FIGHTING UNFAIR CLASSIFICATIONS IN CREDIT REPORTING: SHOULD THE UNITED STATES ADOPT GDPR-INSPIRED RIGHTS IN REGULATING CONSUMER CREDIT?

Vlad A. Hertza*

Access to consumer credit is essential to accumulate wealth. The use of big data and machine learning in assessing creditworthiness can be a great opportunity to generate more accurate credit reports and improve access to credit. However, so far, lenders have used big data and machine learning to generate profits, developing algorithms that unfairly classify consumers. Racial and other protected minorities are disproportionately affected by these practices. Consumer credit is regulated in the U.S. mainly under the Fair Credit Reporting Act (FCRA) and the Equal Credit Opportunities Act (ECOA). These statutes are inadequate to regulate lenders, credit reporting agencies (CRAs), and data brokers which use big data and machine-learning algorithms to assess consumers' creditworthiness. Noticing recent international developments, this Note proposes the General Data Protection Regulation (GDPR), an industry-agnostic data privacy law passed by the European Union (EU), as a model for consumer credit reform. Concretely, the Note proposes expanding consumer credit regulation from CRAs to all actors involved in the processing of consumer data, as well as granting consumers the right to access their data, have it corrected, moved to a different processor, or erased. Furthermore, these rights should be backed by the recognition of a property-like interest in personal data. Part I describes the prevailing use of big data and machine learning in consumer credit, exposing some of the major issues of the consumer credit industry. The Part ends with an overview of the current regulatory regime. Part II explores how the use of big data and machine learning erodes consumer protections, showing how the current regulatory regime fails to adequately protect consumers. Part III introduces the GDPR, an industry agnostic data protec-

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tion regulation adopted by the European Union, as a model for reforming consumer credit regulation in the United States. The Part proposes three ways in which the GDPR can improve the FCRA and the ECOA, and addresses a number of potential counterarguments.

Introduction

Shortly after the global financial collapse of 2008, Kevin Johnson received notice from American Express that his credit limit was being cut from $10,800 to $3800.[1] In the letter, American Express stated that it cut Johnson's credit limit because he "had been shopping at stores frequented by people . . . hav[ing] a poor repayment history."[2] Kevin Johnson is an African American man who, at the time, was working as a media entrepreneur in Atlanta, Georgia[3] and had a solid FICO score of 760.[4]

The FICO credit-scoring model is used by virtually all banks in the United States to determine a consumer's creditworthiness.[5] A FICO score is a number used to predict the likelihood a consumer will default on her or his loan payments,[6] but there is no single FICO score.[7] Credit reporting agencies (CRAs)—the largest of which are Equifax, Experian, and TransUnion[8]—all come up with different FICO scores based on variations in their proprietary algorithms and the information they feed to their models.[9] The models traditionally rely on consumers' financial information including their bill-payment history, current unpaid debts, the number and type of loan accounts they have, the length the accounts have been open, the amount of available credit consumers have used, and new applications for credit, as well as other public information such as debt sent to collection, foreclosures, or bankruptcies.[10]

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1 Tracy Alloway, *Big Data: Credit Where Credit's Due*, FIN. TIMES (Feb. 15, 2015), https://www.ft.com/content/7933792e-a2e6-11e4-9c06-00144feab7de.

2 *Id.*

3 *Id.*

4 *Id.*

5 *See* ROBINSON & YU, KNOWING THE SCORE: NEW DATA, UNDERWRITING, AND MARKETING IN THE CONSUMER CREDIT MARKETPLACE 27 (Oct. 29, 2014), https://www.teamupturn.com/static/files/Knowing_the_Score_Oct_2014_v1_1.pdf (outlining the history of the consumer credit industry).

6 *What Is a FICO Score?*, CFPB, https://www.consumerfinance.gov/askcfpb/1883/what-is-fico-score.html (last updated June 13, 2016).

7 *See id.*

8 CONSUMER FIN. PROT. BUREAU, ANALYSIS OF DIFFERENCE BETWEEN CONSUMER- AND CREDITOR-PURCHASED CREDIT SCORES 7 (Sept. 2012) [hereinafter CFPB 2012], https://files.consumerfinance.gov/f/201209_Analysis_Differences_Consumer_Credit.pdf; *see also* USA.GOV, *Credit Reports and Scores*, https://www.usa.gov/credit-reports (last updated Sept. 10, 2018).

9 *See What Is a FICO Score?*, *supra* note 6; *see also* CATHY O'NEIL, WEAPONS OF MATH DESTRUCTION 142 (2016). CRAs "compile and sell consumer reports, which contain consumer information that is used or expected to be used for credit, employment, insurance, housing, or other similar decisions about consumers' eligibility for certain benefits and transactions." FED. TRADE COMM'N, BIG DATA: A TOOL FOR INCLUSION OR EXCLUSION? UNDERSTANDING THE ISSUES ii (2016) [hereinafter FTC REPORT], https://www.ftc.gov/system/files/documents/reports/big-data-tool-inclusion-or-exclusion-under standing-issues/160106big-data-rpt.pdf.

10 *What Is a Credit Score?*, CFPB, https://www.consumerfinance.gov/askcfpb/315/what-is-a-credit-score.html (last updated June 13, 2016).

There are several issues with this credit-scoring system, however. The data used in credit-scoring models has diversified and grown over time, as lenders can currently collect considerably more information through data brokers or by tracking consumers' online browsing and social media information.[11]

Furthermore, a large percentage of credit scores nationwide contain inaccuracies.[12] However, it is very difficult—if not impossible—to correct the information. For example, it took Patricia Armour, a seventy-three-year-old woman living in Olive Branch, Mississippi, more than two years to have her Experian credit record corrected.[13] The CRA incorrectly categorized a $40,000 mortgage discharged in bankruptcy as unpaid debt.[14] Despite sending relevant documentation showing that the credit report was inaccurate, Experian did not acknowledge the mistake.[15] They only corrected the report after Armour reached out to the state's attorney general and threatened legal action.[16]

Finally, companies have developed alternative models for assessing creditworthiness that can easily elude Fair Credit Reporting Act (FCRA) regulation.[17] For example, the FCRA applies only to information that pertains to an individual, but big data companies can

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[11] Data brokers are companies that collect and sell big data. *See* Alloway, *supra* note 1; *infra* Part II. Big data is defined here as "datasets that are too large for traditional data-processing systems and that therefore require new technologies." Foster Provost & Tom Fawcett, *Data Science and Its Relationship to Big Data and Data-Driven Decision Making*, 1 BIG DATA 51, 54 (2013), https://www.liebertpub.com/doi/pdf/10.1089/big.2013.1508. Artificial intelligence is used here as a computer system's ability to "imitate intelligent human behavior." Bernard Marr, *The Key Definitions of Artificial Intelligence (AI) That Explain Its Importance*, FORBES (Feb. 14, 2018, 1:27 AM), https://www.forbes.com/sites/bernardmarr/2018/02/14/the-key-definitions-of-artificial-intelligence-ai-that-explain-its-importance/ (discussing the various definitions of AI). For one definition of machine learning, see Ron Kohavi & Foster Provost, *Glossary of Terms: Special Issue on Applications of Machine Learning and the Knowledge Discovery Process*, http://robotics.stanford.edu/~ronnyk/glossary.html (last visited Sept. 29, 2018) (defining machine learning as "the application of induction algorithms"). For simplicity, the terms AI and "machine learning"—one of the best-known applications of AI and a tool used to train intelligent machines—are used interchangeably here.

[12] *See, e.g.*, Carolyn Carter et al., *The Credit Card Market and Regulation: In Need of Repair*, 10 N.C. BANKING INST. 23, 24, 41 (2006) (describing abusive credit card practices in the credit card industry and study results finding numerous inaccuracies in credit reports).

[13] Gretchen Morgenson, *Held Captive by Flawed Credit Reports*, N.Y. TIMES (June 21, 2014), https://www.nytimes.com/2014/06/22/business/held-captive-by-flawed-credit-reports.html.

[14] *Id.*

[15] *Id.*

[16] *Id.*

[17] *See infra* Section II.B.

generate household or device-centered reports.[18] These scoring algorithms are not based on the FICO model and raise additional concerns about the use of big data in the consumer credit industry.[19] FICO scoring requires financial information on the consumers, but almost one in five Americans has too little information for CRAs to score them.[20] Lack of a FICO score effectively precludes a person from accessing credit.[21] The unscored must seek credit from lenders using alternative scoring systems.[22] These alternative lenders have eagerly adopted new technologies to take in much more information than traditional scoring models, including "zip codes and Internet[sic] surfing patterns."[23] There is evidence that these e-scores (or alt-scores; scores that are not based on the FICO model) are "arbitrary, unaccountable, unregulated, and often unfair,"[24] and some of the more complex algorithms may be unexplainable.[25] The companies that design these algorithms likely fall outside CRA regulations, leaving consumers with little recourse when they are wronged.

This paper proposes for the first time a number of possible solutions inspired by the EU's General Data Protection Regulation (GDPR), which fully entered into force on May 25, 2018.[26] This new piece of regulation could significantly restrict and regulate the collection and usage of data, as well as broaden individuals' rights over pri-

[18] *See* Julius Adebayo & Mikella Hurley, *Credit Scoring in the Era of Big Data*, 18 YALE J.L. & TECH. 148, 185–87 (2016) (discussing, inter alia, issues related to the narrow definitions of CRAs and credit reports, that easily permit alternative credit scorers to elude regulation).

[19] *See* O'NEIL, *supra* note 9, at 143 (explaining the evolution of credit scores and how new data and technologies play a large part in computing credit scores now).

[20] KENNETH P. BREVOORT, PHILIPP GRIMM & MICHELLE KAMBARA, CONSUMER FIN. PROT. BUREAU OFFICE OF RESEARCH, DATA POINT: CREDIT INVISIBLES 4 (2015) (assessing the number of Americans that have no credit score and as a result have no access to consumer credit).

[21] *See* MIRIAM SEGAL, OFFICE OF ADVOCACY, U.S. SMALL BUS. ADMIN., WHAT IS ALTERNATIVE FINANCE? 1 (2016), https://www.sba.gov/sites/default/files/advocacy/What-Is-Alt-Fi.pdf (studying the alternative financing industry and novel ways used to assess creditworthiness).

[22] *See generally id.* (listing alternative sources of financing for consumers and how alternative lenders assess creditworthiness).

[23] O'NEIL, *supra* note 9, at 143.

[24] *See id.*

[25] Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. 671, 674 (2016) (describing the possible inscrutability of complex algorithms for which coders and people operating the systems may not be able to tell how or why a particular determination was derived).

[26] *See infra* Part III. The GDPR entered into force in May 2018 throughout the EU. Regulation 2016/679, of the European Parliament and of the Council of 27 Apr. 2016 on the Protection of Natural Persons with Regard to the Processing of Personal Data and on the Free Movement of Such Data, and Repealing Directive 95/46/EC (General Data Protection Regulation), art. 99, 2016 O.J. (L 119) 1, 87 (EU) [hereinafter GDPR].

vate data. Unlike data protection regulations in the United States that are tailored to specific industries and/or types of data,[27] the GDPR applies to all data collection and processing that impacts citizens of the European Union. The new regulation is ambitious not only because it tries to force a broad range of internet and cloud computing-centric businesses to introduce sweeping consumer data protections, but also because it recognizes an individual's robust property interest in her or his data.

This paper acknowledges that there is no easy fix for the multiple issues big data and machine-learning algorithms raise in consumer credit reporting. Nonetheless, it argues that the GDPR constitutes a valid source of inspiration for potential future reforms. Part I exposes some of the major issues of the consumer credit industry and describes the prevailing use of big data and machine learning in consumer credit. Part II describes the current regulatory regime protecting consumers' interests through the FCRA and the ECOA statutes and briefly describes how the increasing use of big data and machine learning in credit-scoring systems is further eroding consumer protections. Part III introduces the GDPR's main consumer protection provisions and discusses how they could improve the effectiveness of the FCRA and the ECOA.

I
THE PREVAILING USE OF BIG DATA AND MACHINE LEARNING IN CREDIT REPORTING

Big data and machine learning could improve access to consumer credit, however, these technologies could also allow biases to seep into credit-scoring tools.[28] Millions of Americans do not have access to "fairly-priced and affordable credit" partly because they do not have a valid FICO score.[29] People with low incomes are disproportionately "credit invisible" or unscorable because they have too little

[27] *E.g.*, Children's Online Privacy Protection Act (COPPA), Pub. L. No. 105-277, tit. XIII (1998) (regulating the online collection of data of children under thirteen); Health Insurance Portability and Accountability Act of 1996 (HIPAA), Pub. L. No. 104-191, 110 Stat. 1936 (1996) (protecting, inter alia, health care-related patient information); Fair Credit Reporting Act (FCRA), Pub. L. No. 91-508, tit. VI, 84 Stat. 1127 (1970) (ensuring fair and accurate credit reports, and protecting consumer access to their credit scores).

[28] *See* EXEC. OFFICE OF THE PRESIDENT, BIG DATA: A REPORT ON ALGORITHMIC SYSTEMS, OPPORTUNITY, AND CIVIL RIGHTS 4 (2016) (describing the important economic opportunities that big data and machine learning offer while flagging the social challenges these technologies raise).

[29] *Id.* at 11.

credit repayment information for CRAs to derive a score from.[30] Racial minorities are also more likely to be credit invisible.[31] Scholars and experts in the financial industry hope that machine learning and big data will increase people's access to credit.[32]

However, for the most part, the promises of big data and machine learning have yet to become reality. Section I.A describes issues with the current credit-scoring system. Section I.B explains how credit-scoring issues are exacerbated by the use of big data and machine learning. Section I.C focuses on the emergence of alternative lenders that are not regulated and that are adding big data and machine learning into the mix, emphasizing how new technologies may exacerbate issues related to consumer credit.

A. *Credit Reports: The Gatekeeper for Consumer Credit*

Access to credit has a tremendous impact on consumers' ability to build wealth.[33] Lenders decide whether to extend credit and on what terms based largely on credit scores. Therefore, the information used to build credit reports, and the algorithms used to derive credit scores, are vital in "increasing homeownership rates, access to education, and small business formation."[34] The current credit reporting system has three major consequences. First, unreliable credit reports decrease otherwise creditworthy consumers' ability to access credit. Second, mistakes are notoriously difficult to correct. Finally, FICO models exclude a high number of people with limited or inexistent financial history from the mainstream credit supply.

Studies show that consumer credit scores are arbitrary and riddled with inaccurate information. A 2002 study found that as many as 29% of credit scores differ by at least fifty points between credit bureaus.[35] Other studies have concluded that 50–70% of credit scores

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30 *Id.* (outlining the causes for why many Americans lack a credit score and are locked out of the consumer credit industry).

31 *Id.*

32 Nanette Byrnes, *Artificial Intolerance*, MIT TECH. REV. (Mar. 28, 2016), https://www.technologyreview.com/s/600996/artificial-intolerance/ (discussing concerns over AI use, but showing how technology could be used to improve access to consumer credit).

33 *See* MICHAEL A. TURNER ET AL., POLITICAL & ECON. RESEARCH COUNCIL, GIVE CREDIT WHERE CREDIT IS DUE: INCREASING ACCESS TO AFFORDABLE MAINSTREAM CREDIT USING ALTERNATIVE DATA 10 (2006), http://www.perc.net/wp-content/uploads/2013/09/alt_data.pdf (describing the importance of credit files in extending credit to millions of consumers). People who cannot obtain credit at accessible rates are deprived of the opportunity to improve their livelihoods and are forced to turn to alternative services that charge exorbitant interest rates. *Id.*

34 *Id.*

35 Carolyn Carter et al., *The Credit Card Market and Regulation: In Need of Repair*, 10 N.C. BANKING INST. 23, 41 (2006).

contain inaccurate information.[36] A 2012 Consumer Financial Protection Bureau (CFPB) report found that "[d]ifferent scoring models place consumers in credit-quality categories that are off by one category 19–24% of the time,"[37] which may represent the difference between being classified as a prime, as opposed to a near-prime, consumer. Furthermore, "1% to 3% of consumers are placed in categories that are two or more categories apart."[38] Different categories could result in higher interest annual percentage rates (APR), lower credit limits, or in some cases, being denied credit.[39]

Evidence suggests that credit scoring is also unpredictable, and irrelevant information can impact a person's credit score. For example, Frank Pasquale, an expert in AI, machine learning, and algorithm law, explains how a consumer's decision to lower her or his credit limit could cause the credit score to drop.[40] However, such a decision might have no bearing on that consumer's creditworthiness.

Consider the following anecdotal evidence of how credit scores fail to capture ability to repay additional debt. In the wake of the subprime mortgage crisis, an online service called "Where's the Note" taught visitors how to ask for proof of legal rights to mortgage payments.[41] One would think that in the wake of a series of bankruptcies engulfing the mortgage financing industry, a reasonable consumer would have good reason to inquire about the identity of their financer. However, homeowners who accessed the "Where's the Note" website might have taken a credit score hit as large as forty points.[42]

This presents an even larger concern: consumers have no way of knowing what information impacts their credit scores and to what extent. Credit scoring is "a process that cannot be fully understood, challenged, or audited either by the individuals scored or by the regulators charged with protecting them."[43]

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36 *Id.*

37 CFPB 2012, *supra* note 8, at 20.

38 *Id.*

39 *Id.* at 6. For example, Fannie Mae refuses to buy mortgages with FICO scores under 620. *Id.* When two different models give the same consumer a 610 as opposed to a 630 score, the CRA model Fannie Mae uses might have huge consequences on that consumer.

40 FRANK PASQUALE, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION 24 (2015) (describing how complexity in credit scoring can make what will negatively impact credit scores unpredictable).

41 *Id.* at 23.

42 *Id.* at 24. Barry Ritholtz, *Where's the Note? Leads BAC to Ding Credit Scores*, THE BIG PICTURE (Dec. 14, 2010, 9:15 AM), http://ritholtz.com/2010/12/note-bac-credit-score/ (reporting on one customer's experience with a lowered credit score after asking Bank of America for their mortgage note).

43 PASQUALE, *supra* note 40, at 25.

Consumers suspicious of the accuracy of their credit scores have a hard time getting their credit reports revised, despite legal obligations mandating CRAs to do just that.[44] They face almost insurmountable hurdles when disputing their FICO scoring. First, the CFPB noted in 2012 that the credit scores consumers purchase from financial institutions might be different than those that creditors use.[45] This suggests that consumers might not even know the actual score the lender is using when deciding whether to extend credit. Second, the legal requirements for CRAs to explain their credit assessments are de minimis.[46] As a result, consumers are at an informational disadvantage and have a hard time understanding why they were denied credit. Third, the industry has a strong incentive to avoid complying with legal requirements, such as the obligation to provide a channel for consumers to file complaints and correct mistakes. Remember the case of Patricia Armour: It took her two years and a threat to take legal action (backed by the state's attorney general) to get Experian to correct her file.[47] CRAs are for-profit corporations. Paying customer services representatives to answer complaint calls costs money.[48] Having employees spend time double-checking internal records or making phone calls to third parties to verify information undoubtedly raises the costs of doing business. That is why CRAs have an incentive to do as little as possible to answer consumer grievances.[49] Challenges to credit scores are met with skepticism by reviewers overburdened with claims—anecdotal information indicates that dispute agents review, on average, a claim in merely six minutes.[50] As a result, it is difficult for consumers to prevail.[51]

Unfortunately, even when the data is accurate, researchers claim that information such as past credit activity does not accurately predict a consumer's future ability to repay a loan.[52] Past credit activity—such as loan repayment history and current debt load—is usually a

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44 *See infra* Section II.A.

45 CFPB 2012, *supra* note 8, at 20.

46 *See infra* Section II.A.

47 Morgenson, *supra* note 13.

48 *See* O'Neil, *supra* note 9, at 151–52 (providing an analysis of the economic incentives of lenders to maximize profits at the expense of consumers).

49 *Id.*

50 Pasquale, *supra* note 40, at 22 (discussing a report done for *60 Minutes* in which agents said they reviewed ninety cases a day).

51 *Id.*

52 Ben Schiller, *What if Your Credit Score Measured Your Financial Potential—Not Past Mistakes?*, FastCompany (May 4, 2017), https://www.fastcompany.com/40412660/what-if-your-credit-score-measured-your-financial-potential-not-past-mistakes.

reasonable proxy for future behavior and ability to repay loans.[53] However, a person can easily fall behind on credit card payments due to an unexpected illness or a job loss. FICO scoring models fail to account for such possibilities. In some ways, credit scoring is more a "measure of our past failings, not our potential."[54]

B. Consumer Reporting Agency Use of Big Data and Machine Learning

Big data and machine learning promise to facilitate access to credit. By introducing additional data points, algorithms can better assess consumers' creditworthiness, opening up the credit market to consumers whose files had too little information to make an assessment. Some CRAs have experimented with using "alternative data" to supplement credit reports.[55] An alternative approach is to develop a *method* of scoring for populations that are invisible or unscorable by national CRAs (NCRAs).[56] Researchers describe a vicious cycle for thin-file consumers (both invisibles and unscorables)[57]: Because the information on file is not sufficient, consumers are denied credit, and because consumers are denied credit, they have no way to thicken their credit report files.[58]

One potential solution to this problem is to expand the number of data points CRAs use to draw information for credit reports. Scholars and industry members have proposed the use of non-traditional or alternative data sources for a long time now. The earliest suggestions focused on adding information about payment of utility and telecommunication bills to credit reporting files.[59]

CRAs are relying more and more on big data and machine learning to generate credit reports. A number of major CRAs have

53 *Id.*; *see generally* Ash Cash, *The FICO® Score Powered by Experian and You: Understanding Key Factors*, EXPERIAN (July 29, 2016), https://www.experian.com/blogs/ask-experian/fico-score-powered-experian-understanding-key-factors/ (explaining the rationale behind FICO credit scoring and how it relies on past credit activity to assess creditworthiness).

54 Schiller, *supra* note 52.

55 BREVOORT ET AL., *supra* note 20, at 5.

56 *Id.* The terms "credit invisible" and "credit unscorable" represent different categories of people. However, this paper does not distinguish between the two categories, focusing on their common characteristic: significant difficulties in accessing consumer credit.

57 *See, e.g.*, TURNER ET AL., *supra* note 33, at 8–9. This leads to what the authors call a "knowing-doing" problem; the emergence of a widening gap between the ability to repay a loan and the perceived ability to repay a loan, as expressed by credit scores. *Id.* at 9.

58 *Id.*

59 Namely, these include electricity, heating, running water, gas (utilities), and telephone, internet, and cable subscription (telecommunications). *Id.* at 10.

announced either pilot programs or deployment of products that use alternative and non-traditional data in credit scoring.[60] Alternative data is used both to supplement current models of scoring consumers and to develop scoring systems for people who could not be scored before, centered on alternative and non-traditional data. All three NCRAs have deployed credit-scoring tools that use non-traditional data to calculate credit scores for the credit invisibles and the unscoreable.[61]

So far, studies and practical applications indicate that credit scoring that uses big data and machine learning is more likely to have a discriminatory impact on minorities than traditional credit-scoring tools.[62] These technologies "can reproduce existing patterns of discrimination, inherit the prejudice of prior decision makers, . . . reflect the widespread biases that persist in society" or "have the perverse result of exacerbating existing inequalities by suggesting that historically disadvantaged groups actually deserve less favorable treatment."[63]

First, the use of big data (data mining) requires designers to define target variables (outcomes of interest for the specific task) and class labels (dividing the values of the target variables into different

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60 *See, e.g.*, Press Release, FICO, New FICO Software Enables Data Scientists to Transform Big Data into Predictive Models (Aug. 27, 2013), http://www.fico.com/en/newsroom/new-fico-software-enables-data-scientists-to-transform-big-data-into-predictive-models-08-27-2013 (discussing FICO Model Builder for Big Data, a powerful analytics tool that "enables data scientists to rapidly discover, design and deploy predictive analytics models that find signals in unstructured and massive data sets and turn those signals into actionable insights").

61 PETER CARROLL & SABA REHMANI, OLIVER WYMAN, POINT OF VIEW: ALTERNATIVE DATA AND THE UNBANKED 14 (2017), https://www.oliverwyman.com/content/dam/oliver-wyman/v2/publications/2017/may/Alternative_Data_And_The_%20Unbanked.pdf ("Major credit bureaus (Experian, Equifax and TransUnion) are already starting to incorporate alternative data within their databases, through acquisitions and/or partnerships."). *See, e.g.*, Ann Carrns, *New Credit Score Systems Could Open Lending to More Consumers*, N.Y. TIMES (Oct. 9, 2015), https://www.nytimes.com/2015/10/10/your-money/new-credit-score-systems-could-open-lending-to-more-consumers.html (discussing TransUnion's adoption of CreditVision Link, an alternative system that assigns scores to people with no or low traditional scores); *see also* FTC REPORT, *supra* note 9, at 6 (describing LexisNexis' RiskView tool that includes "educational history, professional licensure data, and personal property ownership data").

62 *See, e.g.*, Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 13–16 (2014) (concluding that far from eliminating discriminatory practices, credit-scoring algorithms tend to rationalize them); *see also* Cassandra Jones Havard, *"On the Take": The Black Box of Credit Scoring and Mortgage Discrimination*, 20 B.U. PUB. INT. L.J. 241, 271–72, 274 (2011) (finding that racial minorities were offered subprime residential loans at disproportionate rates due to discriminatory automated credit scoring in the lead up to the residential mortgage crisis).

63 Barocas & Selbst, *supra* note 25, at 674.

buckets).[64] These target variables are equivalent to information on a specific person; all the data points are proxies. They represent how a person having certain characteristics is likely to behave.[65] Some target variables and class labels need to be subjectively defined by the designer of the application, since there is no direct way to measure them.[66] An example of class label is creditworthiness. Employee performance reviews, or loan-repayment history, are examples of target variables.[67] Algorithms built on a set of defined variables and classes will inherit the same subjective biases the designers have when defining the features.[68]

Second, before use in a real-life setting (e.g., to assess the creditworthiness of a consumer) an algorithm is trained: Large amounts of data and variables are fed into the system, allowing it to determine correlations between variables and how variables impact classes. If the data used to train the machine-learning algorithm is biased, the resulting credit-scoring algorithm will be similarly biased because it will learn to make correlations based on the biased data (i.e., algorithms will not control for the bias in the data).[69] The larger and more complex the data set, the more difficult it will be for outsiders to uncover these biases.

Third, the designer of an algorithm must limit the number of attributes that will be included in an algorithm.[70] Arguably the more information a CRA has on a consumer, the more accurate its creditworthiness prediction will be. However, reflecting every complex circumstance that might impact a consumer's ability to repay a loan will cease to be cost effective at a given point.[71] Online shopping habits can be helpful, but preference for apparel of a certain color or

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64 *Id.* at 678.

65 *See* O'NEIL, *supra* note 9, at 143–47 (clarifying that creditworthiness is not something that can be measured directly; therefore, lenders must rely on proxies that try to predict the likelihood a person will pay back their loans).

66 Barocas & Selbst, *supra* note 25, at 678–79 (explaining the process of developing an algorithm that crunches big data and makes predictions).

67 *Id.* at 679–80.

68 *Id.* at 680.

69 *Id.* at 680–81. Bias can arise in two different ways. First, when prejudiced data is presented as a valid example from which the algorithm makes certain deductions (for example, an automated algorithm fed with information that racial minorities were disproportionately refused admission to a college reflected that practice and systematically disfavored racial minorities). *Id.* at 681–82. Secondly, a data sample is biased when it does not correctly reflect the composition of the population it is purported to analyze (for example, some racial groups are over- or under-represented in datasets, "skewing conclusions that may be drawn from an analysis of the data"). *Id.* at 684–85.

70 *Id.* at 688 (describing how data scientists must work with limited data to predict behavior and how choosing data points might impact results).

71 *See id.* at 688–89.

online streaming preferences are likely not worth the cost of including in the credit report. A company seeking profit from its machine-learning application will be forced to limit the number of attributes its models track at some point. However, the selection of attributes may have a discriminatory impact when attributes that account for/correct a disparate impact on minorities are not reflected.[72]

Fourth, sometimes the same data point is both a rational criteria for assessing creditworthiness and a strong proxy for protected class membership.[73] Consider the example of ZIP codes which could arguably be rational and pertinent factors in determining ability to repay loans, while nonetheless serving as proxy for race or wealth.[74] Users of an algorithm may claim that they are making decisions based on objective and unbiased variables, while relying on protected classifications.

Moreover, the issues described above could cause unintentional discrimination or potentially mask discriminatory *intent* behind apparently objective, data-driven algorithms. The problem is exacerbated by the size and complexity of databases used in credit reporting and the complexity of the machine-learning algorithms,[75] which renders their inner workings quasi-inscrutable.

C. E-Scores: Big Data and Machine Learning Controversially Used in Credit Pre-Screening

A number of financial technology ("fintech") companies purport to predict consumers' behavior, such as the likelihood to purchase certain financial products, while determining their eligibility for such products. In the United States, a number of companies have emerged that provide either crowdfunded loans or perform online marketplace lending services. These companies typically follow one of two business models. In the first case, a company matches investors with borrowers using an online platform: A large number of investors put together small amounts of money and the platform-matched investors with loan applicants using proprietary algorithms that purport to predict

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72 *See id.* at 690 (giving the example of employers using race as a proxy for a candidate's likelihood of having a criminal record when employers lack this information, even though "race is a highly imperfect basis upon which to predict an individual's criminal record").

73 *See id.* at 691–92 (eloquently explaining the process of choosing proxies).

74 *See id.* at 689 (discussing the practice of redlining by financial institutions).

75 *See* Adebayo & Hurley, *supra* note 18, at 192–93 ("[T]ools that employ thousands of data points and complex models could also potentially be used to mask overtly discriminatory policies.").

the applicants' creditworthiness.[76] In the second model, lenders borrow money from traditional lending institutions and investors and grant funds to applicants using an online platform. The firm rates the loans and sells them further as financial products.[77] After the financial crash of 2007/2008, an alternative financing industry based on these models proliferated.[78] Alternative lenders use the lending models briefly described above, as well as new credit reporting methods, while heavily relying on big data collected online, crunched entirely by machine-learning algorithms.[79] These practices remain largely unregulated.[80]

Having a bad credit score (or none at all) prevents consumers from accessing credit.[81] Virtually all traditional lenders use at least one of the national CRA's credit scores when deciding whether to extend credit and under what conditions.[82] According to the CFPB, as of 2010, twenty-six million consumers (or 11% of U.S. adults) were credit invisible and nineteen million (8.3% of U.S. adults) were unscorable.[83] Almost one in five U.S. adults will face problems in accessing credit, regardless of whether they would actually be able to repay their loans. However, unscorable and credit invisible consumers now have a workable, albeit substantially costlier, alternative.

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[76] Steve Goldberg, *LendingTree: An Original Dot-Com Darling Grows Up*, CNBC (Aug. 3, 2014, 1:00 PM), https://www.cnbc.com/2014/08/01/lendingtree-an-original-dot-com-darling-grows-up.html (describing the model of LendingTree, a successful online lending platform).

[77] *See* Davis W. Perkins, Cong. Research Serv., R44614, Marketplace Lending: Fintech in Consumer and Small-Business Lending 1–4 (2018) (providing background on marketplace lending).

[78] *See* Segal, *supra* note 21, at 1; Samantha Barnes, *The Rapid Growth of Alternative Finance*, Int'l Banker (Dec. 1, 2016), https://internationalbanker.com/finance/rapid-growth-alternative-finance/ (noting the broad range of businesses turning to alternative financing). Some alternative financing definitions focus on other significant general characteristics of the industry, such as the existence of online platforms to manage the lending, or on a direct connection between the lenders and the borrowers.

[79] *Id.* at 1. Segal describes marketplace lending as one class of alternative financing that "rel[ies] on data-driven algorithms to evaluate the creditworthiness of borrowers, as distinct from traditional banking practices."

[80] Adebayo & Hurley, *supra* note 18, at 183.

[81] Brevoort et al., *supra* note 20, at 4 (explaining that consumers who have no or limited credit records with national CRAs face significant difficulties in accessing credit).

[82] *See id.* ("NCRA records are often used by lenders when making credit decisions."). *See also Credit Report Basics*, Experian: Ask Experian, https://www.experian.com/blogs/ask-experian/credit-education/report-basics/ ("When you apply for credit, including credit cards, student loans, auto loans, and mortgage loans, lenders check your credit report to make decisions about whether or not to grant you credit and about the rates and terms you qualify for.").

[83] Brevoort et al., *supra* note 20, at 12.

With vast amounts of data available, fintech startups swept in to fill the void.[84] Alternative lending companies do not require a good credit score to offer credit; instead, they rely on thousands of data points to derive a decision in minutes.[85] Proffering that "all data is credit data,"[86] alternative lenders do not limit their assessments of creditworthiness to the types of data that make up traditional credit reports.[87] This emerging industry focuses on consumers' online footprints and draws correlations between a consumer's online behavior and his or her ability to repay loans.[88] Fintech lenders seem to be drawing information and making inferences from a much larger number of data points than traditional CRAs use to assess creditworthiness.[89] For example, consumers' social network information, the size and composition of their online connections, the time they spend to read the terms and conditions of the loans they apply to, and many other data points can impact the creditworthiness assessment.[90]

Alternative lenders do not rely on credit scores, opening the door for unscorable and unscored consumers to obtain credit. Use of big data means that lenders can come to decisions within minutes rather than days or weeks, as is the case with traditional lenders. Alternative lenders rely on various data, sometimes deriving surprising correlations between online data and a consumer's ability to repay. This may include trivial data points, such as use of proper capitalization in filling out an application.[91] Such data is highly likely to equate creditworthiness with lower levels of education or poor English skills

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84 O'Neil, *supra* note 9, at 147 (outlining the history of and proliferation of alternative credit scores and their usage).

85 *See id.* at 158 (describing one company's practices); Thomas H. Stanton, Ctr. for the Study of Am. Gov't Johns Hopkins Univ., Credit Scoring and Loan Scoring: Tools for Improved Management of Federal Credit Programs 10 (1999).

86 Patrick Jenkins, Opinion, *Big Data Lends New Zest to Banks' Credit Judgments*, Fin. Times (June 23, 2014), https://www.ft.com/content/dfe64c0c-fadd-11e3-8959-00144feab7de (quoting Douglas Merrill, founder of ZestFinance).

87 *See* Steve Lohr, *Banking Start-Ups Adopt New Tools for Lending*, N.Y. Times (Jan. 18, 2015), https://www.nytimes.com/2015/01/19/technology/banking-start-ups-adopt-new-tools-for-lending.html (describing how banking start-ups use non-traditional types of data to assess creditworthiness and extend loans).

88 *See id.*

89 *See* Lauren Gensler, *What's in a Score? Why More Lenders Are Using Alternative Data to Approve You for a Loan*, Forbes (Aug. 8, 2017, 9:45 AM), https://www.forbes.com/sites/laurengensler/2017/08/08/fintech-lenders-alternative-data-credit-scores/.

90 Lohr, *supra* note 87; *see also* Jenkins, *supra* note 86 ("[C]onsumers' online behaviour can be a decent proxy for their reliability in managing money."); *supra* note 75 and accompanying text.

91 *See* Lohr, *supra* note 87.

among other features, which in turn correlate with welfare and social status, race, national origin, or immigration status.[92] Equating creditworthiness with some of these features clearly violates the spirit of the ECOA, which was enacted to eliminate discrimination in consumer credit by granting consumers the right to challenge unfair lending practices.[93]

It is true that some consumers may have better chances at accessing credit from these alternative sources.[94] Fintech lenders also provide the advantage of assessing the consumer's eligibility and providing an answer within minutes.[95] Certain scientific studies have found beneficial impacts for consumers of using social-network data in credit scoring.[96] Under certain circumstances, social network data may "provide additional reliable signals about [consumers'] true creditworthiness."[97]

II
Issues with Big Data and Machine Learning Usage in Credit Reporting and the Regulatory Challenges

The issue with alternative credit providers is that they are not regulated by consumer protection statutes such as the FCRA and the ECOA. While placing the fintech industry under FCRA and ECOA scrutiny would be a first step towards protecting consumers from discrimination, this step would not do enough for consumers. This section describes how the current legal framework is inadequate to protect consumers from the dangers of big data and machine learning misuse in assessing creditworthiness.

A. *The United States Legal Framework Protecting Consumer Privacy & Anti-Discrimination Rights*

Consumer protection laws in the United States are industry specific. Consumer credit is mainly regulated under two federal statutes:

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92 O'Neil, *supra* note 9, at 158.

93 *See* Havard, *supra* note 62, at 256.

94 *See* Jenkins, *supra* note 86 (stating that a consumer's credit may improve by as much as forty percent compared to a traditional CRA determination).

95 *See, e.g.*, *id.* (reporting that one fintech company provided results within ten to fifteen minutes); *see also* Lohr, *supra* note 87 (claiming that one fintech company can run the investigation and come up with an answer in as short as two minutes).

96 *See* Yanhao Wei et al., *Credit Scoring with Social Network Data*, 35 Marketing Sci. 234, 249 (2016).

97 *Id.*

the FCRA and the ECOA. This subsection offers a brief overview of these two statutes.[98]

1. The Fair Credit Reporting Act (FCRA)

The FCRA[99] was enacted to ensure fairness in consumer credit reporting and to protect consumer privacy.[100] The statute applies to CRAs, defined as entities that engage "in the practice of assembling or evaluating consumer credit information or other information on consumers for the purpose of furnishing consumer reports to third parties."[101] The FCRA imposes certain procedures that CRAs must implement to ensure the accuracy of their consumer reports,[102] grant consumers access to their own information, and facilitate consumers' right to have possible errors corrected.[103] Furthermore, CRAs may disclose credit reports only to entities that use them for certain permissible purposes, such as to determine credit eligibility.[104]

Lenders that use credit reports are also partly subject to the FCRA. They must provide consumers with "adverse action" notifications, that offer some explanation to consumers when credit reports are used to deny credit, insurance, employment, housing, or other similar benefits.[105] Companies must also provide consumers with "risk-based pricing" notifications whenever they charge consumers a premium for their credit on account of unsatisfactory credit reports.[106]

Under the FCRA, consumers have the right to request and challenge the information in their credit report.[107] Consumers can request that the CRA perform a double check and correct disputed information.[108] And if dissatisfied with the action taken by the CRA, a con-

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[98] The analysis of state-level statutes and regulations that extend federal consumer protections is beyond the scope of this paper.

[99] 15 U.S.C. §§ 1681a–1681x (2012).

[100] Adebayo & Hurley, *supra* note 18, at 184.

[101] 15 U.S.C. §§ 1681(b), 1681a(f). A consumer credit report is broadly defined as "communication of any information . . . 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 . . . for the purpose of . . . establishing the consumer's eligibility for," among other things, credit, insurance, or employment purposes. 15 U.S.C. § 1681a(d).

[102] *See* 15 U.S.C. § 1681e(b) ("Whenever a consumer reporting agency prepares a consumer report it shall follow reasonable procedures to assure maximum possible accuracy of the information concerning the individual about whom the report relates.").

[103] *See* 15 U.S.C. §§ 1681g–1681j; *see also* FTC REPORT, *supra* note 9, at 13.

[104] *See Credit Report Basics*, *supra* note 82.

[105] *See* 15 U.S.C. § 1681m(a).

[106] 12 C.F.R. § 1022.72 (2017).

[107] *See* 15 U.S.C. § 1681g (right to request); § 1681i(a) (right to challenge).

[108] *See* 15 U.S.C. §§ 1681g–1681j; FTC REPORT, *supra* note 9, at 13.

sumer can sue for noncompliance to recover actual damages.[109] The court may direct the CRA to pay the consumer's attorneys' fees and impose punitive damages for willful noncompliance.[110] However, these actions are infrequent due to several major obstacles to successful litigation, including the difficulty of proving actual damages.[111] It is additionally difficult to obtain information to mount a proper attack on the CRAs, as the algorithms used to compute credit scores are protected under trade secret laws and the statute provides immunity for CRAs from defamation actions.[112]

2. *The Equal Credit Opportunity Act (ECOA)*

The ECOA[113] prohibits discrimination based on protected characteristics such as race, color, religion, national origin, sex, marital status, or age.[114] To prove a violation of ECOA, consumers must show disparate treatment—being treated differently on account of a protected characteristic—or disparate impact.[115] Disparate impact occurs when a consumer is subject to facially neutral policies that nonetheless have a "disproportionate adverse effect . . . on a protected class, unless those practices or policies further a legitimate business need that cannot reasonably be achieved by means that have less disparate an impact."[116]

Because of the complexity of credit reporting tools that use big data and machine learning, consumers have a hard time showing disparate treatment, as algorithms potentially mask discriminatory intent.[117] Computers do not have racial biases, but algorithms may replicate the biases of the coders, and the data points the algorithms rely on may constitute proxies for protected categories. The data-driven decision that cut Kevin Johnson's credit limit possibly reflected

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109 *See* 15 U.S.C. § 1681n (willful noncompliance); § 1681o (negligent noncompliance).

110 15 U.S.C. § 1681n(a)(B)(2)–(3).

111 *See* Austin H. Krist, *Large-Scale Enforcement of the Fair Credit Reporting Act and the Role of State Attorneys General*, 115 COLUM. L. REV. 2311, 2321 (2015) (stating that litigation is infrequent and explaining why consumers are unlikely to prevail).

112 15 U.S.C. § 1681h(e) (2012); *see also* Krist, *supra* note 111.

113 15 U.S.C. §§ 1691–1691f (2012).

114 15 U.S.C. § 1691(a)(1).

115 *See* FED. RESERVE, CONSUMER COMPLIANCE HANDBOOK: FAIR LENDING OVERVIEW 1–3 (2006), https://www.federalreserve.gov/boarddocs/supmanual/cch/fair_lend_over.pdf (explaining the two types of discrimination claims available to consumers under ECOA and other statutes); FED. DEPOSIT INS. CORP., FIL-36-96, SIDE BY SIDE: A GUIDE TO FAIR LENDING 23 (1996) (advising lending institutions on how to identify discriminatory lending practices).

116 FTC REPORT, *supra* note 9, at 19.

117 *See* Barocas & Selbst, *supra* note 25, at 674 ("Approached without care, data mining can reproduce existing patterns of discrimination . . . .").

coders' bias that people frequently shopping at certain stores are less creditworthy, and/or relied on home addresses or other location data in making the decision. However, due to a long history of segregation, ZIP codes and location data are often an accurate proxy for race.[118] Furthermore, disparate impact is a notoriously hard claim to show.[119]

While using more data types to assess a consumer's creditworthiness provides concrete benefits, it may nonetheless allow entities that report creditworthiness to evade the consumer protections provided by statutes such as the FCRA and the ECOA. Meanwhile, consumers are unaware of the information that goes into credit reporting and are unable to identify errors in their credit reports.

B. *Inadequate Consumer Protection Under the Current Regulatory Regime*

So far, we have seen how the consumer credit industry works and the issues consumers face when trying to access credit. This Section summarizes and further details the unique challenges that big data and artificial intelligence raises for consumers in accessing inexpensive credit as well as the challenges regulators will face trying to create consumer protections adequate for the age of big data and machine learning.

There is substantial scientific evidence that inaccurate databases and machine-learning algorithms can produce biased results.[120] However, machine-learning applications are highly complex and almost impossible to reverse engineer to determine where the bias occurred.[121] Moreover, both algorithms and data sets are often proprietary and secret, limiting not only access to the underlying data but also the possibility to test them.

After hosting a workshop on the risks and benefits of big data usage, the FTC concluded that the use of big data in credit reporting could have a detrimental impact on low-income and under-served populations.[122] First, scholars are concerned with the "quality[,] . . . accuracy, completeness, and representativeness" of the data.[123] Inaccurate or biased data may lead to inaccurate predictions that repeat

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118 *See* O'NEIL, *supra* note 9, at 145–46.

119 *See, e.g.*, Jennifer L. Peresie, *Toward a Coherent Test for Disparate Impact Discrimination*, 84 INDIANA L.J. 773, 774–75 (2009) (explaining that plaintiff success rates in showing disparate impact are relatively low, partly because statistical evidence is key for showing disparate impact, and confusing and inconsistent judicial tests allow parties and judges to cherry pick favorable statistics).

120 *See supra* Sections I.B & I.C.

121 *See supra* Section I.B.

122 *See* FTC REPORT, *supra* note 9, at i, 33.

123 *Id.* at 8.

and—due to the potential for mass-scale application of big data—propagate biases that erroneously deprive certain populations of offers and opportunities.[124] Second, big data shows correlations not causations, which might lead to faulty decisions, as system designers do not understand the "underlying reasons" for the correlations.[125] Third, big data can be used to categorize consumers in ways that unfairly characterize certain populations.[126] As a result, credit reporting may have a discriminatory impact on women, racial minorities, or less wealthy people.[127] An example of algorithm bias is when credit reports overweigh certain data points, such as consumers' addresses.[128] Consider the harsh reality of racial segregation by neighborhood and the fact that areas inhabited by a high percentage of racial minorities tend to be less wealthy overall. Areas inhabited by higher-than-average ratios of racial minorities are likely to have lower overall credit scores, thinner credit files, and higher default rates on average.[129] Therefore, negatively scoring particular ZIP codes when calculating an individual's credit score negatively impacts racial minorities.[130] This is how segregation, the result of a history of discrimination and a reality that has little bearing on creditworthiness, becomes a proxy for race and a determinant factor in whether a consumer can access credit.

Before data-driven credit scores started to be widely used in the '60s, people looking for a loan applied for credit at a local bank. They would submit an application and the local banker would assess their creditworthiness based on a file containing their personal information and financial transaction history.[131] However, because bank clerks had significant discretion in deciding whether to extend credit to a specific customer, biases—implicit or otherwise—influenced their decisions whether and under what conditions the bank would grant credit.[132] Unsurprisingly, the practice was unfair to women, racial minorities, sexual minorities, and a plethora of people who did not fit the banker's narrow conception of creditworthy customers.[133] Current

124 *Id.*
125 *Id.* at 9.
126 *Id.*
127 *See, e.g.*, Alloway, *supra* note 1.
128 *Id.*
129 BREVOORT ET AL., *supra* note 20, at 6.
130 For example, much higher percentages of African American and Hispanic people are credit invisible. *Id.*
131 *See* O'NEIL, *supra* note 9, at 141.
132 *See id.* at 141–42.
133 *See id.*; *see also* PASQUALE, *supra* note 40, at 22 (discussing how "lax standards of reporting" combined with a "toxic mix of prejudices at the time" to produce "unfair results").

practices allow that history of discrimination to survive, disguised by apparently objective data science. The FCRA ensures that consumers can access their credit reports and have a means to challenge the accuracy of credit scores. Furthermore, the ECOA provides a private cause of action protecting consumers against adverse action based on protected characteristics. However, consumers lack the right to access the data underlying credit reports, the right to know what kind of data goes into creditworthiness assessment, or how different data points are weighed. CRAs and lenders can therefore rely on complex and possibly inscrutable algorithm decisionmaking to motivate their credit-related decisions, effectively depriving consumers of legal protections.[134]

A good credit score is usually a proxy for wealth, and wealth is a good proxy for race and national origin.[135] A wealthy person who is suddenly saddled with debt or is terminated out of the blue can likely weather the storm. On the other hand, a person living from paycheck to paycheck might fall behind on paying off a student loan or a mortgage, severely damaging her or his credit.[136]

Of course, the correlations that algorithms draw from big data are not always false. It makes sense that wealthier people buy expensive items more often or that a person who has a very low income is more likely to need a payday loan. However, when the correlation does not hold, it is almost impossible for the machine to tell that it is making a mistake. Unlike humans, machines have not yet developed a common sense understanding of the data. In other words, if alternative lenders never offer a loan to an otherwise clearly creditworthy person because they live in a poor neighborhood, there is no way for the algorithm to discover the mistake in its determination. As a result, biased algorithms will reinforce human biases by relying on flawed data, having initial algorithm slip-ups, or both. Human intervention could correct common sense errors as long as algorithms are testable and/or scrutable.

The more data points and the more complex these algorithms become, the harder it becomes for consumers to be able to construct a claim against these black boxes. E-scores are not only used by startups, but by large banks as well. When a consumer goes to a big bank

[134] *See* Adebayo & Hurley, *supra* note 18, at 189 ("[I]t may prove practically impossible for consumers, when dealing with big data scoring systems that . . . integrate thousands of variables, to verify the accuracy of their scores and reports . . . ."). It is important to note that the FCRA imposes the onus on consumers to identify the inaccuracies in their credit reports. *Id.* at 189–90.

[135] O'Neil, *supra* note 9, at 149.

[136] *Id.*

website, the bank instantaneously has access to her or his online purchase and web-browsing information as well as the location of the visitor.[137] The bank then uses algorithms to (e-)score the visitor.[138] Section 624 of the FCRA does not allow companies to use credit scores for marketing purposes.[139] However, banks can use e-scores as an alternative to market their financial products. The pre-approved mail and pop-up messages when browsing the web are largely based on e-score determinations.

Banks' reliance on e-scores to advertise financial services might itself have a disparate impact on protected-status populations. In a world where the internet is a large part of access to information, e-scores use data that is proxy for protected status, disproportionately targeting protected-status people with subprime financial products. This in fact channels protected-status individuals towards suboptimal financial products and acts as a long-term gatekeeper to building a better score, as people are ensnared by information they receive based on their e-score.

Big data and machine learning exacerbate difficulties in enforcing the FCRA in other ways as well. At least one study suggests that big data analytics companies are unlikely to comply with the FCRA.[140] As the FTC acknowledges, big data analytics are potential means to evade FCRA requirements by aggregating data on a household or a neighborhood area.[141] It is relatively easy for fintech companies to avoid FCRA and ECOA liability. Credit reporting only includes individual data; a company compiling information on a household, a device ID ("UDID"), or an IP address that does not strictly refer to an individual, falls outside the FCRA definition.[142]

Additionally, only information provided to CRAs is subject to regulation.[143] This does not cover internal use, when alternative lenders collect their own information and use proprietary algorithms.[144] Companies which separate their credit reporting from financial services marketing in separate subsidiaries or departments are

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137 *See id.* at 143–44.

138 *See id.* at 144.

139 15 U.S.C. § 1681s-3 (2012).

140 PERSIS YU ET AL., NAT'L CONSUMER LAW CTR., BIG DATA: A BIG DISAPPOINTMENT FOR SCORING CONSUMER CREDIT RISK 5 (2014), https://www.nclc.org/images/pdf/pr-reports/report-big-data.pdf (finding it unlikely that FCRA obligations are being met).

141 *See* FTC REPORT, *supra* note 9, at 16–17; *see also* Adebayo & Hurley, *supra* note 18, at 184.

142 15 U.S.C. § 1681a(d); *see also* Adebayo & Hurley, *supra* note 18, at 185.

143 15 U.S.C. § 1681a(f).

144 15 U.S.C. § 1681a(d).

also likely not subject to the FCRA.[145] However, marketing only certain financial services to a group of consumers in fact limits the access of those consumers to a subset of financial services, which may be disadvantageous. Because many de facto lenders can avoid the CRA label, consumers are deprived of the possible remedies provided under the ECOA or the FCRA. Finally, it is worth noting that much of the venture capital that alternative lenders have received to pursue their business can be traced back to large banks.[146]

Because e-scores and the companies computing them are not the object of FCRA and ECOA regulation, consumers have no legal recourse to solicit additional information about an adverse credit decision or to dispute it. Moreover, consumers are not able to compartmentalize data to ensure that certain information is not used by CRAs in credit reports or for marketing purposes. Alternative lenders make it clear that they go out of their way to mine as many data points as possible to feed credit decision-making algorithms. Therefore, consumers have little power to filter the information that could impact credit scores ex ante, nor can they see or challenge what data was used ex post. Part III discusses possible ways to give consumers more control over their data, while preventing legal circumvention by some lenders and CRAs.

III
Introducing New Possible Protections for Consumers

Reacting to the emergence of the internet and the digital economy, the European Union started regulating the processing of personal data in 1995.[147] The 1995 directive laid out some of the fundamental principles of data privacy protection, such as transparency (notice and consent required for data processing, and the right to access personal data), legitimate purpose (data may only be processed for legitimate and explicit purposes), and proportionality (the narrow processing of personal information)—principles that still constitute the backbone of consumer protection in the EU today. The boom of

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145 Adebayo & Hurley, *supra* note 18, at 187 (suggesting that the definition of the CRA may create a loophole for big-data companies).

146 *See* Nav Athwal, *The Disappearance of Peer-to-Peer Lending*, Forbes (Oct. 14, 2014, 12:28 PM), https://www.forbes.com/sites/groupthink/2014/10/14/the-disappearance-of-peer-to-peer-lending/ (claiming that large institutional lenders have come to effectively dominate the peer-to-peer lending market).

147 *See The History of the General Data Protection Regulation*, European Data Prot. Supervisor, https://edps.europa.eu/data-protection/data-protection/legislation/history-general-data-protection-regulation_en (last visited Sept. 30, 2018).

internet-based services and platforms that store and process personal information as well as other developments led the EU to adopt in late 2015 the GDPR, a comprehensive data privacy policy.[148]

The EU's newly-adopted GDPR is a good source of inspiration for reforms to the FCRA and ECOA. Unlike the American system, the EU takes an industry-agnostic approach in protecting consumer rights. Acknowledging that the development of the digital economy depends on consumer trust, which requires consumer control over personal data, the EU devised a comprehensive approach to data protection.[149] The GDPR applies across all twenty-eight EU member countries and grants robust protections that enable consumers to better enforce their rights. Furthermore, the GDPR introduces property-like interests in personal information. This Part discusses the ways in which these innovations could solve consumer credit issues in the United States.

A. The Specifics of the General Data Protection Regulation Framework

The EU's General Data Protection Regulation (GDPR) came into force on May 25, 2018.[150] The regulation has a dual purpose: to protect individual rights with regard to personal data processing, while ensuring the free flow of data within the EU.[151]

The statute lays down rules related to the "protection of natural persons with regard to the processing of personal data and . . . relating to the free movement of personal data."[152] Personal data is defined broadly as any information relating to an "identified or *identifiable* natural person."[153] Processing of personal data must comply with a number of principles, broadly defined in the statute: "Personal data shall be . . . processed *lawfully, fairly and in a transparent manner* in relation to the data subject."[154] The GDPR places strict limits on the treatment of personal data such as purpose limitations (collection for specified, limited, and explicit purposes), data minimization, accuracy, storage limitation, integrity, confidentiality, and accountability.[155] By

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148 *See GDPR Timeline of Events*, EUGDPR.ORG, https://www.eugdpr.org/gdpr-timeline.html (last visited Sept. 28, 2018).

149 GDPR, *supra* note 26, at 2.

150 *Id.* art. 99(2).

151 *Id.* art. 1(1)–(2).

152 *Id.*

153 *Id.* art. 4(1) (emphasis added).

154 *Id.* art. 5(1(a)) (emphasis added).

155 *Id.* art. 5(1)–(2).

comparison, the FCRA only restricts *usage* of credit reports for purposes of granting credit, employment, or insurance.[156]

The GDPR provides seven major rights to data subjects.

First, Article 15 grants data subjects the right to obtain confirmation as to whether their personal data is being processed and the right to access that personal information, in addition to requiring the data controller to inform the consumer of her or his rights.[157] These include the right to receive information disclosing the "purposes of the processing"; the "categories of personal data concerned"; the identity of other recipients that have been or will be provided with that information; the "envisaged period for which the personal data will be stored" (or at least the criteria to determine such period); the data subject's right to demand erasure or rectification of the personal data; the right to lodge a complaint; and the existence of automated decisionmaking, including profiling, "and, at least . . . meaningful information about the logic involved, as well as the significance and the envisaged consequences of such processing."[158]

Second, Article 16 clarifies that the data subject can ask the data controller to rectify inaccurate personal data concerning her or him, "without undue delay."[159]

Third, Article 17 clarifies the circumstances in which a data subject can ask a data controller to erase her or his personal information. Some examples include situations where the data is no longer necessary, the data subject has withdrawn consent, and when the data controller unlawfully processed that data, among other circumstances.[160]

Fourth, the data subject may restrict processing of the personal data under Article 18 when the data subject claims that the data is no longer accurate, that the data is no longer needed, or that its processing is unlawful (which includes lack of consumer consent).[161]

Fifth, Article 20 confers data subjects the right to receive their personal data in a "structured, commonly used and machine-readable format" and the right to transmit that data to a different controller.[162] In a consumer credit context, this would likely empower a consumer to demand a lender to transfer all her or his personal data to another lender. The right to data portability is important for two reasons. First,

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[156] 15 U.S.C. § 1681a(d) (2012).

[157] GDPR, *supra* note 26, art. 15.

[158] *Id.*

[159] *Id.* art. 16.

[160] *Id.* art. 17. The article also provides some exemptions designed to protect free speech and persons keeping records for legal compliance purposes.

[161] *Id.* art. 18.

[162] *Id.* art. 20.

it is one of the clearest indications that the GDPR recognizes an interest akin to a person's property right in her or his personal data.[163] Second, empowering data subjects to take their personal data to another controller promotes market competition in providing services that require data collection and processing.

Sixth, Article 21 grants data subjects a right to object to processing (including profiling).[164] When a data subject objects to data processing, a controller must stop processing the data "unless the controller demonstrates compelling legitimate grounds," which would override the interests and rights of the data subject.[165] The legislature likely intended the provisions to empower consumers against online marketers;[166] however, consumers will theoretically be able to ask data processors to stop using personal data where consumers suspect data or algorithmic biases cause unfair classifications. Nevertheless, it is not entirely clear what procedural safeguards the legislators had in mind when they adopted this article.

Finally, Article 22 provides that data subjects have the right not to be subject to a "decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her."[167] The Article provides that the data controller must at least ensure the "right to obtain human intervention on the part of the controller, to express [the data subject's] point of view and to contest the decision."[168] Article 22 has been the object of great debate recently as to whether the GDPR, read overall, provides for a "right to explanation" of the reasoning algorithms used in reaching a decision.[169] In addition to the rights

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163 *See infra* Section III.B.3.

164 *See* GDPR, *supra* note 26, art. 21.

165 *Id.*

166 *See id.* art. 21(2) (addressing the right to object to data processing in the context of online marketing).

167 *Id.* art. 22.

168 *Id.* art. 22(3).

169 *See id.* art. 22; *see also id.* Recitals 63, 71. The statute can arguably be interpreted to support both views. On its face, Article 22, read together with Recitals 63 and 71, suggests that consumers have broad rights to receive information about the data that goes into automated algorithms as well as the methods and logic these algorithms use, amounting to an explanation for decisions. The right to an explanation would force data scientists to disclose algorithm codes or provide some ways to independently check the algorithmic decision. Currently, there is a vigorous debate regarding the scope of the so-called right to explanation, one side claiming that a right to an explanation is included in the GDPR. *See* Bryce Goodman & Seth Flaxman, *European Union Regulations on Algorithmic Decision-Making and a "Right to Explanation*," 38 AI MAGAZINE 50 (2017); *see also* Andrew D. Selbst & Julia Powles, *Meaningful Information and the Right to Explanation*, 7 INT'L DATA PRIVACY L. 233, 233, 235–37 (2017). The other side claims that the right of explanation is extremely narrow and that any trivial human intervention would render the decision not

described above, Article 5(1)(d) requires all data to be accurate, mandating data processors[170] to keep data up to date where necessary.[171]

B. How GDPR-Inspired Privacy Rights Could Facilitate Access to Credit

According to Pasquale, the U.S. credit reporting system is "a process that cannot be fully understood, challenged, or audited either by the individuals scored or by the regulators charged with protecting them."[172] That is why the GDPR rights described above are a good start to improving consumer protections in the credit market.

On one side of the spectrum, traditional lenders rely on CRAs that require a significant amount of financial information to derive credit scores. Individuals who lack financial history or have a past of unsatisfactory repayments will get credit under unfavorable conditions or none at all.[173] When traditional lenders use big data and AI, they do so to prescreen consumers and market the financial products their preexisting FICO scores entitle them to, or inadvertently, when big data somehow spills into such preexisting credit reports (such as the case of Kevin Johnson).[174] Neither usage helps new consumers access credit. Furthermore, consumers are left in the dark because the FCRA and ECOA do not entitle them to know what data and how that data is being used to derive their credit scores.[175]

On the other side of the spectrum, alternative lenders are unfettered by consumer credit regulation and rely exclusively on troves of online information and newly designed AI algorithms to provide financial services to consumers underserved by traditional lenders.[176] The data these alternative lenders use is potentially biased, and their

solely based on an automated decision-making process. *See generally* Sandra Wachter et al., *Why a Right to Explanation of Automated Decision-Making Does Not Exist in the General Data Protection Regulation*, 7 INT'L DATA PRIVACY L. 76 (2017) (arguing that the GDPR does not include a "right to an explanation" and offering legislative suggestions to address that perceived shortcoming). This would mean that the right to explanation is virtually nonexistent because data processors would easily be able to circumvent it by inserting some form of human intervention in the process. *See* Selbst & Powles, *supra* note 169, at 234.

170 For simplicity, unless stated otherwise, this paper uses the term "data processor" broadly to include data controllers.

171 *See* GDPR, *supra* note 26, art. 5(1)(d) ("[E]very reasonable step must be taken to ensure that personal data that are inaccurate . . . are erased or rectified without delay.").

172 PASQUALE, *supra* note 40, at 25.

173 *See supra* Introduction (discussing how CRA scores are calculated).

174 *See supra* notes 140–42 and accompanying text; Alloway, *supra* note 1.

175 *See supra* Section II.A.

176 *See supra* Section I.C.

algorithms likely reproduce the biases of the coders or of the training data sets.[177]

The two ends come together to paint a bleak picture where, through no fault of their own, some consumers must choose between no credit, credit with high interest and harsh repayment conditions, or surrendering control over a large amount of personal information, with no firm guarantee of access to fair credit in return. In any event, racial minorities and people who are less well-off are disproportionately affected by the use of big data and AI in consumer credit.[178]

While recognizing that there is no silver bullet to solve the difficult issues facing the consumer credit industry, this section identifies some ways in which the GDPR could inspire consumer credit legislation reforms. Big data and AI could increase the number of people that have access to credit. However, the discriminatory impact of the new technologies will outweigh the benefits, unless consumer credit regulation grants consumers access rights to the data used to determine their creditworthiness, and also grants consumers the right to deny access to certain personal data. The first steps required to achieve this goal are to extinguish the CRA versus non-CRA distinction up to a certain point, and to strengthen consent requirements and the right to refuse access to personal data.

1. An Industry-Agnostic Approach to Consumer Privacy Is Preferable

Unlike the FCRA and ECOA, the GDPR is an industry-agnostic umbrella regulation for consumer privacy. Any natural or legal person who processes personal data constitutes a "processor," regardless of whether they generate credit reports or not.[179] "Processing" includes any operation performed on personal data, "whether or not by automated means," such as "collection, recording, organization, structuring, storage, adaptation or alteration, retrieval, consultation, use, disclosure by transmission, dissemination or otherwise making available, alignment or combination, restriction, erasure or destruction."[180] Furthermore, an entity is subject to the GDPR even if it only "determines the purposes and means" of the processing, while outsourcing the actual processing operations to a third party.[181] Unlike the FCRA

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177 *See id.*

178 *See supra* Section II.B.

179 *See* GDPR, *supra* note 26, art. 4(8) ("'[P]rocessor' means a natural or legal person, public authority, agency or other body which processes personal data on behalf of the controller.").

180 *Id.* art. 4(2).

181 *Id.* art. 4(7).

and ECOA, where there are doubts as to whether alternative financing companies fall under the statute, the GDPR clearly encompasses any sort of processing of personal data.[182] A similar expansion of consumer credit regulation would cover CRA affiliates such as data brokers, data science services providers, and likely outsider algorithm designers.

Distinguishing CRAs from other entities that process personal data seems artificial and underinclusive when the data processing impacts a consumer's access to credit. Undoubtedly there are companies processing personal data that have nothing to do with creditworthiness assessments. However, an alternative lender is unlikely to be held accountable under the FCRA as long as the company collects and processes data internally, therefore effectively escaping the CRA statutory definition.[183] Furthermore, as we have seen in American Express's decision to cut Kevin Johnson's credit limit, big data can make its way into credit decisions. Traditional lenders purchase significant information from data brokers; however, much of this information does not constitute a credit report under the statute.[184] Nonetheless, as Pasquale suggests, it is no longer possible to separate credit reporting data from the rest of the data within the credit scoring black box algorithm.[185] Data brokers or online-platform providers that want to steer clear of consumer credit regulations could refuse to work with lenders, CRA, and their affiliates. Alternatively, they could allow third parties to buy tailored ads on their platform without allowing them to sync the data with their proprietary algorithm (i.e., processing personal data).

The FCRA does not extend to big data used in marketing financial services. Banks and other lenders may use big data to determine whether consumers are prequalified to certain services. It is common practice to aggressively target consumers based on these assessments.[186] As a result, lenders will offer less desirable financial services based on biased analyses disproportionately to racial minorities, immigrants, or poor people, thereby potentially discriminating against

182 *See id.* art. (4)(1); *supra* note 141 and accompanying text.

183 *See* Adebayo & Hurley, *supra* note 18, at 188–89, 189 n.196 (citing 15 U.S.C. § 1681a(d)(2)(A)(i) (2012)).

184 *See supra* Section I.A (explaining how under the FCRA credit reports are comprised mainly of consumers' past credit-related activity).

185 *See* PASQUALE, *supra* note 40, at 21, 30–32.

186 *See* DAVID SKANDERSON & DUBRAVKA RITTER, FAIR LENDING ANALYSIS OF CREDIT CARDS 15 (2014), https://www.philadelphiafed.org/-/media/consumer-finance-institute/payment-cards-center/publications/discussion-papers/2014/d-2014-fair-lending.pdf (explaining how prescreening marketing of financial products works).

protected-class individuals.[187] Given the extensive use of big data and AI in marketing, consumers will only see ads offering discriminatory financial services. And given the lack of access to reliable information on creditworthiness, consumers are likely to be ensnared by these offers.[188]

Therefore, broadening the application of the FCRA and ECOA statutes to all entities that process consumer credit-related personal information would ensure fairness in access to credit. Rather than focusing on credit scoring, the statute should focus on its initial purpose, which was to promote fair access to credit. A reimagined statute should acknowledge and combat the many opportunities to circumvent the current narrow definition of credit reporting. Access to credit should drive reform, not the processes surrounding credit reporting. A GDPR-like rule including all entities that process personal data or cause others to process personal data that impact a person's chances to access credit on fair terms should be incorporated into the FCRA.

The benefit of industry-specific regulation is flexibility. Strong consumer protections and individual causes of action make sense when an individual is unfairly denied credit because the wrong is so great. However, CRAs and other data processors such as social media platforms do not always need to be regulated at the same level. The FCRA and ECOA offer legal protections for credit-related issues, and recourse to consumers, by targeting lenders and their affiliates. However, businesses outside the consumer credit industry impact individuals' access to credit, and non-traditional lenders offer credit while posing as tech companies and eluding FCRA and ECOA regulation. The disadvantage of over-regulating and forcing some online-centric businesses to cut ties with affiliates that impact consumer credit scores is outweighed by the need to ensure fair access to consumer credit, which is the key to accumulating wealth.

2. *More Stringent Data Processor Obligations and Consumer Rights to Rescind Processing Permission to Stimulate Market Competition*

Transparency under the GDPR imposes affirmative obligations on data processors, requiring processors to provide certain information to consumers about what is happening to their personal data, as well as know-your-rights information regarding the processing of their

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187 *See supra* Section I.C (discussing shortcomings of algorithm-based analysis).

188 *See, e.g.*, PASQUALE, *supra* note 40, at 23 (describing predatory credit reporting practices taking advantage of uninformed consumers).

personal data. Furthermore, transparency requires data processors to respond to data subjects' requests and demands in a timely fashion.[189]

Under the GDPR, a consumer like Patricia Armour[190] can request and transfer information from Experian (in a machine-readable format) to another processor willing to correct the file. Alternatively, she could opt out of the mainstream consumer credit system altogether by exercising her right to be forgotten.

Data processors must disclose the extent of personal information they possess to the data subjects, the identity and contact details of the data processor and any third party recipients of that data, the intended purposes for which data processing consent is requested, the period for which the data will be stored (or if not possible, at least the criteria used to determine that period), and the rights of the consumer.[191] These disclosures make it easier for consumers to reach out to entities retaining their data and to request copies of the information.

Furthermore, the GDPR entitles consumers to receive copies of all information in a machine-readable form, so that they can easily take it to another processor to be readily used.[192] The statute also requires data processors to comply to data subjects' requests "without undue delay and in any event within one month of receipt of the request," and free of charge.[193] Finally, Article 17 confers to consumers the right to be forgotten.[194] In the FCRA and ECOA context, this would allow consumers to remove their data from a CRA or a lender's database when the service provider refuses to review and correct their file.

Stronger consumer rights inspired by the GDPR could lead to a more competitive consumer credit market by forcing lenders to pay attention to consumer needs. The measures described in this subsection would make it easier for consumers to move their data between service providers. This would make it less costly for new market entrants to collect consumer data. Additionally, securing consumer consent and explaining the obligations imposed by GDPR-like consumer rights would likely raise business costs for existing market players, further leveling out the field. Currently, dissatisfied con-

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189 *See supra* notes 150–61 and accompanying text.

190 *See supra* notes 13–16 and accompanying text.

191 *See* GDPR, *supra* note 26, arts. 13–14.

192 *Id.* art. 20.

193 *Id.* arts. 12(3), 12(5) (excepting when the "requests . . . are manifestly unfounded or excessive, in particular because of their repetitive character," in which case the data processor may refuse to act or charge a reasonable fee for the action requested).

194 *Id.* art. 17.

sumers are unable to opt out of credit reporting, making lenders highly passive to consumers' pleas.[195] However, the risk of losing dissatisfied customers would put pressure on all lenders to better comply with consumer requests. As a result, a more competitive consumer credit market could develop because it would eliminate barriers to entry for newcomers and increase operating costs for legacy players.

3. *Property Interests in Personal Data*

The GDPR introduces a property interest in personal data. Under the new regulation, personal data processing is lawful with few exceptions "only if and to the extent" that the data subject has consented to the processing of her or his personal data for a specific purpose.[196] The exceptions include cases where processing is required to comply with other legal obligations of the processor or is necessary to perform a contract the data subject is a party to.[197] The Recitals of the Regulation clarify that consent "should be given by a clear affirmative act establishing a freely given, specific, informed, and unambiguous indication" of the consumer's agreement to the processing of that data.[198] Consent may be given by a written statement (including electronic documents) or by an oral statement.[199] Article 4 incorporates Recital 32's definition of consent into the GDPR.[200] Furthermore, Article 7 requires data controllers to be able to demonstrate consent and make consent forms "clearly distinguishable from the other matters, in an intelligible and easily accessible form, using clear and plain language," and consumers can withdraw consent at any time.[201]

Requiring consent in the context of consumer credit has little meaning on its own.[202] Consumers need credit and are unlikely to forego applying for a mortgage or using credit cards because they disagree with the way lenders use their personal and/or financial information. For many consumers, credit is necessary to purchase long-term assets, for access to education, and for other key products and services. Therefore, it is unlikely that meaningful consumer consent

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195 *See supra* Section II.A.

196 *See* GDPR, *supra* note 26, art. 6.

197 *Id.* art. 6(1)(b)–(c).

198 *Id.* Recital 32.

199 *Id.*

200 *See id.* art. 4(11).

201 *Id.* art. 7(2)–(3).

202 *See generally* Solon Barocas & Helen Nissenbaum, *Big Data's End Run Around Anonymity and Consent*, *in* PRIVACY, BIG DATA, AND THE PUBLIC GOOD: FRAMEWORKS FOR ENGAGEMENT 44, 56–59 (Julia Lane et al. eds., 2014) (describing how consent is not really meaningful when contractual parties do not know what they are consenting to).

can be achieved, considering the disparity of the opposing parties' bargaining powers.

However, a property-like entitlement to personal data confers other benefits. Property rights are not limited to parties in a direct contractual relationship to the data subject. In the consumer credit context, the consent requirement renders every processor of the personal data liable, regardless of their relation to the data subject, allowing consumers to control the spread of their sensitive personal information (even if there is no right to have data deleted). Unlike the current limited-scope liability regime CRAs and lenders face under the FCRA, a property regime opens the possibility for more stringent sanctions for noncompliance. While money damages are standard for liability rules, recognizing a property interest in personal data means that injunctive relief can become the default remedy.[203] The possibility of injunctions can incentivize lenders to be more attentive to consumers' requests for correcting their file information and double-checking the accuracy of data points before using them in assessing creditworthiness. Courts regularly enforce contracts, even internet-based clickwrap,[204] so lenders can more easily isolate themselves from liability in a liability/contract-like system. Recognizing a property interest in personal data however, can help overcome this predicament because some property rights are inalienable (depending on how the property interest is designed in the statute) and contracts would not shield lenders from liability.[205]

4. *Other Policy Concerns*

As a policy issue, access to consumer credit promotes consumption, better education, and the accumulation of wealth, which is a benefit for society.[206] Currently, financial institutions and other lenders treat consumer data as a commodity and they act as rational market actors seeking to maximize profit.[207] However, despite having little

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203 For a thorough explanation of liability rules, property rules, and their default legal remedies, see Guido Calabresi & A. Douglas Melamed, *Property Rules, Liability Rules, and Inalienability: One View of the Cathedral*, 85 Harv. L. Rev. 1089, 1106–09 (1972).

204 *See, e.g.*, Fteja v. Facebook, Inc., 841 F. Supp. 2d 829, 837 (S.D.N.Y. 2012) (collecting cases upholding clickwrap agreements). *But see* Nguyen v. Barnes & Noble, Inc., 763 F.3d 1171, 1178 (9th Cir. 2014) (holding that a conspicuous hyperlink was insufficient to provide the user with constructive notice because it did not require affirmative consent).

205 *See generally* Susan Rose-Ackerman, *Inalienability and the Theory of Property Rights*, 85 Colum. L. Rev. 931 (1985) (explaining that the inalienability of property rights refers to restrictions to the transferability and use of property as a protective response to situations where unencumbered transfers on a free market are undesirable).

206 *See* Turner et al., *supra* note 33, at 10 (discussing the importance of consumer credit for individuals and society).

207 *See* O'Neil, *supra* note 9, at 143–44.

financial downsides for lenders, errors in credit reports may have a terrible impact on consumers and on society as a whole.[208] Furthermore, the cost of correcting credit reports is much higher for consumers than lenders.[209] This is why it makes sense for lenders, as the cheapest cost avoiders, and not consumers, to bear the burden that arises from mistakes in data or algorithms used in assessing creditworthiness. A property-like system is the first step to achieving this.

Admittedly, some of the rights provided under the GDPR would potentially clash with First Amendment protections. For example, an expansive application of the right to be forgotten may require courts to compel private actors to delete certain personal information from their databases, amounting to a restriction of protected speech.[210] Therefore, American legislators would have a hard time fitting the right to be forgotten in the free speech doctrinal landscape. However, this paper does not advocate for a verbatim introduction of the GDPR in the United States. Reform should focus on transparency, so that consumers know who is using their data and how, and on promotion of a free consumer credit market. In a competitive credit market, consumers have the attention of financial service providers because they know how lenders use their data to assess creditworthiness and can have personal data transferred to a different lender when they are dissatisfied.

Finally, American judicial culture is highly reluctant to model legal regimes on foreign laws.[211] At first glance, the GDPR seems to raise legal cultural issues because of potential free speech issues and a history of industry-specific consumer regulations. However, despite the European-flavored individual dignity rhetoric, the building blocks of the GDPR are old legal concepts near-and-dear to the American legal system: recognizing a property interest in information that can be used in a lucrative manner, and giving individuals fair notice and a right to dispute decisions that significantly impact their livelihood.

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208 *See, e.g.*, *supra* notes 13–16 and accompanying text.

209 *See supra* notes 44–51 and accompanying text.

210 *See* Floyd Abrams, *When 2 + 2 Might Equal 5*, N.Y. TIMES (May 7, 2018), https://www.nytimes.com/2018/05/07/opinion/google-right-to-be-forgotten-first-amendment.html (raising First Amendment concerns to a right to be forgotten); Craig Timberg & Sarah Halzack, *Right to Be Forgotten vs. Free Speech*, WASH. POST (May 14, 2014), https://www.washingtonpost.com/business/technology/right-to-be-forgotten-vs-free-speech/2014/05/14/53c9154c-db9d-11e3-bda1-9b46b2066796_story.html?utm_term=.fd41581a9736 (discussing the tension between the First Amendment and the right to be forgotten).

211 *See* John E. Coyle, *The Case for Writing International Law into the US Code*, 56 B.C. L. REV. 433, 433–38 (2015) (finding a growing resistance in the American judiciary to give effect to international law, as well as legislative hostility towards international law).

Conclusion

Access to credit is critical for consumers to accumulate wealth. The use of big data and machine learning in assessing creditworthiness can be a great opportunity to increase the number of people who are able to access credit and to better the accuracy of their credit reports. However, the industry motivation for maximizing profit does not naturally lead in that direction, as increased accuracy of credit reports can raise costs and decrease profits. The law must correct this result; however, the FCRA and ECOA are not capable of doing so for a number of reasons presented in this paper. While it is not a silver bullet to fixing consumer credit problems, the EU-adopted GDPR provides an ample source of inspiration for future reforms, because its industry-agnostic approach and more stringent data processor requirements, as well as the recognition of consumers' property-like rights in personal data, are better suited to regulate lenders in the age of big data and machine learning.