Securitizing Digital Debts

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ABSTRACT

The promise of financial technology ("fintech") and artificial intelligence ("AI") in broadening access to financial products and services continues to capture the imagination of policymakers, Wall Street, and the public. This has been particularly true in the realm of fintech credit where platform companies increasingly provide online loans to consumers, students, and small businesses by harnessing AI underwriting and alternative data. In 2019 alone, fintech lenders represented nearly 50% of total non-credit card, unsecured consumer loan balances in the United States. One of the most prevalent ways fintech credit firms operate is by securitizing the online loans they help originate. In doing so, fintech lenders are able to access the capital markets and further the spread of borrowed capital and credit risk. Against this backdrop of increasing institutional investment in fintech securitized assets, this Article reveals how consumer finance law is playing a subtle but increasingly important role in commercial financial transactions. I do this by exploring how structured finance has come to operate in the fintech credit marketplace and by comparing it to pre-2008 securitization activity in the home mortgage context. In doing so, I critique algorithm-driven credit securitization and point out certain economic and legal risks that make it similar to pre-2008 mortgage securitization, as well as other risks that are unique to fintech finance. These pertain to, among other things, the opacity of loans underwritten through the use of alternative data and machine

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learning, the untested efficacy of such underwriting techniques, and the ways consumer finance laws—such as licensing, usury, and standards-based regulation—and the growth of nonbank finance companies intersect with the securitization process. The paper concludes by offering policy recommendations for addressing these future risks.

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INTRODUCTION

Americans need credit, and the capital markets provide the engine that keeps that credit flowing. Whether to purchase a home, buy a car, pay for school, or even just to make ends meet, debt is a fact of American life.\(^1\) Artificial intelligence, alternative data, and unique business and financing structures, however, are fundamentally changing the way Americans access borrowed capital. This Article explores these financial technologies or “fintech” innovations in how credit flows to American households and, in doing, warns of the potential implications for how we guard the larger economy against risk and crisis.

After a period of supposed recovery, Americans remain in a state of financial precarity. With the rising costs of everything from housing to groceries to medical bills, combined with years of stagnant wages, it’s difficult for many American households to make ends meet. In the past ten years since the financial crisis, household incomes have risen about 15%, yet housing costs are up 26%, medical expenses are up 33%, and college costs are up an astonishing 45%.\(^2\) Moreover, although unemployment remains low, over half of all working Americans have low-wage jobs with median incomes of only $18,000 per year.\(^3\) The ever-shrinking middle class lags in both homeownership and retirement savings, with the financial situation of Millennials being particularly dire.\(^4\) This is to say nothing of what the


\(^4\) Hoffower, supra note 1; see Christopher Ingraham, The Staggering Millennial Wealth Deficit, in One Chart, WASH. POST (Dec. 3, 2019, 7:45 AM), https://www.washingtonpost.com/business/2019/12/03/precariousness-modern-young-adult-hood-one-chart/?fbclid=IwAR2BLiKZo7AbzxGyGR_mawjirqfAWvkwc7Q3q0TFYXPfjijGwFW28N1Q [https://perma.cc/B395-4BTU] (showing wealth disparities between Baby Boomers, Generation X, and Millennials over time).
COVID-19 epidemic will ultimately work on the U.S. economy. As of this writing, the nation is struggling to contain the spread of the virus through shelter-in-place orders that have resulted in the vast majority of the American economy going into a state of dormancy. Millions of Americans are filing for unemployment, and some estimates project the jobless rate could reach 30–40%.

With these economic conditions playing in the background, consumer credit is currently at an all-time high. Households are borrowing more than they ever have before, with about 77% of Americans having at least some debt. This trend is important because individuals with significant debts are vulnerable to even slight changes in their economic situation. They may already be struggling to repay loans, alongside keeping up with the expenses of daily life. This means that unexpected expenses can cause finances to spiral out of control. From a broader perspective, more money spent on repaying debt means less money spent on goods and services in the real economy. As consumer spending accounts for roughly 70% of the U.S. economy, this shift has widespread implications. As of the end of the second quarter of 2019, household debt stands at $13.86 trillion, which is higher than the financial crisis peak in 2008. Figure 1 shows total household debt balances by credit product category.

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Where consumer debt (or, to be more charitable, consumer credit) comes from, however, has shifted over time. In the United States, it finds its origins as early as the 1800s, when items such as sewing machines and furniture were sold under plans where the buyer would pay the purchase price (plus interest) in installments over time. In the 1900s, the advent of the automobile further expanded consumer credit markets. The first cars—Henry Ford’s Model Ts—were too expensive for most Americans to afford, but this problem was solved in 1919 when General Motors started selling its vehicles to buyers on installment credit plans. The 1930s saw a boom in the production of

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13. LENNOX CALDER, FINANCING THE AMERICAN DREAM: A CULTURAL HISTORY OF CONSUMER CREDIT 184 (1999); SARAH A. SEO, POLICING THE OPEN ROAD: HOW CARS TRANSFORMED AMERICAN FREEDOM 38 (2019); see also FLEMING, supra note 12.

14. CALDER, supra note 13, at 185, 191–92; see also James Surowiecki, Masters of Main Street, NEW YORKER (July 5, 2010), https://www.newyorker.com/magazine/2010/07/12/masters-
consumer goods and luxury products, such as washing machines, radios, and furniture. These items could also be purchased using installment credit plans. In the 1950s, the first charge cards came on the scene with Diners Club. The BankAmericard (now VISA) made an appearance during this decade, followed shortly by American Express and Mastercard—all of which allowed consumers to make a wide range of purchases on credit from an endless array of merchants through bank credit. By 1960, there had developed a fairly sophisticated system of credit reporting and by 1964, the Association of Credit Bureaus was exploring the use of computers as a way to store, monitor, and improve the scoring of Americans’ creditworthiness. In the 1980s, Equifax, Experian, and TransUnion (the country’s three major credit reporting companies) were firmly entrenched, and the first credit scoring method—the FICO score—was released, to be followed in 2006 by the VantageScore.

The financial crisis of 2007 shook consumer credit markets. The sharp decline in the value of homes that began in 2006 severely reduced household...
wealth in the United States and put many Americans into deep financial distress, which in turn led to a drop in consumer spending.\textsuperscript{22} The economy lost over eight million jobs, the unemployment rate was as high as 10\%, in excess of 170,000 small businesses closed, and nearly four million individuals lost their homes.\textsuperscript{23} As investors and other suppliers of capital hoarded cash in the aftermath of the crisis, downstream retail lenders were starved and this, in turn, created a sharp contraction in borrowing opportunities for consumers.\textsuperscript{24} Also, post-crisis changes in the rules governing bank capital requirements pushed banks away from lending to consumers directly and toward lending to nonbanks instead.\textsuperscript{25}

The rise of the digital age, however, has brought about a notable shift in credit markets—particularly for consumers and small businesses. In the space left vacant by banks and other traditional lenders has come a wave of tech firms. These financial technology platforms (“fintechs”) are fundamentally challenging many mainstream lending practices, such as long paper applications, face-to-face meetings, and the use of entrenched credit scoring models.\textsuperscript{26} Instead, through underwriting by new age automation—utilizing alternative big data and artificial intelligence—loan processing that once took days for mainstream lenders can now be done in minutes by these fintech firms through the use of online portals and smart phone apps.\textsuperscript{27}

Fintech lending has seen significant growth over time. What was once a small portion of the non-credit card unsecured consumer loan market has now grown sizably, accounting for nearly 50\% of the total market share in March

\begin{itemize}
\item Odinet, supra note 26, at 785.
\end{itemize}
The term fintech has been used to describe a phenomenon that is poised to “disrupt” and “disintermediate” banking and the financial sector as we know it. Some scholars argue that fintech is “distinct from earlier eras of innovation” because of the way it uses “qualitatively different forms of data” and “automated and increasingly self-learning operational systems.”

Others add that “[f]intech is visibly changing the way we conduct financial transactions and use financial services.”

This Article adds to the fintech literature by focusing on how fintech credit firms principally finance their operations (through securitizations) in combination with their business models and underwriting methods to explain how fintech credit poses potential systemic risk concerns to the larger financial sector. Securitization is a familiar term, as it is closely associated with the 2008 housing and financial crisis. Indeed, the securitization of subprime mortgage loans is viewed as the principal driver of the crash. More broadly, I use the study of the securitization of fintech credit as a way to reveal the larger, more macro issues that are arising at the point of convergence between Silicon Valley and Wall Street on the one hand and the states and the federal government on the other when it comes to the provision of consumer credit in the United States. Alternative data, artificial intelligence, and nationwide connectivity are challenging the financial sector as we know it in the U.S.

Economic risk is inherent in the way fintech credit is originated because of the underwriting methods deployed. The use of alternative data about borrowers, such as their social media activity, digital footprint, purchasing habits, and personal preferences, combined with the use of potentially inscrutable AI algorithms that analyze enormous amounts of data to make creditworthiness determinations introduces a level of opaqueness to these important credit products that should concern regulators. Moreover, the way these loans are being securitized or otherwise distributed throughout the capital markets has echoes of the contagion caused by the subprime mortgage securities market of the prior decade.

Additionally, legal risk is also inherent in fintech credit because of the business models being employed by these firms. Many fintech credit firms

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31. Omarova, supra note 29, at 737.
facilitate loans to borrowers, rather than make the loans themselves. Banks and other regulated financial institutions that partner with fintech firms originate the loans, largely in order for the transaction to take advantage of the significant regulatory benefits that are only accorded to these types of chartered financial institutions. Lurking beneath the surface of these business relationships, however, is a pitched battle between the states and the federal government over nonbank credit and the reach of federal power in consumer finance. This has resulted in widespread litigation and has created significant compliance uncertainty.

An additional contribution that this Article makes to the fintech and financial market discussion is to show how fintech is causing a major convergence between policies associated with consumer protection (licensing, disclosures, fairness, etc.) on the one hand and those dealing with commercial and corporate finance (i.e., the capital markets, risk, and failure) on the other. As Erik Gerding has explained in 2009, there is often an underappreciated connection between “regulations designed to protect consumers and regulations intended to protect financial markets from the collapse of financial institutions.”

Fintech securitization raises systemic risk concerns because of this convergence.

This Article is divided into four parts. Part I describes fintech credit firms, including how and why they arose when they did, the types of loans they offer, the growing role of artificial intelligence in loan underwriting, and how these fintech business models have evolved over time. Part II follows by explaining how many of these startup fintech companies finance their operations and lending programs—chiefly through structured finance and tapping the exuberance of the capital markets for all things tech. Having laid the foundation, Part III advances the normative claim of this Article—namely, that fintech credit and related securitizations have worrisome systemic risk potential. For support, this Part lays out the credit risks involved in the use of alternative data and AI in credit scoring and underwriting. I also point out the current litigation and compliance risks that attend many of these loans due to the specific business models used by many fintech online lenders. After making these claims, Part IV provides the implications and the what next. First, I make comparisons to the financial crisis beginnings and draw on the Wall Street voices of the past that extolled the virtues of “innovative” finance in the way of subprime mortgage loans and accompanying securities and derivatives products. Second, I argue that financial regulators at both the state and the federal level should adopt a

defined regulatory agenda when it comes to the growing use of artificial intelligence in financial markets. Specifically, the use of alternative data and AI in credit scoring has implications both for consumers and for the larger market—concerns that are largely being soft peddled or ignored by regulators at present.

I. THE FINTECH CREDIT LANDSCAPE

Fintech lending has enjoyed explosive growth since its earliest inceptions in 2006. The market has benefited from a host of economic and regulatory advantages coming out of the 2008 financial crisis, much of which has opened up channels for additional capital raising—including the ability to access the capital markets through securitization. Since its early days, the financial technology sector has enjoyed tremendous publicity. From Silicon Valley to Wall Street, fintech is described as the future of finance, with its various founders proclaiming that their platforms will change or “disrupt” everything and that banking will never be the same. The market itself has seen significant growth, with total fintech investment worldwide up 28% in 2019 from a year prior. The United States has one of the largest fintech lending markets in the world—second only to China. Industry watchers predict that the U.S. market for fintech loans will reach $1 trillion by 2030, and the $50 billion threshold for loan originations was already crossed in 2018.

The securitization and related risk-based activities of fintech credit firms, which are described first below, are the focus of this Article. However,

34. See, e.g., Nina Gass, 6 Disruptive Fintech Companies Disrupting the Investment and Lending Landscape, DUE (Oct. 6, 2017), https://due.com/blog/disruptive-fintech-companies/ [https://perma.cc/PG5G-PV4F].
38. Id.
a growing number of traditional financial companies, such as banks and other depository institutions, are also adopting fintech strategies in their lending activities.

The following provides an overview of the fintech lending landscape and how it has grown over time. It also shows the evolution of the business model and the growth in the use of artificial intelligence and AI in credit underwriting.

A. Nonbank Firms

Fintech nonbanks lenders generally serve as middlemen that match investors and borrowers.\(^39\) In an historical context, these firms are the finance companies of the digital age.\(^40\) Fintech lenders were first known as “peer-to-peer” or “P2P” lenders because they connected borrowers and retail funders through the use of online platforms, largely dispensing with the need for a traditional bank intermediary.\(^41\) Over time, the rise of institutional investors as the primary funders of these online loans led the market to be referred to as “marketplace lending.”\(^42\) Fintech lenders boast their ability to provide borrowers with quicker and easier access to credit compared to the experience of using a bank or more traditional lender—sometimes involving face-to-face exchanges, lengthy loan applications, and the mailing of documents.\(^43\)


\(^{40}\) Finance companies as referred to here are those nonbank institutions that have provided consumer credit to American households over the years. The Household Finance Corporation is a well-known example of such a company. See Calder, supra note 13.


turnaround time for credit decisions made by these online lenders can be as short as a few hours. Additionally, the loan application is accessed, completed, and submitted entirely online, as the fintech lender has no physical retail location.

Fintech lending has enjoyed significant growth since its early days. What was once a very small part of the unsecured, non-credit card consumer credit market has slowly grown. The consumer credit reporting giant TransUnion stated that in 2018, loans facilitated by fintech lenders accounted for 38% of all non-credit card, unsecured personal loan balances—which is a larger share than that enjoyed by banks, credit unions, and more traditional non-bank finance companies. This number is particularly significant when considering that the share of fintech loan balances only accounted for 5% of the unsecured market around 2013. Table 1 shows the rise in fintech lending market share over time compared to more entrenched competitors.

<table>
<thead>
<tr>
<th>Year</th>
<th>Bank</th>
<th>Credit Union</th>
<th>Non-Bank Finance Co.</th>
<th>Fintech Lender</th>
</tr>
</thead>
<tbody>
<tr>
<td>2018</td>
<td>28%</td>
<td>21%</td>
<td>13%</td>
<td>38%</td>
</tr>
<tr>
<td>2017</td>
<td>30%</td>
<td>22%</td>
<td>13%</td>
<td>35%</td>
</tr>
<tr>
<td>2016</td>
<td>32%</td>
<td>23%</td>
<td>16%</td>
<td>29%</td>
</tr>
<tr>
<td>2015</td>
<td>35%</td>
<td>25%</td>
<td>19%</td>
<td>21%</td>
</tr>
<tr>
<td>2014</td>
<td>39%</td>
<td>28%</td>
<td>22%</td>
<td>11%</td>
</tr>
<tr>
<td>2013</td>
<td>40%</td>
<td>31%</td>
<td>24%</td>
<td>5%</td>
</tr>
</tbody>
</table>

(Source: Transunion Q4 2018 Industry Insights Report)

(3)
Data from TransUnion’s competitor, Experian, show even more surprising growth. Experian notes that in March 2019, fintech credit comprised 50% of the non-credit card, unsecured consumer loan market. An important observation, however, that the data above does not necessarily reveal is that banks and other depository institutions have long shied away from providing unsecured consumer loans outside the credit card market. This means that fintech nonbanks have not taken market share away from banks as much as they have filled a need that banks were unable or else refused to meet in the past.

In terms of firm quantity, there are about 111 fintech lenders in the United States, with a few very large players—such as Prosper and Lending Club—being dominant. With respect to loan products, the fintech credit market can be divided into three categories: consumer loans, student loans, and small business loans. Consumer loans were the most important to the industry’s beginnings as fintech lenders were able to take advantage of banks’ aversion to unsecured consumer loans in preference to credit cards and home equity lines of credit, both of which entail higher interest rates and thus higher returns. Student loans are the second most popular of the fintech credit products.


52. See Odinet, supra note 26, at 804–07.


B. AI and Alternative Data Underwriting

But the largest and often most hyped aspect of fintech lending is the way underwriting is performed. Underwriting is the process of determining whether and to what extent a person is creditworthy. Fintech lenders argue that their underwriting processes have significantly greater reliability in predicting a borrower’s creditworthiness. This is based on the use of nontraditional data aimed at getting a fuller picture of a borrower’s financial capacity, a view that is often in the blind spot of banks and more traditional lenders that rely predominately or exclusively on the FICO or Vantage score. While many fintech lenders indeed continue to use traditional indicators of creditworthiness—such as income levels, reoccurring liabilities, and credit scores—other nontraditional factors play an increasingly significant role. Such borrower information includes or is believed to include where borrowers live, their text messaging habits, their health records, what clubs they belong to, shopping habits, educational history, academic transcripts, standardized test scores, career trajectory, and digital footprint, including social media activity. One “industry executive noted that ‘how many times a person says ‘wasted’ in their [social media] profile . . . has some value in predicting whether they’re going to repay their

56. See Odinet, supra note 26; Christopher K. Odinet, The New Data of Student Debt, 92 S. Cal. L. Rev. 1617 (2019) [hereinafter Odinet, Student Debt]; Laura Noonan, AI in Banking: The Reality Behind the Hype, Fin. Times (Apr. 11, 2018), https://www.ft.com/content/b497a134-2d21-11e8-a34a-7e7563b0b0f4 [https://perma.cc/8SBG-YZYD] (listing customer profiling as a top way that AI is being deployed in banking).

57. Underwrite, MERRIAM-WEBSTER, https://www.merriam-webster.com/dictionary/underwrite [https://perma.cc/7WMD-ZRKF] (“Underwriting is the process that a lender or other financial service uses to assess the creditworthiness or risk of a potential customer.”).

58. See supra Section I.B.

59. Odinet, supra note 26, at 804, 848.

60. This most significant credit score is the FICO score. Thomas P. Lemke, Gerald T. Lins & Marie E. Picard, Mortgage-Backed Securities § 3:6 (2017–2018 ed.);


debt.’” And as one “fintech lender declared on its website: ‘All data is credit data.’”

Additionally, AI machine learning underwriting algorithms process these data to reveal correlations between seemingly irrelevant borrower attributes and that borrower’s ability to repay. These correlations, because of their high-dimensionality, are often beyond what the human brain can detect on its own. Machine learning as a concept can be thought of as a subset of the idea of artificial intelligence or “AI,” which is the broader field that embodies the notion that complex machines can display characteristics of human intelligence. Most of the technological advancements associated with artificial intelligence come from machine learning.

Machine learning deals with creating algorithms (i.e., instructions) to analyze data, internalize those data, and then perform a task that is commonly


64. Odinet, Student Debt, supra note 56, at 1645; see O’NEIL, supra note 62, at 158; see also Hurley & Adebayo, supra note 62, at 165; Odinet, supra note 26, at 785.

65. For an explanation of the basics of algorithms, see Andrew Tutt, An FDA for Algorithms, ADMIN. L. REV. 83, 92 (2017).


67. See Anya Prince & Daniel Schwarcz, Proxy Discrimination in the Age of Artificial Intelligence and Big Data, 105 IOWA L. REV. 1257, 1263–64 (2020); Anderson, supra note 66; Weinberger, supra note 66.


69. See generally STUART RUSSELL, ARTIFICIAL INTELLIGENCE: A MODERN APPROACH (3d ed. 2015) (explaining the mechanics of the concept); IAN GOODFELLOW, YOSHUA BENGIO & AARON COURVILLE, DEEP LEARNING: ADAPTIVE COMPUTATION AND MACHINE LEARNING SERIES (2016) (expanding upon the same).


71. An algorithm is “[a] mathematical or logical process consisting of a series of steps, designed to solve a specific type of problem.” See ALGORITHM, BLACK’S LAW DICTIONARY (11th
associated with intelligence, such as “recognition, diagnosis, planning, robot control, prediction, etc.”

72 Through this process, the algorithm “learns whenever it changes its structure, program, or data (based on its inputs or in response to external information) in such a manner that its expected future performance improves.”

73 The complexity of machine learning—in other words, the conclusions it can draw from massive amounts of data—is ever evolving. For example, deep learning is considered to be a “next level” type of machine learning where the program can find and expand upon even the smallest of patterns within a given data set.

74 One particular kind of deep learning technique involves the use of an algorithm called a neutral network, first conceived of as we know it today by the data scientist Geoffrey Hinton but only operationalized in recent years with the growth in computer power. The name neutral network comes from the fact that the algorithm is a simplified version of the neuron- and synapse-based network within the human brain.

75 The layers of machine learning complexity, however, only continue. Machine learning (including deep learning through the use of neutral networks) can be further divided between supervised, unsupervised, and


73. Id.; see Ryan Calo, Artificial Intelligence Policy: A Primer and Roadmap, 51 U.C. DAVIS L. REV. 399, 405–10 (2017); see also KEVIN P. MURPHY, MACHINE LEARNING: A PROBABILISTIC PERSPECTIVE 1 (2012); Magnuson, supra note 68 (manuscript at 8–9).


75. The concept of a neutral network has been around since the middle of the 20th century, but most researchers thought at the time that the function was limited in what it could do (thus making it of little practical utility). See MARVIN MINSKY & SEYMOUR A. PAPERT, PERCEPTRONS: AN INTRODUCTION TO COMPUTATIONAL GEOMETRY (1969). Hinton, however, showed that a neutral network could use a number of additional layers for decision-making than what was once thought. See Alex Krizhevsky, Ilya Sutskever & Geoffrey E. Hinton, ImageNet Classification with Deep Convolutional Neural Networks (unpublished manuscript), https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf [https://perma.cc/P9PV-RP6N].

reinforced methods. Supervised learning has been the most prevalent of the three. It uses training data to tell the algorithm what to look for, and then the algorithm tries to find that same thing when it is confronted with new information. It is believed that supervised machine learning is the kind most suitable for credit scoring.

Consider the following explanation of how such a supervised programming would occur: the design of a machine learning program involves “training” the algorithm to achieve a certain result—this result is called the “target variable.” For example, the target variable for a machine learning algorithm for underwriting purposes would be the likelihood of full repayment of a loan. The “training data” that would be furnished to the algorithm could consist of information about individuals who have fully and timely repaid loans in the past. The machine learning program would then analyze the training data and find characteristics of these borrowers that correlate with (but not necessarily have a causal relationship to) loan repayment. To be clear, a machine learning algorithm is not concerned with why certain borrower characteristics are (or are not) predictive, rather it only concerns itself with the fact that they are one way or another.

The extent to which fintech lenders and banks that use fintech-AI technology are employing the most sophisticated and inscrutable of machine learning algorithms is unknown. Some of this use may be only for purposes of market hype. For instance, the fintech lender Upstart asserts that it is “the first lending platform to leverage artificial intelligence and machine learning

77. M. GOPAL, APPLIED MACHINE LEARNING 328–29 (2019); KELLEHER, supra note 74, at 25–26; see also Somers, supra note 76.
78. Somers, supra note 76.
83. David Lehr & Paul Ohm, Playing with the Data: What Legal Scholars Should Learn About Machine Learning, 51 U.C. Davis L. Rev. 653, 672 (2017); see also Prince & Schwarz, supra note 67, at 1263–64.
84. Selbst & Barocas, supra note 82, at 1094; see also Prince & Schwarz, supra note 67.
85. Noonan, supra note 57.
to price credit and automate the borrowing process.”86 Moreover, the company states that it uses “non-conventional variables at scale in an underwriting model that improves constantly” largely by “using variables that no other lender considers.”87 But whether complex algorithms like neural networks are in use at present or not, the fact of the matter is that these developments are coming—and fast. AI is reshaping the financial services sector and we can only expect more complex machine (deep) learning models and more massive amounts of alternative data to dominate decision-making in the credit markets. Fintech nonbank lending is only the beginning.

II. THE FINANCING OF FINTECH CREDIT

The way fintech credit is financed in combination with the way these loans are being underwritten is the root of concerns about potential systemic risk. Yet, much of the story of fintech financing and systemic risk is tied to the life cycle of start-up companies intertwined with the specific funding mechanisms used by nonbank financial companies compared to banks. The following explains this unique funding structure.

A. Startup Financing

Fintech nonbank lenders begin as startups. The unique status of startups more broadly has only recently gained recognition in the corporate law literature.88 As Elizabeth Pollman has written: “Early-stage startups are

86. These statements come from job advertisements on Upstart’s website for data scientist and machine learning specialist positions. See Dave Girouard, Upstart Opens R&D Center in Columbus, https://www.upstart.com/blog/upstart-opens-rd-center-in-columbus [https://perma.cc/ZF5T-S8H6].


highly entrepreneurial and focused on innovation and technology.”  

Fintechs are no different, and, indeed, initial startup funding is often derived from the entrepreneurs themselves. This is then followed up by a more substantive round of funding, which typically comes from friends and family, alongside angel investors. Startups may then begin accessing funding through venture capitalists (“VC”)—sometimes through multiple rounds of VC funding. These equity investments are necessary, because the lack of assets and operational history, among other factors, make startups poor candidates for tapping into the bank lending market.

After the start-up achieves first stage success, Pollman explains that there is a shift in focus “to managing a more complex organization” and as the firm begins seeking out more substantial sources of liquidity in order to allow earlier stage investors—such as venture capital firms—to exit. At this point, the firm begins to have the history and record of success necessary to attract the attention of both banks and the capital markets. The capital markets route results in either the issuance of new securities that are offered to the public or else in the issuance of debt instruments (bonds) to the same. For a firm that no longer wishes to issue more equity shares, debt makes sense as a way of financing the company’s activities. However, bank borrowing and bond borrowing entail different considerations. Bank lending is usually more customized to the borrowing firm and allows for more flexibility, since the bank and the borrowing firm have the ability to renegotiate the terms at will. The downside is that the repayment period for loans is typically much shorter

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91. Reed & Barron, *supra* note 90, at 155, 163–64; Pollman, *supra* note 89, at 167. Angel investors are individuals who typically have excess cash to spare and are looking for a higher-yielding investment than what is otherwise offered by more traditional outlets, such as deposit accounts and mutual funds. See Darian M. Ibrahim, *Financing the Next Silicon Valley*, 87 WASH. U. L. REV. 717, 721 (2010).
94. *Id.* at 168–69.
95. *Id.*
than for bonds, which have a longer life cycle.\textsuperscript{98} On the other hand, refinancing a bond is more difficult because of the various parties whose consent must first be obtained. Additionally, the willingness of investors in the capital markets to purchase corporate bonds is tied to the financial health and viability of the issuing firm. If the firm is weak or has an uncertain financial future, the bonds will suffer marketability problems and may thus not generate much capital. Also, payment of the bonds by the company may be secured by specific company property.\textsuperscript{99} This can mean that the corporation’s assets are tied up in the bond issuance and may be seized and monetized in the event of a default.

This tying of the issuing firm’s health/assets to the marketability/performance of the bond is solved, in part, by the securitization process. As Steven Schwarcz notes in his seminal work on the subject, securitization alters “the security holder’s dependence on the debtor/company for payment, by separating the source of payment from the company itself.”\textsuperscript{100} That process, as outlined further below, separates the risks of the company’s failure from the revenue generating assets. Therefore, when investors purchase securities, the value is derived only from the underlying asset, thus the investors’ rights are considered less risky.\textsuperscript{101}

Yet at the same time, the securitization process creates a great deal of opacity, as explored further below, and that opacity combined with the increasingly complex deep learning underwriting techniques of fintech lending creates systemic risk concerns. The following traces the financing of fintech credit firms, culminating in securitization.

\textbf{B. From Early Stages to Securitizations}

Because fintechs are largely nonbank companies, they do not have access to the same kind of funding as banks. This is what makes their funding life cycle more like that of a typical startup. Banks can access funding by using the deposits of their customers.\textsuperscript{102} The bank maintains a certain amount of

\begin{itemize}
  \item \textsuperscript{98} Adam Schrier, \textit{Bank Loans or High Yield Bonds? Maybe Both.}, \textsc{InvestmentNews} (Nov. 28, 2017), \url{https://www.investmentnews.com/bank-loans-or-high-yield-bonds-maybe-both-72788} [https://perma.cc/S6GF-KK5X].
  \item \textsuperscript{100} Steven Schwarcz, Bruce A. Markell & Lissa Lamkin Broome, \textit{Securitization, Structured Finance and Capital Markets} 6 (2004).
  \item \textsuperscript{101} Schwarcz, \textit{supra} note 99, at 1–4.
\end{itemize}
funds on hand for use in customer withdrawals, but the bank is safe in assuming that all or a large portion of its customers will not seek to withdraw funds all at once.103 ‘This, in essence, is the principle behind fractional reserve banking. Banks can also draw upon their other investments—such as investments in securities—for funding needs.104 And perhaps most importantly, banks are able to access cheap loans from the Federal Reserve to meet their various funding needs.105

Nonbanks, on the other hand, do not have such privileged access to government funding or to customer deposits. Instead, they begin like a typical start-up and then progress to the capital markets. This means that fintech funding is often riskier and generally more expensive. A 2018 survey of fintech lenders found that the cost of funding was one of top three concerns in the industry.106

In terms of funding, the business model for fintech credit firms can vary107 but can be generalized as coming into two broad categories.108 The first is the “direct funding” model.”109 These fintech lenders, which include firms like OnDeck, originate their own loans and make them directly to borrowers.110 These direct funders have obtained their capital from different sources over time. The early stages of the fintech lending life cycle, as with other startups, were driven by venture capital.111 Then, direct fintech lenders began to take

103. Id. at 277.
104. Id. at 277–79.
107. For a depiction of these business models, see PERKINS, supra note 50, at 4.
111. Id.
advantage of warehouse lines of credit and other short-term financing from banks, which was made possible by the ability to quickly sell loans to wholesale buyers in the capital markets. Indeed, this back-end market for the selling of loans to institutional investors was considered one of the most innovative aspects of the fintech/marketplace lending model. Fintechs would originate the loans and then quickly sell them, using the revenue from the sale to fund the next batch of loans. This model—often called the “gain on sale” model—served as the initial way fintech credit companies paid for their operations. However, the gain on sale model proved problematic. First, because these institutional buyers demanded high returns to entice them to purchase the loans, the cost of funding for the fintech was quite high. This was a major weakness in the business model. Fintech credit firms found themselves unable to generate enough returns from the sale of their loans in order to pay for their expenses on a sustainable basis.

The answer to this funding problem was securitization. By securitizing the loans they originated, fintechs could access cheaper financing by tapping into the capital markets in a different way to provide funding and to spread risk. Direct fintech lenders reap their profits from a traditional risk-adjusted return analysis—judging how much the investment will yield in returns compared to its riskiness over the investment period. Figure 2 depicts the direct funding model.


116. Huebscher, supra note 110.

117. Id.
The movement away from a pure gain on sale model was accompanied by
the rise of the now dominant fintech business model—one that involves the
fintech credit firm entered into a contractual relationship with a chartered
depository institution/bank (usually at the state level). The bank partner
actually makes the loan, but the borrower completes the loan application with
the fintech firm through the company’s website or smartphone app. Importantly, the underwriting and processing of the loan application is
conducted by the fintech firm. 

The bank partner, however, does not keep the loan on its balance sheet for
very long after having been made. Shortly after the origination, the loan is
sold to the fintech. Once the purchase is complete, the fintech either sells
the loan (along with other loans) to a pre-arranged wholesale buyer or, as is
increasingly the case, securitizes a pool of loans. Figure 3 depicts the bank-
partnership funding model.

118. KPMG, supra note 109, at 6–7; see also id. at 2 (“Over the quarter, we saw continued
collaboration between the fintech sector and corporate players, with an increasing number of
banks, financial institutions and insurance companies forging partnerships with fintech
companies, accelerators and incubators in order to drive innovation within their own
organizations.”); RYAN M. NASH & ERIC BEARDSLEY, THE FUTURE OF FINANCE: THE RISE OF THE
[https://perma.cc/G77T-ZJX3] (“To facilitate the origination of loans and compliance with bank
regulations, many P2P lenders partner with little known WebBank, for instance, a Salt Lake City,
Utah based industrial bank. WebBank was founded in 1997, has about 38 full time employees,
and in 2014 ranked in the 99th percentile for bank profitability per head ($420k of net
income/head.).”). Lenders in this category are said to use the “bank partnership model.” See
Herrboldt, supra note 41, at 13.

120. Id. at 5; see also PERKINS, supra note 50, at 2–3.
122. See id. The fintech lender uses warehouse lines or other forms of short-term/overnight
financing to purchase the loans from the originating bank partner.
123. Odinet, supra note 26, at 790. This is also how the fintech lender finances its loan
purchases from the bank partner. Id. at 790–91.
Banks have been eager to take advantage of the technological advances that fintech credit firms offer—advances that can lead to efficiencies, lower transaction costs, simplification of processes, and ultimately higher profits.\(^\text{124}\) Rather than banks trying to build the technology themselves or purchasing fintech companies, partnerships with existing fintech credit firms have proven popular in markets across the globe.\(^\text{125}\) Through these collaborations, fintechs and banks argue that they now have greater capacity to provide products that are tailored to specific borrower needs, can offer greater credit choice, have more flexibility in providing services, enjoy a heightened level of competitiveness, and can increase credit access across the spectrum.\(^\text{126}\)

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\(^{125}\) See id.

Table 2 provides a list of some prominent fintech credit firms and the bank/depository institutions with which they partner.127

<table>
<thead>
<tr>
<th>Fintech Lender</th>
<th>Bank–Partner</th>
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<tbody>
<tr>
<td>Avant</td>
<td>HSBC &amp; WebBank</td>
</tr>
<tr>
<td>GreenSky</td>
<td>American Express</td>
</tr>
<tr>
<td>Upstart</td>
<td>BankMobile &amp; Cross River Bank</td>
</tr>
<tr>
<td>SoFi</td>
<td>Blue Ridge Bank &amp; Pioneer Bank</td>
</tr>
<tr>
<td>Lending Club</td>
<td>WebBank, NBT Bank, &amp; Comenity Capital Bank</td>
</tr>
<tr>
<td>Opportunity Financial</td>
<td>FinWise Bank</td>
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<tr>
<td>Prosper</td>
<td>WebBank</td>
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<td>Marlette</td>
<td>Cross River Bank</td>
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<td>Upgrade</td>
<td>WebBank</td>
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<tr>
<td>Freedom Financial</td>
<td>Cross River Bank</td>
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<tr>
<td>Amazon</td>
<td>Synchrony Financial</td>
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<tr>
<td>Marcus</td>
<td>Goldman Sachs</td>
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<tr>
<td>Payoff</td>
<td>Alliant Credit Union, First Electronic Bank, First Tech Federal Credit Union, &amp; Technology Credit Union</td>
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</table>

In terms of structure, a securitization sponsor (which can be either a separate financial institution or, as is more often the case, a subsidiary or affiliate of the fintech lender) gathers together the purchased online loans and coordinates the securitization process. The loans are then placed into a special purpose entity/vehicle (usually a trust) and then the trust issues securities that are sold in the capital markets to investors through market dealers. The most prominent dealers in this space are Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, and Bank of America. The securities, once purchased, entitle their holders to the principal and interest payments that are made by the downstream borrowers. Typically the securities within an issuance are placed into different risk categories or tranches. Holders of securities belonging to higher tranches are entitled to payment before those holding securities of lower tranches. Yet, the higher tranchered securities, although less risky, yield less revenue. The lower tranchered securities—albeit riskier—are higher yielding. As such, the fintech credit firm typically retains a certain portion of the risky securities in order to signal to market buyers that the securities being issued are worth investing. The securities are also rated by credit ratings agencies. When engaged by the issuer to do so, these companies give a grade to the securities or class/tranche of securities, which in turn guides the investment decisions of buyers.

The funds generated by the securitization/purchase of the securities are used, in part, to cover the financing expenses of the fintech firm in acquiring the loans from the bank partner or in directly making the loans in the first

129. See id. at 119.
130. PEERIQ, MARKETPLACE LENDING SECURITIZATION TRACKER: Q1|2019, at 6, https://www.peeriq.com/wp-content/uploads/2019/05/PeerIQ-MPL-Securitization-Tracker-Q12019.pdf [https://perma.cc/44XJ-N4JF]. The top three securities dealers—Citigroup, Credit Suisse, and Deutsche Bank—dominate nearly 60% of the market. Id.
131. See U.S. DEP’T OF THE TREASURY, supra note 45, at 6–7; see also FRANSON & MANBECK, supra note 128, at 91–92.
instance. This system, in turn, is much less expensive than the wholesale buyer/gain on sale model. The reason for this is because, in part, the riskiness of the issuer (the fintech) is no longer connected to the performance of the securitized asset (the loans). The transfer of the loans from the originator (the fintech) to the buyer (the securitization trust) is a “true sale” meaning that, as a legal matter, it is treated as a complete and final transfer of the asset so that the assets are no longer the property of the fintech. The importance of this is due to the fact that the investors who purchase the securities backed by the online loan want to ensure that the loans themselves are outside and will not be affected by any potential bankruptcy of the fintech. In other words, the sale must not be revocable upon the fintech’s potential bankruptcy under a fraudulent transfer or related claim. The special purpose entity that holds the loans (the trust) must be treated as a separate legal entity and not subject to bankruptcy consolidation of the fintech. In short, because of this isolation, the securities are considered safer and more marketable, thereby reducing the yield that investors expect. This, in turn, reduces the cost of raising money from a securitization for the fintech.

In the bank partnership model, the fintech lender is paid in two ways. First, it receives a fee/commission for helping to underwrite the loans and arrange the credit transactions on the frontend between the bank partner and the borrower. The firm also receives compensation throughout the life of the loans because the fintech lender will be in the position of servicer, thereby collecting payments from borrowers, keeping a portion of those payments as profit, and then passing on the rest to the securitization trustee.

Despite worry over trade wars by President Trump and fears of a recession, investment remains strong. The first quarter of 2019 saw a
total of $3.6 billion over ten separate fintech securitizations—the fourth highest in fintech securitization history—with the top issuers being SoFi, Kabbage, and Avant. All deals were rated by credit ratings agencies. Combining this amount with all prior fintech securitizations (which began around 2013), total market securitization now stands at $48.1 billion over 152 deals. Figure 4 shows cumulative fintech securitizations over time.

Figure 4
Cumulative Fintech Securitizations
(September 2013–March 2019)

To better understand the process, consider the following example drawn from a late 2018 securitization deal conducted by the fintech credit firm Lending Club. Under this company’s business model, the loans are originated by WebBank (a Utah-chartered bank), with Lending Club handling the loan application intake, the underwriting, and the ultimate credit

144. Id. at 1, 3, 6. This was, however, a 14% drop from the first quarter of 2018. See id. at 3.
145. Id. at 5. The vast majority of fintech securitizations to date have been rated by only two agencies—DBRS and Kroll. See id. at 6.
146. Id. at 2–3.
147. See id. at 3 exhibit1.
recommendation—and all of which is paid through a “transaction fee” that tracks the bank’s origination fee. The loans are then purchased by Lending Club from WebBank within two days of being made.

When Lending Club engages in securitizations, it serves as the sponsor and is the party that creates the special purpose trust to pool the loans. One way the firm engages in securitization deals is by offering what are called CLUB Certificates. Under this structure, a group of unsecured online consumer loans are transferred to a trust (which Lending Club calls variable interest entities or “VIEs”) by Lending Club. The trust then issues “pass-through securities” (called CLUB Certificates), that are collateralized by (i.e., backed and payable from) the loans themselves. The securities are issued to only accredited investors and certain qualified institutional investors, like retirement funds and insurance companies. Lending Club will then enter into an agreement with the trust to handle all loan servicing (for a fee), and Lending Club will retain a 5% interest in the certificates that were issued (which is done to meet regulatory risk retention requirements).

The CLUB 2018-P3 transaction depicted below was an asset-backed securitization of consumer loans worth $272.40 million. After their origination by WebBank and subsequent purchase by Lending Club, the loans were gathered together by a Lending Club subsidiary known as Consumer

149. Fintech lenders boast that their underwriting programs are far superior to those used in mainstream lending. Cf. Joe Nocera, Credit Score Is the Tyrant in Lending, N.Y. TIMES (July 23, 2010), https://www.nytimes.com/2010/07/24/business/24nocera.html [https://perma.cc/H2DS-7U22] (“Essentially, she says, a person’s credit score has become the only thing that matters anymore to the banks and other institutions that underwrite mortgages.”).

150. See LENDINGCLUB CORP., ANNUAL REPORT (FORM 10-K) (2019), at 3, 8–9, https://www.sec.gov/Archives/edgar/data/1409970/000140997019000222/a201810-k.htm [https://perma.cc/EFS5-P7YM]. WebBank, which is a Utah-based industrial loan company, has the exclusive right to originate a certain percentage of the loans facilitated by Lending Club. For healthcare- and education-based loans, NBT Bank and Comenity Capital Bank are the bank partners. Id. at 9.

151. Id. at 8.

152. See id. at 98.

153. Id.

154. Id. at 1.

155. Id. at 116–17.

156. Id. at 117.

157. See id. at 7, 98; see also Kilborn, supra note 42, at 10–11.

158. LENDINGCLUB CORP., supra note 127, at 124. A loan origination fee is a percentage of the loan amount—anywhere from 1% to 6% of the loan amount.

Loan Underlying Bond (CLUB) Depositor LLC and placed into a trust titled Consumer Loan Underlying Bond (CLUB) Credit Trust 2018-P3. Securities were then issued by the trust, which were divided into three types (or tranches), consisting of Class A, B, and C notes. As noted above, the range of note classes indicates their riskiness in terms of which note holders are paid first and which are paid last in the event the loans that the notes back fail to perform (i.e., borrowers don’t pay). Class A note holders are entitled to be paid first, then Class B, and then Class C. Figure 5 depicts the transaction per the securities filing.

Worthy of note—this securitization was not rated by any of the three major ratings agencies (Fitch, Standard & Poor’s, or Moody’s). Instead, the relative newcomer credit rating company Kroll Bond Rating Agency (“Kroll”) scored the transaction. In terms of substance, Kroll gave the Class A notes an A-, the

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160. See LENDINGCLUB CORP., supra note 127, at 120; Letter from Deloitte & Touche LLP to LendingClub Corp. (Nov. 27, 2018), https://www.sec.gov/Archives/edgar/data/1715900/000121465918007332/ex99_1.htm [https://perma.cc/4HPZ-LHXA].
162. For a discussion of the tranching of asset-backed securities in the mortgage context, see ODINET, supra note 21, at 29–31.
163. See id. at 30.
164. See generally LENDINGCLUB CORP., supra note 150, at 9–10 (showing and explaining LendingClub’s “loan issuance mechanism”).
Class B notes a **BBB** rating, and the Class C notes were scored as **BB** grade.\(^{165}\)

According to Kroll, notes that are scored A- are deemed to be of high quality with only a small risk (although on the upper-end of that range) of default.\(^{166}\) BBB means the securities are "of medium quality with some risk of loss due to credit-related events."\(^{167}\)

And a BB rating signifies "low quality with moderate risk of loss due to credit-related events."\(^{168}\) But this explanation belies the true rating. First, Kroll is a relatively new ratings agency and remains small.\(^{169}\)

Second, industry analysts note that this period of low interest rates and cheap funding has resulted in many securities being overrated. Indeed, some predict that when interest rates rise, the market will see a number of bond downgrades.\(^{170}\) This has been particularly true of late in light of the rapid market fears around the spread of the coronavirus.\(^{171}\)

One analyst argues that "half of investment-grade bonds are only one step away from junk status."\(^{172}\)

Moreover, it wasn’t so long ago that subprime mortgages were given triple A ratings by Wall Street credit rating agencies, only for the world to discover that, once tested by changing market conditions, these securities were really nothing more than junk bonds.\(^{173}\)

It is also important to understand that the Lending Club rating was not based solely on Kroll’s assessment of the strength of the underlying loans.\(^{174}\)
In other words, Kroll did not score the notes based solely or even primarily on the likelihood that the relevant borrowers would repay the loans based on the actual individual underwriting. Rather, the score was based in part on historical data about Lending Club coupled with various credit enhancements that Lending Club attached to the securitization to help make it more attractive to investors.

From a broader perspective, these securitization activities perform a number of functions that are critical to the ongoing viability of the fintech lending marketplace. First, as explained above, securitization ostensibly helps protect investors from concerns about the solvency of the company that originates the loans. This is due to the fact that the loans that collateralize the securities are held in a single purpose entity that is legally separate and apart from the fintech company that facilitated or loaned the money and any of its bank partners. In this way, the securities are less risky than the party that originates them. Consequently, investors will pay more for the securities since they need not be worried about the financial condition of the originator. Secondly, the securitization process provides fintech companies with ready access to capital that is cheaper than the original, gain on sale model that the industry employed.

Lastly, securitization has a certain cache to it. As Jonathan Lipson notes, many have often described securitization “as a new kind of ‘technology’” that brings with it attendant allure. For the Silicon Valley firms that populate the fintech landscape, playing in the securitization sandbox carries a certain kind of club membership that legitimizes and validates a financial business’s

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175. Id.
176. Id. A credit enhancement is a type of financial process aimed at lowering the risk of securities for the benefit of investors. These can come in many forms, such as where the trustee or servicer for the securitization keeps a certain amount of funds in reserve to cover potential investor losses in the event of defaults or providing some form of insurance to cover shortfalls in borrower payments. See 26 C.F.R. §§ 1.860D-1(b)(2)(iii), 1.860G-2(c)(2)–(3) (2019) (defining credit enhancements for purposes of discussing real estate mortgage investment trusts (REMICs), which are the forms of special purpose entities that are used for mortgage-backed securitizations).
179. Lipson, supra note 177, at 1243.
180. Id.
181. See id. at 1244.
182. Id. at 1246.
maturity and success. Indeed, over roughly the last three decades the securitization process has become a principal method of raising capital in this country—and fintech has harnessed this process and continues to do so today.

### III. FINTECH CREDIT AND SYSTEMIC RISK

Much like the perils posed by securitization more broadly, fintech raises enhanced issues of risk. As Michael Barr, Howell Jackson, and Margaret Tahyar offer in their influential work on financial regulation: “[w]ith the growth of fintech . . . will new risks emerge, and will market participants and regulators be able to keep up?” They argue that “[w]hile innovation is central for growth,” we should be mindful of the fact that “the complexity and interconnectedness of the financial system means that systemic risk may spread like a contagious disease.” Indeed, in June 2017 the Financial Stability Board—which serves as a global monitoring body for the stability of the international financial system—identified financial technology as an important risk for which governments should be mindful.

That same body warned again in February 2019 that fintech poses “both potential benefits and risks for financial stability.”

To that end, I argue here that the securitization of fintech, increasingly AI-driven credit raises issues of potential systemic risk. Such an analysis comes at a most opportune time, as state and federal lawmakers and regulators are actively involved in a robust (and sometimes contentious) discussion about how best to regulate the fintech space. In July 2018, the Treasury Department under President Trump released a white paper titled “A Financial System That Creates Economic Opportunities: Nonbank Financials, Fintech, and Innovation.” In this report, the Trump Administration indicated its broad

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183. See id. at 1245.
184. See id. at 1231–32; see also Taylor, supra note 37.
186. Id.
support for the financial technology sector and encouraged tech companies that if they helped offer new and innovative ways to invest and bank, then the federal government would support their growth.\textsuperscript{190} Treasury Secretary Steven Mnuchin declared: “We must keep pace with industry changes and encourage financial ingenuity to foster the nation’s vibrant financial services and technology sector.”\textsuperscript{191}

To make my argument, this section provides an overview of the unique risks posed by AI underwriting, which I assert creates an additional level of opacity to the already cloudy financial structure of securitization. It then explains securitization’s dark side and the role it played in the financial crisis.

\textit{A. Umbrella and Caveats}

The complexity and inscrutability of AI creates particularized problems in the context of securitization. Indeed, securitization is by itself already a highly complex legal creature.\textsuperscript{192} This complexity arises, as Steven Schwarcz notes, not because securitizers wish to create inscrutability for its own sake but rather because investors have idiosyncratic investment motivations.\textsuperscript{193} This market desire by investors drives transactions that create a variety of products that can match investor goals.\textsuperscript{194} Securitization structures that call for various assets to be sold, packaged, transferred, and pooled generate opportunities for investors to have access to new types of investment products (like commodities and home loan mortgages) and for businesses to raise money through the capital markets more cheaply than going through a bank or other traditional financial intermediary.\textsuperscript{195} But the downside is that these benefits are only possible through ever-increasing complexity.\textsuperscript{196}

Consider the multifaceted aspects of a typical loan securitization. Schwarcz highlights that securitization transactions involve estimations of default risk, the potential for changes in interest rates, the risk of borrowers

\textsuperscript{191}. Id.
\textsuperscript{193}. Id.
\textsuperscript{194}. Id.
\textsuperscript{195}. Id. at 213–14.
\textsuperscript{196}. Id.
making early payments, loan modeling, and a large degree of assumptions through the use of historical data.\textsuperscript{197} These factors become all the more difficult when the assets in a securitization pool are not homogenous, such as when multiple different kinds of loans with different features are securitized together.\textsuperscript{198} As we saw during the financial crisis, the variability in the loan terms—such as those with adjustable interest rates, negative amortization features, and low loan-to-value ratios—created defaults that historical data did not accurately predict.\textsuperscript{199}

The opacity of AI—an opacity that is predicted to only increase as technology and computational power develops\textsuperscript{200}—in the underwriting of these loans makes their true riskiness impossible or extremely difficult to comprehend. As these loans are turned into marketable securities that make their way across the financial system, driven in large part by favorable credit ratings, yield seeking, and a generalized hype for all things fintech, the risk of contagion becomes more significant and real.

To be clear, my argument is not intended to predict a future economic downturn in any particular period of time or of any specific magnitude that would result from the securitization of these AI digital debts. Rather, my goal is to urge financial regulators to improve their monitoring of certain aspects of the financial sector—particularly the financial technology sector and the growing role of AI—that may pose risk in the future without necessarily needing to take any particularly heavy-handed regulatory action at present. As Rory Van Loo has written with respect to AI and consumer products and services more broadly, “the task of financial stability regulators and scholars is not necessarily to predict the next crisis, or even to make the case that any trigger is likely to cause a crisis.”\textsuperscript{201} We will certainly have another financial crisis, that much is clear.\textsuperscript{202} Indeed, as of this writing, a financial crisis resulting from the COVID-19 coronavirus appears to be unfolding.\textsuperscript{203} But in

\begin{itemize}
\item \textsuperscript{197} Id. at 216–17.
\item \textsuperscript{198} Id. at 217.
\item \textsuperscript{199} Id. at 217–18.
\item \textsuperscript{202} Id.
any event, regulators and lawmakers should aim to reduce the magnitude of any future financial crisis when they are able. As Van Loo notes, many scholars and regulators in the past have signaled a hesitance to study “new triggers that (inevitably) appeared unlikely and unfamiliar until they caused a crisis.” After all, many were surprised that seemingly simple or innocuous consumer financial products—like residential mortgage loans—could contribute or even cause a major financial crisis. The American political system has long engaged in the practice of waiting until a financial crisis wrecks the economy before taking legal steps to prevent, curtail, or manage certain potentially dangerous financial practices. “Regulators have a critical role to play in managing the up sides and the down sides when it comes to financial technology credit and AI.”

B. Blackbox Underwriting

The AI complexity inherent in fintech lending products expands upon the already highly complex nature of traditionally securitized loans. Artificial intelligence and alternative data play a significant role in the credit scoring process, which is predicted to only grow as a foundational tool in the financial markets of the future. Indeed, financial institutions in the United States and abroad, both big and small, have been busily hiring data scientist and machine learning experts to build out their AI capabilities. We should only expect...
that big, alternative data and AI will play an ever-expanding role in the delivery of consumer financial products and services moving forward—and thus greater levels of complexity, as well. This complexity, as unpacked below, has roots in inscrutability, over-reliance on heuristics, the failure of meaningful disclosures, and the risk of AI breakdowns in predictive effectiveness.

1. Inscrutability

With machine learning, predictive power—in other words, the ability to gather large amounts of existing data and “predict the likelihood of uncertain outcomes”—is the key. As I have written about before, the use of sophisticated machine learning algorithms and nontraditional data in loan underwriting poses a host of challenges, not least of which is the inscrutable nature of these decision-making processes. Machine learning introduces a particular kind of impenetrability because while it may be possible to see what kinds of data go into the AI underwriting program and what result comes from it, it will not always necessarily be possible (depending on the type of algorithm deployed) to see how those data resulted in that particular decision.

The true inscrutability, however, arises when the machine learning program uses not only training data that is provided to it by the programmer on the front end but also incrementally and over a period of time reprograms itself in order to meet the end goal by incorporating new information. Thus, the training set does not necessarily limit the decision-making, but rather data drawn from various different sources that are obtained periodically is added.
into the process so that the program learns over time how to be more predictive. As Harry Surden notes, this process of learning “allows for the creation of nuanced models of complex phenomena that may otherwise be too difficult for programmers to specify manually, up front.”

As Anya Prince and Daniel Schwartz have written, an algorithm is not concerned with why certain borrower attributes are or are not predictive—it just cares that they are. This makes understanding why there is a connection between variable A and outcome B a very difficult—some say impossible—task. Andrew Selbst and Solon Barocas explain that what makes machine learning so difficult for law to grapple with is its inscrutability and nonintuitiveness. While its decision is revealed, the decision-making process is a secret because the algorithm is relying on pattern recognition as it combs through a large set of data to discover hidden relationships—and then hidden patterns within those patterns—that, again, are too subtle or distant for humans to recognize or even grasp.

And herein lies the problem related to risk. The underwriting of these loans will largely be beyond the comprehension of individuals due to the very nature of sophisticated machine learning and alternative data. The machine learning underwriting will become so complex, interconnected, and numerous in nature that it will “defy practical inspection and resist comprehension.” Weaving these underwriting intricacies into the securitization process (discussed more fully below) makes the complexity more extreme. The hidden connections will be so distant and

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215. Surden, supra note 210, at 94.

216. Id.


218. Selbst & Barocas, supra note 82, at 1089–90 (discussing the inscrutability of certain algorithmic programs); see also Prince & Schwarz, supra note 67, at 1274 (“[F]or this reason, the ultimate statistical models that AIs derive are often nearly impossible to explain intuitively . . . .”).

219. Selbst & Barocas, supra note 82, at 1089.

220. See Magnuson, supra note 68 (manuscript at 9); see also Lehr & Ohm, supra note 83, at 671.

221. Selbst & Barocas, supra note 82, at 1094.

222. Id.

223. Id. (“While there is a long history to such concerns, evidenced most obviously by the term ‘byzantine,’ the complexity of rules that result from machine learning can far exceed those of
incomprehensible, individuals will have to surrender their trust in algorithms and in others who can vouch for them, rather than exercising any independent risk assessment. The lack of independent judgment and analysis increases the likelihood for the unknowing spread of risk.

2. Heuristics

Investors in algorithmically underwritten loan securities, just as with subprime mortgage-backed securities, rely on heuristics like ratings agencies (and increasingly, the generally hypnotic effect of Silicon Valley and its tech proponents\(^\text{224}\) to assess risk.\(^\text{225}\) The role played by fintech promotion cannot be understated. The hype of fintech, alongside a plentiful amount of cheap borrowing during a lengthy period of low interest rates, has helped the fintech market growth exponentially.\(^\text{226}\) The investment world has readily bought into the magic of fintech and, buttressed by favorable rating agency reports, continues to pour billions into the sector.\(^\text{227}\)

However, the use of heuristic reasoning can generate bias and systemic error.\(^\text{228}\) As financial products increase in their complexity, fewer and fewer analysts and investment experts have “sufficiently nuanced cognition” to adequately understand the financial products being created.\(^\text{229}\) In the run-up to the crisis, many financial analysts oversimplified otherwise complex assets

the most elaborate bureaucracy. The challenge in such circumstances is not a lack of awareness, disclosure, or expertise, but the sheer scope and sophistication of the model.”).


226. See generally KPMG, supra note 39.


228. Schwarcz, supra note 192, at 223.

229. Id. at 223 n.63.
and their accompanying risks since the economy was nominally doing well—a state not unlike that which has existed for the past few years in the U.S.\textsuperscript{230} These favorable economic conditions caused supposed market experts to embrace the natural human propensity to “dismiss low-probability but high-consequence” risks.\textsuperscript{231} In essence, investors and markets more broadly saw and continue to “see what they want to see.”\textsuperscript{232} The fintech lending phenomenon is susceptible to the same kind of over-optimism as short-cut market noise can drown out signals that would otherwise suggest danger. With the market distracted, this leaves only financial regulators as the watchdogs of stability.

3. Disclosures

Importantly, the complexity of fintech securitization makes meaningful disclosures difficult if not impossible. In the context of simple securitizations that do not entail sophisticated AI underwritten loans, the investment securities are created under conditions that make it very difficult for investors to understand and analyze the risk being undertaken.\textsuperscript{233} The subprime mortgage crisis provided an excellent example of how so-called sophisticated investors with the benefit of U.S. securities disclosure laws were nevertheless unable to understand the fragility of what stood behind subprime mortgage-

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backed securities.\textsuperscript{234} No one expected housing prices to decline—indeed, there was a significant level of groupthink around the dependability of ever-rising house prices.\textsuperscript{235} At the time, the renowned chair of the Board of Governors of the Federal Reserve System Alan Greenspan denied that there even was a housing bubble—only to admit his error after the fact.\textsuperscript{236}

Securities disclosures for subprime mortgage-backed securities contained a host of qualifying statements and caveats about the quality of the underlying loans.\textsuperscript{237} That, however, played no part in directing the behavior of investors.\textsuperscript{238} In an August 2008 letter and accompanying report to the Secretary of the Treasury that was authored by the heads of major U.S. financial companies such as Goldman Sachs, JPMorgan Chase, Citigroup, Bank of America and others, the group stated that “there is almost universal agreement that, even with optimal disclosure in the underlying documentation, the characteristics of these instruments and the risk of loss associated with them were not fully understood by many market participants.”\textsuperscript{239} Moreover, the report stated that “[t]he lack of comprehension . . . [reflects] a complex array of factors, including a lack of understanding of the inherent limitations of valuation models and the risks of short-run historical data sets.”\textsuperscript{240} The judgments of the ratings agencies were taken at face value and drove investment decision-making.\textsuperscript{241} And as a result, the hunger for subprime mortgage-backed securities roared on unabated in the capital markets throughout the pre-crisis period.\textsuperscript{242}

As Steven Schwarcz has noted, “[a]lthough experts may be hired to the extent that their costs do not exceed the benefits gained from more fully understanding the complexity, at some level of complexity those costs will

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  \item \textsuperscript{234} Schwarcz, \textit{supra} note 192, at 222.
  \item \textsuperscript{235} \textit{Id.} at 222; see also \textit{ODINET, supra} note 21, at 15–17.
  \item \textsuperscript{237} Schwarcz, \textit{supra} note 192, at 222.
  \item \textsuperscript{238} \textit{Id.} (“Investors did not, however, always appreciate these risks, in large part because the complexity of these securities made the risks very difficult to understand.”).
  \item \textsuperscript{239} CRMPG II, \textit{CONTAINING SYSTEMIC RISK: THE ROAD TO REFORM 53} (2008), http://www.crmppolicygroup.org/docs/CRMPG-II.pdf [https://perma.cc/4JE8-CXNM].
  \item \textsuperscript{240} \textit{Id.}
  \item \textsuperscript{241} \textit{ODINET, supra} note 21, at 30; Schwarcz, \textit{supra} note 192, at 222.
  \item \textsuperscript{242} \textit{ODINET, supra} note 21, at 31.
\end{itemize}
exceed, or at least appear to exceed any potential gain.” This trend is largely driven by the fact that “the cost of hiring experts is tangible, whereas the benefit gained from fully understanding complex transactions is intangible and harder to quantify.”

Heavy reliance on heuristics and market propaganda reigned over subprime mortgage investment decision-making. In today’s market, however, many large institutional investors have become data hawks themselves. Indeed, many institutional investors of fintech credit securities run available underwriting data through their own models (typically using FICO or similar panel data) to cross check the underwriting themselves. But as AI continues to play a larger role in underwriting, this type of crosschecking will not be possible for long. Even if the investors have the underwriting data, they will not be able to replicate the underwriting itself if the fintech’s process involves an AI program that is inscrutable (such as with increasingly complex neutral network algorithms). In this way, the use of black box algorithms results in making an understanding of the true nature of securitized assets even more difficult. The entire system is “increasingly opaque to [both] reasoned human cognition” and analysis by investor deployed AI, which in turn makes it more challenging to “make thoughtful judgments about where risk lies.”

4. Algorithmic Failures

As Hilary Allen explains more broadly, it might be tempting to embrace the use of algorithms in financial transactions because not only can they process vastly larger amounts of data than can humans, but they also can engage in more accurate assessments of risks. Popular opinion proclaims

243. Steven L. Schwarcz, Disclosure’s Failure in the Subprime Mortgage Crisis, 2008 UTAH L. REV. 1109, 1114.
244. Id.
that artificial intelligence will change the world—revolutionizing everything from entertainment and medicine to transportation and everyday household tasks.\textsuperscript{248} It is argued that the use of machine learning will shape the future and change it entirely,\textsuperscript{249} largely for the better.\textsuperscript{250} A senior editor for \textit{The Economist} magazine compared the rise of artificial intelligence in the digital economy to man’s discovery of fire.\textsuperscript{251}

However, there are still reasons to look toward AI with a critical eye.\textsuperscript{252} Allen explains that machine learning algorithms can have programmatic defects or “bugs” in their systems that cause them to behave incorrectly or in suboptimal ways.\textsuperscript{253} Also, she dives deeper to explain that when it comes to predictive algorithms, the desire of the program to generate logical sequences in its decision-making may cause it to favor that which can be measured and otherwise “mask uncertainty.”\textsuperscript{254} This is because, as Kenneth Bamberger explains in the context of business compliance, technological systems suffer from limitations in their ability to “ascrib[e] social meaning to algorithms” and their imperfect attempts “to make human constructs amenable to computers.”\textsuperscript{255} This means that as a program tries to maintain or increase its efficiency (and thus its speed) it may discard relevant information that cannot easily be translated into code.\textsuperscript{256} Yet, this lost information may have subtle relevancy.\textsuperscript{257}

Also, when it comes to risk, algorithms look to historical data to make predictions about the future. Yet, there are inherent limitations in such a data, particularly when it comes to lending based on the time frame from which

\begin{itemize}
\item \textsuperscript{250} Janna Anderson & Lee Rainie, \textit{Artificial Intelligence and the Future of Humans}, PEW RES. CTR. (Dec. 10, 2018), https://www.pewinternet.org/2018/12/10/artificial-intelligence-and-the-future-of-humans/ [https://perma.cc/L5EU-DL49] (“Experts say the rise of artificial intelligence will make most people better off over the next decade . . . .”)
\item \textsuperscript{252} Allen, \textit{supra} note 247 (manuscript at 19–20).
\item \textsuperscript{253} \textit{Id.} (manuscript at 19).
\item \textsuperscript{254} \textit{Id.} (manuscript at 20).
\item \textsuperscript{255} Kenneth A. Bamberger, \textit{Technologies of Compliance: Risk and Regulation in a Digital Age}, 88 \textit{Tex. L. Rev.} 669, 706–07 (2010).
\item \textsuperscript{256} Allen, \textit{supra} note 247 (manuscript at 19).
\item \textsuperscript{257} \textit{Id.} (manuscript at 19–20).
\end{itemize}
the data are drawn. This is essentially the problem described as model or concept drift in the machine learning literature, which is where the relationship between inputs and outputs changes over time. In other words, in a given data set there might be contexts that are hidden from view or not otherwise recognized in the data but that nevertheless drive outcomes. For instance, if data are drawn from an up-credit cycle, then the predictions will necessarily fail to take into account the cyclical nature of the financial markets. The up-nature of the economy is the hidden context that drives the relationship between inputs and outputs and, if the economic conditions were changed, would create different results.

Indeed, Karen Shaw Petrou, I, and others have criticized fintech lending on precisely this basis because these underwriting programs have not yet been tested through a full credit cycle where we can see how they stand up to difficult economic conditions, such as the tightening of credit, higher interest rates, and higher unemployment.

In sum, the backward-looking viewpoint of how algorithms assess borrower risk only considers what has occurred, while true risk assessment is about “future disturbances.” Now to be certain, this does not mean that machine learning decision-making lacks features that are clearly superior to more traditional human cognition. What it does mean, however, is that we should be more cautious about taking the infallibility of machine learning at face value in the finance space. After all, algorithms are not infallible and


260. José Gabilondo, Leveraged Liquidity: Bear Raids and Junk Loans in the New Credit Market, 34 J. CORP. L. 447, 489 (2009) (“For the time being, at least, the consensus is, again, that financial cycles do exist.”).


263. Allen, supra note 247 (manuscript at 20).
can act in unexpected ways. For instance, data scientists Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin published a 2016 paper demonstrating how easily an AI break-down can occur.\footnote{264} The authors presented a neural network algorithm with a training set of images—some depicting wolves and some showing Eskimo dogs (huskies).\footnote{265} Soon after the algorithm was deployed, it was revealed that the program was making classification determinations between the two animals not based on size, shape, and other physical attributes but rather on whether snow appeared in the background of the submitted photo.\footnote{266} Most of the photos in the training set showed the huskies with snow in the background.\footnote{267} This caused the machine learning program to generate a number of false positives (i.e., classifying wolves as huskies in certain settings).\footnote{268} The authors note that “artifacts of data collection can induce undesirable correlations that the classifiers pick up during training” and that “[t]hese issues can be very difficult to identify just by looking at the raw data and predictions.”\footnote{269}

These algorithmic imperfections are not, however, merely academic. In March 2016, Microsoft launched an artificially intelligent chat bot named Tay that was to revolutionize the customer service industry.\footnote{270} The idea was that consumers would interact with Tay over Twitter and, after internalizing these interactions, Tay would tweet out helpful information.\footnote{271} However, within one day of taking in mass data, “Tay became a full-blown racist,” resulting in Microsoft shutting down the program.\footnote{272} In 2015, Google Map searches using pejorative terms for black people followed by the word “house” lead users to the then Obama-occupied White House.\footnote{273} The autonomous security robot K5 plowed over the foot of a sixteen-month old child in a Palo Alto shopping center in July 2016.\footnote{274} Even one of the great giants of artificial intelligence—Facebook—has struggled with ensuring that

\footnote{265} Id. at 8–9.
\footnote{266} Id.
\footnote{267} Id.
\footnote{268} Id. at 9.
\footnote{269} Id. at 8.
its algorithms operate correctly. In 2017, the company admitted that, unbeknownst to its technicians, the Facebook advertising platform allowed advertisers to target individuals who identified as being anti-Semitic—such as by showing ads to profiles that included specific phrases like “Jew hater” or “How to burn Jews.”

Sometimes these algorithmic failures are even more extreme. In May 2016, the city of San Francisco started to experiment with the use of algorithms to predict whether a particular criminal defendant awaiting a trial could be released without risking flight or the commission of another offense. The basis of the program was “to use cold, efficient data to improve the traditional system of cash bail.” In an August 2017 assessment, the algorithm recommended the release of a nineteen-year old facing charges of being a convicted felon in possession of a firearm while he awaited his appearance in court. Although the accused was already on probation in two California counties for auto burglary and was accused twice of violating parole, the algorithm determined that he was “a medium public safety and flight risk” and recommended he be conditionally released. Five days later, the accused was connected to the killing of a seventy-one-year-old man and the robbing of a couple at gunpoint.

A recent example in the world of finance further illustrates the fallibility of algorithmic decision-making. In 2017, a so-called super computer named K1 was developed by an Austrian company to parse through various sources of online data, including social network and media information, to make predictions about the U.S. stock market, which would be accompanied by automatic trading orders to securities brokers. The computer used machine learning to adjust the investment strategy over time for customers. In 2017, the Hong Kong investor Samathur Li Kin-kan handed $250 million of his


277. Id.

278. Id.

279. Id.

280. Id.


282. Id.
own money to K1 to invest.283 By the beginning of 2018, however, Li was regularly losing money—as much as $20 million in a single day—caused largely by a stop-loss order (which is an order to a broker to sell a security once it reaches a certain price) that Li and his lawyers argued should have never been given if, as was purported, “K1 was as sophisticated” as all had been led to believe.284

This is again not to say that big data and machine learning are without benefits. The use of these innovations and types of information has generated a number of business efficiencies and consumer advantages over the past several years alone.285 But, we should be cautious in not allowing ourselves to be swept away in the hype that accompanies the rise of new forms of artificial intelligence technology.286 Technology can misfire.287

Indeed, fintech loans—despite their supposed superiority when compared to the much-derided underwriting methods of banks and more traditional lenders—have not always performed so well. Loan performance data from the credit analytics firm PeerIQ revealed that the 24-month delinquency rates for fintech loans made in 2017 were higher than those in 2016 and in 2015.288 And this was despite supposed improvements in underwriting models along the way.289 In its early 2019 market report, PeerIQ reported that loan delinquencies, as well as charge-offs, saw an increase from the end of 2018.290 The group noted: “[w]e don’t see the purported improvement in underwriting just yet.”291

284. Id.
287. Beardsworth & Kumar, supra note 283.
289. Id. at 1.
290. PEERIQ, supra note 130, at 9.
291. Id.
Aside from the potential credit risks described above, AI securitizations also raise a number of legal risks. These legal risks are largely related to the particular business structure under which a number of prominent fintech credit firms operate. As described in Part II, fintech lenders largely partner with regulated banks or related depositary institutions in order to originate consumer loans rather than make the loans themselves. This business practice has led to private litigation and public enforcement actions against these firms (and sometimes their bank partner). Additionally, the use of alternative data and AI in the underwriting process creates the potential for discrimination in the provision of credit toward legally protected classes. This raises issues of prospective liability under federal and state fair lending laws. This section explains the current legal challenges facing the fintech business model and describes the liabilities that can and often do arise.

1. Licensing

The first major legal risk in fintech securities pertains to licensure. Throughout the United States, various different kinds of nonbank companies that offer financial products and services must be licensed by individual state financial services and banking regulators. These licensed companies range from providers of credit like payday loans to those that transmit money like Western Union and Paypal, to check cashing businesses and mortgage lenders. Importantly, providers or facilitators of consumer loans that are not themselves banks must be licensed—these include fintech lenders.

The licensing process serves a number of purposes, chief of which is to guard against companies entering the consumer finance marketplace when they do not have the financial wherewithal to meet their obligations. A component of this is ensuring that only those with “the requisite character, integrity, and experience” receive a license to lend. The state licensing

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293. ADAM J. LEVITIN, CONSUMER FINANCE: MARKETS AND REGULATION 75–76 (Rachel E. Barkow et al. eds., 2018).

294. Odinet, supra note 26, at 812.

process varies from jurisdiction to jurisdiction, with some being quick to others being more elaborate.\textsuperscript{296} The process typically involves the submission of a license application, background checks, the furnishing of surety bonds, the payment of fees, and the opening of the company’s books for inspection by public authorities, as well as agreeing to various restrictions on business activities.\textsuperscript{297} The posting of a surety bond is designed to show regulators that the business has the financial strength to meet its contractual obligations—particularly those owed to consumers.\textsuperscript{298}

The licensure issue has been particularly troublesome in the fintech lending space. Recall from above that the predominate business model for mature fintech lending companies is to conduct the loan application and underwriting process but then to have a bank partner originate the loan, only to then purchase the loan thereafter. As purely a matter of form, the entity originating the loan is the bank, not the fintech firm. Because of this, many fintechs have argued that they do not need to be licensed by any particular state because they are not originating the loan.\textsuperscript{299} Rather, they merely assist the originator (the bank) in the provision of credit by providing front-end tech-related services.

State financial services regulators and attorneys general have not been receptive to this argument. Rather, they posit that, in substance, the real lender is the fintech company, and the bank is merely a pass-through entity.\textsuperscript{300} This has become known as the “true lender doctrine” whereby a court will look through the form of the contractual relationship and any corporate structures and determine who, in substance, is making the loan.\textsuperscript{301}

The past few years have seen litigation challenging whether fintech lenders are the true originators of these online loans and, thus, whether they must be state licensed.\textsuperscript{302} For example, in March 2018 the Massachusetts banking commissioner entered into a consent decree with the fintech giant Lending Club and its Massachusetts-based subsidiary Springstone Financial,
LLC related to their loan activities, even though Lending Club loans are originated by its bank partners—namely WebBank.\footnote{Consent Order at pmbl., \textit{In re} LendingClub Corp., No. 2018-0001 (Mass. Div. of Banks Mar. 12, 2018), https://www.mass.gov/consent-order/lendingclub-corporation-and-springstone-financial-llc [https://perma.cc/U567-JYBN].} The commissioner alleged that “LendingClub [and Springstone Financial] engaged in the business of arranging small loans for a fee from August 1, 2011 through the present without a small loan company license.”\footnote{Id.} Lending Club agreed, among other things, to pay a $2 million penalty and to “cease and desist from engaging in any business activity that requires licensing or registration” including but not limited to “directly or indirectly engaging . . . in the business of negotiating, arranging, aiding or assisting the borrower or lender in procuring or making loans . . . whether such loans are actually made by LendingClub or by another party . . . .”\footnote{Id. at 1.} The fintech lender also had to payback to consumers a certain portion of the interest and fees it collected.\footnote{Id.} And, to be sure, Lending Club is not alone. In 2017, New Hampshire also settled enforcement actions against Klarna Credit in connection with its loan program through Utah-based WebBank\footnote{Consent Order at 2, \textit{In re} Klarna Inc., No. 17-052 (N.H. Banking Department Nov. 8, 2017), https://www.nh.gov/banking/orders/enforcement/documents/17-052-co-20171108.pdf [https://perma.cc/K7MZ-GK9W] (“After reviewing the information, the Department determined that from 2016 through 2017, Klarna Credit conducted unlicensed small loan lender activity by serving as an intermediary, finder, or agent for forty-six (46) New Hampshire consumers for the purpose of negotiating, arranging, finding, or procuring loans, or commitments for loans from WebBank under the Klarna Credit program through the Klarna Inc. online platform.”).} and RocketLoans in connection with its loan program through New Jersey-based Cross River Bank for operating without appropriate licenses.\footnote{Consent Order, \textit{In re} RockLoans Marketplace LLC, No. 17-071 (N.H. Banking Department Oct. 24, 2017), https://www.nh.gov/banking/orders/enforcement/documents/17-071-co-20171024.pdf [https://perma.cc/923C-SAW8].}

Thus, the dominant business model for fintech lending inherently raises licensure-liability issues. Moreover, in some states like Arkansas, Arizona, Connecticut, and Illinois, debt collectors—quite simply, those that collect debts, usually on behalf of others—also must be licensed.\footnote{See Kristy Welsh, \textit{State by State Collection Agency Requirements}, CREDIT INFOCENTER (Oct. 24, 2017), https://www.creditinfocenter.com/legal/collection-agency-requirements.shtml [https://perma.cc/JBP2-3XRB].} Recall from above that fintech credit firms not only assist in the origination of loans by partner banks but also often conduct the servicing of those loans after they are sold or otherwise securitized. Part of servicing a loan includes engaging
in debt collection activities. This presents yet another layer of licensure problem.

The potential liability that results from making a loan without a proper license has ramifications for investors in fintech securitizations. As noted above, California law deems a loan made by an unlicensed lender void. The same interpretation has been approved by Oklahoma courts when loans are made by unlicensed individuals in that state as well.\(^\text{310}\) Arizona,\(^\text{311}\) Indiana,\(^\text{312}\) Massachusetts,\(^\text{313}\) New Hampshire,\(^\text{314}\) New York,\(^\text{315}\) and North Carolina\(^\text{316}\) all void certain unlicensed loans.\(^\text{317}\) Other states (such as Colorado) do not void the loan, but rather reduce the amount recoverable.\(^\text{318}\) All of these create borrower defenses that can significantly harm the position of the securities investor. And as noted above, it is usually not even the borrower that brings such actions but rather state officials with significant resources and political backing.

2. Usury

Another very salient issue in the fintech lending space (indeed, some would characterize it as being the most significant) deals with the amount of interest and fees charged on these loans—the issue of usury.\(^\text{319}\) The usury questions again come back to the partnerships between fintech lenders and banks. First, the concept of setting proper interest rate limits for lending is generally a matter of state law.\(^\text{320}\) States have long dictated the amount of money that can be charged for the use of money.\(^\text{321}\) Up to today, there is no

\(^{310}\) See Bunch v. Terpenning, 229 P.3d 574, 580 (Okla. Civ. App. 2009) (interpreting a prior version of, but similar to existing, OKLA. STAT. tit. 14A, § 3-502 (2011)).

\(^{311}\) ARIZ. REV. STAT. ANN. §§ 6-601(5)–(7), 6-602(B), 6-603(A), 6-613(B) (2019).

\(^{312}\) IND. CODE ANN. §§ 24-4.5-5-202, 24-4.5-3-502(3) (West 2015).

\(^{313}\) MASS. GEN. LAWS ANN. ch. 140, §§ 96, 110 (West 2002).


\(^{315}\) N.Y. BANKING LAW §§ 340, 355 (McKinney 2013).

\(^{316}\) N.C. GEN. STAT. ANN. § 53-166(a), (d) (West 2005).

\(^{317}\) Complaint, supra note 295, at 7–9.

\(^{318}\) COLO. REV. STAT. ANN. §§ 5-5-201(1), 5-2-301(1)(a), (b), 5-1-301(17) (West 2019).

\(^{319}\) Usury, BLACK’S LAW DICTIONARY (11th ed. 2019) (“Historically, the lending of money with interest . . . Today, the charging of an illegal rate of interest as a condition to lending money . . . An illegally high rate of interest. — Also termed illegal interest; unlawful interest.”).

\(^{320}\) LEVITIN, supra note 293, at 458–59.

general federal usury limit and even the Consumer Financial Protection Bureau ("CFPB") is prohibited by statute from creating one. What has resulted, however, is a patchwork of different usury laws across the states, including with exceptions and special rules for different kinds of loans and different kinds of lenders (i.e., pawn brokers can charge one rate while auto lenders can charge another, etc.). This state of affairs, however, is not particularly problematic if a lender only lends to individuals within a given state. But if a lender makes loans across state lines—indeed, if such lending is done seamlessly over the internet—then the matter of compliance becomes quite difficult. Loan documentation, marketing, and forms would need to be customized depending on the home state of the borrower. Fintech lenders have been faced with just such a problem, as the general interest rate limit in Maine is as high as 31% while in Maryland it can be capped at 8%.

The bank-partnership model, however, is viewed as a form of usury work around. Under the National Bank Act and a now infamous case known as Marquette National Bank of Minneapolis v. First of Omaha, banks chartered at the national level generally have the ability to charge the highest interest rate permissible for any kind of lender in a given state and can even export that interest rate to loans made to borrowers in other states. This means, for example, that a national bank located in Oklahoma can not only charge the highest interest rate allowable in Oklahoma to anyone located in Oklahoma but also can charge that same Oklahoma state law rate to a borrower located in any other state. This phenomena is known as “interest rate exportation” because one can export the interest rate of one state to loans

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322. 12 U.S.C. § 5517(o) (2018); LEVITIN, supra note 293, at 460.
made in other states. State banks are able to do the same thing through the enactment of so-called parity laws by state legislatures that allow state-chartered banks to charge interest at the same rate as any national bank doing business in that state. These equalization efforts were largely completed in 1980 when Congress passed a law that gave the same interest-rate exportation power enjoyed by national banks to federally insured state-chartered banks.

In sum, this means that a state-chartered bank can also charge out-of-state borrowers the same interest rate that is allowable for in-state borrowers. Thus, a state-chartered bank located in Louisiana can charge a Texas borrower the same Utah rate that a national bank doing business in Louisiana can charge, even if that Utah rate is higher than what would otherwise be allowed under Texas law. Over time, the definition of what constitutes “interest” has also been expanded to include fees and other charges in connection with a loan transaction. Today, the combination of these laws means that usury restrictions (while still on the books) have largely been gutted when it comes to bank lending.

This broad power to export the interest rates has proved attractive to fintech lenders because they are in the business of extending credit online and nationwide. Since the fintechs themselves cannot do this (because they are nonbanks), many have partnered with banks in order to avoid state-level usury limits. The partnering institutions mentioned above—such as WebBank, Cross River Bank, and Celtic Bank—are all organized as various forms of state-chartered banks. WebBank and Celtic Bank are chartered in

328. Hannon, supra note 300, at 1269.
329. LEVITIN, supra note 293, at 468.
332. LEVITIN, supra note 293, at 468–69; see also Michael S. Barr, Banking the Poor, 21 YALE J. ON REG. 121, 150–51 (2004); Christopher L. Peterson, Federalism and Predatory Lending: Unmasking the Deregulatory Agenda, 78 TEMP. L. REV. 1, 35 (2005).
333. WebBank and Celtic Bank are chartered by the state of Utah, and Cross River Bank is chartered by the state of New Jersey. See About Us, CELTIC BANK, https://www.celticbank.com/about-us [https://perma.cc/7D8X-LHME]; About Us, WEBBANK, https://www.webbank.com/about-us/about-us [https://perma.cc/JFV6-BPRD]; Idea Financial Closes $70 Million Warehouse Facility with Cross River, BUS. WIRE (June 17, 2019),...
Utah, where they enjoy no usury limit, and Cross River Bank is chartered in New Jersey, which also provides a large degree of interest rate flexibility. As noted above, the dominant business model for fintech-bank partnerships is for the fintech company to do the marketing, loan application intake, and underwriting, while the bank partner actually originates the loan. In this way, the structure is designed so that the loan is made by the state-chartered institution—with all the attendant interest rate benefits.

However, this model has recently come under attack by virtue of the true lender doctrine described above. The basis of the doctrine first appeared in a 2011 Georgia law as an attempt by that state to deal with partnerships between brick and mortar payday lenders and out-of-state banks. The Georgia statute asked whether, in view of “the entire circumstances of the transaction,” it can be shown “that the purported agent holds, acquires, or maintains a predominant economic interest in the revenues generated by the loan.” The doctrine has subsequently been adopted by a number of courts across the country. The result of a successful true lender attack is for the bank’s involvement (and interest rate powers) to be disregarded and for the fintech to be deemed the true lender on the theory that the latter “had the predominant economic interest in the loans and was the ‘true lender’ and real party in interest.”

This issue has come to the fore in a number of recent cases. In 2017, the Colorado financial services regulator commenced litigation against the


Hannon, supra note 300, at 1280; see also GA. CODE ANN. § 16-17-2(b)(4) (2015).

GA. CODE ANN. § 16-17-2(b)(4).


fintech lenders Marlette Funding and Avant in connection with their partnerships with Cross River Bank and WebBank, respectively. Here again the state advanced the argument that the parties with the “predominant economic interest” in the loan transaction were the fintech lenders, not the banks. The complaint explained, in the Marlette action, that the fintech lender paid all of the bank’s cost in connection with the lending program, paid for the marketing of the loan program, and determined who received loans under the program. Further, Cross River Bank “bears no risk that it will lose its principal in the event that consumers default” on the loans because, among other reasons, “Marlette or its designee purchase [the loans] from Cross River Bank within two business days of when the loans are made” and, furthermore, “the purchase price includes the amount that Cross River Bank advanced to the consumer.” Similar claims were raised against Avant in connection with that action.

The litigation remains ongoing, but as recently as January 2019, Colorado amended its complaint to add thirty-six securitization trusts to the litigation. The amended complaint alleges that these trusts, which purchased and securitized loans made by Marlette Funding/Cross River Bank and Avant/WebBank, were not authorized to accept the fees and interest that they received and requested that the court order them to “disgorge any finance charges or fees received beyond those permitted by [Colorado law].” The state argued that a securitization trust is a “creditor” in accordance with Colorado consumer credit law and thus is liable to pay “ten times the amount of the excess charge” collected. While these cases have yet to be resolved, in April 2019, the court held that indeed the securitization trusts were subject

342. Amended Complaint, supra note 340, at 4; Amended Complaint, supra note 341, at 5.
343. Amended Complaint, supra note 340, at 5.
344. Id.
347. Id.
348. Id.; COLO. REV. STAT. ANN. § 5-6-114 (West 2019).
to Colorado law and thus could face significant exposure once the underlying merits were decided.\textsuperscript{349}

Moreover, Colorado is not alone in targeting the bank-partnership model using the true lender doctrine. In 2017, the attorney general of West Virginia brought an action against the fintech credit firms Lending Club and Avant in connection with their bank-related lending programs.\textsuperscript{350} Both companies entered into consent orders whereby they agreed to comply with state law—including interest rate limitations.\textsuperscript{351}

A different but related issue with fintech-bank partnerships and usury deals with the so-called “valid-when-made doctrine.”\textsuperscript{352} It is often raised alongside the true lender theory as an alternative. Banks and other financial institutions that enjoy rate exportation powers (particularly those that partner with fintech lenders) argue that if a loan is valid when it is made, it remains valid even if it is sold or otherwise assigned to others.\textsuperscript{353} Thus, so the argument goes, if a lender makes a loan that, under applicable law does not violate usury limits, then that loan can never be said to violate usury limits even if it is transferred to a party that would not have been able to make such a loan in the first instance.\textsuperscript{354} Therefore, putting aside a successful true lender attack, if the loan was validly made by a bank enjoying rate exportation powers, then the sale of that loan to, for instance, a fintech company and the subsequent securitization of that loan would not impact the privileged status.\textsuperscript{355} As one might imagine, this doctrine is vitally important to the fintech lending business model since so many loans are immediately sold by the bank partner and subsequently securitized.

Recently, however, the very existence of the valid-when-made doctrine has come under attack.\textsuperscript{356} Opponents argue that lenders—particularly online


\textsuperscript{350} Brennan & Zaman, \textit{supra note 302}, at 547.

\textsuperscript{351} \textit{Id.}


\textsuperscript{353} \textit{Nichols}, 32 U.S. (7 Pet.) at 105.

\textsuperscript{354} Brief for the United States as Amicus Curiae at 6, Midland Funding, LLC v. Madden, 136 S. Ct. 2505 (2016) (No. 15-610), 2016 WL 2997343, at * 8.

\textsuperscript{355} See Hannon, \textit{supra} note 300, at 1279.

\textsuperscript{356} For a full discussion of the history of the valid-when-made principle, see Motion for Leave to File Amicus Curiae Brief of Professor Adam J. Levitin in Support of Appellant at 4–5, Rent-Rite Super Kegs West, Ltd. v. World Business Lenders, LLC, No. 1:19-cv-01552-REB (Appeal from Bankruptcy Adversary Proceeding No. 18-1099-TBM) (D. Colo. Sept. 19, 2019),
lenders—merely “rent” a bank in order for the loan to be originated by a party that enjoys rate exportation powers while thereafter (usually within a matter of hours or days) buying and subsequently selling or securitizing the loan in the secondary market. Therefore, so the argument goes, the rate exportation power that was created to first ensure a coherent national banking system and then to give state banks the ability to compete has become a service rented out to nonbank entities for a tidy sum. A similar structure (and attendant criticism) has arisen when online lenders partner with sovereign Native American tribes to also avoid usury and other state law limitations.

The first significant challenge to the valid-when-made doctrine came in 2015 when the Second Circuit decided the case of <i>Madden v. Midland Funding, LLC</i>. In this case, the court was confronted with a situation where Bank of America (a national bank enjoying rate exportation powers) sold defaulted credit card debt to a third party, which then sought to collect on those debts at an interest rate of 27%. The rate would have been permissible for the bank, but it would not have been if the loan was made by the third-party debt collector. The suit asserted that the collection of the loan was unlawful because, among other things, it violated New York state usury limits. The Second Circuit agreed in stating that the debt collector-buyer had not “acted on behalf of a national bank” but rather on its own behalf. Importantly, it noted that extending “[National Bank Act] preemption to third-party debt collectors . . . would create an end-run around usury laws for non-national bank entities that are not acting on behalf of a national bank.”

When appealed, the Supreme Court tellingly refused to grant cert.

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360. 786 F.3d 246 (2d Cir. 2015).

361. Id. at 248.

362. Id. at 247–49.

363. Id. at 248.

364. Id. at 251.

365. Id. at 251–52.

Both the true lender doctrine and the rejection of the valid-when-made
document bring substantial liability to lending programs between fintechs and
their partner banks. Consider that under Arkansas law any interest rate over
17% that is charged by a non-licensed entity is “void as to principle and
interest.” New Hampshire, New York, and North Carolina also entirely void such loans. This, in turn, generates yet another significant risk
in the securitization of these online loans.

3. Special Statutory Liability

Another inherent legal risk in the securitization of fintech loans deals with claims under state and federal unfair and deceptive (and sometimes even abusive) acts and practices statutes (“UDA(A)P”). These laws allow for state and federal officials to generally police activities and firms that are harmful to consumers, including in the consumer finance context specifically. Prentiss Cox, Amy Widman, and Mark Totten explain that these laws are “an alternative to common law remedies in tort and contract, which proved inadequate for addressing fraud in a progressively more complex marketplace.” They are typically enforced at the state level by attorneys general and state financial/banking supervisors, as well as at the federal level by the Federal Trade Commission (“FTC”) and the CFPB. At the state level, these statutes can reach even acts that are considered unconscionable, and the CFPB has the added power to police “abusive” acts and practices. The purpose of these statutes is to provide a general and

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367. ARK. CONST. amend. 89, §§ 3, 6(b).
368. N.H. REV. STAT. ANN. § 399-A:16(I) (2017); id. § 399-A:15(V).
369. N.Y. GEN. OBLIG. LAW § 5-501 (McKinney 2012); N.Y. BANKING LAW § 14-a(1) (McKinney 2013). Loans that exceed the rate are void. N.Y. GEN. OBLIG. LAW § 5-511; see also Szerdahelyi v. Harris, 490 N.E.2d 517, 522–23 (N.Y. 1986) (holding that such loans are void ab initio).
370. N.C. GEN. STAT. ANN. § 53-176(a) (West 2005); id. § 53-166(d).
371. LEVITIN, supra note 293, at 81.
372. id. at 185.
373. id. at 205.
375. Id. at 42.
377. LEVITIN, supra note 293, at 81, 185, 205; see 12 U.S.C. § 5531(a) (2018).
378. LEVITIN, supra note 293, at 81.
equitable remedy for consumer wrongdoing. Some UDA(A)P statutes, such as the California Unfair Competition Law, are rather broad and provide a right of action for not only state officials but also for private individuals. In other states, the law cannot be enforced by private individuals and may include multiple carve-outs for certain types of businesses.

Violations of UDA(A)P laws vary. For instance, the penalty in California (one of the largest consumer markets in the country and home to Silicon Valley) includes potential recovery of attorney’s fees, injunctive relief, a civil penalty of up to $2,500 per violation, and additional penalties if a disabled or elderly person is the victim among other things. A violation of federal UDA(A)P provisions include up to $5,000 per day for a violation, up to $25,000 per day for a reckless violation, and up to $1 million per day for a knowing violation. In 2014 alone, the Bureau brought six actions resulting in penalties of more than $5 million each and two actions with individual penalties exceeding $10 million. More recently, in April 2018, Wells Fargo Bank agreed to pay $1 billion to settle a UDA(A)P action.

In the fintech lending space, UDA(A)P enforcement can come from a number of places. First, the FTC is given the authority to enforce unfair and deceptive acts and practices against nonbanks. Since fintech lenders are considered nonbank companies, the FTC has enforcement authority over them in this respect.

382. LEVITIN, supra note 293, at 83.
383. Id. at 81–84.
384. CAL. CIV. PROC. CODE § 1021.5 (West 2007) (providing for the recovery of attorney’s fees in those cases involving the “enforcement of an important right affecting the public interest”).
385. CAL. BUS. & PROF. CODE § 17203–04.
386. Id. § 17206.
387. Id. § 17206.1.
392. See id.
Second is through the CFPB, whose ability to reach fintech lenders comes in a bit more roundabout way. The Bureau has the power to police unfair, deceptive, and (the Dodd-Frank Act-added) abusive acts and practices against so-called “covered persons,” which are those who offer consumer financial products and services. Such products and services includes “extensions and servicing of credit” made for “personal, family, or household purposes.” This means that those who make consumer loans and those who service them are covered. Also, under the CFPB’s UDA(A)P authority are “service providers” of covered persons, which consist of those that provide a “material service” to a covered person in connection with the offering or provision of a consumer financial product or service.

Fintech credit firms fall into the CFPB’s jurisdiction under these statutes in four ways. First, as noted above, fintechs service the loans that they help originate by collecting payments from borrowers and passing along funds to securitization trusts. This makes them a covered person in that they are in the business of servicing credit. Also as noted above, the fintech company handles the intake of the loan application from the borrower and its passage along to the bank partner. In this way, the fintech is brokering the loan, and brokering consumer credit is also a way to be a covered person.

Third, fintechs are also regulated by the CFPB for being service providers to covered persons. The bank partner is the covered person because it is unquestionably extending credit. The fintech is providing a material service in connection with the making of the loan because the fintech company conducts the marketing, application intake, and the underwriting. This is supported by the statutory illustrative list of giving a material service, which includes designing and operating the consumer financial product or service, as well as processing transactions of the same.

And, lastly, as if these avenues for coverage were not enough, the Bureau also has the power to bring enforcement actions against those that give

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394. Id. § 5531.
395. Id. § 5481(15).
396. Id. § 5481(5).
397. Id. § 5481(26)(A).
398. Id. § 5481(15)(A)(i).
399. Id. § 5481(15)(A)(ii); Broker, BLACK’S LAW DICTIONARY (11th ed. 2019) (“An agent who acts as an intermediary or negotiator, esp. between prospective buyers and sellers; a person employed to make bargains and contracts between other persons in matters of trade, commerce, or navigation.”).
401. Id. § 5481(26)(A).
402. Id. § 5481(26)(A)(i)–(ii).
“substantial assistance” in connection with a UDA(A)P violation. As Adam Levitin explains, substantial assistance “is essentially a flavor of aiding and abetting.” The way a fintech company would be brought in—separate and apart from whether it is a service provider as indicated above—would be if the bank partner was found to have committed a UDA(A)P violation under its online lending program, since the fintech is obviously significantly involved (i.e., materially assists) in the credit process.

Potential UDA(A)P liability resulting from fintech/online lending is not merely an academic question. There has already been some activity in this area, such as in the CFPB’s 2013 enforcement action against the company CashCall, Inc. In that case, CashCall, Inc. and its subsidiary WS Funding, LLC entered into a partnership with a South Dakota-based online lender named Western Sky Financial, which is based on an Indian reservation and is owned by a member of the Cheyenne River Sioux Tribe. Asserting tribal sovereignty claims, CashCall, WS Funding, and Western Sky argued that various state laws (including licensing and usury) did not apply to these loans, which ranged from $850 to $10,000 in amount and carried an annual interest rate of anywhere between 90% and 343%. After the loans were made by Western Sky, they were immediately sold to CashCall and WS Funding.

In the face of opposition by various officials in states where these loans had been made, the lending business shut down, but CashCall and WS Funding continued servicing and collection activities. In late 2013, the CFPB brought a UDA(A)P action against CashCall, WS Funding, and its principals. In January 2016, a federal district court held that despite the role played by Western Sky Financial, the “true lender” was CashCall, stating that the intentionally complicated and sham structure of the Western Sky loan program would have made it impossible for reasonable consumers to know that [Cheyenne River Sioux Tribe] law did not apply.

403. Id. § 5536(a).
404. LEVITIN, supra note 293, at 142.
405. Complaint, supra note 295.
406. Id. at 9–10.
407. Id. at 10.
408. Id.
govern the loan agreements, and thus that their loans were void
and/or not payable under the laws of their home states. A January 2018 ruling imposed a $10 million penalty on CashCall and its
affiliates in connection with their lending program.

Thus, although CashCall and Western Sky Financial had legally
constructed a lending program that was aimed at avoiding state lending laws, UDA(A)P actions can be used as a means to broadly cut through these
business arrangements. And it’s not merely UDA(A)P actions that threaten
the partnership structure so prevalent in fintech lending. In 2018, the
California Supreme Court held that although an interest rate might technically
be legal under state usury laws, it is still possible for the rate to be so
excessive that it is unconscionable (and thus unenforceable) under general
state common law.

4. Fair Lending

Lastly, fintech securitizations are exposed to potential fair lending claims. As noted above, fintech lending programs increasingly use AI and alternative
data to drive their underwriting. The Equal Credit Opportunity Act ("ECOA") and Regulation B prohibit creditors from using a borrower’s race, color, religion, national origin, sex, age, marital status, or receipt of public assistance as motivating factors in making lending decisions. The
ECOA includes advertising and marketing loan products and the application, underwriting, and approval process.

The potential for lending discrimination arises through the use of alternative data to find hidden correlations and then using the results of that

415. See supra Section I.B.
419. Odinet, supra note 26, at 820.
analysis to make credit decisions.\textsuperscript{420} As I have written before,\textsuperscript{421} while it may be true that certain data points like a borrower’s GPA and standardized test scores might be predictive of loan repayment,\textsuperscript{422} they can also be highly correlated to legally protected classes. Yet such an argument is not merely academic—industry leaders have voiced similar concerns. In testimony before a House Financial Services Committee fintech taskforce in July 2019, the CEO of the prominent online lender Upstart stated, “The concern that the use of alternative data and algorithmic decisioning can replicate or even amplify human bias in lending is well-founded.”\textsuperscript{423}

To be sure, the opacity of some forms of AI makes discrimination both likely and difficult to prove. A plaintiff can prevail in an ECOA claim by showing that the lender intentionally discriminated or by proving that (regardless of intent) the lending activity produced a disparate impact on a legally protected class.\textsuperscript{424} This later method (called the disparate impact theory) is most applicable here,\textsuperscript{425} although scholars such as Mihailis Diamantis have questioned whether it might be possible to impute an AI program’s decision-making to the firm itself for purposes of proving intent.\textsuperscript{426}

The disparate impact theory states that a plaintiff may prevail if a practice or policy of the defendant has produced a disparate impact or effect on a legally protected class of persons, provided however that the defendant can resist the attack if it can show that the cited practice or policy is backed by a legitimate business objective.\textsuperscript{427} The policy or practice that is identified as

\textsuperscript{420}See Kate Crawford & Jason Schultz, Big Data and Due Process: Toward a Framework to Redress Predictive Privacy Harms, 55 B.C. L. REV. 93, 96 (2014); see also Kristin Johnson, Frank Pasquale & Jennifer Chapman, Artificial Intelligence, Machine Learning, and Bias in Finance: Toward Responsible Innovation, 88 FORDHAM L. REV. 499, 500–02 (2019); Nilsson, supra note 72 (manuscript at 158).

\textsuperscript{421}Odinet, Student Debt, supra note 56, at 1673–75; Odinet, supra note 26, at 848–49.


\textsuperscript{423}Alternative Data in Underwriting, supra note 214.


\textsuperscript{425}The Supreme Court has yet to actually approve of the disparate impact theory’s use in the context of an ECOA claim, but it approved of its use in the similar context of the Fair Housing Act. See Tex. Dep’t of Hous. & Cmty. Affairs, 135 S. Ct. at 2507. Nevertheless, the CFPB has indicated that it uses the disparate impact theory when exercising its supervision and enforcement powers. See LEVITIN, supra note 293, at 494; see also 12 C.F.R. § 1002.6(a) (2019) (the Federal Reserve’s prior adoption of the test under ECOA); 24 C.F.R. § 100.500(a) (2019) (the disparate impact theory memorialized into HUD regulation under the Fair Housing Act).

\textsuperscript{426}Mihailis Diamantis, The Extended Corporate Mind: When Corporations Use AI To Break the Law, 98 N.C. L. REV. 893 (2020).

\textsuperscript{427}LEVITIN, supra note 293, at 494.
having produced “observed statistical disparities” must be done so specifically and cannot result from “point[ing] to a generalized policy that leads to such an impact.” Once this hurdle is overcome, the plaintiff must show that the policy or practice caused a statistically significant impact (meaning that it must “raise an inference of causation”) on a protected class. The Supreme Court most recently in *Texas Department of Housing and Community Affairs v. Inclusive Communities* noted the difficulty in meeting this second step by explaining that a robust casual connection is required. The Court cautioned that merely showing a racial imbalance alone is not enough because it merely reflects existing “racial disparities [the lender] did not create.” Once causation is shown, the plaintiff must show that negative credit consequences were accorded to members of a protected class relative to similarly situated members outside the protected zone. The question of how much disparate impact is needed to tip the scales and make the claim viable, however, is unknown. Regulation C posits a “four-fifths rule,” but courts generally address the issue on a case-by-case basis.

Once these elements have been established, the defendant can resist the attack by showing a legitimate business necessity for the policy or practice. The meaning of this phrase has been explored by courts in the employment context but less so in the lending sphere. The nearest authority on point comes from a 1997 bulletin by the Office of the Comptroller of the Currency stating that a business necessity showing is sufficient if the policy or practice offered “is statistically related to loan performance, and has an understandable relationship” to the creditworthiness of the borrower that, in the words of the Supreme Court in *Inclusive Communities*, is not “artificial,

431. *Id.*
433. E.E.O.C. v. Joint Apprenticeship Comm. of Joint Indus. Bd. of Elec. Indus., 164 F.3d 89, 98 (2d Cir. 1998) (stating “[t]he rule is not binding on courts, and is merely a ‘rule of thumb’ to be considered in appropriate circumstances”).
434. 29 C.F.R. § 1607.4(D) (2019).
arbitrary, [or] unnecessary." And lastly, if the lender is able to show a business justification, the plaintiff can still prevail if he or she can show that the legitimate business objective could have still been achieved by using an alternative policy or practice that would have had less of a disparate impact.

Meeting the business justification defense could prove quite difficult for lender-defendants. Loan underwriting is chiefly concerned with what individual borrower attributes cause timely repayment rather than which broad proxy attributes correlate with timely repayment. Since machine learning is only concerned with correlations, there is a danger of the algorithm selecting attributes that cannot be justified from a business perspective. Looking to past payment histories, income-to-debt ratios, and types/uses of credit all have a demonstrable relationship to creditworthiness. Indeed, these are all factors used in calculating one’s Vantage or FICO score. But the use of alternative data—such as whether one keeps one’s cell phone charged or the number of one’s social media “friends”—can have no logical relationship to whether someone will repay a loan whatsoever. Yet, alternative data are exactly what fintech lenders are increasingly using in their underwriting, thus making an explainable business justification potentially difficult or at least more spurious.

Despite whatever difficulty a plaintiff may face in bringing an ECOA private cause of action, many fair lending claims need not be fully adjudicated to have a significant impact on the credit marketplace. ECOA can be enforced by both the CFPB and federal banking regulators in certain cases. The significance of this is that if the CFPB brings an ECOA claim against a lender, even if the lender might eventually be able to defend the claim through a

439. MAUREEN BURTON, REYNOLD F. NESIBA & BRUCE BROWN, AN INTRODUCTION TO FINANCIAL MARKETS AND INSTITUTIONS 530–31 (2d. ed. 2002); see also 121 CONG. REC. 16, 740 (1975) (statement of Rep. Annunzio) (“The essential concept of nondiscrimination in the extension of credit is that each individual has a right when he applies for credit, to be evaluated as an individual . . . .”).
440. Odinet, supra note 26, at 850 (“This means that a machine learning program might . . . attribute otherwise facially neutral attributes about a borrower . . . as being correlative to borrower attributes that the law prohibits from being taken into consideration in credit decision making.”).
441. Id.
442. Id.
444. Odinet, supra note 26, at 849.
445. LEVITIN, supra note 293, at 490.
spurious connection between a seemingly irrelevant datapoint and creditworthiness, the negative publicity can often be enough to cause the lender to settle.\textsuperscript{446} Moreover, such a settlement can occur even before a suit is filed, such as when the lender receives a civil investigative demand (called a “CID” in administrative parlance).\textsuperscript{447} Also, attorneys general and state financial services regulators have the ability to bring ECOA claims and claims under their own state-level fair lending statutes, thereby expanding the possibility for liability.\textsuperscript{448}

Here again, holders of securities backed by online loans that are made under conditions that violate ECOA expose investors to yet another legal risk. The claims to repayment will be subject to offsetting claims under fair lending laws. These can sometimes be significant, as ECOA violations can result in actual damages, costs, equitable relief, and some level of punitive damages.\textsuperscript{449} Additionally, fair lending violations may independently constitute a UDA(A)P violation, which adds additional penalties to the bottom line.\textsuperscript{450}

A final note about securitization risks requires addressing repurchase obligations. Much like in the context of securitizations more broadly, fintech loan securitizations can also entail an obligation on the part of the fintech credit firm to repurchase loans from the securitization trust in the event of performance issues (i.e., in the event the loan or a certain number of loans in the pool go into default). For example, Lending Club states in its 10-K for 2018 that “[i]n the case of certain securitization transactions, the Company has also agreed to repurchase or substitute loans for which a borrower fails to make the first payment due under a loan.”\textsuperscript{451} It might even be that certain securitization arrangements require the fintech to repurchase loans in the event of lawsuits like those described above that impact the performance of those loans and thus the return to the investors.

At first blush, this contractual promise might appear to alleviate investor concern regarding the sundry claims and defenses described above. However,
the 2008 financial crisis suggests that these representations and warranties as to what firms will do in the face of adverse credit conditions or events are not always reliable. Consider the situation faced by nonbank mortgage servicers in the wake of the crisis. In many mortgage loan securitization pooling and servicing agreements, the mortgage servicer has an obligation to continue to make fund advances to the mortgage-backed securities holders even when borrowers default.\footnote{452} This means that the servicer is not in the position of passing on the homeowner payments to the investors (because they have dried up) but is instead paying the investors from its own cash reserves.\footnote{453} When the housing crisis was at its peak, the nonbank mortgage servicing giant Ocwen Financial found that the total share of its assets that went toward meeting these investors obligations went from 45% in 2006 to nearly 60% in 2009.\footnote{454} The company’s chief executive testified that unless things changed, the servicer faced insolvency.\footnote{455}

To that end, repurchase obligations are only as good as the solvency of the firm being compelled to repurchase. If the firm is financially weak or the repurchase obligations become too great, then these obligations lose any real significance.\footnote{456} This is particularly salient in the fintech space since fintech credits firms (i.e., nonbanks)—unlike regulated banks, savings associations and credit unions—do not have robust capital or liquidity requirements that mandate a certain level of constant financial health in anticipation of economic downturns, nor do they have access to Federal Reserve funding.\footnote{457} Indeed, despite muscular promises contained in securitization documents about the quality of mortgage loans conveyed and what counterparties would do if these promises proved untrue, housing finance scholars Patricia McCoy and Susan Wachter have shown that such contractual agreements were not effective in either stopping or containing the financial crisis fallout in the residential mortgage securitization market.\footnote{458}

\footnote{452. ODINET, supra note 21, at 123.}
\footnote{453. Id.}
\footnote{454. Id.}
\footnote{455. Id.}
\footnote{456. See id.}
\footnote{458. PATRICIA A. MCCOY & SUSAN WATCHER, Representations and Warranties: Why They Did Not Stop the Crisis, in EVIDENCE AND INNOVATION IN HOUSING LAW AND POLICY (Lee Anne Fennell & Benjamin J. Keys eds., 2017).}
D. The Negotiability Problem

As described above, there are a number of litigation and legal compliance risks that abound in the securitization of online loans under the dominant fintech business model. Some of these can result in the amount collectable on the loans being offset by damages, costs, and sometimes even punitive damages.459 At other times, the risk is that the loan will be deemed uncollectable in large part or in its entirety.460

Importantly, what many investors in these securities likely fail to appreciate is that the typical protections of commercial law do not apply to these loans. In other words, the holders of fintech loan securities are in all likelihood subject to all of the borrower defenses mentioned above in connection with loan collection activities. The reason for this is due to the fact that the protections that would normally be afforded to a person seeking to enforce a loan (or, in this case, a debt security) that is represented by a negotiable instrument under Article 3 of the Uniform Commercial Code do not apply in this context.461 In a paper-based transaction, the loan itself will be represented by a promissory note that (at least usually) meets the requirements of being considered legally “negotiable.”462 The negotiable note can then be transferred from person to person, with each having the ability to enforce the note against the borrower. Importantly, if these later-individuals meet certain requirements of good faith, value-giving, and clean hands (known as being a “holder in due course”463), then they can enforce the note even in the face of most borrower defenses—such as if the original creditor

460. CAL. FIN. CODE § 22750 (West 2015); MD. CODE ANN., FIN. INST. § 11-523 (West 2015); MASS. GEN. LAWS ANN. ch. 140, § 110 (West 2002).
461. The protections are against the so-called personal defenses. Real defenses may still be raised. However, real defenses are few in number and largely do not consist of the types of claims/liabilities described here. U.C.C. § 3-304 (AM. LAW INST. & UNIF. LAW COMM’N 2002); DOUGLAS J. WHALEY & STEPHEN M. MCJOHN, PROBLEMS AND MATERIALS ON PAYMENT LAW 117–18 (10th ed. 2016).
462. See id. § 104; RONALD J. MANN, PAYMENT SYSTEMS AND OTHER FINANCIAL TRANSACTIONS: CASES, MATERIALS, AND PROBLEMS 505 (5th ed. 2011) [hereinafter MANN, PAYMENT SYSTEMS]; WHALEY & MCJOHN, supra note 461, at 9–12. Not all promissory notes are negotiable, but many are. For instance, most all courts have held that the Fannie Mae and Freddie Mac single family promissory note (the most widely used promissory note template in American home lending) is negotiable. See Dale A. Whitman, What We Have Learned from the Mortgage Crisis About Transferring Mortgage Loans, 49 REAL PROP., TR. & EST. L.J. 1, 32 n.113 (2014); see also Ronald J. Mann, Searching for Negotiability in Payment and Credit Systems, 44 UCLA L. REV. 951, 970–72 nn.67–70 (1997).
463. U.C.C. § 3-302; WHALEY & MCJOHN, supra note 461, at 61–62, 505–06.
had defrauded the borrower. This essentially gives a holder in due course of a promissory note a near absolute ability to enforce the credit right against the borrower.

But with these fintech-originated loans, there is no paper promissory note with which to even begin the analysis. Rather, the entire transaction is done online and electronically. Article 3 of the Uniform Commercial Code relies on there being a single, authoritative paper copy of the original promissory note. In other words, the law governing promissory notes (including the conferring of all the benefits of commercial law that follow) dictates that the promise to repay a loan must be in the written form. Fintech-generated loans do not fit this mold.

That is not to say that the realm of electronic promissory notes (so-called e-notes) is lawless, but rather that the interface with the holder-in-due-course doctrine is more uncertain. Two statutes govern e-notes. First is the federal Electronic Signatures in Global and National Commerce Act ("the E-Sign Act"), which authorizes any transaction that must be in writing to also be accomplished electronically, but only if the consumer consents. Second is the state-level Uniform Electronic Transactions Act, which provides similar authorization to electronically transact. The E-Sign Act governs unless a given state has enacted the Uniform Electronic Transactions Act, in which case the latter governs (the uniform act has been adopted by all but a very small handful of states).

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464. U.C.C. § 3-305; WHALEY & MCJOHN, supra note 461, at 117–18; MANN, PAYMENT SYSTEMS, supra note 462, at 508. While it is true that fraud in the factum can be raised in this circumstance, it is not the typical fraud resulting from a misrepresentation that one normally encounters. Id. at 510 n.4.

465. Odinet, supra note 26, at 790.

466. U.C.C. § 3-103(a).

467. Id.; see also WHALEY & MCJOHN, supra note 461, at 14.


469. UNIF. ELEC. TRANSACTIONS ACT (Nat’l Conference of Comm’rs 1999).

470. Gregory T. Casamento & Patrick J. Hatfield, Guidelines for E-Signature and E-Delivery in the Insurance Business, LOCKE LOR (Jan. 2012), https://www.lockelord.com/-/media/files/newsandevents/publications/2012/01/acord-esignwhite-paper2012-highlighted.pdf?la=en&hash=36C37CBAC688839FE5F79748AC638AA9 [https://perma.cc/9ST9-PEWL] (explaining the interplay between the federal E-Sign Act and the state-level UETA). “Under ESIGN, if a state imposes greater restrictions on the use of Electronic Signatures or Electronic Records (such as mandating a particular type of technology), that state’s law is preempted, or overruled, by ESIGN, meaning that the provisions in ESIGN control, not that state’s more restrictive law.” Id. at 2.

In essence, these statutory regimes give general legal recognition to electronic signatures and electronic records whenever a specific law requires that the contemplated transaction must be in writing. Since fintech lending transactions utilize e-notes, it would seem that these statutes might provide the necessary cover for lenders to enjoy holder-in-due-course process benefits. However, the interplay between Article 3 of the Uniform Commercial Code and these electronic transactions statutes is less than certain. As an upfront matter, the E-Sign Act expressly exempts from its purview any document governed by Article 3 of the Uniform Commercial Code. To be sure, the uniform act does not have such a specific exception, but obtaining the benefits of Article 3 through the Uniform Electronic Transactions Act is not an easy task.

First, for an e-note to be treated as the legal equivalent of a negotiable, paper-based promissory note under the uniform act (called a “transferable record”), (i) the borrower must expressly agree that the promise will constitute a transferable record, (ii) the e-note must meet all of the requirements of negotiability, (iii) it must be signed by the borrower, and (iv) the method used to record, register, or evidence a transfer of the e-note must readily establish the identity of the person entitled to “control” it.

These requirements may sound relatively simple, but they are quite exacting. To illustrate the point, consider a sample promissory note that is made available by the fintech lender Prosper Funding through its website. First, as noted above, the borrower has to clearly agree in an affirmative way that the uniform act will apply, and thus the note will fall under the law’s purview. The Prosper note contains the following in all capital letters:

THIS NOTE INCLUDES YOUR EXPRESS CONSENT TO ELECTRONIC TRANSACTIONS AND DISCLOSURES, WHICH CONSENT IS SET FORTH IN THE PARAGRAPH ENTITLED “CONSENT TO DOING BUSINESS ELECTRONICALLY” AS DISCLOSED IN PROSPER’S TERMS OF USE ON PROSPER.COM, THE TERMS AND CONDITIONS OF WHICH ARE EXPRESSLY INCORPORATED HEREIN IN THEIR ENTIRETY. YOU EXPRESSLY AGREE THAT THIS NOTE MAY COMPRISE A “TRANSFERABLE RECORD” FOR ALL PURPOSES UNDER THE ELECTRONIC SIGNATURES

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472. 15 U.S.C. § 7001; UNIF. ELEC. TRANSACTIONS ACT.
474. UNIF. ELEC. TRANSACTIONS ACT § 16 cmt. 6.
475. Id. § 16.
While this language may seem to meet the definition of express, it is buried half at the bottom of page six and half at the top of page seven in section 19 of the note. It might be difficult for a fintech lender to affirmatively demonstrate that the consumer has given meaningful consent, as section 19 of the Prosper note can hardly be said to constitute clear and conspicuous agreement. Not only is it several pages into an otherwise highly legal document (inaccessible to most consumers) and presented such that it cannot be directly brought to the consumer’s attention (as the transaction is accomplished via computer or smartphone), but the actual specific consent itself is located in a different document altogether—“PROSPER’S TERMS OF USE ON PROSPER.COM.” Finding this additional document is not an easy task. Prosper’s terms of use web link is located at the very bottom of the company’s frontpage in small 10.5 font. Commentators and courts interpreting the consent requirement have held that there is no single way to make the determination but rather one must look to “all of the surrounding circumstances, including the context and conduct of the parties.”

Additionally, the e-note must meet the substantive requirements in Article 3 to be a negotiable instrument. Article 3 mandates that commercial paper may only be negotiable if the document is in writing, is signed by the maker of it, constitutes a definite promise or order to pay money to a specific person or to whomever bears the instrument, is payable at a definite time and in a sum certain or in an amount that is determinable, is generally payable without

477. Id. at 6–7.
479. PROSPER, https://www.prosper.com [https://perma.cc/5FGZ-M8Q7].
conditions, and the promise to pay is not accompanied by other extra/additional promises. If any of these requirements are not met, then the document merely constitutes a simple contract and is not entitled to the added benefits under the Uniform Commercial Code’s Article 3.

Returning to the Prosper e-note, the requirements most in doubt are those prohibiting conditions to payment and prohibiting additional promises. The prohibition on attaching conditions to the borrower’s obligation to repay is rooted in the notion of promoting marketability of the note itself—the less uncertainty surrounding the obligation to pay, the more likely one is to find willing buyers of it. As a disclaimer, the prohibition is not absolute. The law does allow certain conditions to attach regardless—such as implied conditions and simple references to other documents like those dealing with security. However, the incorporation of other documents wholly outside the four corners of the note itself is not allowed. Thus, “where the promise to pay is made ‘subject to’ some other contract referred to . . . the obligation is conditional, and negotiability is destroyed.” The Prosper Note contains just such an incorporation in the way of the discussion in section 19 of the company’s terms of use. The provision states that “THE TERMS AND CONDITIONS OF WHICH ARE EXPRESSLY INCORPORATED HEREIN IN THEIR ENTIRETY.” This is precisely the kind of condition on payment that is prohibited. Numerous courts have held that when a note is made subject to, is governed by, or otherwise incorporates by reference the terms of another contract, the note is rendered nonnegotiable.

But the conditional promise issue is not the only problem with the negotiability of Prosper’s e-note. The anti-additional promises rule (sometimes called the “courier without luggage” rule), which stands for the notion that the document should “not state any other undertaking or instruction . . . to do any act in addition to the payment of money,” also causes problems. First, section 6 of the e-note provides that no portion of the loan

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481. U.C.C. § 3-104 (AM. LAW INST. & UNIF. LAW COMM’N 2002).
482. WHALEY & MCJOHN, supra note 461, at 13; MANN, PAYMENT SYSTEMS, supra note 462.
483. See WHALEY & MCJOHN, supra note 461, at 14.
484. See U.C.C. § 3-104(a)(3).
486. Id.
487. PROSPER, supra note 476, at 6.
money will be used “in whole or in part to postsecondary educational expenses . . . as the term . . . is defined in Bureau of Consumer Financial Protection Regulation Z, 12 C.F.R. § 1026.46(b)(3).” Essentially, the provision means that the borrower cannot use the loan to pay for college tuition or fees or any kind of education-related expenses. The reason for this prohibition from Prosper’s point of view is to avoid certain regulatory issues that apply only to student debt. But, from a negotiability standpoint, that is an additional promise because it tells the borrower how the funds can be used. That would negate negotiability.

Similarly, section 18 of the Prosper note provides an automatic opt-in to arbitration for any claims between the borrower and Prosper. Even without going any further, this is a very substantial undertaking in addition to the promise to repay the loan. It does far more than merely “memorialize the borrower’s unconditional promise to pay,” and, indeed, at least one recent New York court has specifically held that such a binding mandatory arbitration clause negates negotiability. And lastly, in connection with the prohibition on incorporating the terms of outside documents, the section 18 arbitration clause refers the parties to the American Arbitration Association for “the Rules and other information about initiating arbitration.” Thus, the terms governing the arbitration process are incorporated by reference—which is again, impermissible.

And these problems of negotiability are not native to Prosper’s e-note. Market leaders like Lending Club and Upstart both have e-notes with similar clauses. All this is to say that the substantive legal issues (and attendant liabilities) that are discussed above will likely apply to these loans—therefore the securities. Unlike with negotiable promissory notes historically, investors in these fintech loan securities will not be insulated from defenses and enforcement actions (and the liabilities that result from them).

490. PROSPER, supra note 476, at 2.
491. PROSPER, supra note 476, at 4–6.
493. PROSPER, supra note 476, at 5.
495. Loan Agreement, LENDINGCLUB, https://www.lendingclub.com/info/loan-agreement.action [https://perma.cc/4FX2-5DZ8] (showing the promissory note as Exhibit A to the Loan Agreement and the Privacy Policy as Exhibit B).
IV. POLICY IMPLICATIONS AND INTERVENTIONS

The potential issues of systemic risk inherent in the nature of AI-originated online loans and the fintech business model must be understood in the larger context of how nonbanks pose systemic risk concerns more broadly. After all, investors necessarily accept some level of risk whenever they purchase securities. Merely because those investments fail does not mean a regulatory response is merited. Rather, it is when the failure of an investment asset has the potential to cause damage to large financial markets that a public policy response is not only appropriate, but necessary.

A. Nonbanks and Contagion

As Jeremy Kress, Patricia McCoy, and Daniel Schwarcz have noted, “[t]he financial crisis demonstrated unequivocally that nonbank financial companies can destabilize the financial system when not regulated appropriately.”\(^{497}\) During the pre-2008 period, nonbanks like AIG, Lehman Brothers, and others used short-term financing—not deposit funding like that used by banks—in order to fund their operations.\(^{498}\) When this funding dried up during the market panic over the health of these companies as their liabilities skyrocketed (largely due to the drop in home prices), the federal government pumped massive amounts of taxpayer dollars into these institutions to save them from insolvency.\(^{499}\) This, as scholars have noted, has increased the incentive for nonbanks to engage in even more aggressive and risky profit-seeking behavior since there is now at least the implicit guarantee of another government bailout should it ever be needed in the future.\(^{500}\) Post-crisis pledges by government officials to end the culture of bailouts have proved to lack credibility, as it is all but certain that a future crisis predicated on the activities of nonbank firms would still result in public interventions.\(^{501}\)

\(^{497}\) Jeremy C. Kress, Patricia A. McCoy & Daniel Schwarcz, Regulating Entities and Activities: Complementary Approaches to Nonbank Systemic Risk, 92 S. CAL. L. REV. 1455, 1465 (2019). For a brief reference to this literature, see id. at 1466 n.41.

\(^{498}\) Id. at 1465–67; see also Kathryn Judge, The First Year: The Role of a Modern Lender of Last Resort, 116 COLUM. L. REV. 843, 854–55 (2016).


\(^{500}\) Kress et al., supra note 497, at 1467 n.49 (overviewing the literature on moral hazard, incentives, and bank bailout).

\(^{501}\) Jonathan R. Macey & James P. Holdcroft, Jr., Failure Is an Option: An Ersatz-Antitrust Approach to Financial Regulation, 120 YALE L.J. 1368, 1375 (2011) (stating that bailouts of systemically important financial institutions are inevitable); Kress et al., supra note 497, at 1468.
Indeed, the coronavirus outbreak currently ravaging the global financial markets has already resulted in money market mutual funds—a type of nonbank investment firm—receiving access to emergency Federal Reserve funding. The federal government had previously bailed out these firms in 2008 to the tune of $2.6 trillion—an intervention that was widely decried and followed by vows that it would never occur again.

Furthermore, although it is true that not all nonbank firms have or will have the potential to create systemic risk, it is difficult to make a definitive evaluation of the issue. Two primary nonbank attributes, however, are generally agreed upon. The first consists of scenarios where a nonbank firm has large financial obligations to others that the nonbank cannot satisfy. This results in the counterparty firm incurring significant losses when the nonbank becomes insolvent quickly and suddenly. The systemic nature of this failure depends upon the interconnectedness of the nonbank firm with the rest of the financial sector—whether through many firms or through several large firms that themselves are interconnected.

The second agreed attribute involves the ability of a nonbank to sell off its assets quickly and on a large scale such that prices for the entire asset class drop. This, in turn, causes other firms that hold assets in that same class to suffer losses because the assets are now worth significantly less—thereby negatively impacting the firm’s balance sheet. This, in turn, can cause insolvencies.


504. Kress et al., supra note 497, at 1469 (noting the finance literature attempting to identify systemic risk indicators for firms).

505. Id. at 1471.

506. Id.

507. Id.

508. Id. at 1471–72.

509. Id.
Again, the current state of fintech lending and its securitization activities does not suggest that such systemic risk is on the horizon. The non-credit card, unsecured consumer loan market is still a rather small portion of the overall credit landscape. Additionally, within this sector not all firms employ the bank-partnership model, which raises specific litigation and legal compliance risks (although many do). One thing is certain, however—the use of artificial intelligence and AI in loan originating is growing at a rapid clip, both among nonbanks and banks. Moreover, nonbank financial companies are playing an increasingly outsized role in the economy. In the past several years, more than half of all mortgage loans came from nonbank lenders. As such, the downsides of the robust use of AI and alternative data combined with the growth in nonbank activities must be monitored and managed.

B. The New “Innovative Finance”

By and large, securitization was viewed as the chief driver of the 2008 financial crisis. The cause was driven by problems (and sometimes outright abuses) in the residential mortgage market. Starting in the early 1990s, many Americans were unable to qualify for mortgage credit under traditional


513. Id.

underwriting standards.\(^{515}\) This was because traditional lending institutions, like regulated banks, were unwilling to make loans to these borrowers who often had no credit history, were marked by indicators of financial distress, and because any such loans would not be eligible for sale to Fannie Mae or Freddie Mac.\(^{516}\)

These disadvantaged borrowers—who became known by the adjective “subprime”—found willing lenders in the form of nonbank financial institutions that were largely unregulated, such as Countrywide Financial, Ameriquest, and Washington Mutual.\(^{517}\) These subprime borrowers were enticed to take out loans on the basis of seemingly favorable repayment terms.\(^{518}\)

Subprime lenders engaged in an assortment of “innovative” underwriting techniques in order to substantiate that the borrower was creditworthy.\(^{519}\) For instance, some lenders created fake pay stubs, employment data, and income information for borrowers.\(^{520}\) One former employee of a major subprime lender associated with Washington Mutual, speaking on condition of anonymity, said that higher-ups at the company would frequently offer gifts to the loan reviewers in exchange for looking the other way on questionable loan applications.\(^{521}\) Sometimes loans were also made using only the borrower’s “stated income” without the lender conducting any kind of independent verification of the information provided—so-called “low-doc” or “no-doc” loans.\(^{522}\)

These loans were designed to eventually default. At some point in the future, borrowers would be subject to adjusted loan terms that they could not afford.\(^{523}\) And if these toxic loans remained solely on the books of the

\(^{515}\) See Gerald Korngold, Legal and Policy Choices in the Aftermath of the Subprime and Mortgage Financing Crisis, 60 S.C. L. REV. 727, 728 (2009); see also ODINET, supra note 21, at 17.


\(^{517}\) ODINET, supra note 21, at 28–29.


\(^{519}\) ENGEL & MCCOY, supra note 21, at 30–32.

\(^{520}\) Id. at 30.

\(^{521}\) Id. at 31; David Heath, At Top Subprime Mortgage Lender, Policies Were an Invitation to Fraud, HUFFINGTON POST (Mar. 18, 2010), https://www.huffingtonpost.com/2009/12/21/at-long-beach-mortgage-a_n_399295.html [https://perma.cc/J3N3-YCAW].

\(^{522}\) ODINET, supra note 21, at 20–21.

\(^{523}\) Id. at 17–18.
subprime lenders who made them, then the crisis would have been contained. The problem was that they didn’t remain with the originating lender. Rather, these loans made their way into the mainstream financial market via securitization.524

Similar to the fintech loans described above, mortgage loans were also bundled into special purpose entities and turned into securities that were sold and traded in the capital markets.525 Securitization became so popular that by 2009, about 90% of all residential mortgage loans in the United States were securitized.526

In the run-up to the financial crisis, investors flocked from far and wide to the “innovative” and increasingly opaque subprime mortgage securities market as large numbers of subprime loans were originated across the United States.527 During this period—as has been the case for the past several years528—many firms were holding large amounts of cash and desired to put this money into high-yield investments.529 Interest rates were low (as they remain as of this writing530), which in turn made borrowing inexpensive and the return on treasury bonds less attractive.531 Inventive and impenetrable


525. Schwarcz, Securitization Ten Years After, supra note 514, at 758.


530. Kenneth Kuttner, How Low Can We Go? The Prospects for Negative Interest Rates, PBS (Sept. 17, 2019), https://www.pbs.org/newshour/economy/making-sense/how-low-can-we-go-the-prospects-for-negative-interest-rates [https://perma.cc/Z7WF-AFU5] (discussing the possibility that the Federal Reserve will set the interest rate target at a negative number, as has occurred in Europe and Japan).

531. Odinet, supra note 21, at 27; see also Larry Cordell et al., The Incentives of Mortgage Servicers: Myths and Realities 3 (Fed. Reserve Bd., Fin. & Econ. Discussion Series, Working Paper No. 2008-46, 2008),
subprime mortgage loans were more lucrative and came to represent a growing portion of all mortgage securitizations. In 1994, only about 4.5% of all mortgage securitizations (about $35 billion) were comprised of subprime loans. That number was up to 9% in 2003 (a ten-fold jump to $332 billion) and it reached 21% in 2005.

Importantly, securitization also took away the built-in risk incentives for mortgage lenders. In years past, lenders assumed the risk that a default might occur if a borrower was unable to repay a loan. This risk caused lenders to focus on the credit-worthiness of their borrowers. If a lender failed to properly assess an individual’s financial position or if the loan was made with terms that would likely result in a default, the lender would ultimately bear the risk of loss. However, securitization removed this self-interested aspect to lending.

Investors in subprime mortgage-backed securities became the parties who would bear the loss of a loan default. However, they could not possibly know or begin to understand the inherent weaknesses of the underlying loans. The pooling of so many mortgage loans, passing through so many hands, and stitched together in fractional pieces before being sold on the capital markets made the ultimate investors—often insurance companies and retirement funds, as well as banks and other mainstream and important financial companies—largely oblivious as to the quality of what they were purchasing. Instead, investors relied on ratings agencies like Moody’s and


533. Id.

534. Id.

535. See id. at 6.

536. ODINET, supra note 21, at 25.


539. ODINET, supra note 21, at 27–29.

540. Id. at 30–31; For an example of a typical and complex private label securitization structure, see FIN. CRISIS INQUIRY COMMISSION, FINANCIAL CRISIS INQUIRY REPORT 83–101
Standard & Poor’s to tell them whether the investment was good or not.\footnote{541} But, as has been documented elsewhere, these ratings agencies often did the bidding of the sponsor of the securitization (who paid the bill) by finding ways to give favorable scores to these otherwise junk securities.\footnote{542} Indeed, the ratings agencies often failed themselves to understand the quality (or lack thereof) of the underlying loans.\footnote{543}

The entire system was buttressed by a near universal reliance on the value of the homes that secured the mortgage loans.\footnote{544} As long as home values remained high and ever rising, any loan losses would be made-up by foreclosures on homes.\footnote{545} At least that was the theory. However, in 2006 the housing bubble burst.\footnote{546} In September 2008, home prices dropped 20\% from the mid-2006 high point.\footnote{547} By September 2010, nearly a quarter of all Americans owed more on their home loans than what their homes were worth.\footnote{548} When the adjustable interest rates reset on these loans, borrowers were unable to refinance and therefore defaulted.\footnote{549} Americans also lacked much savings during this period, with household debt sitting at a record $14.5 trillion in 2008. By 2009, 40\% of all subprime mortgage loans with adjustable rates were in default.\footnote{550}

Suddenly, the mortgage-back securities that sat atop these home loans became worthless.\footnote{551} Unfortunately, these securities were mostly held by major financial institutions, “the health of which was intimately tied to that
of the national and global economy.” Mortgage loan defaults “spread like wildfire,” and enormous losses followed. Since these “financial institutions were deeply intertwined with parts of the economy,” the collapse impacted sectors “far beyond the housing market.” These loan defaults set off “a disastrous chain of events affecting the secondary mortgage markets, the broader financial sector, and the entire United States—and global—economy.”

Fintech loans, with their AI opacity, have the potential to be another type of innovative subprime product. These loans, combined with the way they are distributed throughout the capital markets via securitization, creates prospective systemic risk issues that should not be overlooked by regulators. To be sure, all fintech originated loans are not subprime mortgage loans. There are significant differences between the two. For one, subprime mortgage loans were secured by real estate. This was part of what made the underwriting such an afterthought. Lenders assumed they could look to the ever-increasing value of the home for recourse. Thus, the actual ability of the individual borrower to repay the loan from his or her other assets—such as income relative to other debts—was viewed as irrelevant.

Fintech loans are unsecured—they, by and large, are not backed by any form of collateral, which means there is no underlying asset that can be used to offset losses. This makes the borrower’s ability to repay a matter of vital importance. Yet, there is a type of collateral to which the lender looks—it is

552. Id.
553. Id.
554. Id. at 33–34.
557. See supra Section III.A.
560. See id.
the artificial intelligence underwriting. Faith in the asset is tied to a faith in the machine learning. Yet, like with subprime mortgage-backed securities, investors are not able to accurately gauge the quality of the underwriting. With mortgage-backed securities, the actual loan terms and the overly inflated value of the mortgage real estate were obscured by the securitization process. Investors would have had to engage in significant and costly due diligence of the loan level-data to truly assess the quality of the securities. This was not something that investors were willing to do and so the credit ratings agencies served as the sole force in driving investment decisions.

Fintech loans have an even more significant opacity problem because, as noted above, machine learning underwriting and the use of alternative data largely lie outside general human cognitive abilities. The substantive underwriting, therefore, is at a level that defies any practical attempts at inspection. This plays into the general propensity of investors to “tend to dismiss low-probability but high consequence risks and “see what they want to see.” Even sophisticated institutional investors simply “lack of [an] understanding of the inherent limitations of valuation models,” and they fail to sufficiently comprehend “the risks of short-run historical data sets” when it comes to the role of artificial intelligence in loan underwriting.

Because the machine learning, algorithm-driven process can create a black box effect, the problem is not one of information asymmetry but one of non-information symmetry. The lender itself will not completely

563. See id.
564. See COUNCIL ON FOREIGN RELATIONS, supra note 542.
565. See supra Section I.B.
566. Selbst & Barocas, supra note 82, at 1094.
567. Allen, supra note 231, at 872.
568. Schwarcz, supra note 232, at 58.
569. CRMPG III, supra note 239, at 53.
570. See supra Section I.B.
571. For a discussion on the issues with CDOs see ZVI BODIE, ALEX KANE & ALAN J. MARCUS, INVESTMENTS 388–90 (10th ed. 2013); Lucjan T. Orlowski, Stages of the 2007/2008 Global Financial Crisis: Is There a Wandering Asset-Price Bubble? (Kiel Institute for the World
understand the underlying quality of the financial product and neither will
potential investors. In this way, financial innovation, while potentially
beneficial, can mask risk, and the combination of securitization and AI
underwriting exacerbates this problem because the true risk is even more
unknown—indeed, perhaps unknowable—than in the prior context of
subprime mortgage-backed securities.

C. Toward an AI Financial Regulatory Agenda

First, a more concerted effort should be made by financial regulators to
carefully monitor the effects of artificial intelligence, particularly by
nonbanks, on financial stability. Second, rather than trying to displace
the role played by the states in policing the nonbank provision of financial
products and services to consumers, federal and state financial officials
should work in a more coordinated fashion toward a shared system of
governing fintech credit firms. The following elaborates on both of these
suggestions.

The first step is for regulators to pay more attention to the role being
played by alternative data and machine learning in the consumer credit
market. The current government approach has been limited to largely wait
and see. To the extent there has been activity at the federal level, it has
consisted of promoting business models and relieving regulatory burdens.
It has not been focused on either systemic risk or on the way, as Eric Gerding
offers, that “[c]onsumer financial laws can address systemic risk.”574

For example, aside from the Office of the Comptroller of the Currency’s
(“OCC”) fintech charter,575 the CFPB has created an Office of Innovation576
and launched (as well as made recent revisions to) its trial disclosure577 and

574. Gerding, supra note 32, at 453.
575. See OFFICE OF THE COMPTROLLER OF THE CURRENCY, POLICY STATEMENT ON
FINANCIAL TECHNOLOGY COMPANIES’ ELIGIBILITY TO APPLY FOR NATIONAL BANK CHARTERS
statement-fintech.pdf [https://perma.cc/BC92-BXZM].
577. CONSUMER FIN. PROT. BUREAU, PROJECT CATALYST REPORT: PROMOTING CONSUMER-FRIENDLY INNOVATION (Oct. 2016),
no-action letter programs. The first is aimed at making and designing financial disclosures easier by providing firms with waivers. The idea behind the second program is to provide a method for firms to receive a formal statement from the CFPB that, based on a submitted product or service to be offered to consumers, the agency will generally not bring a supervisory or enforcement action against the company. The latest offering has been a so-called “product sandbox,” which grants applicant firms relief from various regulatory burdens for a set period of years. The Commodity Futures Trading Commission, the Securities and Exchange Commission, the Federal Deposit Insurance Corporation, and OCC have all launched similar efforts aimed at giving financial technology companies waivers or advice in avoiding or minimizing regulatory burdens in hopes of promoting innovation.

What is needed, however, is a coordinated and systemic regulatory agenda that examines systemic risk through the lens of AI and the role it is playing in credit decision-making. The best way for regulators to approach the project of understanding and helping to control systemic risk through the rise of AI in credit markets is, as Allen notes, by “regulating the processes by which these sophisticated financial algorithms are being created.”


584. Allen, supra note 247.
better monitoring through supervision at the point where the risk is created—at loan underwriting. However, the existing regulatory structure in the U.S. does not make such a task easy. As noted above, the CFPB has supervisory power over payday lenders, which (if conceptualized as all small-dollar lenders) would grant the Bureau extensive authority over fintech credit firms. However, the structural issue is that the CFPB is not charged with safety and soundness. As Angela Littwin has noted, “The CFPB has no safety and soundness authority. Its examination procedures, for example, assess the risks that companies’ practices pose for consumers, rather than risks to the companies’ financial health.”

Van Loo suggests the use of the Financial Stability Oversight Council (“FSOC”), which was created in the wake of the financial crisis and is charged with monitoring the U.S. financial sector, in part, to ensure that no entity is ever “too big to fail.” Jeremy Kress, Patricia McCoy, and Daniel Schwarzc have explained that FSOC was created “to strengthen regulation of nonbank financial firms.” However, Van Loo notes that FSOC lacks the legal authority to effectively collect the information needed from firms to properly access the risk their AI activities pose to the larger economy.

To build upon the idea of using FSOC, I suggest that state financial services regulators play a larger role as the traditional regulators of nonbank firms. These state officials grant fintech credit firms their licenses to operate and can indirectly police their activities through licensing regimes and through their regulation of the state-chartered bank partners. These state actors are all purpose in that they have a consumer protection and a safety and soundness mission. The downside, however, is that state financial regulators operate on a state-by-state basis and do not necessarily have a nationwide perspective or mission, even though the fintech firms that they regulate largely operate online across state lines.

Under the laws of nearly every state, financial services regulators have visitorial powers and the ability to collect nonpublic information as part of

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586. Van Loo, supra note 201, at 878.
588. Kress et al., supra note 497, at 1458.
589. Van Loo, supra note 201, at 878.
their nonbank examination procedures. This means that they have the ability to amass the relevant information about the AI activities of these financial firms and, through information sharing, can provide FSOC with the data it needs to engage in effective market monitoring. Also, a tighter connection between FSOC and the state-level regulators would not be entirely novel. FSOC’s charter already provides that one of its nonvoting members is a “state banking supervisor.”

In many states—such as in California and New York where many fintech credit firms are located—the state banking supervisor is the licensor of nonbank firms.

Now to be sure, not all state-level financial services regulators are created equal. Some have much larger staffs and budgets than others. This is where FSOC’s resources can play a significant role. I suggest that the Office of Financial Research—which is an arm of FSOC and created by Congress for the purpose of providing the council with financial data and analysis—build out a team of data scientists. This team would have expertise in artificial intelligence and machine learning and would be loaned out to the state financial services regulators to help them in examining and gathering information from fintech firms in the course and scope of the supervision process. The information gathered on a nation-wide basis would then be shared with FSOC. The expertise of the council’s various members—which are comprised of the heads of all the major financial regulators in the U.S. and is chaired by the Secretary of the Treasury—would be used to formulate optimal regulatory approaches for dealing with the issues around AI in credit markets. Such regulatory approaches could then be implemented on the ground by the state financial services regulators, as well as through requests to Congress for legislative action where needed.

CONCLUSION

Financial technology innovations, such as the use artificial intelligence and alternative data, and their impact on the everyday lives of American households will only continue to be a focus in our political discourse. The


594. See About the OFR, OFF. FIN. RES., https://www.financialresearch.gov/about/ [https://perma.cc/T2HW-QVKR].
upsides of fintech’s growth, however, are often the only messages we hear, while the downsides are underplayed or soft-peddled.

Much of this one-sided narrative has to do with the political economy of regulating the financial sector. Fintech—as the name suggests—marries two of the world’s most powerful sectors: finance and technology. Today, humans still dominate the financial market but, without a doubt, complex forms of artificial intelligence are coming fast and in a big way. Many have dismissed this looming threat to the financial markets because the takeover hasn’t happened as quickly as some of the hype has suggested. However, as Bill Gates once noted: “We always overestimate the change that will occur in the next two years and underestimate the change that will occur in the next ten.”

In a time when money in politics has infected all forms of decision-making, meaningful changes that address wealth and income inequality are needed to tackle the underlying reason behind why so many Americans need to constantly borrow money to gain advancement or merely to make ends meet. Until that happens, access to credit will remain vital. This means that how the new credit—digital and online credit—is regulated should be a matter of high public concern deserving of a thoughtful policy consideration. Financial technology’s role in the American credit system is reopening old wounds while simultaneously recasting them in a new light through the use of data science and artificial intelligence. This project is aimed at helping policymakers think more critically about these current market challenges and how, with the proper legal perspective, they can be overcome.