How Algorithmic Trading Undermines Efficiency in Capital Markets

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This Article argues that the rise of algorithmic trading undermines efficient capital allocation in securities markets. It is a bedrock assumption in theory that securities prices reveal how effectively public companies utilize capital. This conventional wisdom rests on the straightforward premise that prices reflect available information about a security and that investors look to prices to decide where to invest and whether their capital is being productively used. Unsurprisingly, regulation relies pervasively on prices as a proxy for the allocative efficiency of investor capital.

Algorithmic trading weakens the ability of prices to function as a window into allocative efficiency. This Article develops two lines of argument. First, algorithmic markets evidence a systemic degree of model risk—the risk that stylized programming and financial modeling fails to capture the messy details of real-world trading. By design, algorithms rely on pre-set programming and modeling to function. Traders must predict how markets might behave and program their algorithms accordingly in advance of trading, and this anticipatory dynamic creates steep costs. Building algorithms capable of predicting future markets presents a near-impossible proposition, making gaps and errors inevitable. These uncertainties create incentives for traders to focus efforts on markets where prediction is likely to be most successful, i.e., short-term markets that have limited relevance for capital allocation. Secondly,

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informed traders, long regarded as critical to filling gaps in information and supplying markets with insight, have fewer incentives to participate in algorithmic markets and to correct these and other informational deficits. Competing with high-speed, algorithmic counterparts, informed traders can see lower returns from their engagement. When informed traders lose interest in bringing insights to securities trading, prices are less rich as a result.

This argument has significant implications for regulation that views prices as providing an essential window into allocative efficiency. Broad swaths of regulation across corporate governance and securities regulation rely on prices as a mechanism to monitor and discipline public companies. As algorithmic trading creates costs for capital allocation, this reliance must also be called into question. In concluding, this Article outlines pathways for reform to better enable securities markets to fulfill their fundamental purpose: efficiently allocating capital to the real economy.

I. INTRODUCTION

In 2012, traders in the United States submitted over two billion offers to buy and sell securities on major national exchanges, resulting in around seventy-four million completed trades. As a point of comparison, at the height of the internet boom in 2000, traders sent out only around five million quotes and, from these, concluded three million trades. In other words, in 2012, traders were submitting almost 460 times the number of quotes than they did in 2000. Rather than reaching a bargain 60% of the time, as was the case in 2000, traders did so in just 3% of cases in 2012, sending out more than thirty-one quotes for every completed trade.[1] An uptick in trading appetite over the years is almost certainly *not* an explanation for this staggering rise in the number of orders.[2] Rather, these statistics are indicative of a much larger and more fundamental transformation underway in U.S. markets. Reflecting the rise of computer technology, today's marketplace has come to rely heavily on automation and algorithms as an essential part of the trading process. In place of humans submitting orders and routing and processing trades, firms can delegate these tasks to algorithms, computerized instructions that transact in accordance with

1. *Friends Without Benefits*, NANEX (Aug. 9, 2012), http://www.nanex.net/aqck2/3528.html [http://perma.cc/NL6W-PBTB]. These figures show quotes on the New York Stock Exchange (NASDAQ), the American Stock Exchange (AMEX), and ARCA. They likely underreport the quotes on all US trading systems. These exchanges, while significant trading venues, are still a partial segment of the US marketplace that includes numerous regulated exchanges as well as unregulated venues, like dark pools.

2. For example, the Financial Crisis in 2007 caused disruptions in securities trading in the market and prompted adjustments in the volume of stock trading owing to volatility. For discussion, see, for example, Tarun Chordia, Asani Sarkar, and Avanidhar Subrahmanyam, *Common Determinants of Bond and Stock Market Liquidity: The Impact of Financial Crises, Monetary Policy, and Mutual Fund Flows* (Fed. Reserve Bank of N.Y., Staff Report No. 141, 2001), http://www.newyorkfed.org/research/staff_reports/sr141.pdf [http://perma.cc/X5JM-3ULA] (observing, in general, the higher volatility in times of financial crisis and impact on money supply); Dan Strumpf, *Wall Street Adjusts to the New Trading Normal*, WALL ST. J. (June 6, 2014), http://www.wsj.com/articles/wall-street-adjusts-to-the-new-trading-normal-1401910990 [http://perma.cc/C5RX-GCVL] (noting a peak volume of trades in 2009, at the height of the Financial Crisis, with almost two billion shares in Citigroup and Bank of America being traded daily); Azi Ben-Rephael, Flight to Liquidity in the Equity Markets during Periods of Financial Crisis (Jan. 2011) (unpublished manuscript), http://www.lse.ac.uk/fmg/researchProgrammes/paulWoolleyCentre/events/4thAnnualConference/S2_ABenRephael_Paper.pdf [http://perma.cc/9QRX-YERH] (noting the behavior of certain key investors in times of crisis and the pressure to buy and sell securities).

a firm's pre-set strategy.[3] Untethered from the limitations of human cognition, algorithms enable trades to occur at high speed and high volume using pre-programmed decision rules to identify trading opportunities. With the aid of algorithms, traders can deploy a more powerful array of quantitative techniques, statistics, and financial modeling as part of the buying and selling process than previously possible.[4]

These changes prompt fresh reflection about the ability of markets to continue to perform their most basic function: supplying capital to the real economy. In both law and finance, scholars have debated market function and regulation through the lens of efficiency.[5] How well markets are able to reflect information in securities prices often serves as a proxy as a rough-and-ready measure of market health.[6] It is easy to understand why; efficient markets help investors cheaply investigate the most optimal destination for their capital.[7] When prices reflect information accurately, investors can assess their risks and rewards more precisely and better direct their capital to the most worthwhile investments—showcasing allocative efficiency.[8] While predicting the future performance and intrinsic "value" of investments is near impossible, informational efficiency offers a mechanism, albeit an imprecise one, to make beneficial allocative choices with the information at hand.[9] Better informed markets can help capital to reach those companies and areas of the economy that are likely to use it most

3. 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."); *see also* John Bates, *Algorithmic Trading and High Frequency Trading Experiences and Thoughts on Regulatory Requirements*, U.S. COMMODITY FUTURES TRADING COMMISSION 19 (July 14, 2010), http://www.cftc.gov/ucm/groups/public/@newsroom/documents/file/tac_071410_binder.pdf [http://perma.cc/949A-VB6A] ("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 discussion on technological innovation in securities markets and disruption of traditional intermediation, see Chris Brummer, *Disruptive Technology and Securities Regulation*, 83 FORDHAM L. REV. (forthcoming Winter 2015).

4. *See* discussion *infra* Section II.C.

5. *See* discussion *infra* Section II.A.

6. *See* discussion *infra* Sections II.A–C.

7. *See* discussion *infra* Sections II.A–C.

8. *See* discussion *infra* Secions II.A–C. As discussed in more detail in Part II, scholars have engaged in heated debates regarding market efficiency and whether markets are, in fact, efficient. The case for market efficiency has faced strong criticism, for example from behavioral economists.

9. *See* discussion *infra* Sections II.A–C.

productively. Put simply, informational efficiency in the market should help bring about allocative efficiency for the economy.[10]

This Article challenges this conventional wisdom. It argues that algorithmic trading creates trade-offs in the relationship between informational and allocative efficiency. Though algorithms help markets make gains on several measures of informational efficiency, they also create costs for their ability to allocate capital productively. With the considerable reliance that law and regulatory policy place on prices in matters of allocative importance, this decoupling is significant for bedrock assumptions underlying corporate and securities regulation.

At first glance, the shift to automation holds much promise for efficient markets—and, by extension, for capital allocation. Using algorithms, traders can harness data, deploy complex analyses, and submit orders at will to strategically execute their desired strategy.[11] Rather than searching extensively for the ideal trade, or waiting for the best time to send out orders, traders can rely on algorithms to do this hard work for them.[12] Transaction costs can diminish and so too the cost-benefit threshold at which traders might enter markets with their private reserves of information and insight.[13] Looked at from this perspective, securities prices should be more efficient than ever before, reflecting available information almost instantaneously and underpinned by deep data and computation. Not surprisingly, some finance scholars have pointed to the superior informational efficiencies of algorithmic markets, bringing into relief their power to convey information through rapidly responsive prices.[14]

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10. *See* discussion *infra* Sections II.A–C. As discussed in Part II, scholars note that fundamental efficiency represents a largely unattainable standard. Efficient markets—at best—offer informational efficiency. However, this informational efficiency may approximate fundamental efficiency.

11. Scott Patterson, *High-Speed Stock Traders Turn to Laser Beams*, WALL ST. J. (Feb. 11, 2014), http://www.wsj.com/articles/SB10001424052702303947904579340711424615716 [http://perma.cc/F8GA-RNQ8] (noting the competition to reduce the speed at which stocks turnover and the potential for trading speeds to come close to zero through the use of lasers).

12. *See* discussion *infra* Section II.C.

13. For example, if traders do not have to pay high fees in transaction costs to enter markets with their private information, they may do so more often and where they stand to make only modest gains. With higher transaction costs, traders might wait only until such time as they are likely to make more money than it costs to trade.

14. *See, e.g.*, Jonathan Brogaard et al., High Frequency Trading and Extreme Price Movements (Nov. 2014) (unpublished manuscript), http://ssrn.com/abstract=2531122 [http://perma.cc/3XXP-3ESD] (examining transactions on the NASDAQ exchange and arguing that HFT can prevent extreme price swings). For detailed discussion, see, *infra* Sections II.C & III.A.

In seeking out allocative efficiencies, however, the case for automation becomes significantly more problematic. There are two grounds for skepticism. First, pre-programmed algorithms create information loss through a necessary dependence on pre-set programming and models.[15] Algorithmic markets are characterized by a systemic degree of "model risk" caused by widespread reliance on stylized models and programming to capture messy real world behavior.[16] By necessity, algorithms must be programmed in advance of trading.[17] This means that traders must precisely stipulate their trading strategies, assumptions, methodologies, and risk preferences *ex ante*, requiring programmers to predict the scenarios their algorithms will encounter over the course of trading. Especially for high-speed or data-intensive algorithms, programming must account for the absence of human intervention in real time. When trades move in milliseconds and crunch gigabytes of data, algorithms must be able to trade largely independently of their human programmers.[18]

Despite the sophistication of algorithms, capturing unknown risks and uncertainties presents a daunting challenge to traders.[19] The longer the time horizon over which the model is designed to work and the period of time over which securities are to be held, the tougher the

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15. For analysis, see Rebecca Haw Allensworth, *Law and the Art of Modeling: Are Models Facts?*, 103 GEO L. J. 825, 846–73 (2015) (analyzing whether models can be regarded as "facts" in litigation and arguing that models should not be treated as facts given the choices involved in creating models); Mehrsa Badaran, *Regulating by Hypothetical*, 67 VAND. L. REV. 1247, 1282–319 (2014) (analyzing the use of models and their effectiveness in banking regulation).

16. *See* discussion *infra* Section III.B.

17. For definitions of algorithmic trading, see IOSCO TECHNICAL COMM., *Regulatory Issues Raised by the Impact of Technological Changes on Market Integrity and Efficiency: Consultation Report* 10 (July 2011):

> 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 pre-set 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.

18. Michael Kearns & Yuriy Nevmyvaka, *Machine Learning for Market Microstructure and High Frequency Trading, in* HIGH FREQUENCY TRADING 122–23 (David Easley, Marcos Lopez de Prado & Maureen O'Hara eds., 2013) (examining machine learning in high-frequency trading and creating algorithms able to model their likely impact on markets).

19. Dennis Bams, Thorsten Lehnert & Christian C.P. Wolff, *An Evaluation Framework for Alternative VaR* (Ctr. for Econ. Policy Research, Working Paper No. DP3403, 2003), http://ssrn.com/abstract=424360 [http://perma.cc/6UAN-KES4] (showing the challenges of modeling credit risk); Anil Bangia et al., *Modeling Liquidity Risk with Implications for Traditional Market Risk Measurement and Management* (The Wharton Sch. U. Penn., Working Paper No. 99-06, 1998), http://fic.wharton.upenn.edu/fic/papers/99/9906.pdf [http://perma.cc/ UV6P-6ZUS] (arguing that traditional studies of market risk examine a "pure" form of risk that fails to accurately account for certain frictions); *see also* Daniel Farber, *Uncertainty*, 99 GEO. L. J. 901, 905–10 (2010) (noting the challenge of modeling more quantifiable risks versus largely unquantifiable uncertainties).

task of making models robust enough to reflect the market's various complexities.[20] And in very short-term markets, characterized by securities changing hands in microseconds, errors and bad assumptions are impossible to correct in real time. The necessity of predictive modeling, combined with the logistical challenge of real-time intervention, suggests that algorithmic markets face a kind of Goldilocks dilemma. For models to work optimally, market conditions should be exactly attuned to their assumptions and projections. Clearly, this presents a tall order, even at the best of times.

Model risks raise concerns for capital allocation and the ability of prices to function as windows into allocative efficiency. For one, the costs and challenges of modeling create incentives for traders to develop algorithms focused on the short-term rather than longer-term performance of securities. Short time horizons are generally easier to model, making algorithms more accurate and more likely to implement pre-set trading strategies successfully. But here, private gains can come at the expense of a more fundamental picture of corporate health. If traders see more favorable private gains when trading in short-term markets, they are less likely to invest in capturing longer-term market dynamics in the algorithms they build. Where algorithmic traders focus more on short-term trading, the efficiency gains promised by algorithms are skewed in favor of near-term, rather than long-term investments.

Pre-set programming constraints also mean that algorithms cannot reflect information that falls outside of the scope of their programming. This might sound obvious, but it is significant for the quality of prices that markets produce. Precisely because of their constraints, algorithms can struggle to deal with exceptional situations that fall outside of their programming—unexpected news, crashes, or anomalous trading behavior that do not fit precisely set, *ex ante* parameters. Given the high costs of building algorithms, traders have little incentive to precision-program their algorithms to deal with exceptional events that occur infrequently. Instead, it makes more sense for traders to simply withdraw from the market in cases of market

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20. For example, the finance literature has shown that momentum based strategies are generally profitable. Momentum based strategies posit that stocks that have done well (badly) in the last three-to-twelve-month period tend to continue to perform well (badly) in the next three to twelve months. There is a large literature on this phenomenon. See Werner F.M. deBondt & Richard H. Thaler, *Does the Stock Market Overreact?* 40 J. FIN. 793 (1985), for an example showing that markets can overreact or underreact to information seemingly in tension with the efficient markets hypothesis. Also see Louis K.C. Chan, Narasimhan Jegadeesh, & Josef Lakonishok, *Momentum Strategies*, 51 J. FIN. 1681 (1996); Jennifer Conrad & Gautam Kaul, *An Anatomy of Trading Strategies*, 11 REV. FIN. STUD. 489 (1998); and Daniel Kent, David Hirshleifer & Avanidhar Subrahmanyam, *Investor Psychology and Security Market Under-and Overreactions*, 53 J. FIN. 1839 (1998), for additional discussion on momentum-based strategies.

disruption, leaving other traders to pick up the slack. While helpful for individual traders, these dynamics are disruptive for the market as a whole. If algorithmic traders can exit cheaply and do not have to provision for unexpected risks, algorithms may fail to properly price these risks into the programming that drives everyday trades.

Emerging empirical studies from finance scholars lend support to this line of argument. Scholars have found, for example, that high-frequency algorithmic traders tend to trade "directionally" over short time horizons and are highly efficient in reflecting near-term price changes. In other words, they are especially adept at trading in the direction in which markets move in the very short term. Specifically, aggressive high frequency traders have been found to transact in the direction of permanent price changes and appear to best predict price changes over horizons of around three to four seconds.[21] In times of crisis, however, high-speed traders have been found to be unreliable.[22] A study prepared by the Securities and Exchange Commission and the Commodities and Futures Trading Commission, for example, noted that a large number of high frequency traders exacerbated market volatilities by rapidly leaving the market when conditions became stressed unexpectedly. While individual traders saved themselves, the market as a whole saw a catastrophic drop in activity.[23]

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21. *See* Jonathan Brogaard, Terence Hendershott & Ryan Riordan, *High Frequency Trading and Price Discovery* (Eur. Cent. Bank Working Paper Series No. 1602, 2013), http://ssrn.com/abstract=1928510 [http://perma.cc/E26T-3KHA] (arguing that HFT increases price discovery by encouraging trades in the direction of price changes); *see also* Alain Chaboud, Benjamin Chiquoine, Erik Hjalmarsson & Clara Vega, Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market (July 5, 2013) (unpublished manuscript), http://houseoffinance.se/admin/wp-content/uploads/2013/11/HjalmarssonSSRN-id1501135.pdf [http://perma.cc/KT4F-85RF] (noting higher efficiencies through HFT in the foreign exchange market); Austin Gerig, High-Frequency Trading Synchronizes Prices in Financial Markets (Nov. 2012) (unpublished manuscript) (on file with author) (showing that HFT trading encourages prices in related securities to change contemporaneously. The suggestion here is that HFT is making the securities more efficient. However, the author suggests that market stress may lead to stress spreading quickly and links established between securities that are not necessarily linked by fundamentals).

22. *But see* Brogaard et al., *supra* note 14.

23. *See* STAFFS OF THE CFTC AND SEC, FINDINGS REGARDING THE EVENTS OF MAY 6, 2010 45 (2010), http://www.sec.gov/news/studies/2010/marketevents-report.pdf (studying the so-called Flash Crash in May 2010 when the Dow Jones lost almost a thousand points in minutes before rebounding quickly afterwards). This is discussed further in Section II.C of this Article. See, however, events contributing to the Flash Crash in the market for U.S. Treasuries in October 15, 2014. In their official inquest, U.S. regulators observed that high frequency traders active in the U.S. Treasury market remained active during the abnormal event and also provided liqudity. However, the Report observed a sharp reduction in market depth—i.e. the number of quotes in the order book. The Report suggested that HFT traders accounted for the largest share of the reduction in the order book. The Report also noted that HFT firms accounted for the largest share in liquidity removing trades. STAFFS OF THE UNITED STATES TREASURY ET AL., *Joint Staff Report*: *The U.S. Treasury Market on October 15, 2014*, 4–6 (Jul. 13, 2015).

Secondly, model risks and the informational deficits they generate are nearly impossible to correct, a limitation that seriously distorts capital allocation. Scholars have long looked to fundamentally informed traders to supply intelligence and analysis to markets and to fill gaps in information when they arise. With their focus on extracting value-relevant insight from information, fundamental traders like institutional investors drive the process by which markets become efficient. In their now classic exposition, Professors Gilson and Kraakman place informed traders at the heart of vibrant markets: by seeking private gains through their intelligence and data, fundamental traders also nourish markets with researched and reasoned trading.[24]

Algorithmic trading can impose costs on informed traders who confront pervasive conflicts with algorithmic actors that can systematically outrun them.[25] Notably, high-speed algorithmic traders have powerful advantages over more fundamental traders. Specifically, fast traders can decode how an informed trader is likely to transact and get to the trade before anyone else.[26] By free-riding on the intelligence of others, algorithmic traders save themselves time and money while also taking home a share of the winnings. Faced with diminishing gains, informed traders can end up with fewer incentives to invest in long-term research and analysis. When informed actors see their gains systematically reduced or wiped out by swifter algorithmic traders, investing in good-quality information makes little business sense. With

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24. *See* Ronald Gilson & Reinier R. Kraakman, *The Mechanisms of Market Efficiency*, 70 VA. L. REV. 549, 565–92 (1984) [hereinafter *Mechanisms*] (expounding on the main determinants of market efficiency); Ronald J. Gilson & Reinier Kraakman, *Market Efficiency after the Financial Crisis: It's Still a Matter of Information Costs* (Columbia Law and Econ., Working Paper No. 470, 2014), http://ssrn.com/abstract=2396608 [http://perma.cc/95HQ-NM25] [hereinafter *Information Costs*]; Ronald J. Gilson & Reinier R. Kraakman, The Mechanisms of Market Efficiency: Twenty Years On (Nov. 29, 2003) (discussion paper), http://lsr.nellco.org/cgi/viewcontent.cgi?article=1234&context=harvard_olin [http://perma.cc/H6QQ-N2S5]; *see also* Dennis W. Carlton & Daniel R. Fischel, *The Regulation of Insider Trading*, 35 STAN. L. REV. 857, 894–95 (1983) (proposing a revision of insider trading laws to allow managers to reveal inside information through trading); John C. Coffee, Jr., *Market Failure and the Economic Case for a Mandatory Disclosure System*, 70 VA. L. REV. 717, 722–24 (1984) (underlining the importance of information and mandatory disclosure in securities markets); Zohar Goshen & Gideon Parchmovsky, *On Insider Trading, Markets and "Negative" Property Rights in Information*, 87 VA. L. REV. 1229, 1233 (2001) (arguing, unlike Carlton and Fischel, that trading rights in insider information be allocated to information traders as a means of improving informational efficiencies). For an international perspective, see Chris J. Brummer, *Post-American Securities Regulation*, 98 CAL. L. REV. 327, 378–82 (2010) (analyzing how U.S. securities laws import their policy preferences internationally through regulatory clubs).

25. *See* discussion *infra* Section III.C. In popular literature, see, MICHAEL LEWIS, FLASH BOYS: A WALL STREET REVOLT (2014). For discussion, see, e.g., Matt Egan, *Flash Boys in the Hot Seat at Hearing*, CNN MONEY (June 17, 2014), http://money.cnn.com/2014/06/17/investing/high-frequency-trading-hearing/ [http://perma.cc/3L5U-35UK].

26. *See* discussion *infra* Section III.C.

markets continuing to grow more short-term in focus, long-term trading promises a poor trade-off. Actors of all stripes might look to invest their limited capital in less research-intensive markets. Investment in acquiring a long-term picture of the market can suffer as a result.

These insights raise serious questions for regulatory policy, which relies pervasively on prices as a proxy for value-relevant information about Main Street companies and their governance. Prices offer a mechanism to supervise public companies and to discipline them if prices reflect information that company performance is below par. Price-related information routinely acts as a trigger for a wide spectrum of governance mechanisms. For example, securities prices provide a benchmark to tie pay to the performance of managers running a company. If managers do well, their successes and failures should be reflected in the prices at which company securities trade; therefore, using prices as a signal to regulate managerial pay and performance makes considerable sense.[27] Similarly, to maximize value at underperforming companies, the market for corporate control looks to share prices as a hook for takeover battles. Prices can signal that managers have not extracted full value from target companies, setting the stage for tender offers and proxy fights as well as the regulatory scrutiny that invariably accompanies them.[28]

With these promised benefits for capital allocation, regulators invest heavily in bringing price efficiency to markets.[29] Public companies are subject to a mandatory disclosure regime that disseminates corporate information to investors, reducing their costs of procuring information.[30] Regulation also forces exchanges to compete with one another with the aim of reducing the transaction costs involved in trading.[31]

Implicit in these examples lies the enduring notion of prices as a window into long-term allocative value in capital markets generated by a market that processes information quickly and efficiently. As this Article demonstrates, this relationship between informational and fundamental allocative efficiency can no longer be taken for granted in

27. *See* discussion *infra* Section II.C.

28. *See* discussion *infra* Part II.C. The literature on this issue is vast. For a discussion of established rules governing acquisition-related disclosures and reform proposals, see, for example, Lucian Bebchuk et al., *Pre-Disclosure Accumulations by Activist Investors: Evidence and Policy*, 39 J. CORP. L. 1 (2013); *see also* Letter from Wachtell, Lipton, Rosen & Katz to Elizabeth M. Murphy, Secretary, U.S. Sec. & Exch. Comm'n (Mar. 7, 2011), http://www.sec.gov/rules/petitions/2011/petn4-624.pdf [http://perma.cc/Z2WU-37L8].

29. *See* discussion *infra* Section II.C.

30. *See* discussion *infra* Section III.C.

31. *See* discussion *infra* Section III.C.

algorithmic markets. As a result, it is debatable whether today's securities prices offer a thorough, substantive interpretation of corporate value. If not, the law's wholesale reliance on prices for valuation becomes increasingly misplaced.

Part II of this Article examines the growth of algorithmic trading in securities markets. It observes that algorithms represent pre-programmed instructions for trading. Being pre-set, algorithms rely on models and programming that must be calibrated *ex ante* to deal with complex markets in real time, creating a high burden for traders to get it right.

Part III engages with longstanding debates on the efficiency of markets and their capacity to reflect available information in the prices at which securities trade. An analysis of law and finance scholarship shows that prices have traditionally been regarded as a guide for capital allocation in the economy. With prices as a foundation of governance mechanisms for executive compensation regimes, the market for corporate control, and shareholder monitoring, regulatory policy firmly links informational with allocative efficiency in capital markets.

Part IV critiques the rationales interlinking informational and allocative efficiency. It highlights the significance of model risk in securities markets and draws into relief the costs facing fundamental traders in algorithmic markets, which drive them to invest less in mitigating information deficits. Information losses caused by pre-set models can be significant for capital allocation when they prevent prices from functioning as effective governance mechanisms for capital.

Finally, Part V surveys pathways for progressing reform of regulatory policy in securities markets and corporate governance. As innovative markets decouple informational and allocative efficiency, regulators must come up with an alternative as intuitive as prices to offer insight into the fundamental workings of capital markets.

II. THE CENTRAL ROLE OF ALGORITHMS IN MARKETS

Markets and their users have long wrestled with basic logistical limitations to the flow of trading. Traders must reckon with the time and expense of obtaining information, analyzing it, making a decision about whether to trade, and racing to the prime opportunity to do so ahead of any competitor. These transaction costs have traditionally curtailed the volume of information likely to be collected by a trader, the sophistication of her analysis, and the speed at which she might be expected to transact. Algorithms have radically reshaped the terms of the bargain in this age-old dynamic.

The growth of algorithmic trading over the years can be explained by the significant utilities it offers for almost all parts of the trading process.[32] From deciding what to trade and submitting an order to executing and finalizing a transaction, algorithms have enabled markets to far exceed the cognitive bounds of humans in processing information. Rather than rely on human brains to perform the hard tasks of trading in real time, these may be delegated instead to algorithms. With proper programming set in advance, algorithms can harness complex financial models, computations, statistical analysis, and artificial intelligence to transact at speeds measured increasingly in microseconds.

This Part sets the foundation for the central argument in this Article. It shows that algorithmic trading is a largely inevitable and, in many ways, efficiency-enhancing force in modern markets.[33] But the very design of algorithmic trading, notably its reliance on pre-programmed processes to make real-time trading decisions, can also create steep long-term informational deficits to the detriment of capital allocation.

A. Algorithms and Trading

Despite its significance, algorithmic trading has only recently entered the public consciousness.[34] For the most part, the public's imagination has been captured by the phenomenon of high frequency trading (HFT), a subset of algorithmic trading characterized by transactions executed at high volume and in the space of milliseconds or microseconds.[35] News of near catastrophes popularly attributed to HFT, such as the infamous May 2010 Flash Crash, when the Dow Jones dropped almost 1000 points in minutes before rebounding, has drawn attention and suspicion regarding the workings of hyper-fast

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32. *See* Andrei A. Kirilenko & Andrew M. Lo, *Moore's Law vs. Murphy's Law: Algorithmic Trading and its Discontents*, 27 J. ECON. PERSP. 51, 51–52 (2013) (showing the heightened trading volume in the last decade—whereas a doubling of trading volume appears to occur every 2.9 years, rather than 7.5 years, since 1929).

33. *Id.* at 52 (noting that it is "inexorable" that financial markets will look to make their world faster and cheaper).

34. *See, e.g.*, LEWIS, *supra* note 25.

35. *See, e.g.*, STAFFS OF THE CFTC AND SEC, *supra* note 23, at 45 ("HFTs are proprietary trading firms that use high speed systems to monitor market data and submit large numbers of orders to the markets. HFTs utilize quantitative and algorithmic methodologies to maximize the speed of their market access and trading strategies."); *see also* David Easley, Marcos M. López de Prado & Maureen O'Hara, *The Volume Clock: Insights into the High-Frequency Paradigm*, 39 J. PORTFOLIO MGMT. 19 (2012) (suggesting that HFT should be characterized by volume rather than speed of execution).

algorithms.[36] However, this singular focus on HFT fails to capture the rich and varied history of algorithmic trading that has, from the 1970s onwards, come to play an increasingly dominant role in the securities market.[37] Today, algorithmic trading accounts for around 70% of all equity trading volume in the United States.[38] Invariably, it has generated significant changes in how information is collected, who uses it, and the deliberative dynamic of these actors.

Algorithmic trading is variously defined in the literature. Broadly, it reflects the use of precise, pre-programmed computerized instructions in all aspects of executing a trade.[39] This definition holds more significance than first meets the eye.

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36. *See, e.g.*, Graham Bowley, *The Flash-Crash, in Miniature*, N.Y. TIMES (Nov. 8, 2010), http://www.nytimes.com/2010/11/09/business/09flash.html?_r=0 [http://perma.cc/DQ3C-X6R8] (noting that the market suffers a regular stream of mini flash crashes in individual stocks); Graham Bowley, *Lone $4.1 Billion Sale Led to 'Flash Crash' in May*, N.Y. TIMES (Oct. 1, 2010), http://www.nytimes.com/2010/10/02/business/02flash.html [http://perma.cc/Z66R-5RFK]; Edward E. Kaufman Jr. & Carl M. Levin, Opinion, *Preventing the Next Flash Crash*, N.Y. TIMES (May 5, 2011), http://www.nytimes.com/2011/05/06/opinion/06kaufman.html [http://perma.cc/DUW8-X4XP] (discussing the implications of the so-called "Flash Crash" in May 2010 when nearly $1 trillion in value from the stock market was wiped out, before rebounding equally quickly. This marked the biggest one-day price decline in the history of the Dow Jones.); *see also* SAL L. ARNUK & JOSEPH SALUZZI, WHY INSTITUTIONAL INVESTORS SHOULD BE CONCERNED ABOUT HIGH FREQUENCY TRADERS, http://blog.themistrading.com/2009/07/why-institutional-investors-should-be-concerned-about-high-frequency-traders/ [http://perma.cc/9T2E-WLKR] (listing various concerns with HFTs); Michael Mackenzie et al., *SEC to Review 'Flash' Orders*, FIN. TIMES, (July 28, 2009), http://www.ft.com/cms/s/0/039fc8f6-7a11-11de-b86f-00144feabdc0.html #axzz3kPGSbBkJ [http://perma.cc/Y3LN-BVFD] (noting some of the abuses by practices that "flash" orders disseminate information to certain traders before others).

37. Michael J. McGowan, *The Rise of Computerized High Frequency Trading: Use and Controversy,* 9 DUKE L. TECH. REV., 2010, at 1, 4–7 (tracing the history of algorithmic trading in the market, noting the move to using electronic order submission technologies from the ticker tape to the NYSE's Designed Order Turnaround (DOT) and later SUPERDOT order entry systems in the 1970s and 1980s). For an analysis of the rise of high-frequency trading in the context of technological innovation, see, Tom C.W. Lin, *The New Investor*, 60 UCLA L. REV. 678, 688 (2013).

38. 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 #axzz3kPGSbBkJ [http://perma.cc/RV5A-LMHT] (showing that 73% of volume is attributable to high frequency trading. Such trading demands algorithms. It is likely that the volume due to algorithmic trading in general is higher than the figure of 73%); *see also* Jeffrey MacIntosh, *High Frequency Traders: Angels or Devils?*, C.D. Howe Institute Commentary No. 391, at 3–5, http://www.cdhowe.org/pdf/Commentary_391.pdf [http://perma.cc/RZ3P-Y59J].

39. *E.g.*, STAFF OF THE CFTC, GLOSSARY: ALGORITHMIC TRADING, http://www.cftc.gov/ucm/groups/public/@educationcenter/documents/file/cftcglossary.pdf [http://perma.cc/38CL-6768] ("The use of computer programs for entering trading orders with the computer algorithm initiating orders or placing bids and offers."); *Public Consultation: Review of Market in Financial Instruments Directive (MiFID)*, EUROPEAN COMMISSION at 14 (Dec. 8 2010), http://ec.europa.eu/internal_market/consultations/docs/2010/mifid/consultation_paper_en.pdf [http://perma.cc/X25Y-YH6C] ("[A]lgorithmic trading can be defined as the use of computer programmes to enter trading orders where the computer algorithm decides on aspects of execution of the order such as the timing, quantity and price of the order.").

First, automated trading requires investment in constructing a detailed plan before any trading can take place. Traders devise a strategy to buy and sell securities. Programmers then build the computerized algorithm or series of algorithms to execute the strategy in the market.[40] This makes algorithmic trading anticipatory in nature. Rather than deploying human traders to crunch numbers, observe markets, and determine the best trades in real time, algorithmic trading firms rely instead on pre-set algorithms.[41] Of course, humans remain deeply involved. They develop the strategy, program the algorithm, and monitor its operations. Traders take a view in advance as to how the market might behave, their likely risk appetites, and the pay-offs they wish to achieve before using the algorithm.

Second, precisely because algorithms are tasked to perform complex trades using deep data and speed, they must possess some programmed "decision-making" capacity. In other words, algorithms must be capable of evaluating the importance of data, attaching a value to its content, and then making a deal independently of human traders by submitting orders to the market. Rather than waiting for human beings to read the news, regulatory disclosures, or changing prices, algorithms can perform this data collection and analysis.[42] Indeed, recognizing the enormous importance of algorithms as a form of "decision-maker" in the market, artificial intelligence has come to hold considerable appeal.[43] For example, algorithms are often built to anticipate how their own trading impacts the trading of other players and to adapt their trading to reflect consequential price changes.[44]

Third, traders set parameters within which their algorithms trade. At their core, algorithms comprise pre-set mathematical instructions that detail their exact terms of operation. These

40. For insightful discussion, see RISHI K. NARANG, INSIDE THE BLACK BOX: A SIMPLE GUIDE TO QUANTITATIVE AND HIGH-FREQUENCY TRADING, 8–9, 24–62 (2d ed. 2013).

41. *See, e.g.*, Aaron Lucchetti & Brett Philbin, *Now, It is Man vs. Machine*, WALL ST. J., (Aug. 9, 2012), http://www.wsj.com/articles/SB10000872396390443991704577577190049118980 [http://perma.cc/C5RX-GCVL] (discussing a move by Morgan Stanley to reduce its bond trading desk and replace human traders with algorithmic traders).

42. NARANG, *supra* note 40, at 42–43.

43. SCOTT PATTERSON, DARK POOLS: THE RISE OF THE MACHINE TRADERS AND THE RIGGING OF THE STOCK MARKET, 322–35 (2013) (discussing "Star," a machine learning artificially intelligent trading system of a firm known as Rebellion Research, which uses artificial intelligence to trade and has seen success from its strategies); Tommy Wilkes & Laurence Fletcher, *The Algorithms Arms Race*, REUTERS (May 21, 2012), http://graphics.thomsonreuters .com/12/05/BlackBox.pdf [http://perma.cc/L529-TZJ3]. For an insightful discussion about artificial learning in everyday applications like Netflix and the rights to free speech protection, see, Tim Wu, *Machine Speech*, 161 U. PA. L. REV. 1495 (2013).

44. *See, e.g.*, Michael Kearns & Yuriy Nevmyvaka, *supra* note 18 (analyzing the application of machine learning techniques for algorithmic trading).

parameters serve both to enable trading and to constrain the activities of the algorithm in the market. In the absence of real-time human supervision, setting limiting parameters *ex ante* assumes paramount importance.[45] These instructions stipulate the data that an algorithm collects, the rules for sorting out data into usable information, as well as the financial models and risk-calculations for deciding what to trade, when, and for how much.[46] Some algorithms may utilize historical troves of data to gauge past patterns of wins and losses, or survey current markets to figure out immediate trends for momentum-driven trading.[47] Instructions also set limits on when an algorithm should stop trading. Sharp or sudden falls in market prices, unexpected events, or low payoffs may trigger a rapid exit from the market.[48]

To achieve these objectives, algorithms depend on financial models for their operation. Models are used to abstractly represent market conditions and forecast and calibrate relationships between economic variables.[49] They offer tremendous benefit to traders. Models bring organizing assumptions to analysis of financial information and relationships. With swaths of data, models provide a tool to track correlations within the morass of observable data points and to plot a strategy that can make money from a combination of their interactions. They can take diffuse qualitative information and, through their processing, deliver a clearly quantitative output.[50] Commentators recognize that models are not perfect copies of the world. While models can evince great sophistication, they cannot capture every nuance and detail in actual trading.[51] Put bluntly, they simplify the untidy state of the world.[52] Still, by using models, traders can estimate the state of markets and the behavior of their algorithm. This estimation helps

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45. NARANG, *supra* note 40, at 28–44.

46. IRENE ALDRIDGE, HIGH FREQUENCY TRADING: A PRACTICAL GUIDE TO ALGORITHMIC STRATEGIES AND TRADING SYSTEMS (2010), 21–31.

47. *See, e.g.*, Christian Dunis et al., *Optimising Intraday Trading Models with Genetic Algorithms*, 1–5 (2011), http://citeseerx.ist.psu.edu/viewdoc/download;jsessionid=E7F1782A50C6BABA69A68E10943661DD?doi=10.1.1.196.9372&rep=rep1&type=pdf (describing a "genetic" algorithm and some of the parameters describing its operation).

48. For an detailed account, see ALDRIDGE, *supra* note 46, at 13–19, 49–60; and Peter Gomber et al., High Frequency Trading 21–25, (June 6, 2011) (unpublished manuscript), http://ssrn.com/abstract=1858626 [http://perma.cc/D4AL-QB5A], which provides useful surveys of key types of trading algorithms including those driven by volume and time-based trading.

49. ALDRIDGE, *supra* note 46, at 13–19; Emanuel Derman, Metaphors, Models and Theories 10–11 (Nov. 2010) (unpublished manuscript), http://ssrn.com/abstract=1713405 [http://perma.cc/XWB4-ES9H].

50. BD. OF GOVERNORS OF THE FED. RESERVE SYS., SR LETTER 11-7, SUPERVISORY GUIDANCE ON MODEL RISK MANAGEMENT, 1–3 (Apr. 4, 2011).

51. *Id.*

52. Derman, *supra* note 49, at 1, 10–11.

traders to map out costs and benefits *ex ante*. By investing intellectual and economic capital in building good-quality, robustly-tested models, traders can reduce their monitoring and liability costs and bolster their trading performance as a result.

Pre-set algorithmic programming and modeling seek to abstractly represent the state of the market and a desired trajectory for trading.[53] They try to make sense of the swath of data generated by the market to generate a usable output. For example, an algorithm's model might analyze a listed company's past dividends, available data on its debt, and market conditions, and take a position on the current value of the shares.[54] Once the algorithm has calculated the value of shares, it can decide whether to buy or sell shares based on a pre-set strategy. The algorithm might use established valuation modeling techniques from finance theory, crunching large amounts of data to arrive at a more exact valuation for the security using the model.[55] As Rishi Narang, an established practitioner, notes, algorithms can powerfully utilize models common to finance theory by harnessing large amounts of data and deploying combinations of models at the same time, far exceeding the computational capacity of human traders.[56]

B. High-Frequency Trading

Despite its prevalence, regulators have failed to agree on a definition for high frequency trading (HFT).[57] In many ways, HFT is impossible to define. As the Securities and Exchange Commission (SEC) observes, HFT can be identified by a few key characteristics but

53. *Id.*

54. Toshiyasu Kato & Toshinao Yoshiba, *Model Risk and its Control*, 18 MONETARY AND ECON. STUD. 129, 129–32, 146–50 (2000) (noting the various components of a financial model).

55. FRANKLIN ALLEN ET AL., PRINCIPLES OF CORPORATE FINANCE (10th ed. 2011), 74–93, 156–212 (describing models for valuing stock and risk in corporate finance theory).

56. NARANG, *supra* note 40, at 13–19, 23–62.

57. Notably, studies have estimated that HFT drives around 70% of trading volume in equities. It is also regarded as responsible for around 60% of trading volume in the U.S. futures market. HFT is emerging across securities types to include U.S. Treasuries, bonds, and certain swaps. *See* Mackenzie, *supra* note 38, at 22 (noting the increasing presence of high frequency traders in the market); Philip Stafford, Arash Massoudi & Michael Mackenzie, *NASDAQ Sets the Stage for HFT in Treasuries*, FIN. TIMES (Apr. 4, 2013), http://www.ft.com/intl/cms/s/0/6e0ac4de-9d08-11e2-a8db-00144feabdc0.html#axzz3q5mJhxan [http://perma.cc/G4F8-VFTZ] (explaining that Nasdaq's purchase of eSpeed electronic training platform may increase presence of high frequency traders in the bond market). *See generally* Alexander Osipovich, *Algorithmic Trading in Energy Markets*, RISK MAGAZINE, Jan. 2012 (noting the rise of algorithmic trading in energy markets).

is not reducible to them.[58] Securities changing hands in milliseconds and the use of algorithms comprise two notable, necessary characteristics of HFT. In addition, HFT traders tend to locate their servers close to exchanges, use small amounts of daily capital, and transmit large volumes of orders which are cancelled in more than 90% of cases.[59]

But these behaviors are not limited to HFT traders. Many slower traders are often just relatively less speedy (by a matter of milliseconds, if not less). Non-HFTs too rely on algorithms, make and cancel orders, house their servers near exchanges etc., making HFTs and non-HFTs difficult to tell apart in practice.[60]

HFT is costly for its traders to implement. Unable to intervene in real time, good programming is essential to achieve profits and to avoid expensive mistakes.[61] Algorithms, and the technology needed to operationalize them, must be powerful and sufficiently precise to parse large volumes of data and to extract significance for immediate trading.[62] Moreover, with miniscule holding periods, traders stand to make little gain per individual transaction even if strategies succeed.[63]

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58. U.S. SEC. & EXCH. COMM'N, EQUITY MARKET STRUCTURE LITERATURE REVIEW: HIGH FREQUENCY TRADING 4 (2014), https://www.sec.gov/marketstructure/research/hft_lit_review_march_2014.pdf [http://perma.cc/N8HH-TGEA].

59. *Id.*; *see also* Irene Aldridge, Market Microstructure and the Risks of High-Frequency Trading 2–4 (Aug. 19, 2013) (unpublished manuscript), http://ssrn.com/abstract=2294526 [http://perma.cc/65JG-7PEA] (noting that around 95% of limit orders on NASDAQ are cancelled within one minute of being placed).

60. U.S. SEC. & EXCH. COMM'N, EQUITY MARKET STRUCTURE LITERATURE REVIEW: HIGH FREQUENCY TRADING 4 (2014); *see also* Nicholas Hirschey, Do High Frequency Traders Anticipate Buying and Selling Pressure? 1–4 (Apr. 1, 2013) (unpublished manuscript), http://ssrn.com/abstract=2238516 [http://perma.cc/XLE2-TNVU]; Frank Zhang, High-Frequency Trading, Stock Volatility, and Price Discovery 2–3 (Dec. 2010) (unpublished manuscript), http://ssrn.com/abstract=1691679 [http://perma.cc/RW7Q-FMW8] ("HFT refers to fully automated trading strategies with very high trading volume and extremely short holding periods ranging from milliseconds to minutes and possibly hours."). For a discussion of SEC systems and HFT traders, see, Robert Jackson & Joshua Mitts, *How the SEC Helps Speedy Traders* 3–6 (The Ctr. for Law & Econ. Studies, Working Paper No. 501, 2014), http://ssrn.com/abstract=2520105 [http://perma.cc/MT3L-XXDM] which shows favorable dissemination of SEC filings to HFT traders.

61. Nick Baumann, *Too Fast to Fail: Is High-Speed Trading the Next Wall Street Disaster?*, MOTHER JONES, (Feb. 2013), http://www.motherjones.com/politics/2013/02/high-frequency-trading-danger-risk-wall-street [http://perma.cc/P9YC-7FJG] (detailing some of the key events leading up to the collapse of Knight Capital, which was once a major HFT trader, but lost $450 million in forty-five minutes owing to a faulty algorithm); Nathaniel Popper, *High Speed Trade Giants to Merge*, N.Y. TIMES, Dec. 20, 2012, at B1; Alexandra Stevenson, *Knight Capital Fined*, N.Y. TIMES, Oct. 17, 2013, at B9 (detailing the problems that affected Knight Capital and failures to implement proper controls, resulting in an SEC fine).

62. *See, e.g.*, NARANG, *supra* note 40, at 15–16 (arguing that HFT algorithms must engage in significant, complex data mining to react immediately to near-term data).

63. ALDRIDGE, *supra* note 46, at 1–3.

Still, despite the tall odds, HFT has shown itself to be lucrative and capable of attracting significant intellectual and logistical investment.[64]

For one, HFT traders face fewer risks than slower competitors. The ability to enter and exit the market rapidly limits the risks that traders may be left holding. Rather than locking capital in specific investments for a meaningful period of time, over which any of these might fail, HFT traders exit cheaply by virtue of their speed and technology. Holding tiny amounts of risk at any given moment, HFT traders do not need to invest deeply in understanding the longer-term behavior of securities. Rather, they win by anticipating the immediate likely direction of the market and trading rapidly to run faster than others to get there. Unsurprisingly, finance scholars have observed that HFT traders show considerable ability at anticipating market directionality over the span of three or four seconds.[65] Moreover, because traders do not hold securities for a lengthy period of time, they also do not need to provide for risks by holding large amounts of capital. Through the day, they can trade using small amounts of capital to buy and sell batches of securities that turnover rapidly. As the risks they hold are fleeting, HFT firms do not have to be thickly capitalized. The advent of HFT and algorithmic trading has thus seen the arrival of non-traditional, specialized trading firms. Firms like Tradeworx, which by some estimates is responsible for trading around 1.5% of all daily trading in U.S. stocks, exemplify this trend towards the smaller, specialized trading firm.[66]

HFT firms make money by trading securities for tiny moments in time and making a tiny profit on each trade. Their gains are small, incremental, and steady. HFT firms make a sliver of profit on each trade, accumulating gains because transactions are multiplied at high speed and high volume throughout the day.[67] The core of this business model is described by the HFT firm, Virtu Financial. In documents filed

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64. *Id.* at 1 (noting that, anecdotally at least, HFT practitioners delivered positive returns in 2008 even though 70% of low-frequency firms lost money).

65. Jonathan Brogaard et al., High Frequency Trading and Price Discovery 10 (Apr. 22, 2013) (unpublished manuscript), http://ssrn.com/abstract=1928510 [http://perma.cc/RW7Q-FMW8].

66. Scott Patterson, *Man Vs. Machine: Seven Major Players in High-Frequency Trading*, CNBC (Sept. 13, 2010), http://www.cnbc.com/id/39038892 [http://perma.cc/PH7D-XVWU]; Nathaniel Popper & Ben Protess, *To Regulate Rapid Traders, SEC Turns to One of Them*, N.Y. TIMES, Oct. 8, 2012, at B1.

67. IOSCO TECHNICAL COMM., *supra* note 17, at 23–25. For an excellent discussion, see Albert J. Menkveld, *High Frequency Trading and the New Market-Makers*, 16 J. FIN. MKTS. 712, 714 (2013), which notes the emergence of HFT traders as market-makers and their prominent presence in major US exchanges. *See also* Chaboud et al., *supra* note 21, at 1–4, 11–12 (analyzing foreign exchange markets).

for a proposed Initial Public Offering in 2014, Virtu explained that it generated revenue "by buying and selling large volumes of securities and other financial instruments" and earning small amounts of money based on the difference between what buyers are willing to pay and what sellers are willing to accept."[68] Indeed, Virtu noted that it had lost money on only one day in four years of trading.[69] When this strategy works, traders leave the market holding almost no risk on their books.[70]

Finally, it is worth noting that HFT algorithms must be especially capable of reading and valuing news independently. Particularly in this context, sophisticated programming and modeling is essential. Designed to trade in micro and milliseconds, HFT algorithms routinely receive data from newsfeeds, social media, exchanges, and regulatory agencies. They must be able to determine how to trade based on incoming data, mining its content for value-relevant information and submitting orders to reflect this information. To achieve this, HFT algorithms generally scan through incoming news and react rapidly to certain evocative words like "unemployment," "recession," "IPO" etc. In one infamous example in April 2013, a tweet reported that explosions had occurred at the White House and that President Obama had been injured. Within three minutes, the Dow Jones Industrial Average fell almost 150 points. 180,000 Treasury futures changed hands. The S&P 500 lost $136 billion in value. The panic subsided when the tweet was discovered to be the work of malicious hackers. Algorithms, poised to trade on breaking news, recognized terms like "explosion" and "White House" and reacted.[71]

C. Some Examples of Algorithmic Trading Strategies

Algorithmic trading offers opportunities to use trading strategies using computation, data, and speed. Some common uses for algorithms include: (i) making trades that take place at a pre-set price

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68. Virtu Financial Inc., Registration Statement Filing (Form S-1) (Mar. 10, 2014), at 1.

69. *Id.* at 1–3; *see also* MacIntosh, *supra* note 38, at 2, 14–19 (noting also that algorithmic trading has generated the rise of specialist algorithmic trading firms); U.S. SEC. & EXCH. COMM'N, EQUITY MARKET STRUCTURE LITERATURE REVIEW: HIGH FREQUENCY TRADING 4–6 (Mar. 2014).

70. ALDRIDGE, *supra* note 46, at 1–3 (describing characteristics of HFT).

71. *See, e.g.*, Peter Foster, *'Bogus' AP Tweet about Explosion at the White House Wipes Billions off US Markets*, THE TELEGRAPH (Apr. 23, 2013), http://www.telegraph.co.uk/finance/markets/10013768/Bogus-AP-tweet-about-explosion-at-the-White-House-wipes-billions-off-US-markets.html [http://perma.cc/9N6M-M4FP] (explaining that the FBI and SEC launched investigations into the hacked Twitter account); Alina Selyukh, *Hackers Send Fake Market-Moving AP Tweet on White House Explosions*, REUTERS (Apr. 23, 2013), http://www.reuters.com/article/2013/04/23/net-us-usa-whitehouse-ap-idUSBRE93M12Y20130423 [http://perma.cc/56QE-F5DS] (reporting that the fake tweet was likely sent out by the Syrian Electronic Army following their hacking of the twitter account of the Associated Press).

(trigger trades); (ii) performing arbitrage; (iii) market making; (iv) anticipating orders of informed traders; and (v) breaking up orders.[72] These strategies can be beneficial for market quality. Where algorithms trade securities using complex computation, data, and analysis, and reacting rapidly to new information, they can dramatically improve the quality of information introduced and internalized by the market. HFT traders, in particular, have also specialized as modern "market makers," standing ready to buy and sell securities and to keep securities market liquid.

Trigger trades: Computer programs send electronic orders to trade securities in accordance with pre-set strategies.[73] Computers can observe price patterns in a stock and buy or sell the stock at a trigger price decided by a human trader. For an investor looking to buy Public Company shares at $10 dollars a share, an algorithm observes the market and sends a purchase order as soon as the price reaches this figure.

Such strategies can be applied in vastly more sophisticated ways. With the growth of computing power and connectivity, machines can monitor securities prices across marketplaces and trade volumes of stocks at a pre-set price limit. Buyers can engage in "sweeps" of the marketplace to purchase a large number of shares across multiple venues at a set price.[74] Algorithms send orders to venues that trade the stock at the best price or that have the desired volume of securities available,[75] picking off small amounts of the security from different markets.[76] Such sweeps might form part of a larger trading strategy. It is possible to imagine, for example, that large sweeps might impact

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72. This section relies heavily on Terrence Hendershott et al., *Does Algorithmic Trading Improve Liquidity?*, 66 J. FIN. 1, 1–2 (2011), which describes the main types of algorithmic trading, and MacIntosh, *supra* note 38, at 3–7, which discusses algorithmic trading techniques.

73. Algorithmic trading should not be confused with "program trading," which refers to simultaneously trading bundles of fifteen or more stocks worth a combined $1 million or more. It is generally useful for trading portfolios of securities. Program trades were partially blamed for contributing to the October 1987 Crash. Program trading eventually spawned algorithmic trading, which is not constrained by the number of stocks or the amount. For discussion, see Mara Der Hovanesian, *Cracking the Street's New Math*, BLOOMBERG (Apr. 17, 2005), http://www.bloomberg.com/bw/stories/2005-04-17/cracking-the-streets-new-math [http://perma.cc/7MNZ-N5PC].

74. *See generally* Easley et al., *supra* note 35, at 22–26 (providing examples of a price-sampling process and a tactical liquidity provision algorithim).

75. *Id.*

76. Hendershott et al., *supra* note 72, at 5–13, 16–23 (noting the algorithms, strategies, and their impact of market quality).

market price. This then allows a trader to sell or "flip" the securities she has just bought at a profit.[77]

Without algorithms, such types of expansive searches and swift execution would be impossible. A buyer would have to instruct her broker to search the market for the desired number of securities, the broker would have to ensure that it could purchase a large number of securities quickly without moving the market, and then would have to look for onward buyers to generate profit from the strategy. Not only would a broker's search and execution costs be high, but the investor would likely have to hand over a sizable slice of the winnings as broker's commission and in transaction costs arising from slow, uncertain execution.[78]

Arbitrage: Just as algorithms can help to scour markets in search of securities trading at a preferred price, they can also scan markets for securities whose prices may vary between venues. This might happen when shares of a Public Company may be trading at $100 on Exchange X and at $101 on Exchange Y. Assuming that the prices should eventually converge, algorithms help traders seek out opportunities to make money from the tiny price differences between exchanges—or arbitrage. A trader can purchase Public Company shares at $100 on Exchange X and sell it for $101 on Exchange Y, helping prices to correct towards efficiency. With the ability to scan across markets, crunch volumes of data, and deploy complex statistics and probability analyses, algorithms can find not only existing opportunities for arbitrage but also predict future price divergences.[79] Indeed, algorithms have become especially useful at spotting and trading away even minute price differences. Algorithms can quickly scan hundreds of thousands of instruments for price variances, instead of just a few such instrument-types as in past years.[80]

With these abilities, algorithms should make it easier for traders to move the market towards greater price efficiencies. With machines able to research multiple market venues at high speed and with

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77. *Id.* at 2–4. *See, e.g.*, *Bloomberg Launches Smart Algorithm*, AUTOMATED TRADER, http://www.automatedtrader.net/headlines/7419/bloomberg-tradebook-launches-smart-algorithm [http://perma.cc/SS97-DE9V] (describing Bloomberg's SOAR "sweep" algorithm).

78. Hendershott et al., *supra* note 72, at 2–5.

79. FORESIGHT, THE FUTURE OF COMPUTER TRADING IN FINANCIAL MARKETS: FINAL PROJECT REPORT 28–30 (2012) (detailing the ability of powerful computing to engage in a variety of arbitrage strategies).

80. *Id.* at 29–30.

considerable precision, arbitrage becomes easier and cheaper to implement.[81]

Market-making: HFT firms especially have thrived as market-makers in securities markets. This means that they stand ready to buy and sell securities using their own money in order to keep the market liquid and orderly. A major difference between HFT firms and traditional market-makers lies in the ability of HFT to make thousands of such trades in milliseconds. Unsurprisingly, HFT firms have come to dominate exchanges as market-makers. Their superior technology and speed allow them to rapidly enter and exit trades, limiting the longer-term risks and costs they face. By market-making, commentators suggest, HFT firms also provide a genuine service to the market, improving its ability to help investors. With an HFT algorithm standing ready to trade with them, investors can enjoy low cost access to markets, faster execution, and more competitive commissions.[82]

The market has come to depend on HFT traders for this market-making role.[83] This fact came to light in spectacular fashion during the May 2010 Flash Crash. As is now well-known, the Dow Jones experienced a historic single day fall on May 6, 2010—losing over 900 points in minutes before regaining almost a $1 trillion in lost value equally quickly.[84] HFT traders were, in the SEC/CFTC's official inquest,

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81. There is a growing literature in the area of high frequency trading and efficiency. *See, e.g.*, Jonathan Brogaard et al., High Frequency Trading and Price Discovery 19–23 (Apr. 22, 2013) (unpublished manuscript), http://ssrn.com/abstract=1928510 [http://perma.cc/RW7Q-FMW8] (arguing that HFT increases price discovery by encouraging trades in the direction of price changes); Chaboud et al., *supra* note 21, at 21–22 (noting higher efficiencies through HFT in the foreign exchange market). For discussion, see Gerig, *supra* note 21, at 1–5, which shows that HFT trading encourages prices in related securities to change contemporaneously. The suggestion here is that HFT is making the securities more efficient. However, the author suggests that market stress may lead to stress spreading quickly and links established between securities that are not necessarily linked by fundamentals.

82. Menkveld, *supra* note 67, at 714 (noting that spreads fell upon the entry of a HFT firm on the exchange subject to the study). *But see* Terrence Hendershott & Pamela C. Moulton, Automation, Speed, and Stock Market Quality: The NYSE's Hybrid 2–3 (Feb. 2, 2010) (unpublished manuscript), http://ssrn.com/abstract=1159773 [http://perma.cc/98P7-CDL3] (arguing that in NYSE's Hybrid Market, immediate execution increased spreads).

83. *E.g.*, David S. Hilzenrath, *High Frequency Trading Raises Concerns at SEC*, WASH. POST (Feb. 22, 2012), http://washingtonpost.com/business/economy/high-frequency-trading-raises-concerns-at-sec/2012/02/22/gIQAfpLdTR_story.html [http://perma.cc/8TE9-ASQH]; Mackenzie, *supra* note 38. For a summary of current policy concerns and proposals, see FORESIGHT, *supra* note 79, at 13–17. This is particularly important after the May 2010 Flash Crash and smaller Flash Crashes endemic to the market following the emergence of HFT.

84. David Easley et al., *The Microstructure of the Flash Crash,* 37 J. PORTFOLIO MGMT. 118, 118 (2011).

not blamed for starting the crisis.[85] However, their behavior during the crash was deemed a contributing factor to its depth. HFT traders were criticized for *leaving* the market in large numbers rather than for any bad or disruptive trades actually performed.[86] In other words, HFT traders faced scrutiny for fleeing when they should have stayed to ensure the market remained liquid.[87]

Order anticipation: Algorithms can help opportunistic traders engage in "order anticipation" strategies. Broadly, "order anticipation" strategies involve algorithmic traders working out whether a fundamental investor has placed a large order and to use this knowledge to trade ahead of the fundamental investor. For example, a Mutual Fund intends to purchase 10,000 shares of Public Company at $100 per share. An algorithmic trader can benefit when it realizes that the Mutual Fund is looking to place a large order for Public Company shares. The Algorithmic Trader can itself purchase 10,000 shares for $100 each. Or, if it can reliably estimate which way the market is headed, it can accumulate a big inventory of Public Company shares. This strategy can be beneficial because this purchase raises the share price of Public Company shares and may prompt other investors to also become interested in purchasing them. In so doing, the Algorithmic Trader can make money by selling back the 10,000 shares to the Mutual Fund or to other investors at a higher price.

Operationally, order anticipation can work in several ways. Where the Mutual Fund's order is not publicly displayed, for example, if the order has been placed outside of an exchange, algorithmic traders can engage in "pinging" to decipher whether a large order may be lurking in the dark. Here, a trader uses algorithmic strategies to send out "feelers" in the market as a means of detecting the larger order and in which direction the order flow might be going. For example, algorithms are routinely used to send out small "phantom" orders to see if they match with another order. These feeler-orders are often cancelled—indeed, almost 90% of orders in HFT are cancelled.[88] But, if

85. Andrei Kirilenko et al., The Flash Crash: The Impact of High Frequency Trading on an Electronic Market 1–2 (Sept. 24, 2014) (unpublished manuscript) http://ssrn.com/abstract=1686004 [http://perma.cc/8WAZ-58U2].

86. *See* Pradeep Yadav, Vikas Raman & Michel Robe, Man vs. Machine: Liquidity Supply and Market Fragility (July 2014) (unpublished manuscript) (on file with author).

87. STAFFS OF THE CFTC AND SEC, *supra* note 23, at 45–57; *see also* Kirilenko et al., *supra* note 85, at 2 (noting that HFT traders exacerbated the downward swing in the market by removing liquidity).

88. *E.g.,* Scott Patterson & Andrew Ackerman, *SEC May Ticket Speeding Traders*, WALL ST. J. (Feb. 23, 2012), http://www.wsj.com/articles/SB10001424052970203918304577239440668644280 [http://perma.cc/LSC8-YR4N] (reporting 95–98% cancellation rates for HFT firms).

they match, they inform the program of a possibly larger order and the direction in which other traders might be trading. Additionally, algorithmic traders can engage in sophisticated computation and pattern analysis to deduce how large traders might behave. This type of order anticipation depends on algorithms successfully decoding market trends through the use of data, statistics, and analysis, and then getting ahead of the trends. Finally, where securities trade on multiple venues, the Mutual Fund might need to trade on many such platforms to fill a large order. An Algorithmic Trader can see that the Mutual Fund has entered a large order on Exchange 1. It can then speed ahead to Exchanges 2, 3, and 4 to purchase Public Company securities which it can then sell back to the Mutual Fund.[89]

HFT traders have proven adept at implementing a variety of order-anticipation strategies. When order anticipation involves "pinging" for hidden order flows, HFT traders are well equipped to send out large volumes of phantom orders at high speed. Relatedly, speed advantages permit HFT firms to identify opportune orders and to trade ahead of other investors and beat them to the punch.

Breaking up orders: Where the Mutual Fund wishes to enter into a large trade, this news can alert other traders to an incoming opportunity, one which they may wish to take advantage of through an order-anticipation strategy (as above).[90] Without opportunistic traders in the market, an investor would likely pay a lower price.

Traders benefit where they can control how they transact in their large orders to avoid losing out to order anticipators and to ensure that their order does not move the market. Large trades that can be broken up into small segments allow traders to fly under the radar and to avoid competitor attention falling on their trading strategy.[91] From the systemic perspective, one-off large block trades can move the market, potentially setting off abnormal price spikes that can disrupt the market.[92]

Algorithms are helpful in organizing order flows to ensure that block trades can be broken up and traded quietly without moving the market. Pre-set formulae determine how much of the block to sell (or buy) and at what price, helping route trades to venues where those

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89. IOSCO Technical Comm., *supra* note 17, at 23–24 (describing HFT strategies employed). For a detailed description, see U.S. SEC. & EXCH. COMM'N, Concept Release on Equity Market Structure, Release No. 34-61358 (Jan. 14, 2010), 56–58.

90. ARNUK & SALUZZI, *supra* note 36, at 1; MacIntosh, *supra* note 38, at 9–10.

91. Der Hovanesian, *supra* note 73.

92. The most extreme example here is provided by the May 2010 Flash Crash. Here, the SEC and CFTC investigation traced the start of the crash to a very large "sell" order by a large institutional investor. *See* STAFFS OF THE CFTC AND SEC, *supra* note 23, at 2–3.

trades can be executed at the lowest cost.[93] Algorithms can thus even out sharp spikes in prices resulting from the sudden emergence of large trades. Such algorithms hide block trades from view, only revealing a partial picture of the overall trading strategy and preventing opportunistic traders from purloining ideas. On the one hand, this impairs a fulsome understanding of trading behavior. On the other, algorithms reduce the costs to investors of entering the market. It can help key investors participate in the market where they know they can break up their big orders and avoid opportunistic traders from getting to their best trades.

III. MARKET EFFICIENCY AND CAPITAL ALLOCATION

According to established economic theory, markets speak through prices. When traders transact rationally with one another, their interactions reveal what they know about a security and how much they wish to pay to buy or sell it based on their knowledge and risk preferences.[94] Markets are efficient when they facilitate this exchange by reflecting the information and insights of traders in the prices at which securities trade. Efficiency in processing information can, in theory at least, also help foster better allocation of capital in securities markets, so-called allocative efficiency.[95] When investors can easily understand what securities are worth, they can invest their

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93. Hendershott et al., *supra* note 72, at 2–3 (noting that broker-dealers offer their clients a "suite" of algorithms to help them to break large trades up into small blocks).

94. For early discussion, see JAMES LORIE & MARY HAMILTON, THE STOCK MARKET: THEORIES AND EVIDENCE 70–75 (1973); WILLIAM F. SHARPE, PORTFOLIO THEORY AND CAPITAL MARKETS 77–78 (1970); Sanjay Basu, *Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios*, 32 J. FIN. 663, 663 (1977); Daniel R. Fischel, *Use of Modern Finance Theory in Securities Fraud Cases Involving Actively Traded Securities*, 38 BUS. LAW. 1, 3–6 (1982); Gilson & Kraakman, *Mechanisms*, *supra* note 24, at 554–65; Benoit Mandelbrot, *Forecasts of Future Prices, Unbiased Markets, and "Martingale" Models*, 39 J. BUS. 242, 242–43 (1966); Robert E. Verrecchia, *Consensus Beliefs, Information Acquisition, and Market Information Efficiency*, 70 AM. ECON. REV. 874, 874–75 (1980).

95. The literature in this area is vast and debated at length by academics in economics and finance. For discussion, see, Franklin Allen, *Stock Markets and Resource Allocation*, *in* CAPITAL MARKETS AND FINANCIAL INTERMEDIATION 81, 81–108 (Colin Mayer and Xavier Vives eds., 1993), which notes the different capacities of country securities markets to allocate capital; FORESIGHT, *supra* note 79, at 52–53; Jeffrey Wurgler, *Financial Markets and the Allocation of Capital*, 58 J. FIN. ECON. 187, 188–89, 210–12 (2000), which notes that financial markets help improve capital allocation across the economy in an international survey; and Solomon Tadesse, *The Allocation and Monitoring Role of Capital Markets: Theory and International Evidence* 5–6 (William Davidson Inst., Working Paper No. 624, 2003). For a critical perspective on the ability of markets to allocate capital efficiently, see Joseph E. Stiglitz, *The Allocation Role of the Stock Market*, 2 J. FIN. 235, 235, 238 (1981), which notes that efficient capital allocation is difficult to observe empirically and argues that competitive markets may not result in Pareto optimal resource allocation solutions.

capital in those enterprises that are likely to use it most productively and profitably.

Legal academics and finance economists have, since the 1970s, engaged in lengthy and often fraught analyses of the markers of market efficiency—and whether markets are, in fact, efficient.[96] The Efficient Capital Markets Hypothesis (ECMH), the theory that security prices reflect all available information,[97] has enjoyed a devoted following as well as dogged critics throughout its history. From its origins in finance theory, the ECMH migrated in the 1980s into legal scholarship, growing deep roots in securities regulation and corporate governance.[98] While this skepticism has softened the strictures of the ECMH, prices remain a significant source of information for markets and regulators.

In outlining the central pillars of the ECMH and its key critiques, this Part makes two points. First, despite the shortcomings of the ECMH, scholars note that prices can be informative and helpful in providing an approximate gauge of allocative value.[99] In other words, informational value and more fundamental allocative values are linked, even if imperfectly.[100] Secondly, regulation has long relied on prices as a window into fundamental allocative value. As detailed in this Part, central notions in regulation and governance continue to hew closely to

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96. *See, e.g.*, Nicholas Barberis, Andrei Shleifer & Robert W. Vishny, *A Model of Investor Sentiment*, 49 J. FIN. ECON. 307, 315–17 (1998) (discussing behavioral economics and specifically the conservatism and representative heuristic in the context of efficient markets theory); J. Bradford De Long, Andrei Shleifer, Lawrence H. Summers & Robert J. Waldmann, *Noise Trader Risk in Financial Markets*, 98 J. POL. ECON. 703, 704–06 (1990) (critically examining the role of arbitrage in keeping markets efficient); Eugene F. Fama, *Efficient Capital Markets: A Review of Theory and Empirical Work*, 25 J. FIN. 383, 413–16 (1970) (the seminal article on the subject elaborating on the Efficient Capital Markets Hypothesis and theorizing that markets incorporate available information in prices); Gilson & Kraakman, *Mechanisms*, *supra* note 24 (analyzing factors that may lead to market efficiency); Robert J. Shiller, Fumiko Kon-Ya & Yoshiro Tsutsui, *Why Did the Nikkei Crash? Expanding the Scope of Expectations Data Collection*, 78 REV. ECON. & STAT. 156, 163–64 (1996) (discussing the workability of efficient markets in light of the Japanese stock market crash). For a market microstructure perspective, see Paul G. Mahoney, *Market Microstructure and Market Efficiency*, 28 J. CORP. L. 541 (2003).

97. *See* Fama, *supra* note 96, at 384; *see also* Eugene F. Fama, *Market Efficiency, Long-Term Returns, and Behavioral Finance*, 49 J. FIN. ECON. 283, 283–84 (1998) (discussing the ECMH in the context of emerging behavioral critiques of the ECMH).

98. For excellent discussion, see Alon Brav & J.B. Heaton, *Market Indeterminacy*, 28 J. CORP. L. 517, 535–37 (2003) (critiquing the operation of the ECMH in fraud-on-the-market cases).

99. Gilson & Kraakman, *Mechanisms*, *supra* note 24, at 551–53; Gilson & Kraakman, *Information Costs*, *supra* note 24, at 10–12 (noting that even after the Financial Crisis, informational efficiency is still relevant for determining fundamental value efficiency in the market).

100. Gilson & Kraakman, *Information Costs, supra* note 24, at 7 ("We argue in this Article that informational efficiency and fundamental efficiency are related; even if we cannot observe fundamental efficiency, we can with confidence predict that making prices more informationally efficient will move them in the direction of fundamental efficiency.").

the ECMH. This reliance is not accidental. Rather, efficient markets have long been useful to regulators as a mechanism to monitor and encourage better capital allocation by linking key rules in this area to securities market prices.

A. The Importance of Efficiency

In a now infamous quote, Professor Michael Jensen proclaimed that, "there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Markets Hypothesis."[101] And, indeed, in its early history, the ECMH seemed unassailable.[102] In elaborating the central theses, Professor Eugene Fama posits that, in efficient markets, the price of a security fully reflects all available information.[103] In other words, it represents the market's most accurate estimate of the value of a particular security based on its riskiness and the future net income flows that investors holding that security are likely to receive.[104] Where efficient markets exist, traders cannot profit by using existing information available in the market, since this news should already be reflected in securities prices. Rather, the market price of a security only moves with the arrival of new information into the exchange.[105]

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101. Michael C. Jensen, *Some Anomalous Evidence Regarding Market Efficiency*, 6 J. FIN. ECON. 95, 95 (1978); *see also* Richard Roll, *Orange Juice and Weather*, 74 AM. ECON. REV. 861, 871, 879 (1984) (showing that the futures market for oranges was often more accurate than the National Weather Service in forecasting the weather).

102. *See, e.g.*, Gilson & Kraakman, *Mechanisms*, *supra* note 24, at 549–50 ("[T]he ECMH is now the context in which serious discussion of the regulation of financial markets takes place."); *see also* William F. Sharpe, *Discussion*, 25 J. FIN. 418, 418 (1970) ("[I]n a well-functioning market, the prices . . . [of securities] will reflect predictions based on all relevant . . . information. This seems to be trivially self-evident to most professional economists—so much so, that testing seems almost silly.").

103. Fama, *supra* note 96, at 383.

104. *See* Fischel, *supra* note 94, at 4–5; Gilson & Kraakman, *Mechanisms*, *supra* note 24, at 551–52; Jonathan R. Macey & Geoffrey P. Miller, *Good Finance, Bad Economics: An Analysis of the Fraud-on-the-Market Theory*, 42 STAN. L. REV. 1059, 1076–77 (1990).

105. Jensen, *supra* note 101, at 96 ("A market is efficient with respect to information . . . if it is impossible to make economic profits by trading on the basis of [that] information."). *But see* Sanford J. Grossman & Joseph E. Stiglitz, *On the Impossibility of Informationally Efficient Markets*, 70 AM. ECON. REV. 393, 395 (1980) (arguing that markets cannot be informationally efficient according to orthodox ECMH as if traders had no incentive to act on available information, new information would never be incorporated into prices in the first place). For discussion, see Lynn A. Stout, *The Mechanisms of Market Efficiency: An Introduction to the New Finance*, 28 J. CORP. L. 635, 640–42 (2003), which discusses the differences between informational and fundamental efficiency and how information is "fully reflected" in securities market prices; and William K.S. Wang, *Some Arguments that the Stock Market Is Not Efficient*, 19 U.C. DAVIS L. REV. 341, 344–51 (1986).

Professor Fama proposes three distinct versions of market efficiency. How price "fully reflects" available information can be a function of (i) weak; (ii) semi-strong; and (iii) strong forms of efficiency. In their weak form, market prices reflect historical patterns of past prices; the semi-strong version goes further to posit that prices incorporate all publically available information; and, finally, the strong version predicts that securities prices impound *all* information, including non-public data that lies in the hands of corporate insiders and others.[106] Under the strong-form version of efficiency, insider trading serves no profitable purpose: all public as well as confidential information is always fully incorporated into the price at which securities trade.[107]

Beyond simply describing versions of what kind of information is relevant, the ECMH also presupposes a modality by which this information comes to be absorbed into prices. At its most orthodox, the ECMH assumes that traders transact in a manner that is rational, free of bias, and unmoved by temporary fads and impulses.[108] Traders generate efficient prices by competitively trading on their rational estimations of what a security is worth, based on available and relevant information in the market. This reliance on rational, unbiased expectations of asset prices underpins some key insights deriving from the ECMH. Notably, efficient markets depend on arbitrage. That is, conventional theory assumes that, when traders see prices that deviate from an optimal price, they are immediately prompted to trade away the difference. A trader that sees that a security is trading below the trader's estimated value is motivated to buy that asset and to eventually sell it at the price that the asset should be worth. The trader thus brings the price closer to what it "should" be when publically available information is taken into account.[109] Arbitrage represents an important dynamic that animates efficient markets, helping periodic divergences from efficiency return to a state of equilibrium.

The assumption that traders act in a manner that is unbiased offers a way to connect informational and fundamental-value efficiency. Even if one trader incorrectly estimates prices, competing traders

106. *See* Fama, *supra* note 96, at 383–96, 404–10; *see also* EUGENE FAMA, FOUNDATIONS OF FINANCE: PORTFOLIO DECISIONS AND SECURITIES PRICES 139–45 (1976) (discussing these forms of efficiency and basis of establishing their applicability).

107. *See* Macey & Miller, *supra* note 104, at 1077–78 (discussing which form was favored by the Court in *Basic, Inc. v. Levinson*, 485 U.S. 224 (1988), which recognized the fraud-on-the-market theory).

108. Stout, *supra* note 105, at 640–42 (providing a succinct analysis of the importance of traders accurately valuing information according to set parameters).

109. *Id.* at 637–38.

should step in to bring prices into line. Further, arbitrage as a corrective mechanism works only when traders can spot that a security is mispriced. Such traders must be able to notice that asset prices are disconnected from what they "should" be—their true, fundamental value.[110] Capturing fundamental value is a challenging task for any theory. Some scholars argue that theories of fundamental value in asset pricing are simply too complex to be attainable in practice.[111] However, for proponents of the ECMH, the hypothesis offers a best, even if imperfect, fit. Put differently, the ECMH works pretty well most of the time.[112] Egregious market failures, such as stock market crashes, can undermine its reliability.[113] While problematic, however, such events do not necessarily defeat the theory in its entirety. Rather, they point to occasional imperfections that also taint other theories of market behavior. In short, the ECMH is the best the market has, and through arbitrage, informed trading supports a broadly applicable theory of value.[114]

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110. Robert F. Stambaugh, *Does the Stock Market Rationally Reflect Fundamental Values?: Discussion*, 41 J. FIN. 601, 602–04 (1986) (arguing that the ECMH provides a relatively more successful method of valuing assets); *see also* Lawrence E. Blume & David Easley, *Learning to Be Rational*, 26 J. ECON. THEORY 340, 340–43 (1982) (noting the challenges of investors learning price patterns and trading behaviors that help them to understand when prices are not at their correct level); Brav & Heaton, *supra* note 98, at 521–522 (noting that reliable models of fundamental value are virtually nonexistent and that arbitrage is unreliable).

111. *E.g.*, ANDREI SHLEIFER, INEFFICIENT MARKETS: AN INTRODUCTION TO BEHAVIORAL FINANCE 1815–34 (2000) (discussing the interaction between behavioral finance and efficient markets); Lawrence H. Summers, *Does the Stock Market Rationally Reflect Fundamental Values?*, 41 J. FIN. 591, 592 (1986) (arguing for the difficulty of showing fundamental value efficiency); *see also* Brav & Heaton, *supra* note 98, at 520–21 (arguing for market indeterminacy, a skepticism in the ability of markets to reflect fundamental value); Stambaugh, *supra* note 110, at 601–02 (noting the difficulty of developing tests of efficiency).

112. *See, e.g.*, Fischer Black, *Noise*, 41 J. FIN. 529, 533 (1986) ("[W]e can never know how far away price is from value . . . . I think almost all markets are efficient almost all of the time. 'Almost all' means at least 90%.").

113. *See* SHLEIFER, *supra* note 111, at 1827–28 (noting failures of arbitrage in reference to the Great Depression); Peter M. Garber, *Tulipmania*, 97 J. POL. ECON. 535, 543–44 (1989) (discussing the market fundamentals that drove the tulip speculation); Shiller, *supra* note 96; *see also* S.P. Kothari, *Capital Markets Research in Accounting*, 31 J. ACCT. & ECON. 105, 186–88 (2001) (noting evidence of large abnormal returns that pose formidable challenges to the efficient market hypothesis); Charles M.C. Lee, *Market Efficiency and Accounting Research*, 31 J. ACCT. & ECON. 233, 241 (2001) (discussing the difficulty of reconciling the volatility of stock returns with the efficient market framework).

114. *See* Fama, *supra* note 97, at 288–91 (arguing that, while ECMH showcases certain anomalies, anomalies emerging from theories of behavioral finance are just as, if not more, problematic).

B. Making Markets Efficient

The question of how market mechanisms actually reflect information in prices has tested scholars seeking to explain the ECMH and informationally efficient markets in practical terms. In their seminal work, Professors Gilson and Kraakman identify four "mechanisms" that, when left to interact, help efficient markets to emerge: (i) universally informed trading; (ii) professionally informed trading; (iii) derivatively informed trading; and (iv) uninformed trading.[115]

At its simplest, universally informed trading describes the quintessential state of efficient markets when traders possess all available information and cannot gain or lose by transacting on that information.

Professionally informed trading reflects the activity of expert and informed players. Market analysts, industry experts, and professional asset managers, though small in number, can cause the market price to shift because of the information that their trading reveals. These dynamics represent the workings of well-informed, so-called "fundamental" traders that bridge informational and allocative efficiency in practical terms. Informed traders invest in obtaining private information to give them an edge over other market participants. The better their information, the more likely they are to make significant gains vis-à-vis uninformed and lesser-informed traders. Their private interest generates public gains. When many informed traders come together, each knowing something about securities, their collective intelligence helps the market understand the fundamental worth of an asset.[116] When traders are informed about what a security is worth or should be worth, they can act to ensure that their capital is used most effectively by monitoring and disciplining management.[117]

Derivatively-informed trading paints a more complex picture. Instead of trading on information that they themselves possess, derivatively-informed traders transact on the basis of patterns and

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115. Gilson & Kraakman, *Mechanisms*, *supra* note 24, at 568–88.

116. There is considerable literature on the role of fundamental traders in deriving allocative value. See notably, Anat Admati, *A Noisy Rational Expectations Equilibrium for Multi-Asset Securities Markets*, 53 ECONOMETRICA 629, 629–30 (1985); Grossman & Stiglitz, *supra* note 105, at 393–95; and Jiang Wang, *A Model of Intertemporal Asset Prices Under Asymmetric Information*, 60 REV. ECON. STUD. 249, 249–51 (1993).

117. *See, e.g.*, Alon Brav, Wei Jiang, Frank Partnoy & Randall Thomas, *Hedge Fund Activism, Corporate Governance, and Firm Performance*, 63 J. FIN. 1729, 1730 (2008) (discussing the influence that hedge funds have as informed monitors).

trends they detect in the trading activity of professionally informed traders. They focus on anticipating how professional traders are likely to trade. The role of derivatively informed traders is important. Derivatively informed traders can increase efficiencies by highlighting the activities of professionally informed traders. When derivatively-informed traders anticipate possible trends, they earn returns at the expense of professional traders. But they also make sure that professional, private information emerges into the market quicker and at lower cost than if the market were to rely on the activities of professional traders alone.[118] Importantly, Gilson and Kraakman note that such derivative traders only imperfectly and incompletely decode information. Informed traders retain an edge and continuing incentive to keep trading.

Finally, uninformed traders complete the picture. Uninformed traders perform a "cleansing" role in the market. As much as markets use factual information, they also include softer, uncertain data in the realm of forecasts, predictions, and value judgments. Traders each have their own particular view of the world. They cannot know what other traders think and believe. But this information, in efficient markets, should reach the markets anyway. Uninformed trading allows various individual biases to cancel each other out, diminishing the chances that the market reflects distorted prices skewed in favor of one or other viewpoint. Uninformed traders are essential to the market. They help ensure that it reflects a collective viewpoint, free of bias or idiosyncrasies.

C. Prices and Capital Allocation

The ability of prices to function as a window into fundamental value offers a powerful policy tool for monitoring and disciplining economic actors. As finance theory has unraveled the fuller implications of price efficiencies for capital allocation and governance, policymakers have embraced prices as a central component of the regulatory arsenal.

1. Theory

From a theoretical standpoint, prices work to inform as well as discipline companies that consume the risk capital of investors. Prices perform an important expressive function for the market, aggregating

118. *See* Grossman & Stiglitz, *supra* note 105, at 395–97 (identifying a paradox in this theory by arguing that markets would go through a pattern of acquiring information and trading on it until the market itself becomes aware of it, leaving no gains to be made; where no gains exist, traders would stop trading until they came into new information).

the viewpoints of a multiplicity of traders into a responsive, easily-understood signal.[119] This signaling offers valuable insights to investors who do not have to internalize the full costs of investigation. Critically for allocation, the expressive functionality of prices allows them to function as a monitoring and disciplinary device for capital. A few examples serve to illustrate their considerable power in governance.

First, market prices offer a signal of good or bad corporate management. Notably, prices can incentivize mangers to be diligent in pursuing the interests of the company. Tying managerial contracts to share prices and total shareholder returns can give managers a motivation to maintain firm performance and, by extension, the price at which company securities trade.[120] With incentives to keep the share prices robust, managers should work hard to use investor capital effectively.[121] Prices also help managers understand how they and the company are performing. Managers can use prices as a way to glean the opinion of outside investors about their performance. Prices can thus work to create a monitoring and feedback mechanism between managers and the market.[122]

This functionality only works when markets operate efficiently. As Professors Holmstrom and Tirole observe, firm monitoring works best when markets are sufficiently liquid, meaning traders can enter and exit markets easily. Liquid markets attract motivated, informed speculators. With liquidity and informed investor participation, markets and share prices can work effectively as monitoring devices for managers.[123]

Regulation and market practice, unsurprisingly, depend on securities prices as a starting point for regulating executive

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119. *See, e.g.*, James Dow & Gary Gorton, *Stock Market Efficiency and Economic Efficiency: Is There a Connection?* 2–4 (Nat'l Bureau of Econ. Research Working Paper Series, Working Paper No. 5233, 1995) (discussing the signaling role of prices). For a critical perspective on using share prices in corporate governance see, Lynn A. Stout, *Share Price as a Poor Criterion for Good Corporate Law* 3–5 (UCLA School of Law, Law & Econ. Research Paper Series, Working Paper No. 05-07, 2005), http://ssrn.com/abstract=660622 [http://perma.cc/H9LG-E5HQ].

120. Carol Bowie, Steve Silberglied & Liz Williams, *Evaluating Pay for Performance Alignment*, ISS GOVERNANCE SERVS. 1, 6–10 (2014), http://www.issgovernance.com/file/publications/evaluatingpayforperformance.pdf [http://perma.cc/APQ6-GADP] (noting the importance of total shareholder returns as a metric measuring corporate performance for benchmarking executive performance).

121. *See, e.g.*, Dow & Gorton, *supra* note 119, at 2–4.

122. *Id.* (noting the "bi-directional" feedback mechanism between markets and managers). The literature on executive compensation and pay-for-performance is vast and outside the scope of this Article. For a useful survey of the literature, see Marco Becht, Patrick Bolton & Ailsa Roell, *Corporate Governance and Control* 58–65 (ECGI Fin., Working Paper No. 2/2002, 2002), http://ssrn.com/abstract=343461 [http://perma.cc/8826-9A2J].

123. Bengt Holmstrom & Jean Tirole, *Market Liquidity and Performance Monitoring*, 101 J. POL. ECON. 678, 679–80 (1993).

compensation and performance. Among other performance metrics, shareholders regularly look to shareholder returns when deciding whether or not to informally approve management pay packages.[124] Rather than relying on nebulous expressions of corporate success, share prices and shareholder returns offer observers a concrete, quantitative measurement of executive performance. Prices can also reveal manipulation by misbehaving managers. Option backdating and insider trading, when managers artificially massage their pay by secretly selling stock or making sure stock options vest in favorable markets, are key examples. Securities prices are the starting point for any analysis into such behavior.[125]

Second, in addition to monitoring, price signals can also trigger disciplinary mechanisms. Particularly significant is the market for corporate control. As finance and economics scholarship richly details, the market for corporate control works to punish managers that fail to use capital optimally or that extract rents at the expense of firm value.[126] Prices allow corporate raiders to gauge whether the firm is undervalued. Where share prices are low for reasons that do not correlate with a slump in the market or some other systemic reason, takeover specialists have incentives to exert discipline through a hostile takeover. If they succeed, raiders can hope to see a rise in the share price and a profit from their intervention. Selling shareholders may also be motivated to sell to raiders. As shares trade at a low price, the uncertainty risks and cost of keeping capital locked in the company may be too high to justify retaining the shares on their books.[127] The market

124. *See* Dodd-Frank Wall Street Reform and Consumer Protection Act, Pub. L. No. 111-203 § 951, 124 Stat. 1899 (2010) (mandating non-binding, advisory shareholder say-on-pay votes for public companies); Bowie, *supra* note 120, at 7–10 (noting the advantages of using shareholder returns as a metric to measure executive compensation).

125. For summary, see Peter J. Henning, *End of the Options Backdating Era*, N.Y. TIMES: DEALBOOK (Aug. 19, 2013), http://dealbook.nytimes.com/2013/08/19/end-of-the-options-backdating-era/?_r=0 [http://perma.cc/S5LR-ML9Z]. The literature in this area is vast.

126. *See generally* Eugene F. Fama and Kenneth R. French, *Industry Costs of Equity*, 43 J. FIN. ECON. 153 (1997) (noting the challenges of determining the price of equity); Sanford J. Grossman & Oliver D. Hart, *Takeover Bids, The Free-Rider Problem, and The Theory of the Corporation*, 11 BELL J. ECON. 42, 42–43 (1980); David Scharfstein, *The Disciplinary Role of Takeovers,* 55 REV. ECON. STUD. 185, 185 (1988); Martijn Cremers & Vinay B. Nair, *Governance Mechanisms and Equity Prices* 1–2 (Yale Int'l Ctr. for Fin, Working Paper No. 03-15, 2004) (detailing the interaction between takeovers and shareholder monitoring); James Dow, Gary Gorton & Arvind Krishnamurthy, *Equilibrium Asset Prices Under Imperfect Corporate Control* 2–3 (Nat'l Bureau of Econ. Research, Working Paper 9758, 2003).

127. *See* Scharfstein, *supra* note 126, at 186–87 (analyzing when shareholders will tender their shares at low prices); *see generally* Lucian A. Bebchuk, Alma Cohen & Allen Ferrell, *What Matters in Corporate Governance?*, 22 REV. FIN. STUD. 783, 789–96 (2009) (detailing the key factors that can impede effective shareholder monitoring of corporate governance).

for corporate control can thus provide a powerful motivator for weak managers who may otherwise shirk their responsibilities.

Importantly, external discipline can work alongside internal oversight mechanisms. As scholars note, a vibrant and liquid market for a company's securities can motivate large shareholders to increase their shareholding as a means of disciplining management, particularly when prices fall. Shareholder monitoring, combined with external monitoring by takeover activists, can enhance investor power and create meaningful disciplinary constraints on managers.[128] Similarly, external suppliers of credit can look to share prices to determine firm value and investor expectations regarding a company's future performance. Sudden changes in share price may suggest problems in repaying debt—an invitation to lenders to exert greater control and calibrate the cost and conditions attaching to the capital.[129]

2. Implementation

At the level of practice, law and regulatory policy institutionalize the interaction between information and allocative efficiency. Policymakers have supported efficiency economics in two clear ways: (i) by creating a system of laws to facilitate disclosure by public companies, seeking to optimize monitoring and discipline; and (ii) by developing a regulatory framework that looks to foster liquid markets, reducing the entry costs facing investors seeking to trade.[130]

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128. The literature on this issue is considerable. For discussion, see Paul A. Gompers, Joy L. Ishii & Andrew Metrick, *Corporate Governance and Equity Prices*, 118 Q. J. ECON. 107, 107–09 (2003); Charles J. Hadlock & Gerald B. Lumer, *Compensation, Turnover, and Top Management Incentives: Historical Evidence*, 70 J. BUS. 153, 153–58 (1997); and Cremers & Nair, *supra* note 126.

129. Merritt B. Fox, Randall Morck, Bernard Yeung & Artyom Durnev, *Law, Share Price Accuracy and Economic Performance: The New Evidence*, 102 MICH. L. REV. 331, 340–41 (2003); Marcel Kahan & Edward B. Rock, *Hedge Funds in Corporate Governance and Corporate Control*, 155 U. PA. L. REV. 1021, 1047–70 (2007) (noting the rise of bondholder engagement in enforcing loan covenants); Greg Nini, David C. Smith & Amir Sufi, Creditor Control Rights, Corporate Governance, and Firm Value 28–29 (Nov. 2009) (unpublished manuscript), http://ssrn.com/abstract=1344302 [http://perma.cc/Z7SS-SGDG]. For a brief description of takeover rules applying to public companies, see B. Jeffery Bell, *The Acquisition of Control of a United States Public Company,* MORRISON FOERSTER (2015), http://media.mofo.com/files/Uploads/Images/1302-The-Acquisition-of-Control-of-a-United-States-Public-Company.pdf [http://perma.cc/5VTC-LVVV].

130. For an excellent early discussion, see Donald C. Langevoort, *Theories, Assumptions and Securities Regulation: Market Efficiency Revisited*, 140 U. PA. L. REV. 851, 853–56 (1992), which discusses the persistent hold of the ECMH in legal scholarship despite the emergence of critiques in financial economics; *see also* Goshen & Parchomovsky, *supra* note 24, 1243–45 (discussing the importance of securing informational gains as the major role of securities regulation). For an illuminating analysis on the centrality of efficiency in policy, see Jeffrey N. Gordon & Lewis A.

a. Mandatory Disclosure

Public investment in mandatory disclosure laws draws into relief the central role played by market efficiency in capital allocation.[131] Disclosure constitutes the central imperative of the securities-regulation framework.[132] Companies seeking to go public provide markets with a substantial book detailing their inner workings. Once their securities are on the market, companies provide investors with routine updates about their activities and important changes to their organization.[133]

As Professor Merritt Fox observes, mandatory disclosure and informationally efficient markets can strengthen capital allocation within the economy. Mandatory disclosure reduces the search costs involved for investors in procuring detailed information on public companies. Investors face a lower investigative burden when seeking out their choice investments and predicting their future cash flows from the investment.[134] Where investors do not have to spend private capital to discover value-relevant information, they can enter markets more readily. And with reservoirs of accurate information, investors do not have to discount their investments for the risks of expensive investigation. Duplicative searches by investors are avoided. Market

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Kornhauser, *Efficient Markets, Costly Information, and Securities Research*, 60 N.Y.U. L. REV. 761, 810–24 (1985), which casts doubt on relying on the ECMH as a basis for fashioning policy.

131. *See* Fox et al., supra note 129, at 338–41 (discussing how mandatory disclosure laws lead to increased efficiency and beneficial effects on the allocation of resources).

132. Several scholars have argued that disclosure constitutes an unnecessary cost for firms seeking to enter the public markets. In short, public firms would most likely disclose important information of their own volition to attract capital without incurring a steep risk premium. *See, e.g.*, HOMER KRIPKE, THE SEC AND CORPORATE DISCLOSURE: REGULATION IN SEARCH OF A PURPOSE 232–65 (1979) (noting the shortcomings of mandatory disclosure); George Benston, *Required Disclosure and the Stock Market: Rejoinder*, 65 AM. ECON. REV. 473, 473 (1975) (arguing that variances in the returns emerging after passage of the 1933 Securities Act are not relevant); Frank H. Easterbrook & Daniel R. Fischel, *Mandatory Disclosure and the Protection of Investors*, 70 VA. L. REV. 669, 669 (1984) (noting that protection against fraud and ensuring disclosure are the two basic aims of the securities regulation framework). *But see* Coffee, *Market Failure*, *supra* note 24; Fox et al., *supra* note 129, at 338–41 (arguing that mandatory disclosure leads to more accurate share prices and more efficient markets).

133. Companies must produce a detailed registration statement under section 5 of the Securities Act of 1933. Securities Act of 1933 § 5, 15 U.S.C. § 77e (2012). Public issuers must complete periodic filings under sections 13(a), 13(c), 14, or 15(d) of the Securities Exchange Act of 1934. Securities Exchange Act of 1934 § 5, 15 U.S.C. § 78 (2012).

134. On the further, indirect benefits of mandatory disclosure for governance see, John Core, Luzi Hail & Rodrigo S. Verdi, *Mandatory Disclosure Quality, Inside Ownership, and Cost of Capital* 1–2 (Oct. 24, 2014) (unpublished manuscript), which observes the reduction of inside ownership as an indirect consequence of mandatory disclosure.

analysts too benefit through dissemination of critical corporate information.[135]

Certainly, mandatory disclosure regimes are not costless. They place a high burden on public companies in terms of production costs and liability risks, as well as the loss of advantages that secrecy might permit. But they also offer welfare gains for capital allocation. Investors—or those that invest on their behalf like mutual funds—can monitor public companies by exercising shareholder discipline over the companies in which they invest. Managerial compensation can track to company performance. The market for corporate control and takeovers can step in to discipline management that fails to operate the business to its full potential. Through price-signals, investors and third party monitors can calibrate the cost of capital by better understanding the fundamental value inhering within the company.[136]

b. *Constructing Structural Efficiencies*

The SEC also routinely frames its policy goals for market structure in the language of market efficiency. Essential rule making in the area of market design, notably for the National Market System (NMS)[137] as well as regulation of Alternative Trading Systems (ATS)[138] has expressly worked to institutionalize the ECMH in trading design. The NMS establishes a nationwide market, connecting the country's competing exchanges and securities platforms, to create a single trading space. The NMS requires trading venues to disseminate quotations for prices continuously. Price data is no longer the exclusive property of the exchange on which it originates, but instead becomes a public good shared across all exchanges in the interests of transparency

135. Gilson & Kraakman, *Mechanisms*, *supra* note 24, at 593–95 (noting the "central role of information costs"); Goshen & Parchomovsky, *supra* note 24, at 1234 (discussing the importance of market analysts for efficient markets); *see also* Gordon & Kornhauser, *supra* note 130, at 813 (discussing whether the use of abbreviated registration statements restricts competitive research).

136. *See, e.g.*, Coffee, *supra* note 24, at 721–22 (discussing how mandatory disclosure may improve the allocative efficiency of the capital market); Fox et al., *supra* note 129, at 344–45 (noting the signaling role of share prices in investment decisions).

137. 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, 37,532 n.300 (June 29, 2005); *see also* U.S. SEC. & EXCH. COMM'N, MARKET 2000: AN EXAMINATION OF CURRENT EQUITY MARKET DEVELOPMENTS 17 (1994) ("The Division believes that transparency plays a fundamental role in the fairness and efficiency of the secondary markets. Transparency ensures that stock prices fully reflect information and lowers trading costs by improving investors' ability to assess overall supply and demand.").

138. Regulation ATS—Alternative Trading Systems, 17 C.F.R. § 242.300(a) (2015).

and efficiency.[139] The NMS requires execution of trades at the best price anywhere in the NMS and has lowered broker fees by removing fixed broker commissions. While such measures are designed to expand investor access to securities markets, their avowed goal also extends to ensuring that transactions are completed at the lowest transaction cost.[140]

Similarly, Regulation ATS has sought to broaden the National Market by including within its ambit a variety of newer, more informal venues that bring customers together to trade securities.[141] Not quite exchanges, such alternative venues can compete on price with regulated exchanges, encouraging a more competitive and liquid marketplace. Under the NMS and Regulation ATS, securities can trade in multiple markets, with continuous information flowing about prices throughout the system. Traders can search across venues for their best trade and execute this trade at the best price on the market. The NMS is designed to speed up the arbitrage process to help prices move closer to their efficient end-point. When prices diverge between trading platforms, low transaction costs and a large NMS can encourage traders to seek out opportunities for arbitrage, ensuring that markets become efficient quickly and cost-effectively.

To be sure, the NMS has come under considerable critical scrutiny from both practitioners and academics. Commentators have remarked on its well-intentioned ambitions but troubled implementation, which has produced over-complexity and exchanges that compete too hard for business at the expense of standards.[142] Still, the clear aim of NMS and ATS is to encourage the liquidity and investor participation needed for a vibrant, efficient market, a goal in keeping with prevailing theory. In the absence of structural investments in informational efficiency, the benefits offered by capital allocation go unrealized. As prescribed by Holmstrom and Tirole, for example, shareholder monitoring and the market for corporate control can wither in the absence of the liquidity needed for investors and speculators to

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139. For discussion, see Lawrence A. Cunningham, *Capital Market Theory, Mandatory Disclosure, and Price Discovery*, 51 WASH. & LEE L. REV. 843, 862–64 (1994). For critical analyses of the National Market System, see Jonathan R. Macey & David D. Haddock, *Shirking at the SEC: The Failure of the National Market System*, 1985 U. ILL. L. REV. 315, 337–44 (1985); and Norman S. Poser, *Restructuring the Stock Markets: A Critical Look at the SEC's National Market System*, 56 N.Y.U. L. REV. 883, 957–58 (1981).

140. *See, e.g.*, U.S. SEC. & EXCH. COMM'N, *supra* note 137, at 1–2 (describing the Division's goals to achieve the broadest possible investor participation and lowest costs).

141. Tom C.W. Lin, *The New Investor*, 60 UCLA L. REV. 678, 688 (2013).

142. Jacob Bunge, *A Suspect Emerges in Stock-Trade Hiccups: Regulation NMS*, WALL ST. J. (Jan. 27, 2014), http://www.wsj.com/articles/SB10001424052702303281504579219962494432336 [http://perma.cc/36BA-97E2].

enter the market cheaply and often. That policymakers have invested deeply in crafting a regulatory framework to institutionalize the goals of efficiency economics and support the promise of mandatory disclosure should be unsurprising.

IV. INFORMATION EFFICIENCY VS. ALLOCATIVE EFFICIENCY

This Part explores the impact of algorithmic trading on conventional theories of market efficiency—both informational and allocative—from the perspective of regulation. It shows that, while algorithmic trading fosters more short-term informational efficiency by rapidly showcasing incoming news and data, it creates costs for longer-term, fundamental allocative efficiency. This Part develops two strands of argument. The first considers the impact of model and programming risk (referred here together as "model risk")—that is, the risks of algorithmic programming and models leaving gaps in analysis, making incorrect assumptions, and adopting sub-optimal preferences in interpreting information. With system-wide use of algorithms, the question becomes whether prices remain fundamentally informative to effectively act as a governance mechanism for capital allocation, allowing investors to make decisions about corporate monitoring and discipline. This Part suggests some ambivalence regarding model risks in the market and allocative efficiency. While there are clear benefits to models and algorithmic programming in terms of computation and quantitative analysis, they invariably also leave gaps in information that are hard to fill without parallel investment in fundamental research.

The second line of argument claims that algorithmic markets generate costs for informed investors seeking to make investments in fundamental research. High-speed algorithms are skilled at deciphering how informed traders are likely to transact and are able to get to the most lucrative opportunities faster, reducing some of the gains that may accrue to the informed trader. Losing out over time to high-speed algorithmic traders, fundamental traders can see fewer incentives to invest deeply in long-term research and investment. Importantly, lower gains from research can also diminish the motivation of fundamental traders to engage in governance of capital markets, for example, in shareholder monitoring. The costs of exercising such oversight can erode the gains of investment, especially if payoffs are uncertain and long-term in nature.

A. The Case for Informational Efficiency

Clearly, algorithmic trading offers many benefits for conventional measures of market efficiency, with markets becoming better able to reflect available information in prices quickly and accurately. We know that algorithms react swiftly to emerging news events. Indeed, studies show that the importance of speed for news-based trading is paramount.[143] Even millisecond delays in reacting to new information can significantly reduce returns for traders.[144] In one study examining trading following scheduled macroeconomic news releases, the authors observed that delays of three hundred milliseconds reduced returns by 3.08%. Delays of one second diminished returns by 7.33%.[145] Given these reaction times, markets are internalizing incoming news at a staggering pace, such that prices are more responsive than ever before.[146]

We also know that algorithms are able to absorb an ever-expanding reserve of data to inform trading. Beyond conventional data sources like prices or macroeconomic indicators, algorithms are able to collect and collate data from a diffuse range of sources. Social media databases like Twitter or Facebook are especially popular for traders seeking an edge in the market by accounting for prevailing sentiment and likely trends.[147] With traders able to enter markets with large quantities of data, securities prices should, in theory, reflect a rich reserve of information in the prices at which securities trade. Within this competitive, automated environment, there is little probability of news passing unnoticed by algorithmic traders.

Additionally, algorithms can quickly spot and correct minor discrepancies in prices, enhancing the effectiveness of arbitrage. Pursuant to conventional theory, arbitrage constitutes a central mechanism by which markets become efficient, scrubbing away differences in prices between similar assets. Automated traders can scan multiple markets in real time, spot price divergences, predict

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143. Thierry Foucault, Johan Hombert & Ioanid Rosu, *News Trading and Speed* (J. Fin., HEC Paris Research Paper No. 975/2013, 2013), http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2188822 [http://perma.cc/NS4M-KBU3].

144. *Id.*

145. Martin L. Scholtus, Dick van Dijk & Bart Frijns, *Speed, Algorithmic Trading, and Market Quality around Macroeconomic News Announcements* 4 (Tinbergen Institute, Discussion Paper No. 12-121/III, 2012), http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2174901 [http://perma.cc/J4SF-S24L] (noting that, after macroeconomic news releases, there is a good chance that traders will trade in a similar fashion—e.g., that news of high unemployment might lead to more selling).

146. Scholtus, van Dijk & Frijns, *supra* note 145, at 2–5.

147. PATTERSON, *supra* note 43, at 307.

future variations in price, and ensure these are traded away rapidly. With low search costs using algorithms, traders can afford to target even small price differences: the payoffs may well be greater than the costs involved in searching between markets. While current data on the effectiveness of cross-market arbitrage is still limited, early evidence points to tight relationships between related markets and closeness in the prices of similar assets. This suggests that prices should be a more accurate reflection of the underlying information in markets.[148]

Each of these advantages—rapid reactions to news, data processing, and arbitrage—is buttressed by sophisticated financial modeling and programming that helps algorithms to value securities for a best price.

Taken together, there are ample reasons to consider algorithmic trading as a high-point for informationally efficient markets. Prices rapidly reflect a wide range of information and are less vulnerable to divergences. A number of prominent studies in the finance literature speak to this intuition.[149] For example, as noted above, scholars find that HFT algorithms trade in the direction of permanent price changes, particularly with respect to large and liquid stocks.[150] They note that HFT algorithmic traders are adept at forecasting the future direction of trading, at least over three to four seconds.[151] Moreover, markets are liquid, owing to high speed, high volume trading. This brings benefits

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148. William Barker & Anna Pomeranets, *The Growth of High-Frequency Trading: Implications for Financial Stability*, BANK OF CAN. FIN. SYS. REV., Jun. 2011, at 48–50; U.S. SEC. & EXCH. COMM'N, *supra* note 58, at 11.

149. Brogaard, Hendershott & Riordan, *supra* note 21 (noting that HFTs promote price efficiency by trading in the direction of permanent price changes); Allen Carrion, *Very Fast Money: High-Frequency Trading on the NASDAQ*, 16 J. FIN. MKTS. 680 (2013) (finding that prices incorporate information more efficiently on high HFT participation days); Alvaro Cartea, Sebastian Jaimungal & Jason Ricci, Buy Low, Sell High: A High Frequency Trading Perspective (Nov. 25, 2011) (unpublished manuscript), http://ssrn.com/abstract=1964781 [http://perma.cc/RW6H-FELA] (arguing that lesser informed traders are adversely selected out of the market). For a broader market quality rather than efficiency perspective, see Joel Hasbrouck & Gideon Saar, *Low-latency Trading,* 16 J. FIN. MKTS. 646 (2013) (showing that HFT activity increased traditional benchmarks of market quality in the current U.S. equity market structure notably with respect to depth of limit order book and lower spreads).

150. Zhang, *supra* note 50, at 2–3 (arguing that HFT has increased short-term volatility and showcases short-run efficiencies). But see criticisms of analyzing volatility and HFT in light of the short time that HFT has been in the market and the challenges of drawing hard-and-fast causal connections. Some commentators suggest that volatility might attract volatility, rather than foment it in the market. For discussion, see FORESIGHT, *supra* note 79, at 64–65.

151. Brogaard et al., *supra* note 14; Jonathan Brogaard, Terence Hendershott & Ryan Riordan, *High Frequency Trading and Price Discovery* (European Central Bank Working Paper Series No. 1602, 2013); Sarah Zhang & Ryan Riordan, *Technology and Market Quality: The Case of High Frequency Trading* (European Conference on Information Systems 2011 Proceedings, Working Paper No. 95, 2011). For a more comprehensive review of the literature, see U.S. SEC. & EXCH. COMM'N, *supra* note 58 at 8–12.

for investors looking for vibrant, low-cost trading venues where they can enter and exit cheaply and at will.[152] In theory at least, this heightened efficiency should point to more efficient capital allocation across the economy.

B. The Problem of Allocative Efficiency

1. Model Risk

While quantitative models and advanced programming bring considerable computational power to markets, they also generate risks of information loss at significant cost to allocative efficiency. By design, such models use theories from finance, mathematics, economics, and statistics to abstract how different variables interact with one another.[153] Models routinely utilize simplifying assumptions about the way the world works (e.g., that human beings trade rationally, or that they have perfect information).[154] In this way, models help carve out pathways from cause to effect, making sense of large quantities of data and variables to focus on those factors that are most salient to a trading environment.[155] With strong models at work, algorithms can collect enormous amounts of data as input and generate a credible output, underpinned by finance theory, statistics, and historical observations about market behavior.

But, models are also problematic. Commentators have long expressed concerns about "model risk," meaning that models generate overly stylized, simplified representations of otherwise messy economic relationships.[156] Put more simply, models can be unreliable and generate bad outcomes. The sources of such error can be numerous. For

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152. *See, e.g.*, Albert J. Menkveld, *supra* note 67, at 714 (noting the emergence of HFT traders as market-makers and their prominent presence in major US exchanges); Nicholas Hirschey, Do High Frequency Traders Anticipate Buying and Selling Pressure? 1–4 (Dec. 2011) (unpublished manuscript), http://ssrn.com/abstract=2238516 [http://perma.cc/KN7A-QGYM] (showing that HFT traders are able to predict the direction of order flows). *But see* Terrence Hendershott & Pamela C. Moulton, Automation, Speed, and Stock Market Quality: The NYSE's Hybrid (Feb. 2, 2011) (unpublished manuscript), http://ssrn.com/abstract=1159773 [http://perma.cc/K6SJ-VJPQ] (arguing that in NYSE's Hybrid Market, immediate execution increased spreads). For a practitioner perspective, see *US Equity Market Structure: An Investor Viewpoint*, BLACKROCK VIEWPOINTS, Apr. 2014, at 2–3 (stating some benefits of HFT from an investor perspective).

153. BD. OF GOVERNORS OF THE FED. RESERVE SYS., *supra* note 50, at 1–3 ("Models are simplified representations of real-world relationships among observed characteristics, values, and events.").

154. Allan Gibbard & Hal R. Varian, *Economic Models*, 75 J. PHILOSOPHY 664, 664–65 (1978).

155. BD. OF GOVERNORS OF THE FED. RESERVE SYS., *supra* note 50, at 1–3.

156. *See, e.g.*, Kato & Yoshiba, *supra* note 54, at 131–33 (offering examples of various risks affecting financial modeling).

one, models and algorithmic programming can make incorrect assumptions about how markets work. For example, human beings do not always behave rationally when they trade.[157] As a result, models may give too much or too little importance to certain aspects of trading like the various biases scholars regard as being endemic to human beings and their trading behavior.[158] Models may use outdated theories and insights about financial products and their characteristics.[159] Data may be incorrectly interpreted to highlight certain patterns when these do not reflect market reality. For example, algorithms may end up "over-fitting" data to match a past or conventional trading strategy or viewpoint rather than dealing effectively with new data.[160] As Rishi Narang, a well-known HFT trader, argues, algorithms can fit information into existing models, even when analysis suggests that a different approach would be more suitable. When Merrill Lynch merged with Bank of America in 2008, he notes, the price of Merrill's stock rose quickly. An unthinking algorithmic trader might have interpreted Merrill's stock as overvalued, suggesting that selling the stock short would be profitable. However, as Narang points out, there were good reasons to think that Merrill's high stock price was actually justified under the circumstances, a fact that conventional models may have missed.[161] In short, the trading outcomes generated by algorithms may not always be sound.

Model risks also arise when algorithms fail to extract meaning from the gigabytes of data flooding the market. In other words, algorithms can err in mining data for information.[162] Algorithms may over-value some data, under-emphasize it in other cases, make mistakes, and fail to check its truthfulness. This danger is especially live in the case of high speed, high volume algorithms designed to respond in milliseconds to incoming information. Estimated to be

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157. ANDREI SHLEIFER, INEFFICIENT MARKETS: AN INTRODUCTION TO BEHAVIORAL FINANCE 2–4 (2000); Barberis, Shleifer & Vishny, *supra* note 96, at 315–17; Garber, *supra* note 113, at 543–44; Shiller, Kon-Ya & Tsutsui, *supra* note 96, at 163–64.

158. *See generally* DAVID DREMAN, THE NEW CONTRARIAN INVESTMENT STRATEGY (1979) (discussing irrational market trends and the investors who succumb to them); DANIEL KAHNEMAN, THINKING FAST AND SLOW 269–363 (2011) (describing several ways human choice tends to deviate from rationality); HERSH SCHEFRIN, BEYOND GREED AND FEAR: BEHAVIORAL FINANCE AND THE PSYCHOLOGY OF INVESTING (2000); David Hirshleifer, *Investor Psychology and Asset Prices*, 56 J. FIN. 1533 (2001) (discussing trading biases and asset prices).

159. Kato & Yoshiba, *supra* note 54, at 130.

160. Yael Grushka-Cockayne, Victor Richmond R. Jose & Kenneth C. Lichtendahl Jr., *Ensembles of Overfit and Overconfident Forecasts* (Darden Business School, Working Paper No. 2474438, 2014), http://ssrn.com/abstract=2474438 [http://perma.cc/45HC-8MVP] (discussing machine learning algorithms and the risk of data overfit and overconfidence in interpretation).

161. NARANG, *supra* note 40, at 15–16.

162. *See id.*

responsible for around seventy percent of all equity trading volume on U.S. markets, HFT algorithms must be precision programmed to capture enormous amounts of data and to rapidly extract meaning from this input.[163] Traders face a significant technical challenge when building HFT algorithms capable of absorbing swaths of data, ascribing a "value" to information and transacting on that basis.[164] Programming errors in collecting and collating data input can easily arise, causing problems for markets seeking to understand how to value securities in real time. On December 1, 2014, for example, Apple Inc. lost almost forty billion dollars in value owing to unexpected price swings in Apple's shares. Shortly after the start of the trading day, 6.7 million Apple shares changed hands within a one minute period, losing over three percent in value in that short time. While the cause of the surprise sell-off was unclear, its impact was felt across the market.[165]

Model risks are certainly not new. Moreover, the alternative, relying on human brains and intuition, is also far from perfect and is certain to leave deep gaps in data collection and analysis. The challenge for markets lies not in the bare fact of model risks but in its extent. In other words, a market that depends heavily on algorithms across a growing list of security classes generates modeling risk on a system-wide scale. Trading firms develop their own, in-house proprietary models. Regarded as the "secret sauce" for success, firms face competitive pressures to ensure that their particular algorithm emerges a winner by virtue of its superior, speedier, and smarter programming.[166] To stay profitable against their peers, firms have every incentive to invest in models that are sophisticated and complex, able

163. Christian T. Brownlees & Giampiero M. Gallo, *Financial Econometric Analysis at Ultra–High Frequency: Data Handling Concerns* (Universita' di Firenze, Dipartimento di Statistica G. Parenti, Working Paper No. 2006-3, 2006) (noting the technological challenges of recording and processing Ultra High Frequency Data).

164. Kearns & Nevmyvaka, *supra* note 18; NARANG, *supra* note 40, at 43–45.

165. Chuck Mikolajczak, *Apple Tumbles As Much As Six Percent in Unusual Trading*, REUTERS (Dec. 1, 2014), http://www.reuters.com/article/2014/12/02/us-apple-shares-idUSKCN0JF2M420141202 [http://perma.cc/AYS8-YWPG].

166. *See* Michael Lewis, *Did Goldman Sachs Overstep in Criminally Charging Its Ex-Programmer?,* VANITY FAIR (Sept. 2013), http://www.vanityfair.com/news/2013/09/michael-lewis-goldman-sachs-programmer [http://perma.cc/89SD-RZ8C] (discussing the case of a programmer jailed for allegedly stealing Goldman Sachs' trading algorithm); Felix Salmon & Jon Stokes, *Algorithms Take Control of Wall Street*, WIRED (Dec. 27, 2012), http://www.wired.com/2010/12/ff_ai_flashtrading/ [http://perma.cc/58V6-AFFC]; Tommy Wilkes & Laurence Fletcher, *Special Report: The Algorithms Arms Race*, REUTERS (May 21, 2012), http://www.reuters.com/news/picture/special-report-the-algorithmic-arms-race?articleId=USBRE84K07320120521&slideId=609573702 [http://perma.cc/Y23G-8QXK].

to scan ever-greater volumes of data, and use high finance and computation to better implement their trading strategy.[167]

This systemic proliferation of model risk leads to three basic concerns. In the first instance, markets suffer from profound information asymmetries generated by an incomplete understanding of trading models and the gaps they leave. Trading firms construct individual models that are largely impervious to outside scrutiny. Unless traders make a mistake or cause a glitch in trading, it is unlikely that underlying models will come to the attention of other traders or regulators. Rather, algorithms and their mechanics constitute a trader's prized assets whose protection is assured by laws safeguarding industry trade secrets.[168] In the absence of transparency, assumptions cannot be tested, programming questioned, or outcomes understood through an analysis of the process by which they are generated. To the extent that models in algorithmic trading are designed to predict a future state of affairs, understanding the bases governing these projections is essential to filling in mistakes, correcting forecasts, overfit, and biases, for example. From a broader standpoint, this lack of transparency raises a basic inquiry: given their prevalence and significance for prices, are such model risks and imperfections part of the market information that traders should internalize to achieve optimal efficiency?

Second, the systematic nature of model risk combined with the absence of external scrutiny creates incentives for firms to heighten the complexities and capacities of their algorithms. Errors may follow. Specialist trading outfits invest heavily in developing algorithms and in operationalizing them for trading.[169] To prevent algorithms from going stale, their technology must be maintained, past performance tested, and refinements added to best ensure that firms do not lose ground to competitors. Recent years have seen a pronounced turn to cutting edge technologies like "neural networks," "genetic algorithms," or artificial intelligence as a way for traders to gain an edge in the marketplace.[170] In all, traders deal with an expensive trade-off. On the one hand, they face the constant cost of building, upgrading, and testing

167. FORESIGHT, *supra* note 79, at 132–36.

168. *See, e.g.*, Economic Espionage Act of 1996, 18 U.S.C. §§ 1831–39 (2012); United States v. Aleynikov, 676 F.3d 71, 74–75, 79–80 (2d Cir. 2012); Theft of Trade Secrets Clarification Act of 2012, S. 3642, 112th Cong. (2012).

169. *See, e.g.*, Brendan Conway, *Wall Streets Need for Trading Speed: The Nanosecond Age*, WALL ST. J. BLOG (Jun. 14, 2011, 4:38 PM), http://blogs.wsj.com/marketbeat/2011/06/14/wall-streets-need-for-trading-speed-the-nanosecond-age/ [http://perma.cc/B2CS-3EXY].

170. *See, e.g.*, Kearns & Nevmyvaka, *supra* note 18. While a detailed analysis of these technologies is outside of the scope of this Article, these are discussed in depth in FORESIGHT, *supra* note 79.

their algorithms. On the other, if they do not wish to pay, they confront a starker cost, both reputational and monetary, of leaving the market or diminishing their role in it. Arguably, once capital has been sunk in developing algorithms and building an infrastructure to support them, traders may be more likely to choose the former over the latter. Immediate losses are likely to loom large. In contrast, the cost of future losses is more uncertain.

Third, constant innovations in algorithmic markets heighten model error and information loss already present within a highly automated environment. Errors can arise owing to the very fact of constant model updating and innovation. Errors can also arise because new models are constantly being developed to deal with new types of data and unknown future market circumstances. Within today's heavily automated environment where real-time intervention by human beings is often impossible, markets function as an arena for the real-world testing of predictive algorithms. Errors are probable, even to be expected, given that algorithms are likely to encounter data and market environments that they have not seen before.

In this context, it is questionable whether individual firms fully internalize the costs of algorithm error and testing. The opacity of modeling and the status of algorithms as firm secrets mean that detection costs of any mistake are high. Other firms, exchanges, or regulators are unlikely to investigate unless the errors are of sufficient magnitude to warrant investigation. Low-level, routine errors, mistakes, and glitches may fly under the radar unless the damage they cause is extensive.

Empirically, the study of model risks and their costs for markets is in the early stages, making credible causal links hard to draw. Still, some academics are observing anomalous trading behavior in securities that may be seen as reflecting the challenge of model risks in automated markets. In one notable study, the authors reported a sharp rise in so-called "ultra-fast extreme events," crashes and spikes in the price of securities for instances lasting less than 1,500 milliseconds. The authors noted the occurrence of 18,520 crashes and spikes between the years of 2006-2011.[171] In seeking to explain some of the price fluctuations, Professors Dugast and Foucault examine the trade-off for market players between trading fast on new information and waiting to check the veracity and value of new data. They posit that, particularly when information is cheap, traders often trade twice: once when they

171. Neil Johnson et al., *Abrupt Rise of New Machine Ecology beyond Human Response Time*, NATURE SCIENTIFIC REPORTS (Sept. 11, 2013), http://www.nature.com/articles/srep02627 [http://perma.cc/Q4F7-D6MB].

receive the signal; and a second time when they are better placed to process it more carefully. Price fluctuations, they suggest, can arise from this dynamic of traders moving quickly and then correcting their forecasts over time. Looking more broadly, Professor Frank Zhang notes that HFT algorithms contribute to stock market volatility, particularly in the stock of the top three thousand companies (measured in market capitalization).[172] Zhang suggests that HFTs routinely overreact to news relating to the fundamentals of a traded security when the level of HFT trading in the market is high.[173] These incidences of mini-crashes and volatilities might point to the possibility of errors or uncertainties in programming and the challenges of correcting them in a timely way.[174]

2. Creativity versus Constraint

Traders face a delicate trade-off in designing their algorithms: algorithms must be creative in their ability to react to changing markets while also precisely programmed, predictable, and set within tight parameters that their programmers can control. Put simply, traders need to balance creativity and constraint in algorithmic design.

This trade-off is significant for a number of reasons. Constraint provides a way for traders to provision for their risks and rewards *ex ante*. With clear, preset rules governing their algorithms, traders have a better idea about how their algorithm is likely to transact in the real world and to ensure they are properly prepared. In dealing with a predictive program, ensuring that traders fully understand the potential of their algorithm before using it is of paramount importance. But, creativity is also desirable. Particularly at speeds that are too fast for human reaction, when transactions are underpinned by large reserves of data and computation, algorithms trade independently of their human programmers. Ensuring that algorithms are creative and capable of adapting strategies to real-time trading enables complex, ultra-fast algorithmic trading to take place. Ultimately, the fine lines drawn between creativity and constraint allow firms to understand their liability risks and impact on the market.

Because algorithms are constrained by their programming, their ability to recognize and react to circumstances outside of their instructions is limited. When algorithms contend with input from the market that is unusual, their reactions become much less predictable

172. Zhang, *supra* note 60, at 2–3.

173. *Id.*

174. *Id. But see generally* Brogaard, *supra* note 14 (suggesting that HFTs can reduce volatility).

and more likely to trouble programmers and other traders. Complex language, for example, that includes stylized turns of phrase, irony, or humor presents one such problem.[175] As one study observes, algorithmic traders show themselves as being adept at interpreting "hard" information like facts, figures, and data over softer, more contextual input.[176]

A more significant source of risk lies in dealing with complex economic environments, notably extreme market events, like a crash, shifting geo-politics, or sudden mechanical glitch. Catastrophes are difficult and costly to include in programming. Crises are inherently unpredictable. Their eventual seriousness and scope is similarly unknown. Past historical data, while helpful, is unlikely to offer the certainty needed for algorithms to be able to trade in an orderly way when crises do arise. In such cases, the chances of model error are likely to be especially pronounced. Models might be tested against past data, but they may be particularly prone to fail when confronted by new and abnormal events. Predictive programming faces tall odds in matching preset operations to unexpected, real-world events.

This challenge is exacerbated by algorithms reacting with pre-programmed certainty to situations in which uncertainty is endemic. Professors Biais et al., have observed that traders confront deep uncertainties in times of crisis. When trouble arises, traders must re-evaluate their strategies, re-calculate reserves of available funds, and revise internal risk limits. Overcoming this "preference uncertainty" requires time and flexibility to adapt to an evolving market. Pre-set algorithms are likely to be acutely troubled by such uncertainties, making algorithmic decision-making in crises more unpredictable and prone to error.[177] Crises demand that algorithms be creative. Precisely programmed constraints, however, strain algorithmic competence when it is needed most by the market.

175. Ira Basen, *Age of the Algorithm*, MAISONNEUVE MAGAZINE (May 9, 2011), http://maisonneuve.org/article/2011/05/9/age-algorithm/ [http://perma.cc/DM3G-MEX7] (illustrating this problem with an example from the Washington Post: the print edition headline read "Better Never than Late" when Conan O'Brief left NBC, but online, the Washington Post headline was "Conan O' Brien Won't Give Up Tonight Show Time Slot to Make Room for Jay Leno"); Richard Waters, *Unthinking Algorithms Pull Off Clever Parlor Tricks*, FIN. TIMES (Jul. 30, 2014), http://www.ft.com/cms/s/0/6031dac8-170f-11e4-b0d7-00144feabdc0.html #axzz3o7OfGQ1i [http://perma.cc/CYY4-R8G8]. A full discussion of the limits of artificial intelligence is outside the scope of this Article.

176. Zhang & Riordan, *supra* note 151.

177. *Cf.* Bruno Biais et al., *Equilibrium Pricing and Trading Volume Under Preference Uncertainty*, 81 REV. ECON. STUD. 1401, 1402–03 (2014) (noting the complex, lengthy (and human) process of adjusting positions in times of high preference uncertainty, as in a market liquidity shock).

In emerging studies, the costs of constraint in algorithmic programming are gaining prominence. In a prominent study on the May 2010 Flash Crash, when the Dow Jones fell almost one thousand points in minutes before rebounding, the authors highlighted the challenges posed by algorithmic constraint. On the day of the Flash Crash, the study observed a day of general background stress in the market owing to a variety of factors like the European sovereign debt crisis. When a Kansas-based mutual fund sent an order to try and dispose of seventy-five thousand futures contracts, the fund's algorithm precipitated a market-wide sell-off that rapidly mushroomed into what became the Flash Crash. In its conclusions, the authors did not blame algorithms for starting the crisis. However, they did suggest that algorithms may have contributed to its rapid escalation. When the large order arrived into a market that was already troubled, many HFT traders suddenly exited the market. Unable to cope with the selling pressure, HFT algorithms simply shut down, draining the market of its major providers of liquidity and feeding the negative spiral in security prices.[178] Similarly, in another study, Professors Raman et al., show that, in a comparison between the performances of human versus machine during periods of market stress, human judgment prevailed. With the ability to transact more flexibly, human traders delivered stronger outcomes than algorithmic counterparts. Here, the authors underscore the superior performance of human traders in dealing with complex economic environments to deliver more efficient trading outcomes. Algorithms, on the other hand, suffered likely on account of constraints built into their programming.[179] How generally applicable

178. STAFFS OF THE CFTC AND SEC, *supra* note 23; *see also* Kirilenko et al., *supra* note 85. This conclusion is not accepted by some commentators. For example, the research firm Nanex suggests that the buyers of the mutual fund's contracts acted too aggressively in selling the contracts causing the crash. For discussion, see *May 6th 2010 Flash Crash Analysis: Final Conclusion*, NANEX, (Oct. 10, 2014), http://www.nanex.net/FlashCrashFinal/FlashCrashAnalysis_Theory.html [http://perma.cc/J2P5-36RY]. It should be noted that, in April 2015, the CFTC proposed that the May 2010 Flash Crash may have been precipated by the trading of a disruptive individual trader—Navinder Sarao, a lone trader operating from the United Kingdom—whose manipulative "spoof" orders caused such an imbalance as to have triggered the Flash Crash. For discussion, 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 [http://perma.cc/R9ED-PXHQ].

179. Yadav et al., *supra* note 86 (authors having reviewed the National Stock Exchange in Mumbai, India for their study). *But see* Brogaard et al., *supra* note 14. Brogaard argues that algorithms help in controlling volatility in the market in periods of extreme price stress. Brogaard et al. focus on days on which there is high information in markets—for example, after major announcements—and suggest that HFT algorithms mediate this volatility well. As highlighted by Brogaard and others, algorithms do well in processing short-term information in markets, so it seems to follow that they perform well to control volatility on days when information in the market is high.

their conclusions may be remains to be seen by further empirical investigation. Still, it is at least debatable that the performance of algorithms in crisis raises serious concerns.

From one perspective, it is not rational for traders to spend money on developing programming and models for dealing with market stress. Not only are such events relatively infrequent, but they are also expensive to predict. Historic data is less informative in this context. Crisis events are unique, making programming less durable in its application to multiple scenarios. Programming is likely to require considerable investment for developing the sophisticated, creative systems necessary to cope with crises that come around only rarely. With high costs balanced against the infrequency of market crises, it makes sense for traders to opt for a solution that is predictable and effective. In other words, it is rational for traders to build systems that deal with the worst-case scenarios, with blunt, one-size-fits-all tools that shut down activity and ensure the trader can exit the market as quickly as possible. Traders limit the private costs to themselves, though risks can shift to the market as a whole.

A central question, however, is whether algorithmic programs are able to "discount" or otherwise provision for the possibility of crisis in its programming and the prices at which securities trade. Particularly where markets may be under stress and in crisis, it seems worthwhile asking whether algorithmic programming is able to incorporate this information into trading behavior. On the one hand, algorithms will take their cue from a variety of informational sources and respond to trends and investor expectations. On the other, algorithmic traders can have less at stake in the event that a crisis does strike. Rather than stay on the market to keep trading, a rational response for algorithmic traders is to leave as quickly as events fall outside of normal programming. Where exit is cheap, relative to the market as a whole, it raises questions about the ability of algorithms to properly reflect the risks in the market in the prices at which they transact.

3. Implications for Capital Allocation

This Part highlighted a peculiar dichotomy in algorithmic markets: while automated markets bring efficiencies, helping prices reflect large reserves of information rapidly, they can also generate information loss. Model error on a system-wide scale can leave gaps and create difficulties in adapting to new and unexpected conditions and in forecasting long-term changes in prices.

These sources of information loss are deeply significant for capital allocation and regulatory policies that seek to foster it. First, information loss through model error is pervasive and expensive to mitigate. Conventional theories of market efficiency assume that traders each bring individual slivers of information to the market. Some may be uninformed or trade based on derived data, but their particular trading practices add to price formation by offering insights about investor views and expectations.[180] However, model risks present a costly challenge for investors to overcome despite the informational advantages that individual traders may have. At first glance, it seems at least conceivable that investors might try and deal with gaps in trading models by discounting for the risk of information loss in prices. Investors could analyze common algorithms and question their assumptions and methodology to eventually arrive at a determination of the proper "discounting" to apply. By recognizing the gaps left by algorithms, investors can then undertake the research desirable to fill in the missing pieces of the picture.[181]

Despite the intuitive appeal of discounting for model risks, the task appears decidedly complicated in practice. Not only are trading models tightly-guarded secrets, impervious to scrutiny from outside investors, but their interactions cannot easily be predicted by looking at single algorithms alone. Analyzing just one algorithm is likely to convey little about how that algorithm will transact in the real world when it meets and interacts with others in the market. For example, it is questionable whether a study of one of the market-making algorithms operating during the Flash Crash would have offered any hint of the potential for cascading failure caused by its use in dynamic markets. Investors need to analyze a broad totality of model and algorithms in the market to garner a sense of the systemic errors, biases, and gaps left behind. Clearly, this task presents an impossible hurdle to overcome for single investors if not also for regulators overseeing markets as a whole.

A querying perspective might argue that a failure to discount for model errors should not really matter. Informational efficiencies in the market offer a sufficiently clear idea of the market's view about a particular security, meaning that it is unnecessary to work out the implications of *ad hoc* gaps for the purposes of capital allocation. Despite its appeal, however, this perspective has shortcomings. Model risks are numerous and systematic. It is impossible to deduce which

180. Gilson & Kraakman, *Mechanisms*, *supra* note 24 at 565–57.

181. As the Federal Reserve notes in its guidance, this kind of "discounting" process is a common way to make the stylized operations of models match reality.

ones matter and which ones do not without deeper, empirical analysis. For example, even simple modeling errors may assume outsize importance when they are replicated by many traders in the market, amplifying their impact.[182]

Second, programmers are likely to see greatest predictability when transacting in the very short, rather than long term. Looking further ahead into the future is harder than looking into what is likely to happen in the next few seconds. Model risks may be more endemic to longer-term versus short-term models, requiring longer-term programming to be sophisticated, creative, and adaptive to a multiplicity of moving variables. Still, looking into the future is what matters for capital allocation.

Broadly speaking, capital allocation necessitates meaningful engagement with the inner workings of public companies to understand not just the broad strokes but also the substantive details of their conduct. Calibrating pay for performance, sizing up a hostile takeover, or pushing shareholders to discipline directors require granular engagement in analyzing the minutiae of corporate life. In automated markets, however, programming algorithms to place a value on such long-term fundamentals is expensive and its rewards uncertain. These costs arguably create incentives for traders to concentrate on building short-term trading models. Due to their focus on immediate market movements, short-run algorithms deliver greater predictability and allow traders to better strike the balance between creativity and constraint.

This set of incentives suggests that the gains of rapid algorithmic trading may be skewed in favor of short rather than long-term forecasting. Indeed, empirical studies from finance academics have shown algorithmic markets capable of reacting quickly to emerging, immediate news. How persuasively they also absorb information about longer-term fundamentals, however, remains open to question. HFT traders, driving the bulk of liquidity in U.S. equity markets, have the greatest incentive to understand the information needed for the very short-term future. They react to news that is relevant for driving immediate directionality and not much more, responding to choice words and phrases in disclosures rather than wading through their deep detail.[183] This narrow focus poses concerns for price quality in the context of more fundamental information.

182. *See, e.g.*, Chaboud et al., *supra* note 21 (discussing the correlated trading of HFT traders).

183. *See, e.g.*, *High-frequency Trading: Profiting from News*, WHARTON, UNIVERSITY OF PENNSYLVANIA (Apr. 15, 2014), http://knowledge.wharton.upenn.edu/article/high-frequency-trading-profiting-news/ [http://perma.cc/V8UR-SEL5].

Longer-term traders may have less immediate impact on price formation, which falls within the special expertise of high-speed automated traders.[184] As discussed below, they may only intervene where the prices diverge sufficiently from fundamental value as to justify entering the markets to trade—in other words, where the various transaction costs are less than the possible gains on offer.

Third, it is also worth recalling that algorithmic markets are, in some studies at least, strained under conditions of market stress.[185] Where their programming is unable to react to novel, volatile environments, algorithms can distort price formation. Indeed, as algorithms are able to exit the market quickly, they may fail to properly discount for the possibility of reckoning with and pricing in extreme conditions. When looked at from the point of view of capital allocation, this issue is problematic. Pressures on allocation of capital are usually greatest in periods of market stress. However, just when monitors need prices to be most robust to allow for oversight and discipline, price formation mechanisms in algorithmic markets may be at their most tenuous.

C. The Challenge for Informed Traders

Information losses through model errors create gaps in knowledge for investors. On one level, these instances of information loss represent a boon for the informed, research-orientated investor. By delving deeply into fundamental research, such investors can make reasoned investments and, through their trading, contribute to market efficiencies. However, from another perspective, algorithmic trading also creates costs for fundamental investors. These costs reflect the pressures faced by such investors to adapt to new, highly automated, ultra-fast markets. Investment in technology becomes necessary to interpret growing amounts of data and high-volume order flows. But, more significantly, the rise of order anticipation strategies as well as the ability of HFT traders to capture prize orders quickly across fragmented markets raises a further problematic prospect. Informed investors do the work, but high-speed traders take a cut of their winnings.[186] Where informed investors lose incentives to undertake research, instances of model errors, missing gaps, and perspectives in automated trading go uncorrected.

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184. *See* Yesha Yadav, *Insider Trading and Market Structure*, 63 UCLA L. REV. (forthcoming 2016) (noting the structural advantages that HFTs enjoy in accessing exchange information and in price formation).

185. Yadav et al., *supra* note 86.

186. *See generally* LEWIS, *supra* note 25 (providing a popular account).

1. Anticipating Informed Orders

Algorithmic trading is introducing a potentially costly challenge to informed traders. The speed and sophistication of algorithmic traders generates friction between established, informed, fundamental traders and new algorithmic actors angling to free-ride on their research.

In their taxonomy, Professors Gilson and Kraakman explain efficiency as emerging from the interaction of four basic types of traders: (i) universally informed traders that possess information already circulating with the market; (ii) professionally informed traders that invest in research and private information; (iii) derivatively informed traders that seek out how professionals trade before deciding how best to trade themselves; and (iv) uninformed traders that, in the aggregate, reduce bias through their uninformed but privately opinionated perspectives.[187] This taxonomy has generated considerable commentary in scholarship. Still, it helps in illustrating the larger dynamic driving informed trading and the basic trade-offs motivating each type of actor.

The advent of algorithmic trading, and HFT in particular, reshapes these relationships within the market. Algorithmic markets disincentivize more informed, professional traders from bringing their private knowledge to the market. Usually, these informed actors maximize their gains by trading quickly and forcefully on their private information. The longer they wait, the greater the chances that their information loses value.[188] With their first-mover advantage, professionally informed traders can enjoy an upside. Moreover, they add to efficiencies by infusing markets with their information.[189]

However, HFT actors can erode the first-mover advantage that professionally informed traders have enjoyed. With their technical know-how and high-speed advantage, algorithmic traders are able to free-ride off the information of informed traders through order-anticipation strategies. Free-riding represents a rational trading strategy for algorithmic traders, one that reduces their participation costs and increases trading gains. Algorithmic traders are well-equipped to discover how a professional trader is likely to transact. Recall that order anticipation strategies encompass a variety of techniques. These can include sending out dummy orders to see if any

187. Gilson & Kraakman, *Mechanisms*, *supra* note 24, at 568–88.

188. Brogaard, Hendershott & Riordan, *supra* note 21; Martin Scholtus, Dick van Dijk, High Frequency Technical Trading: the Importance of Speed, Working Paper, 2–5 (2012) (noting that even fifty milliseconds of delay can substantially reduce gains).

189. Gilson & Kraakman, *Mechanisms*, *supra* note 24, at 561–62 ("In the broadest sense, information is data that has the capacity to alter one's beliefs about the world or, in our more limited context, one's beliefs about the appropriate price of an asset.").

match, thereby revealing the existence of a large order.[190] Or, in today's system of fragmented exchanges where securities are listed on multiple venues, an HFT trader can see a large trade on one exchange and run ahead of other traders to capture or sell those same shares on other venues in the system.[191] Speed and technology enable the HFT trader to get ahead of its more informed competitor. When this happens, and the HFT captures the best price, the informed trader might see the market move against her, eroding her gains and diminishing her advantage in the market. These advantages can be meaningful. This is especially likely where an informed trader wishes to transact in a variety of securities in the market, not just the shares of one company, to include options and futures and securities of related companies. Speed and anticipatory intelligence enable HFT traders to purchase substitute securities and to trade them before a professional trader is able to complete her transaction. For the HFT, this move captures the informed upside and reduces further gains that might accrue to professionals.[192]

Indeed, order anticipation may be a systematic strategy adopted by some HFT traders. In one intriguing study examining HFT trading in the E-mini futures market, Professor Clark-Joseph notes that strategic order anticipation can provide consistent gains. In a sample of 30 HFT traders, Clark-Joseph observed eight traders earn profits on their aggressive orders in the markets. However, each of these eight firms also lost money on their smallest aggressive orders, suggesting that these small orders provided some informational "exploratory" insight into the likely future direction of demand and market prices. By obtaining private information through aggressive exploratory orders, HFTs traded when their forecasted gain was large enough to justify

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190. It is worth noting that almost ninety-five percent of limit orders on NASDAQ are cancelled within one minute of being placed. The tactics might relate to other types of trades like quote-stuffing or wash trades, rather than those motivated to seek out hidden liquidity. *See generally* Nikolaus Hautsch & Ruihong Huang, *The Market Impact of a Limit Order*, 36 J. ECON. DYNAMICS & CONTROL 501 (2012) (noting that a large number of cancelled orders can showcase their importance as a means of deducing likely hidden orders in the market). *But see* Robert J. Jackson, Joshua Mitts & Wei Jiang, How Quickly Do Markets Learn: Private Information Dissemination in a Natural Experiment (2014) (unpublished manuscript), http://ssrn.com/abstract=2544128 [http://perma.cc/58X6-ZY4Y] (study observing that HFTs can take longer to process fundamental information versus information with news value).

191. *See generally* LEWIS, *supra* note 25 (providing a fictionalized account of Wall Street experts who seek to reform financial markets by eliminating the advantages HFT traders currently enjoy).

192. Robert Jarrow & Phillip Protter, *A Dysfunctional Role of High Frequency Trading in Electronic Markets* 3–6 (Johnson Sch. Research Paper Series, No. 08-2011, 2011) (describing predatory and front-running strategies between HFT and other fundamental traders).

aggressively entering the market.[193] In another study analyzing the impact of machine traders on transaction prices, Professors Cvitanic and Kirilenko posit that transaction prices increase when a machine enters the market. This price increase, they suggest, is unrelated to a change in the fundamentals of the security and represents instead a reflection of the machine trader picking off or "sniping" orders from the top of the order book.[194]

One can argue, of course, that fundamental investors will remain committed to the market. Put differently, if they really wish to buy and sell securities for a long-term investment, they will do so anyway. The fact that the HFT might take some of the advantage may be a small price to pay. HFT also appears to have reduced the costs of trading for investors by supplying ready liquidity and reducing the fees attaching to trades. This suggests a trade-off. Losing out to speedy traders is a transaction cost, offset by the gains of a liquid, cheap market. And indeed, some studies contest the negative effects of HFT on fundamental traders, arguing that there is little evidence they are being harmed.[195]

But other commentators have voiced considerable alarm at increased participation costs that long-term investors contend with in HFT markets. In one study of institutional trades in 120 stocks, the author estimated that the average institutional investor was paying an additional ten thousand dollars per day or more in transaction costs because of HFT. The study suggests that these costs are higher on days when institutional investors are large net buyers or sellers of a security, implying that HFT activity increases in intensity when institutional investors enter the market as large traders in a particular stock.[196] Citing these costs, a number of major investors have sought to take

193. Adam D. Clark-Joseph, Exploratory Trading 3 (Jan. 13. 2013) (unpublished manuscript) http://www.nanex.net/aqck2/4136/exploratorytrading.pdf [http://perma.cc/K5B3-RRRM].

194. Jaksa Cvitanic & Andrei Kirilenko, High Frequency Traders and Asset Prices 3, 14 (Mar. 2011) (unpublished manuscript) http://ssrn.com/abstract=1569067 [http://perma.cc/8KHA-HC7L].

195. For a review of the emerging literature on the costs of HFTs to retail and institutional investors, see U.S. SEC. & EXCH. COMM'N, *supra* note 69, at 29–31.

196. Lin Tong, A Blessing or a Curse? The Impact of High Frequency Trading on Institutional Investors 2–5 (Oct. 2015) (unpublished manuscript) http://ssrn.com/abstract=2330053 [http://perma.cc/5E2Y-MT7J]. From an investor perspective, see Sal L. Arnuk & Joseph Saluzzi, *Toxic Equity Trading Order Flow on Wall Street*, THEMIS TRADING 2 (Dec. 2008), http://blog.themistrading.com/wp-content/uploads/2009/01/toxic-equity-trading-on-wall-street-final.pdf [http://perma.cc/5KQN-U6XW] (arguing that investors are front-run by predatory HFT traders); *see generally* Lewis, *supra* note 25 (arguing that the market is rigged); *see generally* PATTERSON, *supra* note 43 (describing the rise of artificial intelligence systems for securities trading and their effect on the global market).

their business to trading venues free from competition from HFT traders.[197]

To be sure, HFT traders face costs in pursuing aggressive strategies.[198] They must have sufficient capital immediately on hand to move ahead of informed traders, alongside the technology necessary to best competitors. Yet, these costs are more than matched by the potential gains. Not only can HFT traders send out volumes of dummy orders at little private expense, but they also enjoy subsidized access to intelligence in the market. Without having to invest in information collection and its analysis, all the while benefiting from the gains that accrue, HFT traders can vastly improve their bottom line. From one perspective, they increase welfare gains by contributing to value efficiencies. Through their activities, private information arrives quickly into the market, more amplified in its impact than if the informed traders were the only ones transacting.

However, the success of algorithmic traders creates serious challenges for informed professionals. Constantly out-raced, fundamental traders lose money over time. This raises the prospect of fundamental traders waiting to make their important trades only when they are sure that their gains are likely to offset potential losses to HFT traders and others faster in the market.

In this context, fundamental traders may trade less often. They may only trade when they have "big" news that is likely to generate a significant profit, justifying transaction costs and losses to HFT traders. Such informed traders may fail to trade on less significant, less valuable information. Over time, this disengagement might lead informed traders to either leave the market entirely or to transact on less transparent venues.[199]

With their profits reduced, information traders lose incentives to participate meaningfully in the market. They can also end up with weak motivations to invest in research and analysis of existing data. With smaller budgets for research, the credibility of information traders can also diminish. Eventually, as this dynamic plays out, algorithmic traders can end up plumbing informational reserves that are actually much shallower. Information in the market that emerges from this

197. Stephen Foley, *Big Fund Investors Form New Dark Pool Trading Venue*, FIN. TIMES (Jan. 19, 2015), http://www.ft.com/intl/cms/s/0/372de622-a034-11e4-aa89-00144feab7de.html#axzz3o7OfGQ1i [http://perma.cc/4CJR-Z68C] (discussing a trading venue made to respond to the emergence of HFT traders).

198. It should be noted that some studies argue that the market is more liquid because of HFT market-makers. For discussion, see Tong, *supra* note 196, at 3–4.

199. *Id.* at 2 (noting that institutions may move to trade off-exchange on so-called "dark pools"). I discuss the implications of dark-pools in Section IV.2.

interaction may be further away from fundamental value that benefits how markets allocate capital in the economy.

Professional traders might actually face a quite perverse temptation. It makes sense for informed traders to accumulate low-quality intelligence to make gains where they can, knowing their margins are likely to grow thinner over time. As more traders grow motivated to disengage, understanding what their trading means and its significance for capital allocation becomes an increasingly difficult task.[200]

2. Implications for Capital Allocation

The costs of algorithmic trading on informed traders re-cast the conventional dynamics underpinning market efficiency, as described by Gilson and Kraakman. In their classical account, professional, informed traders provide the driving energy for efficient markets. Their research and insights percolate through markets as derivatively and lesser-informed players seek to follow their lead.[201] With prices reflecting fundamental information, markets can function more effectively as reliable allocation mechanisms for capital.

In algorithmic markets, informed traders are giving away some of their first-mover gains to "derivatively" informed HFT traders. Derivatively informed traders can make gains through their faster trading speeds. They also gain by freeriding on the research of specialist informed traders. Rather than expend capital on necessarily undertaking their research, derivatively informed anticipators can maximize gains by investing in even faster, more accurate order anticipation machinery.

These dynamics have implications for long term capital allocation in markets. This Article has highlighted the information losses arising from model errors and their impact on the ability of investors to understand market fundamentals. Diminished gains for informed traders in algorithmic markets can reduce their incentives to deeply analyze the shortcomings of modeling uncertainties and to fill in informational gaps. Alternatively, fundamental traders may perform this function only when the gains from doing so exceed a monetary threshold that justifies the capital expended, making such gap-filling *ad hoc*. Interestingly, algorithmic order-anticipators are well-positioned to analyze and correct for modeling errors in the marketplace. They

200. In finance theory, see Zhang, *supra* note 60, at 12 (arguing that HFT makes markets drift further from fundamental values).

201. Gilson & Kraakman, *Mechanisms*, *supra* note 24, at 568–88.

have an insider's advantage regarding state-of-the-art development of models and the strategic behavior of expert, algorithmic traders. However, specialist algorithmic traders, notably those transacting at high speeds, have little motivation to correct for fundamental informational gaps. Their horizons lie in the immediate future rather than extending meaningfully into the future. On this basis, they are unlikely to have strong incentives to utilize their knowledge to mitigate some of the costs of using algorithmic models systemically in the market.

This line of argument leads to further issues for capital allocation. When fundamental traders face high, long-term costs in algorithmic markets, either through investing in technology or order-anticipation, their motivation to invest in oversight of capital may diminish as a result. Undertaking monitoring and discipline of listed companies imposes its own costs. Shareholders seeking to discipline management confront a multitude of transaction costs beyond monitoring managerial performance. Developing a strategy for intervention, engaging advisors, organizing action, and implementing a plan demands investment from engaged shareholders. If informed traders confront lower returns, they may be less willing to invest in meaningful governance.

There may, however, be an alternative argument. That is, investors may become more circumspect about how they exercise oversight of capital flows. Rather than staging potentially frivolous or speculative actions, informed traders may seek to calibrate their interventions more finely to have the greatest impact. Exercise of discipline through the market for corporate control or through shareholder actions may grow more effective as investors weigh the costs trading against the benefits of exercising oversight of capital in the market.

With this emerging evidence, classical accounts of allocative efficiency and informed trading merit re-evaluation. Broader reflection in this regard is necessary not only for understanding informational gaps in markets and how these affect capital but also for developing better regulatory policies about how capital should be governed.

V. CONCLUSIONS: PATHWAYS FOR POLICY

Thus far, this Article has demonstrated that algorithmic trading problematizes a governing principle underlying regulation: informational efficiency begets allocative efficiency for capital. With the rise of automation, the straightforward relationship between informational and allocative efficiency is in trouble. With systemic reliance on pre-programmed models and a changing, costlier climate for informed investors, traditional paradigms underpinning allocative efficiency are growing weaker, even if markets are more informative on some measures, especially in the short-term. This decoupling of informative and allocative efficiency raises difficult questions for regulators. There are no obvious or easy solutions, especially as the connection between information and allocative efficiency runs deeply and pervasively throughout regulation.

Policy has long looked to market prices as a guide to matters of allocation, to foster rules and regulations that create a robust environment for overseeing those that use investor capital. Now, however, the theoretical basis for these rules is no longer self-evident. This Article does not aim to outline a new, normative framework for the raft of rules that depend on the allocative efficiency of markets. Rather, its goal is to highlight the problem that regulatory policy now confronts. In looking forward, it is worth concluding with some observations about pathways for modernizing traditional ways of conceptualizing capital markets regulation to reflect the increasing automation of today's markets.

A. Forging Better Incentives for Efficiency

Conventional accounts of efficient markets recognize that private incentives drive traders towards the realization of a public good. In other words, the motive of individual traders to profit from private information or from the valuable information of other traders eventually leads markets towards efficiency. Regulation has generally sought to help these incentives flourish. Mandatory disclosure aims to make information available to traders cheaply. A National Market System encourages traders to enter markets to trade, lowering their costs of participation.

As this Article shows, the usual force of these incentives is shifting in automated markets. Informed traders are seeing their gains eroded by HFT firms and competitive pressures, potentially reducing their incentives to invest in fundamental research.[202] In the meantime, algorithmic markets motivate traders to expend capital in increasing the speed and computational prowess of trading systems to enhance the effectiveness of order anticipation strategies.[203] Laws have become the unintended facilitators of these incentives to favor derivatively informed traders over fundamentally informed counterparts.

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202. *See* discussion *supra* Section III.C.2.

203. *See* discussion *supra* Sections III.C.1–2.

Mandatory disclosure rules prime HFT algorithms to react to high-impact words and phrases for short-term trading. When gains may be made by deducing the immediate directionality of markets, rewards from more fundamental, expensive analysis seem less compelling. In addition, commentators note, NMS helps order anticipation strategies to flourish. When traders can travel rapidly between exchanges in search of the best order and search multiple exchanges for insights from informed traders (e.g. through pinging), NMS appears to offer a helping hand to derivatively informed anticipators.[204] In the aggregate, these dynamics can eventually reduce the reserve of substantive, well-reasoned intelligence at a cost to investors and market welfare as a whole.[205] In other words, private incentives to collect information may no longer be as profitable and persuasive as they once were. Private gains from trading may no longer translate as fully into the public good of allocative efficiency.

If achieving allocative efficiency remains the goal of regulatory policy, then its realization may be growing more difficult in algorithmic markets. This calls into question the assumptions undergirding current regulations and demands a fundamental rethinking about how regulation may be better structured to incentivize research by informed traders.

There are, to be sure, no easy solutions to the conundrum of incentivizing informed traders to enter markets when they face costly pressures to compete with HFT. For example, policymakers could curtail the ability of HFTs to send out small "exploratory orders" that signal an order anticipation strategy at work.[206] But, this approach is far from ideal—or even workable. For one, order anticipation by itself is not a prohibited practice.[207] Speculating about the direction of future orders constitutes a normal part of trading, one that is almost impossible to limit for all practical purposes. It is also questionable whether limiting the operational efficacies of order anticipation is desirable. Given that scholars have extolled the benefits of HFT for

204. *See, e.g.*, Clark-Joseph, *supra* note 193; Hirschey, *supra* note 60, at 1–2 (arguing that the high speed of HFT trading and its resulting capture of informed traders' profits disincentives informed traders from investing their time in in-depth research).

205. *See* discussion *supra* Section III.C.2.

206. *See* Clark-Joseph, *supra* note 193, at 3 ("[T]he private information about price-impact generated by an HFT's small aggressive orders enables [her] to trade ahead of predictable demand . . . .").

207. Order anticipation must be distinguished from front-running. Front-running is prohibited. In front-running, a broker trades for her own account with knowledge of a pending block transaction from a client likely to move the price of securities. FINRA, *Rule 5270: Front Running of Block Transactions*, FINRA MANUAL (May 30, 2012), http://finra.complinet.com/en/display/display_main.html?rbid=2403&element_id=10860 [http://perma.cc/9LPB-SXTA].

liquid trading, with easy entry and exit for investors, a cost on HFT strategies is likely to face resistance from all corners of the market, not just from the HFT traders themselves.

A check on the actual speed and flow of trading offers another mechanism to help coax informed fundamental traders back to the market. High-speed markets often reward the fastest trader off the block. With a premium placed on speed, rather than knowledge, traders possess powerful incentives to invest in the technology and infrastructure needed to gain an edge on time vis-à-vis other traders. Professors Budish, Crampton, and Shim argue, for example, that a race based on speed alone is, for all intents and purposes, socially wasteful and, according to the authors, a poor practical fit for the market. They offer a trading model that requires traders to send orders out in batches, not continuously. With traders forced to bundle orders for trading, their idea lies in slowing down and organizing order flows.[208] Arguably, within this more controlled environment, informed traders can re-assert their pre-eminence, freed somewhat from the pressure to constantly compete on technology and speed.

Curtailing speed, however, also has its problems. In moving forward with reform, regulators are likely to struggle with some basic questions. How fast is too fast? Should the market punish traders that innovate on speed and communication technology, an idea largely alien to markets that have traditionally encouraged traders to come to markets quickly with private information? And, will slowing markets cause its own problems, for example, by forcing traders into unregulated venues and markets at home and abroad and reducing liquidity on public exchanges?

Finally, regulators may wish to ask whether informed traders can benefit from more regular access to information from a reformed mandatory disclosure regime. Theory posits that mandatory disclosure helps informed investors to reach private information cheaply. By accessing large reserves of information at low cost, fundamental investors might better engage in research and analysis in relation to the data that they receive. In automated markets, where informed traders stand at a disadvantage to faster firms, expanding access to information can offer a path forward that ultimately rewards informed investors. With more information received more frequently, informed

208. Eric Budish, Peter Crampton & John Shim, The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response 37 (Feb. 3, 2015) (unpublished manuscript) http://faculty.chicagobooth.edu/eric.budish/research/HFT-FrequentBatchAuctions.pdf [http://perma.cc/7HLE-KZ5G] (announcing the adoption of new rules intended to "ensure that financial markets are safer as well as more efficient, investors are better protected, high-frequency trading is regulated and speculative commodity trading is curbed").

traders can carry out regular analysis and research into public companies. To achieve this, a reformed regime might require that mandatory disclosures take place more frequently. Information may be disclosed in small segments at more regular intervals to supply a flow of data to inform all traders. With their superior analytical skills, informed traders should be well placed to transact with an in-depth understanding of available intelligence.

This solution, too, is not without its problems. Critically, it imposes a high cost on listed companies to supply regular disclosures to the market. To solve the problem of allocative efficiency, such a reform diverts the burden from traders to public companies that are forced to reveal more and internalize liability for poor and inaccurate disclosures. There is also little to suggest that such reform will necessarily produce better analysis. Rather than offering a holistic picture of significant data to markets, frequent disclosures might generate useless puffery, noise, and extraneous detail that are not relevant for fundamental trading.

B. Model Transparency

Alongside the costs to informed traders, regulators confront pervasive challenges in interpreting and understanding the trading algorithms that drive securities trading. Relying on advanced, pre-programmed algorithms, markets face the risk that predictive trading processes leave analytical gaps, make poor assumptions, or are restricted by their programming in dealing with real-world markets. Moreover, algorithms are unique to individual traders and constitute tightly guarded secrets, making it costly for investors to understand the frailties of modeling for the purposes of provisioning for them in trading.

The question for regulators is whether to invest in remedying model risk in some way. This first requires policymakers to determine whether system-wide model risks are sufficiently serious for capital allocation and governance to warrant attention. This Article argues that model risks, given their pervasiveness in today's markets, can influence how information is collected and processed in prices. However, there is another perspective. It is arguable that model risks are not new, and that today's algorithms merely represent electronic versions of secret theories and methods long a part of finance. If those risks have been left for markets to control privately, then concerns about algorithmic model risks should be similarly set aside. There is considerable appeal to this view, and the line between manual and algorithmic trading methods is certainly a blurry one. However, model risks still present regulators with novel considerations for the purposes of allocative efficiency.

For one, investors today face far higher costs to decipher the basis on which algorithms devise their transactional decisions. As discussed in the Article, the computational power of many algorithms is without precedence, not only in terms of speed but also with regard to statistics, quantitative analysis, and the volume of data collection. These sophistications place costly demands on investors seeking to decipher what is missing from the market in order to contribute to its informational reserves. Presumably, investigating algorithmic model risks and blind spots eats into the time and money that informed investors already face. Indeed, these costs are probably prohibitive given the secrecy and complexity of algorithms. In this context, simply presuming that investors will decide how best to regulate modeling risks is unsatisfactory. Further, given that informed investors have traditionally been relied on to supply the market with intelligence and also to extract intelligence for the purposes of capital allocation, this gap is problematic for the market as a whole.

Also, as a theoretical matter, allocative efficiency has generally concerned itself with reflecting information about fundamental value in prices. Clearly, this goal is an ambitious one, as fundamental values are, for all intents and purposes, impossible to achieve. However, looked at from the longer-term perspective, algorithms are useful for demystifying the dynamics of efficiency. With knowledge about the models that are used, swaths of electronic trading data and knowledge about the performance of securities, models offer a way to test our hypotheses about efficiency. In other words, considered from a wider lens, the rise of algorithmic trading has the potential to unravel the market's operations like never before. Trading models showcasing the assumptions, parameters, and valuation techniques combined with the data generated by their operation offers a way to examine how traders interact in the real world and the product of this dynamic. Certainly, models are predictive. Their performance may deviate from the expectations of their human traders. However, their workings can still offer insight into the economic and social welfare potential of markets and trading. This learning also offers a way for traders to improve their models and algorithms—and with this, it is conceivable, the better allocation of capital within the economy.

These benefits point to the advantages of bringing greater transparency to the models underlying algorithmic trading. Openness can encourage both an appreciation of the major model risks in trading and help regulators and traders to track the performance of algorithms in the market. Regulators have expressed a desire to scrutinize algorithms as a way to prevent disruptions like the May 2010 Flash Crash. However, their attention remains fixed on market stability, rather than also delving into how algorithms relate to issues of informational and allocative efficiency.[209] Looking forward, it is apt to also examine the feasibility of bringing transparency to algorithmic trading and the manner in which to frame the goals transparency is designed to achieve. Pushing for openness in algorithmic trading will prove a challenge. Put simply, algorithms constitute the prize intellectual property of their programmers and any attempt to reveal these secrets will invariably prompt deep resistance. By way of seeking to balance the demands of traders with the welfare goals of ensuring allocative efficiency in securities markets, regulators will benefit from developing strategies for transparency. For example, traders may disclose their algorithms and models to regulators only. With a compendium of the key algorithms and models in the market, regulators may be well placed to consider some of the information gaps and losses arising out of their collective use. Such general analysis can offer insights, benefitting not just information investors but also traders themselves. As traders innovate, without full knowledge of each other's algorithms in the market, gaining an understanding of the evolution of their common behavior becomes helpful for regulators. In this way, informational efficiencies can come closer to the aspiration of optimal allocative efficiencies in the market.

VI. CONCLUSION

In summary, algorithmic trading has transformed securities markets. It brings many advantages but also imposes serious costs on the major function that securities markets perform: allocating capital efficiently and productively across the real economy. The entrenchment of model risks across the marketplace and pressures on informed investors risk skewing the gains of algorithmic trading in favor of short-term and more cheaply researched information. The implications for regulation are far-reaching and profound, given the extensive reliance that lawmakers and market actors place on prices as a proxy for allocative insights. This Article represents a first step in drawing into relief the significance of algorithmic trading for capital allocation. Its ultimate goal lies in motivating deeper reflection about the prime place of securities prices at the center of regulation and how best to invest

209. *See, e.g.*, Press Release, European Parliament, MEPs Vote Laws to Regulate Financial Markets and Curb High Frequency Trading (Apr. 15, 2014) http://www.europarl.europa.eu/news/en/news-room/content/20140411IPR43438/html/MEPs-vote-laws-to-regulate-financial-markets-and-curb-high-frequency-trading [http://perma.cc/6Y3M-E5TC].

regulatory resources in making markets meaningfully informative. With markets set to grow ever more automated, this represents a critical question for regulators building markets and the rules that govern them for the present and the future.