms) and the applicant uses or expressly accepts the credit offered." 12 C.F.R. § 1002.2(c)(1)(i).

233. WOLKOWITZ & PARKER, *supra* note 18, at 11; *see also* 12 C.F.R. § 1002.9(b)(2).

cants that receive an "adverse action notice" will be better positioned to understand potential issues in their credit files, dispute inaccurate information,[234] and work to improve their credit scores.[235]

Version 2.0 algorithmic lenders may have difficulty providing adverse impact notices because of opacity issues some believe are inherent to learning algorithms.[236] To provide adverse impact notices, lenders must take certain steps, including maintaining adequate records in order to document for borrowers the reasons why they were rejected.[237] Lenders must also "be able to document and justify their models, including the factors considered, the weight applied to those factors, and the credit cutoff determination, in order to demonstrate the empirical backing and legitimate business need of their specific model."[238] Some commentators have suggested that it is virtually impossible for version 2.0 algorithmic lenders to explain their denials because learning algorithms are essentially a "black box."[239] This likely overstates the case, in at least some instances.

234. The FCRA also requires that data relied on be complete, which would be another challenge for algorithmic lenders. NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 23–24 (noting that, "[d]epending on the data source, many pieces of information will be snapshots in time. For example, a lender wanting to analyze patterns of online shopping may do so by using cookies embedded in the consumer's web-browser. However, those cookies will not include items that were returned or that were purchased as gifts."). Technological solutions, such as using inexpensive RFID tracking devices to help merge consumers' online and offline lives, may make this less of a problem in the future than it may currently be. *See e.g.*, Monique Serbu, *Why RFID Is the Best Way to Track Your Merchandise*, BUSINESS.ORG (July 19, 2013) http://www.businessbee.com/resources/profitability/why-rfid-is-the-best-way-to-track-your-merchandise/ [https://perma.cc/Z4RV-6KZB] (describing RFID tracking); Barbara Thao, *Is the 'RFID Retail Revolution' Finally Here? A Macy's Case Study*, FORBES (May 15, 2017) https://www.forbes.com/sites/barbarathau/2017/05/15/is-the-rfid-retail-revolution-finally-here-a-macys-case-study/#79904d1a3294 [https://perma.cc/5AM6-N5X9] (explaining how Macy's uses RFID technology).

235. WOLKOWITZ & PARKER, *supra* note 18, at 11 ("This minimum requirement for transparency of data sourcing is crucial, allowing applicants to understand what elements of their profile proved damaging and to dispute the accuracy of this information with the original data source if the information appears incorrect. However, many loan applicants who are successful never learn which details impact their loan decision—either positively or negatively.").

236. Freeman, Jr. et al., *supra* note 19 (noting that algorithmic lenders may find compliance difficult (or even impossible) because of "the complexity and opaqueness that can be introduced by Big Data analytical techniques").

237. *See id.* ("Regulation B (the implementing regulation of ECOA) requires that lenders maintain records regarding the criteria used to select recipients of prescreened solicitations.").

238. *See* Kaplan et al., *supra* note 127; *see also* Slattery, *supra* note 195, at 268 ("A creditor must notify the applicant of any action on the application. If the creditor takes an 'adverse action' on the application—including a refusal to grant credit—the creditor must provide written justification. The statement must give specific reasons for the adverse action. Under ECOA Regulation B, indications that the action was made "on the creditor's internal standards or policies or that the applicant . . . failed to achieve a qualifying score on the creditor's credit scoring system are insufficient.").

239. Roberts, *supra* note 86 (noting that the notice requirement is likely difficult to comply with for algorithmic lenders); Frank Pasquale, *Bittersweet Mysteries of Machine Learning (A Provocation)*, LONDON SCH. ECONS. POLITICAL SCI.: MEDIA POLICY PROJECT BLOG (Feb. 5, 2016),

In practice, algorithmic lenders may be able to provide sufficient adverse impact notices through technological innovation produced by, among other things, market incentives to reduce opacity in their credit determinations. It is definitely more challenging for version 2.0 algorithmic lenders "to isolate what the reason, or the top three reasons, were that resulted in the decision to decline the applicant."[240] At a minimum, using "thousands of data points in generating a credit decision increases the complexity of such decisions, adding to the reliance of borrowers on scoring platform companies to decipher the key drivers behind the results of their algorithms."[241] But that's at least somewhat true of traditional lenders too, whose credit-scoring algorithms are considered proprietary. And at least one company, ZestFinance, claims to have designed a learning algorithm that surmounts traditional opacity issues and unblacks the box of its technology.[242] It claims that even with complex machine learning "models that may use up to thousands of variables, [ZestFinance] identifies the primary factors driving applicants' scores."[243] ZestFinance claims that its technology "produces simple, easy-to-read adverse action reasons."[244] If Zest can truly produce "intuitive and comprehensible" explanations for its lending decisions, then consumers may be able to learn how to protect themselves, which is the purpose of these adverse action notices.[245] And, more importantly, designing an appropriate set of incentives might "nudge [other] companies developing machine-learning algorithms into incorporating explainability from the outset."[246]

http://blogs.lse.ac.uk/mediapolicyproject/2016/02/05/bittersweet-mysteries-of-machine-learning-a-provocation/ [https://perma.cc/KWD9-JMMR] [hereinafter Pasquale, *Mysteries*] (noting that the CEO of Affirm, an algorithmic lender, recently admitted that he cannot explain why the company makes particular loans and therefore presumably cannot explain when it denies people credit either).

240. Roberts, *supra* note 86 (By contrast, this requirement—enacted at a time when traditional credit measures were the only measures in use—is generally thought to be relatively easy to comply with for traditional lenders.).

241. WOLKOWITZ & PARKER, *supra* note 18, at 11.

242. *Cf. id.* at 6 (discussing how "[s]ome innovative companies are going beyond legally required minimums of disclosure by transparently conveying the types of data sources they use or explaining to consumers how their behavior can drive profile improvements that lead to better rates and offers. Well-informed consumers who are empowered to report erroneous data or shift behaviors to improve their financial standing can enhance data quality and reduce risk for providers while securing better outcomes for themselves.").

243. *See Machine Learning and Compliance? They Can Coexist*, ZESTFINANCE, https://www.zestfinance.com/hubfs/Site%20updates%20May%202017/ZAML%20compliance%20case%20study_2017.05.11.pdf?t=1497423189060 [https://perma.cc/R4DH-HKG8].

244. *Id.*

245. *Id.*

246. Tutt, *supra* note 20, at 109.

Finally, it's possible that algorithmic lenders may have trouble complying with the adverse action requirement in law, but not in spirit. The purpose of the law is to improve credit access and to empower consumers. Some algorithmic lenders are working to do just that. For example, fintech companies such as LendUp and Elevate, work with borrowers to improve their credit indicators.[247] Although these lenders may not know every variable that will ultimately matter to their credit-scoring algorithms, they are aware of the major drivers. For example, both of these algorithmic lenders view prior on-time payments "and participation in financial education modules" to be indicative of low-risk borrowers.[248] Others, such as Lenddo, are able to explain to prospective borrowers about the unconventional types of data that feed into its credit-scoring algorithms, such as social media data.[249] This knowledge may empower prospective borrowers to change how they share information on social media and improve their chances of securing a loan.

In sum, Regulation B's adverse impact notice requirement may be difficult for version 2.0 algorithmic lenders to comply with, diminishing their ability to compete with traditional lenders. Optimistically, these requirements may push algorithmic lenders to create more transparent credit-scoring algorithms, like ZestFinance claims to have done. But it may be that a flexibly-interpreted requirement would help promote the promise of algorithmic lending while avoiding its most perilous aspects. As a result, this is an area ripe for improvement, but not one that needs to be totally revamped.

B. UDA(A)P

The FTC and the CFPB (together, the UDA(A)P Regulators) are empowered to police algorithmic lenders using their UDAP and UDAAP powers, respectively.[250] Both UDA(A)P Regulators can act to prohibit unfair or

247. WOLKOWITZ & PARKER, *supra* note 18, at 12.

248. *Id.*

249. *Id.*

250. Not all bank-affiliated lending models are likely to fall within the CFPB's jurisdiction. *See* Slattery, *supra* note 195, at 264 (arguing that if a P2P lending platform "relied on another nondepository entity to issue the loan, the platform would likely qualify as service provider to that entity and still fall under the CFPB's jurisdiction. If the platform relied on a depository institution that was not 'very large' to execute the loans, however, complications could arise. The CFPB would need to coordinate with the institution's prudential regulator to ensure uniform application and enforcement of regulations."

deceptive acts or practices.[251] In addition, the CFPB alone may prohibit abusive acts or practices.[252] The CFPB's authority was modeled on the FTC's authority and the CFPB draws on FTC guidance to help define unfair or deceptive acts or practices. The remainder of this section will examine the prohibition on unfair, deceptive, or abusive acts or practices (in that order) and whether this prohibition enhances algorithmic lending's promise or creates additional perils.

1. Preventing Unfair Acts or Practices

Version 2.0 algorithmic lenders may incur liability for engaging in unfair acts or practices.[253] An unfair act or practice is one that "causes or is likely to cause substantial injury to consumers which is not reasonably avoidable by consumers themselves and not outweighed by countervailing benefits to consumers or to competition."[254] In other words, there are three elements to establishing that an act or practice is unfair.[255] Each element requires "detailed, fact-specific analysis."[256] The purpose of prohibiting unfair acts or practices is "to protect consumer sovereignty by attacking practices that impede consumers' ability to make informed choices."[257]

While some commentators have suggested that the FTC could effectively police Big Data users through its unfairness authority, it's not clear that either UDA(A)P Regulator can effectively regulate algorithmic lenders

251. *See* 15 U.S.C. § 45(a) (2012); *see also* Hirsch, *supra* note 32, at 346; Slattery, *supra* note 195, at 263 (citing Dodd-Frank Wall Street Reform and Consumer Protection Act, Pub. L. No. 111-203, § 1002(6)(A)-(B), 124 Stat. 1376 (2010)) (The CFPB "has broad authority to regulate participants in consumer financial transactions beyond existing consumer financial protection statutes" pursuant to its organic authority. Under its organic authority, it may regulate "'any person that engages in offering or providing a consumer financial product or service' or any affiliate of such a person.").

252. 12 U.S.C. § 5531 (2010).

253. On at least one occasion, the FTC has invoked its unfairness authority against an algorithmic lender "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." Citron & Pasquale, *supra* note 136, at 23 (emphasis added); *see also* Kagan et al., *supra* note 151.

254. 15 U.S.C. § 45(n) (2015). Others have described the test as requiring an injury that is: "(1) substantial, (2) without offsetting benefits, and (3) one that consumers cannot reasonably avoid." J. Howard Beales, *The FTC's Use of Unfairness Authority: Its Rise, Fall, and Resurrection*, FED. TRADE COMM'N (May 30, 2003), https://www.ftc.gov/public-statements/2003/05/ftcs-use-unfairness-authority-its-rise-fall-and-resurrection [https://perma.cc/K5LX-VHMN]; *see also* Daniel J. Solove & Woodrow Hartzog, *The FTC and the New Common Law of Privacy*, 114 COLUM. L. REV. 583 (2014); Citron & Pasquale, *supra* note 136, at 23 (An "unfair" practice requires "conduct that substantially harms consumers, or threatens to substantially harm consumers, which consumers cannot reasonably avoid, and where the harm outweighs the benefits.").

255. Beales, *supra* note 254.

256. *Id.*

257. *Id.*

in this fashion.[258] To establish that an act of practice is unfair, a UDA(A)P Regulator must first prove that the algorithmic lender's act or practice causes a substantial injury.[259] Substantial injury means any sort of non-speculative and non-trivial harm.[260] Professor Dennis D. Hirsch asserts that because algorithmic lending can cause "diminished access to . . . loans" it imposes "damage that is neither speculative nor trivial," thus constituting "substantial injuries" that "meet the first element of the Section 5 unfairness test."[261]

Although it is clearly true that some people will suffer "diminished access" to credit, this alone will not establish a substantial injury in every case.[262] For example, assume that an algorithmic lender denies credit to a person with a FICO score of 550. This prospective borrower would almost surely be denied credit by a traditional lender as well.[263] If "diminished access" to credit is measured by comparing the decisions of algorithmic lenders to those of traditional lenders, our prospective borrower with a low FICO score is unlikely to be able to prove substantial injury because he or she is unlikely to have been approved for credit elsewhere.[264] And there is a sound policy justification for adopting traditional lenders' underwriting standards as the appropriate baseline; it could encourage algorithmic lenders to focus

258. Hirsch, *supra* note 32, at 354 (arguing that the FTC's unfairness authority provides "a regulatory mechanism . . . capable of weighing the costs and benefits of particular Big Data uses and determining, on balance, whether they are beneficial or harmful").

259. *See* NAT'L CONSUMER LAW CTR., UNFAIR ACTS & PRACTICES § 4.3.2.2 (2017) ("To be unfair under the FTC Act (and under the unfairness standard that the CFPB applies), an act or practice must cause or be 'likely to cause' substantial injury to consumers.").

260. Hirsch, *supra* note 32, at 354 ("These injuries can consist of monetary, economic, health related, or other types of tangible harm. Injuries are 'substantial' where they are more than 'trivial or speculative.'"); *see also id.*

261. *Id.*

262. *Cf.* Consumer Fin. Prot. Bureau v. ITT Educ. Servs., Inc., 219 F. Supp. 3d 878, 913 (S.D. Ind. 2015), *appeal dismissed*, No. 15-1761, 2016 WL 9447163 (7th Cir. Apr. 20, 2016) (finding that the CFPB had stated a claim under its unfairness authority where college steered its students toward loans with high interest and fees, after which approximately 64% of students defaulted, and where the college allegedly coerced its students into taking out these loans by rushing them through the student loan process and "employ[ing] intrusive and overbearing tactics").

263. A borrower that is granted credit by a traditional lender but denied credit by an algorithmic lender may also suffer substantial injury, but is unlikely to be able to establish the algorithmic lender was engaged in an unfair act or practice because the injury would be reasonably avoidable (i.e. by borrowing from the traditional lender). *But cf. id.*

264. Alternatively, if algorithmic lending models are more predictive than traditional underwriting models, we ought to expect that algorithmic lenders will sometimes decline to lend to people who are not likely to repay their debts but who could get a loan from a traditional lender. If an algorithmic lender denies credit to someone who eventually defaults, has it truly harmed that person? In other words, it seems likely that some people are better off not borrowing.

on expanding credit opportunities for sub-prime borrowers, which would seem to promote the promise of algorithmic lending.[265]

However, a court could decide that the appropriate baseline for comparison is not the underwriting standards of traditional lenders but to the hypothetical lending standards of an algorithmic lender using unbiased data. In that case, a prospective borrower with a low algorithmic "credit score" but a high likelihood of repayment might successfully establish substantial injury if the algorithmic lender's biased model fails to recognize the borrower's high likelihood of repayment and the loan is denied. If courts adopt this baseline, a plaintiff may be able to establish substantial injury. However, for reasons discussed below, plaintiffs are likely to struggle to establish that their substantial injury was proximately caused by algorithmic lending bias.[266]

Consumers may be unable to reasonably avoid being substantially injured by version 2.0 algorithmic lenders—the second unfairness element—because of the opaque nature of some credit algorithms.[267] Professor Hirsch asserts that consumer injury is not reasonably avoidable because few consumers understand how algorithmic lending works and how to protect themselves.[268] Hirsch is likely correct that some (or even many) consumers do not understand how algorithmic lending works and, therefore, how to protect themselves because many learning algorithms are thought to be quite opaque.[269] That is, no one can explain to humans why some credit algorithms

265. This does not accord with the practices of many version 2.0 algorithmic lenders, who have mostly targeted prime and near prime borrowers. *See supra* text accompanying notes 120–122.

266. *See infra* text accompanying notes 338–342 (discussing the thousands of data points consumers must review to understand whether inaccurate information is being used); *supra* text accompanying notes 99–100 (discussing how learning algorithms mine data to determine the appropriate variables to consider when making decisions).

267. *Cf.* NAT'L CONSUMER LAW CTR., *supra* note 259, § 4.3.2.3.1 (noting that an injury is not reasonably avoidable by a consumer "when the merchant's sales practices unreasonably create or take advantage of an obstacle to the free exercise of consumer decision-making").

268. Hirsch, *supra* note 32, at 355 ("Few consumers can become aware of and achieve control over the collection of their personal information. Fewer still can understand how companies use data analytics to infer additional information about them and make decisions that affect them. Consumers cannot protect themselves against Big Data's privacy or discriminatory impacts through their market choices. These injuries meet the second Section 5 unfairness element."); *see also* NAT'L CONSUMER LAW CTR., *supra* note 259, §§ 4.3.2.3.1, 4.3.2.3.5 (citing authority for the proposition that "[i]njuries are not reasonably avoidable where a defendant exercises undue influence over a highly susceptible class of purchasers."); *cf.* Consumer Fin. Prot. Bureau v. ITT Educ. Servs., Inc., 219 F. Supp. 3d 878, 913 (S.D. Ind. 2015), *appeal dismissed*, No. 15-1761, 2016 WL 9447163 (7th Cir. Apr. 20, 2016) (finding that student injury was not reasonably avoidable because the college essentially boxed the students in and prevented them from transferring).

269. Matthew U. Scherer, *Regulating Artificial Intelligence Systems: Risks, Challenges, Competencies, and Strategies*, 29 HARV. J.L. & TECH. 353, 369 (2016) (explaining the problem of opacity as "the possibility that the inner workings of an AI system may be kept secret and may not be susceptible to reverse engineering"); *cf. ITT Educ. Servs., Inc.*, 219 F. Supp. 3d at 913.

makes the decisions they do.[270] For example, the CEO of Affirm, a new lending start-up from the founders of PayPal, recently admitted that he could not explain why the company makes particular loans.[271] He said, "I wouldn't know. Our math model says 'OK. Probabilistically, [the borrower's] good for the money.'"[272] Presumably the reverse is also true, that the model indicates that probabilistically, a prospective borrower is not "good for the money."[273] But this does not help a prospective borrower understand why their credit application was denied and how he or she might protect himself or herself in the future.[274]

However, recent evidence suggests that opacity is not as inherent to learning algorithms as previously thought. As noted above, ZestFinance claims to have created a more transparent credit-scoring algorithm.[275] If true, borrowers could take steps to protect themselves, making consumer injury reasonably avoidable and defeating an unfair act or practice claim.[276] Moreover, for prospective borrowers who could obtain traditional forms of credit but are denied credit by an algorithmic lender, that borrower could avoid injury by borrowing from the traditional lender.[277]

Both because ZestFinance claims to have achieved algorithmic transparency, and also because of "a growing consensus among scholars" that

270. Scherer, *supra* note 269, at 356–57 (expressing concern that outside observers "may not be able to detect potentially harmful features of an AI system"); *see also* Price II, *supra* note 99, at 16 ("[M]achine-learning methods often leave the mechanisms in the resulting algorithms fully opaque; even when they are not, they are likely so complex as to defy understanding.").

271. Pasquale, *Mysteries*, *supra* note 239; John Paul Titlow, *With Affirm, PayPal Cofounder Has a New Way for You to Buy Things Without Credit Cards*, FAST COMPANY (Oct. 27, 2015), https://www.fastcompany.com/3052796/paypal-co-founder-has-a-new-way-for-you-to-buy-things-in-stores [https://perma.cc/CXR8-ALNH]; *see also* WOLKOWITZ & PARKER, *supra* note 18, at 7 (describing Affirm as using "Big Data analytics to facilitate lending decisions for consumers financing the purchase of large household items such as furniture, appliances, or electronics").

272. Pasquale, *Mysteries*, *supra* note 239.

273. *Id.*

274. Slattery, *supra* note 195, at 269 ("[I]t is not clear that any entity could provide specific reasons for adverse credit decisions on P2P lending platforms").

275. *See supra* text accompanying notes 242–246.

276. It appears that the first two elements of an unfair act or practice claim are in some tension. If algorithmic lenders don't disclose much information about their algorithm, plaintiffs will have a hard time establishing that they have suffered a substantial injury. But if algorithmic lenders do disclose enough information for plaintiffs to suffer a substantial injury, it may also be true that they've provided a roadmap for prospective borrowers to follow to improve their algorithmic "credit scores," making the injury avoidable.

277. Unlike the students ITT Tech allegedly pressured into taking loans with onerous repayment terms, borrowers can and should shop around for consumer loans. *Cf.* Consumer Fin. Prot. Bureau v. ITT Educ. Servs., Inc., 219 F. Supp. 3d 878, 913 (S.D. Ind. 2015), *appeal dismissed*, No. 15-1761, 2016 WL 9447163 (7th Cir. Apr. 20, 2016).

through transparency (i.e., access to source code, access to inputs, etc.), algorithmic outputs can be adequately policed, I don't think that Hirsch's negative view is necessarily warranted.[278] It may well be that algorithmic lenders can adequately explain the reasons they deny credit to borrowers. Or that the UDA(A)P Regulators' invocation of their unfairness authority may incentivize other algorithmic lenders to design less opaque algorithms. Other possibilities for creating algorithmic transparency—if technically feasible[279]—include legislative mandates or indirect incentives, such as "tax incentives or tort standards that limit the liability of companies that make their AI systems more transparent."[280]

Finally, the effectiveness of algorithmic lending models in reducing costs and increasing credit access, thereby benefiting both prospective borrowers and the lending market, remains to be seen. The third requirement to prove that an act or practice is unfair is that the injury not be "outweighed by countervailing benefits to consumers or to competition."[281] In other words, a UDA(A)P Regulator must generally balance "the costs that the activity imposes on consumers against the benefits it creates for consumers and for business."[282] As Professor Hirsch notes, it's hard to know how this factor comes out.[283] On the one hand, algorithmic lending models can decrease costs, creating competition with traditional lenders and—in a competitive market—benefitting consumers.[284] It can also increase credit access, which

278. *See, e.g.*, Tutt, *supra* note 20, at 110 ("There appears to be a growing consensus among scholars that the ability to require transparency should be one of the first tools used to regulate algorithmic safety. Transparency can take many forms and can range from feather-light to brick-heavy.").

279. "[O]ur inability to understand, explain, or predict algorithmic errors is not only unsurprising, but destined to become commonplace." Tutt, *supra* note 20, at 89–90 (discussing errors made by IBM's Watson and Tesla's self-driving car, and explaining that "[n]o one knows precisely why these algorithms failed as they did and, in the Tesla case, it is not entirely clear the algorithms failed at all"); *see also* Andrew Fogg, *Artificial Intelligence Regulation: Let's Not Regulate Mathematics!*, IMPORT, https://www.import.io/post/artificial-intelligence-regulation-lets-not-regulate-mathematics/ [https://perma.cc/8R9A-AHDE] (arguing three points, including that (i) explaining an AI system's choices "is impossible to achieve, so it should not be legislated," (ii) "attempting to extract an explanation out of a modern Deep Learning model is bound to fail," and (iii) due to the sheer volume of data inputs, a learning algorithm's output "is utterly impossible to explain in one sentence. Or a paragraph. Or a 1000-page book. We can't explain a really complex mathematical function learned from a mountain of data in a way that will satisfy a human. This is what we are facing. Legislating the need for an explanation will not make that contradiction disappear.")

280. Scherer, *supra* note 269, at 374.

281. 15 U.S.C. § 45(n) (2012); *see also* NAT'L CONSUMER LAW CTR., *supra* note 259, § 4.3.2.4.

282. Hirsch, *supra* note 32, at 355.

283. *Id.* at 355–57.

284. It's not clear that this market is sufficiently competitive that cost savings will be passed along to consumers. *Cf.* Xavier Gabaix & David Laibson, *Shrouded Attributes, Consumer Myopia, and Information Suppression in Competitive Markets*, 121 Q.J. ECON. 505, 530 (2006) (discussing price shrouding in the credit card markets).

is critically important for participating in our modern economy. On the other hand, "dumb" algorithms and poorly designed or trained learning algorithms can disparately impact some of the most vulnerable members of our society. Even if algorithmic lenders increase credit access for some, if they do so at the cost of greater inequality in credit access, it's hard to evaluate how a UDA(A)P Regulator would balance access and equity. This is likely to be deeply fact-dependent.

2. Deceptive Acts or Practices

The UDA(A)P Regulators' deceptiveness authority is unlikely to play a significant role in promoting the promise of algorithmic lending. A brief review of recent regulatory activity may be illuminating. In one of the CFPB's first enforcement actions against a fintech company, the CFPB alleged that "Dwolla Inc., a prominent online payment provider, . . . allegedly misrepresent[ed] its data security practices as 'safe,' 'secure,' 'safer [than credit cards],' and 'exceeding industry standards.'"[285] In a 2008 FTC enforcement action against CompuCredit, the FTC alleged the company had deceived consumers "by failing to disclose that consumers' credit lines would be reduced if they used their credit cards for cash advances or for certain types of transactions, including marriage counseling, or at bars and nightclubs."[286] The FTC has also pursued "companies for collecting more data—like a consumer's online search history—than was disclosed to consumers in the company's privacy policies."[287]

These enforcement actions suggest that UDA(A)P Regulators generally use their deceptiveness authority to ensure that any representations made to consumers are consistent with the lender's actual product or business model.[288] This is unlikely to increase the predictive accuracy of credit-scoring algorithms, will certainly not decrease costs, nor remove human bias

285. Lazarev, *supra* note 69.

286. *See also* Kagan et al., *supra* note 151.

287. Tunstall & Caplan, *supra* note 74 ("For instance, the FTC brought an enforcement action involving an online advertising network, Epic Marketplace Inc., when the company apparently disclosed in its privacy policy that it would collect information about consumers' visits to websites within the company's network. The FTC complaint alleges, however, that Epic actually collected data about all sites consumers visited — even those outside of Epic's network. The result: the FTC barred Epic from what it deemed a UDAP, and required the company to destroy all data collected by it." (citing *In re* Matter of Epic Marketplace Inc., F.T.C. No. 112-3182, 2012 WL 6188553 (Dec. 5, 2012))).

288. Prentiss Cox, *The Importance of Deceptive Practice Enforcement in Financial Institution Regulation*, 30 PACE L. REV. 279, 287 (2009).

from the credit-scoring process.[289] But it does empower UDA(A)P Regulators to curtail predatory lending practices by algorithmic lenders, should they engage in such practices.[290] Predatory lending is a practice that algorithmic lending could facilitate and therefore it's important to adequately police it.

3. Abusive Acts or Practices

Finally, version 2.0 algorithmic lenders may be subject to liability for engaging in abusive acts or practices. The CFPB (but not the FTC) has the authority to proscribe and prosecute abusive acts or practices, which are those that interfere with a consumer's ability "to understand a term or condition of a consumer financial product or service."[291] The CFPB's abusive authority also protects against acts or practices that take "unreasonable advantage of: (A) a lack of understanding on the part of the consumer of the material risks, costs, or conditions of the product or service; (B) the inability of the consumer to protect his or her interests when selecting or using a consumer financial product or service; or (C) the reasonable reliance by the consumer on a covered person to act in the interests of the consumer."[292] Abusiveness claims appear to contain "an element of alleged surprise or inability of consumers to understand credit features or contractual rights due to the Covered Person's alleged inadequate disclosures."[293] The CFPB virtually always asserts its "abusive" authority alongside claims of an unfair or deceptive act or practice. Essentially, the CFPB's "abusive" power has lacked its own independent bite, with Adam Levitin describing it as "the dog that didn't bark."[294]

289. To avoid liability for deception, such lenders need only avoid misleading consumers by omitting key information or through active misrepresentations. Kagan et al., *supra* note 151.

290. Jackson, *supra* note 2, at 14 (discussing how data brokers might use Big Data to prey on certain consumers).

291. 12 U.S.C. § 5531(d)(1) (2011). Being limited to "consumer financial products or services" means that this authority does not extend to small business products or services.

292. *Id.* § 5531(d)(2).

293. Donald C. Lampe et al., MORRISON FOERSTER, THE CFPB & UDAAP: A "KNOW IT WHEN YOU SEE IT" STANDARD? 2015 MID-YEAR UPDATE 5 (2015), https://media2.mofo.com/documents/150727cfpbudaap.pdf [https://perma.cc/M92F-JXBP].

294. Adam Levitin, *Dodd-Frank's "Abusive" Standard: The Dog That Didn't Bark*, CREDIT SLIPS (June 20, 2017, 11:40 PM), http://www.creditslips.org/creditslips/2017/06/abusive-the-dog-that-didnt-bark.html#more [https://perma.cc/P79L-GFDN] (noting that "the CFPB has been very sparing in alleging that acts and practices are 'abusive'. The CFPB has brought around 185 enforcement actions to date. Only 22 of these (less than 12% of all enforcement actions) have included counts alleging 'abusive' acts and practices. In all but one instance in these 22 cases, the very same behavior alleged to be 'abusive' was also alleged to be 'unfair' and/or 'deceptive.'").

Despite their novelty in some ways, algorithmic lenders offer somewhat plain vanilla loan products that generally mirror what's available from traditional lenders. As such, they do not seem to be at an increased risk (relative to traditional lenders) of misleading consumers as to the risks, costs, or conditions of their products or services.[295] To the extent they are, however, greater transparency by algorithmic lenders would appear to mitigate some of this risk. But, to the extent that algorithmic lenders use their credit-scoring models to engage in predatory lending practices,[296] the CFPB should use its "abusiveness" authority to curtail those practices.

In summary, UDA(A)P Regulators may be able to push algorithmic lenders towards greater transparency through the selective use of their UDA(A)P authority. And they should be able to prohibit predatory lending with these powers. I would be concerned, however, about using either the UDA(A)P Regulators' unfairness or abusive authority to punish algorithmic lenders for using somewhat opaque credit-scoring algorithms absent clear consumer injury. Algorithmic lenders appear to be moving to create more transparent credit-scoring algorithms and UDA(A)P Regulators should encourage this trend. They should use the flexibility built into the UDA(A)P standards to enjoin novel forms of bad business practices while allowing algorithmic lenders the time to iterate and improve.[297]

C. The Fair Credit Reporting Act

To the extent that it applies, the FCRA may present major challenges to version 2.0 algorithmic lenders because it was designed without algorithmic lending practices in mind. The FCRA "is the nation's oldest financial privacy statute."[298] It was crafted in the late 1960s and enacted in 1970 to promote "the accuracy, fairness, and privacy of information in the files of consumer reporting agencies."[299]

295. Nicholas Smyth, *Attempting to Ascertain CFPB's Theory Of 'Abusive' Acts*, LAW360 (June 10, 2015), https://www.law360.com/articles/664281/attempting-to-ascertain-cfpb-s-theory-of-abusive-acts [https://perma.cc/9GZH-7KBE] (suggesting that the CFPB is unlikely to invoke its "abusiveness" power unless consumer choice is absent or where the products offered are unduly complex).

296. Jackson, *supra* note 2, at 22.

297. James J. Pulliam, *Good Cop, Bad Cop: Market Competitors, UDAP Consumer Protection Laws, and the U.S. Mortgage Crisis*, 43 LOY. L.A. L. REV. 1251, 1296 (2010) ("These advantages are particularly pertinent in the context of the flexible UDAP unfairness standard because an effective advocate can further a UDAP's statutory purpose of adapting to and enjoining novel forms of bad business practices.").

298. Tunstall & Caplan, *supra* note 74.

299. *A Summary of Your Rights Under the Fair Credit Reporting Act*, FED. TRADE COMM'N, https://www.consumer.ftc.gov/articles/pdf-0096-fair-credit-reporting-act.pdf [https://perma.cc/423P-PMW6].

In general, the FCRA applies to those companies that are compiling and selling "consumer information for use in credit, employment, housing, or other similar decisions."[300] To be more precise, and to determine whether the FCRA applies to algorithmic lenders, one must turn to the definition of consumer reporting agency ("CRA"), which is:

> any person which, for monetary fees, dues, or on a cooperative nonprofit basis, regularly engages in whole or in part in the practice of assembling or evaluating consumer credit information or other information on consumers for the purpose of furnishing consumer reports[301] to third parties, and which uses any means or facility of interstate commerce for the purpose of preparing or furnishing consumer reports.[302]

This definition clearly includes the big three credit bureaus, Experian, Equifax, and TransUnion. But, it also applies to many other entities, which may include "creditors, data brokers, employment screening companies, check approval companies, alternative credit bureaus," and, most importantly, some algorithmic lenders.[303]

Bank-affiliated algorithmic lenders must comply with FCRA requirements, but direct lenders are unlikely to be covered by the FCRA because they make loans directly to consumers.[304] As such, direct lenders assemble and evaluate information about potential borrowers for their own use rather than to furnish to third parties.[305] By contrast, the FCRA likely applies to most bank-affiliated algorithmic lenders because they generally assemble

300. Freeman, Jr. et al., *supra* note 19.

301. 15 U.S.C. § 1681a(d)(1) (2015) (defining a "consumer report" as: "any written, oral, or other communication of any information by a consumer reporting agency bearing on a consumer's credit worthiness, credit standing, credit capacity, character, general reputation, personal characteristics, or mode of living which is used or expected to be used or collected in whole or in part for the purpose of serving as a factor in establishing the consumer's eligibility for — (A) credit or insurance to be used primarily for personal, family, or household purposes; (B) employment purposes; or (C) any other purpose authorized under section 1681b [relating to permissible purposes for pulling credit]."); *see also* NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 22 (noting that "a wide variety of information about a consumer satisfies this part of the definition of a consumer report, including most of the information collected by Big Data brokers").

302. 15 U.S.C. § 1681f.

303. NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 21.

304. TREASURY, *supra* note 197.

305. Freeman, Jr. et al., *supra* note 19 ("Because the FCRA does not generally apply where lenders use internally generated data in making credit decisions, lenders relying on their own Big Data for credit determinations may believe that they are exempt from FCRA requirements.").

and evaluate credit information on prospective borrowers to aid their affiliated bank in loaning money to consumers.[306] Where affiliated banks are paying algorithmic lenders to assemble and evaluate consumer credit information, the FCRA will apply.[307] The FTC has also taken this view.[308]

Where the FCRA applies, it imposes at least four obligations on CRAs that are relevant to algorithmic lenders. First, CRAs must "follow reasonable procedures to assure maximum possible accuracy" of their consumer reports.[309] Second, CRAs must put in place procedures that "allow consumers to know what is in their consumer reports."[310] Third, CRAs must allow consumers "to dispute incorrect or inaccurate information."[311] And, finally, any lender that makes "adverse credit determinations (either denial or increased costs)" based on information in a consumer report "must also provide notice to the consumer of the lenders' use of the consumer report information."[312] Each obligation will be addressed in turn, except for the fourth one, which was discussed previously in the context of the ECOA.[313]

The first obligation that version 2.0 algorithmic lenders must comply with—the FCRA's accuracy requirement—may be technically difficult to

306. This difference—that bank-affiliated but not direct lenders face FCRA compliance issues—may encourage banks to purchase rather than partner with fintech companies to avoid FCRA liability.

307. However, the FCRA may not apply if a court or regulator determines that the algorithmic lender is the "true lender," which would make them much more like a direct lender. *Cf.* Sobers, *supra* note 131 (discussing the true lender doctrine and reviewing cases).

308. Freeman, Jr. et al., *supra* note 19 ("Where a lender allows an unaffiliated entity access to the company's own data to assist in making credit determinations, this act may trigger FCRA implications. As stated in the Report, the FTC will likely view third parties offering analytical services performed on the company's own data as meeting the definition of being a CRA under FCRA. Not only does this create legal obligations for the unaffiliated entity with respect to the data, but it also triggers lender-specific notice requirements in the event of adverse credit decisions that would not otherwise exist had the data analysis been kept in-house.").

309. 15 U.S.C § 1681e(b) (2015); *see also* Freeman, Jr. et al., *supra* note 19 (CRAs have "legal duties regarding ensuring the accuracy of consumer reports, providing consumers access to their information, and" correcting errors.)

310. 15 U.S.C. § 1681g(a); *see also* Roberts, *supra* note 86 (The FCRA "requires credit-rating services to disclose the contents of a consumer's file to the consumer and to provide for the consumer to challenge entries in the file."); NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 24 (finding that Big Data brokers typically failed "to comply with the requirement to disclose all information in the consumer's file").

311. Tunstall & Caplan, *supra* note 74; Roberts, *supra* note 86; *see also* NCLC, BIG DISAPPOINTMENT, *supra* note 22.

312. Freeman, Jr. et al., *supra* note 19 ("If, for instance, the lender provides customer-specific information to obtain input on a credit decision, the lender will likely be obligated to provide mandatory notice to the consumer in the event of an adverse decision. If, on the other hand, the lender uses aggregate information to develop general lending guidelines, and based on these guidelines a consumer is denied credit, the lender will be required to disclose the nature of the aggregate information if the lender receives a specific request from the consumer.").

313. *See supra* text accompanying notes 232–249.

satisfy because of the sheer volume of data points version 2.0 algorithmic lenders process.[314] CRAs need to put in place reasonable steps to ensure the maximum possible accuracy of their credit reports.[315] Even though traditional lenders only need to ensure the accuracy of a relatively finite set of data points, more than twenty percent of traditional credit reports have material errors.[316] And approximately seventy percent of disputes over errors on credit reports leave consumers believing that inaccurate information remains on their credit reports.[317] By contrast, algorithmic lenders need to ensure the accuracy of thousands or even tens of thousands of data points. This may lead to an explosion of errors. With so many additional data points, it's no surprise that a survey by the NCLC found that "the Big Data companies' reports showed a remarkable level of inaccuracy."[318] That algorithmic lenders have inaccuracies in their credit reports is no surprise. But it's not clear from this report whether algorithmic lenders' consumer credit reports paint a picture of prospective borrowers that is, in the aggregate, less accurate than traditional credit reports, or whether these inaccuracies are actionable.

Liability for algorithmic lenders is uncertain because, among other things, it's possible that algorithmic lenders do make use of some inaccurate data points but that the total picture provided by algorithmic credit reports are more accurate than traditional credit reports because it creates a "data mosaic."[319] By "cross-referencing a wide range of data points drawn from public records, online habits, spending histories, and more," algorithmic lenders may be able to "produce insights that are more valuable than the sum

314. NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 23 (discussing reasons why the "accuracy requirement" presents a challenging compliance issue for "many Big Data brokers").

315. 15 U.S.C § 1681e(b).

316. *See* Press Release, Fed. Trade Comm'n, In FTC Study, Five Percent of Consumers Had Errors on their Credit Reports that Could Result in Less Favorable Terms for Loans (Feb. 11, 2015), https://www.ftc.gov/news-events/press-releases/2013/02/ftc-study-five-percent-consumers-had-errors-their-credit-reports [https://perma.cc/54RK-HMNK] [hereinafter Press Release, Five Percent]; *see also* Press Release, Fed. Trade Comm'n, FTC Issues Follow-Up Study on Credit Report Accuracy (Jan. 21, 2015), https://www.ftc.gov/news-events/press-releases/2015/01/ftc-issues-follow-study-credit-report-accuracy [https://perma.cc/M2MT-KKTC] [hereinafter Press Release, Follow-Up] (reporting that "one in five consumers had an error that was corrected by a credit reporting agency (CRA) after it was disputed on at least one of their three credit reports"); ELIZABETH WARREN ET AL., THE LAW OF DEBTORS AND CREDITORS: TEXT, CASES, AND PROBLEMS 38 (7th ed. 2014) (noting that "[a] 2004 study by the Public Interest Research Group found that 79% of credit reports contained errors, and that 25% contained errors big enough to change the person's credit scores").

317. Press Release, Five Percent, *supra* note 316; *see also* Press Release, Follow-Up, *supra* note 316 ("However, 84 of these consumers (nearly 70 percent) continue to believe that at least some of the disputed information is inaccurate.").

318. NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 23.

319. WOLKOWITZ & PARKER, *supra* note 18, at 7. No court has evaluated this argument yet.

of their parts."[320] In other words, despite some inaccuracies, "Big Data mosaics" may be able to better "identify meaningful patterns and predict future behavior on a granular level" than traditional lending models.[321] In short, some assert that "[c]ombining massive data sets thoughtfully can lead to greater accuracy and granularity," meaning that consumers get better products offered more efficiently.[322] As such, while algorithmic lenders may rely on more inaccurate data points, they may still see a more accurate representation of consumers propensity to repay their debts.

Moreover, algorithmic lenders may have not yet fully explored the host of ways by which they might improve their data's accuracy. One possibility is for algorithmic lenders to use fewer data points gathered from questionable sources and more data points to which they are expressly granted access. For example, consumers might voluntarily share personal data in exchange for better credit offers. Consumers already voluntarily share enormous amounts of personal information in exchange for "free" email, web search, and access to social networks, among other things. Data obtained through consumer consent is likely to be better quality (i.e. more accurate and reliable),[323] thus presenting fewer compliance risks for algorithmic lenders.[324]

Another alternative for improving data accuracy is used by the data analytics firm, Acxiom. Acxiom is not an algorithmic lender, but it does collect the same sort of data that algorithmic lenders may use in making credit determinations.[325] Acxiom invites people to participate in improving the accuracy of its data by making its data publicly available.[326] Members of the

320. *Id.*

321. *Id.* at 7, 8, and 23 ("By comparing identical or similar data from multiple sources, analytics companies can identify data points, or even whole data sets, that appear to be outliers that should not be trusted."); Jagtiani & Lemieux, *supra* note 108.

322. WOLKOWITZ & PARKER, *supra* note 18, at 9.

323. One concern about Big Data is that it is often linked to a consumer by only the consumer's name. Consumers could effectively verify that data by granting algorithmic lenders access to their accounts.

324. WOLKOWITZ & PARKER, *supra* note 18, at 6 (noting that "[o]ne effective strategy" for reducing compliance risk by increasing data accuracy "is to invite consumers to opt in and voluntarily share more personal information and financial data in exchange for more attractive offers and lower rates. Products that allow consumers to control the balance of trade-offs between greater privacy and greater value can allow both customers and providers to reap greater benefits.").

325. *Id.* at 12.

326. Mary Beth Quirk, *Data Broker Acxiom's New Site Allows Users to View and Edit the Marketing Info It's Collected*, CONSUMERIST (Sept. 4, 2013), https://consumerist.com/2013/09/04/data-broker-acxioms-new-site-allows-users-to-view-and-edit-the-marketing-info-its-collected [https://perma.cc/8GBK-3AEJ].

public are invited "to search for their names and profiles on a public interface, and update or correct information that is outmoded or shows errors."[327] In other words, "Acxiom encourages consumers to be partners in cleaning its data files."[328] Early reports suggest that many data elements in "Big Data" files are inaccurate, but Acxiom's pilot program "provides a clear avenue for consumers concerned about their financial profiles to scrub problematic data points and participate in enhancing its efficacy."[329]

These possible ways to improve data accuracy notwithstanding, algorithmic lenders may be violating the FCRA because the practical effects of data inaccuracies in algorithmic lending models are yet to be determined. As such, the FTC and CFPB[330] may be able to use the FCRA's accuracy requirement to push algorithmic lenders to construct better credit-scoring models, which should make credit more accessible and more affordable for those who are likely to repay their debts.[331] Whether these inaccuracies are likely to lead to unlawful discrimination and therefore whether the FCRA will reduce the perilous aspects of algorithmic lending is uncertain. Currently, regulators appear to be taking a hands-off approach, allowing these companies to experiment with their new lending models.

The second relevant obligation imposed by the FCRA—that CRAs must, upon request, disclose the contents of a consumer's credit report to that consumer—may also be problematic for version 2.0 algorithmic lenders due to data volume and transparency issues.[332] The NCLC has asserted that Big Data brokers typically failed to comply with this requirement.[333] The FTC has also expressed concern that algorithmic lenders may be violating fair lending laws by making lending decisions based on inaccurate data "without affording borrowers the opportunity to correct inaccurate information."[334] But even if algorithmic lenders did provide its data sources to consumers, there may be no reasonable way for a consumer to review their credit files.[335]

327. WOLKOWITZ & PARKER, *supra* note 18, at 12.

328. *Id.*

329. *Id.*

330. To the extent that the true lender is a depository institution, a regulator such as the OCC would be the relevant regulator.

331. *See* Jagtiani & Lemieux, *supra* note 108.

332. 15 U.S.C. § 1681g(a) (2015) (explaining the disclosure requirement and its limits).

333. *See* NCLC, BIG DISAPPOINTMENT, *supra* note 22.

334. Trudel et al., *supra* note 71.

335. "[I]t may prove practically impossible for consumers, when dealing with big-data scoring systems that potentially integrate thousands of variables, to verify the accuracy of their scores and reports or to challenge decisions based on alternative models." Hurley & Adebayo, *supra* note 24, at 189–90.

The sheer number of variables might be overwhelming.[336] In addition, it's not clear that most learning algorithms are yet sufficiently transparent to explain to consumers the basis for the adverse determination (despite a legal requirement to do so).[337]

Similarly, the FCRA's accuracy and disclosure requirements may be outdated and ineffective given the increasing complexity of algorithmic lending. Although CRAs must take reasonable steps to ensure the accuracy of credit reports,[338] the FCRA puts the onus on consumers to review their credit files and dispute inaccurate items.[339] And even though traditional lending decisions are made using far less complex models than those used by algorithmic lenders, there's "a high incidence of inaccuracies in traditional credit reports, leading to elevated rates of interest for certain borrowers."[340] To establish harm with an algorithmic credit report, a consumer would have to review the thousands of data points used by the algorithmic lender to identify an error, and "prove that the error resulted in a faulty score."[341] The process by which thousands of data points are converted into a credit determination "is so complex that even the most sophisticated consumer would likely find it difficult to understand, or to determine whether any inaccuracies in the raw data negatively influenced her final score."[342] This complexity may render many of the protections available under the FCRA

336. *Id.* at 164–67.

337. Roberts, *supra* note 86 (noting that the FCRA "really puts a tremendous degree of emphasis on institutions to understand exactly how their model is working" (quoting Kevin Petrasic)).

338. Hurley & Adebayo, *supra* note 24, at 188 ("CRAs must also use reasonable procedures to guarantee the accuracy of information in consumer reports. Not only must the information in a report be literally true, it also must not be misleading or incomplete.").

339. "Existing laws like the FCRA establish basic accuracy requirements for the data used in credit-assessment tools, however consumers bear the burden of identifying and disputing inaccuracies." *Id*. at 198 ("FCRA's accuracy requirements appear to offer inadequate incentives to increase data accuracy, even in the conventional credit-scoring context where scorers are dealing with fewer types and sources of data.").

340. *Id.* at 178.

341. *Id.* at 179.

342. *Id.* at 182 ("[T]he manner in which the data scientist develops and refines the final creditscoring model can potentially create major barriers to transparency and to consumers' ability to challenge scores. The process of data transformation, metavariable development, feature selection, and, finally, the filtering of significant features through multiple models is so complex . . . ."); *see also* Gordon & Stewart, *supra* note 22 ("These include concerns about data quality and difficulty correcting inaccuracies, including consumers' potential inability to understand complex modeling techniques. The bureau is also concerned that unlike traditional credit factors, which are heavily influenced by the consumer's own conduct, alternative data that relate to peers or broader consumer segments may limit consumers' ability to improve their credit rating.").

more illusory than real.[343] It's unclear if this is a compliance issue that algorithmic lenders will have to deal with, but it once again highlights the need to update the FCRA to reflect that new lending models exist.

The FCRA, the ECOA and the FTC's Section 5 authority were all designed before algorithmic lenders existed. And the CFPB was just getting set up around the same time as the first algorithmic lenders were populating their first spreadsheets. Unsurprisingly, therefore, these laws did not anticipate the new algorithmic lending models.[344] As a result, regulating algorithmic lenders under the current legal regime is a bit like trying to fit a round peg into a square hole.[345] The two largest algorithmic lenders—Prosper and Lending Club—have admitted as much.[346] Both noted in their prospectuses that: "We may not always have been, and may not always be, in compliance with these [consumer financial protection] laws."[347] Simply put, the novelty of these new lending models means that the FTC and CFPB have not yet tested their compliance with the nation's federal consumer financial protection laws. But our state and federal regulators must ensure that these entities do more than simply enrich their shareholders. Our consumer financial protection regulators should seek to increase credit access for those that are reasonably likely to repay their debts, while preventing the worst abuses and types of predation that can exist.[348]

CONCLUSION

Our consumer financial protection laws are outdated. Some have argued that society has reached an inflection point and the pace of financial services

343. NCLC, BIG DISAPPOINTMENT, *supra* note 22, at 24 ("However, even if data brokers were to provide this disclosure, the information may not be comprehensible for consumers due to its sheer volume. Therefore, meaningful disclosure may not be possible when using Big Data. This may prove to be a fundamental flaw with using Big Data for determining eligibility for credit or other FCRA-covered purposes.").

344. *Cf.* Wulf A. Kaal, *Dynamic Regulation for Innovation*, *in* MARK FENWICK ET AL., PERSPECTIVES IN LAW, BUSINESS & INNOVATION (forthcoming) (manuscript at 9–10), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2831040 [https://perma.cc/ZC3W-3GWV].

345. Slattery, *supra* note 195.

346. Collectively, these two enterprises have approximately 80% of the current market. *See* USPIRG & CDD, *supra* note 75 (asserting that, as of 2015, Lending Club and Prosper were dominating the market for unsecured consumer loans issued by marketplace lenders).

347. Slattery, *supra* note 195, at 265 n.320 (citing Lending Club, Prospectus for Registration Statement No. 333-151827, at 26 (June 6, 2011); Prosper Marketplace, Inc., Prospectus for Registration Statement No. 333-14701, at 25 (May 17, 2011)).

348. *Cf. id.* at 265 ("The CFPB can and should resolve these uncertainties to facilitate innovation, market entry, and compliance, particularly with regard to the Truth in Lending Act, Equal Credit Opportunity Act, and Fair Debt Collection Practices Act.").

innovation will continuously outstrip regulatory capacity, such that the optimal level of regulation may be very low.[349] These commentators sometimes suggest that market discipline and consumer pressure, as occurred in the Prime-lining scandal discussed in the introduction, may result in increased consumer welfare relative to more heavy-handed regulation.[350] But this Author is not yet convinced.

Preventing version 2.0 algorithmic lenders from "systematically disadvantaging certain groups" is an important goal that consumer financial regulators ought to pursue.[351] And there are a number of potential approaches that could mitigate the perilous aspects of algorithmic lending while promoting its promise.[352] For example, just as human decision-makers often receive implicit bias training, it may be possible to offer similar training to credit algorithms.[353] Another promising solution may be to "develop a principle of 'equal opportunity by design'—designing data systems that promote fairness and safeguard against discrimination from the first step of the engineering process and continuing throughout their lifespan."[354]

The analysis in the prior section suggests just how outdated the FCRA is in many ways. "Outdated and ineffectual statutes" cannot adapt to "emerging fact-based changes and innovations."[355] It may also point out the limits of a legislative response to algorithmic lenders. Algorithmic financial services products are rapidly iterating and legislation may be "too clumsy and slow to be effective."[356] While Judge Calabresi suggested that the judiciary is the optimal regulator in such cases, "[t]he comparative institutional disadvantage of courts" in regulating consumer credit markets has been repeatedly noted and "there is substantial consensus that . . . litigation is ill suited to produce the most effective results."[357] The most effective solution may be to use the CFPB's supervisory authority to embed regulators within algorithmic

349. *See, e.g.*, Kidd, *supra* note 28, at 166-67

350. *See supra* text accompanying notes 8–17 (discussing Amazon's Prime-lining practices and consumer demand encouraged Amazon to change its practices).

351. EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 5.

352. The CFPB could work with algorithmic lenders to redesign design their credit-scoring models specifically to "help mitigate discriminatory results over time and increase inclusion." *Id.*

353. *But see* Omer Tene & Jules Polonetsky, *Taming the Golem: Challenges of Ethical Algorithmic Decision Making*, N.C. J.L. AND TECH. (forthcoming 2017), https://ssrn.com/abstract=2981466 [https://perma.cc/PQ8X-NFF5].

354. EXEC. OFFICE OF THE PRESIDENT, *supra* note 18, at 5–6.

355. Kaal, *supra* note 344, at 1, 11.

356. Oren Bar-Gill & Elizabeth Warren, *Making Credit Safer*, 157 U. PA. L. REV. 1, 85 (2008).

357. *Id*. at 75 (citing Lewis A. Kornhauser, *Unconscionability in Standard Forms*, 64 CAL. L. REV. 1151, 1180–81 (1976)).

lenders so the CFPB can gather insights on how to best promote the promise of algorithmic lending while preventing harmful credit discrimination.[358]

And the CFPB may be well-suited to ensuring that algorithmic lenders do not systematically disadvantage society's most vulnerable populations.[359] The CFPB was specifically designed "to make difficult tradeoffs between innovation and safety in a fast-paced industry."[360] As a result, it already has the relevant components in place to encourage lenders to develop discrimination-conscious algorithmic design. "It has a research unit focused on 'market areas of alternative consumer financial products or services with high growth rates' and 'access to fair and affordable credit for traditionally underserved communities.'"[361] It has supervisory authority over many non-bank financial institutions by which it can learn more about innovative algorithmic lenders.[362] And it "has highly flexible powers to issue rules preventing financial service providers from 'committing or engaging in an unfair, deceptive, or abusive act.'"[363] In short, the CFPB can be an "alert, potent, and responsive regulator" for algorithmic lenders that repairs the existing (but flawed) regulatory regime and ferrets out and remedies new problems as they emerge.[364] An actively engaged CFPB will encourage algorithmic lenders—who often hire professionals "from significantly less heavily regulated industries"—to invest in educating their workers and empowering their compliance departments.[365]

Algorithmic lending has the potential to "effectively reduce discrimination and promote fairness and opportunity, including expanding access to credit in low-income communities."[366] Any discussion about the potential

358. This might also help overcome the problem that some scholars have noted, which is that many algorithmic lending models involve proprietary elements. *See, e.g.*, Tutt, *supra* note 20, at 107.

359. The CFPB's primary purpose is consumer protection *See* Slattery, *supra* note 195, at 271–272.

360. Tutt, *supra* note 20, at 118.

361. Slattery, *supra* note 195, at 272.

362. *Id.* ("[I]t can monitor service providers, issue subpoenas, adjudicate some violations, and litigate others.").

363. *Id.*

364. *Id*.

365. Freeman, Jr. et al., *supra* note 19. Of course, this requires an active and engaged CFPB and the Trump administration has seemed generally hostile to the bureau. *See* Paul Barrett, *The Head of the Consumer Financial Protection Bureau Isn't Going Down Without a Fight*, BLOOMBERG (July 20, 2017, 10:00 AM), https://www.bloomberg.com/news/articles/2017-07-20/the-head-of-the-consumer-financial-protection-bureau-isn-t-going-down-without-a-fight [http://perma.cc/NBW9-AYJU] (discussing "unceasing hostility from the Trump administration, Congressional Republicans, and the business lobby" faced by former CFPB head, Richard Cordray).

366. Tene & Polonetsky, *supra* note 353, at 30.

threats of algorithmic lending must consider how algorithmic lending compares to the status quo.[367] And the status quo is generally not good. Regulators have demonstrated their willingness to allow algorithmic lenders to try to improve upon the status quo by, for example, providing algorithmic lenders, such as Upstart, a "no action letter."[368] Such letters are issued as "part of the CFPB's 'Project Catalyst' – an effort to encourage innovation by reducing what many see as substantial regulatory uncertainty facing the financial services industry today."[369] No action letters provide some solace to innovative financial service providers, such as version 2.0 algorithmic lenders, by confirming that the CFPB "'has no present intention to recommend initiation of an enforcement or supervisory action against the requester with respect to' that product."[370]

Algorithmic lending 2.0 is not a panacea. Some consumers are likely to be worse off because of algorithmic lenders' use of Big Data.[371] And we must be attentive to the potential for algorithmic lenders to harm the most vulnerable in our society. But we should continue to generally take a wait and see approach before strictly regulating version 2.0 algorithmic lenders because they may represent an improvement over the traditional approach, which has not protected our society's most vulnerable.

Finally, to the extent that algorithmic lending 2.0 maintains the status quo of unequal credit access, it may merely be highlighting structural inequalities in contemporary American society. These structural inequalities may be best remedied through a much more radical solution than strictly regulating algorithmic lenders. Such solutions might include reparations to

367. *Id.*

368. Willis, *supra* note 119. In addition, one of the first major steps the CFPB took to address issues with algorithmic lenders was simply to accept complaints in its consumer complaint database about algorithmic lenders. *See CFPB Now Accepting Complaints on Consumer Loans from Online Marketplace Lender*, CONSUMER FIN. PROT. BUREAU (Mar. 7, 2016), https://www.consumerfinance.gov/about-us/newsroom/cfpb-now-accepting-complaints-on-consumer-loans-from-online-marketplace-lender/ [https://perma.cc/A9CC-96MF]. This appears to be both an effective information-gathering tool for the CFPB and a shaming device that is a form of soft-touch regulation. *Id.*; *see also* Odinet, *supra* note 75 (studying the CFPB's consumer complaint database).

369. Lindsay L. Raffetto, *CFPB Releases Final Policy on No-Action Letters*, GOODWIN: LENDERLAW WATCH (Feb. 22, 2016), http://www.lenderlawwatch.com/2016/02/22/cfpb-releases-final-policy-on-no-action-letters [https://perma.cc/7EUG-SYL6].

370. *Id.* (quoting Policy on No-Action Letters, 81 Fed. Reg. 8,686 (Feb. 22, 2016)).

371. "We must also recognize that the analysis of massive data sets will not benefit all consumers. Some may see a negative shift in their overall financial profile when additional data is considered. Others may simply not generate enough meaningful data points to enhance the amount of information that can be obtained about their histories and habits." WOLKOWITZ & PARKER, *supra* note 18, at 23; CFPB RFI, *supra* note 27, at 11,186.

try to repair the racial wealth and income gaps,[372] or a universal basic income.[373] Both are interesting ideas deserving of far greater attention than this Article has the space to devote.

372. *See, e.g.*, Ta-Nehisi Coates, *The Case for Reparations*, ATLANTIC (June 2014), https://www.theatlantic.com/magazine/archive/2014/06/the-case-for-reparations/361631/ [https://perma.cc/4VPB-S34E].

373. *See, e.g.*, Leora Klapper, *Can Universal Basic Income Boost Financial Inclusion and Transparency?*, BROOKINGS INST.: FUTURE DEVELOPMENT (June 15, 2017), https://www.brookings.edu/blog/future-development/2017/06/15/can-universal-basic-income-boost-financial-inclusion-and-transparency/ [https://perma.cc/X98R-Y5L8].