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Driverless Finance

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While safety concerns are at the forefront of the debate about driverless cars, such concerns seem to be less salient when it comes to the increasingly sophisticated algorithms driving the financial system. This Article argues, however, that a precautionary approach to sophisticated financial algorithms is justified by the potential enormity of the social costs of financial collapse. Using the algorithm-driven fintech business models of robo-investing, marketplace lending, high frequency trading and token offerings as case studies, this Article illustrates how increasingly sophisticated algorithms (particularly those capable of machine learning) can exponentially exacerbate complexity, speed and correlation within the financial system, making the system more fragile. This Article also explores how such algorithms may undermine some of the regulatory reforms that were implemented in the wake of the 2008 financial crisis to make the financial system more robust. Through its analysis, this Article demonstrates that the algorithmic automation of finance (a phenomenon I refer to as "driverless finance") deserves close attention from a financial stability perspective. This Article argues that regulators should become involved with the processes by which the relevant algorithms are created, and that such efforts should begin immediately—while the technology is still in its infancy and remains somewhat susceptible to regulatory influence.

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Introduction

Precautionary concerns are at the forefront of the debate about driverless cars: before autonomous vehicles driven by algorithms are marketed and sold to the public, extensive testing is undertaken to ensure the safety of passengers, other drivers, and bystanders.[1] Safety concerns figure much less prominently, however, in discussions about fintech and the increasing algorithmic automation of finance; this Article seeks to make these discussions more complete by considering how the increased prominence of algorithms could undermine financial stability. Although risks of economic failure may not be as viscerally salient as threats of injury by a rogue driverless car, prior financial crises have had devastating impacts on society—the resulting increases in unemployment, poverty, and crime have indirectly impacted physical and mental health, and even led to premature deaths.[2] This Article therefore argues that a precautionary stance is also justified with regard to what I have termed "driverless finance", and its potential impact on us, the bystanders who will be harmed if a financial crisis damages the broader economy.

"Financial stability" denotes a state of affairs where financial institutions and markets are functioning well and are robust to shocks, such that they can continue to provide the capital intermediation, risk management and payment services on which broader economic growth depends.[3] Financial stability regulation is essentially a precautionary exercise, in the sense that it errs on the side of avoiding the harm to the broader economy that can be caused by institutional and market failure, even though such harms cannot be precisely predicted or quantified.[4]

Effective financial stability regulation requires a broadening of regulatory focus to encompass new innovations and business models as and when they arise—including the latest generation of financial algorithms. While the use of algorithms in finance is nothing new (an algorithm is ultimately just a set of instructions executed by a computer),[5] the ubiquity, sophistication and

[1] For discussions about the regulation of driverless cars, *see* Jack Stilgoe, *Machine learning, social learning and the governance of self-driving cars*, 48 Soc. Stud. Sci. 25 (2018); David C. Vladeck, *Machines Without Principals: Liability Rule and Artificial Intelligence*, 89 Wash. L. Rev. 117 (2014); Michael Mattioli, *Autonomy in the Age of Autonomous Vehicles*, 24 B.U. J. Sci. & Tech. L. 227 (2018).

[2] Hilary J. Allen, *Putting the "Financial Stability" In Financial Stability Oversight Council*, 76 Ohio St. L. J. 1087, 1095–7 (2015).

[3] *See* Hilary J. Allen, *What is "Financial Stability"? The Need for Some Common Language in International Financial Regulation,* 45 Geo. J. Int'l L. 929, 932 (2014).

[4] *See* Hilary J. Allen, *A New Philosophy for Financial Stability Regulation*, 45 Loy. U. Chi. L.J. 173, 178 (2013).

[5] *See* Andrew Tutt, *An FDA For Algorithms*, 69 Admin. L. Rev. 83, 92 (2017).

autonomy of financial algorithms has increased significantly in recent years due to advances in computing power and data usage techniques.[6] High-frequency trading algorithms now execute their trades at speeds impervious to human judgment and interference.[7] In marketplace lending business models, judgment calls about screening and rating potential borrowers have been almost entirely delegated to algorithms.[8] Robo-investing business models similarly delegate the selection and ongoing assessment of investment portfolios.[9] Algorithms are also integral to tokens hosted on blockchain networks and sold in "initial coin offerings" (ICOs)—here, the very product being offered to investors is a type of algorithm known as a smart contract, and transactions are designed to be self-executing and insulated from human intervention.[10] This Article will explore the implications for financial stability of this unprecedented level of algorithmic autonomy in the financial system—autonomy that will only increase with technological advances in machine learning.[11]

Of course, there are natural limitations on any contemporaneous assessment of the impact of increasingly automated algorithms on financial stability. Many of the fintech business models that rely heavily on algorithms have not yet scaled up to a size where they are likely to have a significant impact on the financial system as a whole, or the broader economy.[12] Furthermore, none of these fintech business models have yet to be tested in a crisis or a contracting economy, so we cannot learn from actual instances of failure.[13] That does not mean that this Article's examination is too premature: innovation can move from "'too small to care' to 'too big to fail' (systemically important) in very short periods of time,"[14] especially when the relevant technologies are being adopted by established financial institutions that are already "too big to fail." While it may be tempting to defer considera-

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[6] *See* Fin. Stability Bd., Artificial Intelligence and Machine Learning in Financial Services: Market Developments and Financial Stability Implications 8 (2017), http://www.fsb.org/wp-content/uploads/P011117.pdf [hereinafter, "FSB AI Report"] (discussing the technological developments that have facilitated the latest wave of financial technology).

[7] *See* Part II.C, *infra.*

[8] *See* Part II.B, *infra.*

[9] *See* Part II.A, *infra.*

[10] *See* Part II.D, *infra.*

[11] Machine learning will be discussed more fully in Part I, *infra*. Algorithms capable of machine learning are programmed not to perform a particular task, but to draw lessons from a data set about how to perform tasks in the future. *See* Harry Surden, *Machine Learning and Law*, 89 Wash. L. Rev. 87, 88 (2014).

[12] The FSB (an international group of regulators responsible for setting the international agenda on financial stability issues) recently concluded that "there are currently no compelling financial stability risks from emerging FinTech innovations." Fin. Stability Bd., Financial Stability Implications From FinTech: Supervisory and Regulatory Issues that Merit Authorities' Attention 1 (2017), http://www.fsb.org/wp-content/uploads/R270617.pdf [hereinafter, "FSB Fintech Report"].

[13] *See id.*

[14] Douglas W. Arner, Janos Barberis & Ross P. Buckley, *FinTech, RegTech, and the Reconceptualization of Financial Regulation*, 37 NW. J. Int'l L. & Bus. 371, 404 (2017).

tion of the systemic impact of automated financial decision-making until after we have observed a failure of that technology, the costs of systemic impact may be significant, and *ex post* measures tend to be limited in their ability to contain the fall-out from crises.[15] The potential for serious economic harm (and attendant social costs) necessitates creative thinking about the risks that financial institutions and activities could create, along with proposals for regulation to address those risks *ex ante*.[16]

It is therefore troubling that the Treasury Department's recent report on "Nonbank Financials, Fintech and Innovation" makes almost no mention of the impact that machine learning, smart contracts, and other technological innovations could have on financial stability.[17] Machine learning and smart contracts are currently in their infancy, but there will soon come an inflection point after which financial regulators will be circumscribed in their ability to influence the use of such technology in the financial markets. Policymakers should therefore be thinking *now* about the potential impact of driverless finance on financial stability and the broader economy. This Article seeks to kick-start this debate by exploring how financial stability may be undermined by driverless finance's increased speed and complexity. It also explores how the propensity for increased delegation of decision-making to a few algorithms may lead to destabilizing correlation that undermines financial stability (a phenomenon this article will refer to as "correlation by algorithm"). It will also demonstrate that increased use of algorithms could undercut existing financial stability regulation, including regulatory attempts to instill a more stability-oriented financial culture in financial institutions. Importantly, this Article is not intended to be an even-handed discussion of the costs and benefits of driverless finance. The benefits of fintech innovation have already been much discussed (in the Treasury Department's report and elsewhere);[18] this Article is intended to serve as a counterpoint to that literature by highlighting threats to financial stability that have been neglected by others.

This Article will then consider possible precautionary responses to these threats to financial stability. While regulators should not require conclusive proof of the safety of financial algorithms (something that is probably not feasible in any event), they should regulate the *processes* by which sophisticated financial algorithms are developed. Correlation by algorithm, for example, is likely to prove a challenging phenomenon to address, but

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[15] *See* Allen, *supra* note 2, at 1104.

[16] The FSB has highlighted the need to think broadly about risks to financial stability posed by the various fintech business models, individually and in concert. *See* FSB Fintech Report, *supra* note 12, at 2–3.

[17] U.S. Dep't of Treasury, A Financial System That Creates Economic Opportunities: Nonbank Financials, Fintech, and Innovation (2018), https://home.treasury.gov/sites/default/files/2018-07/A-Financial-System-that-Creates-Economic-Opportunities—-Nonbank-Financi. . . .pdf [hereinafter, "Treasury Report"].

[18] *See id. See also* Rory Van Loo, *Making Innovation More Competitive: The Case of Fintech*, 65 UCLA L. Rev. 232, 232 (2018).

regulators could adopt principles-based regulation that requires that all financial algorithms at least contemplate the possibility of low-probability but high-consequence events—the type of events that bring about financial crises. In order to slow down individual transactions and preserve flexibility in a tightly coupled system, regulators could require that smart contracts embedded in financial assets include some form of circuit breaker, and be hosted on a distributed ledger maintained by identifiable nodes with the power to undo erroneous transactions. More generally, requiring preapproval of financial algorithms before they can be utilized could at least slow the financial system's inexorable march towards mystifying complexity.[19] There is also a place for precaution in regulators' ongoing supervision of firms, ensuring that those firms have the necessary internal governance structures to oversee their usage of automated algorithms and make changes and corrections when risks become apparent.

The remainder of this Article will proceed as follows. First, Part I will make the normative argument for why a precautionary, financial stability-oriented approach to regulating driverless finance should be embraced, drawing analogies from the literature on autonomous vehicles. Part II will then introduce some of the most algorithm-dependent fintech business models, which will be used as examples in Part III. Part III illustrates how increasingly sophisticated algorithms can exponentially exacerbate complexity, speed and correlation within the financial system, rendering the system more fragile. Part III also considers how the latest algorithms may undermine the regulatory reforms that were implemented in the wake of the 2008 financial crisis in order to make the financial system more robust. Part IV offers some preliminary recommendations for how regulators should implement a precautionary approach to driverless finance, focusing on the process by which algorithms are created. The Article concludes on a note of optimism, briefly hypothesizing a best-case scenario in which a precautionary approach results in algorithms that enhance financial stability.

I. A Precautionary Approach to Sophisticated Algorithms

Laws designed to address a world of primarily human actors are being strained by twenty-first century technological innovations that subvert this paradigm.[20] Decision-making is increasingly being delegated to algorithms, and the algorithms themselves are becoming increasingly sophisticated in their decision-making. While previous generations of algorithms could only act in ways dictated by their programmers,[21] algorithms are now being programmed to draw their own decision-making rules from exposure to vo-

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[19] Such approval would not require conclusive proof of a financial product's safety. *See* Allen, *supra* note 4, at 195–96 and accompanying text.

[20] *See* Stilgoe, *supra* note 1.

[21] *See* Vladeck, *supra* note 1, at 120.

luminous data sets[22]—a phenomenon known as machine learning.[23] Driverless cars, for example, will be guided by machine learning algorithms that have been trained using vast proprietary data sets captured by driving around highways and cities (a phenomenon referred to as "fleet learning").[24] Fleet learning involves algorithms drawing patterns from observed data to allow them to make sense of the world outside of the vehicle and to make decisions about how to react to observed stimuli when driving.[25] While many financial firms currently use much simpler, more predictive algorithms in their businesses, one can reasonably expect that as time goes on, financial business models will also become increasingly reliant on machine learning algorithms that draw patterns from selected data sets.[26] Financial regulators face significant challenges engaging even with predictive algorithms,[27] and machine learning algorithms will pose even greater challenges for regulators trying to maintain the safety of the financial system.

Discussing regulatory challenges associated with machine learning generally, Andrew Tutt has identified two broad categories of difficulty: difficulty predicting algorithmic output (in other words, how the algorithms will react in a given set of circumstances), and difficulty explaining why an algorithm acted in a particular way after the fact.[28] To illustrate in the context of driverless cars, the most obvious differences between human and algorithmic decision-making manifest in what are known as "edge cases"—"scenarios that cars seldom encounter, and might be unable to handle without specific training."[29] Here, it is quite possible that the algorithm will make sense of the world and react in a very different way than a human would. It is very hard to predict how the algorithm will direct the vehicle to react in these edge cases, and if something does go wrong, it can be very difficult after the fact to unearth why the algorithm made the decision it did.[30] In finance, decision-making by machine learning algorithms has the potential to be similarly fraught. Such algorithms do not understand financial markets in the same way that humans do: humans tend to rely on narratives to make sense of the world, whereas algorithms tend to focus on statistical

[22] *See* Stilgoe, *supra* note 1, at 29.
[23] *See* Surden, *supra* note 11, at 88.
[24] *See* Stilgoe, *supra* note 1, at 35.
[25] *See* Tutt, *supra* note 5, at 85–86.
[26] *See* FSB AI Report, *supra* note 6, at 33 ("Most market participants expect that AI and machine learning will be adopted further.").
[27] *See* Kenneth A. Bamberger, *Technologies of Compliance: Risk and Regulation in a Digital Age*, 88 Tex. L. Rev. 669 (2010) (discussing the difficulties that regulators face in engaging with computer risk models); Hilary J. Allen, *The SEC as Financial Stability Regulator*, 43 J. Corp. L. 715 (2018) (discussing the difficulties that regulators face in engaging with high-frequency trading algorithms).
[28] *See* Tutt, *supra* note 5, at 101.
[29] Mattioli, *supra* note 1, at 295.
[30] *See* Tutt, *supra* note 5, at 102.

data points.[31] It is true that advances in semantic research may make algorithms more adept at mirroring human understanding at some point,[32] but for the foreseeable future, algorithms are likely to be hampered in their ability to see the big picture in the way that humans do.[33] The unpredictability of algorithmic decision-making in unusual circumstances should set off alarm bells for regulators charged with promoting the safety and stability of the financial system.

Concerns about safety are certainly at the forefront of debates about the algorithms driving autonomous vehicles.[34] Although policymakers continue to grapple with the question of "How safe is safe enough"? when it comes to autonomous vehicles,[35] the general societal consensus seems to be that some degree of precaution with respect to driverless cars is appropriate. By precaution, I mean that policies should err on the side of avoiding significant harm, notwithstanding uncertainty about the nature of such harm and the probability of it occurring.[36] The form of precaution that I advocate for does not require that an activity be proven riskless before it can proceed —it does, however, create a presumption that the benefits of precautionary regulation outweigh the associated costs, notwithstanding that the benefits may be difficult (if not impossible) to quantify.[37]

Ultimately, decisions about the degree of precaution to be utilized are value-laden and reflect cultural attitudes towards risks and the costs of protecting against them. The United States is often characterized as being particularly skeptical of precautionary regulatory regimes, choosing to privilege the promotion of innovation over protection from the risks that such innovation may create.[38] Attempts to pioneer a precautionary regulatory approach to driverless finance in the United States may face significant political challenges as a result. While the United States does not always reject precautionary policies (the precautionary anti-terrorist measures taken by the United

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[31] *See* Andrew G. Haldane, Chief Economist, Bank of England, Speech at Data Analytics for Finance and Macro Research Centre, King's Business School: Will Big Data Keep Its Promise? 12 (Apr. 19, 2018).

[32] *See id.*

[33] *See* Mattioli, *supra* note 1, at 285.

[34] *See* Stilgoe, *supra* note 1, at 46. Algorithms controlling the availability of electricity, and the provision of medical care, have similarly been identified as capable of "inflicting unusually grave harm," and thus the debate about them revolves around safety concerns. *See* Tutt, *supra* note 5, at 117.

[35] *See* Mattioli, *supra* note 1, at 296.

[36] *See* Allen, *supra* note 4, at 191.

[37] *See id.* at 197–98.

[38] "According to prevalent stereotypes today, Americans are said to be individualistic, technologically optimistic, forward-looking, risk-taking, and antiregulatory, confident that new technology and the power of markets will solve every problem and that precaution is a waste of time and a hindrance to progress." Jonathan B. Wiener, *The Rhetoric of Precaution*, *in* The Reality of Precaution: Comparing Risk Regulation in the United States and Europe 7 (Jonathan B. Wiener ed., 2011). Even in the context of driverless cars, Stilgoe argues that regulation may ultimately be less precautionary than desirable because "concerns about liberty are relatively elevated over public safety" in the United States. Stilgoe, *supra* note 1, at 46–47.

States since September 11 are evidence of this),[39] antipathy for precautionary regulation *is* likely to manifest itself in the context of financial stability regulation, where harms resulting from economic failure tend to be less salient than harms to life and limb.[40] Perhaps for similar reasons, regulatory approaches to disembodied software have also tended to be relatively technical and unconcerned with value judgments about risks.[41]

There is almost no discussion of financial stability in the latest Treasury Report on fintech innovation, which instead enthusiastically embraces technological developments and market solutions.[42] As I have argued previously, however, a precautionary approach to financial stability regulation should be pressed despite the political challenges.[43] The fallout from financial crises may sometimes seem abstract, but it can include very real deteriorations in mental and physical health, as well as economic problems like significant reductions in personal wealth and unemployment.[44] Purely *ex post* regulatory measures are limited in their ability to contain the fall-out from systemic failures,[45] and such measures may also have significant unforeseen economic consequences (for example, the extended period of low interest rates that followed the 2008 financial crisis incentivized investment in riskier assets in a search for yield, potentially sowing the seeds of future financial instability).[46] Financial system failure may also have undesirable political consequences: a decade after the 2008 financial crisis, Jeffrey Gordon remarked that "[t]he actions that were necessary to save the financial system from collapse (and to avoid an even worse economic and human outcome) produced a pattern of winners and losers that could not be defended on any principle of desert," setting the stage for the current rise of populism around the world.[47]

Where financial innovation has the potential to generate catastrophic externalities for society at large, taking a "wait-and-see" approach to regulation is inadequate. It is foolhardy to wait to see the systemic damage that increasingly autonomous financial algorithms might inflict before starting to consider their potential impact, even if it is hard to predict precisely what

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[39] *See* Jessica Stern & Jonathan B. Wiener, *Terrorism and Weapons of Mass Destruction*, *in* The Reality of Precaution: Comparing Risk Regulation in the United States and Europe, 286 (Jonathan B. Wiener ed., 2011).

[40] *See* Allen, *supra* note 4, at 194; *see also* Singapore's Personal Data Protection Commission, A Proposed Model Artificial Intelligence Governance Framework 2 (2019) ("The impact on an individual of an autonomous decision in, for example, medical diagnosis will be greater than in processing a bank loan.").

[41] *See* Stilgoe, *supra* note 1, at 35.

[42] *See* Treasury Report, *supra* note 17.

[43] *See* Allen, *supra* note 4. In a recent book chapter, Gordon has also made the case for a precautionary approach to financial stability regulation. *See* Jeffrey N. Gordon, *'Dynamic Precaution' in Maintaining Financial Stability: The Importance of FSOC*, *in* Ten Years After The Crash (Sharyn O'Halloran & Thomas Groll eds., 2018).

[44] *See* Allen, *supra* note 2, at 1095–97.

[45] *See id.* at 1104.

[46] *See id.* at 1104–05.

[47] *See* Gordon, *supra* note 43, at 3.

that impact will be. Business models like marketplace lending and robo-investing aim to serve important niches of the economy that are underserved by the traditional financial system. If such business models fail after gaining significant market share, there may not be any substitutes for their services and the real economy may suffer. In addition, larger established financial institutions that are integral to the proper functioning of the broader economy are increasingly adopting algorithmic approaches to their core businesses in an attempt to remain competitive.[48] These institutions may also decide to invest in ICOs and other offerings of fintech firms, providing yet another conduit for issues with algorithmic finance to impact the more established financial system and the economy at large. This Article therefore argues that regulators should engage in early-stage dialogue with the creators of these new technologies—a precautionary approach to reviewing a technology considers the process by which it is created, instead of restricting regulatory oversight to the finished product.[49]

In this venture, time is of the essence. Although there are many who take the view that regulators should defer regulating fintech until after a market failure has occurred so that the pitfalls of a fintech business model can be laid bare by experience,[50] once the market for a particular financial product or service becomes well-established, opportunity for regulatory intervention becomes limited.[51] This narrowing of opportunity is partly a result of political economy: an established industry will have more clout to resist regulation, and regulators are often loath to upset market expectations about the regulatory treatment of an established product or service.[52] It is also an issue of technology, though—it is far more difficult to alter the workings of a technology once it is operational than it is to help shape it during development.[53] Machine learning and smart contracts, as applied to finance, are in their infancy. If regulators miss this window of opportunity, the technology of driverless finance may become inscrutable and largely unregulatable—but any problems that the technology creates for financial stability and the broader economy will still be borne by society as a whole.[54]

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[48] *See* FSB AI Report, *supra* note 6, at 9, 30. The Treasury Department reports that "[f]irms expect that the effective use of AI, machine learning and big data analysis will be a key source of competitive advantage, which is spurring investment and competition." Treasury Report, *supra* note 17, at 56. Established institutions might also use the existence of fintech competitors as justification for lobbying for lighter touch regulation. *See* Gordon, *supra* note 43.

[49] *See* Stilgoe, *supra* note 1, at 30.

[50] *See, e.g.*, Douglas W. Arner, Janos Barberis & Ross P. Buckley, *The Evolution of FinTech: A New Post-Crisis Paradigm?*, 47 Geo. J. Int'l L. 1271, 1308–09 (2016).

[51] *See* Allen, *supra* note 4, at 223.

[52] *See* Tim Wu, *Agency Threats*, 60 Duke L.J. 1841, 1850 (2011); Kenneth C. Kettering, *Securitization and its Discontents: The Dynamics of Financial Product Development*, 29 Cardozo L. Rev. 1553, 1651 (2008).

[53] *See* Stilgoe, *supra* note 1, at 29–30.

[54] As Omarova has argued, "[u]nless the public side proactively counters new technologies' potentially destabilizing systemic effects, it may soon find itself in an impossible position of having to back up an uncontrollable and unsustainably self-referential financial system."

II. Case Studies: Algorithm-Driven Fintech Business Models

Increased use of algorithms is permeating all aspects of finance,[55] but nowhere is this trend more apparent than in several new fintech business models. By way of background, "fintech" is an umbrella term that is generally understood to encompass mobile payment services, robo-investing, marketplace lending (otherwise known as "P2P lending"), crowdfunding, virtual currencies, and tokens sold in ICOs.[56] Some scholars also include high-frequency trading in their discussions of fintech products and services.[57] Even though they are often grouped together, these business models are very diverse. Importantly for this Article, some are much more reliant on algorithms than others. Because sophisticated algorithms are integral to the robo-investing, marketplace lending, high-frequency trading, and token business models, this Article will use them as examples as it considers the financial stability implications of increased reliance on sophisticated algorithms. Part II will therefore provide a brief introduction to these business models. Importantly, though, this Part should not be viewed as an exhaustive list of the business models that rely heavily on algorithms; even more traditional financial business models are relying increasingly on driverless finance, and thus this Article's concerns have much wider application than the fintech business models profiled in this Part.

A. Robo-Investing

The term "robo-advisor" is popularly used to describe "an automated investment service . . . which competes with financial advisors by claiming to offer equally good (if not better) advice and service at a lower price."[58] While robo-advisory services are being developed for banking and insurance products as well as for securities,[59] this Article will focus on the more developed sector of "robo-investing" in securities. Broadly speaking, this industry uses algorithms to provide automated "customer profiling, asset allocation, portfolio selection, trade execution, portfolio rebalancing, tax-loss harvesting and portfolio analysis."[60] Different firms provide robo-in-

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Saule T. Omarova, *New Tech v. New Deal: Fintech as a Systemic Phenomenon*, 36 Yale J. Reg. 735, 793 (2019).

[55] For a survey of many of the existing applications of machine learning in finance, *see* FSB AI Report, *supra* note 6, at 1.

[56] *See* U.S. Gov't Accountability Office, GAO-17-364, Financial Technology: Information on Subsectors and Regulatory Oversight 1 (2017).

[57] *See, e.g.*, Arner et al., *supra* note 50, at 1291–92; Thomas Philippon, *The Fintech Opportunity* 2 (Nat'l Bureau of Econ. Research, Working Paper No. 22476, Aug. 2016), https://www.nber.org/papers/w22476.pdf.

[58] Tom Baker & Benedict G.C. Dellaert, *Regulating Robo Advice Across the Financial Services Industry*, 103 Iowa L. Rev. 713, 719-20 (2018).

[59] *See id.* at 720–21.

[60] FINRA, Report on Digital Investment Advice 2 (Mar. 2016), https://www.finra.org/sites/default/files/digital-investment-advice-report.pdf.

vesting services in different ways, but most robo-investing models tout their potential to democratize investing by providing low-cost financial advice to customers who may only have small amounts of capital.[61] Robo-investing algorithms may also be more competent than human financial advisers[62] and may avoid the conflicts of interests that plague human advisers (depending on how the selection algorithm is designed).[63] While many robo-investing platforms currently use predictive algorithms, there is enormous interest in applying machine learning techniques to collect information about clients' financial circumstances and improve portfolio selection.[64]

The SEC has noted that most robo-investing services start their relationship with the investor by utilizing an online questionnaire to assess an investor's financial situation and risk tolerance.[65] The subsequent relationship between the robo-investing firm and the investor then varies by business model. Some robo-investing firms "are essentially automated interfaces that offer investment advice and discretionary investment management services without the intervention of a human adviser, using algorithms and asset allocation models that are advertised as being tailored to each individual's investment needs."[66] Other robo-investing services may be designed to provide information to a human intermediary who will ultimately interface with the customer and provide a more comprehensive set of financial planning services.[67] Others, like Betterment,[68] strike a middle ground by offering an automated interface with the option of receiving additional advice from financial professionals.[69] All of these types of businesses are likely to be subject to the same investor protection regulations that non-automated financial advisors face.[70] In the United States, this means that robo-investing

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[61] *See* Baker & Dellaert, *supra* note 58, at 714.

[62] "[A] large body of research in diverse fields demonstrates that even simple algorithms regularly outperform humans in the kinds of tasks that robo advisors perform." *Id.* at 716.

[63] *See id.* at 732.

[64] *See, e.g.,* DELOITTE, THE NEXT FRONTIER: THE FUTURE OF AUTOMATED FINANCIAL ADVICE IN THE UK 22 (2017), https://www2.deloitte.com/content/dam/Deloitte/nl/Documents/financial-services/deloitte-nl-fsi-the-future-of-automated-financial-advice-in-the-uk.pdf.

[65] *See Investor Bulletin: Robo-Advisors,* SEC. EXCH. COMM'N (Feb. 23, 2017), https://www.investor.gov/additional-resources/news-alerts/alerts-bulletins/investor-bulletin-robo-advisers.

[66] Iris H-Y Chiu, *Fintech and Disruptive Business Models in Financial Products, Intermediation and Markets: Policy Implications for Financial Regulators*, 21 J. TECH. L. POL'Y 55, 88 2016.

[67] *See* Baker & Dellaert, *supra* note 58, at 739. FINRA uses slightly different terminology, excluding "financial professional-facing tools" from its definition of "robos." FINRA, *supra* note 60, at 2.

[68] *See* BETTERMENT.COM, https://www.betterment.com/financial-experts/ (last visited July 16, 2019).

[69] FINRA, *supra* note 60, at 3.

[70] Such regulation is likely to take the form of "licensing and education requirements designed to ensure that an intermediary has at least a minimum level of competence regarding the products that the intermediary is licensed to sell; disclosure requirements and antifraud rules that require intermediaries to be honest with their customers; and standards of conduct, such as the fiduciary standard, designed to encourage intermediaries to match their customers with suitable financial services." Baker & Dellaert, *supra* note 58, at 724.

firms are likely to be required to register as either investment advisers or broker/dealers. For example, Betterment has registered with the SEC as an investment adviser and also has a subsidiary broker-dealer registered with FINRA.[71]

B. Marketplace Lending

When fintech lending models first rose to prominence in the wake of the 2008 financial crisis, they promoted the "peer-to-peer" aspect of their process: the model sought to arrange funding for non-traditional borrowers from non-traditional lenders by capitalizing on users' sense of online community.[72] In recent years, however, there has ceased to be much real sense of community or personal connection between borrower and lender. Now, a prospective borrower requests a loan using a secure online platform (provided by a firm like Prosper or LendingClub), and then that platform utilizes a proprietary algorithm to make an initial approval decision based on information gathered from the prospective borrower and other sources.[73] If the prospective borrower meets the necessary criteria, then the lender platform will depersonalize the information it has about the prospective borrower and send the information (including an interest rate for the customer) out to prospective investors.[74] If sufficient investors are interested in funding the loan, the loan will be made, and the lender platform will process repayments and provide administrative services in connection with the loan.[75] These loans

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[71] Athwal Nav Athwal, *Fintech Startups Navigate Legal Gray Areas To Build Billion-Dollar Companies*, TECHCRUNCH (Apr. 19, 2015), https://techcrunch.com/2015/04/19/fintech-startups-navigate-legal-gray-areas-to-build-billion-dollar-companies/.

[72] *See* Kathryn Judge, *The Future of Direct Finance: The Diverging Paths of Peer-to-Peer Lending and Kickstarter*, 40 WAKE FOREST L. REV. 603, 604 (2015).

[73] *See* John L. Douglas, *New Wine Into Old Bottles: Fintech Meets the Bank Regulatory World*, 20 N.C. BANKING INST. 17, 27 (2016). It is possible that such data may be gleaned from non-traditional sources like "social media, public records (property transactions, births, deaths, marriage, divorce, criminal and civil legal matters, and the like), GPS and satellite tracking, and cameras." Jo Ann S. Barefoot, *Disrupting FinTech Law*, 18 FINTECH LAW REP. 1, 5 (2015).

[74] *See* Douglas, *supra* note 73, at 27.

[75] *See id*. The legal structure underlying the business models of the Prosper and LendingClub platforms is somewhat complicated. The loan is not actually made by the platform, but by an established financial institution with which the platform has a relationship. The platform then purchases the loan from the financial institution, using funds provided by the investors. While an investor's right to repayment is tied to the receipt of repayments from the ultimate borrowers, it takes the legal form of an unsecured note issued by the lending platform. *See* Judge, *supra* note 72, at 619; *see also* Eric C. Chaffee & Geoffrey C. Rapp, *Regulating Online Peer-to-Peer Lending in the Aftermath of Dodd-Frank: In Search of an Evolving Regulatory Regime for an Evolving Industry*, 69 WASH. & LEE L. REV. 485, 493 (2012). This structure implicates the securities laws, requiring lending platforms to register the issuance of the notes and make attendant disclosures in an attempt to protect investors—indeed, LendingClub had to suspend business in 2008 in order to bring itself into compliance with these laws. *See* Douglas, *supra* note 73, at 38; Athwal, *supra* note 71.

are often unsecured[76] and are typically for amounts under $50,000 for small businesses and around $10,000 for individual consumers.[77] As such lending has become increasingly popular, the vast majority of the funds loaned has come from large institutional investors, resulting in a shift in terminology from "P2P lending" to "marketplace lending."[78]

Algorithms are central to the business case for marketplace lending: they enable platforms to screen and rate would-be borrowers in a way that is quicker and less resource-intensive than a traditional bank credit assessment.[79] Increasingly, machine learning algorithms are also enabling marketplace lending platforms to expand the pool of borrowers they deem creditworthy.[80] Using such algorithms, platforms can quickly collate and synthesize voluminous amounts of data about the applicant from non-traditional sources (including social media), allowing for a more complete portrait of the credit applicant.[81] The time it would take a human to perform a similar check of such resources would likely be prohibitive. Frank Pasquale and others have raised important concerns about such machine learning algorithms violating privacy and exacerbating discrimination in the provision of credit, but those concerns are beyond the scope of this Article.[82] Instead, our focus is on financial stability concerns; the ability of machine learning algorithms to accurately predict creditworthiness—and accurately reflect creditworthiness in the interest rate to be charged—is therefore more relevant.

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[76] *See* Eleanor Kirby & Shane Worner, *Crowd-funding: An Infant Industry Growing Fast* 37 (Int'l Org. Sec. Comm'ns, Working Paper No. 3, 2014).

[77] *See* Stephen Fromhart, Marketplace lending 2.0: Bringing on the next stage in lending 7 (2017), https://www2.deloitte.com/content/dam/Deloitte/us/Documents/financial-services/us-fsi-markeplace-lending2.pdf.

[78] *See* Lalita Clozel, *Could Online Lending Become the Next Systemic Risk*, AM. BANKER (Oct. 13, 2017), https://www.americanbanker.com/news/could-online-lending-become-the-next-systemic-risk; Judge, *supra* note 72, at 613.

[79] "These lending platforms allow borrowers to have their loans approved faster and funds dispersed quicker than if the borrower sought a loan from a traditional bank." Douglas, *supra* note 73, at 27.

[80] *See* FSB AI Report, *supra* note 6, at 12.

[81] "While it is not known exactly what specific set of alternative data are used by each of the specific fintech lenders, some have mentioned information drawn from bank account transactions such as utility or rent payments, other recurring transactions, and electronic records of deposit and withdrawal transaction. Other items mentioned include insurance claims, credit card transactions, consumer's occupation or details about their education, their use of mobile phones and related activities, Internet footprints, online shopping habit, investment choice, and so on." Julapa Jagtiani & Catharine Lemiux, *The Roles of Alternative Data and Machine Learning in Fintech Lending: Evidence from the LendingClub Consumer Platform* 2–3 (Fed. Reserve Bank of Phila., Working Paper No. 18-15, 2018), https://www.philadelphiafed.org/-/media/research-and-data/publications/working-papers/2018/wp18-15r.pdf.

[82] *See generally*, FRANK PASQUALE, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION (2015). *See also* Rory Van Loo, *The Corporation as Courthouse*, 33 YALE J. REG. 547, 579–80 (2016).

C. High-Frequency Trading

High-frequency trading is sometimes treated as separate from other fintech business models because it is not a consumer-facing product or service. Nevertheless, it is a relatively new financial phenomenon that is highly dependent on algorithms and thus is an appropriate focus of any discussion of driverless finance. High-frequency trading of financial assets is accomplished by algorithms deploying "fully automated trading strategies with very high trading volume and extremely short holding periods ranging from milliseconds to minutes."[83] There are a multiplicity of different high frequency trading strategies, but one widely-shared characteristic is "[t]he strong focus on speed of execution and portfolio turnover;" humans cannot trade quickly enough to profit from this type of strategy, so trading decisions must be delegated to algorithms.[84] Many high-frequency trading firms also use algorithms to help identify and evaluate trading opportunities.[85] When markets are functioning normally, increased high-frequency trading correlates with lowered costs, greater speed, improved market efficiency and increased liquidity for other traders in the markets.[86] However, these benefits (particularly the increased liquidity) tend to disappear when markets go haywire.[87] High-frequency trading has been implicated in many of the last decade's market glitches[88]: the 2010 Flash Crash remains the most significant of these, but there was also a treasury flash crash in October 2014,[89] and a number of so-called "mini flash crashes," in which "[i]ndividual stocks [including Walmart and Google] at times gyrate[d] wildly within fractions of a second, only to reset moments later."[90]

To a large extent, the high-frequency trading algorithms currently being used are predictive, programmed by the so-called "quants." While there are efforts afoot to use more sophisticated machine learning algorithms to make trading decisions, such efforts face major challenges. Significant (human) manpower needs to be continually deployed in defining the borders and granularity of the trading data set for the algorithms to learn from, and

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[83] X. Frank Zhang, High-Frequency Trading, Stock Volatility and Price Discovery 1 (Dec. 2010) (unpublished manuscript) (on file with SSRN), http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1691679.

[84] Tech. Comm. of the Int'l Org. of Sec. Comm'ns, Regulatory Issues Raised by the Impact of Technological Changes on Market Integrity and Efficiency 23 (2011).

[85] *See id.* at 22–23.

[86] *See* Onnig H. Dombalagian, Chasing the Tape: Information Law and Policy in Capital Markets 16 (2015); Tech. Comm. of the Int'l Org. of Sec. Comm'ns, *supra* note 84, at 10.

[87] *See* Merritt B. Fox, Lawrence R. Glosten and Gabriel V. Rauterberg, *The New Stock Market: Sense and Nonsense* 65 Duke L.J. 191, 248 (2015).

[88] *See* Allen, *supra* note 27, at 738.

[89] *See* Matt Levine, *Algorithms Had Themselves a Treasury Flash Crash*, Bloomberg (Jul. 13, 2015), https://www.bloomberg.com/opinion/articles/2015-07-13/algorithms-had-themselves-a-treasury-flash-crash.

[90] Kara M. Stein, Remarks before Trader Forum 2014 Equity Trading Summit (Feb. 6, 2014), https://www.sec.gov/News/Speech/Detail/Speech/1370540761194.

human judgment must be exercised as to which "noise" signals to eliminate from the data set.[91] If the algorithm is restricted to a historical data set, then that may not be predictive of the future. On the other hand, if the algorithm is constantly learning from market movements in real time, then that may slow down the algorithm to the point that it is unable to complete with leaner, faster predictive high-frequency trading algorithms.[92] Notwithstanding these present difficulties, however, future technological advances may render high-frequency trading by machine learning algorithms more feasible, and it is impossible to predict how such algorithms would behave in the event of future market glitches.

D. Tokens and Other "Smart Assets"

This section will conclude Part II with a discussion of token-related business models. When tokens are sold, in many respects, the algorithm *is* the asset: a token is "nothing more than an entry in a ledger that specifies that a particular user . . . is the sole party able to exercise a discrete set of powers associated with the ledger entry."[93] Those powers are established by "smart contracts," algorithms of varying degrees of sophistication that govern the functionality of the asset sold and that are intended to be self-executing and self-enforcing[94]—in other words, the contract is not supposed to be "subject to interpretation by outside entities or jurisdictions."[95] At present, tokens are being sold in ICOs in exchange for virtual currency.[96] Some ICOs feature utility tokens which "grant holders the right to access (or a license to use) a given technology or participate in an online organization. They tend to provide holders with governance rights, such as the right to vote on how the

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[91] *See* Michael Kearns & Yuriy Nevmyvaka, *Machine Learning for Market Microstructure and High Frequency Trading*, *in* HIGH FREQUENCY TRADING 1 (2013), https://www.cis.upenn.edu/~mkearns/papers/KearnsNevmyvakaHFTRiskBooks.pdf.

[92] *See* Paul Golden, *FX: Machine Learning Use Grows, But Lags in HFT* , EUROMONEY (Aug. 2, 2018), https://www.euromoney.com/article/b19b36yppj92q5/fx-machine-learning-use-grows-but-lags-in-hft.

[93] Shaanan Cohney et. al., *Coin-Operated Capitalism*, 119 COLUM. L. REV. 591, 602 (2018).

[94] *See* Kevin Werbach & Nicolas Cornell, *Contracts Ex Machina*, 67 DUKE L.J. 313, 333 (2017). "The term 'smart contract' refers to decentralized computer code that runs on a DLT protocol and manifests some combination of the following characteristics: exerts some control over assets digitally recorded on a DLT protocol, takes some action upon receipt of specified data, [may be part of a DLT-based application], guarantees execution, and writes the resulting state change from the operation of the smart contract into the DLT's ledger." Carla L. Reyes, *If Rockefeller Were a Coder*, 87 GEO. WASH. L. REV. 383–84 (2018).

[95] David Siegel, *Understanding the DAO Attack*, COINDESK (Jun. 27, 2016), https://www.coindesk.com/understanding-dao-hack-journalists/. "The utopian ideal is a "grand merger of law and computer security" which might render the protection offered by [traditional institutions] to be at best superfluous." Cohney et al., *supra* note 93, at 20.

[96] Randolph A. Robinson II, *The New Digital Wild West: Regulating the Explosion of Initial Coin Offerings*, 85 TENN. L. REV. 897, 922 (2018).

online service should be updated or evolve."[97] Other ICOs offer investment tokens, which are "not only functional in nature but provide holders with economic rights, such as a share of profits generated by a project or organization."[98]

Tokens rely on "distributed ledger" technology for the processing of transactions.[99] I have described this technology as "a large, decentralized database that is maintained on a network of computers rather than a single server, and that is updated in real-time,"[100] but there are a number of different variants of the technology. Distributed ledgers may or may not be controlled by a central authority (if not, they are described as "decentralized"), and they may also be "permissioned" or "permissionless" (with permissioned ledgers requiring some form of permission to join the network of computers that maintain the ledger, and permissionless ledgers allowing anyone to join).[101] A related concept is the one of "trustlessness": distributed ledgers may or may not be trustless, in the sense that they do not require third-party verification.[102] Perhaps the most prominent example of a permissionless, trustless, decentralized ledger is the blockchain used to facilitate Bitcoin transactions. However, the Ethereum ledger, rather than the Bitcoin one, is typically used to host tokens and facilitate ICOs (at least for now).[103]

ICOs have been described as the wild west of finance,[104] and the SEC has made clear its concerns about ICOs being used to circumvent investor protection regulations.[105] However, many assets that were once viewed as overly speculative and ripe for fraud have now matured into integral parts of

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[97] Jonathan Rohr and Aaron Wright, *Blockchain-Based Token Sales, Initial Coin Offerings, and the Democratization of Public Capital Markets*, 70 HASTINGS L.J. 463, 475 (2019).

[98] *Id.* at 476.

[99] Distributed ledger technology can also be used to process transactions involving assets other than digital money – including securities and real property. *See* Joshua A.T. Fairfield, *Bitproperty*, 88 S. CAL L. REV. 805, 808–09 (2015). However, an exploration of this application of distributed ledger technology is beyond the scope of this Article.

[100] Hilary J. Allen, *\$ = € = Bitcoin?,* 76 MD. L. REV. 877, 886 (2017). "[E]ach party with the software can access the full ledger, its history, and can send information directly to other nodes, without going through an intermediary." Reyes, *supra* note 94, at 380.

[101] *See* Angela Walch, *The Bitcoin Blockchain as Financial Market Infrastructure: A Consideration of Operational Risk*, 18 NYU J. LEG. & PUB. POL'Y 837, 844 (2015).

[102] *See* Angela Walch, *The Path of the Blockchain Lexicon (and the Law)*, 36 REV. BANKING & FIN. L.713, 722 (2017).

[103] Robinson, *supra* note 96, at 21–22.

[104] *See*, *e.g.*, *id.*

[105] "Those who offer and sell securities in the United States must comply with the federal securities laws, including the requirement to register with the Commission or to qualify for an exemption from the registration requirements of the federal securities laws. The registration requirements are designed to provide investors with procedural protections and material information necessary to make informed investment decisions. These requirements apply to those who offer and sell securities in the United States, regardless whether the issuing entity is a traditional company or a decentralized autonomous organization, regardless whether those securities are purchased using U.S. dollars or virtual currencies, and regardless whether they are distributed in certificated form or through distributed ledger technology." SEC, REPORT OF INVESTIGATION PURSUANT TO SECTION 21(A) OF THE SECURITIES EXCHANGE ACT OF 1934: THE DAO 18 (2017), https://www.sec.gov/litigation/investreport/34-81207.pdf.

standard asset portfolios.[106] It is not difficult to conceive of ICOs as harbingers of an increasingly algorithmic world of finance where smart contracts represent other bundles of rights and obligations that can be bought and sold for sovereign as well as virtual currency. All financial assets are legally constructed;[107] in the future, the legal contracts that comprise financial assets may take the form of self-executing algorithms, rather than being evidenced by the paper contracts that currently set out the rights and obligations of asset holders and issuers. In this Article, I shall refer to financial assets that consist of a self-executing, self-enforcing algorithm as "smart assets" (this choice of name is derived from the term "smart contracts"—it is not intended to convey any judgment about whether such assets are in fact a good idea).

Imagine, for example, a contingent convertible bond. I have previously described such a bond (or "coco", as it is colloquially known) as "a hybrid debt-equity instrument that starts its life as a debt instrument (like a bond) but will convert to common shares upon the occurrence of a 'trigger event,' thus providing the issuing bank with a fresh infusion of common shares."[108] Typical convertible bonds convert to equity at the election of the bondholder; contingent convertible bonds instead convert upon the occurrence of prespecified trigger events relating to accounting or market metrics, or to decisions by regulatory supervisors.[109] Theoretically, the terms of a coco could be translated into computer code as a smart contract (a "smart coco," if you will). The smart contract would be recorded on some type of distributed ledger, and the contract's code would work to automatically make interest payments from the issuer to the holder (the payments would be made in some form of virtual currency—in the future, there may be virtual versions of sovereign currencies like the U.S. dollar). If the holder wished to trade the smart coco, the distributed ledger would be updated to reflect the new holder of the smart coco, and the code would automatically order that interest payments be made to the new holder. Meanwhile, the smart contract would check the information sources specified in its code at the times specified in its code to determine whether a trigger event has occurred. Upon receiving information that a trigger event has occurred, the distributed ledger would immediately reflect that the holder no longer has any ownership interest in the smart coco, but instead has an ownership interest in the equity of the issuer. By design, humans would have no real opportunity to interrupt the performance of the conversion.[110]

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[106] *See* Cohney et al., *supra* note 93, at 594.

[107] *See* Katharina Pistor, *A Legal Theory of Finance*, 41 J. Comparative Econ. 315, 317 (2013).

[108] Hilary J. Allen, *Let's Talk About Tax: Fixing Bank Incentives to Sabotage Stability*, 18 Ford. J. Corp. & Fin. L. 821, 852 (2013).

[109] *See id.* at 852–53.

[110] *See* Werbach & Cornell, *supra* note 94, at 332.

III. Potential Threats to Financial Stability From Financial Algorithms

Part III provides an analytical framework for assessing the threats that increased reliance on algorithms could pose for financial stability. It demonstrates that problems will likely arise from increased complexity and speed, as well as the propensity of algorithms to entrench tendencies towards destabilizing correlation. This Part also suggests that the financial industry's failure to consider the externalities of its activities is likely to be exacerbated by increased reliance on algorithms. This Part uses the business models of robo-investing, marketplace lending, high-frequency trading, and tokens as illustrative examples, but this discussion is not restricted to any particular business model; it has broader application to all algorithm-reliant financial business models, even those that have not yet emerged. Given how nascent the relevant technologies are, this Part does not attempt to provide an exhaustive catalog of the potential threats that driverless finance could pose for financial stability. Nonetheless, the threats that are already apparent are sufficient to raise concerns about how financial stability could be undermined as driverless finance becomes increasingly prominent.

A. *Algorithms and Complexity*

Since the 2008 financial crisis, many have commented on how the increasing complexity of the financial system has rendered it more fragile.[111] This manifests in different ways. For example, in the context of risk assessment, complexity "renders the system increasingly opaque to reasoned human cognition, making it more difficult to make thoughtful judgments about where risk lies,"[112] and exacerbates our pre-existing tendency to underestimate low-probability but high-consequence tail risks[113] (which are the very risks that are most likely to cause financial crises).[114] Complexity also breeds opportunities for regulatory arbitrage and capture, undermining the efficacy of regulation implemented to bolster the stability of the financial system.[115] Such concerns about the adverse impacts of complexity will only be magnified as financial algorithms become increasingly intricate and autonomous.[116]

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[111] *See, e.g.*, Steven L. Schwarcz, *Systemic Risk*, 97 Geo. L.J. 193 (2008); Dan Awrey, *Complexity, Innovation, and the Regulation of Modern Financial Markets*, 2 Harv. Bus. L. Rev. 235 (2012); Saule T. Omarova, *License to Deal: Mandatory Approval of Complex Financial Products*, 90 Wash. U. L. Rev 63 (2012).

[112] Hilary J. Allen, *The Pathologies of Banking Business As Usual*, 17 U. PA. J. Bus. L. 861, 872 (2015).

[113] *See id.*

[114] *See* Allen, *supra* note 4, at 206.

[115] *See id.* at 187, 199.

[116] For example, the FSB has noted that "the complexity and opacity of some big data analytics models makes it difficult . . . to assess the robustness of the models or new unfore-

Admittedly, human beings have a very flawed history of financial risk assessment, one that has seen asset bubbles develop over and over again—as well as panics, once the bubble bursts.[117] At first blush, it might seem that replacing human foibles with sterile computer processing might improve such risk assessment: if we utilize Daniel Kahneman's "System 1" and "System 2" framework to conceptualize human decision-making, we might anticipate that algorithms would be free from the instinctual responses generated by System 1, which were most likely developed as an evolutionary response to the difficulty of processing vast amounts of information quickly.[118] These mental shortcuts or "heuristics" are often ill-suited to generating accurate risk assessments in the financial context.[119] Algorithms specialize in processing vast amounts of information quickly, and thus are less likely to need a coping mechanism like System 1. Instead, they are more likely to resemble the deliberative cognitive process of System 2. However, notwithstanding that algorithms are better equipped to deal with large amounts of information, there are still a number of reasons to be skeptical of entirely automated risk-assessment procedures.

First, and most obviously, algorithms may have bugs that prevent them from working as intended. A second more nuanced concern arises with respect to predictive algorithms: attempting to translate complex decision-making into the formal logic of algorithmic code is bound to result in over-simplifications and unanticipated errors,[120] in particular, to "privilege the measurable and mask uncertainty."[121] The uncertainty associated with tail risks is particularly likely to be masked or ignored because algorithms work most efficiently (meaning firms using algorithms will be able to perform their functions at greater speeds) if there are fewer lines of code. In business models like high frequency trading where speed is a key competitive advantage, attempting to cater for unpredictable tail events by including more lines of code would be viewed as unnecessarily slowing down the functioning of the algorithm.[122] The issue of algorithms and speed will be explored more fully in the next section.

Where speed is less of a competitive advantage, an algorithm could potentially consider a broader universe of variables in making a risk assess-

seen risks in market behaviour, and to determine whether market participants are fully in control of their systems." FSB Fintech Report, *supra* note 12, at 2.

[117] For historical discussions of financial bubbles, see Erik F. Gerding, Law, Bubbles and Financial Regulation (2014), and Carmen M. Reinhart & Kenneth S. Rogoff, This Time Is Different: Eight Centuries of Financial Folly (2009).

[118] *See* Daniel Kahneman, Thinking Fast And Slow, 20–21 (2011).

[119] *See* Andrew W. Lo, Adaptive Markets: Financial Evolution at the speed of thought 252–53 (2017).

[120] "[T]heir translation efforts are colored by their own disciplinary assumptions, the technical constraints of requirements engineering, and limits arising from the cost and capacity of state-of-the-art computing." Bamberger, *supra* note 27, at 708.

[121] *Id.* at 676.

[122] *See* Yesha Yadav, *How Algorithmic Trading Undermines Efficiency in Capital Markets*, 68 Vand. L. Rev. 1607, 1667 (2015).

ment—particularly if the algorithm were capable of machine learning. With machine learning algorithms, a programmer will establish the parameters of the data set that the algorithm should learn from (a process known as "feature selection"),[123] and the algorithm will then make its own decisions about which data to take into account in assessing risks. However, such assessments will be circumscribed by any limitations in the feature selection, and the process by which the algorithm decides which variables are relevant and how to weight them will be opaque to everyone.[124] Furthermore, while such algorithms can observe correlations, they cannot determine causation[125]: they may therefore misjudge the impact of a variable on a risk assessment. If a machine learning algorithm were to make a demonstrable mistake in assessing risk, the technology does not yet exist to teach the algorithm not to make the same mistake again in the future.[126] As such, notwithstanding that algorithmic risk-assessment is likely to be superior to human judgment in some respects, we should be wary of automating the process entirely.

Unfortunately, the more "driverless" an algorithm purports to be, the more likely human beings—whether regulators or market participants—are to defer to its risk assessment without interrogating its underlying processes. These tendencies have been referred to as "automation biases—decision pathologies that hinder careful review of automated outcomes."[127] Such biases can lead humans to "disregard or not search for contradictory information in light of a computer-generated solution that is accepted as correct."[128] Such biases have been demonstrated to be particularly likely to arise in circumstances where it is in a person's financial interest to defer to the algorithm's decision[129] (which can occur when an underestimation of tail risk allows people to believe they are receiving above-market returns on their investments).[130]

There is also a temptation for those proficient in algorithms to exploit these automation biases to avoid the spirit of the regulation, while apparently complying with its letter (a phenomenon referred to as "regulatory arbitrage").[131] Machine learning techniques are already being used by banks to

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[123] *See* Joshua A. Kroll et al., *Accountable Algorithms*, 165 U. Pa. L. Rev. 633, 681 (2017).

[124] *See* Baker & Dellaert, *supra* note 58, at 22.

[125] *See* FSB AI Report, *supra* note 6, at 6.

[126] *See* Tutt, *supra* note 5, at 89; Stilgoe, *supra* note 1, at 11.

[127] Bamberger, *supra* note 27, at 676.

[128] *Id.* at 712.

[129] *See id.*

[130] "To satisfy demand for seemingly higher-yield, lower-risk products, financial institutions often use financial engineering to consolidate risk in the tail where investors are notoriously likely to disregard it . . . When investors do not properly recognize the tail risk inherent in a financial instrument, they are likely to accept a yield that does not properly compensate them for the risk they are taking on, and the instrument is likely to be wildly popular." Allen, *supra* note 4, at 216–17.

[131] Regulatory arbitrage has been described by one commentator as the exploitation of "the gap between the economic substance of a transaction and its legal or regulatory treatment, taking advantage of the legal system's intrinsically limited ability to attach formal labels that

refine their compliance with regulatory capital and other prudential requirements., and the Financial Stability Board has raised concerns that, while legal, these efforts may increase systemic risks by allowing "much tighter liquidity buffers, higher leverage, and faster maturity transformation than in cases where AI and machine learning had not been used for such optimization."[132] Some programmers (or their employers) may even use the complexity of algorithmic programming to purposefully over-engineer and rapidly update code in order to confound competitors and deflect regulatory scrutiny.[133] Frank Pasquale has also raised concerns that the complexity of financial algorithms will be used to cognitively capture the regulators, meaning that the developers of the technology will be able to convince regulators that they, rather than less tech-savvy regulators, should be responsible for determining whether algorithms are complying with extant regulations.[134]

If regulators were to effectively wave the white flag with respect to supervision of complex financial algorithms, the increased use of such algorithms would have a broadly deregulatory effect. For example, if regulators were to determine that the algorithms used by marketplace lending platforms were so complex as to be inscrutable, then that could facilitate a situation where mispriced credit is extended to dubious applicants, fueling a bubble in the assets that such credit is used to purchase.[135] The marketplace lending firm Prosper, for example, assigns "risk ratings" to individual loans to assist investors in selecting loans in which to invest.[136] If such risk ratings were assigned by a machine learning algorithm that learned to assess borrower risk in a way that neglects a shared characteristic of many borrowers, then those borrowers could default en masse in the event of a circumstance unanticipated by the algorithm (the relationship between increased use of algorithms and correlation will be explored in greater detail later in this Part). Investors in marketplace loans typically have little loan-level data and are thus largely reliant on the output of the platform's algorithms to judge possible investments.[137] If those algorithms are inscrutable, then that may en-

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track the economics of transactions with sufficient precision." Victor Fleischer, *Regulatory Arbitrage*, 89 TEX. L. REV. 227, 229 (2010).

[132] FSB AI Report, *supra* note 6, at 31.

[133] *See* Awrey, *supra* note 111, at 263–64.

[134] *See Examining the Fintech Landscape: Hearing Before the Subcomm. Comm. on Banking, Housing, and Urban Affairs*, 115th Cong. 68, 76 (2017) (statement of Frank Pasquale, Professor of Law, University of Maryland Francis King Carey School of Law). Such arguments about technological complexity have succeeded in the past, such as when regulators acceded to the Basel II Capital Accord, which essentially allowed the largest banks to set their own regulatory capital requirements using complex internal modeling. *See* Erik F. Gerding, *The Dialectics of Bank Capital: Regulation and Regulatory Capital Arbitrage*, 55 WASHBURN L.J. 357, 375 (2016).

[135] For a discussion of how securitization demand resulted in nontraditional mortgage lending prior to the financial crisis, *see* Kathleen C. Engel & Patricia A. McCoy, *Turning a Blind Eye: Wall Street Finance of Predatory Lending*, 75 FORDHAM L. REV. 2039 (2007).

[136] *See* PROSPER, A GUIDE TO INVESTING IN MARKETPLACE LENDING 3 (2016), https://www.prosper.com/about-us/wp-content/uploads/InvestorsGuide.pdf.

[137] *See* Kirby & Worner, *supra* note 76, at 41–42.

courage loans that are "over-issued relative to what would be possible under rational expectations."[138]

The Treasury Department has already noted that "[n]ew business models and underwriting tools have been developed in a period of very low interest rates, declining unemployment, and strong overall credit conditions," and that "this industry remains untested through a complete credit cycle."[139] If a bubble were to develop in marketplace loans and then burst, then that could have a deleterious impact on the broader economy. Admittedly, because investors in marketplace loans have no contractual right to receive immediate repayment from the marketplace lending platform (instead, repayment is subject to the terms of the note issued by the platform to the investor and conditioned upon repayment by the ultimate borrower), the marketplace lending model does not appear to be susceptible to runs in the way that banks reliant on deposit funding are.[140] However, because of the opacity relating to the quality of individual marketplace loans and the algorithms used to judge them, any of the following might incentivize investors to panic and stop providing funding for *future* marketplace loans: concerns about the ability of the platforms' algorithms to select creditworthy borrowers, concerns that borrowers are defaulting on existing marketplace loans (particularly if such defaults are correlated),[141] and fears that secondary securitization market demand for marketplace loans is drying up. Marketplace lending has become an increasingly important source of funding for small business enterprises, many of whom roll over these loans in order to meet their funding needs,[142] so if investors were to retreat from renewing funding en masse, then that would harm those enterprises and hamper broader economic growth.[143] There could therefore be significant, tangible consequences if the complexity of marketplace lending algorithms render them impenetrable to regulators and market participants alike.

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[138] Nicola Gennaioli, Andrei Shleifer and Robert Vishny, *Financial Innovation and Financial Fragility* 5 (Fondazione Eni Enrico Mattei, Working Paper No. 114.2010, 2010).

[139] U.S. Department of the Treasury, Opportunities and Challenges in Online Marketplace Lending (2016).

[140] *See* Richard Scott Carnell, The Law of Financial Institutions 50–51 (5th ed. 2013). It is theoretically possible, though, that a P2P lender may refund investments for reputational reasons, just as Citibank did for investors in its Special Investment Vehicles (SIVs) during the financial crisis. This occurred without any legal obligation to do so, and such a course of action could impact the P2P firm's solvency. For a discussion of Citibank's treatment of SIVs during the financial crisis, see Financial Crisis Inquiry Commission, The Financial Crisis Inquiry Report, 380 (2011).

[141] The issue of "correlation by algorithm" will be examined in more detail in Part III.C.

[142] *See* Clozel, *supra* note 78.

[143] One industry participant has estimated that institutional investors now provide "80–90% of the capital deployed through Prosper and Lending Club." Nav Athwal, *The Disappearance of Peer-to-Peer Lending*, Forbes (Oct. 14, 2014), http://www.forbes.com/sites/groupthink/2014/10/14/the- disappearance-of-peer-to-peer-lending. "Institutional investors . . . may herd to avoid falling behind one another by picking the same stocks as each other." Lawrence A. Cunningham, *Behavioral Finance and Investor Governance*, 59 Wash. & Lee L. Rev. 767, 777–78 (2002).

B. Algorithms and Speed

The speed with which algorithms operate can also be a problem for financial stability: as Andrei Kirilenko and Andrew Lo wryly note, "whatever can go wrong will go wrong faster and bigger when computers are involved."[144] Financial algorithms can make and implement decisions too quickly for any human intervention (by their programmers, users or regulators), even when something clearly erroneous has occurred. The fact that algorithms work well most of the time can exacerbate this problem; as has been noted in the driverless car context, "[a] technology that works well right up to the point that it doesn't, particularly when that point demands the attention of a user who has lost concentration, represents a significant regulatory problem."[145] Algorithmically-increased transaction speeds also allow for an increased volume of transacting,[146] and increased volumes of transactions allow for institutions to contract with more counterparties, resulting in an even more interconnected financial system.[147] Increased transactional speed thus facilitates an environment where "the numerous linkages between financial institutions and products function as feedback loops that can speed up and amplify the transmission of shocks throughout the financial system."[148]

Issues resulting from the speed with which financial algorithms process data and respond have manifested most obviously in the context of high-frequency trading, with several algorithmic trading glitches (most notably the Flash Crash) sending financial markets haywire.[149] While such glitches have not yet caused irreversible systemic problems, that does not mean that they will not do so in the future. As I have noted in prior work, increased use of high-frequency trading algorithms can "build rigid feedback loops and tight coupling into the financial system, with the result that a shock in one asset class can be transmitted quickly through the equities markets and disrupt pricing and liquidity in other parts of the financial system in short order."[150] Similar problems could also arise in the robo-investment context: if algorithms were designed to execute trades on behalf of investors without any input from those investors (for example, if they automatically rebalance investor portfolios) and some glitch forced an en masse sale of a particular type of asset, then the price of that asset class would be depressed and financial institutions exposed to that asset class might be forced to sell other as-

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[144] Andrei A. Kirilenko and Andrew W. Lo, *Moore's Law versus Murphy's Law: Algorithmic Trading and Its Discontents*, 27 J. ECON. PERSPECTIVES 51, 52 (2013).
[145] Stilgoe, *supra* note 1, at 17–18.
[146] *See* Omarova, *supra* note 54, at 760–61.
[147] *See id.* at 775.
[148] *See* Allen, *supra* note 112, at 872.
[149] *See* Allen, *supra* note 27, at 738.
[150] *Id.* at 743.

sets in order to maintain their solvency. In this way, such a dynamic could ignite fire sales in a variety of different markets.

When algorithms facilitate the execution of transactions at such a pace, they preclude the exercise of reasoned human judgment and intervention. Such problems can arise not only when algorithms are making decisions about transacting in financial assets, but also when there is an algorithm embedded in the financial asset itself. However, the risks to financial stability that could arise from using smart contracts to speed up the execution of financial transactions have not yet been explored. These smart contracts are algorithms programmed to self-execute upon the receipt of the necessary instructions or data; for proponents of smart contracts, one of their greatest attributes is said to be their "immutability."[151] Unfortunately, the future operations of the financial system are uncertain in the Knightian sense, meaning that future outcomes and their probabilities are unknowable.[152] Because no algorithm can be programmed in advance to address all potential scenarios, subsequent changes may therefore be necessary to vary the operation of the smart contract.[153]

Legal systems interpreting *paper* financial contracts have developed the ability to relax and suspend contractual obligations in order to help preserve financial stability upon the occurrence of a significant unanticipated event.[154] As Katharina Pistor has noted, "in the context of a highly instable financial system, the elasticity of law has proved time and again critical for avoiding a complete financial meltdown."[155] Smart contracts have the potential to harm financial stability by depriving the financial system of some of its flexibility: to the extent that smart contracts are recorded and run on a decentralized distributed ledger, there is no one individual who can vary the preprogrammed operation of that contract[156]—even if the result diverges from the mutual intent of the parties thereto, as well as the public interest.[157] While smart contracts may not turn out to be as immutable as they claim to be (traditional *ex post* legal remedies may ultimately be able to be applied to force the alteration of the distributed ledger on which the smart contract is hosted in order to undo a transaction), the damage may already have been done as a result of the speed with which the smart contract executed its programming in the first place.

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[151] "Legal contracts contain ambiguity and permit formal and informal modifications, but smart contracts are drafted in exhaustive, precise code that seems to set the parties' obligations permanently." Cohney et al., *supra* note 93, at 615.

[152] *See* Pistor, *supra* note 107, at 316.

[153] Paper contracts rely on the legal system to perform this function: "Since the parties cannot foresee all contingencies, they can use vague contract terms to delegate to the courts the task of completing the contract ex post." Jody S. Kraus & Robert E. Scott, *Contractual Design and the Structure of Contractual Intent*, 84 N.Y.U. L. Rev. 1023, 1071 (2009).

[154] *See* Pistor, *supra* note 107, at 320.

[155] *Id.* at 321.

[156] *See* Werbach & Cornell, *supra* note 94, at 332.

[157] *See id.* at 318.

The hypothetical smart coco can be used to illustrate how problems might arise from this lack of flexibility.[158] If a smart coco were designed with a capital-based trigger (meaning that it were programmed to convert to equity as soon as the issuer's ratio of equity to risk-weighted assets fell below a predetermined level),[159] then conversion of the smart coco from debt to equity would be effected immediately upon it receiving information that the issuer's ratio had fallen below the specified level (information about the issuer's ratio would be drawn from an external source—an "oracle," in smart contract-speak).[160] Many large financial institutions use their own internal computer models to calculate their ratios of equity to risk-weighted assets;[161] if a smart contract were designed to communicate directly with the issuer's internal model, a glitch in the operation of that model could force an unwarranted conversion. Because conversion is viewed as undesirable and the trigger event for any coco is designed to be low-probability,[162] an erroneous conversion is likely to incentivize a panic that "is likely to manifest itself in the form of funding shortages for the coco issuer which will impact its ability to operate as a going concern."[163]

If the coco were evidenced by a paper contract, some form of human intervention would be required to effect the conversion, which would allow time for verification that the trigger had in fact been met. A self-executing smart contract would not allow for any such check, however—nor is it clear how a smart contract would respond to a subsequent correction of the oracle's information (unless it were preprogrammed to allow for reversals of conversion). If the smart contract were not programmed to reverse in response to being informed of a problem with the oracle (or if policymakers were to determine that conversion should be waived even if the oracle were correct, in the interests of avoiding a shock to the financial system), a reversal could only be carried out by altering the distributed ledger on which the smart contract was hosted to undo the transaction. Such a reversal would require the consensus of the majority of the nodes with the power to approve transactions on the ledger, and on a decentralized permissionless ledger, it may be hard to identify who those nodes are.[164] In the past, established bodies like court systems and central banks have acted to relax legal obligations to mitigate financial shocks, but their authority and jurisdiction over such

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[158] For an introduction to the possibility of a smart coco, *see* Allen, *supra* notes 108–09.

[159] A 2018 article in *The Economist* noted that while many cocos are set to trigger if their issuer's ratio of equity to risk-weighted assets falls below 5.125%, some cocos specify a trigger as high as 7%. *Coco Bonds Have Not Lived Up to Their Promise*, THE ECONOMIST (Apr. 21, 2018), https://www.economist.com/finance-and-economics/2018/04/21/coco-bonds-have-not-lived-up-to-their-promise.

[160] "In the language of smart contracts, systems that interpret such external fees and verify contractual performance are called 'oracles.'" Werbach & Cornell, *supra* note 94, at 336.

[161] *See* Gerding, *supra* note 134, at 375.

[162] *See* Hilary J. Allen, *Cocos Can Drive Markets Cuckoo*, 16 LEWIS & CLARK L. REV. 125, 156 (2012).

[163] *Id.*

[164] *See* Werbach & Cornell, *supra* note 94, at 373–74.

nodes is likely to be unclear.[165] The result would be a more rigid financial system that is more prone to meltdown.[166]

Abstracting away from our smart coco to financial assets more generally, new sources of systemic risk will be introduced into the financial system by any widely-adopted financial asset that is comprised of a smart contract that speedily and rigidly self-executes.[167] While there may ultimately be more opportunities to vary a smart contract's operation[168]— and more opportunities for legal institutions to adjudicate on the outcome of smart contracts[169]—than proponents of smart contracts care to admit, there will still be uncertainties about when the operation of the smart asset can be changed and challenged, and by whom. The power to vary the operation of a smart contract (by altering the distributed ledger on which transactions relating to the smart contract are recorded) will typically lie with a group of validators. To the extent that the ledger is decentralized and permissionless, coordination and jurisdictional issues may create uncertainty as to whether and when those validators will in fact alter the ledger.[170]

Following an unanticipated event, uncertainty about the operation of a widely-used financial asset comprising a smart contract could paralyze the use, and thus the liquidity, of that asset class (as well as any linked asset classes such as derivatives that reference it). Highly leveraged institutions with significant exposure to such assets might then need to sell those and other assets, potentially depressing asset prices system-wide (a so-called "fire sale externality").[171] The confluence of increased speed and correlation is likely to cause significant damage in these circumstances—the next section will focus in more detail on the role of algorithms in increasing correlation in financial decision-making.

C. Algorithms and Correlation

A panicked fire sale is just one example of "herding," a well-documented phenomenon that is inimical to financial stability. When market par-

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[165] *See* Cohney et al., *supra* note 93, at 611.

[166] *See* Pistor, *supra* notes 154–55 and accompanying text (discussing legal theory of finance).

[167] Pistor notes that in order to avoid systemic failures, safety valves are needed to make financial contracts more elastic when there has been a significant change in circumstances such that "one of the parties cannot reasonably be expected to uphold the contract without alteration." Pistor, *supra* note 107, at 329.

[168] It is clear from the SEC's report on its investigation of the DAO, for example, that the programmers and validators were able to change the protocol of the distributed ledger to return virtual currency to persons from whom it had been stolen. *See* SEC, *supra* note 105, at 9.

[169] *See* Werbach & Cornell, *supra* note 94, at 42–43. The authors argue that smart contracts have no mechanism for addressing grievances after performance of the contract, and that the courts will continue to fill such a role. *See id.*

[170] *Cf.* Reyes, *supra* note 94, at 411–13.

[171] *See* Markus K. Brunnermeier, *Deciphering the Liquidity and Credit Crunch 2007-2008*, 23 J. ECON. PERS. 77, 94 (2009).

ticipants behave in a correlated manner, such participation will often lead to suboptimal outcomes for the financial system as a whole. In particular, herding causes problems by inflating asset bubbles in good times and exacerbating panics—which can take the form of runs, as well as fire sales of assets—once a shock occurs.[172] One concern that has been raised about robo-investing in particular is the potential for algorithms to exacerbate tendencies towards herd behavior by making preferences more monolithic: when financial decision-making is automated and performed by a few algorithms rather than a crowd of individuals,[173] market behavior is likely to become even more correlated.[174] If robo-investing algorithms are "sticky" (in the sense that once an algorithm has been programmed, there is a general unwillingness to tinker too much with its operation),[175] preferences are likely to remain correlated, even when circumstances change. While humans also demonstrate tendencies towards path dependency, the switching costs are presumably lower for changing one's mind than they are for calling in the engineers to reprogram an algorithm in light of changed circumstances.

As Tom Baker and Benedict Dellaert note, "the potential solvency and systemic risks posed by hundreds of thousands, or even millions, of consumers choosing their financial products based on the same or similar models are sufficiently large and different in kind from those traditionally posed by consumer financial product intermediaries to justify regulatory attention."[176] Robo-investing algorithms currently work by assigning an investor to a particular risk profile (FINRA recently surveyed firms and found that "most establish between five and eight investor profiles"), and constructing portfolios for each of those profiles.[177] Here, economies of scale make financial advice cheaper for investors, but also allow algorithms to influence the behavior of far larger groups than would be possible for a single human financial advisor. Obviously, such an approach will correlate investments more than if individualized portfolios were constructed for each customer.[178] In order to avoid the need for costly interpersonal meetings, many robo-investing firms distribute questionnaires to investors online and use the question-

[172] *See* Erik F. Gerding, Law, Bubbles and Financial Regulation 38–43 (2014).

[173] The fintech industry tends towards dominant market players with commanding market share—a so-called "winner-take-all" market. *See* William J. Magnuson, *Regulating Fintech*, Vand. L. Rev. 1167, 1212 (2018).

[174] *See* FSB Fintech Report, *supra* note 12, at 20; *see also* Baker & Dellaert, *supra* note 58, at 742. High-frequency trading algorithms also tend to "react to market events in a herd-like fashion." Allen, *supra* note 27, at 743.

[175] *See* Bamberger, *supra* note 27, at 710–11.

[176] Baker & Dellaert, *supra* note 58, at 713. *See also* Van Loo, *supra* note 18, at 235 (noting that "if advisory fintechs gave similar advice to large numbers of consumers, they could produce their own kind of unpredictable mass market movements" akin to prior systemic risk concerns).

[177] *See* FINRA, *supra* note 60, at 6.

[178] If robo-investing algorithms are developed by third-party vendors rather than in-house, portfolios even across robo-investing platforms may become correlated.

naires as the exclusive basis for their investment recommendations.[179] Such an approach may further increase correlation amongst investment portfolios, to the extent that it reduces the characteristics of individual investors to fewer datapoints.[180] Of course, there are also limitations on the ability of a human investment advisor to gather a complete picture of their clients' needs, but a good argument can be made that the risks of oversimplification and misunderstandings are greater "when advice is provided using an automated tool than advice provided with human interaction, because of a reduced ability to clarify misunderstandings and ask questions."[181] The absence of a human contact may also make it more likely that consumers will fail to advise their robo-investing platform as their personal circumstances change.[182] Notwithstanding that human financial advisers can provide more personalized advice than the current crop of robo-investing platforms, it may prove difficult for human advisers to compete with the cost savings associated with more automated advice models—this may speed the trend towards correlation by algorithm.[183]

As robo-investing platforms increasingly adopt machine learning techniques, some forms of correlation may be mitigated. A machine learning algorithm may be able to continually search the internet for many different types of data to inform its understanding of an individual client's ideal investment portfolio, and it may therefore be able to provide more personalized advice than current robo-investing models.[184] A machine learning algorithm may also be able to learn from changes in the markets and adjust its decision-making accordingly. However, it is impossible to predict what machine learning algorithms will do with the personal and market data they glean;[185] it is also unclear what data set will they use to learn what constitutes a good or bad financial decision in any given circumstance. To the extent that all of the robo-investing algorithms are learning from the same data set of historical market information, they are likely to learn to react in correlated ways.[186] Machine learning algorithms also tend to learn

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[179] *See generally*, SEC, Pub No. 2017–02, Investment Management Guidance Update: Robo-Advisers 1 (Feb. 2017).

[180] *See* European Banking Authority, Pub No. JC 2015 080, Joint Committee Discussion Paper on Automation in Financial Advice 14 (2015). Such data points might include "the investor's tax situation, marital or relationship status, the investor's career and retirement plans, what other investments and assets the investor has, the investor's financial resources and commitments, and the investor's plans for their family in the short and longer term." *Id.* at 14.

[181] *Id. at* 22.

[182] *See id.* at 22-23.

[183] *See* Benjamin P. Edwards, *The Rise of Automated Investment Advice: Can Robo-Advisers Rescue the Retail Market*, 93 Chi.-Kent L. Rev. 97, 106 (2018).

[184] *Cf.* FSB AI Report, *supra* note 6, at 30.

[185] *See id.*

[186] *See* Mattioli, *supra* note 1, at 284 (discussing machine learning and training data in the autonomous vehicle context).

probabilistically,[187] meaning there is a real concern that such algorithms will consistently underemphasize low-probability but potentially high-consequence risks in choosing investment strategies.

If different robo-investing algorithms behave in consistent ways,[188] or if a few robo-investing platforms (and their algorithms) achieve market dominance,[189] then that could create the conditions for both bubbles and panics.[190] A bubble could form, for example, if numerous consumers are advised to invest in the same financial portfolio, or if they are steered to a particular asset by an algorithm that underestimates the asset's associated risks. If that same algorithm advises selling assets, then the occurrence of that event could have a sudden impact on the price of those assets system-wide, and depressed asset prices might force other market participants to sell other assets to deleverage. This would create problems for asset pricing in general and the stability of the financial system as a whole.[191] Even if the algorithm doesn't advise selling, individuals with correlated portfolios may still panic and do so: "each acting individually but, as a group, influencing asset prices and affecting the trading decision of others."[192] This bubble-bust dynamic would be particularly acute in the event that the relevant algorithms were not programmed (or did not learn) to perceive the initial stages of disenchantment with an asset. In such a situation, they might continue to recommend buying as usual (without adjusting for stressed market conditions) until conditions become so fraught as to trigger a panicked response from either the algorithm or investors.[193]

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[187] *See* Tutt, *supra* note 5, at 90.

[188] In the context of high-frequency trading, Yadav has noted that algorithms are often based on similar assumptions, and thus often react to market events in a herd-like fashion. *See* Yadav, *supra* note 122, at 1625. Correlated behavior is also likely to result because the development of machine learning for use in robo-investing applications is currently dependent on a "relatively small number of third-party technological developers and service providers." FSB AI Report, *supra* note 6, at 27.

[189] Van Loo notes that extreme concentration is endemic in digital markets, "in which as few as two or three companies capture the bulk of the market." Rory Van Loo, *Digital Market Perfection*, 117 MICH. L. REV. 815, 828 (2019). In its recent report on fintech, the Treasury Department also noted the network effects that are likely to lead to a concentrated market: "models that have a large market presence, therefore, have a built-in self- reinforcing advantage as their gains in market share improve the model's performance, which could in turn further their gain in market share." Treasury Report, *supra* note 17, at 57.

[190] Baker and Dellaert have noted that "as robo advisors gain scale, there may be collective action problems that arise from ranking and matching services that are individually rational but have perverse consequences for financial product markets." Baker & Dellaert, *supra* note 58, at 743.

[191] *See* Brunnermeier, *supra* note 171, at 94.

[192] *See* Charles K. Whitehead, *Destructive Correlation*, 96 CORNELL L. REV. 323, 347 (2011).

[193] *See* Mattioli, *supra* note 29 and accompanying text (discussing algorithms and edge cases in the autonomous vehicle context).

Excessive correlation may even undermine a robo-investing algorithm's own internal logic:[194] many robo-investing algorithms are based on economic theories (like modern portfolio theory) that have embedded assumptions, particularly about the use of diversification to manage risk.[195] However, diversification is unable to address systematic risks that affect the entire market. If investments are increasingly channeled towards just a few large asset classes (as a result of instructions from the same or similar algorithms), then it will become increasingly likely that a problem with one large asset class will impact investor sentiment about other large asset classes. This type of risk cannot be diversified away, leaving correlated portfolios more susceptible to a shock to the financial markets. This is not just a retail investor issue, either—sophisticated hedge funds are also increasingly relying upon machine learning to inform their trading decisions.[196]

Correlation by algorithm could also result from the marketplace lending business model. Here, firms like Prosper and Lending Club use algorithms to screen potential borrowers and tout their resulting ability to approve borrowers who would not qualify under traditional FICO assessments (through origination and servicing fees, they also profit from approving increased volumes of loans).[197] In an industry where only a few firms (and their algorithms) dominate,[198] there is the possibility that using an algorithm to make credit decisions could result in credit being channeled consistently to the same type of borrower, whereas there might be more variation in approval decisions if credit approvals were based on judgments by different human beings. Correlations in these algorithms' assumptions about who should and should not qualify for credit could have broader systemic implications if they systematically underestimate or misprice the risk associated with a particular type of borrower (particularly if credit approval algorithms are capable of machine learning and learn to become more lax in response to data about the declining interest rates of other lenders, which could result in a race to the bottom).[199]

Correlation by algorithm could also arise in other (perhaps as yet unimaginable) contexts. The Financial Stability Board has already started to urge caution in light of the fact that many of the machine learning applications that have been developed to date rely on a "relatively small number of

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[194] As Whitehead put it, coordination "can erode key presumptions underlying financial risk management, reducing its effectiveness and magnifying a systemic impact of a downturn in the financial markets." Whitehead, *supra* note 192, at 326.

[195] FINRA, *supra* note 60, at 3–4.

[196] FSB AI Report, *supra* note 6, at 18–19.

[197] *See* Andrew Verstein, *The Misregulation of Person-to-Person Lending*, 45 U.C. Davis L. Rev. 445, 469 (2011).

[198] For a discussion of market concentration, see FSB AI Report, *supra* note 6.

[199] To illustrate the plausibility of such a scenario, one can consider the instance where "the price of a book, *The Making of a Fly* by Peter Lawrence, ballooned on Amazon from a few dollars to over twenty-three million dollars because each of two sellers of the item had algorithmically set its price in relation to the other." Yadav, *supra* note 122, at 849.

third-party technological developers and service providers."[200] A single glitch or operational failure could thus impact many otherwise disparate financial service providers. Even if the impact of such a glitch or operational failure were confined to one or a few institutions, uncertainty about the reliability of technology may be sufficient to damage confidence in otherwise unaffected financial institutions. When a financial institution relies heavily upon short-term debt to fund its operations (as many do), a loss of confidence can imperil the continuing availability of that funding, and potentially result in the insolvency of the institution.[201] Correlation by algorithm (whether actual or perceived) is therefore a trend to be watched with care. As the next section will explore, increased reliance on algorithms for financial decision-making may also cause other (more indirect but still problematic) consequences for the stability of our financial system.

D. Algorithms and Industry Culture

Morality is broadly relevant to any discussion of financial stability: even when not fraudulent, many of the behaviors that generate financial crises evince a disregard for the impact of negative externalities on other members of society.[202] There is therefore a place in financial stability regulation for reforms that seek to engender industry-wide cultural norms that can act as a disciplinary force, creating an environment in which financial industry personnel will consider the long-term impact of their risk-taking on society as a whole.[203] Since the 2008 financial crisis, the Federal Reserve Bank of New York, the United Kingdom's Financial Conduct Authority, and many other central banks and financial regulators have been particularly vocal about the importance of shaping institutional cultures in a way that promotes financial stability.[204] Interesting questions are raised about cultural reform, however, when algorithms (which operate by way of on-off rules and linear and logical progressions of decision trees) start to take over tasks that would have in the past been completed by human beings.

Regulatory initiatives aimed at improving financial industry culture have certainly been critiqued. Questions have been raised about whether such efforts will be effective, or whether they are ultimately a distraction

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[200] FSB AI Report, *supra* note 6, at 27.

[201] *See* Allen, *supra* note 108, at 862.

[202] *See* Allen, *supra* note 112, at 870.

[203] "[U]nethical cultures have been recognized as a risk for the global financial system." John M. Conley et al., *Can Soft Regulation Prevent Financial Crises?: The Dutch Central Bank's Supervision of Behavior and Culture*, 51 Cornell Int'l L. J. 773, 777 (2019).

[204] *See id.* at 777. For example, the Financial Conduct Authority has suggested that the efforts of the financial industry might be better channeled towards the public good if firms take steps "to enhance employees' understanding of how their work has a real world impact . . . to ensure that employees do not regard their work as simply 'numbers on a screen,' but acknowledge the importance of a well-functioning finance sector for the wider economy." Financial Conduct Authority, Behaviour and Compliance in Organisations 35 (Dec. 2016), https://www.fca.org.uk/publication/occasional-papers/op16-24.pdf.

from more concrete regulatory efforts. Gwendolyn Gordon and David Zaring, for example, have argued that "if the question is how to ensure a stable banking system, the answer is unlikely to lie solely—or even much—in the embrace of ethics by bankers."[205] Regulators implementing programs targeted at industry culture should undoubtedly be mindful of the limits of cultural change in promoting financial stability and the limits on their ability to effect cultural change at all. However, other forms of regulation are limited too: it is impossible to prescribe rules for every potential context and contingency, and so discretion must therefore be left to financial industry personnel to make appropriate decisions as new situations arise. I have argued that the limitations of regulation justify actively pursuing attempts to render the financial industry more cognizant of the impacts of its risk-taking on others—notwithstanding that such attempts will be exceedingly challenging and will not obviate the need for other, more concrete financial stability regulations.[206] More recently, Chris Brummer and Yesha Yadav have argued that the need for industry self-governance will only become more acute as technology outpaces regulators.[207]

The Dutch central bank's Behavior & Culture supervision initiative, intended to address culture "not as a mere component of legal compliance but as an independent phenomenon with the capacity to cause inappropriate risk-taking by financial institutions," is a promising step in this direction.[208] However, the ability of a good corporate culture to discipline risk-taking is dependent on "social approval, disapproval, praise or embarrassment," as well as esprit de corps, in shaping behavior.[209] These mechanisms are based on human emotions and experiences and, as more and more decisions are delegated to algorithms, the disciplining power of a good corporate culture will be lessened. As a result, the impact of hard-fought regulatory efforts to inculcate a good corporate culture will be further limited.[210]

In particular, the organizational culture literature has recognized certain phenomena like "ethical fading" and "moral self-licensing" that contribute to immoral or unethical behavior within businesses. Increased reliance on algorithmic decision-making is likely to exacerbate the likelihood of such phenomena occurring. Ann Tenbrunsel and David Messick have described "ethical fading" as a phenomenon whereby individuals are able to engage in self-deception as to their culpability, and thus avoid the disciplining impact

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[205] Gwendolyn Gordon & David Zaring, *Ethical Bankers*, 42 J. Corp. L. 559, 586 (2017).

[206] *See* Allen, *supra* note 112, at 909.

[207] Chris Brummer & Yesha Yadav, *Fintech and the Innovation Trilemma*, 107 Geo. L. J. 235, 243 (2019).

[208] Conley, *supra* note 203, at 7.

[209] Andrew W. Lo, *The Gordon Gekko Effect: The Role of Culture in the Financial Industry*, 22 Econ. Pol. Rev. 17, 19 (2016).

[210] "[W]ith greater electronic connectivity—and less actual in-person connection—the basic human ties that foster self-restraint and greater trust may be lost." Tom Glocer, *The Effect of Technology on Bank Culture,* Bank Innovation (Oct. 19, 2016, https://bankinnovation.net/2016/10/the-effect-of-technology-on-bank-culture/.

of beneficial cultural and social norms, "because psychological processes *fade* the 'ethics' from an ethical dilemma."[211] Once the ethics have been drained from the decision making context, "individuals can behave in a self-interested manner and still hold the conviction that they are ethical persons."[212] Some of the mechanisms identified by Tenbrunsel and Messick as facilitating this self-deception are likely to be exacerbated by increased reliance on algorithms. For example, they note that an actor is more likely to avoid a sense of moral responsibility when engaging in acts of omission, rather than commission.[213] Viewed in this light, increased reliance on algorithms may result in less ethical behavior from people who rely on algorithms to discharge their functions, because the more that decision-making is delegated to algorithms, the more the decision makers can divorce themselves from responsibility for the outcomes of those decisions.[214] This phenomenon is already manifesting in finance: at the Federal Reserve Bank of New York's 2016 conference on "Reforming Culture and Behavior in the Financial Services Industry," participants raised the concern that "if new technology can flag technical non-compliance, is there a risk that employees will conflate an automated answer with an ethical decision?"[215] Indeed, psychological research suggests that not only the actors themselves, but even unrelated third parties, may be more likely to judge the actors more leniently when the unethical action has been delegated to an algorithm.[216] This exempts the actors from any opprobrium which might otherwise have caused them to have more regard for the implications of their actions.

Ethical fading may also be an issue for the coders who program the algorithms, in addition to the people who work alongside the algorithms. Programmers may delude themselves as to the acceptability of the internal workings of the algorithm on the grounds that if the past practices were ethical and acceptable, then practices that are similar and not too different are also acceptable. However, "a series of these small steps can lead to a journey of unethical and illegal activities."[217] If programmers do not con-

[211] Ann E. Tenbrunsel & David M. Messick, *Ethical Fading: The Role of Self-Deception in Unethical Behavior*, 17 Soc. Just. Res. 223, 224 (2004).

[212] *Id.* at 225.

[213] "Acts of omission . . . blur the assignment of responsibility, can create self-biased perceptions of causes, shifting blame from self to others. In such circumstances, it is highly likely that individuals' propensity to engage in unethical behavior increases, because shifting responsibility to others allows one to divorce oneself from the moral implications of their actions." *Id.* at 230.

[214] Tutt notes that "(1) algorithmic responsibility will be difficult to measure; (2) algorithmic responsibility will be difficult to trace; and (3) human responsibility will be difficult to assign." Tutt, *supra* note 5, at 105.

[215] Fed. Reserve Bank of N.Y., Reforming Culture and Behavior in the Financial Services Industry: Expanding the Dialogue 18 (2016), https://www.newyorkfed.org/medialibrary/media/governance-and-culture-reform/2016-Culture-Conference-Overview.pdf.

[216] *See* Max H. Bazerman and Ann E. Tenbrunsel, *Ethical Breakdowns*, Harv. Bus. Rev., Apr. 2011, at 9–10. Kroll et al. note that "decisions made by computers may enjoy an undeserved assumption of fairness and objectivity." Kroll *et al.*, *supra* note 123, at 680.

[217] Tenbrunsel & Messic, *supra* note 211, at 228.

sider the impact of small incremental tweaks that they make to an algorithm, simply because those tweaks are small and incremental, they will disregard the collective impact that those changes may have on financial stability. Tenbrunsel and Messick also argue that using "cold language" that disguises the human cost of business decisions is also effective in promoting ethical fading.[218] Algorithmic programming uses even more dehumanized computer programming languages to effect outcomes, which may further disguise the human impact of the algorithm's processes. Decisions that do not contemplate their potential impacts on financial stability may thus become even more likely as algorithm-reliant business models become increasingly prominent.

The phenomenon of "moral licensing" may also be exacerbated by increased reliance on algorithms. "Moral self-licensing occurs when evidence of a person's virtue frees him or her to act less-than-virtuously,"[219] and can manifest at the organizational, as well as the individual, level.[220] At the organizational level, the result is that some people may consider themselves licensed by the good deeds performed by in-group members, and thus feel free to neglect ethical concerns without feeling any compunction in their own self-regard or in shame from others.[221] Prosocial behavior—like consideration by a financial institution employee of the impact of his or her activities on financial stability—can thus be rendered less likely when there is some kind of outward "proof" of the virtue of the employee, or the institution as a whole.[222] If algorithms are seen to be making virtuous decisions (particularly in terms of managing risks), then increased reliance on algorithms could also result in a moral licensing effect, increasing the propensity of human employees to disregard the impact of their own activities on financial stability.

The FCA has recognized that undesirable behavior might be easier for humans to justify in environments of ambiguity and complexity—because "unclear rules permit self-serving interpretations"[223]—as well as in environments where the impact of the undesirable behavior is far removed from the

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[218] *Id.* at 227.

[219] Daniel A. Effron & Paul Conway, *When Virtue Leads to Villainy: Advances in Research on Moral Self-Licensing* 6, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=92587652.

[220] *See id.* at 5.

[221] *See id.* at 6.

[222] In a recent paper exploring the relevance of psychological findings for compliance in financial institutions, the FCA situated this phenomenon of moral licensing in the financial regulatory context by giving the example of the pre-Crisis FSA's practice of vetting individual financial employees to determine their fitness and propriety to perform their roles. In hindsight, the FCA noted that "it is likely that the FSA taking on responsibility for vetting staff ethics gave the impression that firms did not have to make such considerations themselves, leading to a reduction in the internal incentives that could have restrained rule breaking." *See* Financial Conduct Authority, *supra* note 204, at 25.

[223] *Id.* at 22.

actor in question.[224] Decisions about financial stability are already plagued by issues of complexity and causation, and the calculus is likely to become even more complicated and attenuated as algorithms become increasingly responsible for financial decision-making. Furthermore, it will be harder to convey the real-world impact of decision-making to the humans working in the financial industry if their decisions are further intermediated by complex algorithmic decision-makers. Attempts that are afoot to discipline financial risk-taking using virtuous cultural and social norms are therefore likely to be undercut by increased reliance on algorithms. Where algorithms are capable of machine learning, if they are programmed to learn from the decisions of humans who do not prioritize financial stability (perhaps because of ethical fading and moral licensing effects resulting from increased reliance on other algorithms), then this will exacerbate cultural disregard for financial stability in a vicious cycle. For example, a machine learning algorithm might learn from humans that it should consistently "nudge" customers into financial products and services that generate higher margins for the algorithm's proprietor by obscuring the true costs and risks of a product, potentially contributing to a bubble.[225]

Before concluding this pessimistic discussion, it should be acknowledged that I have made the assumption throughout this section that algorithms are incapable of things like empathy, shame and embarrassment that can work to enforce human compliance with cultural and social norms. Although it is currently a subject of hot philosophical and technological debate whether artificial intelligence may someday become capable of empathy,[226] that debate is well beyond the scope of this Article. Here, it suffices to say that although algorithms are already learning to mimic certain aspects of human empathy,[227] it seems likely that the finance industry's increasing reliance on algorithmic processing power will far outpace the development of any genuine algorithmic empathy, circumscribing the impact of regulatory efforts to improve industry culture.

E. Other Concerns Regarding Algorithms and Regulatory Efficacy

Many of the financial stability concerns raised in this Part are simply not susceptible to solutions by private sector means. It is just not possible to

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[224] *See id.* at 23 ("In wholesale markets the negative consequences of rule breaking may appear to be numbers on a screen, even though they can have large impacts on end consumers.").

[225] *See* Rory Van Loo, *Rise of the Digital Regulator,* 66 DUKE L.J. 1267, 1277, 1290 (2017).

[226] *See* Christopher Lum, *Artificial Empathy: The Next Frontier*, ASIAN SCIENTIST (Jul. 17, 2017), https://www.asianscientist.com/2017/07/features/aswp2017-artificial-empathy/.

[227] *See* Natasha Lomas, *Can An Algorithm Be Empathetic? UK Startup EI Technologies is Building Software That's Sensitive to Tone of Voice,* TECHCRUNCH (Aug. 4, 2013), https://techcrunch.com/2013/08/04/empathy/.

program an algorithm to "promote finance stability"[228]: while a programmer can thoroughly check their algorithms and data sets for bugs and take the possibility of tail risks seriously, their appreciation of possible tail risks is limited without sensitive data about the functioning of other market participants.[229] Even an unusually altruistic creator of an algorithm would therefore face limitations on their ability to avoid systemic risk.[230] Financial stability regulators, however, often have powers that enable them to gather the necessary information, and mandates to use that information to make determinations about emerging systemic risks and how to deal with them. Regulators therefore have an important role to play in addressing the increasing automation of financial services.[231] However, innovation in financial algorithms will undoubtedly make their jobs more challenging.[232]

Financial regulators are used to supervising humans with a business and financial background; although financial firms have long used computer models to help manage risks, the output of those models could be construed as a recommendation that was ultimately acted upon by a human being. The increasing automation of decision-making in the financial industry represents a shift that raises challenging questions for regulators about supervision, liability, and enforcement.[233] In terms of supervision, past experience in supervising financial institution compliance functions may no longer give much guidance to the next generation of regulators, to the extent that compliance systems will increasingly have to be varied to oversee decision-making by algorithms rather than humans.[234] In a similar vein, regulatory judgments about the quality of management will have to be adjusted to take into account the challenges that non-technical directors and senior managers will face in overseeing the technological operations of their firms.[235]

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[228] At present, technology limits a programmer's ability to tie computer logic to the achievement of amorphous policy goals. *See* Kroll et al., *supra* note 123, at 646.

[229] *See* Chris Brummer, *Disruptive Securities Regulation*, 84 Fordham L. Rev. 977, 1043 (2015).

[230] In reality, because programmers of financial algorithms (and their employers) cannot appropriate the benefits of financial stability to themselves, there are abundant incentives to ignore systemic risks, and indeed to rush an algorithm to market without fully testing it in order to gain a competitive advantage. *See* Awrey, *supra* note 111, at 263.

[231] "Systemic risk regulation is an example where regulators cannot look to private regulatory strategies. Regulators cannot expect that private actors will be capable of identifying how the actions of individual firms may make the financial system less stable." Eric J. Pan, *Understanding Financial Regulation*, 4 Utah L. Rev. 1897, 1941 (2012).

[232] *See* Brummer & Yadav, *supra* note 207, at 29.

[233] *See* Chiu, *supra* note 66, at 92. For a discussion of algorithms, artificial intelligence and liability in other contexts, see Jack M. Balkin, *The Three Laws of Robotics in the Age of Big Data*, 78 Ohio St. L. J. 1217 (2017); Vladeck, *supra* note 1.

[234] European Banking Authority, *supra* note 181, at 28. If compliance personnel are not able to communicate what they need in terms that a computer programmer would understand, and skilled programmers lack sufficient understanding of financial risk-management and legal requirements to spearhead such an effort themselves, then the compliance function will also be compromised. *See* Bamberger, *supra* note 27, at 708.

[235] *See* Glocer, *supra* note 210; FSB AI Report, *supra* note 6, at 34.

Enforcement strategies will also be affected by the increasing automation of finance. There are already enormous difficulties in using sanctions to deter harmful destabilizing behaviors by humans working in the financial industry, largely because of the difficulties in establishing intent and causation sufficient to punish a particular individual.[236] Policing destabilizing behaviors becomes even more abstracted if the judgment calls are not even being made by humans, but instead by an algorithm programmed by humans (or—even more abstracted—by an algorithm capable of machine learning).[237] Regulatory attention will naturally shift to the financial institution employees who design and train the algorithms, but financial stability regulators have little experience in dealing with computer programmers and data scientists, and this is likely be a challenging transition (questions also abound about the liability of financial institutions when the harm can be traced back to technology developed by a third party vendor).[238] In some instances, it may not even be possible to discern the person (or persons) responsible for a particular algorithm. A smart contract embedded in a financial asset, for example, could be created and maintained by a loosely connected group of anonymous programmers with no well-delineated legal relationship to each other or the asset.[239]

Increased automation of finance may also undermine macroprudential regulatory strategies adopted in the wake of the 2008 financial crisis to promote financial stability. While this "macroprudential toolkit" can be conceived of in different ways, it certainly includes regulatory capital requirements, liquidity requirements, and stress tests, amongst other things.[240] These tools will struggle with autonomous algorithmic finance. For example, entirely new classes of smart assets can be created out of whole cloth by anyone with computer programming knowledge—there is no real limiting factor on the supply of these assets, which exponentially multiplies their potential risks.[241] There will be considerable uncertainty about how to

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[236] *See* Allen, *supra* note 112, at 909–10.

[237] Vladeck observes that "society will need to consider whether existing liability rules will be up to the task of assigning responsibility for any wrongful acts [that fully autonomous machines] commit." Vladeck, *supra* note 1, at 121. He has even raised the intriguing possibility of conferring legal personhood on autonomous intelligent machines to allow them to be held liable for their decision-making. *See id.* at 150.

[238] *See* FSB AI Report, *supra* note 6, at 26.

[239] *See* Marcel T. Rosner & Andrew Kang, *Understanding and Regulating Twenty-First Century Payment Systems: The Ripple Case Study*, 114 MICH. L. REV. 649, 663 (2016).

[240] *See* Ben S. Bernanke, Chairman, Bd. of Governors of the Fed. Reserve Sys., Remarks at the Federal Reserve Bank of Chicago 47th Annual Conference on Bank Structure and Competition, Implementing a Macroprudential Approach to Supervision and Regulation (May 5, 2011), http://www.federalreserve.gov/newsevents/speech/Bernanke 20110505a.pdf. These tools seek to strengthen the financial system as a whole by controlling defaults and credit crunches and reducing the risk of fire sales. *See* Anil K. Kashyap, Richard Berner and Charles A.E. Goodhart, *The Macroprudential Toolkit*, 59 IMF ECON. REV. 145–46 (2011).

[241] Omarova notes that cryptoassets are "(a) untethered from, and thus unconstrained by, any productive activity in the real economy and (b) tradable in potentially infinitely scalable virtual markets." Omarova, *supra* note 54, at 742.

assess the risks associated with those assets, and thus about the levels of regulatory capital and liquid assets that an institution with exposure to those assets should be required to maintain.[242] Even the regulatory capital and liquidity requirements applied to more traditional asset classes may turn out to be miscalibrated, as a result of unappreciated correlations amongst asset classes arising from more uniform algorithmic financial decision-making models. If these requirements are indeed miscalibrated, then that would increase the likelihood that financial institutions are insufficiently cushioned against a financial shock. The result would be that if that shock were to occur, institutions would be forced to engage in asset fire sales that depress asset prices system-wide—or become insolvent.

Macroprudential regulation also requires ongoing monitoring of the financial system for evolving risks to stability;[243] the complexity and speed of algorithmic transacting will make this already confounding task even more challenging. The predictive capacity of stress tests, for example, may be undermined because hypothetical stress test scenarios created without the benefit of experience of an automated financial system failure may not tell regulators much about how the system will fare when something goes awry in the future. If something does go wrong, the increasingly automated nature of finance may also undermine the ability of regulators to mitigate panic by disrupting the mechanisms by which a shock is transmitted through the system.[244] Emergency measures like circuit breakers, for example, may not be able to be deployed in time to force market participants to take a collective pause and make a more rational assessment of market prices and risks.[245] Regulators and central banks have sometimes used communications strategies to restore confidence and prevent panic selling in the past,[246] but it is unclear how strategies designed to appeal to human sentiment will be interpreted by algorithms. It is even unclear how algorithms will respond to more concrete actions like bail-outs or guarantee schemes: will they be program-

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[242] The Basel Committee on Banking Supervision, an international standard setter that develops prudential rules relating to banks' exposure to different asset classes, is considering whether to "whether to formally clarify the prudential treatment of crypto-assets across the set of risk categories." FINANCIAL STABILITY BOARD, CRYPTO-ASSETS: REPORT TO THE G20 ON WORK BY THE FSB AND STANDARD-SETTING BODIES 7 (Jul. 16, 2018), http://www.fsb.org/wp-content/uploads/P160718-1.pdf.

[243] *See* Bernanke, *supra* note 240.

[244] Anabtawi & Schwarcz have observed that *ex post* financial stability measures tend to take the form of providing financial safety nets (whether by providing financial support to a firm or purchasing assets to support market pricing), and disrupting the mechanisms by which risks are transmitted through the system. *See* Iman Anabtawi & Steven L. Schwarcz, *Regulating Ex Post: How Law Can Address the Inevitability of Financial Failure*, 92 TEX. L. REV. 75, 77 (2013).

[245] *See id.* at 117–18 (discussing circuit breakers).

[246] *See* Douglas R. Holmes, *Communicative Imperatives in Central Banks*, 47 CORNELL INT'L L.J. 15, 33 (2014).

med to recognize and respond favorably to such emergency intervention?[247] While politically unpalatable, many believe that such measures are sometimes necessary to prevent problems in the financial system from pushing the economy into a depression[248]—the rise of driverless finance may limit the efficacy of future bailouts as a method of quelling market panics, however. As they are increasingly forced to reckon with driverless finance, financial stability regulators will find themselves in the unenviable position of having to reassess much of what they know about how the financial markets function.

IV. Implications for Regulatory Policy

Regulators face significant challenges as they approach nascent technologies, which are often shrouded in Knightian uncertainty[249] (in the sense that the potential risks associated with such technologies and their probabilities are unknown, and therefore rational assessments of risks cannot be calculated).[250] There is always the concern that early regulation will stifle beneficial innovation, but waiting for affirmative proof of a technology's risks before addressing them can be very costly for society—in some contexts, such costs can be catastrophic and irreversible.[251] Furthermore, if "the public's interest [remains] entirely unrepresented during the industry's formative period,"[252] regulators will face challenges in altering the workings of a technology once it is operational.[253] This Article has therefore argued that, in the context of increasingly automated algorithmic finance, early regulatory intervention is vitally important—notwithstanding limitations on regulators' ability to precisely identify and quantify the potential impacts of such risks, and notwithstanding benefits that will potentially be foregone.[254]

In terms of foregone benefits, most of the excitement about algorithm-driven business models like marketplace lending and robo-investing is driven by the promise of increasingly efficient and inclusive financial services.[255] If financial stability regulation attempts to curb the use of increas-

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[247] For a discussion of how such mechanisms have been deployed to restore confidence in assets and stabilize the financial system, *see* Anna Gelpern & Erik F. Gerding, *Inside Safe Assets*, 33 Yale J. on Reg. 363, 399–404 (2016).

[248] *See, e.g.*, Martin Neil Bally & Douglas J. Elliott, *Avoid Depression, Don't Ban Bailout*, Brookings, May 12, 2010.

[249] *See* Tim Wu, *Agency Threats*, 60 Duke L.J. 1841, 1848 (2011).

[250] *See generally,* Frank H. Knight, Risk, Uncertainty, and Profit 197–232 (1921).

[251] *See* Allen, *supra* note 4, at 191–92.

[252] Wu, *supra* note 249, at 1850.

[253] *See supra* notes 51–53 and accompanying text.

[254] Pasquale has made a similar argument that policymakers should not "abandon long-standing principles of financial regulation to make way for forms of financial automation that have yet to be proven." Pasquale, *supra* note 134, at 16.

[255] *See generally,* Prepared Remarks of CFPB Director Richard Cordray at Money 20/20, Las Vegas, NV (Oct. 23, 2016) (transcript available at https://www.consumerfinance.gov/about-us/newsroom/prepared-remarks-cfpb-director-richard-cordray-money-2020/).

ingly autonomous algorithms, then that could restrict the development of, or access to, products and services that might ultimately benefit individual consumers and investors.[256] However, as Pasquale has insightfully noted, "we should be wary about the ability of technology alone to solve much larger social problems of financial inclusion, opportunity, and fair, non-discriminatory credit provision."[257] Restricting technological development will not doom these public policy goals—it will simply require other (potentially more targeted and deliberate) approaches to achieving them. Furthermore, I have previously argued that when the regulatory goals of financial stability, investor/consumer protection, and efficiency conflict, "financial stability is the normative regulatory goal designed to benefit the broadest group of people" and should be the "apex" concern.[258] This Part therefore provides some concrete recommendations for precautionary action with respect to algorithmic finance, in light of the potential risks highlighted in Part III.

A. Regulating the Innovation Process

A precautionary approach to reviewing a technology considers the *process* by which it is created, instead of restricting regulatory oversight to the finished product[259] (although oversight should continue once the product is finished). One way in which such process can be regulated is by requiring preapproval from a governmental authority before a technology can be marketed;[260] in an earlier article, I outlined the benefits of and mechanics for implementing a precautionary preapproval process for new financial products. To summarize briefly, a preapproval process would force an innovator "to approach the financial regulator with all the relevant information about its new product, rather than the regulator scrambling to keep up with the innovation process."[261] As a precondition to approval, the regulator could require the innovator to "conduct stress tests and consider the systemic con-

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[256] *See* Van Loo, *supra* note 18, at 232. However, in a previous article, I raised the possibility that in some circumstances "fintech's promise of increased access to financial services might seem less like a boon, and more like a way to increase rents at the expense of an expanding group of uninformed consumers." Hilary J. Allen, *Regulatory Sandboxes*, 87 Geo. Wash. L. Rev. 579, 609 (2019). In a similar vein, we should remain wary of the possibility that the "democratization" of financial services through robo-investing and marketplace lending is being pursued in order to develop large monetizable data sets for machine learning, with little regard for consumer protection or financial stability.

[257] Pasquale, *supra* note 134, at 18.

[258] *See* Allen, *supra* note 27, at 731. Gordon has also argued that stability should be the "apex goal" of financial regulation. *See* Gordon, *supra* note 43.

[259] *See* Stilgoe, *supra* note 1, at 10.

[260] Tutt has called for the establishment of an FDA to pre-approve machine learning algorithms more generally—this Article restricts its focus to algorithms performing financial functions. *See* Tutt, *supra* note 5, at 83.

[261] Allen, *supra* note 4, at 222.

sequences of any new financial product and present their findings to the regulator."[262]

Because financial market participants "think and plan strategically, and then make decisions based on their plans," the predictive capacity of premarket testing of financial products will always be more limited than similar testing of physical systems,[263] but a preapproval process is still valuable. Not only does a preapproval regime shift some of the costs of testing the innovation to the innovator, if the innovator "knows that it will need to explain or justify a product to a regulator, but does not think it will be able do so because the product is overly complicated or poses significant systemic risk, [it] may abandon or simplify the product without any regulatory instruction."[264] Such an outcome would be beneficial because it would put some bounds on increasing complexity, which can only really be constrained by preventing new products from entering the financial system.[265] A preapproval regime could similarly constrain the emergence of new types of assets that might otherwise multiply the amount of risk in the financial system.[266]A preapproval process also creates a forum for dialogue between industry and regulators, which can help educate regulators on new technologies.[267] In an ideal world, such dialogue would help forge a less adversarial and more cooperative partnership between regulator and industry, where all parties recognize that financial stability is a mutually beneficial outcome and work cooperatively towards achieving it.[268]

Financial products can never be pronounced conclusively safe,[269] but they can be required to meet certain standards before being made available to the financial markets. As part of a preapproval process, regulators could require that certain capabilities be built into financial algorithms before they are approved. For example, to alleviate concerns about a smart asset causing harm by executing too quickly in erroneous circumstances,[270] regulators could require that some form of circuit breaker be programmed into it, enabling a third-party arbitrator or regulator to pause the smart contract's self-execution in emergency circumstances.[271] Abstracting from the algorithm it-

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[262] *Id.* at 223.

[263] Robert Weber, *A Theory for Deliberation Oriented Stress Testing Regulation*, 98 MINN. L. REV. 2236, 2265 (2014).

[264] Allen, *supra* note 4, at 224.

[265] *See* Omarova, *supra* note 111, at 66.

[266] *See id.* at 136. Omarova notes that concerns about the ability of new financial products to multiply risk in the financial system are especially pronounced in the fintech context, where "fintech technology can be, and is, used to synthesize tradable financial assets effectively out of thin air." Omarova, *supra* note 54, at 775.

[267] *See* Allen, *supra* note 256, at 642–43.

[268] *See id.*

[269] *See* Allen, *supra* note 4, at 195–96.

[270] *See supra* notes 153–58 and accompanying text.

[271] The Singapore Personal Data Protection Commission (PDPC) has noted that in "safety-critical systems, organizations should ensure that a person be allowed to assume control." SINGAPORE PDPC, A PROPOSED MODEL ARTIFICIAL INTELLIGENCE FRAMEWORK 9 (Jan. 2019), https://www.pdpc.gov.sg/-/media/Files/PDPC/PDF-Files/Resource-for-Organisation/AI/

self, regulators may wish to regulate the construction of the distributed ledgers on which smart contracts are hosted. For example, there could be requirements that smart assets only be hosted on centralized, permissioned distributed ledgers. Because such ledgers are controlled by central authorities that authorize the persons who can validate the transactions on the relevant ledger, there would be an identifiable formal cohort of validators that could be relied upon to quickly correct erroneous transactions when necessary.[272]

One might initially assume that regulators would need to access an algorithm's source code in order to test compliance with regulatory requirements and pre-approve a financial algorithm, but this might not ultimately be a fruitful exercise (and requiring it would provoke a potentially unnecessary political fight with the financial industry—many financial algorithms are guarded "just as Coca-Cola guards its beverage formula").[273] Joshua Kroll and others note that "inspecting source code is a very limited way of predicting how a computer program will behave" in a given situation,[274] and that even very simple bugs can evade the scrutiny of their expert programmers[275] (outside regulators would have even greater difficulty in deciphering and predicting the operation of algorithmic source code).[276] But regulators do not need source code to determine whether required features have been included; they can simply run an algorithm in testing mode and see how it responds.[277] Regulators could also compel the programmer of a predictive algorithm to explain its workings to regulators more generally (including the factors that the algorithm was programmed to consider and how they were weighted). Such explanation would be valuable both in terms of highlighting risks that the algorithm may pose for the institution deploying it, as well as contributing to regulators' understanding of systemic concerns. If a problem

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A-Proposed-Model-AI-Governance-Framework-January-2019.pdf. In a related context, Van Loo has queried whether some kind of slow-down mechanism needs to be programmed into digital personal assistants like Apple's Siri or Amazon's Alexa. *See* Van Loo, *supra* note 189, at 879.

[272] *See* Werbach & Cornell, *supra* note 94, at 377–78.

[273] *See* Van Loo, *supra* note 225, at 1291. The Commodity Futures Trading Commission tried to obtain access to high-frequency traders' source code, but ultimately abandoned the effort in the face of industry pressure. *See* Allen, *supra* note 27, at 763.

[274] Kroll et al., *supra* note 123, at 638.

[275] *Id.* at 647. Arbesman writes that "a program of only 1,000 lines (relatively short for even pretty simple programs, and much shorter than most programs used in "the wild") already has . . . more than a trillion trillion potential pathways that can be traversed, assuming that branch points occur every so often in the computer code. To check all possible paths—understanding the implications and soundness of each one—is not only infeasible, it is impossible." Samuel Arbesman, Overcomplicated: Technology at the Limits of Comprehension, 80 (2016).

[276] "For those on the outside seeking to hold algorithms to account, the challenge of legibility is even greater." Stilgoe, *supra* note 1, at 30.

[277] A regulator "could still learn a great deal without analyzing source code or collecting large troves of detailed information." Rory Van Loo, *The Missing Regulatory State: Monitoring Businesses in an Age of Surveillance*, 72 Vand. L. Rev. 1563, 1603, 1621 (2019).

is identified as part of this process, errors in predictive algorithms tend to be—relatively—easy to fix.[278]

Machine learning algorithms present a more challenging case, because of the inability of programmers to explain their workings[279] or teach them not to repeat a previous mistake.[280] Given the present uncertainty regarding the operation of this technology, regulators may wish to start with a high-level, principles-based regulatory approach that requires financial firms developing machine learning capabilities to ensure that the algorithms be as predictable and explainable as the technology allows.[281] Ideally, such an approach would encourage innovation in, and collaboration with regulators on, the management of systemic risks at a time when there is considerable uncertainty regarding how to approach machine learning.[282] For example, algorithms could be programmed to be able to explain their own decision-making and the data considered in reaching that decision.[283] To help mitigate the unpredictability of the operation of a machine learning algorithm during a tail event, steps could be taken to ensure that these algorithms learn something about the possibility of such events.

There are a variety of different approaches that can be taken to training machine learning algorithms. One strategy that has been adopted to avoid "overfitting" (a problem where the model becomes "too specialized or specific to the data used for training") is for algorithms to be programmed to make random guesses and learn from the outcomes.[284] Unfortunately, in a tightly coupled and reflexive system like the financial system, the outcomes of random guesses in normal times will not be predictive of the consequences of doing the same thing in a time of stress. A different strategy will be needed if we want financial algorithms to learn that their responses to tail events may have destructive potential and modify them accordingly. In the autonomous vehicle context, machine learning algorithms use what is known as "fleet learning" to develop an understanding of low-probability scenarios

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[278] "If something goes wrong, the programmer can go back through the program's instructions to find out why the error occurred and correct it." Tutt, *supra* note 5, at 93.

[279] *See* Kroll et al., *supra* note 123, at 638.

[280] *See* Tutt, *supra* note 5, at 89; Stilgoe, *supra* note 1, at 35.

[281] For a discussion of the utility of principles-based regimes in regulating unfamiliar technologies, see CENTER FOR FINANCIAL MARKETS (MILKEN INSTITUTE), FINTECH: BUILDING A 21ST-CENTURY REGULATOR'S TOOLKIT 6–7 (Oct. 2014), http://assets1c.milkeninstitute.org/assets/Publication/Viewpoint/PDF/3.14-FinTech-Reg-Toolkit-NEW.pdf. For further discussion of the problems of predictability and explainability, see Tutt, *supra* note 5, at 101–04.

[282] "A principles-based regime gives regulatory agencies an umbrella framework under which to deploy informal regulatory strategies to deal more flexibly with new industry practices as they arise." Allen, *supra* note 256, at 603.

[283] *See* SINGAPORE PDPC, *supra* note 271, at 13. "[T]here is reason to believe that algorithm designers can design machine-learning algorithms with attention to ensuring explainability." *See also* Andrew D. Selbst & Solon Barocas, *The Intuitive Appeal of Explainable Machines*, 87 FORDHAM L. REV. 1085, 1087 (2018); Joshua A. Kroll, *The Fallacy of Inscrutability*, 376 THE ROYAL SOC'Y PUB (2018), https://doi.org/10.1098/rsta.2018.0084. Tutt, *supra* note 5, at 108.

[284] *See* Kroll et al., *supra* note 123, at 684.

and how to deal with them.[285] An equivalent process to fleet learning would not be effective in training financial algorithms about how to react in crisis situations, though, because low-probability events in the financial system do not happen randomly over a long period of time (which would allow for incremental learning). Instead, such events tend to happen all at once (sometimes decades after the last significant crisis), leaving the algorithms no time to learn how to react.[286] In order to mitigate systemic risk, financial algorithms capable of machine learning may therefore need to be exposed to hypothetical scenarios that emphasize worst-case scenarios and demonstrate the consequences of correlated responses to such events.

Study of the stress testing hypotheticals that are currently used in the financial industry may yield insights on how to perform feature selection for financial algorithms capable of machine learning,[287] but extant financial stress testing methodologies certainly will need to be adapted for this purpose.[288] Often, stress testing relies on historical data that may not be predictive of future stress scenarios involving more automated algorithmic decision-making.[289] Also, the stress tests that are currently deployed tend to be focused on a particular outcome[290]—macroprudential stress tests, for example, are designed to determine whether a financial institution has sufficient capital to withstand a systemic shock.[291] When training a machine learning algorithm, the capitalization of the firm deploying the algorithm would not always be the main focus—often, the interaction of the algorithm with other algorithms in the financial system will be more important. The hypothetical scenarios used should therefore not be engineered towards testing for a particular outcome, but instead should be designed to find out "what would happen if . . . ," in order to train algorithms to anticipate and mitigate the systemic repercussions of their decisions.

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[285] *See* Surden, *supra* note 11 and accompanying text.

[286] Crawford observes that the rarity of such events makes it difficult to practice and receive feedback on reactions. *See* John Crawford, *Wargaming Financial Crises: The Problem of (In)Experience and Regulator Expertise*, 34 Rev. Banking & Fin. L. 111, 160 (2015).

[287] "As part of the regulatory toolkit, macro stress tests should contain such (systemic risk) externalities by ensuring that the financial sector is sufficiently capitalized to continue financial intermediation in a severe economic downturn. To simulate a severe economic downturn, regulators define a hypothetical stress scenario by specifying shocks to different macroeconomic and financial variables. The adverse scenario is translated into losses to assets on the balance sheet of banks using models that capture the sensitivity of banks' exposures to the stress scenario. These losses are assumed to be first borne by equity capital. The required capitalization of a bank is assessed using measures (the capital ratios) of the financial performance of the bank after application of the stress test model." Viral Acharya et al., *Testing Macroprudential Stress Tests: The Risk of Regulatory Risk Weights*, 65 J. Mon. Econ. 36, 36 (2014).

[288] Stress tests do not yet model the impact of the disruptions that could be caused by artificial intelligence. *See* Van Loo, *supra* note 189, at 879.

[289] *See* Weber, *supra* note 263, at 2240 (discussing the historical focus of many stress testing methodologies).

[290] *See id.*

[291] *See* Acharya et al., *supra* note 287, at 38.

Robert Weber has referred to this type of approach to stress tests as "deliberation-oriented"; he describes such an approach as "privileg[ing] dynamic scenarios; draw[ing] from business operations culture; rel[ying] on imagination; consider[ing] the interactivity of tested variables; remain[ing] open to uncertainty."[292] The difficulty and cost of developing the scenarios for this type of stress test should not be understated. This is something that only the largest financial institutions would be capable of doing in-house— and from a public policy perspective, it is not clear that it would be desirable for them do so.[293] If a firm does create its own hypothetical training scenarios, regulators at the very least should require records and explanations of the scenarios used.[294] For most market participants, though, the regulator will need to provide some form of hypothetical scenario to be used as training data. Regulators could devise such scenarios by requiring the proprietors of certain financial algorithms to have their algorithms participate in "war games," which are coordinated simulations designed to "inspire creative problem solving and to spur [them] to think about unthinkable outcomes."[295] Participation in such war games could also function as a training exercise for the algorithms—a chance to practice reacting to tail events and receive feedback on the outcome of their decisions in a theoretically stressed context.[296]

By training all machine learning algorithms with the same hypothetical scenarios, attempts to encourage these algorithms to take into account the possibility of destabilizing correlated behavior may ultimately serve to further correlate the behavior of the algorithms. To mitigate this, the war games conducted by regulators should focus on the reflexivity of algorithmic interactions (meaning that when algorithms learn to react to the scenarios they have been exposed to, the operation of the scenario itself becomes altered).[297] Regular adjustments to the scenarios should also be made to reflect changed circumstances and understandings about sources of risks, and the channels through which such risks can be transmitted through the system.[298]

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[292] Weber, *supra* note 263, at 2240.

[293] Such an approach could raise similar concerns as the internal models approach to capital regulation: "the Basel II Accord allowed certain large financial institutions to set their own regulatory capital levels according to their proprietary risk models . . . financial institutions used these models to lower their capital requirements." Gerding, *supra* note 134, at 375.

[294] *See* Singapore PDPC, *supra* note 271, at 11, 14.

[295] Weber, *supra* note 263, at 2264. To some extent, these wargames could be simulated using agent-based modeling on computers—while the predictive capacity of such models has been critiqued for making heterogeneous assumptions about the behavior of market participants, such heterogeneous assumptions may become increasingly appropriate as more and more decision-making is delegated to algorithms. Where behavior is relatively predictable, "complexity arises from the interaction of agents, not from the structure of the agents' individual decision-making rules." Crawford, *supra* note 286, at 166.

[296] *See* Crawford, *supra* note 286, at 160.

[297] For a discussion of reflexivity, *see* Awrey, *supra* note 111, at 257–58; Crawford, *supra* note 286, at 162.

[298] For a discussion of the current understanding of risk transmission channels, *see* Kashyap, Berner & Goodhart, *supra* note 240.

B. Ongoing Oversight

As the technology becomes better understood and best practices emerge over time, best practices for algorithmic design could be enshrined in formal rules regulating the creation of those algorithms, limiting the deregulatory potential that has been observed in some other principles-based regimes.[299] However, while it is critically important that regulators involve themselves in the process by which financial algorithms (and the ledgers on which they are hosted) are created, there is also a place for regulatory engagement with algorithms after they become operational. Supervision efforts will give regulators opportunities to participate in the ongoing testing and training of algorithms, as well as opportunities to assess institutional capacity to manage the operational risks associated with cyberthreats and third-party vendors.[300] Regulatory supervision should also evaluate an institution's governance and culture.[301]

In the first ever Proposed Model Artificial Intelligence Governance Framework, Singapore's Personal Data Protection Commission (PDPC) has recommended some internal governance structures and measures to assist organizations in overseeing their own use of artificial intelligence.[302] These recommendations could inform financial regulatory supervision of financial institutions that rely on machine learning algorithms. The PDPC's framework stresses the importance of an enterprise risk management structure that interrogates the selection and continued use of any machine learning model, with a view to remediation if something goes wrong, and with a particular focus on errors and bias in the training data used.[303] It also recommends that "ethical considerations [associated with artificial intelligence] be introduced as corporate values and managed through ethics review boards or similar structures."[304] Importantly, the PDPC recognizes that sometimes the societal risks associated with a particular machine learning application will be sufficiently great that a firm should not use it at all.[305] In this vein, financial regulators should seek to promote deliberative and ethical use of com-

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[299] "[D]evolution of responsibility to industry—in the absence of the firm boundaries and sanctions that would be found in a rules-based regime—can sometimes have deregulatory consequences." Allen, *supra* note 256, at 601.

[300] For a discussion of cyberthreats, *see* Kristin N. Johnson, *Symposium Financial Regulation: Reflections and Projections: Risk Management and Regulatory Oversight: Cyber Risks: Emerging Risk Management Concerns for Financial Institutions*, 50 GA. L. REV. 131, 139 (2015). For a discussion of the operational risks associated with relying on third-party suppliers of cloud computing and data services, *see* FSB Fintech Report, *supra* note 12, at 2.

[301] *See* Part III.D, *supra*.

[302] *See* SINGAPORE PDPC, *supra* note 271, at 5.

[303] *See id.* at 6. One financial industry observer noted that "a human in the loop is essential: we are, unlike machines, able to take into account context and use general knowledge to put AI-drawn conclusions into perspective." FSB AI Report, *supra* note 6, at 7 (quoting FINEXTRA AND INTEL, THE NEXT BIG WAVE: HOW FINANCIAL INSTITUTIONS CAN STAY AHEAD OF THE AI REVOLUTION (2017)).

[304] SINGAPORE PDPC, *supra* note 271, at 5.

[305] *See id.* at 7.

puter modeling as part of the broader cultural initiatives discussed in Part III.D, aiming to disrupt some of the problematic aspects of algorithmic deference and "automation bias."[306]

Unfortunately, the prophylactic regulation recommended by this Article is unlikely to be completely successful in preventing financial algorithms from causing systemic problems. Regulators will therefore need to be able to audit significant algorithmic failures after the fact (both for enforcement purposes and to improve the quality of their *ex ante* regulation going forward).[307] To facilitate future audits, regulators may want to mandate from the outset measures to ensure that a machine learning algorithm is "traceable," meaning that "its decision-making processes are documented in an easily understandable way."[308] Possible options include requiring "an *audit trail* to document the decision-making process," "implementing a *black box recorder* that captures all input data streams," and mandating data storage requirements.[309] Compliance with such measures may prove very expensive for firms and so, as a practical matter, regulators may ultimately need to scale their application to the size and operations of the regulated firm, weighing the likelihood of systemic harm against the cost of compliance.[310]

C. A Note on Jurisdictional and Resource Constraints

Thus far, Part IV has presumed regulatory jurisdiction over the programmers of financial algorithms (in other words, Part IV has so far presumed that each programmer works for a financial institution that is regulated by a regulator with a financial stability mandate). However, there are financial institutions that are not regulated by any financial stability regulator,[311] as well as financial institutions that elude regulatory oversight en-

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[306] *See supra* notes 127–30 and accompanying text.

[307] In calling for a Consolidated Audit Trail of the equities markets, former SEC Commissioner Kara Stein noted:

> The Flash Crash and other events in our markets demonstrate the need for CAT. Only through a consolidated audit trail can we truly know what is happening in our marketplace, with trading activity cascading across multiple trading venues and asset classes. The linkages, complexity, and fragmentation of our markets outstrip the current ability to monitor, analyze, and interpret market events. Only through CAT can we develop regulations that are truly driven by facts. Only through CAT can regulators appropriately survey our high-speed and high volume marketplace.

Kara M. Stein, The Dominance of Data and the Need for New Tools: Remarks at the SIFMA Operations Conference (Apr. 14, 2015) (transcript available at https://www.sec.gov/news/speech/2015-spch041415kms.html).

[308] Singapore PDPC, *supra* note 271, at 15.

[309] *Id.*

[310] The Dodd-Frank Act provides a precedent for such a scaled approach, reserving the most onerous regulation for the largest and most interconnected firms. *See* Dodd-Frank Wall Street Reform and Consumer Protection Act § 115, 12 U.S.C. §?5325 (2010).

[311] For a discussion of the lack of financial stability mandates for many U.S. financial regulators, *see* Allen, *supra* note 2, at 1091. While I have previously articulated the need for national financial stability regulators with broad cross-sectional oversight of all activities that

tirely by working in a jurisdiction or providing a service that is not covered by any regulatory regime.[312] Non-financial firms with significant technology operations and data resources (sometimes referred to as "techfins") are also largely unsupervised by financial regulators, notwithstanding that some of them are starting to provide types of financial services.[313] Finally, a programmer may not even be connected with any institution at all, as is currently the case with many of the creators of tokens. This does not mean that there is no one available to regulate: there are inevitably people who create and profit from such decentralized technologies, and they could theoretically be regulated.[314] Similarly, intermediaries may emerge as a matter of convenience even if such intermediation is not strictly necessary for a decentralized technology to function[315]—these intermediaries can also theoretically be regulated. However, establishing jurisdiction over these persons is likely to be challenging in practice.

Fortunately, regulated financial institutions have such a significant presence in the financial markets that regulatory requirements that delineate what those institutions can invest in may ultimately have a helpful standard-setting function for *all* financial assets, even those traded outside of the regulated financial sector. Furthermore, financial institutions are well-recognized conduits (both in terms of their web of contracts with other institutions and their leverage-fueled propensity to sell assets at fire sale prices) for transmitting financial shocks to other market participants, allowing such shocks to metastasize into a financial crisis.[316] To the extent that financial institutions do not have direct or indirect exposure to an asset class, the ability of a problem with that asset class to generate instability is circumscribed (even though it is still possible that problems with a class of smart assets that is widely traded outside of regulated financial institutions could have an impact on the proper functioning of the financial system).[317] Regulators could therefore mitigate systemic risk by discouraging financial institutions from investing (directly, or indirectly through mechanisms like derivatives) in tokens or other smart assets unless such assets meet certain established criteria and are hosted on distributed ledgers that similarly meet established crite-

may impact financial stability, the United States has not taken this approach (although countries like the United Kingdom and Australia have). *See id.* at 1092.

312 *See* FSB Fintech Report, *supra* note 12, at 2.

313 *See* Dirk A. Zetsche *et al.*, *From Fintech to Techfin: The Regulatory Challenges of Data-Driven Finance* 10–11, 13 (Eur. Bank. Inst. Working Paper Series, Paper No. 6, 2017), http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2959925.

314 *See* Omri Marian, *Blockchain Havens and the Need for Their Internationally-Coordinated Regulation*, 20 N.C. J. of L. & Tech. 4 (forthcoming 2019), https://ssrn.com/abstract=3357168.

315 *See id.* at 15.

316 For a discussion of the current understanding of risk transmission channels, see Kashyap, Berner & Goodhart, *supra* note 240.

317 *See* Allen, *supra* note 100, at 927–28.

ria.[318] Such discouragement could take the form of significant regulatory capital or liquidity requirements for non-compliant smart assets, for example.[319] In sum, notwithstanding very real jurisdictional challenges, financial stability regulators have a real opportunity to effect change *indirectly*, through the financial institutions that they *do* oversee. In order to do so, though, they will require significantly increased resources.

Many of the recommendations made in this Part can only be implemented if financial stability regulators are sufficiently computer literate to interface effectively with computer algorithms and, as machine learning becomes more prominent, data science expertise will also become a vital regulatory skill set. Hiring personnel with such expertise will no doubt be expensive, and teething pains are to be expected as personnel with this type of experience integrate into the (arguably somewhat staid) culture of financial regulatory agencies. However, if one accepts this Article's premise that a precautionary approach to regulating increasingly autonomous financial algorithms is necessary, such expansion of regulatory capabilities should begin immediately, with necessary funding support from the relevant governmental bodies.[320] Where the recommendations made in this Part can be implemented (or at least begun) with existing regulatory capabilities, those efforts should also commence immediately.

Conclusion

Driverless cars and driverless finance are both likely to perform well—perhaps even better than when a human is in control—most of the time. Both, however, are likely to react in unpredictable and potentially dangerous ways when confronted with unanticipated low-probability events. Notwithstanding this similarity, regulatory attitudes towards these two types of technologies have been very different so far: regulatory policy regarding autonomous vehicles has had a much more precautionary bent than the regulation of automated financial decision-making. This Article has argued that, given the gravity of social harm that can flow from financial crises, policymakers need to turn their attention to finance's potential harms, and that the *processes* by which financial algorithms are being developed should come under particular regulatory scrutiny. Such efforts are time critical—we may soon reach an inflection point after which attempts by regulators to influence the development of the relevant technology will be ineffective.

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[318] *See supra* notes 268–70 and accompanying text. In a similar vein, the European Banker's Association has recommended policies that discourage regulated financial institutions from trading and holding virtual currencies. *See* European Banking Authority, EBA Opinion On Virtual Currencies 5–6 (2014), https://www.eba.europa.eu/documents/10180/657547/EBA-Op-2014-08+Opinion+on+Virtual +Currencies.pdf.

[319] *See* Allen, *supra* note 108, at 828–32 (discussing capital requirements).

[320] As Pasquale notes, "regulators' lack of resources is not simply the natural state of affairs" but is instead a policy decision. Frank Pasquale, *Law's Acceleration of Finance: Redefining the Problem of High-Frequency Trading*, 36 Cardozo L. Rev. 2085, 2088 (2015).

This Article will finish on a note of optimism, however. Human beings don't have a particularly good track record of avoiding financial crises,[321] and the development of autonomous finance could ultimately result in a financial system that is more resilient than the one we currently have.[322] This will not be achieved through deregulation, however, but through partnerships between regulators and programmers that render financial algorithms more mindful of, and more resilient to, systemic impacts. A forum for this type of partnership is already being trialed on a small scale in many countries in the form of the "regulatory sandbox."[323] The changes being wrought to the financial industry by the rise of driverless finance may generate other opportunities to engineer a collaborative relationship between financial regulators and industry participants, allowing for new financial technologies to be harnessed at the programming stage in a public-private partnership to improve financial stability.[324] However, if the development of driverless finance is left unchecked by regulation, financial crises will quite possibly become more frequent and severe than in our more analog past.[325]

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[321] This is amply demonstrated in Carmen Reinhart and Kenneth Rogoff's book, *This Time is Different: Eight Centuries of Financial Folly*. Reinhart & Rogoff, *supra* note 117.

[322] The FSB believes that more autonomous finance, if done properly, has the potential to "offer compliance oversight tools; enhanced data simulations for institutions and across markets; real-time connectivity to monitor and respond to risks; and it can help address complexity challenges at large institutions (e.g. 'too complex to manage'). These applications can help financial institutions, as well as supervisors, better understand causal relationships and better manage risks, and regulatory compliance. Moreover, AI and machine learning can aid supervision by allowing the identification of new relationships in data, without the filter of pre-specified models." FSB Fintech Report, *supra* note 12, at 56. *See also* FSB AI Report, *supra* note 6, at 25.

[323] For a discussion of this regulatory innovation, *see* Allen, *supra* note 256.

[324] For a thorough exploration of the possibilities and preconditions for a financial stability-minded public-private partnership, *see* Saule T. Omarova, *Wall Street As Community of Fate: Toward Financial Industry Self-Regulation*, 159 U. Pa. L. Rev. 411 (2011).

[325] As systems increase in complexity, the frequency of problems also tends to increase. *See* Samuel Arbesman, Overcomplicated: Technology at the Limits of Comprehension 98 (2016).