Artificial Intelligence, Machine Learning, and Bias in Finance: Toward Responsible Innovation

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ARTIFICIAL INTELLIGENCE, MACHINE LEARNING, AND BIAS IN FINANCE: TOWARD RESPONSIBLE INNOVATION

Kristin Johnson, * Frank Pasquale**, & Jennifer Chapman***

INTRODUCTION

Over the last decade, a growing number of digital startups launched bids to lure business from the financial services industry.¹ Armed with what they claim are vast quantities of data and sophisticated algorithmic platforms capable of interpreting the data,² these financial technology ("fintech")³


3. In previous publications, Frank Pasquale has examined “incrementalist” fintech, which utilizes technology to provide standard financial services, and “futurist” fintech, in which the entire financial system is remade due to distributed technologies. See Exploring the Fintech Landscape: Hearing Before the S. Comm. on Banking, Hous. & Urban Affairs, 115th Cong. (2017) (statement of Frank Pasquale, Professor of Law, University of Maryland). In this Essay, we use the term “fintech firms” to refer to nondepository financial services firms that integrate artificial intelligence technology and predictive analytics into their business models. We acknowledge that, while there is no universally adopted definition for the term “fintech,” many use the term as a catchall for a broader group of financial services firms that integrate a diverse body of technologies and engage in digital transfers, storage, payments systems, and lending, as well as the origination of virtual currency and robo-advising. See, e.g., Rory Van Loo, Making Innovation More Competitive: The Case of Fintech, 65 UCLA L. REV. 232, 238–40 (2018).
firms have revived long-standing debates regarding the architectural design, regulatory framework, and role of the financial services industry.

Financial product developers and financial service providers have long engaged statistical and probability models as well as predictive analytics to forecast performance. So fintech is not entirely new. However, sometimes a change in quantity can amount to a change in quality. That may be happening in fintech now, as the inclusion of increasingly comprehensive databases, as well as new methods of analysis, means that many fintech firms deploy extremely complex algorithms (including assemblages of earlier models) to predict the likelihood of repayment and profitability of customers. According to some futurists, financial markets’ automation will substitute increasingly sophisticated, objective, analytical, model-based assessments of, for example, a borrower’s creditworthiness for direct human evaluations irrevocably tainted by bias and subject to the cognitive limits of the human brain. However, even if they do occur, such advances may violate other legal principles.

Consider, for example, the application of learning algorithms in credit markets. Some fintech firms aim to adapt learning algorithms to consider nontraditional data in assessing creditworthiness and claim that they will integrate historically excluded individuals into credit markets and expand

4. See infra Part I.A.
5. See infra Part II.A.
8. See infra Part I. Note that customers who are late with payments may be much more profitable than a traditionally good credit risk, since they will be paying more in interest and fees.
access to credit to the thirty-three million unbanked and underbanked households in the United States,12 as well as the nearly two billion individuals and families globally who lack access to financial services13—a group disproportionately composed of women and people of color.14

How might fintech firms accomplish such a lofty goal? Early fintech firms promising to better integrate underresourced communities into financial services markets typically introduced digital money transfer services that facilitated cash distributions among users (such as PayPal, Apple Pay, or Venmo)15 and credit platforms that offered digitally distributed consumer loans. Money transmission services can provide vital peer-to-peer platforms for those who lack access to conventional bank branches or personal checking and savings accounts. Because credit is an indisputably important resource for low-income families in smoothing consumption16 and creating economic stability,17 evaluating the integration of automated decision-making algorithms in credit markets raises underexplored normative concerns including the transparency and accountability obligations of fintech firms, the social welfare effects of permitting fintech firms to operate in credit markets, and the necessity of effective state and federal supervision of fintech firms’ pricing (interest rates), marketing techniques, and structuring of credit products.

With a few quick taps on a smart phone, consumers can access a growing universe of apps that offer discounted interest rates on consumer loans to borrowers with “near prime,” “subprime,” and well-below subprime credit

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12. FDIC, 2017 FDIC NATIONAL SURVEY OF UNBANKED AND UNDERBANKED HOUSEHOLDS 1 (2018), https://www.fdic.gov/householdsurvey/2017/2017report.pdf [https://perma.cc/F7TP-SMHZ] (indicating that 6.5 percent of U.S. households (or 8.4 million households) were unbanked in 2017 and 18.7 percent of U.S. households (24.2 million) were underbanked, meaning that the household had a checking or savings account but also obtained financial products and services outside of the banking system).


scores. For proponents, the launch of fintech firms marks a new frontier in the ever-expanding utopian vision of the “technological sublime” or faith-like devotion to the potential for technology to transform us into a more equitable and just society.

Consumer advocates are justifiably skeptical. While legally prohibited today, well-documented discriminatory, exclusionary, and predatory credit market practices persist. In light of creditors’ history of exploiting unbanked and underbanked communities, even fintech firms’ plans for greater inclusion demand careful scrutiny.

Consider the disturbing tales emerging of digital debt platforms peddling payday loan–style arrangements masked by the opaque and unassailable shroud of innovation and financial inclusion. Kevin Donovan and Emma Park share harrowing narratives of aggressive marketing campaigns by text message that entice borrowers already consumed by “perpetual debt” to borrow at expensive, ballooning interest rates. Further, in the event that they fail to repay the loans, some fintech firms harass overextended borrowers with incessant and embarrassing payment alerts on their mobile phones. Cash-strapped borrowers who lack the resources to meet their daily expenses enter a downward spiral of indebtedness. Borrowers on the


20. Louise Seamster & Raphaël Charron-Chénier, Predatory Inclusion and Education Debt: Rethinking the Racial Wealth Gap, 4 SOC. CURRENTS 199, 199–200 (2017) (describing the targeting of minority homebuyers and students who borrow to fund mortgage or education debt as predatory inclusion); Richard Rothstein, A Comment on Bank of America/Countrywide’s Discriminatory Mortgage Lending and Its Implications for Racial Segregation, ECON. POL’Y INST. (Jan. 23, 2012), https://www.eipi.org/publication/bp335-boca-countrywide-discriminatory-lending [https://perma.cc/28RB-BF6V] (describing the Department of Justice’s settlement with Bank of America and concluding that “[t]he lending industry seems to have systematically targeted African Americans and Hispanics for these risky subprime loans”).


debt treadmill intensify efforts to earn money only to face a “wageless life”—enslaved by and laboring to repay outstanding digital debt.25

This regime of indebtedness is nothing new for underserved communities that lack savings and enter into personal unsecured loans to overcome emergencies or to fund basic household needs.26 Low-income consumers pay remarkably more for basic financial services such as check cashing, money transfers, and short-term loans.27

Without access to credit on fair and reasonable terms, it can be extraordinarily expensive to be poor.28 For families with fragile financial circumstances, credit may serve as a lifeline, enabling them to meet short-term debt obligations.29 Due to the rising costs of education, housing, health care, and even food, ever more consumers navigate an ever-widening web of debt. According to the Federal Reserve Bank of New York’s Center for Microeconomic Data, at the close of the second quarter of 2019, families and individuals faced over $13 trillion in debt obligations.30 Students and their families currently owe approximately $1.5 trillion in student loan debt, even

25. Id.
26. See, e.g., Dalie Jimenez, Ending Perpetual Debts, 55 HOUS. L. REV. 609, 610 (2018) (“[L]aw and practice conspire to create a class of virtually perpetual debts that psychologically and actually burden those individuals for much longer than economically and socially justified.”); see also Ronald J. Mann & Jim Hawkins, Just Until Payday, 54 UCL A L. REV. 855, 857 (2007) (“Payday lenders offer short-term loans at high interest rates to consumers with impaired credit histories. . . . The duration, amount, and fee all can differ from provider to provider, but as a general rule, the loans are small, the repayment period is short, and the annualized interest rate is high. [For] example, with a fee of $30 for a two-week loan of $200, the annual interest rate is almost 400 percent.”); Nathalie Martin & Robert N. Mayer, What Communities Can Do to Rein In Payday Lending: Strategies for Successful Local Ordinance Campaigns Through a Texas Lens, 80 LAW & CONTEM P. PRO BS. 147 (2017); Mehrsa Baradaran, Opinion, Payday Lending Isn’t Helping the Poor. Here’s What Might, WASH. POST (June 28, 2016), https://www.washingtonpost.com/news/in-theory/wp/2016/06/28/payday-lending-isnt-helping-the-poor-heres-what-might/ [https://perma.cc/8CJZ-3GSR] (“These loans do not make customers better off. Many stay indebted for months or even years and most pay interest rates of between 300 and 2,000 percent. By the time they’ve paid off the loan, they are further in the hole than when they started.”).
28. Barbara Ehrenreich, It Is Expensive to Be Poor, ATLANTIC (Jan. 13, 2014), https://www.theatlantic.com/business/archive/2014/01/it-is-expensive-to-be-poor/282979/ [https://perma.cc/K582-V5FY] (giving examples of ways the poor spend more on basic needs, such as housing, food, and childcare).
29. On the dangers of making credit a key determinant of whether and how basic needs are met, see generally Abbye Atkinson, Rethinking Credit as Social Provision, 71 STAN. L. REV. 1093 (2019).
as federal promises of loan forgiveness are under threat.\textsuperscript{31} Homeowners have borrowed $9 trillion in mortgage debt.\textsuperscript{32}

Consumers’ general distrust of legacy financial institutions,\textsuperscript{33} frustration with scandals in financial markets,\textsuperscript{34} and the pervasive abuses and exclusion of underserved communities by financial institutions paved the way for insurgent fintech firms to capture a rapidly increasing role in consumer financial services markets.\textsuperscript{35} Fintech firms are set to capitalize on the efficiencies generated by machine learning, a form of artificial intelligence,\textsuperscript{36} to lower transaction fees, increase the rates paid on savings deposits, and expedite financial transfers and payments in real time.\textsuperscript{37} While some fintech firms operate as digital-only, end-to-end platforms that directly service individuals and families, others partner with conventional, state or federally chartered, financial intermediaries such as depository banks.\textsuperscript{38} Collectively, these fintech firms comprise a new class of competitors: neo-banks.

As artificial intelligence increasingly influences the terms and availability of credit, this nascent technology will perform key gatekeeping functions, determining who receives access to credit and on what terms. For those with access, algorithms may decide all material terms of any credit arrangement.\textsuperscript{39}


\textsuperscript{32} FED. RESERVE BANK OF N.Y., supra note 30.


\textsuperscript{36} We use the general term “artificial intelligence” to refer to a diverse but related body of technologies that simulate human decision-making and learning behavior. The technologies include, among others, machine learning, deep learning, and neural networks. See Michael L. Rich, Machine Learning, Automated Suspicion Algorithms, and the Fourth Amendment, 164 U. PA. L. REV. 871, 880 (2016).


\textsuperscript{38} See infra Part II.A.

In other words, learning algorithms may help regulators and lenders fulfill an altruistic promise of inclusion, compensating for decades of discrimination and exclusion in financial markets. However, should learning algorithms fail to fulfill this promise, fintech firms may hardwire predatory inclusion, existing inequities, and unconscious biases into financial markets for the next several generations, compounding wealth gaps and undermining the welfare of the most vulnerable communities.

This Essay proceeds as follows. Part I describes fintech firms’ integration of learning algorithms and their anticipated economic and social welfare benefits—enhanced efficiency, accuracy, and accessibility. Part II sketches the emerging regulatory landscape. Over the last decade, federal banking regulators signaled and adopted policies that preempted state regulatory authority over fintech firms. In the summer of 2018, the Office of the Comptroller of the Currency (OCC) announced its intention to allow fintech firms to apply for special purpose charters that would permit fintech firms to operate, in many respects, as national banks (“Fintech Charter Decision”). Consistent with a decades-long campaign to expand the scope of its authority, the OCC’s seemingly innocuous announcement reflects the agency’s increasingly aggressive interpretation of the scope of its statutory mandate. The OCC’s Fintech Charter Decision creates gaps in the supervision of fintech firms and encourages market participants to engage in regulatory arbitrage. Part II argues that federal special purpose charters set the stage for regulatory arbitrage and may enable fintech firms to minimize their exposure to state antidiscrimination and consumer protection regulations. Reducing regulatory oversight of these important legal and ethical norms in a dynamic and evolving market defined by a technology that may import unconscious biases and disadvantage lower-income individuals and families raises red flags.

Part III concludes with brief reflections regarding the necessity for courts and regulators to balance the promised benefits of fintech firms’ neo-banking initiatives with the historic and special gatekeeping role of banking platforms. Unilateral deregulatory action by state or federal regulators may undermine efforts to ensure effective oversight of fintech firms that seek to extend access to safe and affordable banking services.

I. NEO-BANKING ON THE RISE

A. Artificial Intelligence (AI) and the Future of Finance

Emerging credit intermediaries aim to capitalize on a new generation of consumers and their preference for using mobile devices to shop, make payments, and manage finances. These platforms aspire to capture a portion of fees associated with scoring, lending, and servicing a massive consumer debt market (estimated to be nearing $14 trillion as of June 2019).41

40. See infra Part II.
41. FED. RESERVE BANK OF N.Y., supra note 30; Mark DeCambre, U.S. Consumer Debt Is Now Above Levels Hit During the 2008 Financial Crisis, MARKETWATCH (June 25, 2019),
Bypassing the collection of tedious paper applications and cumbersome supporting documentation, digital credit decisions reduce the cost of underwriting.\footnote{Julapa Jagtiani & Catharine Lemieux, Fintech Lending: Financial Inclusion, Risk Pricing, and Alternative Information (Fed. Reserve Bank of Phila., Working Paper No. 17-17, 2017), https://www.philadelphiafed.org/-/media/research-and-data/publications/working-papers/2017/wp17-17.pdf [https://perma.cc/W2J5-4553].} Beyond these gains, empirical studies establish that advanced statistical models and predictive analytics enhance lenders’ ability to calculate default and prepayment risks.\footnote{Amir Khandani et al., Consumer Credit-Risk Models via Machine-Learning Algorithms, 34 J. BANKING & FIN. 2767, 2787 (2010).} Fintech advocates celebrate the introduction of automated decision-making (ADM) platforms, claiming that ADM platforms mitigate risks related to discrimination against legally protected groups since a computer system is not, in and of itself, capable of the mental processes (whether conscious calculation or barely conscious emotions or unconscious biases) associated with humans’ discriminatory action.\footnote{Potential Benefits and Risks of the Increased Use of Data in Financial Services Applications: Hearing Before the S. Comm. on Banking, Hous. & Urban Affairs, 116th Cong. (2018) (statement of Brian Knight, Director, Innovation and Governance Program, Mercatus Center at George Mason University).} According to its advocates, ADM eliminates some pernicious animus.\footnote{See FTC, supra note 2, at 19.} However, ADM may only shift the locus of discrimination from the bank manager’s desk to the programmer’s computer screen or to the data scientists’ training sets since data are never brute or raw—they are always collected, analyzed, and used by people, who may have the same conscious calculations, barely conscious emotions, or unconscious biases at play in their own observations. Artificial intelligence (AI) technologies may aggregate data or analyze information gathered and processed through image or voice data that reflect unconscious bias.\footnote{Rich, supra note 36, at 873.} Disparate impacts are also, of course, a major concern.

To enhance predictive capabilities, AI methods rely on supervised and unsupervised learning.\footnote{See generally ETHEM ALPAYDIN, INTRODUCTION TO MACHINE LEARNING (2d ed. 2010).} This refers to how the algorithm optimizes its output based on repeated analyses of the data set. In supervised learning, the algorithm is trained with well-labeled and classified data, whereas there are no training data in unsupervised learning.\footnote{For accessible explanations of supervised and unsupervised learning, see Bernard Marr, Supervised vs Unsupervised Machine Learning—What’s the Difference?, FORBES (Mar. 16, 2017, 3:13 AM), https://www.forbes.com/sites/bernardmarr/2017/03/16/supervised-vs-unsupervised-machine-learning-whats-the-difference/ [https://perma.cc/HV5A-PJDF] and Devin Soni, Supervised vs. Unsupervised Learning, MEDIUM (Mar. 22, 2018), https://towardsdatascience.com/supervised-vs-unsupervised-learning-14f68c32ea8d [https://perma.cc/5JKS-43F5].} Unsupervised learning infers information from the data set and can be highly resource intensive, as the data set is tested against a massive number of potential patterns.\footnote{Marr, supra note 48; Soni, supra note 48.}

networks, common algorithms in supervised learning, mimic aspects of the human brain in order to generate results that older methods of statistical analysis could not produce.\textsuperscript{50}

Like traditional algorithms, AI can provide an analytic predicate for ADM.\textsuperscript{51} Unlike traditional algorithms, however, much of contemporary AI is either opaque or so complex that an effort to explain its “reasoning” would be about as useful as a map of all the synapses and other chemical reactions in the brain that occur when, say, a manager decides whether to grant or deny an employee’s request for a vacation day.\textsuperscript{52} Machine learning is an application of AI that trains algorithms to improve on algorithmically programmed decision-making processes, meaning the algorithm may assess the shortcomings in its decision-making process in early iterations and improve upon its analyses and predictions regarding likely outcomes based on the data.\textsuperscript{53}

Machine learning can automatically detect patterns in data.\textsuperscript{54} Upon discovering patterns, machine learning can be programmed to apply these patterns to predict future outcomes based on the supplied data.\textsuperscript{55} These methods engage in complex decision-making and apply logic to resolve uncertainty.\textsuperscript{56}

With ample and ongoing data inputs, machine learning enables an algorithm or ensembles of algorithms engaged in “continuous improvement on a given task” to improve performance.\textsuperscript{57} However, it is important to understand the term “learning” here as a metaphor and not “the more holistic concept referred to when people speak of human learning.”\textsuperscript{58} As Michael Rich has observed, “machine learning does not require a computer to engage in higher-order cognitive skills like reasoning or understanding of abstract concepts.”\textsuperscript{59} This leaves AI methods vulnerable to pursuing forms of analysis that might be set aside as suspect by a seasoned finance professional (whether an attorney, analyst, trader, or other professional).\textsuperscript{60}

\begin{thebibliography}{99}
\item[51] Rich, \textit{supra} note 36, at 880.
\item[54] Rich, \textit{supra} note 36, at 874.
\item[55] Id.
\item[57] Rich, \textit{supra} note 36, at 880.
\item[58] Id.
\item[59] Id.
\item[60] On the importance of AI complementing, rather than replacing, human judgment, see generally Frank Pasquale, \textit{Professional Judgment in an Era of Artificial Intelligence and Machine Learning}, \textit{Boundary 2}, Feb. 2019, at 73 and Frank Pasquale & Glyn Cashwell,
Instead “machine learning applies inductive techniques to often-large sets of data to ‘learn’ rules that are appropriate to a task.”61 In other words, the “intelligence” of a machine learning algorithm is oriented to outcomes, not process; a “smart” algorithm is designed to reach consistently accurate results on a chosen task, even if the algorithm does not “think” like a person. Machine learning is in this way reminiscent of an idiot savant: like a calculator multiplying fifteen-digit numbers faster than any human can, in a narrow, well-specified area, it can reach conclusions faster than any human can.62 As more dimensions of optimal outcomes are added to the solution space, machine learning may gradually improve with “experience” (that is, more data sets, which of course can often only be constructed with a great deal of contingent and contestant human work to gather and “clean” data).63 However, complicated and ill-defined problems are hard to even pose to a machine learning system. One key question for those advocating machine learning in finance is whether underwriting and similar decisions can and should be simplified and coarsened to match the available technology, or whether they are more properly kept at extant levels of complexity.

Learning algorithms model, but cannot replicate, the complexities of cognition and emotion that are the hallmarks of human thinking processes. Instead, these algorithms analyze data sets to predict outcomes.64 Although computers can mimic human decision-making now, they will need to evolve quite a long way to even begin to replicate in silico what is commonly done in the human brain.

The details of machine learning help mark critical distinctions between human and computer decision-making. In machine learning, an initial data set is subdivided into a training set, a verification set or validation set, and a test set.65 The algorithm begins by analyzing the training set, thereby learning the initial group classification rules.66 For example, a machine-vision algorithm to distinguish images of light brown dogs from those of light brown bagels may “learn” that most bagels lack the characteristic pattern of three dark areas (eyes and a nose) possessed by nearly all images of dogs’ faces.67 These classification rules are then applied to a verification or validation set and the results are then used to optimize the rules’

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62. Id. at 873.
64. See Rich, supra note 36, at 881.
65. Id.
66. Id.
67. This may seem like a trivial problem, but it can be difficult. See Michael Schramm, ‘Puppy or Bagel’ Game Will Keep You Guessing, USA TODAY (Mar. 10, 2016, 6:32 PM), https://www.usatoday.com/story/college/2016/03/10/puppy-or-bagel-game-will-keep-you-guessing/37414107/ [https://perma.cc/3C3T-AJ28]. Note, too, that a baby would likely learn the distinction between a dog or a bagel after a few encounters with each; a machine learning program may take hundreds or thousands of images to do so.
parameters. \textsuperscript{68} Lastly, “the optimized rules are applied to the test set” and the results of this stage establish a confidence level and support level for each rule\textsuperscript{69}: “Rules with a low support level are less likely to be statistically significant. . . . The confidence level of a rule describes how often objects in the test set follow the rule. It is, in essence, a measure of the strength of the algorithm’s prediction.”\textsuperscript{70}

The key to developing the algorithms used in these situations is to evaluate the output of each algorithm with the desired result; this allows the machine to learn by making its own connections within available data.\textsuperscript{71} Algorithms tend to be trained using a four-step process.\textsuperscript{72} Google Image’s image recognition learning algorithm is a classic example of this process.\textsuperscript{73} First, the algorithm is shown a set of known images (for example, ten thousand pictures of ducks).\textsuperscript{74} Second, the algorithm develops complex internal rules based on nonlinear processes.\textsuperscript{75} Such rules may have nothing to do with our usual ways of recognizing ducks (e.g., by beak, feathers, and feet). Rather, they may seize upon perceptions unavailable to humans (such as a precise distance between eyes, a pattern of foot webbing unnoticeable by the human eye, or some combination of hundreds of other measurements that might never come to mind to a person).\textsuperscript{76} Third, the algorithm tests those rules on a test set (i.e., which of these are ducks?).\textsuperscript{77} Fourth, the algorithm adjusts its internal rules based on the success of the test.\textsuperscript{78} These steps are repeated ad infinitum until the algorithm can accurately and consistently classify the images.\textsuperscript{79}

“[B]y exposing so-called ‘machine learning’ algorithms to examples of the cases of interest . . . the algorithm ‘learns’ which related attributes or activities can serve as potential proxies for those qualities or outcomes of interest.”\textsuperscript{80} Machine learning enables algorithms that analyze data to “become more accurate over time when completing a task.”\textsuperscript{81} Thus machine

\textsuperscript{68} Rich, supra note 36, at 882.
\textsuperscript{69} Id.
\textsuperscript{70} Id. ("[T]o restrict which rules the algorithm will use to ensure predictions are made only on the basis of statistically significant correlations, programmers often require rules to meet a minimum support level.").
\textsuperscript{71} Id.
\textsuperscript{72} Id.
\textsuperscript{73} Id.
\textsuperscript{74} Id.
\textsuperscript{75} Id.
\textsuperscript{76} Id. at 882–83.
\textsuperscript{77} Id. at 882.
\textsuperscript{78} Id.
\textsuperscript{79} Id. Recently, the repetition of testing has led to environmental concerns. One study estimates that training one machine learning model uses more carbon than five cars (including the carbon footprint of their manufacture). Karen Hao, Training a Single AI Model Can Emit as Much Carbon as Five Cars in Their Lifetimes, MIT TECH. REV. (June 6, 2019), https://www.technologyreview.com/s/613630/training-a-single-ai-model-can-emit-as-much-carbon-as-five-cars-in-their-lifetimes/ [https://perma.cc/7G4D-WHGY].
\textsuperscript{80} Solon Barocas & Andrew Selbst, Big Data’s Disparate Impact, 104 CALIF. L. REV. 671, 678 (2016).
\textsuperscript{81} Rich, supra note 36, at 880.
learning methods are becoming more pervasive throughout society in situations where optimal outcomes can be quantified or otherwise evauatively ranked. Such methods are used in a variety of classification tasks from identifying spam emails to diagnosing diseases. But as they spread from evaluating tumors to evaluating persons, far greater ethical concerns arise.

B. Bias and Discrimination Concerns in Finance and AI

As the previous section explains, in theory, facially neutral algorithms mitigate the risk that consumers will face intentional discriminatory treatment based on legally protected traits such as race, gender, or religion that commonly characterize face-to-face decisions in financial services. Evidence demonstrates that incomplete or inaccurate data sets may influence the objectivity of learning algorithms. Even more alarming, learning algorithms may easily identify the most expedient path or ideal variable for solving a problem and making a decision, even if it entirely misses the point of the training. This approach may result in the learning algorithm independently identifying a facially neutral attribute in data sets that serves as a proxy for a legally protected trait and executing discriminatory results—even if developers expressly programmed the algorithm not to discriminate on the basis of the same protected trait.

Data mining systems across the board are capable of reproducing the biases created by human decisions. This occurs because the data inputted into the computer has been simplified to teach the computer to learn by example, oftentimes a flawed example. Developers have created predictive algorithms that mine personal information to make guesses about individuals’ likely actions and risks. “[M]any credit-scoring mechanisms include factors that do not just assess the risk characteristics of the borrower; they also reflect the riskiness of the environment in which a consumer is utilizing credit, as well as the riskiness of the types of products a consumer uses.”

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82. Id. at 882.
85. Id.
89. Id. at 127–28.
90. Kim, supra note 87, at 860, 875, 885.
A robust literature describes a variety of predatory tactics that creditors have employed to target vulnerable borrowers. Credit intermediaries extend credit to borrowers with limited or impaired credit histories but often demand higher, arguably exorbitant, interest rates from these borrowers. Notwithstanding their awareness of the exploitive and abusive credit terms, vulnerable borrowers may conclude that they have few, if any, other options.

Historically, consumer lending firms and credit card companies engaged in aggressive advertising and solicitation practices, such as bait-and-switch or offers of teaser low interest rates. Annually, creditors swarm students on university campuses, creating a carnival-like atmosphere of blaring music and freebies and inviting the students to enjoy cheap, easy credit.

Advanced machine learning and AI will enhance the ability of creditors, payday lenders, and other predatory market participants to target vulnerable consumers, exacerbating extant problems.

An increasing number of commentators express concern that failing to address bias may weaponize ADM platforms. Recently, for example,

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96. Engel & McCoy, supra note 93, at 1261.


Social media erupted with outrage after journalists discovered Amazon’s “Prime-lining,” a pattern of denying some of its services to disadvantaged neighborhoods, eerily reminiscent of historical redlining. Social media posts revealed that Amazon concentrated its Prime delivery service in predominantly white neighborhoods. These concerns about what Roberto Unger has called “the most advanced modes of production” should apply a fortiori in financial contexts, given the power of such firms.

As sophisticated learning algorithms continue to evolve, the established dynamic and comprehensive accountability standards that address consumer protection and bias will prove challenging. Recently adopted federal banking regulations embrace a deregulatory approach that may encourage innovation but leave the most marginalized individuals and families deeply vulnerable to exploitation and discrimination as fintech firms dominate the financial markets. The next Part explores this deregulatory trend.

II. THE CHALLENGE OF REGULATORY OVERSIGHT AND FINTECH

On July 31, 2018, the OCC announced its decision to resolve the regulatory uncertainties regarding the application of banking regulations to fintech firms and to permit these newly minted nondepository entities to apply for national bank charters in the Fintech Charter Decision. The OCC’s action spurred federal court claims seeking a declaratory judgment that the federal agency had exceeded its authority under its enabling statute by issuing charters to nondepository fintech firms and soliciting a permanent injunction to prevent the OCC from chartering fintech firms.

This Part evaluates the OCC’s rationale for adopting the Fintech Charter Decision. Exploring the claims by state banking supervisors reveals the necessity of state and federal oversight for fintech firms operating as, for example, money transmitters or consumer credit platforms. This Part concludes that preempting state oversight leaves low-income and


101. See Douglas S. Massey, Origins of Economic Disparities: The Historical Role of Housing Segregation, in SEGREGATION: THE RISING COSTS FOR AMERICA, supra note 21, at 39, 69 (describing “redlining” as a systematic practice of using discriminatory risk-rating residential maps for credit and insurance underwriting policies). The maps characterized predominantly African American neighborhoods as undesirable, which led residents to face stricter underwriting guidelines or reduced access to higher quality credit and insurance products. Id.

102. Ingold & Soper, supra note 100.


underresourced communities vulnerable to historic predatory and discriminatory tactics disguised by high-tech innovation.105

A. The Fintech Charter Decision and Federal Preemption

Fintech firms typically adopt one of two approaches: (1) a digital-only services platform that provides financial services directly to consumers106 or (2) a partnering platform that operates as an intermediary.107 The latter category of fintech firms interpose themselves between consumers and regulated (bank and nonbank) financial institutions. Fintech firms acting as intermediaries may enter into exclusive partnership arrangements, leveraging the fintech firm’s integration of learning algorithms and the regulated financial institution’s established reputation, relationships, and expertise. Perhaps most importantly, platforms partnering with regulated financial institutions attain the privileges and benefits from their affiliation with federally chartered banking institutions.

In accord with the distinct design of our nation’s “dual banking system,” both federal and state regulators have the power to issue bank charters.108 Banks that receive state charters are subject to the day-to-day supervision of state banking regulators109 but cannot evade federal regulation. Federal regulators supervise federally chartered banks and, to mitigate the challenges of complying with dual—and, at times, incongruent—regulatory obligations, federally chartered banks need only comply with limited state regulatory mandates.110

The National Bank Act (NBA) authorizes the OCC to issue federal bank charters to qualifying financial institutions.111 The statutory language of the NBA grants the OCC broad authority to introduce regulations associated with


106. Rocket Mortgage is an end-to-end, online mortgage lending platform operated by Quicken Loans, a nonbank mortgage originator. See ROCKET MORTGAGE BY QUICKEN LOANS, https://www.rocketmortgage.com (last visited Oct. 6, 2019).

107. GreenSky is a consumer credit platform that pairs consumers seeking to purchase retail goods or certain services with credit and financial institutions licensed to originate and distribute consumer loans. See GREENSKY, https://www.greensky.com (last visited Oct. 6, 2019).


109. Id. at 1.


issuing charters112 and to determine licensing criteria.113 In 2003, the OCC amended the regulations governing its authority to issue charters ("2003 Amendments"), creating a path for the agency to issue special purpose national bank (SPNB) charters to nondepository firms.114 To receive an SPNB charter, however, an entity must be engaged in the "business of banking," meaning the firm conducts at least one of the following core banking functions: receiving deposits, paying checks, or lending money.115

For a decade following the 2003 Amendments, the OCC’s newly promulgated authority lay dormant. In 2016, the OCC published a white paper exploring the regulatory impact of emerging fintech firms.116 And in December 2016,117 at an event at the Georgetown University Law Center, then-Comptroller Thomas Curry announced the OCC’s decision to “move

113. Id. The NBA grants the OCC authority to prescribe rules and regulations to carry out its responsibilities associated with issuing charters. Id. Under the NBA, “upon careful examination of the facts,” the comptroller of the currency will determine if an applicant for a national banking charter “is lawfully entitled to commence the business of banking” and issue “a certificate” indicating that the business has complied with the standards required for firms engaged in the business of banking. Id. § 27.
115. Id. Under the “bank powers clause” in section 24 of the NBA, the OCC has the authority to charter national banking associations by granting them “all such incidental powers as shall be necessary to carry on the business of banking” and then listing five express powers. 12 U.S.C. § 24 (2012). The express powers of national banks under section 24 include: (1) discounting and negotiating notes; (2) receiving deposits; (3) trading currency; (4) making loans on personal security; and (5) circulating notes. Id. The terms “incidental powers” and the “business of banking” are not expressly defined in the NBA but include activities authorized at the discretion of the comptroller, within reasonable bounds. See id. §§ 21, 24, 26–27.
117. See generally EXPLORING SPNBS, supra note 116.
forward with chartering financial technology companies that offer bank products and services.”

As a result of the OCC’s Fintech Charter Decision, each class of fintech firms (digital-only platforms or partnering platforms) may apply for an SPNB charter. While subject to federal regulatory oversight, fintech firms that receive an SPNB charter may be exempt from state regulations that the OCC concludes prevent or significantly interfere with the exercise of banking powers authorized under federal law.

According to the OCC, enabling fintech firms to apply for SPNB charters levels the playing field between fintech firms and conventional depository banks, promotes uniform eligibility criteria, and ensures consistency in the development and enforcement of legal standards across the increasingly diverse body of entities providing financial services. The OCC also boasts that the breadth and depth of federal expertise in banking and risk management oversight, the benefits of federal insurance on deposits and national banks’ safety and soundness (e.g., “contingency” plan development), and ethical obligations (to increase inclusion and fair access to financial markets) leave little room to challenge the OCC’s decision to preempt state financial services regulators’ supervision of fintech firms. Proponents argue that the absence of federal oversight will spur a race to the bottom, as states compete to attract fintech firms to their jurisdiction. This account is, however, misleading.

The arguments articulated in support of granting the OCC exclusive jurisdiction over fintech firms are weak, inaccurate, and, in some instances, simply wrong. Even assuming all of the economic arguments supporting federal regulation are persuasive, there are important normative reasons to reject OCC oversight of fintech firms. The OCC’s Fintech Charter Decision may have detrimental implications for lower-income consumers that will rely on nondeposit banking entities for credit and financial services.

To that end, state regulators and consumer protection advocates have raised alarms. The New York State Department of Financial Services (DFS) and the national Conference of State Bank Supervisors (CSBS) each initiated federal lawsuits seeking to enjoin the OCC from issuing charters on the grounds that issuing SPNB charters to nondepository entities exceeded the agency’s authority under the NBA.122

In their initial complaints, state regulators challenged the OCC’s decision to preempt state authority as “lawless, ill-conceived, and destabilizing of

121. EXPLORING SPNBs, supra note 116, at 2.
financial markets that are properly and most effectively regulated” by states.123 The DFS condemned the OCC policy for “put[ting] New York financial consumers—and often the most vulnerable ones—at great risk of exploitation by federally chartered entities improperly insulated from New York law.”124

Because the OCC had not yet implemented a rule permitting fintech firms to apply for SPNB charters, the federal district courts concluded that the initial federal claims by the DFS and CSBS challenging the Fintech Charter Decision were not ripe for review.125 Following the OCC’s formal announcement of the Fintech Charter Decision, the DFS reintroduced the claim for declaratory relief and an injunction preventing the OCC from granting fintech firms charters.126 Setting aside the procedural issues and jurisdictional and constitutional claims raised by the DFS and CSBS, there are several fundamental weaknesses in the OCC’s rationale for preempting state regulatory oversight.

First, the DFS and CSBS argued that the OCC’s Fintech Charter Decision and the adoption of the 2003 Amendments exceeded the OCC’s authority under the NBA.127 Critically, the DFS and CSBS questioned the OCC’s authority to declare that nondepository firms are engaged in the “business of banking”;128 the DFS and CSBS argued that Congress and state legislators carefully labored for more than a century to create a delicate balance between federal and state regulators’ oversight of entities that are “banks” and nonbank financial institutions.129 The OCC’s Fintech Charter Decision “upsets the balance” between state and federal regulators and “extends federal banking law’s blanket preemption to numerous areas currently subject to [state] laws and supervision.”130

As noted in the previous section, entities engaged in the “business of banking” perform one of three core functions: receiving deposits, paying

123. Complaint for Declaratory and Injunctive Relief at 1, Vullo, No. 17 Civ. 3574 (NRB) (S.D.N.Y. May 12, 2017), ECF No. 1 [hereinafter Vullo Complaint]. The DFS claimed that issuing SPNB charters to nondepository institutions exceeds the OCC’s authority under the NBA and unjustly defies the DFS’s regulatory authority over these institutions. Id. However, the OCC’s motions to dismiss these two complaints were granted. Conference of State Bank Supervisors, 313 F. Supp. 3d at 302; Vullo, 2017 WL 6512245, at *10.
124. Vullo Complaint, supra note 123, at 1–2.
126. Vullo v. OCC, 378 F. Supp. 3d 271, 280 (S.D.N.Y. 2019). The court denied the OCC’s motion to dismiss the state agency’s claims that the OCC exceeded its authority under the NBA by permitting fintech firms that are nondepository entities to apply for SPNB charters. Id. at 278.
127. The DFS also claimed that the OCC’s Fintech Charter Decision violated the Tenth Amendment. Id. at 299. The federal district court did, however, dismiss the DFS’s claims alleging that the OCC’s Fintech Charter Decision violated the Tenth Amendment. Id.
128. According to the NBA’s original language, entities applying for SPNB charters must conduct activities that constitute the “business of banking.” 12 C.F.R. § 5.20(e)(1)(i) (2019).
130. Vullo, 378 F. Supp. 3d at 286.
checks, or lending money. The OCC’s Fintech Charter Decision is the first attempt in the agency’s 140-year history to regulate nondepository institutions as “banks.”

Once the OCC formally adopted the Fintech Charter Decision and the DFS resubmitted its claims, the Southern District of New York denied, in part, the OCC’s motion to dismiss the DFS claims and concluded that “[a] key feature of the dual banking system is that, with certain exceptions, any entity that is not a deposit-receiving bank—including non-depository fintech companies—is left largely to the prerogative of the states to regulate.” The DFS’s claims poignantly articulated the primacy of a state’s regulatory authority over nondepository fintech firms and condemned the OCC’s blanket preemption as upsetting the balance of the dual banking system. As the court explained, the OCC’s Fintech Charter Decision directly encroaches upon the sovereign interests of the state of New York.

B. Automating Predatory Inclusion

The Fintech Charter Decision presumably permits nondepository fintech firms operating as money transmitters and payday lenders to apply for SPNB charters. As nonbank entities, money transmitters and payday lenders have traditionally been subject to state but not federal regulation. As the DFS complaint noted, because of the disproportionate number of vulnerable consumers who rely on these types of entities, the shift in regulatory oversight is, simply stated, “troubling.” The explosive growth of fintech firms using ADM platforms to solicit vulnerable consumers at an unprecedented volume and velocity in financial services areas such as money transmission, mortgage lending, unsecured consumer lending, and debt collection demands careful oversight.

The OCC’s Fintech Charter Decision compromises states’ regulatory and enforcement authority over fintech firms with SPNB charters acting as money transmitters and payday lenders, which enables these entities to evade state interest rate caps and usury laws. These businesses may “trap consumers in a cycle of high-interest borrowing that they can never repay, leading to the sort of economic and social devastation like that seen in the recent foreclosure crisis.”

As 270 entities—community, labor, civil rights, faith-based, and military and veterans groups—observed earlier this year, “over 90 million Americans

131. 12 C.F.R. § 5.20(e)(1)(i).
133. Id.; see also Otoe-Missouria Tribe of Indians v. N.Y. State Dept’ of Fin. Servs., 974 F. Supp. 2d 353, 361 (S.D.N.Y. 2013), aff’d, 769 F.3d 105 (2d Cir. 2014) (recognizing New York State’s primacy in regulating payday loans when no conflicting federal law exists).
134. Vullo, 378 F. Supp. 3d at 286-87 (explaining that “[t]he threats to New York’s sovereignty are so clear that OCC does not even mention, let alone contest, the state’s interests”).
135. Vullo Complaint, supra note 123, at 15.
136. Id.
live in jurisdictions where payday lending is illegal.”

These state consumer protection laws help consumers “save billions of dollars each year in predatory payday loan fees that trap people in long-term, devastating cycles of debt.”

Second, the Fintech Charter Decision creates risk management concerns that erode consumer protections related to uninsured losses. Safeguards governing state and federal depository institutions protect consumers from risks of loss related to liquidity and solvency crises. Fintech firms holding nondepository SPNB charters will presumably not be subject to the supervision of the Federal Deposit Insurance Corporation. As a consequence of the OCC’s Fintech Charter Decision, these firms may also be free from state bonding requirements, liquidity, and capitalization standards.

Third, the OCC’s Fintech Charter Decision deprives state regulators of registration and licensing fees that fund consumer protection and antidiscrimination enforcement actions. The operating expenses of DFS and other state financial services regulators “are funded by assessments levied by the agency upon New York State licensed financial institutions.”

The authority to issue charters enables state banking regulators to oversee the operational activities of these types of businesses and funds and the collection of charter fees funds states’ enforcement of consumer protection and antidiscrimination laws.

Notwithstanding the OCC’s claims, early evidence suggests that the agency does not have a well-established method to ensure any of the proposed regulatory benefits. According to Kenneth Thomas, the OCC is


138. Payday Lending-Free States Cry Foul over OCC “Fintech” Charter, supra note 137; see Davis & Lupton, supra note 137.

139. Vullo, 378 F. Supp. 3d at 296 (“First, the Federal Reserve Act requires national banks to obtain membership in the Federal Reserve System and insurance under the Federal Deposit Insurance Act (FDIA). But a national bank must be ‘engaged in the business of receiving deposits’ to obtain insurance under the FDIA. Chartering national banks that do not receive deposits—which are ineligible for insurance under the FDIA and therefore unable to join the Federal Reserve System—would introduce an anomaly into this scheme.” (citations omitted) (quoting 12 U.S.C. § 1815(a)(1) (2012))).

140. Id. at 279–80.

141. See Vullo Complaint, supra note 123, at 14–17.

142. Id. at 17.
unlikely to apply the rigorous standards of inclusion set out in existing legislation such as the Community Reinvestment Act (CRA). To appease fintech firms, Thomas argues, the OCC likely will engage in a policy that is at best “CRA-lite” and at worst “an outright CRA exemption.” If the OCC genuinely enforces obligations subjecting fintech firms to examinations, public evaluations, ratings, and community input consistent with the traditional understandings of notions of greater inclusion, fintech firms likely will balk and shy away from federal charters.

These are not mere hypothetical concerns; as the New Economy Project has documented, online lenders “have been subject to a long list of state and federal enforcement actions, settlement agreements, and investigations.” Moreover, they may lure unsuspecting borrowers away from much more sustainable alternatives, including publicly vetted options.

Federal preemption severely restricts state financial services regulators’ oversight. While our nation’s dual banking system permits financial institutions to apply for either state or federal charters, electing to apply for a federal charter enables a bank to escape certain day-to-day regulations imposed by state banking authorities: national banks are exempt from state rules addressing licensing, enforcement, and interest rates. States cannot adopt or enforce laws that prevent or significantly interfere with the national banks’ ability to exercise powers granted by federal charters.


144. Id.


147. See Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank) § 1044(a), 12 U.S.C. § 258(i)(1) (2012). In 2007, prior to the adoption of the Dodd-Frank Act, the U.S. Supreme Court upheld the OCC’s preemptive authority over licensing and supervisory enforcement, See Watters v. Wachovia Bank, N. A., 550 U.S. 1, 7, 21 (2007). Two years later, in 2009, the Court concluded that the OCC did not have the exclusive right to enforce nonpreempted state laws against national banks, See Cuomo v. Clearing House Ass’n, 557 U.S. 519, 529 (2009) (preserving the power of state attorneys general to enforce valid state laws against national banks). The Dodd-Frank Act clarified the legal standard for preemption and established that the NBA may preempt state consumer financial law only if:
Consequently, many of the benefits touted by proponents of the Fintech Charter Decision may well be illusory.

The Fintech Charter Decision is a recent example of a series of aggressive preemptive actions by the OCC to expand the agency’s scope of authority and federally chartered banks’ permitted activities.148 Consider, for example the OCC’s decision to permit federally chartered banks to engage in over-the-counter credit derivatives transactions. Beginning in the late 1980s and ending in 2008, shortly before the onset of the recent financial crisis, the OCC issued a series of interpretive letters asserting its regulatory authority over this innovative, emerging class of financial assets.149

Scholars and commentators have sharply criticized the OCC’s “excessively broad” interpretation of the meaning of the statutory language that establishes the ambit of its regulatory mandate.150 As described above, the NBA authorizes the OCC to determine the scope of permissible activities for federally chartered banks engaged in the “business of banking.” Although the safety and soundness of financial markets should serve as a guiding principle for the “business of banking,” few have questioned the agency’s authority to define the scope of federally chartered banks’ permitted activities.151

Emboldened by its unchecked authority, the OCC utilized the interpretive letter campaign during the period leading up to the recent financial crisis to permit banks to engage in options, futures, forward contracts, and swap arrangements that exposed the banks to catastrophic losses. Curiously, the OCC and other senior banking regulators justified their decision by

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150. See, e.g., id. at 1041, 1100–06.

151. See id. at 1055 n.64 (“[T]he issue of what constitutes the ‘business of banking’ seems to have completely dropped off legal scholars’ radars shortly after [NationsBank of N.C., N.A. v. Variable Annuity Life Ins. Co., 513 U.S. 251 (1995)] was decided. Since the mid-1990s, there has been no serious academic analysis of the evolution and scope of this fundamental concept in banking law. Partly, this loss of interest may be a result of the OCC’s successful campaign to assert its broad view as the dominant theory blessed by the U.S. Supreme Court.”).
promoting the notion that derivatives would enable the banks to better manage risks. According to the OCC:

[B]anks may use these [derivatives] contracts to manage certain risks resulting from their expressly permitted banking activities. In these areas, the use of options is connected to the underlying banking activities, such as managing risks in the bank’s investment portfolio and dealer-bank activities, and managing interest rate risks associated with asset/liability management.152

In the wake of the financial crisis, the largest financial institutions and thousands of surviving small- and medium-sized banks solicited federal aid. Markets endured a near-decade of tumult and employment opportunities, savings, and access to credit markets disappeared for millions of lower-income families. As Saule T. Omarova explains, the impact of the tools in the OCC’s “arsenal of statutory interpretation cannot be underestimated.”153

The Fintech Charter Decision replicates the agency’s erroneous and deeply problematic approach to navigating agency action.

III. COLLABORATING TO ADDRESS BIAS AND PROTECT CONSUMERS

In the run-up to the financial crisis, federal authorities preempted state law meant to protect consumers.154 The stated aim was to ensure financial inclusion and innovation, but the unintended consequences were disastrous. Federal authorities were not adequately staffed to monitor, let alone deter or punish, widespread fraudulent practices.155 Agencies like the OCC have also flattened diverse state policies into a one-size-fits-all, cookie-cutter approach.156 We all know the results.157 It now appears that the OCC may be repeating its past mistakes.

153. Omarova, supra note 149, at 1059.
154. FIN. CRISIS INQUIRY COMM’N, THE FINANCIAL CRISIS INQUIRY REPORT: FINAL REPORT OF THE NATIONAL COMMISSION ON THE CAUSES OF THE FINANCIAL AND ECONOMIC CRISIS IN THE UNITED STATES 112 (2011), https://www.gpo.gov/fdsys/pkg/GPO-FCIC/pdf/GPO-FCIC.pdf [https://perma.cc/NH6D-DDCV] (“Once OCC and OTS preemption was in place, the two federal agencies were the only regulators with the power to prohibit abusive lending practices by national banks and thrifts and their direct subsidiaries.”); id. at 350 (“The Office of Thrift Supervision has acknowledged failures in its oversight of AIG. . . . John Reich, a former OTS director, told the FCIC that as late as September 2008, he had ‘no clue—no idea—what [AIG’s] CDS liability was.’” (alteration in original)).
157. Fortunately, the Supreme Court quickly signaled after the crisis that its preemption approach here had gone too far. See generally Arthur E. Wilmarth, Jr., Cuomo v. Clearing House: The Supreme Court Responds to the Subprime Financial Crisis and Delivers a Major Victory for the Dual Banking System and Consumer Protection, in THE PANIC OF 2008: CAUSES, CONSEQUENCES AND IMPLICATIONS FOR REFORM 295 (Lawrence E. Mitchell & Arthur E. Wilmarth, Jr. eds., 2010).
As Part I explained, expanding access to credit may attract predatory lenders and unsavory lending practices. The OCC’s Fintech Charter Decision described in Part II may undermine state regulators’ efforts to enforce the full range of consumer protection and antidiscrimination statutes.

This Part surveys the most commonly proposed solutions and argues that the evolving and complex nature of learning algorithms requires state and federal regulators to collaborate to ensure the efficacy of critical consumer protection and antidiscrimination measures. We argue that regulators must consider limiting the use of algorithms in consumer credit markets. While the extant literature has generally focused on “fixing” black box AI in finance, this Essay argues that regulators should evaluate the use of machine learning algorithms and establish a formal rule that limits or, in some instances, strictly bans the use of algorithms.

A. Transparency, Explainability, Auditing, and Beyond

Over the last several years, scholars and data scientists have crafted a careful and detailed portrait of the potential for big data analytics to lead to biased, unfair, or prejudicial outcomes. Deconstructing the technical aspects of ADM, scholars have identified several stages in the development process of ADM platforms where programmers may unintentionally incorporate bias: inputs, training, and programming.

Fintech firms employing ADM platforms increasingly describe creditworthiness decisions as a form of behavioral analysis or behavioral scoring. Lenders have increased their use of big-data profiling techniques, using complex algorithms to detect patterns about consumers’ daily lives and as a means for predicting consumer behavior. Everything from internet searches or shopping patterns to social media activity has suddenly become relevant and may be used to “score” individual consumers. A careful examination reveals evidence that new approaches may lead to bias if not effectively monitored.

A 2004 study by the National Association of State Public Interest Research Groups found that 79 percent of credit reports contained errors. Twenty-five percent of credit reports contained significant errors that would result in

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158. *See supra* Part I.
159. *See supra* Part II.
163. *Id.* at 152.
164. *Id.* at 155–56.
denial of credit. Specifically, 54 percent had inaccurate personal information, 30 percent listed closed accounts as open, and 8 percent did not list major credit accounts.

Building these errors into the digital economy will amplify inaccuracy and entrench errors into automated systems that are faster, more ubiquitous, and nearly impossible to correct. Accurately identifying sources of bias in credit decisions may be as critical to risk management oversight as predicting default and prepayment risks.

To address concerns regarding bias, scholars, commentators, and regulators propose a number of solutions designed to engender algorithmic accountability that are focused on the problems of commensurability and accountability generated by quantitative and algorithmic analysis. To better pursue those critiques, we must demand more explainability from AI models and applications. Explainable AI is interpretable and enables a degree of qualitative functional understanding. Explainable AI examines the reasons that an algorithm makes a specific decision to enable humans to interpret the decision-making process. There are a few reasons why explainability could help resolve the issue of biases: below, trust, greater visibility of flaws in an algorithm, and enhanced performance and control are discussed.

Explainability can build trust between the algorithm and the user trying to understand it. Trust can be viewed in two different ways. First, there is trust in the sense of trusting a prediction sufficiently to act on it. Second, there is trust in regard to trusting a model. This equates to “whether the user trusts a model to behave in reasonable ways if deployed.” Both of these “are directly impacted by how much the human understands a model’s behaviour, as opposed to seeing it as a black box.” Determining trust in an individual prediction is incredibly important. When AI makes a prediction, that prediction “cannot be acted upon [in] blind faith” because the results could be devastating. A model as a whole needs to be trusted.

before it is deployed. 178 “[U]sers need to be confident that the model will perform well on real-world data . . . ” 179

Second, when firms use an explainable AI system, that system provides greater visibility over unknown flaws and can provide assurance that the system is operating as expected. 180 This understanding “provides insights into the model, which can be used to transform an untrustworthy model or prediction into a trustworthy one.” 181 For example, the Association for Computing Machinery asks that “institutions that use algorithmic decision-making . . . produce explanations regarding both the procedures followed by the algorithm and the specific decisions that are made.” 182 This principle is focused around explaining two things to users: the process and the results. 183

Third, explainability can help with performance and control. 184 If you can understand how the model works, you can tweak and optimize the model that you are using. 185 If a model is explainable, “it forces the basis of decision-making into the open and thus provides a way to question the validity” of the decision-making. 186 “[E]xperts can [then] assess whether the relationships uncovered by the model seem appropriate, given their background knowledge of the phenomenon being modeled.” 187 Detecting biases in the model or data set is easier if you can understand what the model is doing and why it arrives at its predictions. 188

Explainability requirements may not come naturally to experts in AI and machine learning. However, the requirements are necessary if we are to apply extant discrimination laws and develop a regulatory system capable of deterring correlation-driven biases. The need now in finance is not simply for extant regulatory entities to come in after the damage has been done and to rectify discriminatory or otherwise problematic behavior. Rather, we are in need of an industrial policy to steer underwriting technologies towards forms that are capable of being regulated and reformed. 189 Without such incentives for (and steering of) the development of AI in finance, cherished values of equal opportunity will be even further marginalized.

178. Id.
179. Id.
180. Id.
181. Id.
183. Id.
184. PWC, supra note 169.
185. Id.
187. Id. at 1123.
188. Cf. id.
189. Accord Anya Prince & Daniel Schwarcz, Proxy Discrimination in the Age of Artificial Intelligence and Big Data, 105 IOWA L. REV. (forthcoming 2020) (manuscript at 2) (promoting regulation “requiring firms to employ statistical models that isolate only the predictive power of non-suspect variables”).
In the debate regarding regulatory preemption, consumer advocates have warned that the “lack of transparency around the processing of data and automated algorithms may lead to increasing information asymmetries between the financial institution and the individual and consumers are thus left with less awareness and a lack of understanding and control over important financial decisions.”\textsuperscript{190} By impeding opportunities for regulators to promote such transparency, the OCC’s Fintech Charter Decision exacerbates the challenges of identifying and implementing useful solutions for accountability, responsibility, and transparency concerns.

B. Coordinated Regulation

Prescribing the proper scope of explainable learning algorithms represents one of several challenges that regulators will face as technology continues to evolve. Federal oversight of fintech firms will certainly involve crafting and adapting dynamic rules. In light of these challenges, even if federal regulators intend to offer SPNB charters to fintech firms, the power of state regulators and attorneys general to develop and enforce rules governing the integration of learning algorithms in consumer finance must be preserved. The Dodd-Frank Act codified \textit{Barnett Bank of Marion County, N. A. v. Nelson},\textsuperscript{191} rejecting the OCC’s attempt from two years earlier to assert preemptive authority over bank licensing and supervisory enforcement.\textsuperscript{192} Any federal fintech rules should clearly reflect that federally chartered banks remain subject to the consumer protection, inclusion, and antidiscrimination laws adopted and enforced by the states in which they operate. As indicated by the U.S. Supreme Court’s recent conclusion in \textit{Cuomo v. Clearing House Ass’ n},\textsuperscript{193} while the OCC is the sole regulator of national banks, federal preemption does not preempt states from enforcing fair-lending laws.\textsuperscript{194}

To ensure robust and durable consumer protections, state and federal regulators should collaborate to create a uniform “floor” of standards. State and federal banking supervisors must agree on which regulator will exercise primary regulatory authority with respect to that floor. States must be allowed to innovate as laboratories of democracy to quickly respond to emerging threats. The OCC does not have the authority under the NBA as interpreted by the Court in \textit{Barnett} and \textit{Clearing House} to preempt state enforcement of state consumer protection regulations.

\textsuperscript{191} 517 U.S. 25 (1996).
\textsuperscript{192} See supra note 147.
\textsuperscript{193} 557 U.S. 519 (2008).
\textsuperscript{194} See id. at 524–36.
Federal regulators may agree to relax standards and weaken enforcement of disparate impact standards, further exposing consumers to biased decisions by ADM platforms.195

The exponentially significant number of fintech firms and the speed of their operations’ ability to target the most vulnerable consumers present unprecedented concerns in consumer financial services markets. According to a recent report by the U.S. General Accountability Office (GAO):

[In 2017, personal loans provided by these lenders totaled about $17.7 billion, up from about $2.5 billion in 2013. In addition, these lenders’ small business loans and lines of credit grew from about $582 million in 2013 to $4.2 billion in 2017, and their student loans and student loan refinancing grew from about $3.4 billion in 2015 to $7.8 billion in 2017.]196

Based on the regulatory framework governing financial markets, the Consumer Financial Protection Bureau (CFPB) could serve an important role in establishing the minimum standards applied for integrating ADM technology and ensuring transparency and explainability, as well as compliance with consumer protection and antidiscrimination norms. However, personnel matters just as much as institutional capacity. State regulators and consumer advocates rightly express concerns that a change in the CFPB’s priorities and the reorganization of the CFPB over the past few years may impede rigorous enforcement. Recent scandals at Wells Fargo and other national banks heighten concerns that national banking regulators may not rigorously monitor compliance with consumer protections.197

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197. See Bethany McLean, How Wells Fargo’s Cutthroat Corporate Culture Allegedly Drove Bankers to Fraud, VANITY FAIR (May 31, 2017), https://www.vanityfair.com/news/2017/05/wells-fargo-corporate-culture-fraud [https://perma.cc/7RC5-PUS6]. In 2016, Wells Fargo announced a settlement agreement with the CFPB, the OCC, and the City and County...

198. See, e.g., Danielle Keats Citron, The Privacy Policymaking of State Attorneys General, 92 NOTRE DAME L. REV. 747 (2017) (demonstrating that state authorities have an important role to play in data regulation).


DFS had previously led national and state regulators by introducing a “BitLicense” and regulating digital currency businesses and intermediaries that hold custody of digital assets.\footnote{201}{See Virtual Currency Business Activity (BitLicense), N.Y. St. Dep’t Fin. Services, https://www.dfs.ny.gov/apps_and_licensing/virtual_currency_businesses [https://perma.cc/CWY6-W98J] (last visited Oct. 6, 2019).}

As Danielle Keats Citron observes regarding another data-intensive area of regulation:

State attorneys general have been nimble privacy enforcement pioneers, a role that for practical and political reasons would be difficult for federal agencies to replicate. Because attorneys general do not have to wrestle with the politics of agency commissioners or deal with layers of bureaucracy, they can move quickly on privacy and data security initiatives. Career staff have developed specialties and expertise growing out of a familiarity with local conditions and constituent concerns. Because attorneys general are on the front lines, they are often the first to learn about and respond to privacy and security violations. Because constituents express concern about privacy and data security, so in turn do state attorneys general who tend to harbor ambitions for higher office.

This is an auspicious time to study the contributions of state privacy enforcers. Even as Congress has been mired in gridlock, attorneys general have helped fill gaps in privacy law through legislation, education, and enforcement. They have worked with state lawmakers on consumer privacy issues.\footnote{202}{Citron, supra note 198, at 750.}

The same is true of state financial regulators, particularly New York’s DFS. They are a vital counterbalance to sudden swings in policy priorities that can occur on the national level.

CONCLUSION

Will fintech firms adopting AI technology successfully expand access to credit markets and foster the inclusion of unbanked or underbanked consumers—those consumers with thin or impaired credit files? To be sure, the advent of AI technology has some potential to improve legacy banking, catalyze new market infrastructure, and spur development that may benefit unbanked and underbanked consumers. However, such positive outcomes are far from likely if regulators are unable to engage in effective supervision of fintech firms’ algorithms.

Rather than enhance regulatory oversight, the OCC decision to allow nondepository fintech firms to operate as special purpose nonbank entities may stymie careful evaluation and supervision of whether fintech firms live up to their promise. This will leave vulnerable consumers exposed to perilous predatory behavior. The OCC’s intervention undermines state regulatory authorities’ efforts to monitor consumer lending markets, impose long-standing consumer protections, and enforce measures designed to mitigate predatory inclusion against fintech firms.
The United States needs to ensure thoughtful collaboration among state and federal regulators to proactively address any structural changes in the market for banking charters and careful consideration of the best approach to achieve early and widely endorsed interventions that promote the accountability, transparency, and explainability of their algorithmic processing of consumer information.