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The Failure of Liability in Modern Markets

Yesha Yadav

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INTRODUCTION

IN April 2015, the Department of Justice charged Navinder Sarao for his role in causing the Flash Crash—the near-1,000-point drop-and-

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rebound in the Dow Jones Index that roiled markets in May 2010.[1] Sarao, a small-time British trader operating out of his parents' suburban basement, stood accused of putting together a string of illusory, fake orders that fooled markets enough to spark the largest single-day drop in the index's history.[2] Commentators rightly contest whether a bit-player like Sarao could have unleashed a near-catastrophe on U.S. securities markets single-handedly.[3] Yet, the complaint—and its causal account—point to a troubling dilemma facing scholars and policy makers today. This Article shows that the longstanding liability framework undergirding securities regulation looks increasingly fragile in the face of modern market design. With trading growing ever more automated—characterized by complex algorithms, a proliferation of specialist traders, and interconnections between markets—single weak links can create outsize costs. This evolution in market design poses a profound challenge for well-established liability regimes governing fraud, negligence, and mistakes. Trading firms are easily capable of creating far larger risks than they can either provision for ex ante or pay for ex post. In decoupling the riskiness of trading firms from their capacity to realistically bear the cost of their conduct, market structure casts doubt on the law's

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[1] John Cassidy, The Day Trader and the Flash Crash: Unanswered Questions, New Yorker (Apr. 23, 2015), http://www.newyorker.com/news/john-cassidy/the-day-trader-and-the-flash-crash-unanswered-questions [https://perma.cc/5VR5-YJJ5].

[2] Andrei Kirilenko et al., The Flash Crash: The Impact of High Frequency Trading on an Electronic Market 1 (May 5, 2014) (unpublished manuscript), http://www.cftc.gov/ucm/groups/public/@economicanalysis/documents/file/oce_flashcrash0314.pdf [https://perma.cc/CWK7-5KP6]. Sarao has been charged with wire fraud, commodities fraud, and the offense of "spoofing," referring to the practice of submitting orders with the intention of cancelling them to convey a false impression of demand. On the day of the Flash Crash, it is alleged that the false orders that were submitted by Sarao amounted to around 29% of all "sell" orders on the E-mini futures exchange, creating downward pressure that eventually culminated in the Crash. For detail, see Criminal Complaint, United States v. Sarao, No. 15-CR-75 (N.D. Ill. Feb. 11, 2015).

[3] See, e.g., Craig Pirrong, Did Spoofing Cause the Flash Crash? Not So Fast!, Streetwise Professor (Apr. 22, 2015), http://streetwiseprofessor.com/?p=9331 [https://perma.cc/M9CH-B8RQ]. Indeed, the CFTC and the SEC had earlier argued that the Flash Crash was caused by a sell algorithm from a Kansas mutual fund to dispose of 75,000 contracts on the S&P's E-mini futures exchange, Waddell Reed, that set off a chain reaction eventually culminating in the Flash Crash. See Eric M. Aldrich, Joseph Grundfest & Gregory Laughlin, The Flash Crash: A New Deconstruction 2, 4–7 (Jan. 25, 2016) (unpublished manuscript), http://ssrn.com/abstract=2721922 [https://perma.cc/HY8Y-P4P7] (disputing that Mr. Sarao could have been a proximate cause of the Flash Crash, as alleged by the Justice Department and the CFTC). On the interaction of trading technology, intermediation, and regulation, see Chris Brummer, Disruptive Technology and Securities Regulation, 84 Fordham L. Rev. 977 (2015).

ability to credibly constrain as well as punish mistakes and misbehavior in trading.

While scholars have vigorously debated the design of liability regimes in securities regulation, few dispute the underlying need for a guiding framework in this context.[4] Securities amount to little more than simple claims on the future value of a company's cash flows. Without credible, trustworthy information to substantiate these claims, investors face deep uncertainties in valuing them and in determining how much of their capital to invest. The risk of fraud, mistakes, or manipulation in presenting information can dissuade investors from bringing their money to markets or force them to rationally discount for the risks and the costs of verification.[5] A regulatory framework that punishes misinformation constrains those whose expressive conduct and communication matter to investors.[6] Given this importance, scholars have devoted extensive attention to the regime underlying fraud and misrepresentation in securities regulation, generating a vast literature studying its effectiveness. But, investors face a much broader set of risks than just the harm of misinformation. In particular, they depend on the operation of trading mechanisms to buy and sell their securities and to permit timely entry into and exit from investments. Without such mechanisms, investors face being left holding sticky securities or missing out on profitable trading windows. Exchanges, brokers, and other intermediaries operationalize the trading process and allow investors to interact fluidly within the marketplace.[7] Though attracting much less scholarly attention, regulation also controls these "execution" and "liquidity" risks through an intricate sys-

[4] See discussion infra Section I.A.

[5] The literature in this area is considerable. For an excellent summary from the corporate finance perspective, see Aswath Damodaran, Equity Risk Premiums (ERP): Determinants, Estimations and Implications—The 2013 Edition 11–12 (Mar. 23, 2013) (unpublished manuscript), http://ssrn.com/abstract=2238064 [https://perma.cc/TH4Y-F3LC]. For a general study of valuation, see, for example, Richard A. Brealey, Stewart C. Myers & Franklin Allen, Principles of Corporate Finance, pt. 1, at 1–146 (10th ed. 2011) (examining the role of valuation techniques in making investment decisions). On the importance of information in securities regulation, see, for example, Zohar Goshen & Gideon Parchomovsky, On Insider Trading, Markets, and "Negative" Property Rights in Information, 87 Va. L. Rev. 1229, 1232–36 (2001).

[6] See discussion infra Subsection I.B.1. For a historical perspective on key regulatory initiatives, see A. C. Pritchard & Robert B. Thompson, Securities Law and the New Deal Justices, 95 Va. L. Rev. 841, 843–46 (2009); Steve Thel, The Original Conception of Section 10(b) of the Securities Exchange Act, 42 Stan. L. Rev. 385, 391–94 (1990) (examining the original intention behind Rule 10b-5 and its evolution subsequently through jurisprudence).

[7] See Damodaran, supra note 5, at 12–13 (discussing the equity premium for illiquidity).

tem of rules, regulations, and best practices to deliver robust trading systems.[8]

The dense volume of rules comprising the liability regime in securities regulation obscures the observation that, for the most part, it measures compliance according to three well-established legal standards: (1) intent, (2) negligence, or (3) strict liability. Certain infractions, notably fraud or manipulation, demand that authorities show that defendants acted with intent to deceive and disrupt trading.[9] In other cases, defendants face sanction when they act negligently by failing to abide by a standard of reasonable care.[10] Finally, for certain harms, particularly for more technical breaches, regulation can punish using strict liability.[11] These standards of liability are familiar to lawyers and their application is well established under jurisprudence and scholarship. By choosing one or another type of liability for a particular offence, regulation calibrates the costs that defendants—as well as authorities—face in maintaining order in the marketplace.[12] With a robust disciplinary system in place, an effective liability framework should prevent undue discounting by investors.[13]

These familiar standards of liability, however, are rapidly losing their disciplinary power in modern automated markets. Recent years have

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[8] Craig W. Holden et al., The Empirical Analysis of Liquidity, 8 Found. & Trends Fin. 263, 312 (2013) (discussing the various transaction costs impacting investors by virtue of market structure).

[9] Santa Fe v. Green, 430 U.S. 462, 471–74 (1977) (quoting Ernst & Ernst v. Hochfelder, 425 U.S. 185, 197–201, 214 (1976)).

[10] See e.g., SEC Regulation Systems Compliance and Integrity, Exchange Act Release No. 34-73639, 2014 WL 6604803 (Nov. 19, 2014) (to be codified at 17 C.F.R. pts. 240, 242, 249) ("Regulation SCI will require SCI entities to establish written policies and procedures reasonably designed to ensure that their systems have levels of capacity, integrity, resiliency, availability, and security adequate to maintain their operational capability and promote the maintenance of fair and orderly markets . . . .").

[11] Gregory Scopino, Do Automated Trading Systems Dream of Manipulating the Price of Futures Contracts? Policing Markets for Improper Trading Practices by Algorithmic Robots, 67 Fla. L. Rev. 221, 253 (2015) (observing instances of strict liability for technical regulatory breaches in the case of futures markets).

[12] A. Mitchell Polinsky & Steven Shavell, Economic Analysis of Law 8–13 (Harvard Law Sch. John M. Olin Ctr. for Law, Econ. & Bus., Discussion Paper Series No. 536, 2005). See discussion infra Section I.B.

[13] See Damodaran, supra note 5, at 10–11. On informational efficiency in securities markets, see Eugene F. Fama, Efficient Capital Markets: A Review of Theory and Empirical Work, 25 J. Fin. 383, 387–88 (1970) [hereinafter Fama, Efficient Capital Markets]; Eugene F. Fama, Market Efficiency, Long-Term Returns, and Behavioral Finance, 49 J. Fin. Econ. 283, 284 (1998) [hereinafter Fama, Market Efficiency].

been marked by a shift towards a near-fully automated marketplace, with algorithms—preprogrammed electronic instructions—driving almost all aspects of trading.[14] Instead of relying on human beings to perform the task of submitting orders, routing them to exchanges, and concluding and completing trades, these functions are instead undertaken by algorithms. Unlike human traders, computers can transact in microseconds, at high volumes, and deploy an enormous reserve of data and quantitative input to inform trading.[15] Algorithmic trading—as measured by the subset of hyper-fast, data-driven high-frequency trading ("HF trading")—is responsible for around 50 to 70% of equity volume and an estimated 60% of all trading in futures markets in the United States.[16]

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[14] Thomas H. Cormen et al., Introduction to Algorithms 5–6 (3d ed. 2009) ("Informally, an algorithm is any well-defined computational procedure that takes some value, or set of values, as input and produces some value, or set of values, as output. An algorithm is thus a sequence of computational steps that transform the input into the output." (emphasis omitted)); John Bates, Algorithmic Trading and High Frequency Trading: Experiences from the Market and Thoughts on Regulatory Requirements, at *27 (July 2010) (unpublished manuscript), http://www.cftc.gov/ucm/groups/public/@newsroom/documents/file/tac_071410_binder.pdf [https://perma.cc/EEK8-Z8G9] ("An algorithm is 'a sequence of steps to achieve a goal'—and the general case of algorithmic trading is 'using a computer to automate a trading strategy.'"). For regulatory definitions, see, for example, Tech. Comm. of the Int'l Org. of Sec. Comm'ns, Regulatory Issues Raised by the Impact of Technological Changes on Market Integrity and Efficiency 10 (July 2011), http://www.iosco.org/library/pubdocs/pdf/IOSCOPD354.pdf [https://perma.cc/82WZ-LKLR] ("In its simplest guise, algorithmic trading may just involve the use of a basic algorithm . . . to feed portions of an order into the market at preset intervals to minimise market impact cost. At its most complex, it may entail many algorithms that are able to assimilate information from multiple markets . . . in fractions of a second").

[15] Yesha Yadav, Insider Trading and Market Structure, 63 UCLA L. Rev., (forthcoming 2016) (manuscript subsec. II.A.4, at 29–30).

[16] Reports suggest that algorithmic trading is responsible for around 70% of all trading in equities in the United States by volume. Additionally, algorithms also support trading in derivatives markets, notably, those for futures. Michael Mackenzie, High Frequency Trading under Scrutiny, Fin. Times (July 28, 2009), http://www.ft.com/intl/cms/s/0/d5fa0660-7b95-11de-9772-00144feabdc0.html#axzz3yJctry00 (discussing that around 73% of equities traded by volume trade in high-frequency markets); Alexander Osipovich, Algorithmic Trading in Energy Markets, Risk Mag. (Jan. 10, 2012), http://www.risk.net/energy-risk/feature/2136141/algorithmic-trading-energy-markets [https://perma.cc/V7PP-GB7M] (estimating as much as two-thirds of equity trading is driven by algorithms); Philip Stafford, Arash Massoudi & Michael Mackenzie, NASDAQ Sets Stage for HFT In Treasuries, Fin. Times (Apr. 4, 2013), http://www.ft.com/intl/cms/s/0/6e0ac4de-9d08-11e2-a8db-00144feabdc0.html#axzz3z3QohDaX (detailing the proposed use of HF trading for U.S. Treasuries).

When added to trading by (relatively) slower algorithms, these figures reach considerably higher.[17]

Automation raises serious concerns for the effectiveness of the traditional liability framework and the allocation of costs it imposes in securities trading. This Article makes two claims.

First, existing theories of liability apply weakly in a market that is overwhelmingly composed of preprogrammed trading algorithms.[18] Unpredictable error is endemic to their operation. To trade high volumes of securities in milli- and microseconds, algorithms must be programmed in advance of trading and designed to trade independently in real time.[19] Humans cannot make trade-by-trade decisions in high-frequency markets ("HF markets"). Instead, they must anticipate how markets will behave and program their algorithms in advance of the trading day. These predictive programs must account for changing, uncertain market environments. They must include instructions to deduce how other traders will transact and how their own trades will affect prices in real time.[20] Algorithms can be very sophisticated. But they cannot possibly anticipate exactly how future markets will behave. In the necessary absence of certainty, programming can only approximate future environments in programming, representing a best guess as to likely market performance.[21]

Predictive programming challenges the central pillars of the liability regime. From the ex ante standpoint, typical assumptions underlying deterrence and punishment do not work well. Theory suggests that traders will weigh the costs and benefits of their conduct in deciding whether to

[17] Indeed, the SEC reports that a study by the Australian securities regulator concluded that algorithms were involved in almost 99.6% of all trades. Div. of Trading & Mkts., U.S. Sec. & Exch. Comm'n, Equity Market Structure Literature Review Part II: High Frequency Trading 5–6 (2014). It is also worth noting that Navinder Sarao was not a high-frequency trader ("HF trader"), but rather one utilizing slower off-the-shelf algorithms to conduct his trading strategy. See Cassidy, supra note 1.

[18] Yesha Yadav, How Algorithmic Trading Undermines Efficiency in Capital Markets, 68 Vand. L. Rev. 1607, 1612–17 (2015) (examining the impact of predictive algorithms for allocative efficiency).

[19] See U.K. Gov't Office for Sci., Foresight: The Future of Computer Trading in Financial Markets 20–50 (2012) (noting the uses and benefits of algorithmic trading strategies).

[20] See Michael Kearns & Yuriy Nevmyvaka, Machine Learning for Market Microstructure and High Frequency Trading, *in* High-Frequency Trading: New Realities for Traders, Markets and Regulators 91, 115–22 (David Easley, Marcos López de Prado & Maureen O'Hara eds., 2013).

[21] Yadav, supra note 18, at 1621–22.

meet the standard of compliance. If their conduct will result in more costly punishment than their gains, they should be deterred from going forward.[22]

Predictive algorithmic trading, however, makes this calculation significantly more difficult. With preset algorithms, error and imprecision are inevitable. Indeed, because errors can spread across the marketplace in seconds, the full magnitude is also not always ascertainable ex ante. Traders face a difficult choice in deciding what to do and how to trade. On the one hand, they can make their algorithms as simple as possible and program them to transact within very predictable parameters. Or, they can build algorithms to be as sophisticated as possible, capable of responding to a wide variety of conditions. But neither option is satisfactory. On the first option, simple algorithms will not generate much profit, particularly in HF markets or in complex, quantitative conditions. To be workable, simple programs can only operate in the very short term when circumstances are most predictable, making them of little use practically. The second option—while enabling algorithms to function expansively—is also the most risky. Complex algorithms can make incorrect assumptions, misinterpret data, or fail to anticipate events. In short, using preset algorithms, the usual trade-off governing compliance applies poorly.[23] Traders have limited practical room to avoid error in HF markets.

Second, traditional standards of liability cannot easily deter or punish misbehavior in markets where the risks of trading can spread rapidly across the system of national exchanges. Such "contagion" is powerfully in evidence in automated trading, particularly at higher speeds.

For a start, owing to the speed and efficiency of algorithms, harms originating in one market can spread widely. With preprogrammed algorithms primed to react instantly to new information—even if incorrect—problems can continue until they are caught and corrected. Ultrafast informational linkages between trading venues promise efficiency gains, with new information reflected rapidly in securities prices across the

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[22] See Polinsky & Shavell, supra note 12, at 26–31.

[23] U.K. Gov't Office for Sci., supra note 19, at 28–30; Kearns & Nevmyvaka, supra note 20, at 94–96 (describing dynamic machine learning models and the complex interplay of variables underpinning their operation); Tommy Wilkes & Laurence Fletcher, The Algorithmic Arms Race, Reuters, May 21, 2012, http://uk.reuters.com/article/idUKL4E8GAAML20120521 [https://perma.cc/XN77-UMYV].

system.[24] But the effects of erroneous or deceptive decision making can also exert a far wider impact than might have been possible in analog, less automated trading. Finance scholarship highlights this risk. In one prominent study, Professor Gerig observes that HF trading tends to synchronize prices across the financial system.[25] While beneficial in good times, the study notes that this synchronicity can also result in errors proliferating in times of stress, heightening the impact of single failures for the system as a whole.[26] The risk of small errors to manifest in disproportionately serious harms is further reinforced by the tendency of many traders to use similar programming that responds in like ways to new information. Particularly in relation to high-frequency traders ("HF traders"), scholars have remarked that correlated trading between market actors is clearly observable.[27] When viewed alongside the risks of synchronicity, correlated trading can result in errors spreading broadly as well as deeply in the marketplace.

Applying conventional liability standards to "contagious" algorithmic trading reveals room for damaging risk taking by market actors. Negligence-based liability—that measures compliance by reference to the objective standard of reasonable behavior—is a case in point.[28] Liability for negligence bites only when actors engage in unreasonable harmful

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[24] Albert J. Menkveld, High Frequency Trading and the *New Market* Makers, 16 J. Fin. Mkts. 712, 737 (2013).

[25] Austin Gerig, High-Frequency Trading Synchronizes Prices in Financial Markets 1, 3, 7 (Jan. 2015) (unpublished manuscript), http://ssrn.com/abstract=2173247 [https://perma.cc/L4S7-X4AK] (presenting evidence of synchronized changes in prices in related securities across securities markets).

[26] Id. at 7.

[27] See Alain Chaboud et al., Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market, 69 J. Fin. 2045, 2046–47 (2014) (demonstrating correlated trading behavior in foreign exchange HF trading). See generally Jonathan Brogaard, Terence Hendershott & Ryan Riordan, High Frequency Trading and Price Discovery, 27 Rev. Fin. Stud. 2267, 2302–04 (2014) (Eur. Cent. Bank, Working Paper No. 1602, 2013) (describing higher market efficiency in markets with HF traders).

[28] Guido Calabresi, The Cost of Accidents: A Legal and Economic Analysis 26–27 (1970) ("[T]he principal function of accident law is to reduce the sum of the costs of accidents and the costs of avoiding accidents."). From the perspective of theory, this Article simplifies the rich history and debates underpinning the evolution of tort law and negligence. A full discussion of tort theory is outside of the scope of this Article. For insightful analysis of the evolution of tort law and key debates, see John C.P. Goldberg, Twentieth-Century Tort Theory, 91 Geo. L.J. 513, 514–30 (2003). On the limits of traditional theories underpinning tort theory, see Scott Hershovitz, Harry Potter and the Trouble with Tort Theory, 63 Stan. L. Rev. 67 (2010) (examining shortcomings of traditional economic analysis of tort law, and highlighting numerous benefits and effects of tort law that are underappreciated by economists).

behavior. As observed by Professors Shavell and Polinsky, unlike strict liability, where the very fact of harm is enough to result in sanction, the reasonableness standard leaves room for actors to cause some harm, just so long as their conduct is reasonable.[29] To the extent that engaging in reasonable risk taking is rational and profitable, traders have every incentive to pursue it: They benefit from the gains that accrue, but do not internalize the full cost of their risk taking. Even some unreasonable risk taking may go unpunished so long as the costs to authorities of making the case and punishing the careless action dissuade enforcement.[30]

For algorithmic markets, however, the room for maneuvering implicit in the reasonableness standard is problematic. Even reasonable risk taking creates potential for outsize harms. The propensity for error in algorithmic trading as well as the chance of small errors to generate large harms suggests that the negligence standard may, in fact, leave instances of reasonable but ultimately dangerous risk taking unpunished.

If the negligence standard is problematic, strict liability or intent-based standards offer alternatives that might provide a better fit to match the risks of algorithmic trading and to calibrate the standard of behavior. If policy favors a more exacting standard of accountability to limit the chance of harm, strict liability can force traders to internalize the full costs of their carelessness. Regulators can also act on strict liability breaches cheaply. All they have to show is the fact of the harm.[31] On the other side, if policy favors more tolerance for careless traders, regulators can demand intent or recklessness as the central requirement for liability. This high threshold can excuse large-scale errors if there is no deceptive or malicious intent behind them, giving wide berth to error-prone traders.

Both alternatives, however, have significant drawbacks. Strict liability raises serious practical and conceptual concerns. Predictive programming implies an endemic propensity for ad hoc, unpredictable error, meaning that strict liability can give rise to widespread breaches. Enforcement may be arbitrary as a result. Also, with risks capable of

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[29] Polinsky & Shavell, supra note 12, at 29.

[30] See discussion infra Subsection I.B.2. Outside of the law and economics perspective, scholars argue that considerations of social welfare can also impact the interpretations of doctrine and pursuit of tort actions. See, e.g., Robert L. Rabin, The Historical Development of the Fault Principle: A Reinterpretation, 15 Ga. L. Rev. 925 (1981) (charting the historical evolution of the negligence standard).

[31] See Polinksy & Shavell, supra note 12, at 9, 29.

spreading rapidly across many markets, the cost of harms can far exceed the amount that a single trader might be able to bear. Conversely, an intent-based standard encourages risk taking by letting traders off the hook for risky but nonmalicious behavior. Both strict liability and intent-based standards, therefore, can leave a swathe of misbehavior to go unpunished.

The costs of an ineffective liability framework extend deeply into market function. Pervasive mistakes and misbehavior skew the quality of information underlying trading and, with this, the ability of prices to contribute to the allocation of capital in the real economy. If investors cannot fully trust the marketplace to safeguard capital, they are likely to leave it or reduce the intensity of their participation.

In concluding, this Article examines strategies to safeguard markets against the risk of error and misbehavior in the absence of strong, effective laws. It proposes greater focus on structural design to create institutional pathways for safer trading.[32] First, it shows that exchanges play an especially key role in overseeing markets due to their closeness to HF trading. This proximity means that exchanges are the first eyes on trading activity with tools to discipline problem traders and to halt or limit trading in times of crisis. But the incentives of exchanges to exercise effective supervision stand in tension with the gains they generate in terms of fees and prestige from those they regulate. This tension may result in exchanges being lax in disciplining important trading firms or in halting trading in an effort to avoid reputational damage. This Article proposes measures to require exchanges to contribute to the cost of losses arising on account of algorithmic mishaps when individual traders fall short and do not have sufficient funds. With real skin in the game, exchanges are likely to be better incentivized to exercise stronger oversight of traders. Second, the Article suggests exploring the viability of relying on tweaking structural design to promote better behavior. Notably, reducing trading speed can improve the ability of markets to verify information and reduce costly errors. Some reductions in speeds, even by fractions of a second, may help slow information contagion through the market and make it easier for exchanges to contain its spread, offsetting in part the endemic risks of error in predictive, algorithmic trading. In co-opting

[32] Edward K. Cheng, Structural Laws and the Puzzle of Regulating Behavior, 100 Nw. U. L. Rev. 655, 656–75 (2006) (arguing for reliance on structural solutions to regulate behavior, versus reliance on legal fiat, rules, and regulations, which may lack effectiveness).

exchanges more forcefully into the goal of safeguarding markets, this proposal ultimately seeks to bolster investor confidence in markets and improve capital allocation in the economy.

This Article proceeds in five parts. Part I examines the reliance that markets place on credible information flows and robust operational mechanics of exchange. A detailed body of laws has evolved to safeguard these resources, to assure investors of their robustness, and to prevent undue discounting of investment capital. This Article distills this complex network of rules into the three core standards of liability: (1) intent, (2) negligence, and (3) strict liability. Part II analyzes algorithmic trading to assess its dependence on preprogrammed algorithms and the interconnections it forges between markets that can result in even small errors having outsize, system-wide impact. Part III analyzes the application of traditional liability standards on algorithmic markets to demonstrate that these standards are rapidly becoming less effective in deterring or punishing mistake and misconduct. In response to the weakening legal framework, Part IV explores pathways for reform and focuses on structural, institutional solutions that can fill the gaps left.

I. MARKET QUALITY, MISTAKE, AND MANIPULATION

Information drives markets. Securities represent a simple claim on the future cash flows of a company. Without a reliable means to understand how a company works, its organization and pathways for future growth, investors cannot know whether to place their capital at risk. To make it cheaper for investors to arrive at considered decisions, ensuring smooth information flows constitutes a central goal for regulation. Realizing this goal necessitates focus on two mechanisms: (1) disclosure of reliable information to investors; and (2) securing the operational structure of trading to safeguard against errors, misbehavior, and manipulation that can skew the signaling value of prices. This Part examines these two core regulatory objectives. It explores the hard constraints that law imposes on securities markets to bolster the credibility and accuracy of information flows as well as rules to maintain a smooth functioning of the trading process. While the laws are clearly far too extensive to cover in this Article, I focus on analyzing the three cornerstone standards of liability that broadly anchor them: (1) intention and recklessness, (2) negligence, and (3) strict liability, as they relate to securities regulation.

A. Information and Markets

Theory establishes that information constitutes the central imperative for markets and traders.[33] According to conventional economic thinking, markets harness the profit-driven motives of individual traders to create deep reservoirs of information on publicly traded securities.[34]

Demand and Supply for Information: It is almost tautological to note that investors need a rich supply of information to make sound investment decisions. Corporate finance explains the basic problem. If investors are to be coaxed to part with their capital for a period of time, they need to know whether they will make a return from this investment. Information is critical to this analysis.[35] The more money that investors must spend privately on acquiring this information, in checking it and analyzing its insights, the less they might be willing to put into the capital markets. As Professor Damodaran observes, the deeper the uncertainties facing investors, the higher the premium they will demand from businesses in need of financing.[36] Enterprises that depend on this money will lose out on much-needed capital to fund their expansion, receiving just a fraction of what investors can supply. In turn, investors will fail to increase the value of their own capital when they cannot take advantage

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[33] Fama, Efficient Capital Markets, supra note 13, at 387–88 ("A market in which prices always 'fully reflect' available information is called 'efficient.'"); see also Andrei Shleifer, Inefficient Markets: An Introduction to Behavioral Finance (2000) (noting the impact of behavioral economics); Ronald J. Gilson & Reinier H. Kraakman, The Mechanisms of Market Efficiency, 70 Va. L. Rev. 549, 549–53 (1984) (examining how information enters markets and is incorporated into prices); Yadav, supra note 18, at 1645–47 (discussing the impact of information for allocative efficiency). For critiques of efficient markets, see, for example, Sanford J. Grossman & Joseph E. Stiglitz, On the Impossibility of Informationally Efficient Markets, 70 Am. Econ. Rev. 393 (1980); Lawrence H. Summers, Does the Stock Market Rationally Reflect Fundamental Values?, 41 J. Fin. 591 (1986). In the legal literature, see, for example, Lynn A. Stout, The Mechanisms of Market Inefficiency: An Introduction to the New Finance, 28 J. Corp. L. 635 (2003) (observing criticisms of market efficiency from the legal standpoint and underscoring the impact of alternative economic theories); William K.S. Wang, Some Arguments that the Stock Market is Not Efficient, 19 U.C. Davis L. Rev. 341 (1986).

[34] See, in particular, Gilson & Kraakman, supra note 33, at 569–72; see also Henry G. Manne, Insider Trading and the Stock Market 138–41 (1966) (highlighting the adverse impact of the prohibition against insider trading on informational flows and price formation); Dennis W. Carlton & Daniel R. Fischel, The Regulation of Insider Trading, 35 Stan. L. Rev. 857, 866–68 (1983) (discussing the significance of insider trading for informed markets).

[35] Damodaran, supra note 5, at 10–11.

[36] Id. at 11–13.

of lucrative investment opportunities. Taken together, poor information flows can jeopardize efficient capital allocation within the real economy.

In seeking to resolve this problem, policy makers have long favored an intensive regime of mandatory disclosure to regularly supply information to the market.[37] Rather than forcing investors to internalize the costs of searching and investigating enterprises, regulation requires companies to shoulder the burden of disclosure in return for their securities to trade in public markets.[38] Despite the costs to issuers, securities regulation firmly adheres to the principle that issuers maintain a continuous supply of detailed information about securities to investors.[39] Beyond just supplying information, regulation demands that this disclosure be credible and accurate. Capital-hungry issuers are likely to exaggerate their winnings and underemphasize their risks. To force reliable disclosure, civil and criminal liability attaches to incorrect or fraudulent revelations by companies. Discussed below, the most significant of these comes under Section 10(b) of the Securities Exchange Act of 1934 and its Rule 10b-5 that creates civil and criminal liability for intentional deceits.[40] As a catch-all safety net stretching across all types of securities

[37] John C. Coffee, Jr., Market Failure and the Economic Case for a Mandatory Disclosure System, 70 Va. L. Rev. 717, 720–29 (1984) (discussing the benefits of mandatory disclosure); Merritt B. Fox et al., Law, Share Price Accuracy, and Economic Performance: The New Evidence, 102 Mich. L. Rev. 331, 339–41 (2003) (explaining the relationship between mandatory disclosure and share prices). For a notable point of view on the absence of the need for regulation to mandate disclosure, see Omri Ben-Shahar & Carl E. Schneider, More Than You Wanted to Know: The Failure of Mandated Disclosure 3–12 (2014) (discussing the failure of mandatory disclosure to inform personal choices); Homer Kripke, The SEC and Corporate Disclosure: Regulation in Search of a Purpose 284–86 (1979).

[38] Compare Fox, supra note 37, at 333–35 (noting the benefits of mandatory disclosure), with George J. Bentson, Required Disclosure and the Stock Market: Rejoinder, 65 Am. Econ. Rev. 473, 473–75 (1975) (suggesting that the costs of mandatory disclosure do not justify the benefits); Kripke, supra note 37, 284–86 (noting the drawbacks of mandatory disclosure).

[39] Key here are Section 5 of the Securities Act of 1933, ch. 38, 48 Stat. 74, 77–78 (codified as amended at 15 U.S.C. § 77e (2012)) (governing disclosure during public offerings of securities), and Sections 13, 14 and 15 of the Securities Exchange Act of 1934, ch. 404, 48 Stat. 881, 894–96 (codified as amended at 15 U.S.C. §§ 78m–78o (2012)) (governing continuous disclosure).

[40] The Securities Exchange Act of 1934, ch. 404, § 10(b), 48 Stat. 881, 891 (codified as amended at 15 U.S.C. § 78j); 17 C.F.R. § 240.10b-5 (1988); Ralph C. Ferrara & Marc I. Steinberg, A Reappraisal of *Santa Fe*: Rule 10b-5 and the New Federalism, 129 U. Pa. L. Rev. 263, 266 n.19 (1980) (analyzing the role of intent in the determination of liability under Section 10(b)); David M. Phillips, An Essay: Six Competing Currents of Rule 10b-5 Jurisprudence, 21 Ind. L. Rev. 625, 627 (1988) (describing the broad rationales and reasoning guiding Section 10(b) jurisprudence); Margaret V. Sachs, The Relevance of Tort Law Doc-

trading, Rule 10b-5 constitutes the major source of constraint for traders intent on distorting information flows through their frauds.[41]

Information and the Trading Process: In addition to maintaining fulsome information flows for investors, capital allocation also benefits if this information can be easily understood. If investors must spend time and money to parse the meaning of each disclosure, they will incur high transaction costs that diminish their appetite for investment. According to the famous Efficient Capital Markets Hypothesis ("ECMH"), an efficient market offers an accessible mechanism to help investors under-

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trines to Rule 10b-5: Should Careless Plaintiffs be Denied Recovery?, 71 Cornell L. Rev. 96, 99–101 (1985) (examining the place of negligence-based liability for Rule 10b-5 claims and contributory negligence by plaintiffs). The key case law in this area—notably, *Ernst & Ernst v. Hochfelder*, 425 U.S. 185 (1976); *Santa Fe Industries v. Greene*, 430 U.S. 462 (1977); and *Aaron v. SEC*, 446 U.S. 680 (1980)—establish the centrality of intent and deception in Rule 10b-5 jurisprudence. In other words, negligence is insufficient and disclosure negates liability with respect to Rule 10b-5. It should be noted that Rule 10b-5 is not the only provision that controls poor information flows in the market. Notably, sections 11 and 12 of the Securities Act of 1933, ch. 38, 48 Stat. 74, 82–83 (codified as amended at 15 U.S.C. §§ 77k–77l (2012)), impose liability in the context of public offerings. These provisions make issuers, underwriters, and dealers liable in the context of a public offering for securities. They do not, therefore, affect secondary market traders that are involved in open-market trading. See, e.g., Gustafson v. Alloyd Co., 513 U.S. 561 (1995) (noting the application of Section 12(a)(2) liability for misleading prospectuses to public offerings); Pinter v. Dahl, 486 U.S. 622 (1988) (imposing liability for Section 12(a)(1) on sellers and those who solicit purchasers for value).

For further discussion, see Donald C. Langevoort, Deconstructing Section 11: Public Offering Liability in a Continuous Disclosure Environment, 63 L. & Contemp. Probs. 45, 47 (2000) (suggesting reforms for the liability regime associated with Section 11); Steve Thel, Free Writing, 33 J. Corp. L. 941, 942–44 (2008) (noting the liability regime for free writing and free writing prospectuses under Section 12(a)(2) of the Securities Act 1933); see also Marcel Kahan, Securities Laws and the Social Costs of "Inaccurate" Stock Prices, 41 Duke L.J. 977, 985 (1992) ("Disclosure requirements . . . may lead to the dissemination of more (and more reliable) information than would otherwise become public, thereby enabling investors to arrive at a more accurate assessment of a company's fundamental value." (footnotes omitted)); Paul G. Mahoney, Mandatory Disclosure as a Solution to Agency Problems, 62 U. Chi. L. Rev. 1047 (1995) (suggesting an alternative "agency cost" theory to explain mandatory disclosure requirements).

[41] Thel, supra note 6, at 392–94 (arguing that the history of Section 10(b) points to this Section as being a more expansive anti-speculation provision). It should be noted that, prior to the enactment of the Dodd-Frank Act, there was considerable doubt regarding the application of Rule 10b-5 to over-the-counter derivative securities traded by sophisticated parties. This potential lacuna has been closed by the Dodd-Frank Act. Dodd-Frank Wall Street Reform and Consumer Protection Act, Pub. L. No. 111-203, tit. VII, § 753, 124 Stat. 1376, 1750–54 (2010); see also Commodity Exchange Act, 7 U.S.C § 2(g) (2012); Commodity Futures Modernization Act, Pub. L. No. 106-554 app. E, tit. I, 114 Stat. 2763A-365, 2763A-365 to 2763A-413 (2000); Gramm-Leach-Bliley Act, Pub. L. No. 106-102, § 206(a), 113 Stat. 1338, 1393–94 (1999).

stand the value of information. The ECMH posits that securities prices reflect all current available information. Prices represent the cumulative intelligence of all traders coming to transact with one another in an unbiased manner, showing the worth of future cash flows as a function of what traders are willing to pay to either buy or sell a security.[42] Although the ECMH only offers an insight into "informational efficiency"—reflecting the value of available data on a company and its security—scholars also use it to roughly approximate fundamental value efficiency. In other words, while prices might offer a glimpse into the current value of news and views on a company, they can also offer insight into what this company is really worth in the longer term.[43]

Informed traders are critical to this process. Investors that have deeply researched a security will understand its worth more exactly. When they decide to trade, their view of what price to pay should generate the greatest gain. Others are likely to follow their lead; the quickest among them would be able to enjoy a sliver of profit as market prices come to reflect their actions. Finally, uninformed traders take the opposite side of any transaction because they are keen to sell at any price or because they possess limited information on their securities.[44] The trading process performs a central role in disseminating information about securities, ensuring that a broad swathe of investors can see the sum impact of current available information for a public company.[45]

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[42] See Fama, Efficient Capital Markets, supra note 13; Fama, Market Efficiency, supra note 13; Gilson & Kraakman, supra note 33, at 553–54 (analyzing the trading dynamics that make prices efficient); Yadav, supra note 18 (discussing market efficiency and algorithmic trading). For critiques of the ECMH, see, for example, Grossman & Stiglitz, supra note 33 (noting conceptual contradictions underlying the ECMH); Schleifer, supra note 33 (offering a critique from a behavioral economics perspective); Summers, supra note 33 (noting the limited power of statistical tests to provide evidence of market efficiency). For critiques from a legal standpoint, see, for example, Stout, supra note 33 (discussing challenges from alternative economic theories, notably behavioral finance); Wang, supra note 33 (discussing various types of inefficiency in securities markets).

[43] Alon Brav & J.B. Heaton, Market Indeterminacy, 28 J. Corp. L. 517, 530–39 (2003) (discussing the dynamic of informational efficiency in markets and its interaction with fundamental value efficiency). For a critical perspective on informational efficiency as a proxy for allocative efficiency, see Joseph E. Stiglitz, The Allocation Role of the Stock Market: Pareto Optimality and Competition, 36 J. Fin. 235, 235–37 (1981).

[44] This interaction is proposed and described in detail in Gilson & Kraakman, supra note 33, at 579–88.

[45] Literature on this process is considerable across law, finance, and economics. For a fuller discussion of the literature, see Yadav, supra note 18, at 1631–44.

Safeguarding the Trading Process: The dynamic outlined above can only function if the operational processes underpinning informational exchange can be safeguarded. Without this, investors that cannot trade in a timely way lose their advantage and are forced to internalize a higher cost of capital. Investors also lose when those responsible for processing the trade, like brokers or exchanges, are careless, disruptive, or ill-equipped to handle orders. Frictions in the smooth execution of trades exert real costs that factor into investor decision making. As argued by Professor Perold, traders must contend with the costs of an "implementation shortfall" arising from the difference in returns between a trader's theoretical, ideally designed securities portfolio and the reality.[46] The actual, real returns—versus the desired ones—change owing to a range of execution costs that can complicate the decision dynamic of trading.

Problems with execution exert a damaging impact on market efficiency and the signaling value of prices. The many forms of such disruption are too numerous to examine in detail in this Article. Broadly, however, execution costs might arise: (1) owing to costs created by individual traders and the interaction of their orders with those of others; and (2) problems caused by more "systemic" factors involving exchanges or intermediaries (e.g., brokers) that connect investors within the marketplace. With respect to the first category, investors confront risks created by their own trading systems as well as adverse knock-on effects caused by those of other traders within the market's ecosystem. Imagine, for example, that instead of submitting an order to buy 100 shares, an investor sends out an order for 100,000 shares by mistake. This order matches, is confirmed by an exchange, and becomes final. Such an error can easily happen, for example, when using electronic systems that create the risk of a "fat finger" trade. The error-prone trader is now left holding more securities than she needs and forced to spend money to pay for extra, unwanted securities. One response here would be to cancel the trade—to reverse the purchase of the 100,000 securities and to replace it with the correct order (100 shares). But this approach can create prob-

[46] Holden et al., supra note 8, at 289–91 (noting the costs of trading); Robert Engle & Robert Ferstenberg, Execution Risk, 33 J. Portfolio Mgmt. 34, 34–35 (2007) (discussing the risks-return trade-off underpinning trade execution); André F. Perold, The Implementation Shortfall: Paper Versus Reality, 14 J. Portfolio Mgmt. 4, 4–7 (1988); see also Matthias Kahl et al., Paper Millionaires: How Valuable Is Stock to a Stockholder Who Is Restricted from Selling It?, 67 J. Fin. Econ. 385, 385–87 (2003) (discussing the costs to those that cannot freely sell their securities).

lems for those that sold securities to the trader. They may have used money from the sale to buy their own securities, which they will need to liquidate if they have to return this money to the error-prone trader. Worse, price changes for securities can further complicate such reversals. In short, the error and subsequent reversals might prompt a ripple of problems across a multiplicity of investors and skew the signaling value of securities prices.

Such cases are all too common. On August 1, 2012, for example, Knight Capital, a well-established trading firm, sought to route a total of 212 customer orders through to the New York Stock Exchange ("NYSE"). The router instead released more than 4 million (rather than 212) orders to transact in more than 397 million shares in the space of 45 minutes. By the time the defective routing program was corrected, Knight Capital had accumulated several billion dollars in positions and approximately $460 million in losses—approximately $10 million dollars in losses for every minute that the erroneous router was in operation. Despite the egregious error, the trades were deemed final, pushing the firm to the edge of bankruptcy.[47]

Errors are obviously harmful to price quality, but a keen sense of market behavior can help traders to work out clever manipulative schemes that distort prices and profit from deceit.[48] Market manipulation is clearly undesirable. Honest investors suffer because a manipulator systematically wins. The market suffers because prices become disconnected from fundamentals. Examples of manipulation in securities markets are plentiful. The case of Navinder Sarao—who seemingly profited from a series of "spoof" trades prior to the Flash Crash—is just one. According to the complaint, Sarao sent out illusory sell orders designed to create a false impression of selling pressure,[49] which prompted the price

[47] Knight Capital was eventually bought by the prominent high-frequency firm ("HF firm"), Global Electronic Trading Company (Getco) on the eve of bankruptcy. Nick Baumann, Too Fast to Fail: Are High-Speed Traders Hurtling Toward the Next Financial Meltdown?, Mother Jones, Feb. 2013, at 36, 41; Nathaniel Popper, High-Speed Trade Giants to Merge, N.Y. Times, Dec. 20, 2012, at B1; Press Release, U.S. Sec. & Exch. Comm'n, SEC Charges Knight Capital with Violations of Market Access Rule (Oct. 16, 2013), http://www.sec.gov/News/PressRelease/Detail/PressRelease/1370539879795 [https://perma.cc/8TQF-SBM4].

[48] John D. Finnerty, Short Selling, Death Spiral Convertibles, and the Profitability of Stock Manipulation 62–63 (March 2005) (unpublished manuscript), http://ssrn.com/sol3/abstract=687282 [https://perma.cc/D3W3-6PA5] (detailing manipulative strategies and naked short selling).

[49] Criminal Complaint, supra note 2, at 3–4.

of securities to fall. When these prices fell, Sarao could profit by buying securities at a low price. He could then submit "spoof" buy orders that artificially drove up the price, helping Sarao to maximize profit when he sold securities.[50] Other examples of manipulative behaviors include wash sales and matched orders. These techniques involve traders making fictitious trades or submitting orders designed to match, generating artificial prices without, in fact, changing the beneficial ownership of securities.[51]

With respect to the second category, instances of error and manipulation can increase if the operational architecture of the market fails to perform. The systemic nature of exchanges means that problems afflicting their operation can generate pervasive costs affecting the entire market. If exchange platforms are slow, prone to mishandling orders, or easy to manipulate, investors must provision to deal with these problems. Confidence in prices can deteriorate widely because the process driving their formation is unreliable.[52] Instances of exchanges performing sub-optimally are also commonplace. The May 2010 Flash Crash is illustrative. Following the complaint against Sarao, commentators have pointed a finger at the Chicago Mercantile Exchange—a venue where Sarao routinely traded—for failing to discipline the spoof trader long before the Flash Crash transpired despite noticing Sarao's problematic trades.[53] Exchanges also drew notice for failing to anticipate and control the chain reaction leading to the Flash Crash, to maintain trading on the market, and to control the depth of the rapid collapse.[54]

In addition to such large-scale impact, exchanges can suffer more routine malfunctions that disrupt trading in single securities. Facebook's highly publicized initial public offering ("IPO") on the NASDAQ in

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[50] See Cassidy, supra note 1; Kirilenko et al., supra note 2, at 5–6; Pirrong, supra note 3.

[51] Press Release, Fin. Indus. Regulatory Auth., NASD Charges Peter Kellogg with Fraudulent Wash and Matched Trades (Nov. 5, 2003), https://www.finra.org/newsroom/2003/nasd-charges-peter-kellogg-fraudulent-wash-and-matched-trades [https://perma.cc/MEX2-GKH7].

[52] John J. Merrick, Jr. et al., Strategic Trading Behavior and Price Distortion in a Manipulated Market: Anatomy of a Squeeze, 77 J. Fin. Econ. 171, 172–75 (2005) (showing the price impact of market manipulation).

[53] Kara Scannell et al., CME Faces Scrutiny over Warning Signs on 'Flash Crash Trader,' Fin. Times (Apr. 23, 2015), http://www.ft.com/intl/cms/s/2/47959da4-e9c0-11e4-b863-00144feab7de.html [https://perma.cc/A46Z-UUZK]. On the changing role of exchanges, see, e.g, Onnig H. Dombalagian, Exchanges, Listless?: The Disintermediation of the Listing Function, 50 Wake Forest L. Rev. 579, 587–94 (2015).

[54] See Kirilenko et al., supra note 2.

May 2012 is case in point. NASDAQ moved forward with the Facebook IPO despite a noticed glitch in its order-matching system. Following the launch, NASDAQ's system, unsurprisingly, failed to properly match orders, leaving almost 30,000 orders for Facebook securities unfulfilled.[55] The glitch marred Facebook's $16 billion launch and deeply dented NASDAQ's reputation, resulting in a fine, as well as loss of business.[56]

The increasing reliance on technology has heightened the pressure on top exchanges to assure the robustness of their trading systems and to keep large-scale, as well as more routine, risks in check.

Such disruptions—flash crashes, misfiring algorithms, and manipulations—can be deeply harmful. A first look at such events, however, might suggest otherwise. High-speed flash crashes, for example, look like a zero-sum game: prices fall and then rapidly recover, with these downward spirals too fleeting to be meaningful. Moreover, such glitches might disproportionately impact HF traders and could simply be internalized as a cost of doing business. But considered more deeply, such assumptions do not hold. For one, prices might not return to normal after flash crashes or other glitches, or may only do so slowly. In 2008, the stock of United Airlines lost almost 75% in value, falling from around $12 per share to $3 a share and forcing exchanges to stop trading in United's securities. The cause was traced back to newswires erroneously picking up a story about United's bankruptcy—six years after the event. As trading resumed once the mistake was spotted, the price did not return to normal, but only reached $10.92 by the close of the day. Such unpredictable movements in securities prices bode ill for those that trade as securities prices fall.[57] When exchanges do not reverse the effect of mishaps—for example, as took place in the case of Knight Capital—losses can be lasting and difficult to predict as a transaction cost of trading.

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[55] Press Release, U.S. Sec. & Exch. Comm'n, SEC Charges NASDAQ for Failures During Facebook IPO (May 29, 2013), http://www.sec.gov/News/PressRelease/Detail/PressRelease/1365171575032 [https://perma.cc/96BN-NAH4].

[56] See Jenny Strasburg & Jacob Bunge, NASDAQ Is Still on Hook as SEC Backs Payout for Facebook IPO, Wall St. J. (Mar. 25, 2013), http://www.wsj.com/articles/SB10001424127887323466204578382193806926064 [https://perma.cc/AK36-QJKP]; Jessica Toonkel & John McCrank, Alibaba Worried About Facebook IPO as Considered NASDAQ Versus NYSE, Reuters (Sept. 15, 2014), http://www.reuters.com/article/us-alibaba-ipo-nasdaq-insight-idUSKBN0HA09G20140915 [https://perma.cc/JUZ9-NJNZ].

[57] Kim Zetter, Six-Year-Old News Story Causes United Airlines Stock To Plummet—Update Google Placed Wrong Date On Story, WIRED Mag. (Sept. 8, 2008), http://www.wired.com/2008/09/six-year-old-st/ [https://perma.cc/ZWS4-K4L7].

Frequent flash crashes and periodic glitches also point to a serious disruption in the flow of trades and in the ebb and flow of demand and supply for a particular security. Where the market suffers from a pervasive risk of such events, doubts might reasonably be raised about its capacity to offer a stable, reliable forum for transacting large amounts of capital.

In summary, good information and low execution risks are critical to well-functioning markets. If investors are to be motivated to participate in the marketplace, they need assurances that it is safe and free of manipulation and error. Without such assurance, theory posits that investors will discount the capital they supply, undermining the ability of the marketplace to allocate capital in the real economy. The sources of error are numerous. Investors can be careless or misbehave deliberately. Additionally, problems can arise because exchanges and their trading systems fall short. In all cases, however, markets grow weaker in their ability to fulfill their core economic function, that is, to mediate the flow of capital and information.

B. The Liability Framework

The significance of robust, informative markets and the many disruptions that can undermine their integrity have resulted in an array of rules, regulations, and best practices to safeguard trading. A network of regulators is responsible for enforcing these rules. This network comprises public bodies like the Securities and Exchange Commission ("SEC") and the Commodities and Futures Trading Commission ("CFTC") as well as self-regulatory organizations like the Financial Industry Regulatory Authority ("FINRA") and exchanges like the NYSE and NASDAQ.[58] Scholars have written extensively about the resources that

[58] For discussion, see Stavros Gadinis & Howell E. Jackson, Markets as Regulators: A Survey, 80 S. Cal. L. Rev. 1239, 1329–35 (2007) (noting the allocation of supervisory and regulatory responsibilities between different public and private regulatory bodies). See also Merritt B. Fox, Securities Disclosure in a Globalizing Market: Who Should Regulate Whom, 95 Mich. L. Rev. 2498, 2610–18 (1997) (discussing the extraterritorial significance of U.S. securities rules); David A. Lipton, The SEC or the Exchanges: Who Should Do What and When? A Proposal to Allocate Regulatory Responsibilities for Securities Markets, 16 U.C. Davis L. Rev. 527, 545–47 (1983) (discussing the division of oversight between the SEC and exchanges); Jonathan R. Macey & Maureen O'Hara, Regulating Exchanges and Alternative Trading Systems: A Law and Economics Perspective, 28 J. Legal Stud. 17, 20–28 (1999) (discussing the regulatory power of listing rules; the authors further elaborate on the significance of alternative trading platforms and how these might be integrated into the system of

taxpayers spend to oversee markets and have debated the efficacy of this expenditure.[59] This Article does not survey the multiplicity of rules and regulations that underpin this oversight or revisit these scholarly debates. Rather it distills this dense patchwork of regulation into the three broad categories of liability that ultimately anchor their application: (1) intentional behavior, (2) negligence, and (3) strict liability. In each case, regulation imposes varying costs on market actors in constraining their behavior and in determining how regulators deploy resources in enforcement.

1. Intent and Recklessness

Deceit and manipulation of markets constitute the most egregious violations of regulatory norms and are primarily sanctioned under Sections 10(b) and 9 of the Securities Exchange Act, including Rule 10b-5.[60] These provisions punish fraud and deceit in securities trading and also encompass harmful schemes designed to manipulate markets. As Professor Grundfest observes, the amount of damages that defendants have to pay out for Section 10(b) violations can often be unclear in practice. The quantum—both monetary and reputational—can end up being staggeringly high, particularly when pursued by investors in private suits using the class action.[61] On paper at least, defendants are liable to pay out-of-

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monitoring securities markets); Paul G. Mahoney, The Exchange as Regulator, 83 Va. L. Rev. 1453, 1460–65 (1997) (noting private contractual regulation under the aegis of the exchange); Morris Mendelson & Junius W. Peake, Intermediaries' or Investors': Whose Market Is It Anyway?, 19 J. Corp. L. 443, 444–50 (1994) (analyzing the challenges to self-regulation).

[59] See, e.g., Howell E. Jackson & Mark J. Roe, Public and Private Enforcement of Securities Laws: Resource-Based Evidence, 93 J. Fin. Econ. 207, 208–09 (2009) (showing that resource expenditure increases the more developed markets and emphasizes the significance of public enforcement).

[60] Securities Exchange Act of 1934, Pub. L. No. 73-291, §§ 9, 10(b), 48 Stat. 881, 889–91 (codified as amended at 15 U.S.C. §§ 78(i), 78(j)(b) (2012)). Rule 10b-5 is promulgated under Section 10(b) of the Exchange Act, 17 C.F.R. § 240.10b-5 (2015). For the sake of completeness, it is worth noting that Section 9 of the Securities Exchange Act of 1934 provides a narrower antifraud prohibition. It prohibits manipulation of securities prices with specific intent of inducing the sale and purchase of the manipulated security or for conducting wash trades. Given the narrowness of the provision and its requirement for specific intent, it is rarely relied upon by regulators seeking to bring an action against a trader. For discussion, see Joseph A. Grundfest, Damages and Reliance Under Section 10(b) of the Exchange Act, 69 Bus. L. 307, 338–39 (2014).

[61] See Grundfest, supra note 60, at 308–10 (noting that settlements in securities class actions from 1997 to 2013 have totaled almost $73 billion, with class action attorneys receiv-

pocket damages attributable to their fraud.[62] On U.S. secondary markets, this measure can represent an enormous sum that can be well in excess of any profits that the defendant extracted from its bad behavior.[63] Invariably, settlements are common, if indeed the norm.[64] The vast majority of investor class actions are pursued against public companies for instances of fraud or deliberate misstatement.[65] The number of investor suits alleging market manipulation, however, is vanishingly small, leaving regulators to shoulder the lion's share of responsibility for enforcement in this area.[66]

ing an estimated $14 billion dollars in fees for their services and the largest portion of this activity being Section 10(b) litigation (citing Cornerstone Research, Securities Class Action Filings, 2013 Year in Review, at 3 fig.2, 7 fig.6 (2014), https://www.cornerstone.com/GetAttachment/d88bd527-25b5-4c54-8d40-2b13da0d0779/Securities-Class-Action-Filings-2013-Year-in-Review.pdf [https://perma.cc/FE2A-J79X])).

[62] See Amgen Inc. v. Conn. Ret. Plans & Tr. Funds, 133 S. Ct. 1184, 1191–3 (2013); Basic Inc. v Levinson, 485 U.S. 224, 242, 248–50 (1988). But see Janus Capital Grp. v. First Derivative Traders, 131 S. Ct. 2296, 2301–02 & n.6 (2011) (significantly restricting the scope of secondary person liability).

[63] Grundfest, supra note 60, at 310–11. For scholarly critique of the Rule 10b-5 action, see John C. Coffee, Jr., Reforming the Securities Class Action: An Essay on Deterrence and Its Implementation, 106 Colum. L. Rev. 1534, 1534–37 (2006); Amanda M. Rose, The Multienforcer Approach to Securities Fraud Deterrence: A Critical Analysis, 158 U. Pa. L. Rev. 2173, 2176, 2180 (2010) [hereinafter Rose, Multienforcer Approach] (noting the weakness of the compensatory rationale in Rule 10b-5 class actions, as damages paid by public companies suggest that large diversified institutional investors are often just pocket-shifting); Amanda M. Rose, Reforming Securities Litigation Reform: Restructuring the Relationship Between Public and Private Enforcement of Rule 10b-5, 108 Colum. L. Rev. 1301, 1337–40 (2008); see also William W. Bratton & Michael L. Wachter, The Political Economy of Fraud on the Market, 160 U. Pa. L. Rev. 69, 72–82 (2011) (examining the effectiveness of the class action for compensating investors and deterring fraud); Jill E. Fisch, The Trouble with *Basic*: Price Distortion after *Halliburton*, 90 Wash. U. L. Rev. 895, 896–900 (2013) (analyzing the significance of price distortion as an element of the Rule 10b-5 class action); Donald C. Langevoort, *Basic* at Twenty: Rethinking Fraud on the Market, 2009 Wis. L. Rev. 151, 152–56 (surveying the history of the fraud-on-the-market presumption); Amanda M. Rose, Response, Fraud on the Market: An Action Without a Cause, 160 U. Pa. L. Rev. PENNumbra 87, 87–89 (2011) (critiquing the theoretical rationales for the Rule 10b-5 class action). For an important account of the economic analysis of sanction and punishment from the expressive as well as compensatory perspective, see Robert Cooter, Prices and Sanctions, 84 Colum. L. Rev. 1523, 1523–24 (1984). For a discussion of civil versus criminal liability for corporate misfeasance, see V.S. Khanna, Corporate Criminal Liability: What Purpose Does It Serve? 109 Harv. L. Rev. 1477, 1492–96 (1996) (examining the rationales for choosing criminal versus civil liability for corporate misfeasance).

[64] See Rose, Multienforcer Approach, supra note 63, at 2221.

[65] Cornerstone Research, supra note 61, at 5–6 (noting that around 95% of all securities class action filings involved allegations of misstatements in the financial statements).

[66] Tara E. Levens, Too Fast, Too Frequent? High-Frequency Trading and Securities Class Actions, 82 U. Chi. L. Rev. 1511, 1514–15 (2015); see also ATSI Commc'ns v. Shaar Fund,

The hallmark of actions to pursue fraud and manipulation lies in the requirement to show that defendants intended to lie or to deliberately alter prices in securities markets.[67] Manipulation actions, in particular, can be especially difficult to pursue. Authorities must adduce evidence of manipulative intention (scienter) to artificially distort price formation. This can be straightforward for incontrovertible cases of manipulative behavior, such as outright lying to amplify securities prices, illusory wash or spoof trades, or open collusion between major traders to fix prices.[68] Such manipulative schemes do nothing more than reflect an artificial, prearranged scheme to trade and disconnect prices from any underlying economic trading activity.

But, it can be much harder where trades appear to be facially legitimate, though reveal themselves to be more manipulative when looked at deeply.[69] In such "open-market manipulations," suspicions attach to defendants that engage in (seemingly) legal trading activity but whose underlying end-purpose is to distort the price of a security. Historically, the taint of open-market manipulation has attached to controversial practices like aggressive short selling—or the strategy known as "marking the close." When marking the close, traders engage in heavy trading just before the markets are set to close for the day. Price impact can be especially strong because there is no time left for other traders to enter the fray and change the price for themselves.[70]

The evidentiary problem in challenging open-market manipulations is severe: In the absence of some smoking gun, practices like aggressive

493 F.3d 87, 101–02 (2d Cir. 2007) (describing the difficult standard for bringing a manipulation claim).

[67] Ernst & Ernst v. Hochfelder, 425 U.S. 185, 193 (1976). It should be noted that Section 747 of the Dodd-Frank Act of 2010 gives derivatives regulators greater authority to sanction manipulative and fraudulent activity. Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010, Pub. L. No. 111-203, § 747, 124 Stat. 1739, 1739 (codified as amended at 7 U.S.C. § 6c(a)(5) (2012)).

[68] *ATSI Commc'ns*, 493 F.3d at 102–03 (examining whether aggressive short selling constituted, by itself, an incontrovertible case of manipulation and concluding that it did not); Levens, supra note 66, at 1515; Scopino, supra note 11, at 228–31 (discussing examples of common manipulation).

[69] See Santa Fe Indus. v. Green, 430 U.S. 462, 476 (1977) (noting that market manipulation "refers generally to practices, such as wash sales, matched orders, or rigged prices, that are intended to mislead investors by artificially affecting market activity"); Levens, supra note 66, at 1511–15 (comparing manipulation actions with more traditional class actions for misstatement and fraud in the context of HF trading); Scopino, supra note 11, at 264–70 (discussing the challenge of bringing manipulation actions).

[70] SEC v. Masri, 523 F. Supp. 2d 361, 369–70 (S.D.N.Y. 2007).

short selling or trading heavily at close of business are legal and indeed perfectly rational depending on one's investment objective.[71]

The fine distinctions entailed in distinguishing a bad motive from an acceptable one are reflected in the considerable difficulty that courts have experienced in outlining the scienter requirement for open-market manipulation. Indeed, according to the Third Circuit, scienter is not enough by itself. Rather, authorities must also demonstrate that a defendant wished to create a false impression of market activity by circulating bad information in the market.[72] This extra need to demonstrate an injection of bad information represents one way to single out instances of nefarious manipulation from more legitimate, investment-orientated trading.

The D.C. Circuit, by contrast, deals with the difficulty of picking out the good from the bad by adopting a more expansive approach. In *Markowski v. SEC*, the court required a simple showing of scienter for manipulation to go forward—without any additional need to show false information,[73] lightening (somewhat) the burden on authorities.

Finally, the Second Circuit elevates scienter into the sole defining requirement for a finding of manipulation. In *SEC v. Masri*, the Second Circuit, wrestling with the question of whether marking the close should be regarded as manipulative under Section 10(b), concluded in that case that it was not.[74] As the court noted, traders typically traded more frequently towards the end of the day out of a legitimate investment need, for example, to close out and manage their end-of-day positions.[75] Still, the court did not rule out the possibility that such trading could be an open-market manipulation—though it limited the practical reach of the law. The intent to manipulate had to be the *sole intent* driving the manipulation—and nothing else.[76] Should the defendant harbor investment

[71] For example, it is much cheaper to borrow securities to short sell, rather than buying securities to sell them on. If one knows that a company's stock is likely to fall in price, short selling offers a much more efficient means of conveying negative opinion. For a detailed discussion of the cases, see Levens, supra note 66, at 1552–55.

[72] GFL Advantage Fund v. Colkitt, 272 F.3d 189, 205 (3d Cir. 2001).

[73] 274 F.3d 525, 529 (D.C. Cir. 2001).

[74] See discussion in *Masri*, 523 F. Supp. 2d at 370–75.

[75] Id. at 370.

[76] Id. at 372.

intent alongside a manipulative one, she would not be held liable for manipulation.[77]

The cost-benefit trade-off for regulators seeking to bring the fraud or manipulation claim is a difficult one. Scholars have long recognized the complexities of inferring a state of mind from a defendant's behavior.[78] Not only can likely evidence of liability be subject to numerous interpretations, but it can also be vulnerable to the biases of regulators. As Professors Gulati, Rachlinksi, and Langevoort note, hindsight bias can prime regulators to misconstrue evidence to find "fraud by hindsight" even if the evidence is equivocal.[79] Indeed, the Supreme Court's decision in *Tellabs, Inc. v. Makor Issues & Rights, Ltd.* expressly acknowledges that evidence of state of mind is often subject to multiple inferences, some of which may be suggestive of innocent motives while others are less clear.[80]

Further, scienter is especially difficult to find in the case of open-market manipulations that straddle a fine line between legitimate and problematic. In such cases—considering the Second Circuit's insistence on sole intent as a defining feature of liability—the cost-benefit threshold to bring cases of open-market manipulation becomes even higher

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[77] Michael A. Asaro, 'Masri' and Open-market Manipulation Schemes, 239 N.Y. L.J., no. 91, May 12, 2008, at 4, LexisAdvance Legal News, https://advance.lexis.com/api/permalink/2e1a8026-55b6-44c4-89f6-a4baf1ce7f27/?context=1000516.

[78] Kim A. Kamin & Jeffrey J. Rachlinski, Ex Post ≠ Ex Ante: Determining Liability in Hindsight, 19 Law & Hum. Behav. 89, 91, 101 (1995) (examining the problem of greater likelihood to find blame with the benefit of ex post review); Donald C. Langevoort, The Epistemology of Corporate-Securities Lawyering: Beliefs, Biases and Organizational Behavior, 63 Brook. L. Rev. 629 (1997) (noting the challenges for lawyers of overcoming biases in corporate cultures to understand their client's behaviors and those of managers driving corporate culture); Donald C. Langevoort, Organized Illusions: A Behavioral Theory of Why Corporations Mislead Stock Market Investors (and Cause Other Social Harms), 146 U. Pa. L. Rev. 101 (1997) (analyzing corporate motivations to deceive when neither managers nor the company trades in securities). On pleading, see Stephen J. Choi & A.C. Pritchard, The Supreme Court's Impact on Securities Class Actions: An Empirical Assessment of *Tellabs*, 28 J.L. Econ. & Org. 850, 851–52 (2012) (showing that the *Tellabs* ruling eased the pleading standards for scienter in some circuits, notably the Ninth Circuit, while hardening them in other circuits).

[79] Mitu Gulati, Jeffrey J. Rachlinski & Donald C. Langevoort, Fraud by Hindsight, 98 Nw. U. L. Rev. 773, 773–74 (2004); Kamin & Rachlinksi, supra note 78, at 91 (describing the effect of hindsight bias on liability findings); see also Donald C. Langevoort, Reflections on Scienter (and the Securities Fraud Case Against Martha Stewart that Never Happened), 10 Lewis & Clark L. Rev. 1, 16 (2006) (examining the challenge of parsing awareness versus purpose in determinations of scienter).

[80] 551 U.S. 308, 323–24 (2007).

than what might be ordinarily expected for fraud or conventional manipulation. Either regulators must believe that a truly large open-market manipulation has been perpetrated or they must have compelling evidence as to the sole manipulative intent of the manipulator. Without one or the other, regulators face considerable uncertainty in pursuing their actions.

This trade-off leaves wiggle room for market actors that wish to engage in manipulation. For difficult cases involving open-market trading with price impact, traders need to harbor some ancillary investment rationale in order to avoid trouble. With limited private class actions in the context of manipulation, regulators bear the disciplinary burden. To the extent that evidentiary and enforcement costs are high and driven by the pressure of the public purse, even intentional manipulations can go unchecked.[81]

2. Negligence

Punishing unreasonable behavior in securities markets constitutes an essential means to maintain their informational integrity. Traders, intermediaries, and exchanges can be held liable for failing to maintain an objectively reasonable standard of performance—in other words, if they act negligently.[82] In place of the traditional measure of negligence damages in civil actions, wrongdoers in securities markets face a variety of financial and other sanctions. Under the Securities Enforcement and Penny Stock Reform Act of 1990, the SEC enjoys wide-ranging powers

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[81] See U.S. Sec. & Exch. Comm'n, Fiscal Year 2013 Agency Financial Report 27–30 (2013), https://www.sec.gov/about/secpar/secafr2013.pdf [https://perma.cc/2JJQ-XMNE] (noting the expanding areas of responsibility following the financial crisis, including oversight of the OTC derivatives market as well as stricter rules for money market funds, for example); James D. Cox, Randall S. Thomas & Dana Kiku, Public and Private Enforcement of the Securities Laws: Have Things Changed Since Enron?, 80 Notre Dame L. Rev. 893, 897–903 (2005) (empirically examining changing trends in public enforcement of securities fraud). See, however, the Fair Funds program, where recoveries from defendants are used to compensate investors; for discussion of the effectiveness of this program, see Urska Velikonja, Public Compensation for Private Harm: Evidence from the SEC's Fair Fund Distributions, 67 Stan. L. Rev. 331, 359–91 (2005). On the issue of budgetary constraints, see additionally, Donald C. Langevoort, Managing the "Expectations Gap" in Investor Protection: The SEC and the Post-Enron Reform Agenda 48 Vill. L. Rev. 1139, 1141 (2003) ("The SEC has lived nearly all its life in a world of chronically inadequate resources, for reasons that are complex but I suspect at least include the business community's unwillingness to let go of the underlying rents.").

[82] See Goldberg, supra note 28, at 524 (discussing the rise of modern judges employing the concept of reasonable care as constituting the acceptable standard of conduct).

to enforce past and imminent violation of securities laws.[83] In addition to financial penalties, the SEC can also impose nonmonetary sanctions, like injunctions, stop orders, cease-and-desist orders, and disgorgement of gains obtained as a result of violating a cease-and-desist mandate.[84] Penalties are often the subject of negotiation between the SEC and the violator, rather than long litigation in administrative or judicial proceedings.[85]

The range of actions to which such liability can apply is extensive. For this Article, it is worth briefly illustrating the application of the negligence standard by reference to a rule increasingly influential in maintaining structural safeguards in markets, enacted in the wake of the May 2010 Flash Crash.

Market Access Rule: The Market Access Rule is designed to stop technological mishaps and risky trading practices.[86] According to the Market Access Rule, the SEC requires broker-dealers that connect investors to an exchange to establish a system of risk management and supervision that is reasonably designed to manage financial and regulatory risks. Brokers conduct business in several key ways: (1) they execute an order for a client on the exchange, (2) they send the client's order to another broker, or (3) they let the client (like a high-frequency firm ("HF firm")) utilize the broker's system to directly access the exchange. Broker-dealer firms can also trade using their own money for their own account. The rule requires brokers that connect investors to markets to take responsibility for implementing reasonable processes to control both le-

[83] Securities Enforcement Remedies and Penny Stock Reform Act of 1990, Pub. L. No. 101-429, §§ 102, 203, 104 Stat. 931, 933–35, 939–40 (codified as Securities Act of 1933 § 8A(a), 15 U.S.C. § 77h–l(a) (2012)); Securities Exchange Act of 1934 § 21C(a), 15 U.S.C. § 78u–3(a) (2012)). For discussion, see Cox, Thomas & Kiku, supra note 81, at 897–906 (empirically observing SEC enforcement efforts post-Enron); James D. Cox, Randall S. Thomas & Dana Kiku, SEC Enforcement Heuristics: An Empirical Inquiry, 53 Duke L.J. 737, 763–77 (2003); Gregory E. Van Hoey, Note, Liability for "Causing" Violations of the Federal Securities Laws: Defining the SEC's Next Counterattack in the Battle of *Central Bank*, 60 Wash. & Lee. L. Rev. 249 (2003) (analyzing the "causing" remedy under the Act and the powers of the SEC).

[84] Securities Enforcement Remedies and Penny Stock Reform Act of 1990 § 102; Securities Exchange Act of 1934 § 21C(e).

[85] On recent trends, see Marc J. Fagel, Securities Enforcement: The State of SEC Enforcement Heading into 2015, 29 Insights: Corp. & Sec. L. Advisor, no. 2, Feb. 2015, at 1, 2, http://www.gibsondunn.com/publications/Documents/Fagel-State-of-SEC-Enforcement-Insights-2.2015.pdf [https://perma.cc/3AYE-7U78] (noting the 2014 increase in recourse to SEC administrative proceedings owing to hardline settlement demands by the SEC).

[86] Exchange Act Rule 15c3-5, 17 C.F.R. § 240.15c3-5 (2015).

gal and operational risks.[87] There is considerable logic to this rule. Brokers are essential intermediaries in the trading process, possessing detailed knowledge of a wide swathe of investors as well as deep institutional experience of trading on numerous exchanges. It follows that they should be well placed to understand the risks of trading and to determine an objectively reasonable standard as to quality.[88] The demands of the rule are wide-ranging. For example, brokers must establish reasonable systems to maintain appropriate limits for client orders, to prevent the entry of mistaken orders, and to only allow trading where clients have complied with legal and operational requirements.[89]

Despite its recent history, the impact of the rule has been powerfully felt. Knight Capital—the firm that mistakenly transmitted millions of orders and racked up around $460 million in losses[90]—is a case in point. Knight was held liable for violations of the Market Access Rule for not implementing reasonable systems to control the entry of erroneous orders.[91] Evidence of this negligence included, for example, a failure by Knight employees to react to group emails alerting the firm of the defects in the order routing mechanism as well as unreasonable reliance on human monitors.[92] The SEC cited numerous violations and fined Knight Capital $12 million.[93] In addition, the SEC also fined Morgan Stanley $4 million for failing to control the actions of a rogue trader engaged in

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[87] Id.

[88] Stanislav Dolgopolov, Insider Trading, Chinese Walls, and Brokerage Commissions: The Origins of Modern Regulation of Information Flows in Securities Markets, 4 J.L. Econ. & Pol'y 311, 313–18 (2008) (noting the essential role of market intermediaries in regulating financial markets); Tamar Frankel, Fiduciary Duties of Brokers-Advisers-Financial Planners and Money Managers 9–11 (Bos. Univ. Sch. of Law, Working Paper No. 09-36, 2010), http://www.bu.edu/law/workingpapers-archive/documents/frankelt101009revsep2010.pdf [https://perma.cc/6ZDC-VQ8C] (observing the essential role of brokers as a critical force in securities markets).

[89] U.S. Sec. & Exch. Comm'n, Responses to Frequently Asked Questions Concerning Risk Management Controls for Brokers or Dealers with Market Access (Apr. 15, 2014), https://www.sec.gov/divisions/marketreg/faq-15c-5-risk-management-controls-bd.htm [https://perma.cc/K9KB-3MLY].

[90] Knight Capital Americas LLC, Exchange Act Release No. 70,694, 107 SEC Docket 2303, at *2, 2013 WL 5673736 (Oct. 16, 2013) (Order Instituting Administrative and Cease-and-Desist Proceedings, Pursuant to Sections 15(b) and 21C of the Securities Exchange Act of 1934, Making Findings, and Imposing Remedial Sanctions and a Cease-and-Desist Order).

[91] Id. at *11–13.

[92] Id. at *6–7.

[93] Id. at *18; Alexandra Stevenson, Knight Capital Fined, N.Y. Times, Oct. 16, 2013, at B9.

fraudulent transacting in the securities of Apple Inc.[94] Here, Morgan Stanley allowed the fraudster to trade around $525 million worth of securities in a day, more than $300 million in excess of its daily trading limit.[95]

Reliance on the negligence standard—rather than one that looks to intent—represents a distinct allocation of regulatory cost and benefit between market actors and enforcers. Theory notes that the standard of reasonableness encourages actors to internalize the cost of their activities—to a point. As Judge Posner explains, the negligence standard seeks to ensure that single actors take precautions up to the point at which it is cheaper than the costs of the harm.[96] Being at fault—meaning, failing to live up to the standard of care—represents a failure to cheaply take the precautions that would have prevented a much costlier harm from occurring. To put it differently, a standard that makes it more expensive for an actor to provision for the harm than to bear the cost of the harm itself—is unreasonable and wasteful.[97] And to put it yet another way, the negligence standard gives actors room to maneuver. Actors need not take every precaution possible (this would be overly expensive), but only such steps as are effective to eliminate the chance of accidental harm.[98]

Scholars have long sought to determine the most efficient allocation of ex ante provisioning costs between actors to work out the optimal balance of who should bear the costs of compliance. This question is especially live in an ecosystem comprising multiple actors that could each, in theory, be expected to internalize the risk of harm. Conceivably, in a hypothetical market, multiple actors could have taken steps to prevent

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[94] Press Release, U.S. Sec. & Exch. Comm'n, SEC Penalizes Morgan Stanley for Violating Market Access Rule (Dec. 10, 2014), https://www.sec.gov/News/PressRelease/Detail/PressRelease/1370543668817 [https://perma.cc/7QPE-BB3X].

[95] Id; see also Press Release, Fin. Indus. Regulatory Auth., FINRA Charges Wedbush Securities for Systemic Market Access Violations, Anti-Money Laundering and Supervisory Deficiencies (Aug. 18, 2014), http://www.finra.org/Newsroom/NewsReleases/2014/P578458 [https://perma.cc/4KJW-36DB] (discussing sanctions imposed on Wedbush Securities that provided access to exchanges for broker-dealers and other market firms and noting that Wedbush had failed to implement proper controls and as a result trading firms were able to engage in a large number of wash trades and other manipulative practices).

[96] Richard A. Posner, A Theory of Negligence, 1 J. Legal Stud. 29, 33 (1972).

[97] Id. at 29–33. For a succinct critique of this view, see Goldberg, supra note 28, at 544–59. For a critical perspective on the conventional cost-benefits analyzed by traditional tort theory see Hershovitz, supra note 28.

[98] Polinsky & Shavell, supra note 12, at 9.

the Knight Capital debacle: (1) Knight Capital, (2) the exchange(s), or (3) Knight's counterparties. In response, the classical Coasean model would postulate that, in the absence of transaction costs, parties might allocate the costs of compliance amongst each other in a way that is most optimally efficient.[99] But, with transaction costs, Judge Calabresi and Professor Hirschoff argue that the costs of compliance should be borne by the actor that is the "cheapest cost avoider."[100] The costs of provisioning should fall on those that are the best placed to take precautions most cost-effectively, reducing wasteful expenditure by others. On this basis, the goal of the law—exemplified by the Market Access Rule—should be to allocate responsibility to those actors best placed to incur the lowest costs of reasonable precaution relative to the costs of harms.

The allocation of costs under the negligence standard raises two significant implications. First, as noted above, the negligence standard requires actors to comply with a reasonable, objective standard. As Professors Shavell and Polinsky observe, this means that actors can take some risks so long as this satisfies the standard of reasonableness. Or, actors might take risks whose returns will exceed the costs of the harm (and the costs of penalties). Rationally, actors gain by: (1) taking reasonable risks, or (2) by taking unreasonable but cheap risks.

Second, it is possible that firms might be motivated to also take modestly unreasonable risks—even if the penalties will be higher than the returns—because regulators also face costs in enforcing rules. In seeking to punish negligence, regulators must first investigate whether the standard of care has, in fact, been breached. These costs can limit enforcement to those cases where the harms are more serious.[101] In securities

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[99] Steven Shavell, Economic Analysis of Accident Law chs. 2, 4, 5 (1987) (elaborating on the economic costs and benefits of negligence and strict liability); Guido Calabresi, Some Thoughts on Risk Distribution and the Law of Torts, 70 Yale L.J. 499 (1961) (examining the economic theories underpinning tort liability and risk distribution); R.H. Coase, The Problem of Social Cost, 3 J.L. & Econ. 1, 15–16 (1960) (examining the optimal allocation of value between rational actors in the absence of transaction costs).

[100] Guido Calabresi & Jon T. Hirschoff, Toward a Test for Strict Liability in Torts, 81 Yale L.J. 1055, 1060–65 (1972).

[101] Polinsky & Shavell, supra note 12, at 13, 25; Steven Shavell, The Fundamental Divergence Between the Private and the Social Motive to Use the Legal System, 26 J. Legal Stud. 575, 575–81 (1997) (exploring the incentives for public versus private motivations for enforcement). It is worth noting that in 2014, the SEC brought a record number of actions for breaches of securities laws, including for negligence and strict liability rules, as part of its "broken windows" initiative that seeks to punish even minor breaches of the law. The idea is

markets, with complex transactions and vast amounts of data to unravel, enforcement costs can be far from trivial. Even in a case as visibly catastrophic as the Knight debacle, the SEC required over fourteen months to establish violations of the Market Access Rule. It has been reported that the SEC only succeeded in making its claim after a whistleblower came forward.[102] Would-be violators obviously take a risk in guesstimating the likelihood of enforcement. Still, for low-visibility violations, or where the harms might be less serious, even unreasonable conduct may escape liability.[103]

3. Strict Liability

Conventionally, tort law tends to reserve the punishment of strict liability for the most harmful and dangerous offenses and when the law seeks to fix a particular standard of conduct. Regulators do not need to show intent or a breach of a standard of reasonableness. All that is needed is a showing of harm attributable to a defendant. Reflecting the chilling deterrence that strict liability should provoke, penalties can also be severe, often extending to cover all the damage that follows from the harm and allowing only limited defenses.[104] In securities law, by contrast, strict liability follows a different trajectory. With some notable exceptions,[105] strict liability generally punishes automatic, or "technical," breaches of the law.[106] As with negligence, penalties are usually worked out in settlement negotiations with defendants.[107] To take an example from the derivatives market, the Commodity Exchange Act makes it un-

to deter violations that might once have gone unpunished. Indeed, commentators suggest that the SEC might choose to pursue a negligence claim instead of spending resources on a more serious fraud-based claim. For details see Fagel, supra note 85, at 1–4.

[102] See Stevenson, supra note 93.

[103] A. Mitchell Polinsky & Steven Shavell, The Optimal Tradeoff Between the Probability and Magnitude of Fines, 69 Am. Econ. Rev. 880, 884–86 (1979).

[104] See, e.g., Rylands v. Fletcher [1868] LR 3 (HL) 330, 337–42 (Eng.) (discussing occasions warranting strict liability).

[105] See Section 12(a)(1) of the Securities Act of 1933 for breach of Section 5, as well as Section 11 of the Securities Act of 1933 for misstatements in the Registration Statement. Securities Act of 1933 §§ 12(a)(1), 11, 15 U.S.C. §§ 77k, 77l (2012). For excellent discussion, see Frank Partnoy, Barbarians at the Gatekeepers?: A Proposal for a Modified Strict Liability Regime, 79 Wash. U. L.Q. 491, 495–510 (2001).

[106] Scopino, supra note 11, at 245–55.

[107] Fagel, supra note 85, at 3–4.

lawful for traders to send out orders that end up making prices untrue.[108] The provision is expansive. Once it can be shown that a defendant submitted unlawful orders that caused prices to become untrue, liability can attach.

It makes sense that securities regulators might include strict liability provisions within the canon, even for relatively minor technical breaches or foundational harms. The costs of investigation are low. If harms are easily observed (e.g., failure to submit a regulatory report), the breach can be immediately subject to action. More importantly, the strict liability breach might work as a substitute sanction where negligence or intent is harder to evidence. Rather than work hard to make a case for a breach of reasonable standards or manipulation, it can be easier to point to a strict liability breach (e.g., submission of orders that make a price untrue). If strict liability increases the bargaining power of regulators, or reduces their information asymmetries vis-à-vis a defendant—by bringing the violator into a negotiation—authorities face lower enforcement costs.

In summary, a vast body of rules and regulations governs price formation, not only the information that is central to it, but also the mechanisms that process that information and generate exchange between investors. While this corpus of regulation is extensive, it can also be analyzed through the main heads of liability that impose constraint and sanction on a variety of market actors. Through intent, negligence, or strict liability, the law imposes a deliberate compliance burden on market actors as well as on regulators to enforce the law. This allocation of liability costs is established and deeply studied. However, its current design faces a significant challenge in fully automated, algorithmic markets.

[108] Commodities Exchange Act, Pub. L. No. 74-675, § 4c(a)(2)(B), 49 Stat. 1491, 1494 (codified as amended at 7 U.S.C. § 6c(a)(1), 6c(a)(2), 6c(a)(2)(B) (2012)); In re Gelber Grp., CFTC No. 13-15, 2013 WL 525839, at *3 (Feb. 8, 2013); see also Gregory Scopino, The (Questionable) Legality of High-Speed "Pinging" and "Front Running" in the Futures Markets, 47 Conn. L. Rev. 607, 644–54 (2015) (discussing prohibited trading practices under the Commodity Exchange Act for their harmful nature).

II. THE PROBLEM OF AUTOMATION

Algorithms have become commonplace in our daily lives—and markets are no exception.[109] Trading algorithms constitute preprogrammed instructions that are crafted to achieve a particular goal in the processes underpinning securities transactions.[110] Their considerable utility has made them all but indispensable in developed markets. Algorithms drive around 50–70% of all equity trading by volume in the United States, as measured by HF trading that requires algorithms to function.[111] Their preeminence extends across numerous types of securities, including futures, swaps, as well as the all-important U.S. Treasuries market.[112] With their many advantages for trading, however, algorithms also create unfamiliar risks.[113] This Part analyzes the basic features in algorithmic markets to discuss the key problems and costs that they create. This analysis sets the stage to examine the impact of these new, under-

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[109] For discussion, see Stuart Minor Benjamin, Algorithms and Speech, 161 U. Pa. L. Rev. 1445 (2013) (analyzing whether algorithms should have First Amendment free speech rights); Tim Wu, Machine Speech, 161 U. Pa. L. Rev. 1495 (2013) (discussing the widespread use of algorithms in search engines, social media, and entertainment, and the feasibility of protecting algorithmic free speech).

[110] See supra note 14 (discussing the key features of algorithms and their use in trading securities); infra, note 117 (same).

[111] See sources cited supra note 16.

[112] See, e.g., Tom Kingsley et al., HFT: Perspectives from Asia—Part 1, Bloomberg Tradebook: Equities (Jun. 11, 2013), http://www.bloombergtradebook.com/blog/hft-perspectives-from-asia-part-i/ [https://perma.cc/M3X3-MDPC] (discussing the growth of HF trading in Australia, Japan, and Singapore); Osipovich, supra note 16 (discussing use of algorithmic trading in energy markets); Stafford, Massoudi & Mackenzie, supra note 16. In the futures market, for example, a 2012 study reported that HF trading contributed to 60% of the volume on U.S. futures exchanges. For a discussion, see Tom Polansek, High-Frequency Trading Does Not Raise Futures Volatility—Study, Reuters, Aug. 27, 2013, http://www.reuters.com/article/trading-fast-study-idUSL2N0GS1XH20130827 [https://perma.cc/F6LY-YEPA]. For a discussion on automated trading and current controversies, including discussion of HF trading and market fragmentation, see Merritt B. Fox, Lawrence R. Glosten & Gabriel V. Rauterberg, The New Stock Market: Sense and Nonsense, 65 Duke. L.J. 191, 191–97 (2015).

[113] But see Levens, supra note 66 (examining the impact of HF trading on Rule 10b-5 securities class actions); Scopino, supra note 108, at 686–94 (analyzing the legality of "pinging," a common technique in HF trading). On the phenomenon of HF trading and principles for regulating it, information technology, and artificial intelligence, see Tom C.W. Lin, The New Financial Industry, 65 Ala. L. Rev. 567 (2014); Tom C.W. Lin, The New Investor, 60 UCLA L. Rev. 678, 687–93 (2013); Michael J. McGowan, The Rise of Computerized High Frequency Trading: Use and Controversy, 16 Duke L. & Tech. Rev., no. 0016, Nov. 2010, pt. I.

theorized risks on the traditional framework governing liability in securities markets.

A. Primer on Algorithmic Trading

Algorithmic trading refers to the use of preset electronic instructions in securities transactions. Rather than instruct a human trader to buy 1,000 shares of publicly traded *Company X* at $50 per share, this task can instead be programmed into an algorithm. As soon as the share price hits the desired threshold, an algorithm converts this input into an actual order to buy 1,000 shares that is forwarded to an appropriate exchange. This simple transaction, however, obscures the enormous gains—and risks—that algorithms hold for the trading process.

Algorithmic trading needs traders to program their proprietary strategies into specific, computerized decision rules. Firms must be able to abstractly represent their trading ideas and intuition in hard, rules-based programming.[114] To work effectively, these instructions must encompass a range of processes: (1) collecting data for trading; (2) submitting orders/canceling orders; (3) establishing the price, amount, and type of trades to make; (4) anticipating the impact of trading on future price changes;[115] (5) responding to unplanned events; and (6) determining when to stop trading. All of these considerations ultimately operationalize a trading strategy. Depending on the strategy (e.g., trading on momentum), algorithms can harness complex financial models that convert data into a usable value that calibrates what algorithms buy and on what terms they buy it.[116] Owing to computerized programing, algorithms can internalize far larger quantities of data, of higher sophistication, and at much faster speeds than human traders can.[117] This brings a distinctly

[114] Yadav, supra note 18, at 1620.

[115] See Kearns & Nevmyvaka, supra note 20, at 91–93.

[116] Iréne Aldridge, High-Frequency Trading: A Practical Guide to Algorithmic Strategies and Trading Systems 21–31 (2010) (discussing in detail HF trading strategies); Kearns & Nevmyvaka, supra note 20, at 95–96; Yadav, supra note 18, at 1621–22.

[117] Tech. Comm. of the Int'l Org. of Sec. Comm'ns, supra note 14, at 10 ("In its simplest guise, algorithmic trading may just involve the use of a basic algorithm . . . to feed portions of an order into the market at preset intervals to minimise market impact cost. At its most complex, it may entail many algorithms that are able to assimilate information from multiple markets . . . in fractions of a second."); U.K. Gov't Office for Sci., supra note 19, at 28–30.

powerful dynamic to long-familiar, well-established trading approaches.[118]

Speed, in particular, has given algorithms special influence on trading design. Scholars observe that the urge to trade fast is a hallmark of markets.[119] The quicker a firm can reach the market with its intelligence, the more profit it stands to make. As Professors Gilson and Kraakman illustrate, traders compete for informational gains to extract the maximum benefit before prices shift and markets become efficient.[120] Algorithmic markets similarly utilize speed as an essential—even predominant—focus of a trading strategy.[121] Preprogrammed algorithms can mine data, process it, and deliver an order far faster than human beings. This enables traders to use algorithms to buy and sell securities in milliseconds and microseconds, holding securities for tiny slices of time.[122] Speed allows HF traders to become adept at executing three important strategies.

First, HF traders can provide an ever-ready counterparty to investors that wish to trade. If a high-frequency algorithm ("HF algorithm") purchases 1,000 shares of *Company X* at $50 a share, it can quickly sell them to an investor that wishes to buy these securities. Rather than hold onto these shares, flipping them allows traders to make a profit on the

[118] There is no overarching definition of HF trading. Broadly, it is identified by some salient characteristics, like the speed of turnover of trades, co-location between exchange and the algorithmic trader, high number of order cancellations, and specialized traders that transact with the aim of ending the day with no risk (securities) left on their books. See Div. of Trading & Mkts., U.S. Sec. & Exch. Comm'n, supra note 17, at 4; U.S. Commodity Futures Trading Comm'n & US Sec. & Exch. Comm'n, Findings Regarding the Market Events of May 6, 2010, at 1, 45 (2010) (examining the events of the Flash Crash). For discussion, see Jeffrey G. MacIntosh, C.D. Howe Inst., High Frequency Traders: Angels or Devils? 3–5 (2013), http://www.cdhowe.org/pdf/Commentary_391.pdf [https://perma.cc/B6EQ-PWLF]; Yadav, supra note 18, at 1622–23; see also Haim Bodek, The Problem of HFT: Collected Writings on High Frequency Trading & Stock Market Structure Reform 2–4 (2013) (discussing the impact of HF trading on market structure dynamics to facilitate faster order submissions and execution).

[119] David Easley, Marcos López de Prado & Maureen O'Hara, The Volume Clock: Insights into the High-Frequency Paradigm, *in* High-Frequency Trading, supra note 20, at 1, 1.

[120] Gilson & Kraakman, supra note 33, at 569–72.

[121] See Rishi K. Narang, Inside the Black Box: A Simple Guide to Quantitative and High-Frequency Trading 244–45 (2d ed. 2013).

[122] See, e.g., Easley, López de Prado & O'Hara, supra note 119, at 5–7 (noting the significance of volume in defining and understanding high-frequency trading); Brogaard, Hendershott & Riordan, supra note 27, at 2303–04 (noting the advantages of high-frequency trading in fostering at least short-term price discoveries). The authors show that HF trading helps markets move in the direction of permanent price changes, at least in the short term, as measured in seconds.

difference between the buying and selling prices (the spread). The HF trader can earn steady profits by being a constant counterparty for investors, particularly if it can trade tens of thousands of times over a day and incrementally earn small spreads on each deal. Importantly, by offering ready entry into the market, HF traders bring enormous advantages for investors. Investors enjoy immediate execution, removing any uncertainty about whether they will succeed in finding a trading party. Also, investors can trade more cheaply because HF traders absorb very little economic risk of holding onto securities. Unsurprisingly, scholars have lauded the role that HF traders play in "making markets." One study, for example, noted that spreads for trading fell by almost 50% after a major HF trader commenced transacting on the exchange studied.[123]

Secondly, algorithmic traders can capture information and trade on it rapidly ahead of others.[124] Algorithms can be programmed to collect information from a variety of sources. They can incorporate this data into algorithmic models, value it, and deliver an input in the form of a trading approach. An HF algorithm that receives data about an earnings report of a company, for example, can rapidly turn these data into a series of orders, based on a preset programmed strategy.

Algorithms have grown sophisticated at collecting and weighing data for transactions.[125] In addition to price data from various exchanges, HF traders can also connect to regulatory reports and disclosures, news, and social media sources like Twitter.[126] Scholars observe that HF algo-

[123] Menkveld, supra note 24, at 714. For a fuller discussion of the costs faced by investors, see Yadav, supra note 15, (manuscript pt. IV.A.1, at 41–43).

[124] Yadav, supra note 15, (manuscript at 7–8).

[125] For example, securities markets are examining so-called neural network methods to enhance stock value prediction models. These neural networks utilize data mining and pattern analysis to model future stock market changes. For analysis see Abhishek Kar, Stock Prediction Using Artificial Neural Networks (n.d.) (unpublished manuscript), http://www.cs.berkeley.edu/~akar/IITK_website/EE671/report_stock.pdf [https://perma.cc/3CZE-669B] (showing a 96% accuracy rate in predicting stock prices using certain neural network methods); Mahdi Pakdaman Naeni et al., Stock Market Value Prediction Using Neural Networks 132–33 (2010) (unpublished manuscript), http://people.cs.pitt.edu/~hashemi/papers/CISIM2010_HBHashemi.pdf [https://perma.cc/5YV8-7WYJ].

[126] Ioanid Roşu, Fast and Slow Informed Trading 2 (May 10, 2015) (unpublished manuscript), http://ssrn.com/abstract=1859265 [https://perma.cc/LP2P-L4ZF] (noting that HF algorithms react rapidly to news and events); see also Vikas Raman, Michel A. Robe & Pradeep K. Yadav, Man vs. Machine: Liquidity Provision and Market Fragility 26–27 (June 29, 2015) (unpublished manuscript), http://www.stern.nyu.edu/sites/default/files/assets/documents/Man%20vs%20Machine%20Liquidity%20Provision%20and%20Market%20Fragility.pdf [https://perma.cc/389G-C7QB] (showing that algorithms struggle in times of

rithms can often be programmed to collect volumes of deeply granular data in order to react and extract even small benefits from the inflow of news.[127] Demand from HF trading has spawned an industry of data providers specializing in filtering and coding news from a range of sources.[128] Competition for market-moving information has made routine information releases—like government reports or corporate disclosures—into highly anticipated events. One 2004 study reported that releases of U.S. macroeconomic data were immediately accompanied by higher volumes of trading that remained elevated for some time. This extra volume of trading occurred even where the releases delivered information that was in line with expectations—and, therefore, might already have been factored into securities prices.[129] A 2012 study showed that even tiny delays in trading of between 10 milliseconds to a second following an announcement could lead to significant decreases in returns for traders.[130] On calmer days, a delay of around 50 milliseconds in trading was enough to diminish performance substantially.[131]

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market stress). But see Jonathan Brogaard et al., High-Frequency Trading and Extreme Price Movements 2–3 (Nov. 2014) (unpublished manuscript), http://ssrn.com/abstract=2531122 [https://perma.cc/GBV9-PSW8] (suggesting that HF algorithms mediate short-term volatility in markets).

[127] Kearns & Nevmyvaka, supra note 20, at 95.

[128] Matthew Phillips, How Many HFT Firms Actually Use Twitter to Trade?, Bloomberg Businessweek (Apr. 24, 2013), http://www.bloomberg.com/bw/articles/2013-04-24/how-many-hft-firms-actually-use-twitter-to-trade [https://perma.cc/4TBD-JG6F]; RavenPack Products, RavenPack, http://www.ravenpack.com/products [https://perma.cc/79W6-A7ND] (stating, for example, that they code their feeds for "sentiment," novelty, and relevance). RavenPack claims to sell its news feeds to twelve out of the top twenty performing hedge funds. Phillips, supra. See also Sources, GNIP, http://gnip.com/sources/ [https://perma.cc/V666-AZRL] (providing social data like Twitter, Facebook, and YouTube).

[129] Alain P. Chaboud et al., The High-Frequency Effects of U.S. Macroeconomic Data Releases on Prices and Trading Activity in the Global Interdealer Foreign Exchange Market 4 (Bd. of Governors of the Fed. Reserve Sys., International Finance Discussion Paper No. 823, 2004); Alain P. Chaboud, Sergey V. Chernenko & Jonathan H. Wright, Trading Activity and Exchange Rates in High-Frequency EBS Data 19–20 (Bd. of Governors of the Fed. Reserve Sys., International Finance Discussion Paper No. 903, 2007).

[130] Martin L. Scholtus, Dick van Dijk & Bart Frijns, Speed, Algorithmic Trading, and Market Quality Around Macroeconomic News Announcements, 38 J. Banking & Fin. 89, 90 (2014).

[131] Martin L. Scholtus & Dick van Dijk, High Frequency Technical Trading: The Importance of Speed 4 (Tinbergen Inst., Working Paper No. 12-018/4, 2012), http://ssrn.com/abstract=2013789 [https://perma.cc/YE55-PBUB]; Exaggerated Prices Moves Around News Events, Nanex (Jan. 8, 2014), http://www.nanex.net/aqck2/4527.html [https://perma.cc/62WP-7D5N] (noting greater volatility around news events due to competition to get to quotes).

Overall, scholars have underlined the enormous profits to be gained by data analysis and news trading. In their study, Professors Foucault, Hombert, and Roşu show that speed makes a meaningful difference for traders. Speculators that can race ahead of others account for a larger fraction of trading and drive short-run price changes. In a separate study, Professor Roşu notes the tendency of fast traders to move on information, generating profits and volume. After extracting desired gains, traders exit the market, on-selling securities in a "hot potato" fashion.[132]

HF trading on incoming price changes and other information can also prove beneficial for markets. As outlined in Part I, information constitutes the fundamental imperative of markets as the essential fuel for efficient prices. In theory, rapid trading on information should mean that markets are more efficient, absorbing information quickly, as well as broadly, to reflect a far wider range of information than may have been possible in past eras of trading. In support, some finance scholars have observed that HF trading does, in fact, contribute to better price efficiencies, particularly in the near term.[133] Moreover, these efficiencies extend widely across exchanges and asset classes.[134] As Professor Gerig shows, HF traders rapidly convey information across the market, such that (short-term) efficiency gains are not restricted to a single market. Prices across the system synchronize rapidly to reflect incoming information.[135]

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[132] Thierry Foucault, Johan Hombert & Ioanid Roşu, News Trading and Speed, 71 J. Fin. 335, 337–38, 340 (2016); Roşu, supra note 126, at 4, 6–7.

[133] Chaboud et al., supra note 27, at 2047–48 (noting the efficiencies and lower arbitrage opportunities in the foreign exchange market between different pairs of currencies, euro-yen, dollar-yen, and euro-dollar).

[134] Scott Patterson, High-Speed Stock Traders Turn to Laser Beams, Wall St. J. (Feb. 11, 2014), http://www.wsj.com/articles/SB10001424052702303947904579340711424615716 [https://perma.cc/5VCX-DS3Y] (discussing industry plans to connect exchanges by laser beam rather than using fiber-optic cables). From the policy standpoint, the SEC has set out an ambitious agenda to deal with HF trading. Mary Jo White, Enhancing Our Equity Market Structure, U.S. Sec. & Exchange Commission (June 5, 2014), http://www.sec.gov/News/Speech/Detail/Speech/1370542004312#.U9XhGfldVqU [https://perma.cc/66QS-32QB]. Relatedly, the New York State Attorney General has sought to pursue HF traders and news providers for enabling HF traders to receive preferential access to news services. For more detail, see William Alden, Barclays Faces New York Lawsuit over Dark Pool and High-Frequency Trading, N.Y. Times: DealBook (June 25, 2014), http://dealbook.nytimes.com/2014/06/25/n-y-attorney-general-to-accuse-barclays-of-fraud-over-dark-pools/?_r=1 [https://perma.cc/68GZ-VNUH].

[135] Gerig, supra note 25, at 1–2. For a review of the literature, see Div. of Trading & Mkts., U.S. Sec. & Exch. Comm'n, supra note 118 (discussing current research on the informational efficiency of algorithmic trading and contributions of HF trading to market quality).

Third, algorithmic trading and HF trading can also be deployed towards more nefarious ends. Engaging in deceptive and manipulative behavior or in conduct determined to interfere with the transactions of other traders may be easier to accomplish with the aid of HF algorithms. HF algorithms enable traders to trade rapidly at high volumes, sending out millions of orders at the push of a button. Manipulative schemes like wash trades or spoofing, or practices like marking the close, can be undertaken much more effectively with the aid of algorithmic precision.

Take the case of Trillium Brokerage Services. Trillium submitted waves of false buy and sell orders with a view to inducing other market participants to transact. Once Trillium's own orders were filled at the artificially high or low prices, it cancelled the spoof orders. Facilitated by HF algorithms, Trillium performed this type of spoofing 46,000 times over several weeks.[136]

Other types of trading may be more disruptive, rather than obviously manipulative in nature. They may seek to make it harder and costlier for other traders to participate in the marketplace. For example, to ensure they can get the best position in the trading queue, traders can use HF algorithms to submit hundreds of thousands of orders to exchanges in short bursts of time. A large number of orders in the market—calibrated to varying price points—are likely to have a better chance of beating the competition to match with the most lucrative opportunity available on the exchange.[137] Sending out a large number of orders comes at low cost to the trader.[138] But it can offer promising gains where big trades match at the best price. The orders that fail to match are simply cancelled by the algorithm. By some estimates, more than 90% of all HF trading orders are cancelled rapidly after submission.[139] Still, these techniques can

[136] Colin Barr, Fast-Trading Firm Hit with Big Fine, Fortune (Sept. 13, 2010), http://fortune.com/2010/09/13/fast-trading-firm-hit-with-big-fine [https://perma.cc/MGP8-YVSJ] (reporting on the fine imposed by FINRA).

[137] Nikolaus Hautsch & Ruihong Huang, The Market Impact of a Limit Order, 36 J. Econ. Dynamics & Control 501, 514 (2012); Scopino, supra note 108 (questioning the legality of pinging).

[138] It should be noted that this does not mean that operationalizing strategies is simple. Transaction costs attaching to implementing strategies can be considerable. For analysis, see Yuriy Nevmyvaka et al., Electronic Trading in Order-Driven Markets: Efficient Execution (2005) (unpublished manuscript), http://www.cis.upenn.edu/~mkearns/papers/optexec.pdf [https://perma.cc/4HNN-TZSN].

[139] Scott Patterson & Andrew Ackerman, SEC May Ticket Speeding Traders, Wall St. J. (Feb. 23, 2012), http://www.wsj.com/articles/SB10001424052970203918304577239440668644280 [https://perma.cc/A9D3-9EDA].

be a source of massive disruption. In June 2014, Citadel Securities, the brokerage affiliated with the Citadel hedge fund, came under scrutiny for its quote submission algorithm that sent hundreds of thousands of orders to exchanges with only a tiny few of these orders actually executing. Citadel was blamed for flooding exchanges with bursts of 10,000 orders per second to buy and sell millions of shares at various points in the day, with none of these orders moving to execution.[140] In one case, Citadel sent eight to nine orders per microsecond to NASDAQ to purchase 100 shares of Penn National Gaming, resulting in 65,000 orders being dispatched to NASDAQ in under a minute. Every one of these orders was cancelled, and no transactions in Penn National Gaming securities took place.[141] Though Citadel argued that these orders were sent erroneously rather than with a deliberate, disruptive strategy in mind—an argument that regulators accepted—commentators have disagreed vigorously.[142]

Critically, in all cases, HF algorithms depend on detailed, precise programming in order to function. This programming must be sufficient to operate without the intervention of human traders interacting with the program in real time. HF algorithms must accurately anticipate how markets will behave on a particular day and to be capable of reacting to changing market circumstances independently, must adjust their trading to evolving environments and interactions with other traders.[143] If programming is defective or if it fails to accurately include instructions appropriate to events and circumstances, HF algorithms cannot function effectively.[144]

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[140] Fin. Indus. Regulatory Auth., Letter of Acceptance, Waiver and Consent, No. 20100223345-05 (June 2, 2014), [https://perma.cc/UY9F-CPPP].

[141] The Quote Stuffing Trading Strategy, Nanex (Aug. 15, 2014), http://www.nanex.net/aqck2/4670.html [https://perma.cc/FQ8U-YQ3B] (noting the trades of Penn National Gaming—a case that did not explicitly appear in the FINRA Letter of Acceptance, Waiver and Consent to Citadel).

[142] See id.

[143] Yadav, supra note 18, at 1620–21; see also Kearns & Nevmyvaka, supra note 20, at 105 (exploring how the failure to program HF algorithms for market stress contributed to the Flash Crash).

[144] Raman, Robe & Yadav, supra note 126, at 2–5 (noting that human traders function better than machines in managing crisis); see also Kirilenko et al., supra note 2, at 2 (examining the behavior of HF algorithms during a crisis—the Flash Crash—to suggest that HF traders respond by reducing their market presence). But see Brogaard et al., supra note 126, at 2–4 (observing the benefits of HF trading for short-term price discovery and efficiency).

B. Market Structure and Automation

Algorithmic trading depends on market infrastructure to succeed. Exchanges have evolved to accommodate systems that are equipped to facilitate information flows, order submission, routing, matching, and execution in microseconds or less.[145] These structural foundations, while exhibiting great leaps in technology, also make markets more vulnerable to the risks presented by algorithmic trading.

Interconnection: Markets exhibit deep interconnection between different exchanges, as well as between the types of securities that are traded on them. This is not an accident. It has arisen as a result of a deliberate policy choice followed since the 1970s to join competing U.S. exchanges into a National Market System ("NMS") for publicly listed securities. This NMS depends on many of the same players to make markets and supply liquidity.

The National Market System: Market efficiency aims to secure the most accurate price for a security, reflecting publicly available information. But if prices become a product of transaction costs—broker fees, exchange fees, uncertain execution, and so on—efficiency suffers alongside the usefulness of prices as a guide to value. Regulation NMS, a set of rules passed by the SEC, represents an attempt to bring competing exchanges together under one national banner—the NMS.[146] Those trading within this system can see the same securities listed across multiple competing exchanges. Exchanges compete to deliver the best price and—according to Regulation NMS—investors must be guaranteed execution of their order at this best national price. Efficiency should increase owing to competition between exchanges to attract investors, reducing transaction costs.[147] Further, investors can correct price discrepancies between different exchanges. If *Company X* shares trade at $50.02 on the NYSE and at $50.01 on the NASDAQ, then traders can easily buy securities on the NASDAQ and sell them on the NYSE.

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[145] For regulatory issues in relation to co-location and direct information feeds, see Yadav, supra note 15, (manuscript pts. II.A.2–II.A.3, at 26–29).

[146] Securities Acts Amendments of 1975, Pub. L. No. 94-29, § 7, 89 Stat. 97, 111–17; Regulation NMS—National Market System, Exchange Act Release No. 34-51808, 70 Fed. Reg. 37,496 (June 29, 2005); Lawrence A. Cunningham, Capital Market Theory, Mandatory Disclosure, and Price Discovery, 51 Wash. & Lee L. Rev. 843, 862–64 (1994).

[147] Order Protection Rule, 17 C.F.R. § 242.611 (2015); Div. of Mkt. Regulation, U.S. Sec. & Exch. Comm'n, Market 2000: An Examination of Current Equity Market Developments 1–5 (1994).

Eventually, through this "arbitrage," the price for *Company X* shares across the NMS should stabilize at the most efficient price.[148]

Importantly, the NMS necessitates the creation of strong communication and information flows between exchanges. Securities trade across multiple markets. Price signals from one exchange impact how prices form across the NMS. HF traders are especially well placed to profit from the structural gains of the NMS. They can trade across multiple exchanges rapidly, making markets on several venues as well as correcting even tiny price discrepancies cheaply through arbitrage.[149] In addition, HF traders can trade across different types of securities. If *Company X* shares are trading at $50 per share, an HF trader might also trade in futures or options referencing *Company X* shares.[150] In light of the interconnections cultivated under the NMS, it is unsurprising that Professor Gerig observes rapid price convergence between exchanges and security types on U.S. exchanges.[151]

Common Sources of Liquidity: Market interdependence is economically institutionalized by common reliance on a select cohort of traders to make markets. As outlined above, HF traders have thrived as market makers—standing ready to buy and sell securities with investors. HF traders can operate across several markets and be relied upon to supply trading opportunities (liquidity) for other investors.[152]

Conventionally, if a trader experiences a problem on the NYSE transacting in *Company X* stock and loses money, it might also scale back its participation on the NASDAQ, as well as on other exchanges (e.g., those that trade *Company X* futures or option securities). It might also stop making markets in securities with similar risk profiles to those of *Company X*. Indeed, in the event that the problem becomes severe, and the

[148] For a detailed discussion of mechanisms and risks of latency arbitrage by HF trading, see Roman Kozhan & Wing Wah Tham, Execution Risk in High-Frequency Arbitrage 58 Mgmt. Sci. 2131, 2138–39 (2012).

[149] MacIntosh, supra note 118, at 7–10.

[150] See Kin-Yip Ho, Wai-Man (Raymond) Liu & Jing Yu, Public News Arrival and Cross-Asset Correlation Breakdown: Implications for Algorithmic Trading 1–4 (Mar. 15, 2012) (unpublished manuscript), http://ssrn.com/abstract=2023079 [https://perma.cc/DX59-T54N] (examining the relationship between stock futures and the underlying market for stocks during news releases. The paper studies how algorithmic trading impacts trading in both the futures and the underlying market in cases of news arrivals and information uncertainty).

[151] Gerig, supra note 25, at 1.

[152] The definition of liquidity in financial economics is complex and contested. This is not a definition of liquidity, but a simplified explanation of the economic functionality offered by HF market makers.

trader's capital comes under serious risk, the rational response for the trader would be to stop trading altogether. In their influential paper, Professors Brunnermeier and Pedersen show that liquidity in a security is directly linked to the funding available to traders. If traders do not have reliable funding sources (e.g., in a crisis), they are less likely to trade, reducing yet further the liquidity in securities trading.[153] This powerful economic interaction between a trader's funding and market health is especially relevant in algorithmic markets. With automated and HF traders driving 50 to 70% of volume in equities, 60 to 80% in some futures markets, and around 50% in the U.S. Treasury markets, any decision to curtail or limit trading in one market can be systematically disastrous not just for that market but for others as well.[154]

III. APPLYING LAW TO MARKETS: THE LIMITS OF LIABILITY

Algorithmic trading challenges traditional theories of liability in securities markets and the allocation of enforcement costs they impose between regulators and market participants. This Part applies familiar paradigms in liability to the modern reality of automated markets and shows that these are quickly losing relevance. The implications of this shortfall are well established. In the absence of a guiding framework to sanction mistake and misbehavior in securities trading, heightened risks of error can undermine investor engagement and appetite for market participation. If liability constraints are ineffective in disciplining firms, the costs are reflected in a poorer, less efficient price formation process.

A. Intent and Recklessness

Punishing intentional and grossly reckless harms under Rule 10b-5 creates numerous conceptual complexities in HF markets. As one of the most powerful tools in the regulatory canon, these challenges invariably

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[153] Markus K. Brunnermeier & Lasse Heje Pedersen, Market Liquidity and Funding Liquidity, 22 Rev. Fin. Stud. 2201, 2201–04 (2009).

[154] See Mackenzie, supra note 16; Alexandra Scraggs & Susan Walker Barton, Treasuries Wilder Than Ever as Ultrafast Bond Traders Rise Up, BloombergBusiness (Oct. 13, 2015), http://www.bloomberg.com/news/articles/2015-10-12/treasuries-wilder-than-ever-as-ultra-fast-bond-traders-rise-up [https://perma.cc/8S52-JJUD]; Richard Haynes & John S. Roberts, Automated Trading in Futures Markets 2–4 (Mar. 13, 2015) (unpublished manuscript), http://www.cftc.gov/idc/groups/public/@economicanalysis/documents/file/oce_automatedtrading.pdf [https://perma.cc/EE3G-P79Y].

raise more fundamental questions about the viability of Rule 10b-5 to effectively and fairly police the modern marketplace.[155]

Evidencing Manipulation: At first glance, HF markets overturn the traditional allocation of resources needed to investigate manipulation by actually *lowering* the costs of detection. In evidentiary terms, manipulative traders have nowhere to hide. For one, algorithms leave an obvious paper trail of transactions that should give regulators a leg-up in spotting the manipulation and in making the case for punishment. All trades are computerized. They travel through an exchange's trading systems and are tracked by other algorithms in real time. Further, regulators should also be able to see easy evidence of intent. Once probable signs of manipulation and deliberate disruption emerge, authorities can seek access to the actual algorithmic programming of problem traders to reveal the design underlying the algorithm. Putting aside the costs of interpreting data for the time being, algorithmic trading should offer much richer grounds to respond to intentional price distortions. As exemplified by the cases of Sarao or Trillium Brokerage, spoofing activity can now be deduced through the pattern of hard data generated by the dubious activities of the defendants. From an enforcer's standpoint, this state of affairs is a far cry from the back-room dealings and the nudges and winks that might have characterized attempts at manipulation in nonautomated markets.

Algorithmic Characteristics: While algorithmic trading should make it easier to evidence familiar manipulation, Rule 10b-5 is underprotective against more novel forms of deliberate algorithmic mischief.

Intent seeks to establish a subjective motivation on the part of the trader to commit a fraud or manipulation. In algorithmic trading, this intent becomes actionable where it is reflected within the programming driving the algorithm. In some cases, this is easy: The form of manipulation is familiar and is the obvious strategic aim of the algorithm. As stated above, in the algorithms used by Sarao or Trillium Brokerage, the traders appeared to be driven by the goal of creating false perceptions of market activity through well-known spoofing strategies.

But the inquiry becomes vastly more complicated where preset algorithms are designed to accomplish legitimate strategies in disruptive ways. For a start, traders are required to finely tune their algorithms to

[155] On the challenges of bringing a class action Rule 10b-5 challenge in HF trading, see Levens, supra note 66, at 1549–55.

recognize and avoid deceptive behavior.[156] This can pose a conundrum. The law itself is notoriously complex, such that preprogramming its intricacies into automated processes represents a tricky proposition.[157]

But more importantly, even where preset algorithms are programmed to accomplish acceptable strategies—like market making, arbitrage, or information trading—deliberately disruptive behavior can be a rational strategy. In short, it can be efficient to deceive or disrupt markets. For example, algorithms programmed to trade cost-effectively will likely find it cheaper to send out and cancel high volumes of orders to capture the best deals. This might cause a problem for other traders who might struggle to enter the market as a result. Crucially, without sending out vast batches of (cancelled) orders to jostle for information on the best orders or to distract others for the top spot on the queue, trading can become vastly more costly.[158] Recall that if markets move rapidly, waiting even for milliseconds means that someone else gets the best trade and returns plummet rapidly. For algorithms transacting with other algorithms, such instances of deliberate disruption might represent the modality by which even legitimate strategies are undertaken. Such strategies can be harmful if they force traders to absorb the costs of fending them off. More problematically, the market suffers if prices reflect noise created by such evasions or a degree of discounting on the part of traders internalizing higher transaction costs. In turn, where corporate issuers must deal with the risk of frequent disruptions in the prices at which their securities trade, they may think harder before their public listing.

Where algorithms engage in rationally efficient but disruptive behavior to execute legitimate strategies, Rule 10b-5 would appear to offer little protection. To the extent that the subjective intent of the trader is missing in specific bad actions, Rule 10b-5 is likely to fall short.[159] Indeed, if such practices are widespread and visible in the algorithms of a

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[156] Scopino, supra note 11, at 255–58 (observing that high artificial intelligence in algorithms means that they can engage in behaviors that may not be intended by trader). Professor Scopino raises the challenge of how best to ascribe blame in markets when many algorithms may be operating "independently" to the extent that they exercise artificial intelligence in their trading design.

[157] For example, the law remains unclear on whether recklessness qualifies as sufficient basis for a Rule 10b-5 action.

[158] But see Scopino, supra note 108 (questioning the legality of pinging).

[159] See, e.g., SEC v. Masri, 523 F. Supp. 2d 361, 372, 375 (S.D.N.Y. 2007) (holding that subjective bad intent must be an overriding cause guiding transactions in order for Rule 10b-5 liability to attach on grounds of manipulation).

large swathe of traders, then punishing such conduct as deceptive becomes even more difficult. It may be arguable that—where disruptions are widespread and even expected on account of the features of algorithms—individual traders may be aware of this danger and account for it in their own programming. Still, the costs of such conduct can accrue to the market as a whole, where exchanges, investors and regulators must capture data that is more pervasively impacted by disruptive tactics and countermeasures.[160]

Uneven Application: Secondly, if Rule 10b-5 cannot easily apply to common, deliberately disruptive conduct, its application necessarily becomes restricted to only the most egregious cases. In other words, instead of being a strong, protective sword to be wielded against willful wrongdoing in the market, as the expansive wording of Rule 10b-5 would suggest, it seems to fit only the most obvious kinds of manipulation. Strategies like spoofing, wash trades, self-trading, or price manipulation might see sanction, particularly if intentional mischief is their primary goal. But, other types of bad conduct may escape sanction.

Indeed, this seems to be the pattern emerging from the small number of Rule 10b-5 actions that have been brought by the SEC and the CFTC in the context of algorithmic trading. Actions have focused on clearer instances of manipulation (e.g., Trillium). Other cases of intended disruption—such as stuffing exchange systems with (eventually) cancelled quotes—largely do not see enforcement owing to their widespread use for the execution of otherwise legitimate strategies. This differing treatment of intentionally disruptive conduct raises obvious concerns from the point of view of fairness. Some traders face higher costs owing to their use of conventionally manipulative techniques, while others see little scrutiny under Rule 10b-5 owing to their use of newer practices more pervasively part of HF markets. That is not to say the latter category might see no sanction. It might fall within a lighter head of liability such as negligence (e.g., the Market Access Rule). Further, it is also arguable that regulators have always enforced rules selectively to save resources. Still, where traders see varying distributional consequences for their participation, there are incentives for bad actors to seek out ways to opt-in to lower-cost enforcement regimes. If problem firms wish to make gains

[160] Adam D. Clark-Joseph, Exploratory Trading 1 (Jan. 13, 2013) (unpublished manuscript), http://www.nanex.net/aqck2/4136/exploratorytrading.pdf [https://perma.cc/GD9E-6BBR] (noting the systematic use of small batches of orders and cancelled orders to explore potentially large orders and ascertain information).

through disruptive strategies, it makes sense to take advantage of lighter scrutiny by using common disruptive algorithmic techniques.

B. Negligence

Liability for negligence—the failure of firms to live up to a reasonable standard of conduct—represents the workhorse of the disciplinary framework. Its place in securities regulation is pervasive. As seen in the Market Access Rule, its application is significant in the architecture of trading, requiring those that link markets with investors to maintain a reasonably robust standard of oversight.

But reliance on the negligence standard poses a difficulty in algorithmic trading, particularly as it relates to HF firms. HF algorithms, by design, imply a degree of intrinsic error in their operation. For HF algorithms to maintain execution speeds measured in microseconds and milliseconds, they must be preset and predictively model market behavior. Of course, to bolster predictability, traders might analyze historical trading patterns and deduce the most probable market scenarios. But, preset, predictive programming requires traders to derive abstract, stylized instructions from data to drive their trading on any given day. If the market fails to exactly conform to predictive settings, algorithms may only be able to imperfectly represent the information they receive and process.[161] Given the impossibility of prediction—even for extremely short periods of time—preset HF algorithms mean that some tolerance for error may be required.

Anecdotally, at least, there is growing evidence of more frequent mistakes in trading, reflecting the limitations of preset trading programs. For example, scholars have observed a rise in sub-second mini-flash crashes that see prices suddenly crash and recover in tiny fractions of a second. Between 2006–2011, one study noted the occurrence of 18,520 spikes and crashes that each lasted for around 1,500 milliseconds.[162] In addition to such sub-second events, larger unexplained crashes in single securities are commonplace. In February 2011, for example, Apple Inc. saw a rapid, inexplicable fall in its share price that declined from a high of $360 per share to $349 per share in just four minutes. Though the stock

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[161] Yadav, supra note 18, at 1607.

[162] Neil Johnson et al., Abrupt Rise of New Machine Ecology Beyond Human Response Time, Nature Scientific Reports (Sept. 11, 2013) at 3, http://www.nature.com/articles/srep02627 [https://perma.cc/LWE2-NNCE].

eventually recovered, this flash crash in Apple wiped almost $10 billion from its market capitalization.[163] Similar events have occurred in the stocks of various household names, including financial firms like Citigroup.[164] Scholars seeking to explain a rise in mini-flash crashes posit that HF algorithms may be reacting quickly to new information before refining their response as clarifying information filters in.[165] Recall that near-term profits from new information can decline rapidly in HF markets. In this competitive context, traders will rationally program algorithms to trade on all information first and only later check its veracity rather than to risk losing out on the gains on offer.[166] If liability fails to impose any real costs, the potential benefits further motivate such conduct.

In acknowledging the persistence of inherent risk of error in HF markets, regulators face two broad options in crafting a reasonableness standard: (1) to give firms a wide berth, allowing them to generate fairly large costs before being found liable; (2) or narrow room for maneuver that imposes costs for less serious infractions. Neither approach is particularly satisfactory. On the side of greater latitude—a reasonableness standard that expressly acknowledges error and reduces its costs for private firms—has obvious shortcomings. Traders will have fewer incentives to control the operation of their algorithms. They might use their algorithms for more risky trading: to trade aggressively on new information without checking its accuracy; or to engage in tactics designed to scupper the activity of competing traders (e.g., by sending out a large number of unfulfilled orders). This tolerant approach risks creating costs for other traders as well as for the market that must provision more heavily for flash crashes and other disruptions.

But the stricter approach too can be problematic. Such an approach would dictate that algorithms that generate harms over a low level of se-

[163] Phillip Elmer-DeWitt, Snapshot of an Apple Flash Crash, Fortune, (Feb. 11, 2011), http://fortune.com/2011/02/10/snapshot-of-an-apple-flash-crash/ [https://perma.cc/Z7A7-TM4Y].

[164] Graham Bowley, Flash Crash, in Miniature, N.Y. Times, Nov. 8, 2010, at B1. For a more complete list, see Mini Flash Crashes on the Rise, Nanex (Jan 28, 2014), http://www.nanex.net/aqck2/4543.html [https://perma.cc/V2NK-PQS4].

[165] Jérôme Dugast & Thierry Foucault, False News, Informational Efficiency, and Price Reversals 3–4 (Oct. 2014) (unpublished manuscript), https://www.banque-france.fr/uploads/tx_bdfdocumentstravail/DT-513_01.pdf [https://perma.cc/B4N9-SSEW] (noting that traders can trade fast on a signal and only test whether it is accurate later).

[166] Id. at 4–5 (noting that selling pressures cause speculators to trade before checking the signal).

riousness be punished as negligent. This would require traders to construct ex ante a far more robust arsenal of structural and programming precautions to avoid generating liability. Under regulations like the Market Access Rule, those facilitating access to HF firms might also face more stringent oversight. While forcing traders to more fully pay-to-play, some limitations of this approach must also be acknowledged.

Interconnection, Correlation, and Flight: First, even a strict notion of reasonableness may be insufficient to prevent the occurrence of serious harms in the marketplace. Put simply, even small instances of error can spawn large market reactions.

For one, HF markets are more deeply interconnected than ever before. Price reactions are liable to spread rapidly across multiple exchanges and asset types. HF algorithms are preprogrammed to respond instantly to new information and to the errors and mischiefs of other traders—with human beings unable to intervene in real time to correct mishaps. While automation injects efficiencies across the marketplace, errors also follow similar transmission mechanisms.[167] This is evidenced by the May 2010 Flash Crash. Whether it was Navinder Sarao's trading or a Kansas mutual fund's attempt to sell 75,000 E-mini futures (as has also been posited by regulators), the impact of discrete activity mushroomed catastrophically across the marketplace.[168]

The trajectory of such systemic ripple effects can also be unexpected and difficult to predict. Knight Capital, for example, caused disruptions across various exchanges in the National Market. A prominent market research firm reported on some of the system-wide impacts of Knight's faulty router during the thirty-odd minutes in which it was malfunctioning. On the day of the collapse, the NYSE, ARCA and AMEX exchanges (where Knight was active) saw an additional 4.4 million trades, 544 million shares, and $11.8 billion in trading value than the previous trading day. This rise in activity on the NYSE, ARCA and AMEX came at the cost of a decline in activity on the NASDAQ.[169]

In addition to such interconnections, correlated algorithmic programming can amplify the impact of even small trading behaviors. Correlation risks can arise because HF algorithms can be programmed in similar

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[167] Id. at 2; Gerig, supra note 25, at 2–3.

[168] Kirilenko et al., supra note 2, at 5–6.

[169] Knightmare on Wall Street, Nanex (Aug. 1, 2012), http://www.nanex.net/aqck2/3522.html [https://perma.cc/P5HD-UFUE] (note that these figures are for the thirty minutes between 9:30 a.m. and 10:00 a.m. when the Knight router was malfunctioning).

ways. Rather than exhibit a large diversity in programming to offset correlation, commonalities can heighten the expressive and transactional effect of small problems and hasten the spread of risks between markets. One notable study of the foreign exchange market, for example, reported that HF trading exhibited a higher than normal expected degree of correlation within the market studied.[170] While this may be an acceptable state of affairs in good times, it may be far less tolerable in times of stress. To be sure, commentators are engaged in debates regarding the impact of HF trading on measures of volatility and market quality—with differing points of view emerging.[171] Yet, looked at from the perspective of error costs and the spread and amplification of negative signals, HF markets exhibit risks that may go beyond those anticipated by traditional negligence regimes in securities regulation.

Finally, the risks of market interconnection and correlation are amplified yet further by the possibility that traders suddenly flee the market. As discussed in Part II, traders may retreat from the market if their sources of funding grow scarce or come under jeopardy. As posited by Professors Brunnermeier and Pedersen, liquidity in securities trading will dry up when traders begin to see their own source of funds dissipate. This dynamic is self-reinforcing. The more securities grow illiquid, the faster traders will leave, sending markets into a "liquidity spiral."[172]

The risk of such liquidity spirals is heightened in HF markets. Exit is cheap. Traders only assume momentary exposures to securities. Rather than work hard to unload large portfolios of securities in a deteriorating market, HF traders can instead exit rapidly. If market flight comes at low cost—and the exposure to spiraling markets brings mounting uncertainty—it is rational for traders who can leave to do so as quickly as possible. As HF markets can spread risks in milliseconds through multiple markets, the threshold at which traders decide to leave might materialize very quickly. This potential for HF traders to amplify crisis through rapid exit has been highlighted in two prominent regulatory inquests. In the May 2010 Flash Crash, the SEC and the CFTC noted that HF traders

[170] Chaboud et al., supra note 27, at 2075.

[171] Compare, e.g., Brogaard, Hendershott & Riordan, supra note 27, at 2268 (arguing that HF trading can smooth volatility in markets), with X. Frank Zhang, High-Frequency Trading, Stock Volatility, and Price Discovery 2–3 (Dec. 2010) (unpublished manuscript), http://ssrn.com/abstract=1691679 [https://perma.cc/75NU-NGFP] (noting the transient and unstable nature of liquidity offered by HF trading).

[172] Brunnermeier & Pedersen, supra note 153, at 2218–20.

began to quickly leave the market as trading grew unpredictable. Similarly, in a flash crash impacting the market for U.S. Treasuries in October 2014, regulators pointed to the diminished participation of HF traders as a contributing factor to sudden volatility in this all-important market.[173] In both cases, many (but not all) HF traders stopped trading—an arguably rational response to deteriorating and unpredictable conditions. Despite the ease and convenience such exits offer traders privately, they bring disaster to the public market. Seen through the theoretical lens of the Brunnermeier-Pedersen model, such exits foment sudden drops in market liquidity, forcing markets to adopt an emergency footing.

Incentives to Take Risks: Second, a negligence standard set at a stringent threshold can motivate traders to take costly risks. Where traders internalize high provisioning costs ex ante to put reasonable precautions in place, they may be incentivized to recoup their costs by engaging in more risky trading. As analyzed by Professors Shavell and Polinsky, the negligence standard allows traders to engage in some risk taking as long as it falls within the ambit of reasonableness.[174] A negligence standard in HF markets still allows for some risk taking as long as it is objectively reasonable. With this latitude, traders may be motivated to push the limits of the permissible in order to reap higher rewards, particularly if their provisioning costs are high. Indeed, traders may even chance unreasonable risks if the likelihood of detection is low. After all, regulators must expend resources to detect wrongdoing and to bring actions to enforce the negligence standard. It is likely that a particularly tight threshold for negligence will generate a high number of potential defendants. With scarce resources, regulators might only act in response to the most brazen or most costly infractions. This can leave a swathe of risk taking to go unsanctioned in the market—exactly the opposite of what a stricter negligence threshold is designed to achieve.

[173] U.S. Treasury, Joint Staff Report: The U.S. Treasury Market on October 15, 2014, at 3, 5–6 (July 13, 2015) (noting that, as a group, HF traders still remained "engaged" during the window. The report noted a sudden deterioration in liquidity and that the HF traders constituted the group with the largest reduction in the order book); Kirilenko et al., supra note 2, at 2–4.

[174] Polinsky & Shavell, supra note 12, at 8–13.

C. Strict Liability

The spate of near disasters impacting HF markets—and the insufficiency of the negligence standard—might make the case for strict liability to be imposed more pervasively in securities regulation. Rather than rely on strict liability to punish routine technical infractions—it might be better applied to constrain conduct liable to generate large-scale harms. Such an approach would align securities regulation more closely with the larger body of tort law that typically relies on strict liability to punish behavior that is dangerous and generative of large harms. Without a requirement to make the legal case—unlike negligence—regulators face fewer costs and may be more engaged in enforcement.

As much as this approach seems attractive on its surface, a strict liability regime to combat the harms of algorithmic trading also poses a number of problems and shortcomings.

The Limits of Programming: First, strict liability may provide an imprecise fit where harms arise from the intrinsic imprecision of predictive programming. Generally speaking, strict liability can be rationalized if the conduct and the harms arising from it may be effectively anticipated and controlled ex ante. Where this is the case, firms can calibrate their behavior in accordance with their degree of risk aversion.[175] As shown in this Article, however, preset algorithmic programming—necessary to HF trading and other complex algorithms—is not always predictable nor are the costs of running their programs fully ascertainable from the outset. Indeed, because it is predictive, programming will only approximate future events in its trading instructions. In this regard, preset algorithms can give rise to understandable but idiosyncratic errors in anticipating complicated markets that can, in turn, generate widespread crisis. In short, unpredictable mistakes will occur if predictive algorithms are used, irrespective of the care that market actors take. Fat finger trades, aggressive trading on new information, or dealings on unverified information can cause unexpected mini-flash crashes in single securities or prompt other algorithms to overreact. Technical errors can lead to unforeseeable areas of markets being impacted and harmed (e.g., lower volumes on the NASDAQ on account of excess trading on NYSE). Indeed, the impact of errors may be magnified because other traders react automatically to erroneous trading or they retreat from the market if activity grows risky.

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[175] Id. at 10–13.

This idiosyncratic dynamic stands in contrast to more conventional strict liability regimes that traditionally govern liability for consumer products or large accidents. Hypothetically, a toy manufacturer might anticipate that five percent of its products are likely to be defective. This estimate should help the manufacturer work out what kind of harms might result from this pool of defective products. Further, experience from prior disasters can offer insight about the scale of future liability. From the ex ante standpoint, knowing that five percent of its toys might be faulty, the manufacturer can put systems in place to track and monitor distribution. Importantly, from the ex post perspective, the manufacturer can provision financially for the harm, internalizing the liability costs of potential deficiencies in its manufacturing process.[176]

In HF markets, anticipating and provisioning for these dynamics is challenging at best and unachievable at worst. Predictive programming means that errors can arise even if traders take every care in trying to assure the safe operation of their algorithms. They can happen without warning or foreseeability. This poses a conceptual difficulty for traders seeking to avoid liability by designing their algorithms to minimize problems. It also raises enormous uncertainty for traders regarding how best they might provision for the costs of unexpected, singular errors like flash crashes or other glitches. Any strict liability regime, therefore, can provide only a false sense of security.

The Compensation Problem: Strict liability for HF trading also fails to fulfill the promise of meaningfully compensating other market actors for the harm that errors can generate. Where harms may be large and their trajectory unexpected, the seriousness of the resulting damage may be too large for any single firm to pay. This problem is acute in HF markets where errors and mistakes may spread quickly between exchanges and asset classes.[177] As a result, liability costs may be far too extensive for any one firm to internalize.

This combination of potentially high penalties from even minor mistakes can create distorted incentives for traders. If firms know that their activities may give rise to large-scale harm, where damages may easily wipe them out, they may end up with stronger motivation to take risks. Particularly given that algorithms pose an intrinsic risk owing to the fact of preprogramming and unexpected interactions with other algorithms

[176] My thanks to Professors Gil Seinfeld, John Pottow, and Scott Hershovitz for the analogy.

[177] Gerig, supra note 25, at 7.

and market dynamics, it seems rational for traders to consider taking high risks. In short, traders face two choices: (1) use simple, less profitable strategies; or (2) use higher risk, higher reward strategies. If both carry the nontrivial risk of certain high damages, traders should rationally pursue the riskier option from time to time (frequent risky behavior may result in a higher chance of detection). Of course, if traders use a simple strategy, the probability of causing large-scale damage should decrease—and risk-averse traders may well continue to adhere to simpler strategies. But a strict liability regime in inherently error-prone markets poses a difficult problem. If traders know that even nonserious conduct might wipe them out, why not go for broke?

D. Contribution

Liability regimes—for both strict liability and negligence—may also allocate costs between multiple actors, reducing damages and blame on a defendant if someone else is also partially responsible. If others have contributed to the harm, worsened its seriousness, or otherwise engaged in conduct that exhibited similarly harmful behavior to the defendant, then their contribution could reduce the damages owed by the defendant.

While contribution by multiple bad actors might work in conventional torts, its application to HF markets is more difficult. The core dilemma facing regulators is the prescriptive one: How must other traders behave if a problem emerges in the marketplace?

HF algorithms are preset to trade independently in real time. HF algorithms mine data, including information about the trades of other investors, the order flow, and fluctuating prices. If a problem occurs, say, a mini-flash crash in Apple's stock or rapid trading on a false news report, traders will react to that data in accordance with their preset programming. They will assume it to be true and continue trading based on their already-set instructions. This automatic, preset trading can amplify the problem, force its spread across many markets, and generate larger losses because many algorithms have to trade on emerging data—agnostic as to its veracity. In August 2012, for example, Goldman Sachs traded with an erroneous algorithm in the options market that caused it to purchase around 800,000 option contracts in seventeen minutes, causing widespread disruptions on multiple exchanges.[178] Still, counterparties continued to trade with Goldman, entering profitable deals for themselves to the detriment of the famed Wall Street institution. It should have been obvious to market participants that something was very wrong. The sudden volume on the market was, by some estimates, hundreds of times more than what it would be on any given day.[179] Luckily for Goldman, exchanges agreed to unwind the trades, causing the contract parties to take a loss. Yet, the incident raises the question whether other traders might also be liable for continuing to trade with Goldman and for contributing to the crisis.[180]

There is no easy response to this question. For one, if market conditions are unusual, they will confuse an algorithm's preset programming. In such cases, regulators will have a hard time showing that the program made an actionable mistake that should incur liability. Most crises are individual and different. The fact that an algorithm does not account for a random crisis should not be all that surprising. On the other side, regulators will also find it difficult to make the argument that algorithms should then have stopped trading or retreated. As discussed in this Article, the consequences of essential, liquidity-providing algorithms beating a hasty retreat are unpredictable and likely to lead to rapid deteriorations in the health of the market (e.g., a kind of Brunnermeier-Pedersen problem, as seen in the May 2010 and October 2014 Treasury Flash Crashes). In the absence of human intervention to correct mishaps, regulators essentially face a Hobbesian choice: either algorithms continue to trade on bad information in order to protect the health of the market even if this means that problems proliferate; or algorithms reduce their presence, cauterizing the spread of bad information but potentially risking the healthy supply of liquidity to the market.

[178] For discussion of this incident, see Arash Massoudi & Tracy Alloway, 17-Minute Trading Glitch Put Goldman's Reputation on the Line, Fin. Times (Aug, 22, 2013), http://www.ft.com/cms/s/0/37fff9c6-0b36-11e3-bffc-00144feabdc0.html#axzz3ylB5avOH.

[179] Id.

[180] This incident is to be contrasted with that of Knight Capital when trades were not unwound. In this case, owing to rules relating to the options exchange, amongst other factors, the trades were unwound, sparing Goldman Sachs the kind of liabilities that brought Knight Capital close to bankruptcy. See id.

E. The Paradox of Data

At first blush, HF markets offer major advantages for regulators. Regulators have access to vast amounts of data coming from transaction trails, order flows, and subsequent mishaps to determine whether liability should attach. They can examine the actual algorithms used by traders and analyze their potential for problematic behavior. Building the evidentiary case for mistake, mishap, or fraud should be easier than in years past, reducing the costs of processing cases through litigation and enforcement. Reflecting this apparently enormous boon for the regulatory process, the SEC's Rule 613 creates a Consolidated Audit Trail designed to track all trading activity within the NMS.[181] Exchanges must supply specific information on each quote and order into a central repository—as well as details on problem events.[182]

This wealth of data, however, obscures the complexity of the information that these data convey. Rather than lower the costs of enforcement and offer easy evidence for authorities, algorithmic data trails create new and sometimes serious costs for regulators.

Quantity and Complexity: First, commentators cite the extraordinary explosion of data in HF markets and the corresponding challenge of interpreting their significance. For example, on August 5, 2011, the market research firm Nanex reported processing over a trillion bytes of data for U.S. equities, options, futures, and indexes for a single day of activity. In 2010, this figure was 250 billion bytes.[183] In addition to simple volume, these data are also complex to interpret. Market data can include information that is unconnected to market events, including cancellations, wrong orders, random submissions, and idiosyncrasies relating to the exchange that collects the data.[184] While some data are certainly better than no data—and thus regulators are in a superior position to decades past—it still requires regulators to invest resources in their interpretation and analysis. The same data on the same event can often be subject to

[181] Consolidated Audit Trail, 17 C.F.R. § 242.613(a)(1) (2014).
[182] Id.
[183] Enough Already!, Nanex (Apr. 2, 2012), http://www.nanex.net/Research/Emini2/EMini2.html [https://perma.cc/9AGA-5KBR].
[184] Christian T. Brownlees & Giampiero M. Gallo, Financial Econometric Analysis at Ultra–High Frequency: Data Handling Concerns 2 (Universita' di Firenze, Dipartimento di Statistica G. Parenti, Working Paper No. 2006-3, 2006), http://ssrn.com/abstract=886204 [https://perma.cc/PCL8-5XND] (noting the enormous data created by HF trading and the challenge of mining that data for analytical value).

varying interpretations, complicating the process of ascribing liability to the real wrongdoer. This is perhaps most clearly illustrated by the varying explanations offered for the cause of the May 2010 Flash Crash. In a joint report by the SEC and CFTC in September 2010, regulators pointed the finger at a large order to sell 75,000 E-mini futures contracts dispatched by a mutual fund in Kansas. The downward impact of this order triggered a sell-off and eventually resulted in many algorithms simply withdrawing from the market, prompting a sharp downward spiral in liquidity.[185] In April 2015, the CFTC offered another explanation. Rather than ascribing the triggering event to an unexpected sell order from Kansas, the CFTC and the Justice Department pointed to the spoofing algorithm used by Sarao.[186] Indeed, complex events like flash crashes can be quite impervious to explanation, notwithstanding the volumes of data they generate. The joint report by the U.S. Treasury and others into the October 2014 Flash Crash could find no real "cause" to explain the sudden, sharp fluctuations in U.S. Treasury prices—only various possible contributing factors.[187]

Misaligned Incentives: Secondly, informational costs extend into the bargaining dynamics at work between regulators and traders. Growing technology and sophistication can create information asymmetries between the regulator and traders that utilize complex algorithms. The regulator seeks access to proprietary information unique to a trader in order to understand its algorithms. The regulator lacks detailed knowledge about the specific technology and techniques that the algorithm utilizes.

With these asymmetries, traders have little incentive to aid regulators by facilitating a transfer of information between themselves and the regulator. From the policy perspective, this asymmetry can provide a benefit to the trader. It provides a modicum of immunity for the trader to the extent that regulators have to work harder to acquire incriminating information about the trader and the algorithm. With this room to maneuver, traders have flexibility in programming their algorithms to behave opportunistically, with potential to generate private gains even if this might create costs and externalities for the market.

Importantly, with reserves of information at their disposal, traders are motivated to extract rents from the informational advantages that they

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[185] Kirilenko et al., supra note 2, at 9.
[186] See Aldrich et al., supra note 3, at 2–3.
[187] U.S. Treasury, supra note 173, at 4–6.

have. This informational leverage offers several advantages. Traders are in a position to negotiate with their regulators to arrive at a solution that creates the lowest cost for the trader. Looking at Rule 10b-5, for example, traders with deep informational advantages may be better positioned to barter around the strictures of a Rule 10b-5 offence for a lower penalty. Instead of penalizing a trader for fraud and manipulative behavior—with the inevitable moral sanction and financial price this implies—regulators may instead punish a trader for a relatively lesser infraction that does not require a high investment to procure private information or where the trader agrees to supply enough information for lower liability. And indeed, reflecting these challenges of making a Rule 10b-5 case against algorithmic traders, the number of successes to date amount to just a handful. The SEC only settled its first Rule 10b-5 action against an algorithmic trader in October 2014. The SEC accused Athena Capital Research, an HF firm, of manipulative trading practices on the NASDAQ for actions that took place between April and December 2009—a full five years before the conclusion of the SEC case.[188] This delay in settling the case may simply indicate that pursuing HF traders may not have been a priority for the SEC, particularly after the financial crisis.[189] But, commenters have pointed to the deeper challenges inhering in such action, and of understanding and reconstructing complex algorithmic strategies with only limited information to clarify the nature of the abuse.[190]

[188] Press Release, U.S. Sec. Exch. Comm'n, SEC Charges New York-Based High Frequency Trading Firm With Fraudulent Trading to Manipulate Closing Prices (Oct. 16, 2014), https://www.sec.gov/News/PressRelease/Detail/PressRelease/1370543184457 [https://perma.cc/6BSX-FM7T].

[189] Certainly, information costs are not fixed and regulators can gain increasing knowledge over time to overcome asymmetries. Public enforcers can access a menu of coercive powers that force private actors to disclose information. For example, regulators are developing rules to demand better disclosure from HF traders. FINRA, the U.S. self-regulatory authority for broker-dealers, has moved forward with a set of proposals targeted at eliciting information from securities traders. It has proposed various reforms that will require HF traders to supply information about their algorithmic trading business, including on the personnel that devise strategies and also about the strategies themselves, such as the systems and controls in place to control their operation. FINRA, however, does not appear to require detailed designs for single trading algorithms. Letter from Richard G. Ketchem, Chairman and CEO, Fin. Indus. Regulatory Auth., Update: Board of Governor's Meeting, to Executive Representative, (Sept. 19, 2014), http://www.finra.org/industry/update-finra-board-governors-meeting-6 [https://perma.cc/8XX8-TWSL].

[190] See U.S. Treasury, supra note 173, at 55; see also Levens, supra note 66, at 1512–13 (examining the use of the class action mechanism to sanction manipulation in HF trading);

F. Summary

The traditional liability framework in securities markets appears increasingly fragile in the face of algorithmic trading. In its implementation, the law struggles to either deter harms or to punish losses through a workable sanction and compensation regime. This Article reveals three key weaknesses in the current liability regime.

Intent: On the one hand, intentional deceptions should be much easier to spot and punish. The greater volume of algorithmic data should reduce the costs of enforcing an otherwise thinly evidenced offence.

While this might be the case with respect to long-familiar, established forms of manipulation, the law struggles to deal with intentional attempts to disrupt markets using more novel types of algorithmic maneuvers. Particularly where algorithms utilize deliberate disruption as a part of a legitimate strategy (e.g., momentum trading or market making), Rule 10b-5 has little impact. Without attempts to broaden the definition of what constitutes deliberate disruption and manipulation in algorithmic trading, Rule 10b-5 fails to punish evenly across the market.

Negligence: The negligence standard is also insufficiently protective and can create incentives for dangerous risk taking. The reasonableness standard allows firms to engage in some risk taking, so long as it conforms within the parameters of objectively reasonable behavior. This leeway, however, is problematic. HF markets are characterized by deep interconnections that can result in even small errors amplifying in impact across the NMS. Such hyperefficiencies in securities trading also increase the difficulty of ascribing contributory liability. Where other preset algorithms simply react to mistakes, amplifying their impact, it becomes harder to ascribe contributory blame. The large volumes of data and the complexity of interpreting them can also raise the cost punishing mistakes and misbehavior. Again, markets end up underprotected. Reasonable risk taking can give rise to outsize harms and the losses suffered can go uncompensated.

Strict Liability: Finally, preset algorithms are anticipatory in design, meaning that errors and imprecision are unavoidable. Liability can be too widespread to really be informative about risky behavior. Enforce-

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Peter J. Henning, Why High Frequency Trading is so Hard to Regulate, N.Y. Times: DealBook (Oct. 20, 2014), http://dealbook.nytimes.com/2014/10/20/why-high-frequency-trading-is-so-hard-to-regulate/?_r=0 [https://perma.cc/QKJ7-8BYM] (discussing the legal challenges of regulating HF trading).

ment may be patchy and arbitrary, potentially punishing only those mistakes whose effects are especially harmful. Compensation too may be unrealistically high where frequent errors impact the NMS and requiring single traders to provision for such harms may be too costly.

The interaction of these three heads of liability—designed to provide a heavy overlay of protection over securities trading—instead leaves markets vulnerable to pervasive risk taking, mistake, and manipulation. Notwithstanding the heavy costs spent on enforcing the regulation in securities markets, shortfalls in compliance serve to undermine their operation and their ability to allocate capital.

IV. Pathways Forward: A Structural Approach

This Article shows that conventional theories of liability in securities markets—and the allocation of costs that they impose between regulators and firms—offer a poor fit for HF markets. With markets moving inexorably towards full automation, the failure of liability to effectively constrain bad behavior ex ante and to compensate harmed markets ex post should pose significant concerns for policy makers. This Part discusses the implications of this disconnect for reform.

The shortcomings of the law in offering a robust and effective framework to prevent and punish deception and disruption in securities markets point to the need for structural solutions to remedy the deficit. Rather than rely primarily on a network of rules and regulations, structural remedies can robustly supplement the law and fill in gaps in deterrence and compensation. A structural solution can work to prevent mishaps from occurring and to facilitate their detection ex ante. This kind of approach is not new to the literature. Professor Cheng, notably, examines the shortcomings of "fiat" in criminal law—patchy enforcement, routine defection, expensive but ineffective surveillance—and argues for structural solutions as part of a more thoughtful approach.[191]

A. Supervision and Compensation

Exchanges occupy a place of enormous prominence within the oversight framework for securities markets.[192] The scope and intensity of this role has varied through the years but it remains an essential supplement

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[191] Cheng, supra note 32, at 657–9.
[192] Gadinis & Jackson, supra note 58, at 1242–1243; Mahoney, supra note 58, at 1454.

to public oversight.[193] Exchanges scrutinize who trades on their floors. They supply the technology and infrastructure to facilitate that trading. Critically, they ensure that all participants comply with detailed rules regarding their conduct on the exchange.[194]

Exchanges are, by dint of structural necessity, frontline regulators in HF markets. From the logistical standpoint, exchanges stand in closest physical proximity with the sharpest view of mistakes, mishaps, and manipulation. This closeness means that they should see information first and ahead of any public regulators. The greater the distance that information has to travel (e.g., to public regulators outside the exchange), the longer the delay involved in interpreting its content and riskiness. Finally, exchanges also have deep reserves of information on the traders admitted to the venue. They should possess a historical reserve of past trading and patterns of infractions. This perspective makes exchanges uniquely placed to control the spread of risks in the market through tools like trading halts and circuit breakers. Particularly, for dealing with more systemic errors and manipulations, exchanges arguably represent the "cheapest cost avoiders" in the words of Judge Calabresi.[195]

However, as much as exchanges are essential private supervisors, they are also deeply embedded within the profit structure underpinning algorithmic trading. Within a NMS, comprising competing exchanges, individual exchanges benefit from the trading volumes (and fees) available through algorithmic trading and HF trading. Scholars observe that exchanges compete vigorously for traders—sometimes offering inducements in the form of rebates and discounts for liquidity-supplying traders.[196] These dual roles—as overseer of traders and as institutions dependent on these same firms for profit and prestige—stand in profound tension. Exchanges may be reluctant to punish traders heavily for causing mischief, particularly those that are the most active. Exchanges may impose lighter fees and may be reluctant to trigger a timely shutdown when it might cause reputational problems. As seen in the case of

[193] For exchange rules, see, for example, CME Rulebook, CME Group, http://www.cmegroup.com/rulebook/CME/ [https://perma.cc/RS66-XU32].

[194] SEC Regulation Systems Compliance and Integrity, Exchange Act Release No. 34-73639, 2014 WL 6604803 (Nov. 19, 2014) (to be codified at 17 C.F.R. pts. 240, 242, 249).

[195] See Calabresi & Hirschoff, supra note 100, at 1060.

[196] Katya Malinova & Andreas Park, Subsidizing Liquidity: The Impact of Make/Take Fees on Market Quality, J. Fin. (forthcoming) (manuscript at 1–2), http://ssrn.com/abstract=1823600 [https://perma.cc/T3FG-N5KL].

NASDAQ's botched launch of Facebook's IPO, exchanges can lose standing where they halt operations because of glitches.[197]

Conflicts of interest that affect the ability of exchanges to discharge their supervisory functions can prove enormously costly for markets. Mistakes and mischief can proliferate unchecked if traders are not forced to fully internalize the costs of their risk taking. As this Article demonstrates, in an interconnected, hyperefficient automated market, the costs of small mischiefs can be far in excess of the seriousness of the original harm. In this context, an essential first step in improving market function lies in ensuring that exchanges invest in the proper oversight of markets and thus in reducing the impact of endemic conflicts of interest. To do this, this Article suggests that exchanges be held financially liable where disruptive traders and their activities can be traced to an exchange and where the trader itself cannot fully pay out on the losses it causes.

Rationale: This Article identifies several key—and new—risks in securities markets that current standards of liability cannot contain: (1) small disruptions can give rise to system-wide costs; (2) individual traders may not be able to fully compensate for damage; (3) preset, HF algorithms can increase the challenge of identifying causality and contribution in causing harms; and (4) with an ineffective liability framework in place, price formation and capital allocation can suffer.

Greater liability for exchanges offers a necessary remedy to help cure these risks in securities markets. For a start, if exchanges are required to pay out—even partially—in the event that trading mistakes, mishaps, or manipulation arise, they have real skin in the game to exercise more exacting scrutiny of securities markets. In effect, exchanges provide a backstop to losses created by errors and deceptions originating on their venue. Not only are exchanges likely to be more vigilant to even small risks (because these might rapidly spread), but they may also provision more thoroughly against such risks arising ex ante (e.g., more intensive monitoring). Bad actors may be more powerfully deterred if exchanges display greater willingness to enforce the rules of the road to increase the costs of wrongdoing on traders. Without easy and cheap access to exchanges, traders will simply be forced out of business.

Second, the fuller costs of deception, error, and carelessness may be more effectively internalized if exchanges are also liable to pay out in addition to misbehaving or error-prone traders. As noted above, small

[197] See Strasburg & Bunge, supra note 56; Toonkel & McCrank, supra note 56.

harms can have outsize cost consequences. The Knight Capital mishap is case in point. Single traders may be institutionally unable to pay out on losses. From the compensatory perspective, this state of affairs is clearly undesirable. Firms do not internalize the costs of their dealings. This can incentivize firms to take on more risks than they should precisely because they can benefit from the upside and they do not have to suffer the full downside of their actions. Within this context, if exchanges pick up the shortfall, the compensation for losses can more accurately reflect the complete impact of the risk taking for the system as a whole. To be clear, this proposal does not contemplate requiring exchanges to be responsible for all manipulation, mistakes, or negligence in securities markets. Rather, it is designed to encourage exchanges to take fuller responsibility for disruptions that implicate the mechanics of market structure as a core component of the undertaking. This focus places harms more closely within the purview of exchange supervision and control, levering their proximity to the trading process to better catch the harms arising in HF markets.

Liability Standard: This proposed liability raises a difficult question. What standard of liability should be applied in determining whether exchanges should be forced to contribute to defraying the costs of losses? In other words, should exchanges be on the hook when they breach a strict liability, negligence, or fraud standard? This inquiry is especially thorny in the context of the present analysis. This Article argues, after all, that none of these standards provide a good fit to constrain or compensate harms arising in HF markets. Still, a response to this question is desirable to anchor a theory of liability for exchanges and to set expectations regarding compliance costs for market participants.

In considering this question, it is worth underlining the broader policy objective driving the creation of stronger liability for exchanges. As this Article suggests, ineffective constraints on individual traders as well as insufficient capacity for these private actors to provision and pay for liability fosters a lack of trust in the marketplace. Investors can lose confidence in markets. And capital allocation suffers accordingly. With this in mind, both the fraud standard and the negligence standard leave gaps. A fraud standard allows enormous leeway, imposing liability only when an exchange is intentionally deceptive or grossly reckless in discharging its duties. In the case of negligence, an exchange becomes liable when it is unreasonably lax in monitoring and controlling bad behavior. Given these gaps in coverage, investors and the market can still lose out if a trader cannot pay for harm and an exchange does not have to either. This shortfall, then, raises the possibility of examining strict liability as the likely standard to impose. At first glance, based on this Article's argument, this option is clearly problematic. Strict liability is generally a poor fit in unpredictable, HF markets, where predictive programming means that unforeseen errors should be common. However, looked at more deeply, there may be more reason to justify holding exchanges strictly liable in this context. Importantly, exchanges are well positioned to do a more thorough job than a single trader of policing the market, gathering information, and anticipating trading trajectories. They are also best placed to stop harms from intensifying through the many tools at their disposal (e.g., warnings or circuit breakers). Unlike a private trader who cannot predict when errors might arise or stop cascading harms when they do, exchanges should have a more honed ability to oversee markets, detect problems, and to deploy a range of controls. This theory of liability is not perfect. HF trading remains complex and dynamic. However, given their position on the frontlines of trading, exchanges may be best placed to overcome, in part, the major critiques leveled at strict liability in HF markets. There may be concerns that exchanges should not be required to insure against the harms caused by private traders. However, in HF markets, exchanges are uniquely placed to oversee an intrinsically error-prone form of trading. In the case of a system-wide amplification, exchanges are essentially the only institutions in the market that can effectively dampen its spread. Without liability, exchanges might have this unique position and power in the market, but their incentives to use it may be limited by reputational concerns and conflict of interest.

A Market Disruption Fund: A NMS, connecting multiple exchanges across the marketplace, allows for mistakes on one exchange to spread to others. This suggests that exchanges are profoundly vulnerable to one another's lapses in oversight. If one of them falls short in spotting trouble, taking steps to discipline bad actors, and stopping risks from materializing, then the ill effects can reach across marketplaces and security types. Examples are numerous. The May 2010 and October 2014 Flash Crashes, Knight Capital's collapse, as well as the misfiring Goldman Sachs algorithm that multiplied trading volume on the options exchange by a factor of over a hundred, all illustrate deep interdependence between today's exchanges.[198]

The potential for large losses shared and attributable to multiple marketplaces underlines the benefits of creating a "market disruption fund" to more reliably make good on the losses. Such a fund would represent a pooling of resources between the different exchanges and would be used to pay out in case of liability of one of the exchanges.

At first glance, a collective fund appears to go against the goal of making exchanges individually responsible—and invested—in tightly overseeing their operations. However, a fund also ensures that the NMS is clearly supported by a large reserve of resources to encourage payouts arising on account of disruptive trading behavior. As argued in the Article, losses can be large. They can be widespread. The actions of single exchanges may impact others—and others may also fall short in containing damage. In this context, it makes sense that risks likely to implicate multiple players within the NMS would be backstopped by a shared reserve. Critically, a fund should promote greater interdiscipline between exchanges. Where the actions of a single exchange may be likely to disrupt others and place demands on the collective fund, exchanges may be motivated to exert pressure on one another for better oversight. From the perspective of those who use the market—including investors, issuers, and other intermediaries—the fund should increase confidence in the performance of market infrastructure to allocate capital.

A shared fund might also help in the administration of compensation to investors and to assure confidence in the market. This Article does not delve into the details of administering compensation for losses caused by disruptions in automated market structure. However, a fund might help to smooth this process. In particular, rather than make a claim against a particular trader—a tricky task for any investor—those harmed may instead seek a claim against the fund.[199] The fund, in turn, can then seek recompense from the trader or set of traders implicated in the harm. This places financial and administrative onus on the shared facility. However, it can help to make the compensatory process credible and workable. More importantly, it further bolsters the incentives of exchanges to exercise diligence over their traders.

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[198] See supra notes 1, 47, 141, & 178.

[199] My thanks to Professor Kyle Logue for the insight.

Exchange liability and the creation of a compensation fund do not represent a perfect solution to systematic disruptions in the market. For example, exchanges facing extra liability and monitoring costs to insure against losses will charge higher fees from traders as compensation. Traders will likely pass these fees onto their investor-clients or, facing higher transaction costs, be more circumspect in entering the market. The trade-offs are invariably difficult. However, a stronger liability regime provides an essential means to achieve an important end. The broader policy goal is straightforward: to reduce the high costs from errors and deceptions arising in HF markets and to restore credibility to markets. Investors engaged in policing markets can help achieve this goal by forcing exchanges and traders to pay greater attention to the new risks underlying the HF trading process. Their claims, then, while privately beneficial, foster a more profound public good. They work to realize the larger systemic purpose of restoring confidence to markets and improving their efficiency and ability to allocate capital to productive economic interests.[200]

B. Controlling Contagion

In seeking to reduce losses, exchanges can calibrate the speed of trading to better manage the risks they face. With trades occurring in microseconds, speed can constitute an intensifying factor in the harms arising in HF markets. Bad information can spread rapidly through multiple markets, far faster than human traders can step in to control a situation. As made clear in the May 2010 Flash Crash as well as in the October 2014 Treasury Flash Crash, the rapid escalation of a crisis can arise suddenly and leave regulators at a loss to explain the triggering cause. A structural approach to controlling the spread of harms lies in calibrating the speeds at which trades occur. Rather than allowing traders to compete at ever faster speeds in markets, structure can place some limits on how fast trades can occur. If signs of trouble appear—for example, if a large sell order enters the system and risks panicking traders—limits on speed can reduce the chance of a sudden, deep spiral across markets. Importantly, where exchanges have a clearer view of signs of distress and time to implement safeguards (e.g., a circuit breaker to stop sharp spikes and declines in prices), such protective measures may be more ef-

[200] My thanks to Professors Michael Barr and Sherman Clark for helpful discussions and insights on this issue.

fectively implemented. For example, if a large sell trade in *Company X*'s shares might spook the market, limits on speed might reduce the velocity with which this news impacts other markets. Exchanges that trade the options and futures of the *Company X* securities might be prepared to implement circuit breakers or to warn key liquidity providers that a spike in demand is expected. Furthermore, if some speed restrictions exist, algorithms can have time to control their reaction with more and better news about *Company X*. Recall that Professors Dugast and Foucault have speculated that mini-flash crashes may be due to firms transacting on false news and only refining their response once accurate news emerges.[201]

Finance scholars are increasingly turning to examine reforms to HF trading as a part of securities market reform. They advocate for structural speed brakes to limit the flow of orders through the system. Rather than allowing continuous HF trading, orders might be better processed in periodic "batches" that slow down the pace of trading.[202] Indeed, some scholars argue that—in excess of certain speeds—hyperfast trading can actually be socially wasteful, counseling against an unbridled race to nanoseconds in execution time.[203] Still, other commentators advocate caution in focusing too heavily on speed as a defining feature of HF trading. They argue that speed-based thinking obscures the reality that certain traders have always transacted faster than others and profited from this expertise.[204]

In this debate, differing views might reflect divergences in the larger policy goals that scholars espouse. From the point of view of efficiency-driven scholars, checks on speed diminish the attainment of ever-more complete degrees of informational efficiency. Information can enter markets more slowly. Those who might have invested in developing the technology to track and value data in milliseconds can end up with weaker incentives to invest in such strategies.

From the point of view of reducing mistakes and mishaps in markets, however, speed limits can provide benefits. Information can be more

[201] Dugast & Foucault, supra note 165, at 5–6.

[202] Eric Budish, Peter Crampton & John Shim, The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response, 130 Q.J. Econ. 1547, 1549 (2015).

[203] Id. at 1594; Daniel Fricke & Austin Gerig, Too Fast or Too Slow? Determining the Optimal Speed of Financial Markets 1 (unpublished manuscript), http://ssrn.com/abstract=2363114 [https://perma.cc/3RJW-GQBJ] (arguing that the optimal interval between trades is between 0.2–0.9 seconds).

[204] See discussion in Easley, López de Prado & O'Hara, supra note 119, at 8.

easily verified. Mishaps may result in smaller harms (e.g., Knight Capital). Cascades of crisis may be more effectively controlled through other investors or exchanges. Indeed, such brakes also may be efficiency enhancing. Where trading and price formation is less vulnerable to distortion and disruption, investors may be less likely to discount their investment capital. In short, markets may be more efficient at encouraging capital allocation in the real economy.

The question becomes how best to calibrate and when to implement speed breaks structurally. This inquiry presents a particularly thorny challenge because, traditionally, regulation has never sought to coercively limit trading speeds as a matter of systematic institutional design. Arguably, with the establishment of the NMS, regulatory policy has followed an exactly opposite course.

Within this unfamiliar context, it may be beneficial to consider more targeted speed limits that apply when the risks of misconduct, misbehavior, and systemic harms are especially high. The arrival of market-moving disclosures like regulatory announcements or key corporate disclosures (e.g., earnings announcements) might represent a sensitive moment where the risks of mishap may be high, pointing to the need to slow down trading. Some illustrations may be helpful. On January 10, 2013, for example, trading in Treasury futures was halted eight-tenths of a second prior to the release of the Department of Labor's Employment Situation Report. In the milliseconds before the release, trading activity became so high so quickly that the exchange's circuit breaker was triggered. The halt lasted almost four seconds—a lengthy period when measured in microseconds.[205] Similarly, in November 2013, Treasury futures were halted again, this time for a period of five seconds during an employment news release.[206] Reducing transactional speeds at such moments may be beneficial, allowing news to percolate more fully into the market before aggressive (potentially correlated) trading. Of course, such slowdowns must be carefully thought out. Even if trading in *Company X* securities are slowed down, traders might yet be able to trade as normal in substitute securities (like those of *Company X*'s close competitors). This might cause problems for the competitor if trading be-

[205] Treasuries Halted during Employment Release, Nanex (Jan. 10, 2014), http://www.nanex.net/aqck2/4530.html [https://perma.cc/YGK5-L3F7].

[206] Treasury Futures Halted (Again), Nanex (Nov. 8, 2013), http://www.nanex.net/aqck2/4481.html [https://perma.cc/U2M6-BWNL].

comes overly aggressive to compensate for speed restrictions in parts of the market.

In addition to important information releases, speed brakes can also be helpful in more volatile market conditions. At first glance, this proposition seems counterintuitive and unfriendly to investors. In volatile times, investors need to adjust their exposures and exit into and out of investments. They benefit from liquid markets that comprise active, fast trading. But volatile markets may be especially vulnerable to rapid contagion. Hypersensitivity to bad news may prime investors for panic. Critically, however, preset HF algorithms are likely to struggle in unusual conditions. With rising uncertainty and stuttering programming, HF algorithms may be willing to exit the market quickly, leaving exchanges to slip into the "liquidity crash" of diminishing liquidity and trader flight, as happened in both the May 2010 and the October 2014 Flash Crashes.[207]

Speed limits may prevent the sudden exit of HF traders from the market. Where information contagion is slowed, its spread may be contained. Vulnerable exchanges may be better positioned to alert traders and to ready emergency maneuvers (e.g., circuit breakers). And traders have more time to internalize a larger reserve of information to nuance their reaction, potentially reducing the pressure on programming. These propositions are speculative. Slowing speeds, even by small fractions of a second, is contentious and goes against regulatory and market tradition. Furthermore, while slower speeds might contain the spread of harms, they will not stop certain kinds of mishaps or deceptions from taking place: fat finger trades, wash trades, and collusive conduct can persist despite structural brakes to minimize the scale of the damage.

CONCLUSION

HF markets challenge core paradigms in securities regulation—none more so than the framework allocating liability for wrongdoing in securities trading. This Article shows that traditional measures of determining liability and compensating for harms fall short in algorithmic trading. Preprogrammed predictive trading—with securities transacting in milliseconds—demands a tolerance for error. Additionally, exchange interconnections through the NMS as well as heightened information asymmetries mean that the scale of harms can be far larger than the seri-

[207] Kirilenko et al., supra note 2, at 22–23.

ousness of the original error. To varying degrees, current regimes governing intentional misconduct, negligence, and strict liability align poorly with the central features of algorithmic trading. This Article takes a first step in exploring the implications of modern market structure on well-established legal paradigms governing liability. It makes clear that thoroughgoing rethinking is needed if core laws anchoring the framework are to be brought in line with the pace of modern markets. This Article proposes focusing first on structural solutions that institutionalize strong oversight, containment, and compensation. A robust structural approach can fill the gaps left by ineffective laws. More broadly, this Article draws into relief the eroding effectiveness of long-established liability standards in an automated age. With technological progress inevitable, our laws must also evolve in response.