FINTECH LENDING AND THE UDAAP AUTHORITY

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INTRODUCTION

In the more than 20 years since IBM's Deep Blue vanquished chess grandmaster and reigning world chess champion, Garry Kasparov, in a pair of best-of-six matches, several major companies have invested vast sums of money to develop additional game-playing, machine-learning algorithms.[1] In 2016, AlphaGo demolished Lee Sedol, a world champion Go player, 4-1 in a series of matches by, among other things, making "a move no human would ever play, stunning experts and

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[1] Murray Campbell et al., *Deep Blue*, 134 ARTIFICIAL INTELLIGENCE 57, 57 (2002) ("Deep Blue is the chess machine that defeated then-reigning World Chess Champion Garry Kasparov in a six-game match in 1997."); Peter Cowling, *Why Tech Giants are Investing Millions in AI that Can Play Video Games*, THE CONVERSATION (Oct. 30, 2017, 5:25 AM), http://theconversation.com/why-tech-giants-are-investing-millions-in-ai-that-can-play-video-games-84151 ("Big firms have been investing vast sums in winning games for more than 20 years, since the triumph of IBM's Deep Blue against the world chess champion, Garry Kasparov.")

fans and utterly wrong-footing world champion Lee Sedol."[2] In 2017, Libratus defeated "four of the top-ranked human Texas Hold'em players in the world over the course of 120,000 hands" during a 20-day poker competition.[3] Other algorithms have also defeated top players in checkers, chess, Scrabble, and *Jeopardy!*.[4]

These companies aren't trying to dominate your family game nights. Instead, they are betting that many of the techniques and strategies used to create world-class game-playing algorithms can be deployed for other purposes as well. In other words, they're looking to create general purpose artificially intelligent (AI) systems.

This article focuses on the use of AI in credit-underwriting determinations. A new breed of lenders are amassing hordes of data (Big Data) and using the machine-learning techniques to improve existing credit-underwriting models. First emerging in 2006, these new lenders are sometimes called marketplace lenders, algorithmic lenders, or fintech lenders.[5] Fintech lenders are

[2] Richard Trenholm, *'AlphaGo': Go Ringside for the Time AI Beat the World's Best*, CNET (Nov. 27, 2017, 2:53 AM), https://www.cnet.com/news/alphago-ringside-ai-greg-kohs-interview-deep-mind-lee-sedol/ ("Thirty-seven moves into one of the most historic games ever played, the machine did something incredible."). There is an interesting movie about this match available on Netflix. See AlphaGo, NETFLIX, available at https://www.netflix.com/title/80190844.

[3] Tonya Riley, *Artificial Intelligence Goes Deep to Beat Humans at Poker*, SCIENCE (Mar. 3, 2017, 2:15 PM), http://www.sciencemag.org/news/2017/03/artificial-intelligence-goes-deep-beat-humans-poker ("In a 20-day poker competition held in Pittsburgh, Libratus bested four of the top-ranked human Texas Hold 'em players in the world over the course of 120,000 hands."); *see also* Cade Metz, *A Mystery AI Just Crushed the Best Human Players at Poker*, WIRED (Jan. 31, 2017, 07:00 AM), https://www.wired.com/2017/01/mystery-ai-just-crushed-best-human-players-poker/.

[4] Metz, *supra* note 3.

[5] *See* Christopher K. Odinet, *Consumer Bitcredit and Fintech Lending*, 69 ALA. L. REV. 781 (2018); see also DELOITTE, A TEMPORARY PHENOMENON?

usually online, nonbank financial companies, and they commonly use nontraditional, tech-centric methods to market themselves to prospective borrowers, evaluate borrower creditworthiness, and to match prospective borrowers with sources of credit.[6] Examples include Lenddo and ZestFinance.[7]

This essay proceeds as follows. First, it briefly explains fintech lending, focusing on its differences from traditional

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 United States, Prosper, was founded in 2006"); 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), available at https://www.apks.com/en/perspectives/publications/2016/1/ftc-report-on-big-data [https://perma.cc/C5UYM4L8] (claiming that "Big Data is quickly becoming a fixture in the consumer lending industry"); Matthew Adam Bruckner, *The Promise and Perils of Algorithmic Lenders' Use of Big Data*, 93 Chi. Kent L. Rev. 3 (2018) (using the term algorithmic lenders as a synonym for fintech lending).

[6] Maria T. Vullo, *Online Lending Report*, New York State Department of Financial Services (July 11, 2018), available at: https://www.dfs.ny.gov/reportpub/online_lending_survey_rpt_07112018.pdf (defining marketplace lending as consisting of entities that "mostly or solely operates online and uses investment capital, automation, data analytics and technology-enabled underwriting models for direct or indirect origination of primarily unsecured loans to consumers and small businesses."); *see also* Alan S. Kaplinsky & James Kim, *NYDFS calls for application of NY usury limits to all online lending and more regulation in online lending report*, Ballard Spahr (July 12, 2018) (commenting (mostly critically) on the New York State Department of Financial Services online lending report).

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

lending. Next, this article argues that fintech lenders are most likely to achieve their promise of democratizing credit access while avoiding illegal credit discrimination if they have an attentive, but patient regulator. Unfortunately, recent statements and actions by interim Consumer Financial Protection Bureau (CFPB) director Mick Mulvaney suggest that the CFPB may prefer to rely more heavily on market forces to limit illegal discrimination than may be optimal.[8] While this approach may encourage further innovation by fintech lenders, it may also disrupt the competitive landscape, and encourage fintech lenders to be less attentive to compliance issues than might ultimately benefit society.

I. THE RISE OF BIG CREDIT DATA

Although the use of algorithms in credit underwriting 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.[9] Although the exact details of the FICO score are a closely guarded secret, a FICO score is an algorithmic output.[10] In other words, a FICO

[8] Jeff Sovern, *Mick Mulvaney Turned the CFPB From a Forceful Consumer Watchdog into a Do-Nothing Government Cog*, THE CONVERSATION (June 29, 2018, 6:35 AM), https://theconversation.com/mick-mulvaney-turned-the-cfpb-from-a-forceful-consumer-watchdog-into-a-do-nothing-government-cog-98842 (noting the decrease in enforcement actions initiated by Mick Mulvaney relative to Richard Cordray).

[9]. 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].

[10]. *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

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.[11]

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 loan with the bank's loan officer[12] and fill out the necessary paperwork.[13] 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.[14] If satisfied, the bank would lend to the prospective borrower. Because such loans are usually unsecured and there is typically no co-signor, these loans are usually

owed; (iii) length of credit history; (iv) new credit; and (v) types of credit used).

11. *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.").

12. Mikella Hurley & Julius Adebayo, *Credit Scoring in the Era of Big Data*, 18 YALE J.L. & TECH. 148, 155 (2016) ("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.").

13. *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].

14. *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").

only made to people who are "very good credit risks or to people with whom the lender has a relationship."[15] 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.[16] These fintech[17] lenders also use algorithms, but have combined algorithmic lending with Big Data. Fintech lenders are usually non-bank financial companies that operate mostly online and use financial technology to market themselves to prospective borrowers, evaluate borrower creditworthiness, and to match prospective borrowers with sources of credit.[18] Another common thread with fintech lenders is the

15. *Id.*

16. *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 REPORT, *supra* note 5 (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 5 (claiming that "Big Data is quickly becoming a fixture in the consumer lending industry").

17. 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).

18. 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]; 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-

"use of non-traditional methods to determine creditworthiness."[19]

Each fintech lender has its own proprietary blend of data and analytics, but it remains possible to generalize somewhat about these companies.[20] Fintech 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 creditworthiness of potential borrowers."[21] In other words, fintech lenders use different inputs and a different process to evaluate prospective

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).

19. 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]; *see also* Freeman, Jr. et al., *supra* note 5 (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").

20. 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").

21. *See* Odinet, *supra* note 5, at 106; *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 &

borrowers than traditional lenders, who typically focus primarily on a borrower's credit score.[22] For example, "Lenddo makes use of more than 12,000 data points gathered from social websites, such as Yahoo, Google, LinkedIn, Twitter and Facebook, to assess a consumer's potential to pay off loans."[23] Other fintech 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."[24]

CDD] (noting that fintech companies still use traditional measures of creditworthiness, such as FICO scores).

22. USPIRG & CDD, *supra* note 21; *see* Request for Information Regarding Use of Alternative Data and Modeling Techniques in the Credit Process, 82 Fed. Reg. 11,183, 11,184 (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] (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 refers to data customarily provided by consumers as part of applications for credit, such as income or length of time in residence.").

23. Bank, *supra* note 19; *see also* USPIRG & CDD, *supra* note 21 (noting that "marketplace lenders are using online data from sources such as Facebook, Google, . . . shopping trends on various websites," and Yelp).

24. TREASURY, *supra* note 16, 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 &

ZestFinance is a prototypical fintech lender. 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."[25] In other words, fintech lenders are expanding the world of credit data (and algorithmic inputs) well beyond that used by traditional lenders.[26] Instead of limiting their use of data to information that has a reasonably clear relationship with creditworthiness, fintech lenders are embracing the unclear correlations that machine-learning systems can uncover in their Big Data troves. For example, fintech lenders are using "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" to evaluate a person's creditworthiness.[27] In short, fintech lenders

PARKER, *supra* note 26, at 12 ("LendUp incorporates borrowers' repayment behavior.").

25. 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].

26. In this regard, their intentions are not much different than traditional lenders. *See* EVA WOLKOWITZ & SARAH PARKER, CTR. FOR FIN. SERVS. INNOVATION, BIG DATA, BIG POTENTIAL: HARNESSING DATA TECHNOLOGY FOR THE UNDERSERVED MARKET 4 (2015), http://www.morganstanley.com/sustainableinvesting/pdf/Big_Data_Big_Potential.pdf [https://perma.cc/9WY8-WZMG] ("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.").

27. 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]; *see also* Rachel O'Dwyer, *Are You Creditworthy? The Algorithm Will Decide*, UNDARK

are collecting every byte of data they can to feed into their credit-scoring algorithms.

In addition to their expansive use of Big Data, fintech lenders also use machine-learning algorithms to make credit decisions. A learning algorithm is an algorithm that learns to make creditworthiness determinations, largely on its own.[28] Instead of human programmers deciding which data points are correlated with creditworthiness and how much weight to give each "feature," a learning algorithm is usually given a set of data on which to train itself.[29] From the data given to it by programmers, the algorithm decides which features are relevant and how to weigh them.[30] In other words, learning algorithms are

(May 7, 2018), available at https://undark.org/article/algorithmic-credit-scoring-machine-learning/ (noting that Branch, a fintech lender operating in Sub-Saharan Africa may use "text message logs, social media data, financial data, and handset details including make, model, and browser type" to assess a prospective borrower's creditworthiness.)

28. As contrasted with algorithms that are programmed by engineers. *See, for example*, Andrew Tutt, *An FDA for Algorithms*, 69 ADMIN. L. REV. 83, 94 (2017) (discussing Deep Blue's programming).

29. Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87, 93 (2014) ("[M]achine learning algorithms are able to automatically build accurate models of some phenomenon ... without being explicitly programmed."); *see* Hurley & Adebayo, *supra* note 12, at 181 ("ZestFinance may rely on statistical algorithms to automatically identify the most significant metavariables.").

30. 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* 29, at 93. This is not true in every case. In some cases, programmers may continue to manually curate some features of learning algorithms. *See* David Lehr and Paul Ohm, *Playing with the Data: What Legal Scholars Should Learn About Machine Learning*, 51 U.C. DAVIS L. REV. 653, 664 (2017) (describing "the very nature of machine learning" as being "one that takes the human element largely out of

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.[31] In addition, learning algorithms are dynamic rather than static.[32] A learning algorithmic is constantly updating the relevance and salience of various features.

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.[33] The algorithm may then mine this data to identify variables that correlate with loan repayment and assign appropriate weights to these variables.[34] If it's been programmed well and the training data is good, the variables and weights the algorithm identifies

embedding correlations and inferences in an algorithm.").

31. *See* Bennie Mols, *In Black Box Algorithms We Trust (or Do We?)*, ACM News (Mar. 16, 2017), available at: https://cacm.acm.org/news/214618-in-black-box-algorithms-we-trust-or-do-we/fulltext; *see also* Lehr and Ohm, *supra* note 30, at 657 (complicating the view of algorithms as black boxes by suggesting various ways to peer inside of algorithmic black boxes, and also by suggesting that observable data inputs are often more important than less observable data analysis).

32. Jane Bambauer and Tal Zarsky, *The Algorithm Game*, NOTRE DAME L. REV. (forthcoming 2018).

33. *Cf.* Michael Feldman et al., *Certifying and Removing Disparate Impact*, 21 ACM SIGKDD INT'L CONF. ON KNOWLEDGE DISCOVERY & DATA MINING 259 (2015) (explaining how data mining works, as trying to find "the best set of decision rules among a large set of candidate rules").

34. *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.").

should be useful for determining the creditworthiness of prospective borrowers as well.[35] 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 train itself to predict the likelihood that future borrowers will repay their loans.

II. THE PROMISE AND PERIL OF ALGORITHMIC LENDING

Fintech lenders may produce significant benefits for consumers relative to traditional lenders. 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."[36] Most notably, fintech lenders promise to increase credit access by identifying people who are good credit risks using non-traditional lending criteria. 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.[37]

35. *Cf. id.*

36. EXEC. OFFICE OF THE PRESIDENT, BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS 4 (2016), https://obamawhitehouse.archives.gov/sites/default/files/microsites/ostp/2016_0504_data_discrimination.pdf [https://perma.cc/4JNR-LDNS]; *see also* Dennis D. Hirsch, *That's Unfair! Or Is It? Big Data, Discrimination and the FTC's Unfairness Authority*, 103 U. KY. L. REV. 345, 362 (2014). The new administration's position is currently unknown.

37. NAT'L CONSUMER LAW CTR., BIG DATA: A BIG DISAPPOINTMENT FOR SCORING CONSUMER CREDIT RISK 12 (2014), https://www.nclc.org/images/pdf/pr-reports/report-big-data.pdf [https://perma.cc/EG78-TLY8] [hereinafter, NCLC, BIG DISAPPOINTMENT]; 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-

But fintech lending is not a panacea. As the Obama White House declared in its Big Data report, the challenge is "to support growth in the beneficial use of [B]ig [D]ata while ensuring that it does not create unintended discriminatory consequences."[38] And 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 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."[39] 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-

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).

38. EXEC. OFFICE OF THE PRESIDENT, *supra* note 36, at 4; *see also* Hirsch, *supra* note 36, at 346.

39. EXEC. OFFICE OF THE PRESIDENT, *supra* note 36, 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 30, 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").

identifying names with suggestions that a person has been arrested than it does with white-identifying names.[40] This is true "regardless of whether the company placing the ad reveals an arrest record associated with the name."[41] 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.[42] Ultimately, the study simply noted that racial bias exists in this space, but was unable to explain why.[43]

Although fintech lenders' use of Big Data promises to predict the creditworthiness of those who were previously credit invisible, the use of certain data points may also allow for illegal discrimination. For example, fintech 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, "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."[44]

Similarly, Big Data can be used to compare a prospective borrower's shopping patterns to those of previous borrowers.

40. 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").

41. *Id.* at 4.

42. *Id.* at 8, 13.

43. *Id.* at 14.

44. 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].

And 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 [had] a poor repayment history with American Express.'"[45] 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.[46]

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.[47] Some simple proxies for race include zip

45. NCLC, BIG DISAPPOINTMENT, *supra* note 37, at 27–28.

46. "Big Data can lead to decision-making based on the actions of others with whom consumers share some characteristics." FTC REPORT, *supra* note 24, 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* Danielle Keats Citron & Frank A. Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 4 (2014).

47. *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).

code, surname, and college attendance data.[48] 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.[49] And yet the CFPB provided Upstart, a fintech lender, with a "no action" letter confirming that the CFPB 'has no present intention to recommend initiation of an enforcement or supervisory action against" Upstart, despite the company's use of college attendance data in its underwriting decisions.[50]

There is no simple way to avoid the problem that fintech 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

48. *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 30, at 682 (discussing the use of attendance at HBCUs as a proxy for race).

49. Barocas & Selbst, *supra* note 30, 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* 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].

50. Lindsay L. Raffetto, *CFPB Releases Final Policy on No-Action Letters*, GOODWIN: LENDERLAW WATCH (Feb. 22, 2016), http://www.lenderlaw-watch.com/2016/02/22/cfpb-releases-final-policy-on-no-action-letters [https://perma.cc/7EUG-SYL6] (quoting Policy on No-Action Letters, 81 Fed. Reg. 8,686 (Feb. 22, 2016)); Willis, *supra* note 49 (noting that Upstart, a fintech lender, uses "the identity of the college attended by the applicant" in its underwriting process).

that, absent affirmative interventions, fintech lending will perpetuate bias.[51]

III. THE REGULATORY REGIME AND ITS ISSUES

The examples in this Article are meant to highlight the many reasons to be concerned about fintech lenders' use of Big Data, particularly the concerns about its potentially discriminatory effects on prospective borrowers. Perhaps consumer protection statutes are the answer. 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."[52] This section will discuss one such law and evaluate the likelihood that it is effective in reducing the threats and promoting the promise of fintech lending.

Many consumer protection agencies have been paying close attention to fintech lenders, with several issuing targeted warnings.[53] For example, former "CFPB director, Richard

51. Barocas & Selbst, *supra* note 30, at 671.

52. 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 18 (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 5.

53. 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 22, at 11,185–86; TREASURY, *supra* note 16, at 1; Angela M. Herrboldt, *Marketplace Lending*, SUPERVISORY INSIGHTS (Fed. Deposit Ins. Corp., Washington, D.C.), Winter 2015, at 12,

Cordray, warned that '[a]ll lenders, from startups to large banks, must follow consumer protection laws.'"[54] The Federal Trade Commission (FTC) has been notably active. It recently held a series of forums on fintech lending, where Equal Credit Opportunity Act (ECOA) and Fair Credit Reporting Act (FCRA) issues were repeatedly raised.[55] 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.[56]

In the subsection that follows, this Article will focus on the application of a single law, the CFPB's Unfair, Deceptive, and

https://www.fdic.gov/regulations/examinations/supervisory/insights/siwin15/si_winter2015.pdf [https://perma.cc/3GF2-MUCN]; FTC REPORT, *supra* note 24.

54. Lazarev, *supra* note 16.

55. 15 U.S.C. § 1691 (2015) (ECOA); 15 U.S.C. § 1681 (2015) (FCRA); *see also* Tunstall & Caplan, *supra* note 20.

56. 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) 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).

Abusive Acts or Practices (UDAAP) authority, to fintech lending, and consider whether this statute helps protect against the most perilous aspects of fintech lending and whether they help fintech lenders fulfill their promise.[57] Although Dodd-Frank consolidated a great deal of consumer financial regulatory supervision in the CFPB, it also provided for concurrent enforcement of UDAAP by State Attorneys General.[58] As the CFPB has signaled its desire to pull back from vigorously protecting consumers through enforcement actions,[59] this "dual-enforcement system provide[s] an additional layer of enforcement".[60]

A. UDAAP

The CFPB, the FTC, and State Attorneys General (collectively, the "UDAAP Regulators") are empowered to police fintech lenders using their UDAAP[61] powers.[62] Through its UDAAP authority, each UDAAP Regulator can act to prohibit

57. The FTC's enforcement of its UDAP power will also be discussed.

58. Mark Totten, *Credit Reform and the States: The Vital Role of Attorneys General After Dodd–Frank*, 99 IOWA L. REV. 115, 168 (2013) (discussing the "implications of the Dodd–Frank dual-enforcement scheme"). And the FTC has authority to supervise unfair or deceptive acts and practices.

59. Sovern, *supra* note 8.

60. Totten, *supra* note 58, at 168-69.

61. The FTC does not have the power to prohibit abusive acts or practices.

62. Not all bank-affiliated lending models are likely to fall within the CFPB's jurisdiction. *See* 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, 264 (2013) (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."

unfair, deceptive, or abusive acts or practices.[63] 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 fintech lending's promise or creates additional perils.

1. Preventing Unfair Acts or Practices

Fintech lenders may incur liability for engaging in unfair acts or practices.[64] 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."[65] In other words, there are three elements to establishing

63. 12 U.S.C. § 5531 (2010); *see also* Hirsch, *supra* note 36, at 346; Slattery, *supra* note 62, 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.").

64. 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 46, at 23 (emphasis added); *see also* Kagan et al., *supra* note 39.

65. 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

that an act or practice is unfair.[66] Each element requires "detailed, fact-specific analysis."[67] The purpose of prohibiting unfair acts or practices is "to protect consumer sovereignty by attacking practices that impede consumers' ability to make informed choices."[68]

While some commentators have suggested that the power to prevent unfair acts or practices is sufficient to effectively police Big Data users, it's not clear that this is true.[69] To establish that an act or practice is unfair, a UDAAP Regulator must first prove that the fintech lender's act or practice causes a substantial injury.[70] Substantial injury means any sort of non-speculative and non-trivial harm.[71] Professor Dennis D. Hirsch asserts that because fintech lending can cause "diminished access to . . .

[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 46, 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.").

66. Beales, *supra* note 65.

67. *Id.*

68. *Id.*

69. Hirsch, *supra* note 36, 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").

70. *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.").

71. Hirsch, *supra* note 36, 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.*

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."[72]

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.[73] For example, assume that a fintech 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.[74] If "diminished access" to credit is measured by comparing the decisions of fintech 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.[75] And there is a sound policy justification for

72. *Id.*

73. *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").

74. A borrower that is granted credit by a traditional lender but denied credit by a fintech lender may also suffer substantial injury, but is unlikely to be able to establish the 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.*

75. Alternatively, if fintech 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.

adopting traditional lenders' underwriting standards as the appropriate baseline; it could encourage fintech lenders to focus on expanding credit opportunities for sub-prime borrowers, which would seem to promote the promise of fintech lending.[76]

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 a fintech 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 fintech 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 fintech lender's bias data.[77]

[76] This does not accord with the practices of many fintech lenders, who have mostly targeted prime and near prime borrowers. *See* TREASURY, *supra* note 16, at 13 (noting that 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."); *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%)"); NCLC, BIG DISAPPOINTMENT, *supra* note 37, 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). *But see* WOLKOWITZ & PARKER, *supra* note 26; Jagtiani & Lemieux, *supra* note 37, at 14.

[77] *See* Bruckner, *supra* note 5, at 55 (discussing the thousands of data points consumers must review to understand whether inaccurate information is being used); *supra* text accompanying notes 34–35 (discussing how learning algorithms mine data to determine the appropriate variables to con-

Consumers may be unable to reasonably avoid being substantially injured by fintech lenders—the second unfairness element—because of the opaque nature of some credit algorithms.[78] Professor Hirsch asserts that consumer injury is not reasonably avoidable because few consumers understand how fintech lending works and how to protect themselves.[79] Hirsch is likely correct that some (or even many) consumers do not understand how fintech lending works and, therefore, how to protect themselves because many learning algorithms are thought to be quite opaque.[80] That is, no one can explain to humans why some credit algorithms makes the decisions they

sider when making decisions); *see also id.*, at 17 (discussing how learning algorithms mine data to determine the appropriate variables to consider when making decisions).

78. *Cf.* NAT'L CONSUMER LAW CTR., *supra* note 70, at § 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").

79. Hirsch, *supra* note 36, 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 70, at §§ 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).

80. 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.

do.[81] Not even the companies themselves. For example, the CEO of Affirm, a lending start-up from the founders of PayPal, admitted that he could not explain why the company makes particular loans.[82] He said, "I wouldn't know. Our math model says 'OK. Probabilistically, [the borrower's] good for the money.'"[83] Presumably the reverse is also true, that the model indicates that probabilistically, a prospective borrower is not "good for the money."[84] 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.[85]

81. Scherer, *supra* note 80, 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 34, 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.").

82. Frank Pasquale, *Bittersweet Mysteries of Machine Learning (A Provocation)*, LONDON SCH. ECONS. POLITICAL SCI.: MEDIA POLICY PROJECT BLOG (Feb. 5, 2016), http://blogs.lse.ac.uk/mediapolicyproject/2016/02/05/bittersweet-mysteries-of-machine-learning-a-provocation/ [https://perma.cc/KWD9-JMMR] [hereinafter Pasquale, *Mysteries*]; 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 26, 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").

83. Pasquale, *Mysteries*, *supra* note 82.

84. *Id.*

85. Slattery, *supra* note 62, at 269 ("[I]t is not clear that any entity could provide specific reasons for adverse credit decisions on P2P lending platforms").

However, recent evidence suggests that opacity is not as inherent to learning algorithms as previously thought.[86] As noted above, ZestFinance claims to have created a more transparent credit-scoring algorithm.[87] If true, borrowers could take steps to protect themselves, making consumer injury reasonably avoidable and defeating an unfair act or practice claim.[88] Moreover, for prospective borrowers who could obtain traditional forms of credit but are denied credit by a fintech lender, that borrower could avoid injury by borrowing from the traditional lender.[89]

Both because ZestFinance claims to have achieved algorithmic transparency, and also because of "a growing consensus among scholars" that through transparency (i.e., access to source code, access to inputs, etc.), algorithmic outputs may be adequately policed, I don't think that Hirsch's negative view is necessarily warranted.[90] It may well be that fintech lenders can

[86] Andrew Selbst and Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. (forthcoming 2018), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3126971 (arguing that the problem with some learning algorithms "is not a lack of transparency, technical expertise, or inscrutability, but an inability to weave a sensible story to account for the statistical relationships in the model.")

[87] *See* Bruckner, *supra* note 5, at 40.

[88] 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.

[89] 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).

[90] *See, e.g.*, Tutt, *supra* note 28, at 110 ("There appears to be a growing consensus among scholars that the ability to require transparency should be

adequately explain the reasons they deny credit to borrowers.[91] Or that the UDAAP Regulators' invocation of their unfairness authority may incentivize other fintech lenders to design less opaque algorithms.[92] Other possibilities for creating algorithmic transparency—if technically feasible[93]—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."[94]

Finally, the effectiveness of fintech 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

one of the first tools used to regulate algorithmic safety. Transparency can take many forms and can range from feather-light to brick-heavy.").

91. *But see* Selbst & Barocas, *supra* note 86 (arguing that algorithmic decisions may be explainable in some sense, but that the explanation may be difficult to make sense of and, therefore, to act on).

92. *Id.*

93. "[O]ur inability to understand, explain, or predict algorithmic errors is not only unsurprising, but destined to become commonplace." Tutt, *supra* note 28, 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.")

94. Scherer, *supra* note 80, at 374.

benefits to consumers or to competition."[95] In other words, a UDAAP Regulator must generally balance "the costs that the activity imposes on consumers against the benefits it creates for consumers and for business."[96] As Professor Hirsch notes, it's hard to know how this factor comes out.[97] On the one hand, fintech lending models can decrease costs, creating competition with traditional lenders and—in a competitive market—benefitting consumers.[98] It can also increase credit access, which is critically important for participating in our modern economy. On the other hand, static algorithms and poorly designed or trained learning algorithms can disparately impact some of the most vulnerable members of our society. Even if fintech 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 UDAAP Regulator would balance access and equity. This is likely to be deeply fact-dependent.

2. Deceptive Acts or Practices

The UDAAP Regulators' deceptiveness authority is unlikely to play a significant role in promoting the promise of fintech 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.,

95. 15 U.S.C. § 45(n) (2012); *see also* NAT'L CONSUMER LAW CTR., *supra* note 70, at § 4.3.2.4.

96. Hirsch, *supra* note 36, at 355.

97. *Id.* at 355–57.

98. 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).

a prominent online payment provider, . . . allegedly misrepresent[ed] its data security practices as 'safe,' 'secure,' 'safer [than credit cards],' and 'exceeding industry standards.'"[99] 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."[100] 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."[101]

These enforcement actions suggest that UDAAP 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.[102] This is unlikely to increase the predictive accuracy of credit-scoring algorithms, will certainly not decrease costs, nor remove human bias from the credit-scoring process.[103] But it does empower UDAAP Regulators to curtail predatory lending practices by fintech lenders,

99. Lazarev, *supra* note 16.

100. *See also* Kagan et al., *supra* note 39.

101. Tunstall & Caplan, *supra* note 20 ("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))).

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

103. 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 39.

should they engage in such practices. 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, fintech lenders may be subject to liability for engaging in abusive acts or practices. The CFPB and State Attorneys General have 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."[104] This authority is also intended to protect 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."[105] 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."[106] The CFPB virtually always asserts its "abusive" authority alongside claims of an unfair or deceptive act or practice. Essentially, the CFPB's "abusive"

104. 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.

105. *Id.* § 5531(d)(2).

106. 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].

power has lacked its own independent bite, with Professor Adam Levitin describing it as "the dog that didn't bark."[107]

Despite their novelty in some ways, fintech lenders offer somewhat plain vanilla loan products that generally mirror what's available from traditional lenders.[108] 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.[109] To the extent they are, however, greater transparency by fintech lenders would appear to mitigate some of this risk. But, to the extent that fintech lenders use their credit-scoring models to engage in predatory lending practices, the CFPB should use its "abusiveness" authority to curtail those practices.

107. 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 [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.'").

108. Vullo, *supra* note 6 ("Online lending is just a delivery channel for products that have existed for many years and have been offered by a variety of financial institutions for many years.")

109. 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); *but see* Vullo, *supra* note 6 (expressing concern that some fintech lenders do not "provide borrowers with standardized and understandable information regarding their loans, including the pricing of the loans.").

In summary, UDAAP Regulators may be able to push fintech lenders towards greater transparency through the selective use of their UDAAP authority. And they should be able to prohibit predatory lending with these powers. I would be concerned, however, about using either the UDAAP Regulators' unfairness or abusive authority to punish fintech lenders for using somewhat opaque credit-scoring algorithms absent clear consumer injury. Fintech lenders appear to be moving to create more transparent credit-scoring algorithms and UDAAP Regulators should encourage this trend. They should use the flexibility built into the UDAAP standards to enjoin novel forms of bad business practices while allowing fintech lenders the time to iterate and improve.[110]

IMPLICATIONS

Preventing fintech lenders from "systematically disadvantaging certain groups" is an important goal that consumer financial regulators ought to pursue.[111] And UDAAP authority is an important stick for regulators to use to encourage fintech lenders to avoid illegal discrimination. Although the CFPB is well-suited to ensuring that fintech lenders do not systematically disadvantage society's most vulnerable populations,[112] there have been numerous indications recently that the CFPB

110. 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.").

111. EXEC. OFFICE OF THE PRESIDENT, *supra* note 36, at 5.

112. The CFPB's primary purpose is consumer protection *See* Slattery, *supra* note 62, at 271–272.

will not vigorously enforce the nation's consumer protection laws.[113]

This is unfortunate. The CFPB was specifically designed "to make difficult tradeoffs between innovation and safety in a fast-paced industry."[114] As a result, it already has the relevant components in place to encourage fintech 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.'"[115] It has supervisory authority over many non-bank financial institutions by which it can learn more about innovative fintech lenders.[116] And it "has highly flexible powers to issue rules preventing financial service providers from 'committing or engaging in an unfair, deceptive, or abusive act.'"[117] In short, the CFPB can be an "alert, potent, and responsive regulator" for fintech lenders.[118] An actively engaged CFPB could encourage fintech lenders—who often hire professionals "from significantly less heavily regulated industries"—to invest in educating their workers and empowering their compliance departments.[119]

113. *See* Sovern, *supra* note 8.

114. Tutt, *supra* note 28, at 118.

115. Slattery, *supra* note 62, at 272.

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

117. *Id.*

118. *Id.*

119. Freeman, Jr. et al., *supra* note 5. 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-with-

It is important that the fintech lending not be overregulated because fintech lending has the potential to do better than traditional lenders in "promot[ing] fairness and opportunity, including expanding access to credit in low-income communities."[120] But fintech lending is not a panacea. Some consumers are likely to be worse off because of fintech lenders' use of Big Data.[121] Thus, we need a regulator who will be attentive to the potential for fintech lenders to harm the most vulnerable in our society.

Thankfully, even if the CFPB continues to decline bringing enforcement actions, others can fill its shoes. For example, the New York State Department of Financial Services (DFS) has recently issued a report calling for the increased regulation of fintech lenders who loan money to consumers and small businesses residing in New York State.[122] Among other conclusions, the DFS has promised to seek to ensure that consumer protection laws are applied equally to all lenders operating in New York State, and that New York's usury limits are enforced.[123] For those who believe that regulation is often important to ensuring the smooth functioning of markets, this is a welcome sign.

out-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).

120. Omer Tene & Jules Polonetsky, *Taming the Golem: Challenges of Ethical Algorithmic Decision Making*, 19 N.C. J.L. AND TECH. 125, 164 (2017).

121. "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 26, at 23; CFPB RFI, *supra* note 22, at 11,186.

122. Vullo, *supra* note 6.

123. *Id*.