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ABSTRACT

Consumer interaction with the financial market ranges from applying for credit cards, to financing the purchase of a home, to buying and selling securities. And with each transaction, the lender, bank, and brokerage firm are likely utilizing artificial intelligence (AI) behind the scenes to augment their operations. While AI's ability to process data at high speeds and in large quantities makes it an important tool for financial institutions, it is imperative to be attentive to the risks and limitations that accompany its use. In the context of financial markets, AI's lack of decision-making transparency, often called the "black box problem," along with AI's dependence on quality data, present additional complexities when considering the aggregate effect of algorithms deployed in the market. Owing to these issues, the benefits of AI must be weighed against the particular risks that accompany the spread of this technology throughout the markets.

Financial regulation, as it stands, is complex, expensive, and often involves overlapping regulations and regulators. Thus far, financial regulators have responded by publishing guidance and standards for firms utilizing AI tools, but they have stopped short of demanding access to source codes, setting specific standards for developers, or otherwise altering traditional regulatory frameworks. While regulators are no strangers to regulating new financial products or technology, fitting AI within the traditional frameworks of prudential regulation, registration requirements, supervision, and enforcement actions leaves concerning gaps in oversight.

This Article examines the suitability of the current financial regulatory frameworks for overseeing AI in the financial markets. It suggests that regulators consider developing multi-faceted approaches to promote AI accountability. This Article recognizes the potential harms and likelihood for regulatory arbitrage if these regulatory gaps remain unattended and thus suggests focusing on key elements for future regulation—namely, the human developers and regulation of data to truly "hold AI accountable." Therefore, holding AI accountable requires

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identifying the different ways in which sophisticated algorithms may cause harm to the markets and consumers if ineffectively regulated, and developing an approach that can flexibly respond to these broad concerns. Notably, this Article cautions against reliance on self-regulation and recommends that future policies take an adaptive approach to address current and future AI technologies.

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I. INTRODUCTION

In 1965, Intel founder, Gordon Moore, predicted that the number of transistors in a microchip would double every two years, leading to faster, smaller, more efficient, and cheaper computational power over time.[1] Moore's prediction has largely come true.[2] Over the past eight years, there has been significant growth in computational power, which has led to unprecedented innovation and development in the field of

1. David Rotman, *We're Not Prepared for the End of Moore's Law*, MIT TECH. REV. (Feb. 24, 2020), https://www.technologyreview.com/2020/02/24/905789/were-not-prepared-for-the-end-of-moores-law [https://perma.cc/T6AE-T8H2].

2. *Id.*

artificial intelligence (AI).[3] Together, these breakthroughs have driven forward a new wave of innovation and disruptive technologies,[4] embedding AI in countless aspects of our day-to-day lives.[5] From the simple task of parallel parking,[6] to complex robotic surgeries,[7] AI is changing the world in which we live, arguably in a net positive way.

The impact of AI is particularly prominent in the financial markets.[8] The ability of algorithms to quickly process vast quantities of data makes them valuable tools for financial institutions where time is money and data is king.[9] Today, machine learning (a branch of AI) helps banks make credit decisions, fight fraud, identify illicit financial transactions, design investment strategies, trade securities, and enhance personal banking, among other tasks.[10] Financial firms have adopted AI to assist with regulatory compliance by improving processes for know-your-customer checks and for modeling systemic risk.[11] In short, AI is rapidly changing the operation and, importantly, the regulation of the financial markets.

The growing prevalence and complexity of AI within the financial markets present novel regulatory challenges and raise

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3. Specifically, prior to 2012, computational power doubled every two years. *See* Tibi Puiu, *AI Is Outpacing Moore's Law*, ZME SCI. (Dec. 16, 2019), https://www.zmescience.com/science/ai-is-outpacing-moores-law/ [https://perma.cc/T78V-Y4KC]. Post-2012, however, computational power has been doubling every 3.4 months. *Id.*

4. *See generally* Clayton M. Christensen, Michael E. Raynor & Rory McDonald, *What Is Disruptive Innovation?*, HARV. BUS. REV., Dec. 2015, at 44, http://glassyad.ir/magazine/economics_marketing/2015/Others/Harvard_Business_Review_USA_-_December_2015.pdf [https://perma.cc/S7NL-S76U] (defining disruptive innovation as "a process whereby a smaller company with fewer resources is able to successfully challenge established incumbent businesses").

5. *See* Steven Zeitchik, *Maybe 2022 Should Be the Year We Turn Over Decision-Making to the AI*, WASH. POST (Dec. 31, 2021, 7:00 AM), https://www.washingtonpost.com/technology/2021/12/31/new-year-resolutions-ai-artificial-intelligence/ [https://perma.cc/VF2H-Y8A6].

6. Lance B. Eliot, *Parallel Parking Mindless AI Task for Self-Driving Cars: Time to Step It Up*, AI TRENDS (June 29, 2017), https://www.aitrends.com/ai-insider/parallel-parking-mindless-ai-task-self-driving-cars-time-step/ [https://perma.cc/KNF3-PFHU].

7. *See* Cade Metz, *The Robot Surgeon Will See You Now*, N.Y. TIMES (Apr. 30, 2021), https://www.nytimes.com/2021/04/30/technology/robot-surgery-surgeon.html [https://perma.cc/VDL3-6KYY].

8. *See* Daniel Faggella, *Artificial Intelligence Applications for Lending and Loan Management*, EMERJ (Apr. 3, 2020), https://emerj.com/ai-sector-overviews/artificial-intelligence-applications-lending-loan-management [https://perma.cc/DK22-TLK3].

9. *See id.*

10. *See id.*; William Magnuson, *Artificial Financial Intelligence*, 10 HARV. BUS. L. REV. 337, 348 (2020).

11. *See* Magnuson, *supra* note 10, at 342.

questions about the future and efficacy of financial regulation.[12] Traditional financial regulation relies on a patchwork of regulators utilizing varied regulatory approaches—such as prudential regulation,[13] disclosure, or ex post enforcement actions—to ensure market efficiency, liquidity, and integrity.[14] However, as is often the case with innovation, AI technology is developing more quickly than lawmakers can respond, putting lawmakers and regulators at a disadvantage vis-à-vis the entities and activities they are supposed to oversee.[15] Importantly, AI does not easily fit the categorizations within the existing legal framework, resulting in regulatory gaps, reactive rather than proactive regulation, or ill-fitting frameworks that exacerbate risks and cramp innovation.[16]

This Article is a preliminary exploration of the future of AI regulation in the financial markets that focuses on the issue of accountability. To achieve the most effective use of AI in the financial markets, there must be a way to hold AI accountable.[17] However, merely imposing the existing regulatory framework on AI is unlikely to provide the regulatory oversight desired.[18] Rather, holding AI accountable requires an honest appraisal of how AI is different and how these differences can result in new and greater harms being imposed on the markets and society if left unchecked.[19] Because AI is constantly

12. *See* Finale Doshi-Velez & Mason Kortz, Accountability of AI Under the Law: The Role of Explanation 2 (2017) (Berkman Klein Ctr. for Internet & Soc'y Working Paper), https://dash.harvard.edu/bitstream/handle/1/34372584/2017-11_aiexplainability-1.pdf?sequence=3&isAllowed=y [https://perma.cc/7JC2-J957].

13. Prudential regulation aims to increase the stability of the whole financial system as well as the risk management of individual financial institutions to ensure the institution has "safe[] and sound[]" practices. *See infra* Section II.A; *Banking Supervision*, FED. RSRV. EDUC., https://www.federalreserveeducation.org/about-the-fed/structure-and-functions/banking-supervision [https://perma.cc/6GE3-8AVP] (last visited Apr. 21, 2021).

14. *See* CONG. RSCH. SERV., R44918, WHO REGULATES WHOM? AN OVERVIEW OF THE U.S. FINANCIAL REGULATORY FRAMEWORK 4–6 (2020), https://sgp.fas.org/crs/misc/R44918.pdf [https://perma.cc/2V9Y-NACX].

15. *See* Magnuson, *supra* note 10, at 341–42.

16. *Id.* at 339–40.

17. *See* Doshi-Velez & Kortz, *supra* note 12. While AI accountability could be applicable to regulators or third parties, this Article focuses on a regulator's ability to effectively hold AI accountable. Given the essential role of regulators in ensuring the stability, integrity, and efficiency of the market, it is important to consider how regulatory accountability may be achieved as a first principle. The ability of third parties to sue or seek to hold AI developers or AI users liable is beyond the scope of this Article and deserves its own exploration. *See* Magnuson, *supra* note 10, at 366.

18. *But see* Magnuson, *supra* note 10, at 365–66.

19. *See* Hilary J. Allen, *Driverless Finance*, 10 HARV. BUS. L. REV. 157, 159–60 (2020).

evolving,[20] so too must regulatory efforts; future regulation must develop new ways to oversee AI and ensure there are parties who can be held liable for AI's accompanying risks and harms.[21] Thus, at its core, AI accountability is seeking to find some measure of balance between the benefits of AI, on the one hand, and its drawbacks and risks, on the other hand. Lawmakers and regulators must approach this task expansively, with an appreciation for the fluidity of AI and the financial markets. Recognizing that this is no small feat, this Article's goal is modest: it considers what features ought to be included in future regulatory frameworks and highlights one specific feature regulators ought to adopt sparingly, to effectively hold AI accountable in the financial markets.[22]

Part II of this Article discusses the uses of AI in the financial markets. This Part also identifies the hurdles that complicate AI regulation, specifically lack of transparency and data dependency. Part III describes three primary approaches regulators take in regulating AI within the financial markets. The shortcoming of each approach is highlighted to underscore the challenges AI poses for the traditional regulatory framework. Finally, Part IV analyzes elements that regulators and lawmakers should adopt to create a robust regulatory approach as AI becomes more ubiquitous in the financial markets.

II. AI IN THE FINANCIAL MARKETS

From the basic automation of internal processes, to the complex algorithms that model systemic risk for systemically important financial institutions,[23] AI is both assisting and revolutionizing the operation of financial markets.[24] AI has facilitated greater democratization of credit, faster and more precise investment strategies, and better risk management processes.[25] Part II explores

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20. *See* Magnuson, *supra* note 10, at 342–45.

21. *See* Allen, *supra* note 19, at 160.

22. Throughout, this Article refers to holding "AI accountable." *See, e.g.*, *supra* note 17 and accompanying text. The authors recognize that AI is not a legally recognized entity under the law, so AI qua AI cannot be held accountable any more than one can hold a computer or telephone accountable. *See* Roman V. Yampolskiy, *Could an Artificial Intelligence Be Considered a Person Under the Law?*, PBS (Oct. 7, 2018, 10:01 AM), https://www.pbs.org/newshour/science/could-an-artificial-intelligence-be-considered-a-person-under-the-law [https://perma.cc/G5JX-5KH8]. Therefore, holding "AI accountable" means holding AI developers or entities that deploy AI accountable for the consequences of AI. For simplicity and consistency, however, this Article will refer to "AI accountability."

23. *See* Magnuson, *supra* note 10, at 348–51.

24. *See id.* at 348.

25. *See id.*

three examples of AI in the financial markets: (1) consumer finance, (2) high-speed trading, and (3) risk management. This Part then discusses two primary drawbacks associated with AI: the black box problem and data dependency.

A. Uses of AI in the Financial Markets

For roughly the past decade, financial technology (fintech) and traditional financial services providers have been leveraging AI technology to revolutionize their financial product offerings and the markets in general.[26] While the use of AI in the financial markets is varied, three primary examples are often cited when discussing the integration of AI into the financial markets. First, credit decision-making models provide greater access to credit by leveraging AI to analyze large amounts of alternative data to determine a borrower's credit risk.[27] Second, traders utilize AI-powered algorithms to develop investment strategies and execute trades at incredible speeds.[28] Lastly, financial institutions have incorporated AI into their risk management processes to assist in the complex modeling required to comply with prudential regulations.[29]

1. Consumer Finance

One of the fastest-growing applications of AI in the financial markets is in credit decisioning.[30] Traditionally, lenders use a risk-based strategy in which the bank assesses borrower risk based on only a few data points such as FICO scores, debt, income, and credit history.[31] Some lenders use AI to analyze larger types and amounts of data such as the borrower's education, address stability, rent payment history, and "digital footprint," which includes online shopping, browsing history, and social media activity.[32] Using these alternative data points effectively expands credit access to individuals traditionally

26. *See id.*

27. *See* Faggella, *supra* note 8.

28. *See* Yesha Yadav, *How Algorithmic Trading Undermines Efficiency in the Capital Markets*, 68 VAND. L. REV. 1607, 1609 (2015).

29. *See* Emily Liner, *Understanding SIFIs: What Makes an Institution Systemically Important?*, THIRD WAY (Oct. 3, 2017), https://www.thirdway.org/report/understanding-sifis-what-makes-an-institution-systemically-important [https://perma.cc/495U-XQ8V].

30. *See* Magnuson, *supra* note 10.

31. *See* Faggella, *supra* note 8.

32. *See id.*

deemed "credit invisibles," many of whom are minorities.[33] As the Federal Reserve noted, the use of AI and nontraditional data has the potential to "improve the accuracy and fairness of credit decisions while also increasing overall credit availability."[34]

One example of AI-enabled credit decision-making is Upstart's Credit Decision API.[35] Upstart's AI models incorporate fifteen hundred variables tailorable to each lender's specific credit policies.[36] The models also automatically generate Adverse Action Notices for rejections, which are a legal requirement for credit lenders.[37] Not to be displaced by fintech, industry players like Equifax and Experian have also incorporated AI into their credit models.[38]

Yet, these algorithms may also amplify racial biases and credit inequities.[39] Developers and lenders often lack visibility into how the models classify and process an individual's data points,[40] which can result in "proxy discrimination."[41] Further, if the algorithms use data that reflect past discriminatory decisions or data that correlate to race, outcomes may result in a form of digital redlining.[42] Such improper

33. *See id.*; Monica Steinisch, *Alternative Date: Helpful or Harmful?*, CONSUMER ACTION NEWS, Summer 2017, at 1, 4.

34. Lael Brainard, Governor, Bd. of Governors of the Fed. Rsrv. Sys., Speech at the AI Academic Symposium: Supporting Responsible Use of AI and Equitable Outcomes in Financial Services (Jan. 12, 2021), https://www.federalreserve.gov/newsevents/speech/brainard20210112a.htm [https://perma.cc/C3X7-JRBE] [hereinafter Speech at the AI Academic Symposium].

35. Alex Rouse, *Introducing the Credit Decision API for Banks*, UPSTART, https://www.upstart.com/blog/introducing-credit-decision-api [https://perma.cc/S6AY-WG26] (last visited Jan. 22, 2022).

36. *Id.*

37. *Id.*

38. *See* Alex Hickey, *Equifax Debuts Machine Leaning-Based Credit Scoring System*, CIO DIVE (Mar. 28, 2018), https://www.ciodive.com/news/equifax-debuts-machine-learning-based-credit-scoring-system/520095 [https://perma.cc/NTV7-S4U3]; Gregory Wright, *Bringing Machine Learning to Data Analytics*, EXPERIAN: INSIGHTS BLOG (May 9, 2017), https://www.experian.com/blogs/insights/2017/05/machine-learning-with-analytical-sandbox [https://perma.cc/MRM3-P7GB].

39. Sian Townson, *AI Can Make Bank Loans More Fair*, HARV. BUS. REV. (Nov. 6, 2020), https://hbr.org/2020/11/ai-can-make-bank-loans-more-fair [https://perma.cc/448F-CE6M].

40. *See* Loren Picard & Joe Flanagan, *AI May Just Create the Illusion of Good Credit Decisions*, AM. BANKER (May 7, 2017, 9:00 PM), https://www.americanbanker.com/opinion/ai-may-just-create-the-illusion-of-good-credit-decisions [https://perma.cc/2YCD-N7AS].

41. *See* Anya E.R. Prince & Daniel Schwarcz, *Proxy Discrimination in the Age of Artificial Intelligence and Big Data*, 105 IOWA L. REV. 1257, 1266 (2020); *see also* AARON KLEIN, BROOKINGS INST., CREDIT DENIAL IN THE AGE OF AI (2019), https://www.brookings.edu/research/credit-denial-in-the-age-of-ai/ [https://perma.cc/7PZ2-THSZ] (explaining that "proxy discrimination" occurs when "the predictive power of a facially-neutral characteristic is at least partially attributable to its correlation with a suspect classifier.").

42. Speech at the AI Academic Symposium, *supra* note 34.

outcomes may go unnoticed as existing consumer protections for credit decisions are largely based on transparency—specifically, the right to know why you are denied credit under the Equal Credit Opportunity Act (ECOA).[43] But, because of the inherent difficulty of generating explanations understandable to humans,[44] credit decision-making algorithms may struggle to comply with these legal requirements.[45] For example, the algorithm may not have an explainable decision path, especially if there is no single reason for denial.[46]

Relatedly, the use of "alternative data" raises privacy, ethical, and legal concerns as to the boundaries of what data can be collected and how it should be used.[47] "[J]ust because there is a statistical relationship does not mean that it is predictive, or even that it is legally allowable to be incorporated into a credit decision."[48] Therefore, it is important to develop guardrails that prevent these negative outcomes as AI usage increases in credit decisions.

Thus, while AI is improving credit accessibility for historically marginalized groups,[49] it may also reinforce discriminatory lending and strip away individual privacy.[50] As AI is relied upon to make these types of important decisions, it is imperative that regulators find ways to ensure that AI does not exacerbate the problems it is intended to address, namely credit access, particularly for marginalized groups.[51]

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43. KLEIN, *supra* note 41; *see* Equal Credit Opportunity Act, 15 U.S.C. § 1691; *Your Equal Credit Opportunity Rights*, FED. TRADE COMM'N: CONSUMER INFO. (Jan. 2013), https://www.consumer.ftc.gov/articles/0347-your-equal-credit-opportunity-rights [https://perma.cc/L3MD-SPNP].

44. *See infra Part II.B.*

45. *See* KLEIN, *supra* note 41.

46. *See id.*

47. *Id.*; BD. OF GOVERNORS OF THE FED. RSRV. SYS., CONSUMER FIN. PROT. BUREAU, FED. DEPOSIT INS. CORP., NAT'L CREDIT UNION ADMIN. & OFF. OF THE COMPTROLLER OF THE CURRENCY, INTERAGENCY STATEMENT ON THE USE OF ALTERNATIVE DATA IN CREDIT UNDERWRITING (2013), https://www.federalreserve.gov/supervisionreg/caletters/CA%2019-11%20Letter%20Attachement%20Interagency%20Statement%20on%20the%20Use%20of%20Alternative%20Data%20in%20Credit%20Underwriting.pdf [https://perma.cc/KAV8-JH2R].

48. KLEIN, *supra* note 41.

49. *See* Shannen Balogh & Carter Johnson, *AI Can Help Reduce Inequity in Credit Access, but Banks Will Have to Trade Off Fairness for Accuracy – for Now,* BUS. INSIDER (June 30, 2021, 8:30 AM), https://www.businessinsider.com/ai-lending-risks-opportunities-credit-decisioning-data-inequity-2021-6 [https://perma.cc/NYW9-69GE].

50. *See* KLEIN, *supra* note 41.

51. *See id.*

2. High-Speed Trading

Machine learning and algorithms have become ubiquitous in trading—not only the actual buying and selling of securities and commodities in the markets, but also the development and execution of investment strategies.[52] Firms harnessing AI's computational power can set the algorithm's instructions to a preset trading strategy to submit orders and route and process trades at speeds much faster than possible with only human traders.[53] More recently, machine learning has been incorporated into trading algorithms to enable them to learn from available data, assess inputs to identify trading opportunities, and implement complex investment strategies.[54] Over the past ten or more years, algorithmic trading has risen in prominence and, at times, accounted for at least 60 percent of all trading done in the markets.[55]

Some scholars note that unlocking AI-powered, high-speed trading benefits the financial market through lowered costs, increased liquidity for traders, and improved informational efficiencies because of the "rapidly responsive prices."[56] However, in abnormal market conditions, the algorithm's speed backfires.[57] And, in these instances, the prevalence of AI increases the likelihood of an AI-induced systemic event akin to the Flash Crash of 2010.[58]

Efforts to address and regulate financial algorithms are complicated by AI's dependence on "good" data, preset programming, and models over which developers have little control after launch.[59] A

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52. *See* Yadav, *supra* note 28, at 1609–10.

53. *Id.* at 1611.

54. *See* Paul Wilcox, *Capsule Networks: Deep Learning Computer Vision for Stock Forecasting*, NEURAVEST (July 15, 2019), https://neuravest.net/capsule-networks-deep-learning-for-stock-forecasting/ [https://perma.cc/78EY-E7FW] (discussing convolutional neural networks application to trading).

55. Hakan Samuelsson, *What Percentage of Trading Is Algorithmic? (Algo Trading Volume)*, THE ROBUST TRADER (Jan. 8, 2022), https://therobusttrader.com/what-percentage-of-trading-is-algorithmic/ [https://perma.cc/8DAA-NHVU].

56. Yadav, *supra* note 28, at 1611; Allen, *supra* note 19, at 170.

57. *See* Allen, *supra* note 19, at 170.

58. *See id.*; Hilary J. Allen, *The SEC as Financial Stability Regulator*, 43 J. CORP. L. 715, 737–38 (2018) (detailing various crashes attributed to high frequency trading algorithms). The Flash Crash of 2010 involved the US stock market losing—and then recovering—nearly one thousand points in the span of roughly an hour, an event driven by manic, software-driven selling. Mark Melin, *Here's What Actually Caused the 2010 "Flash Crash"*, BUS. INSIDER (Jan. 30, 2016, 9:57 AM), https://www.businessinsider.com/what-actually-caused-2010-flash-crash-2016-1 [https://perma.cc/LS9M-VLHX]; *see* Jamie Condliffe, *Algorithms Probably Caused a Flash Crash of the British Pound*, MIT TECH. REV. (Oct. 7, 2016), https://www.technologyreview.com/2016/10/07/244656/algorithms-probably-caused-a-flash-crash-of-the-british-pound/ [https://perma.cc/2DWU-CZ6E].

59. *See* Magnuson, *supra* note 10, at 353–57.

developer's ex ante choices regarding trading strategies, assumptions (e.g., about the behavior of the market and other actors), methodologies, and risk preferences must attempt to predict the situations that the algorithms may face, then code and train the algorithms to act appropriately on its own and at high speeds.[60] In other words, if the algorithms' parameters are inaccurate, imprecise, or based on outdated data, the resulting outputs may distort the market rather than achieve a successful trading strategy.[61] If the algorithms base their decisions on data and trends from one period of time that looks fundamentally different from the market in which the algorithm currently operates, then the algorithms may disrupt the markets to the detriment of other market actors.[62]

Notably, machine learning algorithms are susceptible to herd-like behavior of two kinds, each of which can have negative consequences for the financial markets.[63] First, similarly designed financial algorithms that analyze similar financial information may reach the same conclusions.[64] Second, dissimilar financial algorithms may incorporate the results of other algorithms in its decision-making without reference to the soundness of the other algorithm's decision.[65] Thus, in the aggregate, the reactions of many financial algorithms to new information can exacerbate market volatility and instability and, in turn, increase systemic risk within the markets.[66]

Overall, AI trading has improved liquidity, making it easier and cheaper for traders, particularly retail traders, to access the secondary capital markets.[67] These benefits, however, may be at the expense of market stability[68]—making it all the more important that financial regulators credibly deter and mitigate against these risks to the broader financial markets.

60. *See* Yadav, *supra* note 28, at 1612.
61. *See id.* at 1612–16.
62. *See id.* at 1617–22; Magnuson, *supra* note 10, at 357; Allen, *supra* note 19, at 171.
63. *See* Magnuson, *supra* note 10, at 364–65.
64. *Id.* at 364.
65. *Id.* at 364–65.
66. *Id.* at 357.
67. Allen, *supra* note 19, at 170.
68. *Id.*

3. Risk Management

Financial institutions rely on AI to identify and manage risks that threaten the "safety and soundness" of the institution.[69] Both regulators and regulated institutions manage risk by using algorithmic computational power to process large quantities of bank transactions and other data, make predictions about future issues, and identify existing and potential sources of risks within the institution, such as liquidity demands or market movements.[70] These outcomes then dictate the level of scrutiny with which prudential regulators oversee the institution to mitigate the institution's systemic risk.[71]

To illustrate, prudential regulators impose capital requirements on financial institutions mandating that banks hold certain levels of capital to reduce the risk of bank runs.[72] Moreover, entities deemed systemically important financial institutions (SIFI) are subject to additional capital requirement surcharges and stress testing requirements, among other enhanced prudential regulations.[73] The largest SIFIs may be classified as global systemically important banks (G-SIB), which impose even higher capital surcharges depending on the riskiness of the institution, in addition to the SIFI enhanced prudential regulations.[74] Because enhanced regulations are extremely costly, financial institutions are incentivized to ensure that internal risk management measures are robust and accurate to avoid fines or unexpected compliance costs.[75]

With the integration of AI into risk management, the model may itself be a source of risk. For example, the algorithm may overestimate (or underestimate) potential risks when faced with real-world inputs that differ from or are more nuanced than data on which it was

69. *See* Speech at the AI Academic Symposium, *supra* note 34. Prudential regulators, also referred to as "safety and soundness" regulators, review financial institutions in two ways: CAMELS ratings and the "5-Cs." *Banking Supervision*, *supra* note 13. CAMELS rating looks at the bank's capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk. *Id.* Essentially, this rating assesses the overall health of the financial institution and its ability to manage risk, which subsequently dictates the bank's prudential regulations. *Id.* The "5-Cs" approach focuses on the bank's lending activity and rates the bank by assessing a sample of the bank's loans based on capacity, collateral, condition, capital, and character. *Id.*

70. *See Banking Supervision*, *supra* note 13; Speech at the AI Academic Symposium, *supra* note 34.

71. *See Banking Supervision*, *supra* note 13; Liner, *supra* note 29.

72. *See* Liner, *supra* note 29.

73. See *id.* for a discussion of the process for SIFI and G-SIB designation and regulation.

74. *Id.*

75. Speech at the AI Academic Symposium, *supra* note 34.

trained.[76] Such miscalculations can have devastating impacts because financial institutions are susceptible to financial contagion.[77] Prudential regulators consider a bank's exposure to contagion risk when determining whether the financial institution should be classified as a G-SIB, thereby subjecting the institution to enhanced prudential standards such as higher capital and liquidity requirements.[78] Therefore, if the bank's initial internal risk assessment underestimates its contagion risk, the bank may be pushed into higher G-SIB (and G-SIB capital surcharge) tiers.[79]

Federal Reserve Governor Brainard highlighted the increased stakes for financial institutions that rely upon AI for "crucial tasks" to ensure compliance with "safety and soundness" regulations:

> For example, they need to be sure that the model would not make grossly inaccurate predictions when it confronts inputs from the real world either that differ in some subtle way from the training data or that are based on a highly complex interaction of the data features.[80]

As such, financial institutions need to be confident that their algorithms are robust and their predictions are reliable in order to reap the expected benefits of AI in risk management.[81]

In sum, AI is shaping the markets in significant ways, but it is also introducing new sources of risks.[82] Excluding AI from the markets is neither desirable nor feasible;[83] therefore, it is necessary to

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76. *See* PHILIPP HÄRLE, ANDRAS HAVAS, ANDREAS KREMER, DANIEL RONA & HAMID SAMANDARI, THE FUTURE OF BANK RISK MANAGEMENT 13 (2015), https://www.mckinsey.com/~/media/mckinsey/business%20functions/risk/our%20insights/the%20future%20of%20bank%20risk%20management/the-future-of-bank-risk-management-full-report.pdf [https://perma.cc/8Y6F-F4HA].

77. *See id.* Contagion risk is a type of nonfinancial risk that banks must assess as part of overall risk management. *Id.* Because of the interconnectedness of today's global financial system, there is a risk of financial contagion where volatility and negative market developments in one part or portfolio of a bank can spread to other parts of the financial institution, the broader financial market, and even to other parties. *See id.*

78. *Id.*

79. *Id.*; FIN. STABILITY BD., 2020 LIST OF GLOBAL SYSTEMICALLY IMPORTANT BANKS (G-SIBS) (2020), https://www.fsb.org/wp-content/uploads/P111120.pdf [https://perma.cc/Y9LP-MXWW] (detailing the enhanced standards for each "bucket" of G-SIBs).

80. Speech at the AI Academic Symposium, *supra* note 34.

81. *Id.*

82. Allen, *supra* note 19, at 170.

83. *See id.* (discussing some of the benefits AI brings to the market); ORÇUN KAYA, DEUTSCHE BANK RSCH., HIGH-FREQUENCY TRADING: REACHING THE LIMITS (2016), https://www.dbresearch.com/PROD/RPS_EN-PROD/PROD0000000000454703/Research_Briefing%3A_High-frequency_trading.pdf?undefined&realload=QJgjZ4lUB0gdDpFjoW9epAcERwOBdE/P4CrZGy/0fhI/KQOMvci~p1aITx07FWnX [https://perma.cc/3WD2-ETCD] (discussing the extensive role AI plays in the markets); Darrell M. West & John R. Allen, *How*

understand the root cause of these risks in order to better hold AI accountable.

B. The Problem with AI

There are two issues at the core of the seemingly varied problems that accompany AI in the financial markets: lack of transparency and data dependency.[84] The lack of transparency problem is often articulated as the "black box problem" and refers to the difficulty humans have when attempting to understand or explain how AI arrives at its output.[85] Data dependency, as its name suggests, refers to AI's overreliance on data, which may be flawed or inaccurate, resulting in negative consequences for the markets or users.[86] Each issue is discussed in greater detail in the subsections below.

1. The Black Box Problem

The black box problem refers to the opacity inherent in AI algorithms that makes it difficult, if not impossible, to understand the algorithm's decision-making process (or to predict its outcomes).[87] In developing machine learning algorithms, programmers specify a goal or goals for the algorithm to achieve but do not specify how the algorithm should solve the problem.[88] Rather, the algorithm builds its own model by dynamically learning from data provided, assessing inputs, and incorporating new data to solve the problem.[89] In learning through trial and error from the available data, the algorithm can make decisions, find patterns, and solve problems—all without human involvement.[90] How the algorithm determines its output is often unknown to the programmer, thereby rendering the decision-making process opaque

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Artificial Intelligence Is Transforming the World, BROOKINGS (Apr. 24, 2018), https://www.brookings.edu/research/how-artificial-intelligence-is-transforming-the-world/ [https://perma.cc/2KMQ-SWVS].

84. *See* Magnuson, *supra* note 10 at 355–59; Speech at the AI Academic Symposium, *supra* note 34.

85. *See* Speech at the AI Academic Symposium, *supra* note 34.

86. Magnuson, *supra* note 10, at 355–56.

87. Yavar Bathaee, *The Artificial Intelligence Black Box and the Failure of Intent and Causation*, 31 HARV. J.L. & TECH. 889, 902–03 (2018).

88. *Id.* at 907.

89. Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54, 68–69 (2019) ("[T]oday, machine learning algorithms are trained on a body of data that is selected by designers or by past human practices. This process is the 'learning' element in machine learning; the algorithm learns, for example, how to pair queries and results based on a body of data that produced satisfactory pairs in the past.").

90. *See* Bathaee, *supra* note 87, at 891.

even to the algorithm's coders.[91] Accordingly, the black box problem presents two regulatory challenges.[92] From an ex ante perspective, if regulators continue to rely on supervision and oversight to hold AI accountable, there must be recognition of the innate opacity of these algorithms in designing an effective regulatory regime.[93] From an ex post perspective, it is unclear whether the current liability and securities supervisory and enforcement regimes are suited to and capable of adequately regulating algorithms.[94]

The ability of algorithms to make decisions, independent of human involvement, raises issues related to liability.[95] The current securities regime requires a level of intentionality in wrongdoing that may not be possible to demonstrate if AI engages in misconduct.[96] While an easy retort may be that lawmakers should hold programmers liable for the actions of their algorithms, proving that the programmer possessed the requisite level of intent or recklessness to be liable for the conduct of the AI is not a straightforward feat under the securities laws.[97] As such, the current liability framework's requirement of deliberate, intentional human wrongdoing may not capture misconduct done through, with, or by an algorithm.[98]

2. Data Dependency

Part of what makes AI so powerful is its ability to process vast quantities of data in very short timeframes.[99] The processing capabilities of algorithms—which enable pattern recognition beyond the linear, traditional approaches to data—are far superior to that of humans.[100] In short, AI depends on data to work.[101] However, this data dependency brings with it a host of concerns, especially regarding the quality and source of the data being used.[102] The soundness of the types

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91. *Id.* at 903.

92. *See generally* Gina-Gail S. Fletcher, *Deterring Algorithmic Manipulation*, 74 VAND. L. REV. 101 (2021).

93. *See id.* at 107.

94. *See id.* at 105; Yesha Yadav, *The Failure of Liability in Modern Markets*, 102 VA. L. REV. 1031, 1073–86 (2016).

95. *See* Fletcher, *supra* note 92, at 105.

96. *See id.*

97. *See id.*; Yadav, *supra* note 94, at 1074–75.

98. *See* Yadav, *supra* note 94, at 1075.

99. *Id.* at 1064.

100. *Id.* at 1065.

101. Magnuson, *supra* note 10, at 355.

102. *See id.* at 356 (discussing the data dependency problem).

of financial decisions delegated to algorithms depends on the human developer's choice of training data and how that developer codes the algorithm to use the data.[103] Data can have built-in biases that perpetuate problematic decision-making, or they may have inaccuracies that cause the algorithm to undervalue the likelihood of rare but seismic events.[104] Thus, the quality of the data depends upon the knowledge and sophistication of developers who must identify and rectify inaccurate or otherwise harmful data sets.[105]

Even beyond the possibility of flawed data, algorithms may be programmed to react similarly to data and market developments, potentially resulting in a feedback loop among algorithms in the market.[106] This herd-like behavior can have a significant impact on market volatility, negatively affecting liquidity and market stability.[107] As noted above, herd-like behavior could exacerbate the consequences of a disastrous asset valuation bubble or magnify the momentum in a particular trend leading to a dramatic and catastrophic market collapse.[108] Further, if several financial institutions or actors rely on AI caught in a feedback loop, it will become difficult for the market to self-correct, thereby obscuring the efficiency and transparency of the market.[109]

Also, financial market applications of AI face the problem of "non-stationary" behavior.[110] Because algorithms in financial markets must generally rely upon historical data, the types of statistical trends that an algorithm may discover based on past market conditions may not be appropriately generalized for future market conditions and new data.[111] Thus, not only can flawed data amplify harmful biases, but an algorithm's outputs may be inaccurate or improper because the prior data is inapplicable to future-looking predictions.[112]

Lastly, there are social, ethical, and privacy concerns regarding the increasing value of data and large data sets.[113] Controlling vast amounts of data is a major competitive advantage and creates a significant incentive for firms to collect as much data as possible, which

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103. *Id.*
104. *Id.*
105. *Id.* at 363.
106. *See id.*
107. *See id.* at 363–65.
108. *See id.* at 357.
109. *Id.*
110. *Id.* at 360.
111. *Id.*
112. *See id.*
113. *See id.* at 357–58.

can lead to new and legally gray methods of gathering more data.[114] Observers need not look further than the countless lawsuits and complaints against social media sites for their data collection, data storage, and use of user data for advertising purposes.[115] Data dependency, therefore, not only poses a problem for how AI operates but also imposes negative externalities on third parties in its quest for ever more data.

III. REGULATING AI TODAY

The regulation of AI is, in many ways, uncharted territory for regulators.[116] Undoubtedly, AI has revolutionized the markets,[117] and its development ought to be encouraged. But it has also introduced particularly thorny and pernicious problems that raise concerns about its use in the markets.[118] To date, regulators have relied primarily on their traditional framework of supervision and enforcement to address the problems that arise with machine learning in the financial markets.[119] While supervision and enforcement are necessary elements of an overall regulatory approach to the financial markets, more is needed to adequately address the issues attendant with the integration and operation of AI in the markets.[120] Part III considers the current patchwork regulations that address AI and highlights their shortcomings.

A. Prudential Regulation

In general, prudential regulation ensures that financial institutions have "safe and sound" banking practices with a specific focus on the institution's risk management and risk mitigation strategies.[121] The main prudential regulators are the Federal Reserve Board of Governors who, along with other entity-specific bank regulators, determine the "safety and soundness" rules that define acceptable behavior and risk management for financial institutions.[122]

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114. Ryan Calo, *Artificial Intelligence Policy: A Primer and Roadmap*, 51 U.C. DAVIS L. REV. 399, 420–23 (2017).

115. *See* Magnuson, *supra* note 10, at 358.

116. *See* Calo, *supra* note 114, at 428.

117. *See generally* Yadav, *supra* note 94.

118. *Id.* at 1036–37.

119. *See id.* at 1089.

120. *See id.* at 1073.

121. *See supra* note 13 and accompanying text.

122. *See Banking Supervision*, *supra* note 13.

Moreover, regulators use supervisory power to oversee and modify participants' conduct through examination or investigations.[123]

The banking industry is no stranger to the use of complex algorithmic models and quantitative analyses for risk management.[124] Faced with a wide range of financial activities and products, banks have turned to data-driven algorithmic models to assist with complex tasks such as measuring risk, determining capital and reserve adequacy, and valuing credit exposures.[125] In response, prudential regulators, such as the Federal Reserve, have used rulemaking power to set the parameters for financial institutions' use of complex algorithms. Similarly, regulators have used their supervisory powers to evaluate models and processes that firms have in place for developing and monitoring algorithms.[126] Additionally, the Consumer Financial Protection Bureau (CFPB), along with other federal banking regulators, issued a Request for Information on the use of AI by financial institutions, signaling that its examinations may become more critical of how firms use and manage risk associated with AI models.[127]

Broadly speaking, there are two methods that prudential regulators focus on when regulating model risk: the model's source code and performance.[128] First, regulators can require a particular degree of source-code transparency and explanations for the model's outputs by relying on a disclosure and transparency scheme.[129] Disclosure approaches can be useful for targeted testing of the model's decision-making when presented with specific inputs.[130] Yet, "source code is notoriously complex and inscrutable" for both less complex

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123. CONG. RSCH. SERV., R44918, WHO REGULATES WHOM? AN OVERVIEW OF THE U.S. FINANCIAL REGULATORY FRAMEWORK 3 (2020), https://sgp.fas.org/crs/misc/R44918.pdf [https://perma.cc/2V9Y-NACX].

124. *See* BD. OF GOVERNORS OF THE FED. RSRV. SYS., SR 11-7, SUPERVISORY GUIDANCE ON MODEL RISK MANAGEMENT 1 (2011), https://www.federalreserve.gov/supervisionreg/srletters/sr1107.pdf [https://perma.cc/HMC6-R55Z] [hereinafter MODEL RISK MANAGEMENT GUIDANCE]; Lael Brainard, Governor, Bd. of Governors of the Fed. Rsrv. Sys., Speech at Fintech and the New Financial Landscape: What Are We Learning About Artificial Intelligence in Financial Services? (Nov. 13, 2018), https://www.federalreserve.gov/newsevents/speech/brainard20181113a.htm [https://perma.cc/DR4S-LEP4] [hereinafter Speech at Fintech and the New Financial Landscape].

125. MODEL RISK MANAGEMENT GUIDANCE, *supra* note 124, at 1.

126. *See* Speech at Fintech and the New Financial Landscape, *supra* note 124.

127. Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning, 86 Fed. Reg. 16837 (Mar. 31, 2021).

128. *See generally* Erik F. Gerding, *Code, Crash, and Open Source: The Outsourcing of Financial Regulation to Risk Models and the Global Financial Crisis*, 84 WASH. L. REV. 127 (2009).

129. Doshi-Velez & Kortz, *supra* note 12, at 2–4; FRANK PASQUALE, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION 142–43 (2015).

130. Magnuson, *supra* note 10, at 376.

preprogrammed AI and more complex unsupervised AI algorithms. Thus, even simple mistakes may be difficult to discover, particularly if they are novel.[131] Further, static testing of the source code does not provide insight into how the model will interact in its environment on its own without constant examination from regulators.[132]

Second, regulators can follow the traditional prudential approach by promulgating additional expectations for dynamic testing and auditing protocols under the umbrella of the "safety and soundness" mandate.[133] For example, in 2011, the Federal Reserve's "Supervisory Guidance on Model Risk Management" emphasized that financial institutions utilizing AI tools must embed "safety and soundness" principles, namely critical analysis and controls, throughout the development, implementation, and deployment of models.[134] This guidance advised institutions that effective model risk management must include "effective challenge" to the model accomplished through testing the theory and logic underlying the model's design, validating the data and the model, and testing the model's performance over a range of inputs.[135] Additionally, the effective challenge includes implementing governance policies and controls for the model's development, implementation, use, and validation.[136] In sum, firms that materially rely upon algorithms for risk management must maintain a high level of supervision over their models by closely monitoring model performance, making appropriate adjustments, and utilizing supplemental information when necessary.[137]

Furthermore, the Federal Reserve highlighted similar expectations for financial institutions that outsourced AI-based tools and services.[138] Federal Reserve Governor Brainard recently signaled an important expansion of regulation suggesting that the Federal Reserve may propose baseline expectations for banks that use AI

131. *Id.* at 377.

132. *See* Joshua A. Kroll, Joanna Huey, Solon Barocas, Edward W. Felten, Joel R. Reidenberg, David G. Robinson & Harlan Yu, *Accountable Algorithms*, 165 U. PA. L. REV. 633, 647 (2017).

133. *See* Speech at Fintech and the New Financial Landscape, *supra* note 124.

134. *Id.*; MODEL RISK MANAGEMENT GUIDANCE, *supra* note 124, at 4.

135. MODEL RISK MANAGEMENT GUIDANCE, *supra* note 124, at 4.

136. *Id.*

137. *Id.*

138. Speech at Fintech and the New Financial Landscape, *supra* note 124; BD. OF GOVERNORS OF THE FED. RSRV. SYS., SR 13-19/CA 13-21, GUIDANCE ON MANAGING OUTSOURCING RISK (2021), https://www.federalreserve.gov/supervisionreg/srletters/sr1319.htm [https://perma.cc/H54F-VCGE] [hereinafter GUIDANCE ON MANAGING OUTSOURCING RISK].

models to complement traditional "safety and soundness" policies.[139] The proposed expectations would require interpretable models to be reviewed by regulators and, for opaque models, would require black box testing methods to "derive their explanations post hoc based on the model's behavior."[140]

Overall, regulators have embraced a risk-focused supervisory approach that tailors the level of regulatory scrutiny to the potential risks posed by the specific approach, tool, model, or process used.[141] The Federal Reserve believes such an approach enables regulators to balance the proper mitigation of AI risks with responsible innovation that may expand consumer access and convenience as well as provide greater efficiency, risk detection, and accuracy for the risk management operations of financial institutions.[142] Since 2011, however, the models used by financial institutions have become increasingly complex as newer AI techniques, such as machine learning, are incorporated.[143] This renders much of the Federal Reserve's published guidance on model development obsolete and inapplicable, effectively leaving AI unregulated from a prudential standpoint.[144]

B. Registration & Supervision

Regulators rely on their registration and supervisory authority to oversee market actors and their activities.[145] The two primary financial market regulators, the Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC), require market participants to register prior to trading, which plays a key role in the oversight and supervision of the markets.[146] The SEC, for example, requires issuers to provide specific information regarding the company, its financial condition, and future plans before offering

139. Speech at the AI Academic Symposium, *supra* note 34.

140. *Id.* Broadly speaking, interpretable models are capable of generating explanations that humans can understand. *See* Doshi-Velez & Kortz, *supra* note 12, at 3–4. On the other hand, opaque models may be too complex or otherwise incapable of generating such interpretable explanations. *See* Speech at the AI Academic Symposium, *supra* note 34.

141. Speech at Fintech and the New Financial Landscape, *supra* note 124.

142. *Id.*

143. *Id.*

144. *See supra* Section II.A.

145. *See, e.g.*, GUIDANCE ON MANAGING OUTSOURCING RISK, *supra* note 138.

146. CONG. RSCH. SERV., R44918, WHO REGULATES WHOM? AN OVERVIEW OF THE U.S. FINANCIAL REGULATORY FRAMEWORK 3 (2020), https://sgp.fas.org/crs/misc/R44918.pdf [https://perma.cc/2V9Y-NACX].

any securities to the public.[147] Similarly, the CFTC requires all persons who trade in futures and derivatives to register with the agency or seek an exemption prior to trading.[148]

The SEC and the Financial Industry Regulatory Authority (FINRA) have implemented a series of algorithmic trading rules that require registration and impose regulatory supervision.[149] For example, under FINRA Rule 1220, two categories of persons are required to register as a "Securities Trader" and pass a qualifying examination: (1) those responsible for the design, development, or modification of an algorithmic trading program and (2) those responsible for the day-to-day supervision and monitoring of algorithmic trading.[150] The rule's purpose is to force firms to identify and register the persons who "possess knowledge of and responsibility for, both the design of the intended trading strategy…and the technological implementation of such strategy…sufficient to evaluate whether the [algorithm] is designed…to achieve…regulatory compliance."[151]

Further, traders are required to adopt a "reasonable supervision and control program" to mitigate potential issues that may arise from algorithmic trading.[152] In offering guidance to the industry on what an effective supervisory program ought to look like, FINRA includes certain considerations.[153] For example, FINRA recommends that firms review their trading strategies and activities holistically and implement intra-firm risk committees to identify and assess the risks

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147. Securities Act of 1933, Pub. L. No. 73-22, 48 Stat. 74 (codified as amended at 15 U.S.C §§ 77a–77mm); *see* DON MAYER, DANIEL WARNER, GEORGE SIEDEL & JETHRO K. LIEBERMAN, LEGAL ASPECTS OF CORPORATE MANAGEMENT AND FINANCE (2012), https://saylordotorg.github.io/text_legal-aspects-of-corporate-management-and-finance/s20-01-the-nature-of-securities-regul.html [https://perma.cc/2ZG4-YK2M].

148. *Who Has to Register*, NAT'L FUTURES ASS'N, https://www.nfa.futures.org/registration-membership/who-has-to-register/index.html [https://perma.cc/2RJF-REDZ] (last visited Jan. 23, 2022).

149. *New Requirements for Algorithmic Traders May Prove Challenging*, VENABLE (Sept. 13, 2016), https://www.venable.com/insights/publications/2016/09/new-requirements-for-algorithmic-traders-may-prove [https://perma.cc/W3XG-SMB2].

150. *Rule 1220. Registration Categories*, FIN. INDUS. REGUL. AUTH., https://www.finra.org/rules-guidance/rulebooks/finra-rules/1220 [https://perma.cc/VR34-SWA8] (last visited Aug. 20, 2021); *see* FIN. INDUS. REGUL. AUTH., REGULATORY NOTICE 16-21, QUALIFICATION AND REGISTRATION OF ASSOCIATED PERSONS RELATING TO ALGORITHMIC TRADING 3 (2016), https://www.finra.org/sites/default/files/Regulatory-Notice-16-21.pdf [https://perma.cc/JQ82-MLVT] [hereinafter REGULATORY NOTICE 16-21].

151. REGULATORY NOTICE 16-21, *supra* note 150.

152. *Algorithmic Trading*, FIN. INDUS. REGUL. AUTH., https://www.finra.org/rules-guidance/key-topics/algorithmic-trading#overview [https://perma.cc/7JFU-X2F2] (last visited Aug. 20, 2021).

153. *Id.*

that accompany algorithmic trading.[154] FINRA also recommends that firms focus on developing, testing, and validating their algorithms to ensure regulatory compliance.[155] Altogether, the SEC and FINRA have a reasonable registration and supervision framework applicable to algorithmic trading that imposes ex ante requirements on persons when developing and deploying algorithms.[156] Moreover, the regulatory framework also provides regulators with data on how algorithms are operating in the markets and the impact of these trading strategies on the market.[157]

Recently, the CFTC also adopted regulations aimed at addressing algorithmic trading risks.[158] In December 2020, the agency adopted "risk principles" to guide algorithmic trading in the commodities markets.[159] The three risk principles applicable to commodities exchanges require: (1) rules to prevent, detect, and mitigate market disruptions; (2) risk controls; and (3) notification of the CFTC of significant market disruptions.[160] With the new regulations, the CFTC has shifted to a supervisory approach that provides exchanges with flexibility to implement rules that can evolve and grow alongside the markets and technological innovation.[161]

Both the SEC and the CFTC have taken a principles-focused approach to regulating algorithmic trading,[162] which has its benefits and drawbacks. In relying on principles,[163] the agencies provide market actors with flexibility to evolve with new technologies and market realities.[164] However, a principles-only approach can be so amorphous

154. *Id.*

155. *Id.*

156. *See* FIN. INDUS. REGUL. AUTH., REGULATORY NOTICE 15-09, EQUITY TRADING INITIATIVES: SUPERVISION AND CONTROL PRACTICES FOR ALGORITHMIC TRADING STRATEGIES (2015), https://www.finra.org/sites/default/files/notice_doc_file_ref/Notice_Regulatory_15-09.pdf [https://perma.cc/4UK6-4GT6] [hereinafter REGULATORY NOTICE 15-09] (proposing various risk management options for algorithmic trading firms).

157. *See id.*

158. COMMODITY FUTURES TRADING COMM'N, RELEASE NO. 8188-20, CFTC APPROVES TWO FINAL RULES AND TWO PROPOSED RULES AT JUNE 25 OPEN MEETING (2020), https://www.cftc.gov/PressRoom/PressReleases/8188-20 [https://perma.cc/F8TU-EXPW].

159. Electronic Trading Risk Principles, 86 Fed. Reg. 2048, 2048, 2072 (Jan. 11, 2021) (to be codified at 17 C.F.R. pt. 38).

160. *Id.* at 2048.

161. *See id.* at 2073.

162. Donna Parisi, Geoffrey Goldman & Azam Aziz, *CFTC Considers New Approach to Regulation of Electronic Trading*, SHEARMAN (Sept. 15, 2020), https://www.shearman.com/Perspectives/2020/09/CFTC-Considers-New-Approach-to-Regulation-of-Electronic-Trading?sc_lang=zh-CN [https://perma.cc/3QPV-KRTX].

163. Electronic Trading Risk Principles, 86 Fed. Reg. at 2049.

164. *Id.*; *see* Parisi et al., *supra* note 162.

that it ultimately regulates nothing.[165] The absence of any prescriptive rules to guide the creation or use of AI in the markets gives a lot of discretion to market actors.[166] Additionally, regulatory enforcement of principles may be difficult because the line between acceptable and unacceptable or reasonable and unreasonable can be indeterminate.[167]

Notably, financial regulation utilizes both direct government oversight and oversight by self-regulatory organizations (SROs).[168] SROs are private entities that write and enforce rules and standards of conduct for member organizations, subject to broader government oversight.[169] For example, the SEC oversees several SROs, including FINRA and the National Securities Exchanges.[170] Operating under the SEC's oversight, FINRA writes standards of conduct for broker-dealer members and its associated persons, has the power to discipline rule breakers, and may exclude entities from broker-dealer activities.[171] Accordingly, the broker-dealer space is regulated by both FINRA rules and enforcement as well as specific SEC regulations under the Securities Exchange Act of 1934.[172]

SRO delegation in the financial industry has distinct benefits for investor protection, including the promotion of expertise and lower regulatory costs.[173] Proponents of SROs claim that self-regulatory bodies are better capable of attracting industry expertise as well as combining this expertise with contextual flexibility to enable innovation

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165. Electronic Trading Risk Principles, 86 Fed. Reg. at 2073.

166. *Id.*

167. *See* Rostin Behnam, Comm'r, Commodity Futures Trading Comm'n, Dissenting Statement Regarding Electronic Trading Risk Principles (Dec. 8, 2020), https://www.cftc.gov/PressRoom/SpeechesTestimony/behnamstatement120820 [https://perma.cc/7PW9-F2SU]. Specific to the CFTC, there is the additional critique that the recently adopted electronic trading-risk principles do not improve upon or change the status quo. *Id.* Although the risk principles impose a "new" framework of supervision on algorithmic trading, they mostly restate actions that exchanges *already* do. *Id.*

168. CONG. RSCH. SERV., R44918, WHO REGULATES WHOM? AN OVERVIEW OF THE U.S. FINANCIAL REGULATORY FRAMEWORK 20 (2020), https://sgp.fas.org/crs/misc/R44918.pdf [https://perma.cc/2V9Y-NACX].

169. *Id.*

170. *Id.*

171. Magnuson, *supra* note 10, at 373–74 (discussing broker-dealer self-regulation under FINRA).

172. *See* Letter from Robert W. Cook, President & Chief Exec. Officer, Fin. Indus. Regul. Auth., to Sen. Elizabeth Warren (Feb. 23, 2021), https://www.warren.senate.gov/imo/media/doc/FINRA%20Response.pdf [https://perma.cc/T7ND-SMEH].

173. CFA INST., SELF-REGULATION IN THE SECURITIES MARKETS: TRANSITIONS AND NEW POSSIBILITIES 5 (2013), https://www.cfainstitute.org/-/media/documents/article/position-paper/self-regulation-in-securities-markets-transitions-new-possibilities.ashx [https://perma.cc/87PX-952R].

while still addressing risk.[174] Additionally, delegation to SROs shifts the burden and cost of monitoring and enforcement to the industry.[175] However, the benefits of delegation are countered by significant concerns regarding accountability and conflicts of interest.[176] SROs are commonly criticized due to the inherent conflict of interest between its regulatory goals and the interests of its members.[177] Thus, despite the perceived advantages of self-regulation,[178] there are legitimate concerns that SROs may face significant conflicts that limit their ability to effectively police the markets and protect investors from their members' misconduct.[179]

C. Enforcement Actions

For regulations and rules to be substantively meaningful and effective, they must be followed, which typically requires enforcement. Enforcement powers can be used to achieve two goals: deterrence and compliance.[180] Specifically, enforcement powers provide regulators with the leverage necessary to deter bad actors and induce compliance by uncooperative entities through large financial losses, greater supervision, and other punitive consequences.[181] For example, the SEC's Division of Enforcement claims that its enforcement actions have specific benefits for improving integrity and fairness in the market.[182]

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174. *Id.* at 6.

175. *See* Jody Freeman, *The Private Role in Public Governance*, 75 N.Y.U. L. REV. 543, 648 (2000); *What We Do*, FIN. INDUS. REGUL. AUTH., https://www.finra.org/about/what-we-do [https://perma.cc/6ZTS-WSRJ] (last visited Aug. 20, 2021) (stating that FINRA operates "at no cost to taxpayers").

176. *See* Freeman, *supra* note 175, at 647.

177. *See* Barry M. Mitnick, *Capturing 'Capture': Definition and Mechanisms*, *in* HANDBOOK ON THE POLITICS OF REGULATION 34, 35 (David Levi-Faur ed., 2011) (discussing regulatory "capture"). For example, in 2016, Senators Elizabeth Warren and Tom Cotton sent a letter to FINRA claiming that the organization failed to take appropriate disciplinary action to curb repeated misconduct by its members. Letter from Sen. Elizabeth Warren & Sen. Tom Cotton to Richard G. Ketchum, Chairman & Chief Exec. Officer, Fin. Indus. Regul. Auth. (May 11, 2016), https://www.warren.senate.gov/files/documents/2016-5-11_Warren-Cotton_Letter_to_FINRA.pdf [https://perma.cc/S2E6-2Q58].

178. *See* Freeman, *supra* note 175, at 647–48.

179. *State Securities Regulators Outline Opposition to Investment Adviser SRO*, N. AM. SEC. ADM'RS ASS'N (Sept. 13, 2011), https://www.nasaa.org/5590/state-securities-regulators-outline-opposition-to-investment-adviser-sro/ [https://perma.cc/7M75-Z8ZZ].

180. *See, e.g.*, Harry First, *The Case for Antitrust Civil Penalties*, 76 ANTITRUST L.J. 127, 134 (2009).

181. *See* Andrew P. Morriss, Bruce Yandle & Andrew Dorchak, *Choosing How To Regulate*, 29 HARV. ENV'T L. REV. 179, 230–31 (2005).

182. DIV. OF ENF'T, SEC, 2019 ANNUAL REPORT 1 (2019), https://www.sec.gov/files/enforcement-annual-report-2019.pdf [https://perma.cc/QR9X-TTBX].

These include removing bad actors, stopping frauds, preventing losses, and returning funds to harmed investors.[183] Enforcement powers can also secure compliance through cooperative models, which emphasize compliance rather than strictly punishing wrongdoing.[184] Further, the Supreme Court highlighted several situations in which enforcement is preferable to rulemaking as a regulatory model.[185] For example, enforcement is desirable when unforeseeable and highly specialized problems arise, and when "the agency may not have had sufficient experience with a particular problem to warrant rigidifying its tentative judgment into a hard and fast rule."[186] Consequently, enforcement actions provide regulators with a precise yet flexible tool to address new problems compared to traditional command-and-control regulation.[187]

Regulators have a range of tools within their enforcement powers to ensure compliance, including fines, penalties, cease and desist orders, consent orders, license revocation, as well as the ability to institute informal enforcement actions or formal actions such as administrative proceedings and civil actions.[188] The SEC has used enforcement actions and civil litigation to monitor intentional misuse and unintentional malfunction of algorithms in securities trading.[189] In 2011, for example, the SEC charged three investment advisers with securities fraud for willfully concealing that an error in its quantitative investment model disabled one of the model's risk controls and resulted

183. *Id.*

184. Clifford Rechtschaffen, *Deterrence vs. Cooperation and the Evolving Theory of Environmental Enforcement*, 71 S. CAL. L. REV. 1181, 1189 (1998).

185. *See* SEC v. Chenery Corp., 332 U.S. 194, 202–03 (1947).

186. *Id.*

187. *See* Christine Parker, *Reducing the Risk of Policy Failure: Challenges for Regulatory Compliance* 21 (Organisation for Econ. Co-operation & Dev., Working Paper No. 77, 2000), https://www.oecd.org/gov/regulatory-policy/1910833.pdf [https://perma.cc/SZR2-96M6].

188. VAL SRINIVAS, DANIEL BYLER, RICHA WADHWANI, ALOK RANJAN & VAMSI KRISHNA, DELOITTE CTR. FOR FIN. SERVS., ENFORCEMENT ACTIONS IN THE BANKING INDUSTRY: TRENDS AND LESSONS LEARNED 16–18 (2015), https://www2.deloitte.com/content/dam/insights/us/articles/bank-enforcement-actions-trends-in-banking-industry/DUP1372_EnforcementActionsBanking_120815.pdf [https://perma.cc/QL6E-KCH7]; CONG. RSCH. SERV., R44918, WHO REGULATES WHOM? AN OVERVIEW OF THE U.S. FINANCIAL REGULATORY FRAMEWORK 2–3 (2020), https://sgp.fas.org/crs/misc/R44918.pdf [https://perma.cc/2V9Y-NACX].

189. *See, e.g.*, SEC, RELEASE NO. 2011-37, SEC CHARGES AXA ROSENBERG ENTITIES FOR CONCEALING ERROR IN QUANTITATIVE INVESTMENT MODEL (2011), https://www.sec.gov/news/press/2011/2011-37.htm [https://perma.cc/G3YU-LBJV] [hereinafter SEC RELEASE NO. 2011-37] (intentional misuse); SEC, RELEASE NO. 2018-300, SEC CHARGES TWO ROBO-ADVISORS WITH FALSE DISCLOSURES (2018), https://www.sec.gov/news/press-release/2018-300 [https://perma.cc/6X3X-NAZB] [hereinafter SEC RELEASE NO. 2018-300] (unintentional malfunction).

in $217 million in investor losses before being secretly rectified.[190] Model risk also stems from unintentional model error.[191] An example of this is the SEC enforcement action against the robo-adviser, Wealthfront Advisers LLC.[192] The SEC charged Wealthfront with making false statements about investment products and publishing misleading advertising after its statements regarding its advertised tax-loss harvesting strategy when, in fact, the wash sale detection algorithm failed to flag such transactions for 31 percent of accounts enrolled in the strategy.[193]

The Federal Trade Commission (FTC) is another active regulator that routinely relies on enforcement actions to address anti-competitive and "AI-generated consumer harms."[194] Recently, the FTC warned that it would pursue enforcement actions against firms that sell or use algorithms and AI that result in discriminatory outcomes in violation of Section 5 of the FTC Act, the Fair Credit Reporting Act, and the ECOA.[195] Notably, the FTC settled a complaint against photo app developer, Everalbum, for misleading consumers by misrepresenting users' ability to control the company's use of their photographs to train facial recognition algorithms.[196] In the Everalbum action, the remedy included "disgorgement" of the improper data as well as deletion of the facial recognition models and algorithms developed with the ill-gotten data.[197] In an agency publication, the FTC emphasized that AI best practices should include good data, routine testing of algorithms for discriminatory outcomes, transparency and honesty about the capabilities of a company's technology, and accountability.[198]

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190. SEC RELEASE NO. 2011-37, *supra* note 189.

191. See *Robo Advisor Wealthfront Sanctioned by SEC*, CONVEX LEGAL (Jan. 16, 2019), https://convexlegal.com/sec-sanctions-robo-adviser-wealthfront [https://perma.cc/X5A5-NML4].

192. SEC RELEASE NO. 2018-300, *supra* note 189.

193. *Id.*; *Robo Advisor Wealthfront Sanctioned by SEC*, *supra* note 191.

194. Rebecca Kelly Slaughter, Acting Chairwoman, Fed. Trade Comm'n, Remarks at the Future of Privacy Forum: Protecting Consumer Privacy in a Time of Crisis (Feb. 10, 2021), https://www.ftc.gov/system/files/documents/public_statements/1587283/fpf_opening_remarks_210_.pdf [https://perma.cc/KG2K-DPP5].

195. *See* Elisa Jillson, *Aiming for Truth, Fairness, and Equity in Your Company's Use of AI*, FED. TRADE COMM'N (Apr. 19, 2021, 9:43 AM), https://www.ftc.gov/news-events/blogs/business-blog/2021/04/aiming-truth-fairness-equity-your-companys-use-ai [https://perma.cc/C937-ZB5X].

196. *Id.*

197. *Id.*; Rebecca Kelly Slaughter, *Acting FTC Chair Slaughter Speaks on Protecting Privacy and Data Security*, COLUMBIA L. SCH.: THE CLS BLUE SKY BLOG (Feb. 16, 2021), https://clsbluesky.law.columbia.edu/2021/02/16/acting-ftc-chair-slaughter-speaks-on-protecting-privacy-and-data-security/ [https://perma.cc/DTV4-3ACJ].

198. *See* Jillson, *supra* note 195; Andrew Smith, *Using Artificial Intelligence and Algorithms*, FED. TRADE COMM'N: BUS. BLOG (Apr. 8, 2020, 9:58 AM), https://www.ftc.gov/news-

The SEC and other regulators may refer violations to the DOJ for criminal prosecution.[199] Previously, the DOJ addressed the use of pricing algorithms and antitrust compliance by pursuing criminal charges for AI-enabled illegal activity.[200] For example, working with the FTC, the DOJ settled AI-related enforcement actions against three ticket brokers who used an algorithm to purchase large amounts of tickets and then resell them at higher prices in violation of the Better Online Ticket Sales Act.[201] In 2015, the DOJ filed antitrust charges against an e-commerce executive for developing pricing software, and then colluding with co-conspirators to use the price-setting algorithms to coordinate the prices of posters sold online.[202]

However, overreliance on enforcement can hamper industry growth and may not be administratively feasible.[203] Over the years, policymakers and regulators have issued new rules and expanded existing ones to address various problems.[204] The cumulative effect has been a complex web of requirements that are difficult and expensive for large firms to understand and comply with, let alone middle-and small-sized firms.[205] Thus, enforcement actions may penalize smaller firms for failing to keep up with these regulations.[206] Further, in an uncertain regulatory landscape, emerging technologies face a

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events/blogs/business-blog/2020/04/using-artificial-intelligence-algorithms [https://perma.cc/XTL3-6K6M]; *see also* REGULATORY NOTICE 15-09, *supra* note 156 (proposing various risk management suggestions for algorithmic trading firms).

199. Elad L. Roisman, Hester M. Pierce, Allison Herren Lee & Caroline A. Crenshaw, *Statement on Proposed 2011 Fraud-Detection Program and Related 2012 Opinion of the DOJ Office of Legal Counsel*, U.S. SEC. & EXCH. COMM'N (Jan. 7, 2021), https://www.sec.gov/news/public-statement/statement-proposed-2011-fraud-detection-program [https://perma.cc/V6FP-4K5K].

200. *See* CREIGHTON MACY, DAN GRAULICH & MATTHEW BESTER, ANTITRUST COMPLIANCE AND PRICING ALGORITHMS 2 (2019), https://www.bakermckenzie.com/-/media/files/people/graulich-daniel/bloomberg-law-antitrust-compliance-and-pricing-algorithms-dec-2019.pdf?la=en [https://perma.cc/2BJG-TZJU].

201. U.S. DEP'T OF JUST., RELEASE NO. 21-84, JUSTICE DEPARTMENT AND FTC ANNOUNCE FIRST ENFORCEMENT ACTIONS FOR VIOLATIONS OF THE BETTER ONLINE TICKET SALES ACT (2021), https://www.justice.gov/opa/pr/justice-department-and-ftc-announce-first-enforcement-actions-violations-better-online-ticket [https://perma.cc/45TQ-NPGR].

202. U.S. DEP'T OF JUST., RELEASE NO. 15-421, FORMER E-COMMERCE EXECUTIVE CHARGED WITH PRICE FIXING IN THE ANTITRUST DIVISION'S FIRST ONLINE MARKETPLACE PROSECUTION (2015), https://www.justice.gov/opa/pr/former-e-commerce-executive-charged-price-fixing-antitrust-divisions-first-online-marketplace [https://perma.cc/85F5-AJ6G]; *see also* MACY ET AL., *supra* note 200.

203. *See* Parker, *supra* note 187, at 7–8, 14.

204. *Id.* at 14.

205. *Id.*

206. *Id.* at 15 (discussing the effect of regulation complexity).

double-edged sword. On the one hand, deploying such technology without regulatory blessing may result in significant fines and penalties when regulators determine ex post that these actions are impermissible.[207] On the other hand, more cautious market actors may decide not to launch and may curb innovation altogether, fearing the risk of regulatory uncertainty.[208] Enforcement, therefore, can be a flexible mechanism for regulators to address financial AI, but singular reliance upon enforcement powers is unsustainable.[209]

IV. LOOKING TO THE FUTURE

Implementing a regulatory framework for AI in the financial markets is a difficult and wide-ranging feat. AI is complex and ever-changing,[210] rendering some forms of backward-looking regulations obsolete before they have a chance to be enacted.[211] Thus, regulators must be forward-looking in their approach to remain relevant and effective.

To do so, regulators should be mindful of four elements when developing a regulatory framework to hold AI accountable in the financial markets. First, future policies should not shy away from tying AI accountability to (a) specific human(s) that develop, test, and deploy these tools. Second, AI's data dependency problem means that effective regulation must include data regulation as well. Third, given the high stakes surrounding AI, government regulators ought to rely on self-regulation sparingly. Fourth, regulators should be aware that policies created specifically for existing AI techniques, such as machine learning, may not be as relevant or effective for newer AI technologies that leverage deep learning techniques, such as generative adversarial neural networks and capsule networks.

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207. Gregory N. Mandel, *Regulating Emerging Technologies*, 1 LAW INNOVATION & TECH. 75, 78–81 (2009).

208. *See* SRINIVAS ET AL., *supra* note 188, at 17 (discussing the impact of enforcement actions on the banking industry); Turner Wright, *SEC Enforcement Actions Cost Crypto Firms and Individuals $1.7B in Penalties*, COINTELEGRAPH (May 12, 2021), https://cointelegraph.com/news/sec-enforcement-actions-cost-crypto-firms-and-individuals-1-7b-in-penalties [https://perma.cc/72CQ-J27A] (discussing how enforcement actions have impacted issuers of cryptocurrencies).

209. *See* Parker, *supra* note 187, at 7.

210. Daniel Shapiro, *Artificial Intelligence: It's Complicated and Unsettling, but Inevitable*, FORBES (Sept. 10, 2019, 8:58 AM), https://www.forbes.com/sites/danielshapiro1/2019/09/10/artificial-intelligence-its-complicated-and-unsettling-but-inevitable/?sh=2322032e26f2 [https://perma.cc/4R38-HLCQ].

211. *Cf.* Roberta Romano, *Regulating in the Dark and a Postscript Assessment of the Iron Law of Financial Regulation*, 43 HOFSTRA L. REV. 25, 27 (2014) (explaining that backward-looking regulations in dynamic environments fail to keep up with industry practices).

A. Humans in the Loop

One element that ought to be part of the AI landscape is humans. Developers design AI to minimize future human intervention as much as possible;[212] however, human involvement should not be shunned entirely. Rather, it is necessary to include humans at key intervals to ensure that there is accountability for the algorithm's decision-making and impact on the markets.[213]

For example, the Financial Stability Board describes a "human in the loop" system in which there is a designated responsible director manager for AI.[214] Under this system, there ought to be distinct human roles in model risk management for ownership, controls, and compliance where the model owner would assume ultimate accountability and "be responsible for ensuring that models are properly developed, implemented, and used."[215] A human would also be responsible for proper validation, approval, and updates of the models.[216]

FINRA adopted a lighter version of this system in 2017.[217] FINRA rule 1220 (b)(4)(A) requires "each associated person [with a member] who is primarily responsible for the design, development or significant modification of an algorithmic trading strategy relating to equity, preferred or convertible debt securities, or who is responsible for the day-to-day supervision or direction of such activities" to meet the same minimum competency standards for knowledge of securities regulations as is applicable to individual securities traders, e.g., pass

212. *See* Emilie C. Schwarz, *Human vs. Machine: A Framework of Responsibilities and Duties of Transnational Corporations for Respecting Human Rights in the Use of Artificial Intelligence*, 58 COLUM. J. TRANSNAT'L L. 232, 254–55 (2019).

213. *See* Gaurav Aggarwal, *How Humans-in-the-Loop AI Can Help Solve the Data Problem*, FORBES (Oct. 27, 2021, 8:30 AM), https://www.forbes.com/sites/forbestechcouncil/2021/10/27/how-humans-in-the-loop-ai-can-help-solve-the-data-problem/?sh=76330c3048b6 [https://perma.cc/UPP3-JLEH].

214. *See* FIN. STABILITY BD., ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN FINANCIAL SERVICES 7 (2017), https://www.fsb.org/wp-content/uploads/P011117.pdf [https://perma.cc/X23J-9MZV]. The Financial Stability Board is an international body that develops and promotes standards for financial stability. *See generally* DOMENICO LOMBARDI, BROOKINGS INST., THE GOVERNANCE OF THE FINANCIAL STABILITY BOARD (2011), https://www.brookings.edu/wp-content/uploads/2016/06/FSB_Issues_Paper_Lombardi.pdf [https://perma.cc/38TU-68P5] (discussing the creation and role of the Financial Stability Board).

215. *See* FED. DEPOSIT INS. CORP., FIL-22-2017, SUPERVISORY GUIDANCE ON MODEL RISK MANAGEMENT 15 (2017), https://www.fdic.gov/news/financial-institution-letters/2017/fil17022a.pdf [https://perma.cc/WB8C-7VFU].

216. *See id.*

217. *See generally* REGULATORY NOTICE 16-21, *supra* note 150.

the Series 57 exam and register as a Securities Trader.[218] To make this rule more robust, FINRA should require not just competency but also impose ultimate responsibility on this person for the failings of the algorithm, without the need for deliberate misconduct. This would incentivize traders to triple-check their work and limit the potential for misuse of algorithms.

B. Data Regulation & Validation

Given the extent to which AI depends on data,[219] data regulation and verification must be included in a holistic regulatory approach. The centrality of data to AI applicability means that the inputs used to test and design the algorithm are of paramount importance to the algorithm's integrity.[220] Recognizing the importance of regulating the data, various state Attorney Generals have called for the CFPB to revise its no-action letter policy regarding AI use in credit decisions.[221] As discussed earlier, Upstart's credit decision-making model not only utilizes a modern method, but also is encouraged by regulators.[222] Specifically, under its current policy, the CFPB takes a friendlier approach to alternative data.[223] For example, the CFPB has issued two No-Action Letters to Upstart stating that it has no present intention to take enforcement or supervisory action against the company under the ECOA, based on its use of alternative data in its underwriting.[224]

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218. *See id.* at 1, 3. FINRA rule 1220(b)(4)(A) replaced NASD rule 1032(f), which is the subject of the regulatory notice.

219. Joe McKendrick, *The Data Paradox: Artificial Intelligence Needs Data; Data Needs AI*, FORBES (June 27, 2021, 11:59 AM), https://www.forbes.com/sites/joemckendrick/2021/06/27/the-data-paradox-artificial-intelligence-needs-data-data-needs-ai/?sh=15d51fcf71a5 [https://perma.cc/6MPP-YX9U].

220. Sameer Rane, *Complementing Data Quality Management with AI/ML for Meaningful Data Insights*, TATA CONSULTANCY SERVS.: BUS. & TECH. INSIGHTS (July 6, 2021), https://www.tcs.com/blogs/artificial-intelligence-data-quality-management [https://perma.cc/KW3D-MS4X].

221. Letitia James, N.Y. Att'y Gen., Comment Letter on Proposed Policy on No-Action Letters and the BCFP Product Sandbox (Feb. 11, 2019), https://ag.ny.gov/sites/default/files/cfpb_nal_and_sandbox_comment_final.pdf [https://perma.cc/826Y-WNFH] [hereinafter Comment Letter].

222. *See supra* Section I.A.1; Rouse, *supra* note 35.

223. Comment Letter, *supra* note 221.

224. Letter from Christopher M. D'Angelo, Assoc. Dir. for Supervision, Enf't & Fair Lending, Consumer Fin. Prot. Bureau, to Thomas P. Brown, Paul Hastings, LLP (Sept. 14, 2017), https://files.consumerfinance.gov/f/documents/201709_cfpb_upstart-no-action-letter.pdf [https://perma.cc/K38G-8DFU]; Letter from Edward Blatnik, Acting Assistant Dir., Off. of Innovation, Consumer Fin. Prot. Bureau, to Alison Nicoll, Gen. Couns., Upstart Network, Inc. (Nov. 30, 2020), https://files.consumerfinance.gov/f/documents/cfpb_upstart-network-inc_no-

Notably, the policy has some important features aimed at increasing regulatory oversight of the AI's use.[225] Pursuant to the No-Action Letters, Upstart is required to notify the CFPB of significant changes to its model prior to implementation.[226] Upstart is also required to provide the CFPB with its source code used to model risk assessment, test its model for adverse impact, and provide the results of these tests to the CFPB, among other things.[227]

One thing to highlight in this regard is that regulators ought to consider whether and to what extent data regulation and verification should also require regulatory access to AI source code.[228] A few years ago, as part of its proposed rules to regulate trading algorithms, the CFTC proposed source code access as part of its regulatory framework.[229] Arguably, this inclusion doomed the proposed rule as the industry, and many others, considered this a bridge too far.[230] However, this Article challenges this knee-jerk reaction and posits that access to the source code should be viewed as a necessary element of AI supervision and oversight. Indeed, data verification without source code access lacks efficacy. In other words, without insight into how the algorithm uses the data through accessing the source code, data verification is an empty exercise.[231] To be clear, however, source code access is insufficient in and of itself in regulating AI, but it is a necessary and important aspect in regulating algorithms and minimizing their potential harms.

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action-letter_2020-11.pdf [https://perma.cc/Q2GF-FVZP] [hereinafter Letter from Blatnik to Nicoll].

225. *See* Letter from Blatnik to Nicoll, *supra* note 225.

226. *Id.*

227. *Id.*

228. *See* Kroll et al., *supra* note 131 (discussing static analysis of an algorithm's source code only).

229. *See* Regulation Automated Trading, 81 Fed. Reg. 85,334, 85,337 (proposed Nov. 25, 2016); COMMODITY FUTURES TRADING COMM'N, FACT SHEET - SUPPLEMENTAL NOTICE OF PROPOSED RULEMAKING ON REGULATION AUTOMATED TRADING (2016), https://www.cftc.gov/sites/default/files/idc/groups/public/@newsroom/documents/file/regat_fact-sheet110316.pdf [https://perma.cc/B3RM-CU8G].

230. *See* Regulation Automated Trading, 80 Fed. Reg. 78,824, 78,947 (proposed Dec. 17, 2015) ("Regulation AT dramatically lowers the bar for the federal government to obtain this information [a source code repository for algorithms]."); *see also* Gregory Meyer & Philip Stafford, *US Regulators Propose Powers To Scrutinise Algo Traders' Source Code*, FIN. TIMES (Dec. 1, 2015), http://www.ft.com/cms/s/0/137f81bc-944f-11e5-b190-291e94b77c8f.html#axzz47pavqdzF [https://perma.cc/L4Y7-ZS28] (explaining concerns of HF trading firms in response to the new regulation).

231. *See generally Examining the CFTC's Proposed Rule: Regulation Automated Trading: Hearing Before the H. Comm. on Agric.*, 114th Cong (2016).

C. Limited Self-Regulation

In developing and designing a regulatory regime for AI, a licensing and certification regime, similar to the Food and Drug Administration,[232] is a promising possibility. A regulatory licensing regime would require firms to submit applications with detailed information regarding the AI's function, client protection features, the regulatory capital allocated for the financial and operational risk of the AI, and contingency plans for the AI's failure to a government agency.[233] Undoubtedly, such a regime would be costly and could run the risk of stifling innovation;[234] there would be great difficulty in changing or updating authorized AIs as these would likely require additional licensing or certification.[235] However, a licensing regime could establish a baseline of what types of AI programs are acceptable or low risk and, in this way, could steer innovation and development in a regulatory-preferred direction.

The challenges associated with direct government oversight raise the possibility of industry-led self-regulation.[236] The financial markets are exceedingly familiar with the self-regulatory model, which relies on the private sector to develop and adopt its own codes of conduct and best practices.[237] These industry standards could ensure that algorithms developed have fair, efficient, and stable outcomes, resulting in greater benefit to both users and society.[238] Proponents of industry

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232. *See The FDA Licensing Process*, U.S. FOOD & DRUG ADMIN., https://www.fda.gov/science-research/licensing-and-collaboration-opportunities/fda-licensing-process [https://perma.cc/D4YE-5743] (Feb. 26, 2018).

233. Katyal, *supra* note 89, at 111; Kroll et al., *supra* note 132, at 673 (discussing certification); Dirk A. Zetzsche, Douglas Arner, Ross Buckley & Brian W. Tang, *Artificial Intelligence in Finance: Putting the Human in the Loop* 34–35 (Ctr. for Fin., Tech. & Entrepreneurship, Univ. of H.K. Fac. of L. Rsch. Paper No. 2020/006, 2020), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3531711 [https://perma.cc/7HSA-5KRU] (discussing licensing).

234. Zetzsche et al., *supra* note 233, at 35.

235. *Id.*

236. *See* Kroll et al., *supra* note 132, at 702–03.

237. *See* CFA INST. CTR. FOR FIN. MKT. INTEGRITY, SELF-REGULATION IN TODAY'S SECURITIES MARKETS: OUTDATED SYSTEM OR WORK IN PROGRESS? iii (2007), https://www.cfainstitute.org/-/media/documents/article/position-paper/self-regulation-in-todays-securities-markets-outdated-system-or-work-in-progress.ashx [https://perma.cc/B7B6-WNES].

238. Katyal, *supra* note 89, at 108–10; *see* John Markoff, *How Tech Giants Are Devising Real Ethics for Artificial Intelligence*, N.Y. TIMES (Sept. 1, 2016), https://www.nytimes.com/2016/09/02/technology/artificial-intelligence-ethics.html [https://perma.cc/JEM7-9MZD]. For example, the Association for Computing Machinery proposed seven principles for algorithmic transparency and accountability:

codes of conduct argue that such best practices can serve as a benchmark for regulatory and public auditing to ensure accuracy and accountability.[239] How well voluntary standards mesh with formal government regulations will depend on the government agencies' relationship with that industry, whether that be positive or more skeptical.[240] Moreover, there is a significant risk of inadequate regulation or oversight given the ability for codes of conduct to simply aggregate private preferences, rather than prioritize risk regulation and public concerns.[241]

Importantly, policymakers should take a critical approach to self-regulation. Self-regulation is an often-proposed solution to deal with complex industries, such as finance and AI.[242] This Article encourages policymakers to approach self-regulation cautiously. This is not because self-regulation is objectionable per se, but because the stakes are too high for industry regulation to be the primary mechanism to oversee AI in the financial markets. Self-regulation is fraught with conflicts of interest because it asks industry insiders to subordinate their self-interest to that of the public.[243] These conflicts limit the efficacy of self-regulation and possibly the vigor with which the industry would be regulated.[244] Regulating AI in finance should remain a public regulatory function and not be delegated to self-regulation because the potential issues supersede (or ought to

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> (1) awareness of possible biases in design, implementation, and use; (2) access and redress mechanisms to allow individuals to question and address adverse effects of algorithmically informed decisions; (3) accountability, ensuring that individuals are held responsible for decisions made by algorithms that they use; (4) an explanation regarding both the procedures that the algorithm follows as well as the specific decisions that are made; (5) data provenance, meaning a description of the way that the training data was collected, along with 'an exploration of the potential biases induced by the human or algorithmic data-gathering process'; (6) auditability, enabling models, algorithms, data and decisions to be recorded for audit purposes; and (7) validation and testing, ensuring the use of rigorous models to avoid discriminatory harm.

Katyal, *supra* note 89, at 109.

239. *See* Katyal, *supra* note 89, at 112.

240. *See* Freeman, *supra* note 175.

241. *See id.* at 648–49.

242. *See generally* Saule T. Omarova, *Wall Street as Community of Fate: Toward Financial Industry Self-Regulation*, 159 U. PA. L. REV. 411 (2011).

243. *See id.* at 467–68 (discussing the controversy surrounding SROs in the securities industry namely, the "the conflict of interest inherent in their dual function as regulators and profit-seeking economic enterprises").

244. *See* Mitnick, *supra* note 177, at 34–36 (defining regulatory "capture" to describe situations where "government regulation tend[s] to serve the interests of regulated parties over more general public interests"). *See generally* BARRY M. MITNICK, THE POLITICAL ECONOMY OF REGULATION 206–33 (1980) (discussing political and economic theories of capture).

supersede) the private interests of programmers and firms in developing AI. The lack of AI expertise among the financial regulators should not serve as a reason to promote self-regulation of AI in the financial markets.[245] Rather, it ought to emphasize the importance of bolstering and improving the technological capacities of those charged with overseeing the markets.

D. Looking Further into the Future

A major theme of this Article is that technology continues to develop at a speed that regulation cannot catch up with, let alone overcome. One new trend relates to generative adversarial artificial intelligence,[246] and the "intentional manipulation of input data in order to fool [AI] systems or lead them to unintended results."[247] For example, wrongdoers may be able to identify the patterns of behavior that trigger fraud alerts and alter their behavior to avoid the algorithm's detection.[248] Additionally, hedge funds or other quant firms that increasingly rely upon high-speed trading algorithms may be concerned that competitors who discover trading strategies based on proprietary algorithms will be able to manipulate the market using this information.[249] Such AI innovations present dangerous threats to the integrity of an AI algorithm and to the broader cybersecurity of the financial institution that employs it.[250]

While this Article focuses on machine learning, developers are quickly designing and implementing faster and smarter deep-learning techniques.[251] In addition to generative adversarial networks, capsule networks provide the benefit of being able to model a "hierarchical structure of part-to-whole relationships" between the features extracted from the data.[252] In contrast, machine-learning techniques can only extract the distinct features of data but cannot model the

245. *See* Magnuson, *supra* note 10, at 372 (noting that regulators would need to obtain high-level expertise in AI and machine learning).

246. For a discussion of generative adversarial AI, see Thomas Wood, *What Is a Generative Adversarial Network?*, DEEP AI, https://deepai.org/machine-learning-glossary-and-terms/generative-adversarial-network [https://perma.cc/44CL-CNZR] (last visited Mar. 9, 2022).

247. *Id.* at 365.

248. *See id.*

249. Wilcox, *supra* note 54.

250. *See id.*

251. *See* Nadav Maman, *The Advanced Threat Potential of Deep Learning*, DEEP INSTINCT (Sept. 15, 2019), https://www.deepinstinct.com/blog/the-advanced-threat-potential-of-deep-learning [https://perma.cc/Z2NZ-4PTW].

252. Wilcox, *supra* note 54.

interrelationships between these features.[253] Technology continues to advance at an amazing pace and, as is often the case, significantly outpaces the rate at which regulators can properly assess and address any outsized risks posed by these complex, emerging technologies.[254]

V. CONCLUSION

AI has revolutionized financial markets in significant ways.[255] It has increased access for historically marginalized communities,[256] decreased transactions costs,[257] and increased risk management within large, systemically important institutions.[258] But with these benefits, there are attendant risks. As AI continues to expand its footprint in the financial markets, it is imperative that regulators take a fresh look at whether traditional regulatory frameworks can properly and effectively address its associated risks. As regulators try to balance the benefits of AI against the challenges of holding AI accountable, they ought to be guided by the importance of human responsibility for AI conduct and the significance of data regulation to proper AI operation. Additionally, regulators should be wary of expanding self-regulation to deal with the risks of AI. Holding AI accountable is no easy feat; it requires a forward-looking approach that considers the benefits of the technology and its risks for the markets and society as a whole.

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253. *See id.*

254. *See generally* Camino Kavanagh, New Tech, New Threats, and New Governance Challenges: An Opportunity to Craft Smarter Responses? (Aug. 2019) (Carnegie Endowment for Int'l Peace Working Paper), https://carnegieendowment.org/files/WP_Camino_Kavanagh___New_Tech_New_Threats1.pdf [https://perma.cc/ETQ2-YKTS].

255. *See* Lukas Ryll, Mary Emma Barton & Bryan Zheng Zhang, *AI Has Started a Financial Revolution - Here's How*, WORLD ECON. F. (Feb. 4, 2020), https://www.weforum.org/agenda/2020/02/how-ai-is-shaping-financial-services/ [https://perma.cc/5ZSH-P26C].

256. *See* Balogh & Johnson, *supra* note 48.

257. *See* Arthur Bachinskiy, *The Growing Impact of AI in Financial Services: Six Examples*, TOWARDS DATA SCI. (Feb. 21, 2019), https://towardsdatascience.com/the-growing-impact-of-ai-in-financial-services-six-examples-da386c0301b2 [https://perma.cc/U897-EJY4].

258. *See id.*