A Sociology of Algorithms: High-Frequency Trading and the Shaping of Markets

Donald MacKenzie

February 2014

First draft

Author's Address:
School of Social and Political Science
University of Edinburgh
Chrystal Macmillan Building
Edinburgh
EH8 9LD
Scotland
D.MacKenzie@ed.ac.uk

ABSTRACT

Increasingly, financial markets themselves and most actors in them are algorithms. Drawing on 39 interviews with practitioners of fully automated high-frequency trading (HFT), and a wider historical–sociology study of the development of trading venues, this paper investigates the practices of HFT and how they differ in three different contexts (two types of share trading and foreign exchange). It discusses how linkages among the ecologies (in Abbott's sense) of HFT, of trading venues, and of regulation have shaped the development of HFT; how past events continue to shape HFT practices; and how some venues practice "Zelizerian" boundary-work, e.g. seeking to differentiate "good" from "bad" algorithms.

INTRODUCTION

What becomes of economic sociology when markets and most participants in them are computer algorithms? That is now the case for many financial markets, such as in U.S. shares and U.S. and European futures. Drawing on NASDAQ data from 2007-08 ─ a long time ago, given the pace of technical change ─ Hasbrouck and Saar (2010) depict a "millisecond environment" dominated by agents that they suggest can only be machines: they find patterns of activity that indicate that those agents react to market events in as little as two to three milliseconds, a hundred times faster than the fastest human. Analyzing data from multiple exchanges for 2006-11, Johnson et al. argue that a transition has taken place from a "mixed human-machine" environment to an "all-machine ecology" in which "machines dictate price changes." They identify large numbers of very short time periods — many too short for human beings to intervene — in which prices crash or spike (by ± 0.8 percent or more) and then recover. A crash or spike that, for example, lasts only 25 milliseconds must, they infer, be machine-driven (Johnson et al. 2012, pp. 5 and 10).

Such claims are suggestive rather than definitive: as will be discussed below, there are difficulties in establishing even basic empirical facts such as the relative proportions of trading for which human beings and algorithms are responsible.[1] Nevertheless, there is persuasive evidence that some (but by no means all) financial markets have now moved into the third of three broad configurations:

[1] The term "algorithm" is used in the sense in which interviewees use it, to refer not just to a set of instructions that is sufficiently precise to be turned into a computer program but to that program running on a physical machine and having effects on other systems.

1. Market actors are all human beings, and "the market" involves direct interaction among human beings.
2. The market is an algorithm, but the actors remain mostly human beings; they interact with the market via computer screen, keyboard and mouse.
3. The market is an algorithm, and most actors in it are also algorithms.

Nearly all existing sociological studies of electronic trading (e.g., Zaloom 2006; Preda 2009a and 2013; Saavedra, Hagerty, and Uzzi 2011) are of the second configuration or of the remaining human actors in the third configuration. The existing literature contains only glimpses of the third configuration: what Knorr Cetina (2013) calls "the interaction order of algorithms" remains largely opaque to economic sociology.[2] The most extensive — but still relatively brief — empirical discussion is Lenglet's (2011) ethnographically-based examination of the use in a brokerage firm of the "execution algorithms" discussed in the third section below, and of the resultant issues of regulatory compliance. There is a nascent sociological literature on algorithms more broadly (see, e.g., Mackenzie 2006; for a fascinating study of one particular algorithm, see Poon 2007 and 2009), but again there is a tendency to focus on algorithms with which human beings interact directly, such as the PageRank algorithm in Google (see, e.g., Hillis, Petit, and Jarrett, 2013).

Clearly, Latour and Callon's "actor-network theory" (see, e.g., Latour 2005) and Callon's actor-network economic sociology (e.g., Çalişkan and Callon 2009 and 2010) must apply to markets in which most actors are algorithms. Actor-network theory is prepared to apply the term "actor" to non-human entities such as

[2] Muniesa (2003, pp. 305-307) describes the use of algorithms to trade at the close of trading on the Paris Bourse; Beunza and Stark (2004, pp. 393-396) discuss the use of "robots" (statistical arbitrage programs that most likely implemented their trades automatically); Preda (2013, pp. 41-43) discusses human traders seeking to identify the traces of algorithms in market data.

algorithms, and this reminds us that it would be a mistake to treat trading algorithms simply as the delegates of human beings. As Adrian Mackenzie notes, "[a]n algorithm selects and reinforces one ordering at the expense of others" (2006, p. 44), but that ordering may not be the one its human programmers intended. Unexpected behavior by trading algorithms has led to well-publicized disasters, such as the $440 million loss incurred in 45 minutes by Knight Capital on August 1, 2012.[3] Human users of algorithms may not always accurately understand even their routine behavior:

> [S]omeone could be in all honesty saying [their algorithms are] doing [something] when in fact they are doing something else: they're just not measuring it right. (Interviewee AP)

However, to develop a sociological analysis of automated trading it is necessary to go beyond generic actor-network considerations to more specific matters. Amongst the best sociological work on the relationship between "markets" and "technologies" is that of Knorr Cetina and Preda, who distinguish between two broad architectures that correspond roughly to the first two of the three configurations sketched above:

1. A "network-based architecture" in which "coordination emerges from passing things through the pipes that link the network nodes" (Knorr Cetina and Preda 2007, p.116). Preda (2006), for example, has shown how one such "pipe" ─ the stock ticker, a telegraph-style device that

[3] It appears that an algorithm used by Knight did not process incoming messages recording the execution of its orders as its programmers had intended. The algorithm thus kept submitting repeat orders, leading to the accumulation of huge unintended trading positions. Knight's human staff seem initially not to have been able to switch the algorithm off.

relayed in close to real time the prices at which shares had been bought and sold and the number of shares transacted ─ reshaped stock markets.

2. A “flow” architecture or “scopic mode of coordination,” based on “collecting and ‘appresenting’ things simultaneously to a large audience of observers,” especially via computer screens, and “assembl[ing] on one surface dispersed and diverse activities, interpretations and representations which in turn orient and constrain the response of an audience” (Knorr Cetina and Preda 2007, pp. 116 and 126).

The form of algorithmic trading on which I focus here — high-frequency trading or HFT — operates at speeds beyond human capabilities. “If you’re sending [market data] to a human,” you have to slow it down, said an interviewee, because otherwise it becomes an uninterpretable blur on screen: “you can’t see it.” As Knorr Cetina (2013) suggests, algorithmic trading therefore in some respects undermines “scopic coordination,” but the new architecture of which it forms part is only beginning to attract the attention of economic sociologists.

That much algorithmic action has effects that human beings “can’t see” has given rise to much suspicion of and hostility to HFT. As Preda (2009b) points out, the observability of financial markets has historically been tied to the establishment of their legitimacy. As stock markets were bounded off and framed as legitimate institutions, and as a boundary was drawn between “gambling” and “investment,” finance was often legitimated as a domain in which “success should be ensured by constant and diligent observation” (2009b, p. 20). So how can one legitimate a domain that sometimes seems no longer observable, at least not to those without specialist algorithmic equipment? Does HFT create “a treacherous market ruled by machines” (Anon. 2010)? That is not simply a question of external legitimacy but of internal controversy. As will be seen below, even those who run trading venues on which HFTs operate sometimes adopt a denunciatory tone. They sometimes seek to exclude them, to place barriers in their way, and to perform what, following Geiryn (1999), can be called “boundary-work.” As Zelizer (2012, p.145) observes:

> In all economic action … people engage in the process of differentiating meaningful social relations. For each distinct category of social relations, people erect a boundary, mark the boundary by means of names and practices, establish a set of distinctive understandings that operate within that boundary, designate certain sorts of economic transactions as appropriate for the relation, bar other transactions as inappropriate…

For example, some trading venues seek to differentiate between what they see as (in effect) “good” and “bad” algorithms, and how they do so resonates with efforts within HFT to delineate a sphere of unproblematically legitimate algorithmic action and separate it off from other forms of HFT. Strikingly, even in these modern, competitive markets, firms whose trading algorithms make too much profit can find themselves expelled from trading venues or electronically stigmatized as “opportunist.”

Trading venues are the most immediate environment within which HFT algorithms act. It is difficult — though not entirely impossible — for them to act unless markets have themselves become algorithms, in other words unless the meeting of demand and supply and the consummation of deals takes place within a computer system. How that has happened historically has begun to be investigated by sociologists: see Muniesa (2003 and 2005) on the automation of the Paris

Bourse, Pardo-Guerra (2010a and 2010b) on the London Stock Exchange, and Beunza and Millo (2013) on the New York Stock Exchange. The key argument in this literature is laid out most clearly by Muniesa (2011), who conceptualizes the mechanization of a market as a process of "explication" or (in the terminology of Deleuze 1990) of "expression." Mechanization, Muniesa argues, is not "the laborious unveiling … of something that is already there, implicit," not for example simply the direct translation of existing human processes into software. Instead, it is "a creative, performative, generative, provocative process" (Muniesa 2011, p. 2). There are different ways to turn a market into an algorithm, and the choices involved ─ including the apparently "technical" choices ─ are sometimes fiercely contested, and often highly consequential: the development of automated markets exhibits "sequence effects" (Abbott 2001, p. 286 and passim.) and path-dependencies (Arthur 1984, David 1992). Past choices ─ sometimes reflecting very specific, local priorities ─ facilitate and constrain present possibilities. This implies that an adequate sociology of HFT and other trading algorithms must be a historical sociology: it must examine not just current practices but the past choices and events that shape them.

That historical sociology turns out also to have to be a political sociology in the sense of Fligstein (1996 and 2001). "Markets are politics," as Fligstein argues. The sociotechnical "structures of markets" are indeed frequently "attempts to mitigate the effects of competition with other firms" (Fligstein 1996, p. 656), and incumbent market participants have typically either resisted the automation of financial markets and the emergence of HFT, or sought to shape automation so as to minimize the threat it poses. "[S]tates play an important role in the construction of market institutions," as Fligstein (1996, p. 600) notes: for example, as will be shown below, the operations of HFT algorithms trading U.S. shares are strongly shaped by the legacy of the efforts of a government regulatory body, the Securities and Exchange Commission (SEC), to reform share trading.

A natural vocabulary for the necessary historical sociology of HFT is offered by Abbott's (2005) "linked ecologies."[4] An "ecology," in Abbott's sense, is a domain "best understood in terms of interactions between multiple elements that are neither fully constrained nor fully independent." In an ecology, "the elements constrain or contest each other," rather than behaving in an entirely atomistic way or their bevavior being fully determined by a social structure or technical system (Abbott 2005, p. 248). That, we shall see, is a good characterization of high-frequency trading as a technical sphere: its elements (algorithms) interact directly with other algorithms and indirectly with each other, rather than acting in isolation or being parts of a unified technical system. "Ecology" also captures well the characteristics of HFT as a *socio*technical domain. HFT firms (which are typically small, privately-held proprietary tracking firms, essentially combinations of people, significant but not huge amounts of capital, algorithms, and computer and communications hardware) jossle for what Abbott calls "locations," for "things [they] are attempting to control" (Abbott 2005, p. 250): here, for market share and sometimes also for legitimacy.

[4] Another candidate vocabulary would be that of "fields," developed by Bourdieu and now widely employed in U.S. sociology (see, e.g., Fligstein and McAdam 2012). Abbott (n.d.) suggests that Bourdieu's "fields" have too fixed a topology, and if that were an intrinsic feature of conceptualization in terms of "fields," it would render that conceptualization unsuitable here, because, as discussed below, the topology of the ecologies of HFT and market venues is not fixed. It is not clear that a fixed topology is intrinsic to analysis in terms of fields, but Abbott's model has been chosen here because of his explicit rejection of fixed topologies and the appropriateness here of his concept of a "hinge."

Crucially, however, HFT is a *linked* ecology, one of a set of ecologies "each of which acts as a (flexible) surround for others" (Abbott 2005, p. 246). As already suggested, HFT is linked to the ecology of trading venues (and again "ecology" is an appropriate conceptualization: there are multiple trading venues in each of the main domains of automated trading, and they too compete for both market share and legitimacy) and to the ecologies of regulation — both formal, government regulation and private regulation by the big banks. None of these spheres entirely encloses the others without itself being enclosed by them. Regulation, say, might appear to be external to HFT and to trading venues, but it is not. For example, the single most powerful regulator of the trading of U.S. shares is the SEC, and in the 1975 Securities Acts Amendments it was tasked by Congress with linking U.S. share trading venues in such a way as to enhance competition. However, for twenty years the SEC made little real progress, until initially unrelated developments in trading venues (developments that were linked in their turn to the emergence of HFT) facilitated its task. The development of algorithmic trading was not the result of social-structural or technological determinism, but the emergence of one of Abbott's "hinges": "strategies that work" in more than one ecology (Abbott 2005, p. 255). A "hinge" is not necessarily an alliance between actors in different ecologies. Here, it is a set of developments that, largely inadvertently, linked processes of change in different ecologies. The sedimented result of this intimately shapes today's high-frequency trading of U.S. shares.

Two conceptual points about the invocation here of "linked ecologies" require clarification. First, following actor-network theory, this article makes no attempt to separate the "social" from the "technical." Each of the three ecologies discussed — HFT, trading venues, regulation — is, as suggested above re HFT, a sociotechnical domain in which humans write algorithms and algorithms augment and diminish human capabilities, replace humans, and sometimes confound their plans. Second — and its flexibility in this respect is the key virtue of the idea of linked ecologies — the "topology" of how the three ecologies affected each other was not historically fixed. HFT, for example, began as a "micro" activity largely enclosed in and shaped by "macro" characteristics of trading venues that were "social facts" that HFT's practitioners simply had to accept, but as HFT has developed it has come partially to enfold those venues: they are now shaped by it, more than vice versa.

After discussing the methods employed and explaining the overall forms of interaction among the three main types of algorithm discussed here (trading venues' matching engines, which consummate trades; execution algorithms used by institutional investors to buy or sell large blocks of shares; and HFT algorithms), the article develops its argument in three stages. First, the section, "The Practices of High-Frequency Trading," describes common features of how HFT algorithms act in all the markets discussed here. Next, the historical process sketched above — the emergence of a "hinge" connecting HFT, developments in trading venues, and the regulatory ambitions of the SEC — is described in more detail. Finally, the differences between the practices of HFT in three different markets (one main case, and two comparator cases) are examined to show how historical processes and efforts at boundary-drawing shape those practices:

i. U.S. "lit" trading venues for shares.[5] This is the main case discussed: these venues are directly shaped by the historical "hinge" connecting them to HFT and to regulation. However, the effects on today's

[5] As discussed below, a "lit" venue is one in which the electronic order book is visible to the humans and algorithms that trade on the venue; in a "dark" venue it is not visible.

markets of that shaping process are riven by a deep contradiction, which *inter alia* has made a specific form of algorithmic action — the Intermarket Sweep Order — pivotal to the high-frequency trading of U.S. shares.

ii. U.S. “dark” trading venues for shares. As will be shown, these are markets in which the boundary work outlined above (drawing what are sometimes seen as “moral” distinctions among algorithms) is most prominent. Here, competition amongst venues for market share and competition for legitimacy are interwoven intimately, and amongst the consequences are that HFT algorithms are subject to direct surveillance by venues, with some HFT firms excluded or electronically stigmatized as “opportunistic.”

iii. Foreign-exchange trading venues. These markets, vitally important in themselves, also serve as a historical comparator case to U.S. share trading. With no equivalents of the SEC and the historical “hinge,” efforts to replicate in foreign exchange electronic markets created in U.S. shares have evolved in a different direction. The difference, we shall see, is encapsulated today in a controversial algorithmic practice, “last look,” that has no real equivalent in algorithmic share trading.

METHODS

High-frequency trading is a difficult domain to research either quantitatively or qualitatively. The barrier to quantitative research is that, with very limited exceptions, financial-market data available to researchers do not contain data fields that indicate whether the participants in a transaction were humans or algorithms, or if the latter whether the algorithm was a HFT algorithm.[6] In one important U.S. case, economists have gained access to data containing anonymized trading-account identifiers, in which HFTs are identifiable via their distinctive trading styles, but access to that Commodity Futures Trading Commission (CFTC) dataset is no longer available and publications based on it have been suspended.[7] In consequence, although it is quite common to find published figures on the proportion of trading that is HFT (see, e.g., Table 1), these figures are only estimates, primarily interview-based.

Qualitative research on HFT is also hard. HFT firms are, as noted above, most commonly privately-held partnerships that do not report publicly on their activities, and often go to some lengths to protect the confidentiality of their trading: as a former specialist in automated trading puts it, “[i]n this business, everyone knows that loose lips get pink slips” (Durbin 2010, p. 2). Despite this obstacle, however, 39 founders, employees or ex-employees of HFT firms agreed to be interviewed by the author about the practices of HFT, the contingencies that bear upon these practices, and (in the case of interviewees with long experience of the sector) the history of HFT. (In the quotations from these interviews, interviewees are identified chronologically from AA, the first HFT interview, conducted in October

[6] NASDAQ has made available to a number of financial economists a dataset for a sample of 120 stocks for 2008, 2009 and one week of February 2010. The dataset contains a field for each transaction that NASDAQ has populated, based on its informal knowledge of firms’ business models, as HH, NN, HN, or NH. A transaction labelled HN, for example, is one in which a high-frequency trading firm (“H”) hits a bid or lifts an offer posted by a non-HFT (“N”). The resultant work (especially Brogaard, Hendershott, and Riordan 2013 and Hirschey 2011) forms a useful crosscheck of some of this paper’s interview-based findings.

[7] This dataset contained futures market data held by the regulator, the CFTC, on which the CFTC’s Office of the Chief Economist (OCE) and some academic economists linked to the OCE had started to work. An early paper based on this dataset (Baron, Brogaard, and Kirilenko 2012) was reported by the *New York Times* on December 3, 2012, under the heading “High-Speed Traders Profit at Expense of Ordinary Investors” (Popper and Leonard 2012). The CFTC suspended the publication of results from the analysis of this dataset, and to date it has not resumed.

2010 to BM, the last interview, conducted in February 2014. In the five cases in which the same person was interviewed more than once, a numeral identifies which of the interviews is being cited.)

The interview sample was constructed in two main ways. The first was by identifying, from published sources such as reports in the specialist press, as many as possible of the HFT firms active in Chicago, New York, London, and Amsterdam (the four most important sites of HFT worldwide). If those press reports or the firms' websites (not all HFT firms have publicly visible sites) identified the firms' founders or named individuals with responsibility for trading activities, and if a telephone number could be found (many HFT firms' websites do not disclose their addresses or telephone numbers, but these can often be obtained by other means) those individuals were then telephoned. This "cold calling" was successful in just over half the cases in which it was attempted, generating 16 interviews. The second way of identifying interviewees was ad hoc: approaching speakers at an HFT industry meeting, using a list of potential interviewees provided by an industry analyst, drawing on personal recommendations by earlier interviewees, and making use of social media networking and happenstance contacts.[8]

Clearly, no claim of representativeness can be made for this sample, which is, for example, made up disproportionately of senior high-frequency traders: the social-media contacts and a happenstance contact were mostly quite junior, but the other means of identifying interviewees nearly always led to better known — and therefore more senior — people. Nor was it possible to follow even a semi-structured interview schedule: the overwhelming need was to keep the conversation going, and

[8] For example, a member of the audience at a talk given by the author on HFT identified himself as a high-frequency trader.

keep it focused on the practices of HFT (the author struggled in one interview with two former Chicago pit traders who had joined an HFT firm to stop them simply talking about the pits). It was easy inadvertently to ask a question that disrupted the interview because the interviewee felt unable to answer it:

> Interviewee AD1: Some companies don't wait for the exchange to tell them what's trading.
>
> Author: Oh, so how do you manage to…?
>
> Interviewee AD1: that I can't… I mean not only would I lose my job, I might lose my legs too!

> Author: Do you use ISO [Intermarket Sweep Order] orders?
> Interviewee AF: Can't say

Indeed, trying directly to question interviewees in detail about the techniques employed by their firms could easily have caused the interview simply to be terminated.

However, information proffered by the early interviewees made it possible gradually to identify a set of HFT techniques that are widely known in the sector, widely practiced, and thus acceptable topics of questioning. Interviewees would say of such techniques: "everyone knows that" (interviewee AA); "today that's High Frequency Trading 101" (AH). Similarly, early interviews provided glimpses of contingencies affecting the practice of HFT in particular domains, contingencies (such as "last look" in foreign exchange), that are little known to outsiders, but common knowledge in those domains. Again, it proved possible gradually to build up a sense of what those contingencies are, and in later interviews to focus more directly on them. Although the research was not originally designed as comparative, it became clear as the interviews proceeded that there were marked differences between the practices of HFT in different domains (especially shares and foreign exchange), and later interviews focused in part on those differences.[9]

Because of these iterative aspects, the interviews with high-frequency traders were more like solving a jigsaw puzzle (with no picture to guide one) than conducting a survey. Fortunately, however, matters were more straightforward when researching the ecologies surrounding HFT. Particularly in the case of U.S. shares, the overall histories of both the main trading venues and of regulation are reasonably well documented, making it possible to draw on documentary sources for the broad picture, and to focus the interviews on trading venues of three kinds: those that documentary sources and initial interviews suggested were pivotal in the development of HFT; those that set out to monitor the behavior of HFT algorithms and engage explicitly in boundary-drawing; and foreign-exchange venues, because these offer an interesting comparator case to share-trading venues. (See table 2 for full set of interviews drawn on here.)[10] “Cold calling” trading-venue representatives led to an interview in all but five cases, a much higher success rate than with HFTs.

Despite the limitations of the financial-economics literature on HFT caused by the data problems referred to above, there is one crucial issue on which interview-based conclusions can be cross-checked against that literature: the capacity of HFT techniques to predict short-term price changes. This issue particularly needs

---

[9] HFT in futures is discussed in (author ref.); the author’s research on HFT in fixed income is only just beginning. In both areas it is clear that incumbents strongly resisted (and in fixed income, still resist) automation and HFT. The process that nevertheless allowed these to succeed in futures differed from the case of equities focused on here: the regulatory ecology was close to irrelevant; the key developments were internal to the ecology of trading venues (see author ref.).

[10] To keep the number of interviews from becoming too large, it was decided not to interview regulators, because documentary sources on the development of regulation were adequate.

checked, because that predictive capacity seems to fly in the face of the "efficient market hypothesis" of financial economics, which decrees price changes not to be predictable. Fortunately, as will be seen below, economists' quantitative findings support the interview-based conclusions of this paper in this respect.

MATCHING ENGINES, EXECUTION ALGORITHMS AND HFT ALGORITHMS

To say of a market that it is an algorithm is, in most of the markets discussed in this paper, to say that deals on it are consummated by a matching engine that manages an electronic order book. To explain what a matching engine does, it is easiest to use a visual representation of an order book of the kind that confronts the remaining human beings interacting with a market. Figure 1 is a screen shown to me by an interviewee testing one of the execution algorithms discussed below. It shows the order books on a number of trading venues for the shares of the New York savings and loan, Astoria Financial. (My interviewee was not aware that his algorithm was trading Astoria shares: when I asked him what the symbol "AF" stood for, he did not know.) On the left of the screen are bids to buy Astoria shares: for example, a bid or bids on NASDAQ to buy 192 shares at $7.74; a bid on Arca to buy 800 shares, also at $7.74; and so on. On the right are the corresponding offers to sell.

Consider one of the order books for Astoria shares, for example NASDAQ's (figure 2). The crucial functions of a matching engine are to maintain an order book such as this and to search for bids and offers that match. In the book in figure 2, there is no match. However, a match would be created by a human or algorithm entering a bid to buy shares at $7.75 or below or an offer to sell them at $7.74 or above (such orders are called “marketable limit orders”). Once the matching engines finds a match, it consummates the trade and sends the two parties electronic confirmations of the trade. Unlike in a traditional “human” market, no negotiation is involved; indeed, in share trading (but not always in foreign exchange) the whole procedure is entirely impersonal and anonymous.

In addition to the remaining human participants in markets, two broad categories of trading algorithm interact with matching engines. The first is execution algorithms. These are used by institutional investors, or brokers acting on their behalf, to buy or sell large blocks of shares or other financial instruments. Execution algorithms break up those blocks and bring them to market in a way designed to minimize “market impact” (a large buy order, for example, will typically cause prices to rise before it is fully executed). For example, one standard class of execution algorithm is “volume participation” algorithms, which keep track of the volume of transactions over a rolling time period (a minute, for example), and place new orders that are a set proportion of that volume, the rationale being that market impact is typically lower when markets are active. The other broad category of trading algorithm is proprietary trading algorithms, of which the subclass on which this paper focuses is HFT algorithms.[11] Unlike execution algorithms, these do not set out to buy or sell a specific quantity of the instrument being traded: indeed, they are programmed to avoid accumulating the risky trading position that would be created by buying a lot more than they sell, or vice versa. Rather, the goal of those who use

[11] Another type of proprietary trading algorithm is statistical arbitrage algorithms. Like most HFT algorithms, these also seek to predict patterns of price changes, but over a longer timescale, from a few minutes to a day or more.

HFT algorithms is to make money by trading, using the techniques discussed in the next section.

By placing or cancelling orders, HFT and execution algorithms interact directly with matching engines, and via the latter interact indirectly with each other. Those who write execution algorithms design them to hide their activities — to “take [a] huge order and chop it up into little tiny pieces and, if we do it right, anyone who’s looking at it can’t tell that there’s a big buyer: it looks like tiny, little retailish trades [i.e. trades by lay investors] … and no-one knows who or what is happening” — from human professional traders, proprietary-trading algorithms, and even other execution algorithms. (Many execution algorithms are now just as sophisticated as most HFT algorithms, and employ the same techniques of price prediction.) For example, a proprietary algorithm that can successfully detect the digital footprint of an execution algorithm that is in the process of buying a large block of shares can make money at its expense by buying shares ahead of it and selling them to it at a profit. Patterns of algorithmic behavior can emerge that can indeed be understood only “in term of interactions between multiple elements that are neither fully constrained nor fully independent” (Abbott, as quoted above). For instance, two or more volume participation algorithms can start to influence each other’s behavior. As interviewee AE put it, “every time one of them prints,” in other words executes a trade, it boosts the volume of transactions, leading the others to seek to trade as well:

> It causes all the other guys [algorithms] to print, which causes the first one to print, and the stock will just go ‘zhwoom’ [rise sharply] until they’re all done [have made the programmed purchases] and then it’ll go ‘pfft’ [fall sharply] again.

(Interactions of this generic kind among algorithms are the most likely cause of the short-lived price spikes and crashes observed by Johnson et al. 2012.) Other algorithms programmed to spot episodes of “price momentum” (see below) can profit from such episodes, and there is even a further level of interactive behavior, AE reported. In this, the process of mutual influence among volume participation algorithms is deliberately simulated, with the goal of exploiting the “momentum” algorithms that “discover” such episodes and join in.

THE PRACTICES OF HIGH-FREQUENCY TRADING

It would be quite mistaken, however, to imagine that the behavior of HFT algorithms is always, or even mostly, sophisticated, reflexive “gaming” of this kind. As the term “high-frequency” suggests, HFT is based on large volumes of trading, and intricate “gaming” strategies are unlikely to scale up successfully. Sometimes, HFT is as simple as detecting a financial instrument on sale on one venue at a lower price than it is being bid for on another, but such “arbitrage opportunities” (as market participants call them) are now small enough and infrequent enough, interviewees reported, that they too could not form the basis for a large-scale business. Rather, the core HFT practices are a variety of broadly applicable techniques of very short-term price prediction.

To give a flavor of those techniques, consider two of them that are used by the algorithms of the firms of all the interviewees who were prepared to discuss such matters in any detail. The first is “order-book dynamics.” At its simplest, said interviewee AH, that is a matter of an algorithm calculating whether “the bid [is] bigger than the offer?” Consider, for example, the order book in figure 2, in which the best (i.e. highest) bid consists of 192 shares and the best (i.e. lowest) offer consists of 488. There, the offer is bigger than the bid, suggesting that, “probabilistically, the next [price] tick is likely to be [down]” (interviewee AF). (That this form of prediction works, and that HFT firms employ it, is one of the issues on which the interviews are supported by the financial-economics literature.)[12] It is also possible to include, in the algorithm’s calculation of what interviewee AN called “book pressure,” the sizes of bids below the best bid and offers above the best offer. This makes an algorithm’s calculation more vulnerable to “spoofing,” to other algorithms or human traders placing bids or offers not with the intention of buying or selling but simply to create the impression of excess demand or supply. (In figure 2, for instance, there are large bids at $7.72 and $7.71, but unless prices fell very fast they could be cancelled before being executed.) There are, however, ways of HFT algorithms defending themselves against “spoofing,” said interviewee AZ, such as omitting or underweighting very recently placed bids and offers when the algorithm calculates the balance between the two, the rationale being that orders that have been in the book for longer are less likely to have been placed by a spoofer.

A second widely used HFT predictive technique employs the price movements of financial instruments that are closely related to the instrument being traded, especially when those instruments are known typically to “lead” the latter. A crucial example is “futures lag”: the use by HFT algorithms trading shares or exchange-traded funds of movements in the prices of the corresponding share-index futures. (An index future is a derivative whose pay-off depends on the movement of

[12] Using the NASDAQ dataset described in note 6, Brogaard, Hendershott and Riordan (2013) show that the relative size of the best bid and offer does have predictive power, and the direction of HFTs’ marketable orders is consistent with their trading being informed by this.

an underlying share-price index such as the S&P 500 or NASDAQ 100; an exchange-traded fund is a stock whose price similarly tracks the aggregate prices of the shares making up such an index.) The interviews — and, once again, the literature of financial economics (Hasbrouck 2003) — indicate that changes in index-future prices tend to lead those both of the corresponding exchange-traded funds and of the underlying shares. This makes index-future price changes a crucial predictor of changes in the prices of those funds and shares.

Order-book dynamics and prediction using the price changes of closely related instruments are only two of the predictive techniques used by HFT algorithms. It is also, for example, possible for them to predict price movements using what interviewee AN called “time and sales”: the timing, price and size of transactions in the instrument being traded. One long-established form of this (its use is documented in Beunza and Stark 2004) is “mean reversion”: the tendency of prices to revert, after a temporary disturbance caused for example by a large execution algorithm, to a slowly-moving average. Another, already mentioned, is “momentum”: the attempt to identify and exploit disturbances that are likely to have some longevity. Quite a different form of predictive technique is the use by HFT algorithms of macroeconomic or company-specific “news,” now widely disseminated in machine-readable form. An algorithm that can act on such news before it is fully incorporated into prices can profit handsomely.

So multiple sources of prediction are available to HFT algorithms. Although a small HFT firm may deploy an algorithm based on just one source, the interview data suggests that larger firms’ algorithms typically aggregate these multiple sources in real time. Very commonly, but not universally,[13] the result of the aggregation is an automated estimate of the "theoretical value" (interviewee AG2), "fair value" (AG2 and AR), "theoretical price" (AO), "fair price" (AF), "perfect price" (AN) or "microprice" (AO) of the shares or other instrument being traded. These terms are synonyms; in the context of HFT, they mean "the price you can reasonably expect to transact at in the near future" (AG2), where the "near future" might be anything from less than a second to a couple of minutes. This price is most easily thought of as the dependent variable in a multiple regression, in which the independent variables are predictors such as the bid:offer imbalance, the prices of related instruments, etc. (BG). However, other firms' algorithms employed different forms of aggregation. Thus interviewee AN described an elaborate automated "polling" system in which the weights given to the "votes" of different predictors varied according to market conditions.

Once a HFT algorithm has estimated a theoretical value of the instrument it is trading, or has simply formulated a prediction that its price will rise or fall, what can it then do? There are two broad choices. It can act "passively" or "make liquidity" (as market participants would put it): it can place in the electronic order book bids and/or offers with prices that cannot be executed immediately. Alternatively, it can act "aggressively" or "take liquidity": it can submit a marketable order that will be executed as soon as it is received by the matching engine. For example, in the book shown in figure 2, an offer to sell shares at $7.74 is marketable, "aggressive," and

[13] Thus interviewees AI, AQ and AU reported that their algorithms' predicted efforts did not take the form of estimating a theoretical value.

"liquidity-taking"; an offer to sell shares at $7.75 is non-marketable, "passive," and "liquidity-making."[14]

As that higher price shows, liquidity making has potential economic advantages. Other things being equal, a non-marketable order that another algorithm or human being transacts against is executed at a more favorable price than a liquidity-taking order, and (at least in share trading in the U.S.) it also receives a "rebate": to encourage liquidity-making, the trading venue will make a small payment (around 0.3 cents/share) to a firm that has entered a liquidity-making order that has been executed against. Furthermore, the placement of liquidity-making orders inherits, in some contexts, the legitimacy of a traditional human role, that of the market maker who always stands ready both to buy and to sell the instrument being traded. An important subcategory of HFT firms (represented in my sample by interviewees AC, AG, AO, AQ, AW, BH, BI, BJ, BK, BL and to some extent BF and BG) position themselves primarily as "electronic market-makers." In some contexts, indeed, the distinction between liquidity-making and "aggressive" liquidity-taking is freighted with moral significance. One interviewee, who was trying to persuade others in his automated but not fully high-frequency trading firm to shift their emphasis from making to taking liquidity, reported that their reaction was as if he had asked them "to stab their sister."

The primary activity of a market-making HFT algorithm is to keep its buy orders at or close to the best bid price ($7.74 in figure 2) and sell orders at or close to the best offer price ($7.75), with the goal of having others execute against both its

[14] In what follows, the more technical term "liquidity-making" is preferred to the more colloquial "passive," because in the context of HFT the connotations of the latter are misleading: algorithms that place "passive" orders are frequently frenetically active (see below).

bids and its offers. The algorithm thus aims to earn the “spread” between the bid and offer prices (one cent, in this example), along with two rebates; i.e., a total of around 1.6 cents per share bought and sold. Market-making sounds simple, but isn’t. A market-making algorithm needs constantly to place new orders and cancel existing orders as prices move, and needs to keep buying and selling broadly balanced to avoid accumulating a position that will lose money if prices move adversely.[15] Its need to predict price movements is no less than that of an “aggressive” algorithm. If, for example, a market-making algorithm is making markets in the QQQs (an exchange-traded fund that tracks the value of the shares in the NASDAQ-100 index), and the price of NASDAQ-100 futures goes up, the market-making algorithm’s offer prices almost instantly become “stale,” and can profitably be “picked off” by an aggressive algorithm. So the market-making algorithm must cancel those existing offers and replace them with offers at a higher price before (in market-making terminology) it is “run over.”

The risk of being “picked off” or “run over” is only one of the disadvantages of liquidity-making algorithmic action that need weighed against the economic advantage outlined above. There is no certainty when — or indeed whether — a non-marketable bid or offer placed in the order book will be executed (and, of course, if it is not executed the algorithm will never earn the spread or a rebate). In contrast, aggressive, liquidity-taking algorithmic action, employing marketable (and thus immediately executable) orders, offers much greater certainty. Under some circumstances, that certainty outweighs the economic disadvantage of those orders (that they involve “paying the spread” and earn no rebate), especially if an algorithm

[15] Because of this, a market-making algorithm will often “shade” its prices, for example posting particularly attractive offers to reduce its inventory of the asset being traded if that inventory has become uncomfortably large.

has identified a profit opportunity sufficiently large to outweigh the additional cost of aggressive action. There is also a certain cognitive advantage to aggressive action. HFT firms nearly always "back test" new algorithms extensively, simulating their performance using past market data. Aggressive, liquidity-taking algorithmic action "is an easier thing to simulate," said interviewee AZ: with passive, liquidity-making action you have a more difficult job "predict[ing] whether you would have gotten the fill or not."

There is a substantial degree of differentiation among HFT algorithms in respect to the actions they take: some almost always make liquidity; some nearly always act "aggressively" and take liquidity. Indeed, that differentiation extends to the firms that employ them, which seem largely to specialize either in liquidity making or liquidity taking. "[I]t's funny how there are some firms today who almost exclusively provide liquidity and other firms who almost exclusively take liquidity," said interviewee BF: "it's almost like two very different strategies and thought processes." (This is another point on which the interviews can be checked against a financial-economics study. A paper based on the Commodity Futures Trading Commission dataset that did temporarily enter the public domain [Baron, Brogaard, and Kirilenko 2012] found that "the aggressiveness of a given HFT firm [the degree to which its trading is liquidity-taking] is highly persistent" [p. 27].)

Despite the ethos of secrecy that surrounds at least some HFT firms, the interviews suggested that because of factors such as the movement of personnel between firms, the main techniques of HFT are common knowledge in the sector. "There are secrets but there are no secrets," was how interviewee AI put it. With HFT algorithms therefore often using similar predictive techniques, competition amongst them often boils down to relative speed.[16] To receive data on order-book charges with minimum delay, and to submit orders and cancellations of orders as quickly as possible, HFTs pay trading venues hefty fees to "co-locate": to place the servers on which their algorithms run in the same building as the server on which the matching engine runs. Share-trading HFTs that use futures prices as predictors have to invest in the faster possible links — three years ago, a new fiber-optic cable following a new, more direct route; now, a series of microwave towers — between Chicago (the main U.S. futures-trading matching engine is located in Chicago's outer suburbs) and the data centers in northern New Jersey in which shares are traded.

The importance of relative speed gives HFT something of the character of a technological "arms race".[17] It also gives salience to very specific features of matching engines, of the physical machines on which those engines run, and of other parts of trading venues' computer systems. These parts include the servers that process incoming orders before passing them to the matching engine, transmit "confirms" (messages to the computer systems of the parties to a trade telling them that one of their orders has been executed), and disseminate news of trades to the market at large via the venue's datafeed. Recall interviewee AD's fear that giving me a specific piece of information might cause him to "lose my job" and perhaps "my legs too." Two years after that October 2011 interview, it suddenly became clear what that piece of information was, when the *Wall Street Journal* (Patterson, Strasburg, and Pleven 2013) revealed that the computer system of the Chicago Mercantile Exchange (the prime U.S. futures-trading venue) typically sent "confirms"

---

[16] Absolute speed matters too, for example in helping a market-making algorithm minimize the risks it is taking by adjusting its bids and offers as quickly as possible as market conditions change.

[17] For a formal model of HFT's "arms race" component, see Budish, Cramton, and Shim (2013).

one to ten milliseconds before disseminating news of the trade on the wider datafeed. (Interviewee AD later told me this was indeed what he had been unable to say.) That time difference is economically important. Consider, for example, an HFT employing "futures lag" to trade shares or exchange-traded funds. If it was also making liquidity in those futures, it could "take [its own] fill as market data," as another interviewee put it: when it received a "confirm" that its futures bids had been hit or its offers lifted, it could infer that prices were moving before those movements were apparent on the Chicago Mercantile Exchange datafeed.

Press reporting of such matters can, however, give a misleading impression of the typical size of HFTs' profits. Much of the high-frequency trading of shares, for instance, involves predicting a "tick" of prices up or down, and the unit of price for U.S. shares costing $1 or above is a cent. That latter figure gives a better sense of the scale of profits: interviewee AF, for example, reported that for his firm a profit or loss of a cent per trade is indeed typical. Prediction, however, is probabilistic, and so many trades lead to losses. This interviewee reported that his firm's trades were profitable only around 53 percent of the time, which implies an average profit of around 0.06 cents per share traded. When I prompted another interviewee with a higher estimate (a "fifth of a cent per share"), he corrected me:

> Oh, I wish it was that big! There's not that much, it's even, yeah, I mean five mils [0.05 cents per share traded], ten mils [0.1 cents], that sort of thing. (interviewee AH)[18]

There was broad agreement amongst those interviewees who were prepared to discuss HFT's profits — and amongst those in "dark" venues that monitor those

[18] "Mil" is the term employed in U.S. share trading for a hundredth of a cent.

profits — that a tenth of a cent per share traded was a roughly accurate indicator of the order of magnitude of those profits.[19] However, the most recent of the interviews (e.g., BI) suggested that average profit has slipped to around a twentieth of a cent.

Given the controversy surrounding HFT, and in particular the widespread accusation that it preys upon execution algorithms, it might be that interviewees were deliberately underestimating HFT's profitability. In addition, there may be response bias: perhaps the HFT firms that could not be identified or at which no-one could be persuaded to be interviewed were disproportionately profitable. Higher figures for profit rates can indeed be found in the financial-economics literature and in the published accounts of Knight Capital, the one major U.S. HFT firm that (prior to its recent takeover by HFT market-maker Getco) reported publicly. However, for contingent reasons those figures may be unrepresentatively high.[20] A press report (Massoudi and Mackenzie 2013a) is consistent with recent interviewees' suggestions of current profits of around a twentieth of a cent per share, not a tenth.

Certainly, my fieldwork impressions were not of great prosperity. Five interviewees were interviewed twice; by the time the second interview took place, two had lost their jobs. When interviewing at HFT firms, I was sometimes taken on a brief tour of their offices, and often it was possible to see these when arriving for and

[19] E.g. interviewee AK: "… you're operating on making a fraction of a penny per trade … tenth of a penny per share."

[20] The HFT figures in Brogaard, Hendershott, and Riordan (2013) equate to an average trading revenue net of fees per share traded of around 0.4 cents per share. However, they have no data on costs other than fees and their data (described in note 6 above) is mostly for 2008-9, and interviewees reported that period, especially 2008, to be years of exceptionally high HFT profits. Knight's annual reports for 2009-11 (e.g., Knight Capital Group, Inc. 2012) contain data on market-making revenues and expenses that suggest profitability in the region of 0.14-0.19 cents per share traded. However, Knight's activities were broader than HFT (e.g., execution of retail orders), which may explain these relatively high profit rates.

leaving the interview (most HFT firms' premises are not large). Especially in the later interviews, it was quite common to see unoccupied desks. For instance, I visited one large HFT trading room in both March 2012 and May 2013. The number of occupants had visibly shrunk between the two visits, and that impression was confirmed by two interviewees. However, HFTs still transacted enormous quantities of shares. Even in 2013, with overall U.S. share-trading volumes having shrunk markedly from their 2008-9 peaks, HFTs were buying or selling around 5 billion shares a day, and were in all likelihood a party to the majority of transactions.[21] Even a medium-sized HFT firm in a modest office with a staff of a couple of dozen can trade of the order of 50 million shares a day, and HFTs have become central, as the next section will discuss, to share trading in the U.S.

THE HINGE: HFT, TRADING VENUES, AND REGULATION

The rise of HFT in U.S. share trading came about from the interaction of three ecologies: HFT itself; trading venues (especially new venues called ECNs, or electronic communications networks, a series of which were created in the mid to late 1990s); and regulation.

Let us begin with regulation. The U.S. financial markets had and have not one regulator but several, including six Federal bodies with regulatory responsibilities (the Federal Reserve, Federal Deposit Insurance Corporation, Office of the

[21] The average daily volume of U.S. shares traded in 2013 was around 5 billion (Angel, Harris, and Spatt 2013, p. 4), but each transaction involves both a buyer and a seller, so each day around 5 billion shares were bought and 5 billion sold. A reasonable estimate of the HFT share of those purchases and sales is 50-55 percent (e.g., Table 1 and Mackenzie 2012), meaning that the daily total of purchases and sales by HFTs was around 5 billion. If HFT profitability is on average 0.1 cents per share bought or sold, this means that HFTs trading U.S. shares made in aggregate around $5 million per trading day, or $1.25 billion per year. This figure is not large when compared, e.g., with the profits of even a single large bank.

Comptroller of the Currency, Office of Thrift Supervision, Commodity Futures Trading Commission, and Securities and Exchange Commission) and state regulators such as New York’s Department of Financial Services. There have historically been both overlaps and gaps in regulatory jurisdiction, and episodes of “turf warfare” (e.g., between the SEC and CFTC: see author ref.). While among Federal regulators share trading has been the largely uncontested terrain of the SEC, the latter shared broader jurisdiction over it with designated “self-regulatory organizations” (notably the New York Stock Exchange and the National Association of Securities Dealers, which ran NASDAQ). Furthermore, with share trading prominent in American culture, Congress and the executive branch paid far more attention over the decades to the trading of shares than to that of other instruments. That too has been a force buffeting the SEC, whose Chair and Commissioners are appointed by the President, subject to Senate ratification, and usually have explicit party-political affiliations. It is noteworthy, for example, that while there have been a plethora of efforts to reform share trading, those efforts are far sparser in the SEC’s other main regulatory domain, bonds.[22]

The SEC was a quintessential New Deal institution. It was created in 1934, in the face of the Great Depression, under a president who had declared in his inaugural address that “the money chargers have fled from their high seats in the temple of our civilization” (Seligman 1982, p. 29). The SEC’s establishment followed the searing political theater of the Senate Banking Committee hearings, which had exposed pervasive Wall Street wrongdoing. (Amongst dramatic moments was the unscheduled testimony on April 26, 1932 of Fiorello LaGuardia, soon to be Mayor of

[22] The absence of these efforts in the U.S. bond market, the world’s most important, may well be a factor in the relatively small role played by HFT in fixed-income trading (see Table 1).

New York, accompanied by a phalanx of New York police officers, two of whom carried a trunk full of documents, many of them cancelled checks: the evidence of bribes paid by intermediary turned whistle-blower A. Newton Plummer to reporters to write false stories concerning stocks in which his patrons had an interest.)[23]

A persistent theme in the SEC's efforts to reform share trading was its suspicion of the two main self-regulatory organizations with which it shared jurisdiction. The New York Stock Exchange (NYSE) and NASDAQ were in effect a duopoly: companies could choose on which of the two to list their shares, but thereafter those shares traded almost exclusively on the chosen venue. Regional stock exchanges, for example in Boston, Philadelphia and San Francisco, could trade NYSE shares, but were generally not fully effective competitors to the NYSE. A NYSE "specialist" (market maker) enjoyed a near-monopoly position in the trading of the stock for which he was responsible (both specialists and floor brokers were nearly always men), and while NASDAQ broker-dealers ostensibly competed with each other there was sometimes tacit collusion among them (see author ref.). From the early 1970s onwards, the SEC's reform efforts — which previously had taken the form primarily of rule-making — started to focus also on technology as a way of improving efficiency and exposing these privileged insiders to competition. In the Securities Acts Amendments of 1975, Congress altered the legislation that had created the SEC, with the goals "to remove barriers to competition" and "to remove

[23] Seligman (1982, p.16). LaGuardia's testimony is available at http://archive.org/stream/stockexchangepra02unit/stockexchangepra02unit_djvu.txt, accessed December 27, 2013.

impediments to and perfect the mechanisms of a national market system for securities."[24]

How, though, should that "national market system" be designed? One proposal was for a "hard CLOB," or Composite Limit-Order Book, a central, national, electronic order book into which all brokers, dealers or trading-floor market makers, "wherever physically located," would enter their bids and offers "on an equal competitive footing" (Seligman 1982, p. 521). However, although the Cincinnati Stock Exchange successfully experimented in the late 1970s with an electronic order book, the other exchanges saw the "hard CLOB" as a threat and successfully promoted a different design, the Intermarket Trading System, launched in 1978.

The Intermarket Trading System linked NYSE, the American Exchange and the regional exchanges (NASDAQ was not part of it until 2000). It operated in conjunction with the Consolidated Quotation System, also launched in 1978, which disseminated information on bids and offers available on the different exchanges. If a human broker or "specialist" on an exchange trading floor could see a superior price available on another exchange, he was not supposed to "trade through" that price by dealing on his own exchange at an inferior price, but had to use the Intermarket Trading System to send a "commitment to trade" to the relevant specialist on the exchange with the better price. That specialist then had a set time period — as late as 2002, 30 seconds — to decide whether or not to trade (Hendershott and Jones, 2005). If prices were moving fast, that gave the specialist valuable time to see if they would rise or fall (the provision was in effect a version of what in foreign exchange is called "last look": see below). The Intermarket Trading System thus never threatened

[24] The Securities Acts Amendments of 1975 are available at http://www.gpo.gov/fdsys/pkg/STATUTE-89/pdf/STATUTE-89-Pg97.pdf, accessed January 19, 2014.

the dominance of the New York Stock Exchange's specialists. As late as 2005, 80 percent of trading of NYSE-listed shares was on NYSE: see Angel, Harris, and Spatt (2013, p. 20).

The episode indicated the limits on SEC's capacity to impose its will on the self-regulatory organizations and entrenched trading venues. More profound change required a shift *within* the ecology of trading venues. Central to that shift was Island, a new trading venue set up in 1995, originally to cater primarily for traders known to their established rivals as "SOES bandits." (SOES was NASDAQ's automated Small Order Execution System, and "bandits" used it, for example, to pick off NASDAQ broker-dealers' stale price quotes.) Island made it possible for "bandits" to trade directly with each other. Its fees were very low, and its order book was visible to anyone trading on the system (unlike, e.g., the NYSE order book, to which specialists had privileged access). Island's matching engine was simple and ultrafast, and news of all changes in the order book was disseminated by a specially designed fast datafeed called ITCH; another specialized computer protocol, OUCH, facilitated rapid submission of orders and cancellations of orders. While on NASDAQ, NYSE, and other U.S. venues the "tick size" — the minimum increment of price — was an eighth or a sixteenth of a dollar, Island's tick size was 1/256th of a dollar, making it possible for market makers on Island to undercut their established counterparts by small (but, from a SOES bandit's or other day trader's viewpoint, economically important amounts). Market making was also encouraged by the "rebates" described above; Island was the first venue to introduce rebates.[25]

[25] The development of Island is treated in more detail in (author ref.), so that development is simply summarized here.

These features of island reflected specific local priorities. Its developers worked in 50 Broad Street in lower Manhattan, a building also occupied by two of the "bandit" firms for which it catered; one of those firms, Datek, was its original financial backer. The top priority of SOES bandits and many other day traders was speed[26] — hence Island's emphasis on that — and Island's developers (especially its chief architect, Josh Levine) had a libertarian bent, a distaste for oligopolies such as that of NASDAQ's broker-dealers, and a strong commitment to "democratizing" markets: hence the low fees, publicly visible order book, and the small tick size that made it possible to undercut broker-dealers.

Those features of Island — which were also adopted at least to a degree by the later ECNs (electronic communications networks) that had to compete with it — came to act as a "hinge" in Abbott's sense, linking developments in trading venues to HFT on the one side, and to regulation on the other. The linkage to HFT was straightforward. It *was* possible prior to Island to conduct algorithmic trading analogous to today's HFT, but it was difficult. Thus HFT interviewee BF recalls what happened to algorithm-generated orders submitted via the New York Stock Exchange's supposedly automated "SuperDot" order entry system. They were routed automatically to the appropriate specialist's booth on the NYSE floor, but the execution of these orders was controlled manually by the specialist. Even at the best of times, the execution of an order or the cancellation of an order took several seconds, and sometimes the execution of an order would be delayed for much longer, even if it appeared as if there ought to be matching orders already in the book. "Thirty seconds would go by; sixty seconds would go by." This interviewee

[26] A survey of such traders by Bernstein & Co. in 2000 "found that 58 percent … rate immediacy of execution as more important than a favorable price" (Blume 2000, p. 9).

came to detect a pattern in such delays and inferred a cause: “somebody’s coming to the market with a big buy order. The specialist knows that the stock is going to run up and basically he would freeze his book …” If you were “very agile,” some of these frustrations could be turned into opportunities,[27] but “you had to basically put up with those kind of things … you had to learn to live within the realities that you confronted.”

Island utterly changed those “realities”: a marketable order received via OUCH by its matching engine would be executed in around two milliseconds (interviewee G1). Although this speed, and Island’s other features, were not originally designed to facilitate HFT (as noted, its original clientele were manual day traders), they had that effect. Fast matching also motivated what later became HFT’s characteristic spatial feature, the co-location of the servers hosting trading algorithms in the same building as the server running the matching engine. Transmission delays of a few milliseconds in fiber-optic cables were not salient when matching took several seconds, but with two-millisecond matching a HFT algorithm would be badly disadvantaged unless it was running on a server next to Island’s matching engine in the basement of 50 Broad Street.

Island’s (and the other ECNs’) features also acted as a “hinge” connecting trading venues to regulation. Those features made possible what Congress and the SEC had declared they wanted, but had largely failed to bring about: effective competition among trading venues. Using Island and the other ECNs, electronic market-makers could routinely undercut their traditional counterparts, and their doing

[27] If execution of a buy order was delayed in this way, “[y]ou could all but predict” it was because a large buy order was being executed on NYSE. So interviewee BF’s firm would sometimes quickly place a bid for the same shares on Instinet (an early electronic venue designed for use by institutional investors) to benefit from the coming price rise.

so made Island and the other ECNs in many respects more attractive places to trade than the traditional venues. Under Arthur Levitt, appointed SEC Chair by Bill Clinton in 1993, the SEC went some way to seizing the opportunity presented by this change in the ecology of trading venues. It helped the ECNs gather momentum, for example with the SEC's new Order Handling Rules, introduced in 1997, which forced NASDAQ's broker-dealers to display ECN prices to their customers when these were better than the broker-dealers' own quotes. Amongst the features of Island that the SEC helped generalize was tick sizes (minimum increments of price) much smaller than the traditional eighths of a dollar: in 2000, the SEC imposed "decimalization" (the pricing of shares in dollars and cents).

The linkage between HFT, Island and the other ECNs, and the SEC was a hinge, not an alliance. Though the SEC's reforms helped facilitate HFT, there is no evidence that the SEC intended to promote it, or even that SEC officials were aware of its existence (prior to 2005, HFT received almost no publicity even in the specialist financial press, and it was 2009 before its existence became widely known). Nor was the SEC simply an ally of Island. "[U]nder pressure from the exchanges" (interviewee AQ), the SEC insisted in 2002 that Island joined the slow, specialist-dominated Intermarket Trading System. Island "couldn't operate in that world" (AQ), but found a stratagem. The requirement to join applied only to venues with visible quotes, so Island "went dark," making its order book invisible. It hurt its market share (Hendershott and Jones 2005), but kept it able to provide fast matching not interrupted by the 30-second delays of the Intermarket Trading System. There was certainly no meeting of minds between the SEC and Island, which was fiercely libertarian and deeply sceptical of the virtues of regulation of any kind. Island had emerged from a trading community stigmatized as "bandits," whose members often came from the “wrong side of the tracks” in class terms (Patterson 2012, p. 100 and passim). “Bandits” were prone to brushes with the law and regulation. Interviewee BF, who believes his firm to be the first HFT active on Island, recalls being warned off by an investment banker who said “those guys are a bunch of crooks.”

REGULATION NMS AND INTERMARKET SWEEP ORDERS

Though a hinge not an alliance, the linkage between HFT, ECNs, and regulation bore fruit. Thirty years of conflict over the shaping of share trading in the U.S. culminated in a 2005 measure that still governs that trading: Regulation NMS [National Market System] (Securities and Exchange Commission 2005). The barriers that the Intermarket Trading System placed in the way of fast, electronic trading were swept aside: if a quotation was available only from a human being on a trading floor, it could now freely be “traded through.” Only bids or offers that could be hit or lifted electronically and near-instantaneously were protected. The SEC’s goal of effective competition to NYSE and its specialists was finally achieved: in four short years from 2005, NYSE’s share of the trading of NYSE-listed stocks fell from 80 percent to just over 20 percent (Angel, Harris, and Spatt 2013, p. 20).

Simultaneously, however, “Reg NMS” (as it is universally known) contained echoes of the compromise with the exchanges that gave birth to the Intermarket Trading System: in its structure, Reg NMS is closer to that system than to the defeated alternative, the single, national Consolidated Limit Order Book. Trading venues compete with each other, but the form of that competition is not integration into a single order book. Rather, each venue still has its own order book, and how it operates that order book is governed, as with the Intermarket Trading System (only more rigidly so) by rules prohibiting trade throughs. Consider, for example, the set of order books shown in figure 1, in which what in Reg NMS is called the “national best offer” of Astoria Financial shares is \$7.75. Reg NMS prohibits any venue from selling Astoria shares at any price higher than \$7.75: to do so would be a prohibited “trade through.” Reg NMS similarly prohibits “locking” another venue or venues. Suppose NASDAQ, for instance, received an order to buy 1,000 Astoria shares at \$7.75. It can execute 488 shares against the offers in its order book, but is prohibited from posting in its order book a bid to buy the remaining 512 at \$7.75. The rationale is that shares are still on offer on other venues at \$7.75, so the bid can be executed on those venues. To post the bid on NASDAQ would “lock” those other venues, in the terminology of Reg NMS.

The Reg NMS “order protection” rules — largely inherited from the Intermarket Trading System — force the designers of a matching engine to add (either in the engine itself or in separate software) an algorithm that checks whether a new order *can* be executed or entered into the order book, or whether it violates the prohibitions on “trade throughs” and “locking.” This is done by checking the characteristics of the order against the national best bid and offer as determined by the multi-venue datafeeds known as the “consolidated tape.”[28]

The checking algorithm has major effects on how HFT algorithms can operate. First, checking takes time, slowing order entry and execution. Second, it is

[28] These national best bid and offer are calculated continuously by the U.S.’s two Securities Information Processor computer systems (one for stocks listed on the New York Stock Exchange and its associated venues; one for NASDAQ). Each SIP, as they are known, receives quote and transaction data from all the exchanges trading the stocks for which it is responsible, and calculates and disseminates the national best bid and offer. Although the SIPs have been greatly improved in recent years, the process of transmission, processing and retransmission makes these datafeeds lag behind raw datafeeds direct from trading venues’ matching engines.

often checking against a past state of the world: the consolidated tape is slower than venues' direct datafeeds, and so an HFT algorithm may "know" that the bids or offers on the tape have actually been executed against or cancelled. (Reg NMS, we might say, is implicitly Newtonian — it implicitly presupposes that instantaneous communication across space is possible — while HFT operates in an Einsteinian world in which the time that communication takes, even at the speed of light, is salient.) Third, the checking of compliance with Reg NMS constrains "aggressive" HFT algorithms that seek to "sweep the book" (hit multiple existing bids or lift multiple existing offers at multiple prices), because such purchases or sales will be delayed until they no longer appear to trade through the national best bid and offer. Fourth, Reg NMS also constrains the activities of liquidity-making HFT algorithms, because the entry of their orders into a venue's order book will be delayed until they no longer "lock" other venues. (Delay is a problem for a liquidity-making algorithm, because for such an algorithm to make a profit, at least some of its bids or offers must be executed against, but the chances of this happening depend on where they are in the queue of other bids or offers at the same price. In share-trading matching engines these queues operate on a time-priority basis: the first order to be entered into the book is the first to be executed.)

Reg NMS, however, makes provision for a special category of order that a venue's matching engine can execute or enter directly into its order book without invoking the checking routine: an Intermarket Sweep Order.[29] This is an order bearing a computerized flag indicating that the firm submitting it has also sent orders that will remove from the order books of all other trading venues any existing bids or

---

[29] The Intermarket Sweep Order exception to Reg NMS is defined in section 242.600(b)(30) of Securities and Exchange Commission (2005).

offers that would otherwise be traded through or locked by the order bearing the flag. The SEC seems to have built provision for Intermarket Sweep Orders into Reg NMS to avoid the latter stopping large orders from big investors being subject to delay (Securities and Exchange Commission 2005, p. 37523), but these orders have become crucial to the successful practice of HFT: as well as avoiding delays caused by Reg NMS's "Newtonian" rules, use of the Intermarket Sweep Order flag can speed order entry or execution simply because the trading venue's computer system need not invoke the routine that checks an order's consistency with Reg NMS.

All the HFT interviewees who were prepared to talk about Intermarket Sweep Orders said they were important. Interviewee BF, for example, reported that they "created speed opportunities": if you didn't use them, "you'd be behind the queue." "[A] large amount of wealth transfer happens here," said interviewee AF. However, not every algorithm (until recently,[30] not even every HFT algorithm) can employ an Intermarket Sweep Order flag: only registered broker-dealers are permitted to use it (and that registration brings heavy extra costs via compliance requirements), although broker-dealers can delegate the right to use it to trusted customers such as experienced HFTs. Those whose algorithms cannot use the flag are disadvantaged, said interviewee AF (whose HFT firm is not a broker-dealer): a HFT "can send an order with a ISO flag to post first, then later all those investors who were trying to post will post behind you with inferior time priority." Drawing on data from 2010, Madhavan (2012) reports that 28 percent of U.S. share trading, and 21 percent of trading in exchange-traded funds, involved the use of Intermarket Sweep Orders;

[30] Interviewee AP, in October 2012, reported that "the … problem with people not being able to send ISOs has been solved."

McInish, Upson, and Wood (2012) report higher incidences (40-45 percent) of their use in the trading of stocks in the S&P 500.

The use of Intermarket Sweep Order flags is one aspect of a broader issue: the shaping of the behavior of HFT (and other) algorithms trading U.S. shares by Reg NMS. Much — though not all — of this shaping is via what a liquidity-making algorithm with access to fast, direct datafeeds and predictive capacity needs to do, in order to ensure the maximum benefit from that access and this capacity by gaining the most favorable possible position in the time-priority queue. This issue erupted into controversy in 2012, when algorithmic trader Haim Bodek, founder of Stamford, Connecticut options trading firm Trading Machines LLC, told the SEC and *Wall Street Journal* that trading venues were making specialized types of order available to help liquidity-making HFTs optimize their positions in time-priority queues subject to Reg NMS (Patterson and Strasburg 2012).[31] HFT interviewees denied that these order types were secret. "If you read the [*Wall Street*] *Journal* you were misled," said interviewee AQ: a "fairly clear description of how they [the specialized order types in question] operate" was available. "All those things are out there," said BF. However, no-one denied that specialized order types were important. "They're hugely

[31] Options traders such as Bodek hedge their positions by buying or selling shares, and traditionally have done that by taking liquidity. Trading Machines's strategy was to do it by making liquidity (Patterson 2012, p. 23), which, if could be done in a timely way, would be economically advantageous for the reasons discussed above. However, the firm repeatedly found that its orders were not being executed, presumably because of unfavorable queue positions. Much of the controversy focused on the "Hide Not Slide" order on the trading venue Direct Edge. "Sliding" refers to the procedure of repricing orders so that they can be displayed in a way that complies with Reg NMS (e.g., reducing the price on a bid so that it no longer locks the market). An order that has been "slid" is then repriced at the original price if the market moves in such a way that its display is consistent with Reg NMS, but normally its position in the time-priority queue is determined by when this repricing takes place. In contrast, the time priority for a Hide Not Slide order is determined by the time of the order's initial placement; it is entered into the order book but not displayed until its display is permissible under Reg NMS, hence the name Hide Not Slide. For an explanation — published at the time of Direct Edge's introduction of Hide Not Slide — see Anon (2009).

important," said interviewee AP: "it's been around forever, they [journalists] just found out about it." "It does go on," said AR.

DARK POOLS AND ALGORITHMIC BOUNDARY DRAWING

The controversy over specialized order types was one manifestation of wider contestation over the legitimacy of HFT. As noted above, a common accusation is that HFT algorithms prey upon institutional investors' execution algorithms: "You're basically getting your face ripped off," said an interviewee whose firm supplies these algorithms. Furthermore, the issue of legitimacy resonates within HFT itself. Those HFT firms whose algorithms specialize in liquidity making can, as also noted above, feel themselves as acting more "morally" than those whose algorithms take liquidity, and claim for themselves the legitimacy of the traditional role of the market maker. HFT market-making firms thus sometimes seek to draw within the domain of economic action a boundary of the kind described by Zelizer (2012). For example, when I mentioned the name of another HFT firm to the head of communications at interviewee AC's firm, she distanced that firm from her's: her firm's business was "more pure-play market making." Interviewee AC agreed, distinguishing his firm from others that "trade in any style that looks like it might make some money." Interviewee AQ drew the same distinction: "We're an electronic market-maker. We unfortunately fit under the definition of high-frequency trading."

Drawing a boundary between electronic market-making and other forms of HFT would be easier if market-making algorithms only made liquidity, and never took liquidity. Sometimes, however, a market-making algorithm cannot fully control risk by "shading" its bids and offers, and needs to take liquidity to reduce its risk. No market-making HFT firm of which I am aware bans its algorithms from ever taking liquidity, and junior traders do not always feel the boundary impinging on their design and use of algorithms: “you can really do anything,” said interviewee AW, who works for a firm that positions itself as a market maker.

Another form of algorithmic action that is a candidate for being “bar[red] … as inappropriate” (Zelizer 2012, p. 145) is algo-sniffing: a HFT algorithm setting out to detect and exploit execution algorithms. Indeed, algo-sniffing is sometimes explicitly disavowed by HFTs that position themselves as market makers: it’s “not something we’ve done,” said interviewee AC; “we dismissed the idea.” “We choose not to do it, but someone like us could do it,” said interviewee AQ. However, AP’s warning, quoted above, about the difficulty of humans being certain what their algorithms are really doing indicates the difficulty of barring algo-sniffing. All the HFT firms in which interviewees were prepared to go into this level of detail use the dynamics of order books as a source of prediction, and some firms, rather than programming their algorithms to detect patterns identified by human beings, employ machine learning techniques, in which the algorithm itself searches for patterns with predictive power. It is not clear that even the algorithm’s owner can then be certain that its success is not actually based on algo-sniffing, rather than, for example, detecting a less specific form of price “momentum.” (Interviewee AQ, who was strongly committed to his firm’s identity as an electronic market-maker, said the firm went as far as to eschew machine learning: “[w]e have no pattern recognition [in the firm’s algorithms].”)

Furthermore, the validity of seeking to draw a boundary between electronic market-making and “aggressive,” “opportunistic,” or “algo-sniffing” HFT is fiercely contested. Interviewee BI, for example, saw liquidity-taking (and not just for risk management purposes) as entirely consistent with a market-making role, preferring to refer to the activity as “liquidity-satisfying.” Many U.S. HFT interviewees were in varying degrees libertarian, viewing algo-sniffing as just as legitimate as other forms of behavior within the law. (“[T]he guy who’s trying to hide the supply-demand imbalance [by using an execution algorithm],” said a broker: “why is he any better of a human being than the person trying to discover [that imbalance]” by running an “algo-sniffing strategy”?) Some particularly strong libertarian interviewees even defended “spoofing” (adding spurious orders to order books so as to deceive algorithms using order-book imbalances as a basis of prediction).

Despite all the difficulties that surround them, attempts within HFT to distinguish between market making and other forms of HFT resonate with efforts by the owners of trading venues to draw a similar boundary. In 2011, “Light Pool,” a new “lit” venue — a venue with an order book visible to participants — was created by Credit Suisse, with this boundary-work as its chief rationale. However, the main context of this boundary-work is “dark pools,” which are trading venues whose order books are not visible to those trading on them. The two earliest dark pools were Posit (set up in 1987) and Liquidnet (set up in 1999), and they were followed by a series of dark pools established by major investment banks. The first was Credit Suisse’s Crossfinder, launched in 2006; others such as Goldman Sachs’s Sigma X, Lehman Brothers’ (now Barclays’) LX, and UBS’s ATS soon followed.

The goal of most dark pools is to be a venue in which a “natural” seeking to buy a big block of shares can trade with another “natural” seeking to sell a corresponding block, without the existence of either order being visible to professional traders such as HFTs. (A “natural” is the industry term for an institutional investor genuinely wishing to buy or sell in large quantity; the term can of course carry the connotation that other motivations for buying or selling are unnatural.) However, there may often simply not be a “natural” wanting to buy when another wants to sell (or vice versa), so it can be difficult to achieve adequate liquidity in a dark pool without allowing professional traders to participate. By 2013, around 15 percent of U.S. share trading was in dark pools (Angel, Harris, and Spatt 2013, p. 22), and by then most of them no longer catered simply for large trades between “naturals.” HFTs had joined them, and the average size of trades in most dark pools — at around 200 shares — was no larger than those in lit markets (Massoudi and Mackenzie 2013b).

The defining characteristic of a dark pool — the invisible order book — impinges on those HFT practices of prediction that depend on order-book dynamics, but other sources of prediction remain available and HFT market-making remains entirely feasible: indeed, it may well be necessary to adequate dark-pool liquidity. However, the wider controversy over HFT interacts with frequent suspicions that information “leaks” from dark pools, making some of them “toxic,” as interviewee AE put it. Asked what he meant by calling a dark pool “toxic,” he replied: “I mean that there’s high-frequency trading dudes in there.” There are fears that if HFT algorithms can detect large orders in dark pools, they can then trade profitably in lit markets. For example, a typical way of executing a large institutional order is to make as many purchases or sales as possible in dark pools, and then execute the remainder in lit markets. A particular fear, therefore, is that an algorithm that can detect the order in a dark pool, at least probabilistically, can position itself to profit when the purchase or sales in lit markets begin.

If a dark pool is seen as “toxic,” institutional investors will not want to use it, so it is important to dark-pool operators to convince those investors that their pools control algorithmic behavior that leads to toxicity. As well as dark-pool operators giving their markets technical features designed to make common HFT techniques more difficult,[32] they also directly monitor the behavior of the algorithms and other participants trading in them. Seven interviewees involved with dark pools described measures they take, and there are also useful accounts in the specialist trade press (Mehta 2011; Chapman 2012a&b). One venue is confident enough of its liquidity that it does not allow known HFTs to join it. Another classifies participants into three categories ("contributors," "neutral," and "opportunistic") and expels those classed as "opportunistic." Yet another uses a five-point scale of this kind, but does not expel the "opportunistic." Instead, it makes the categorization available to its matching engine, and allows users of the dark pool to choose to restrict the categories of other participants eligible to trade with their algorithms, so that they can avoid the "opportunistic" if they want. Another venue, owned by a major supplier of execution algorithms to institutional investors, builds the results of its monitoring into those algorithms when these operate in its own dark pool (for example, to help those algorithms avoid other participants that the monitoring suggests will be successful opportunists in particular circumstances).

Given the quantities of data that need analyzed to determine whether a firm's algorithms are "opportunistic," this boundary-work is itself largely algorithmic. A common technique — three interviewees reported use of it — is to estimate a firm's short-term profitability, for example by monitoring how the price of the shares it trades move over the second after the consummation of each trade involving it. Too high a profit rate is taken as an indicator of opportunism. Another variable that is

[32] For example, Light Pool, as a "lit" market, has to accept Intermarket Sweep Orders, but an algorithm seeking to sweep Light Pool has to send its order via the National Stock Exchange, a small trading venue based in Jersey City. "It takes almost half a second," said an interviewee: "that's almost eternity for a high-frequency trader."

used is the proportion of a firm's algorithms' trades that are liquidity-taking; if that figure is high, that too is taken as suggesting opportunism. Interestingly, only two of the seven interviewees whose trading venues engaged in this boundary-work viewed it explicitly as moral in nature. The view that "this is business," as one interviewee put it, was more common. (Other motivations for surveillance and for boundary-work that were cited were simply that "clients do want it"; that it was important to be able to demonstrate that when an investment bank's own trading desks traded in its dark pool — which is not uncommon — their trading was benign; and that in a situation in which dark pools were being heavily criticized by the leaders of "lit" markets such as the New York Stock Exchange, it was vital to be able to show regulators that behavior in dark pools is under "full control.")

As noted above, the boundary that is drawn within HFT as a result of surveillance by dark pool operators seems often to coincide with that drawn by the HFT firms that position themselves as electronic market-makers. As one venue operator put it in interview, in distinguishing algorithmically between "good flow and … bad flow … between the good guys and the bad guys," the "good guys" were "market makers." The very act of surveillance pushed algorithmic behavior in this direction, noted another. Some HFTs rejected surveillance designed to curb their algorithms: "I had one prominent high-frequency shop that on principle refused [to join the venue managed by this interviewee], saying that … the very concept demonized high-frequency trading and therefore we could f-off." Other HFTs, however, embraced surveillance and expressed willingness to modify the behavior of their algorithms to meet its demands. "Tell me how I do," a representative of one electronic market-maker told *Traders Magazine* (Chapman 2012a), "and I'll adjust. … I want to be scored. Everyone should be scored."

LAST LOOK AND THE LINKED ECOLOGIES OF FOREIGN EXCHANGE

Foreign exchange is another domain in which there are restrictions on and surveillance of HFTs, and their consequences for the practices of HFT are even greater than those of the analogous measures in share-trading dark pools. Like NASDAQ prior to the incursion of the ECNs, foreign exchange traditionally was — and to a significant extent it remains — a "dealer market." Currencies were not traded on an exchange, but "over-the-counter," in other words directly between institutions.[33] Most market participants — more minor banks, other corporations, hedge funds, and institutional investors — did not trade among themselves: they traded only with dealers, by accepting the latter's quotes. In foreign exchange, the main dealers are all big banks. Dealers did and do trade with each other, via interdealer brokers, messaging systems (see Knorr Cetina and Bruegger 2002), or one or other of the two main interdealer electronic-trading venues, Reuters and EBS (Electronic Broker System). The latter was created in 1990 by a consortium of dealer banks, and bought in 2006 by the interdealer broker ICAP (Knorr Cetina 2007 gives an excellent account of trading on EBS).

Just as first NASDAQ and then the New York Stock Exchange were challenged by the ECNs, so this dealer-market configuration in foreign exchange was challenged at the end of the 1990s and in the early 2000s by new electronic trading venues modelled on the ECNs. These new venues had something of the character of what Abbott calls "avatars": they were the result of attempts to create incarnations of institutions from one domain (share trading) in a different domain,

[33] Currency futures, however, were and are exchange-traded.

foreign exchange. However, “the internal forces of competition in the avatar’s ecology tend to drive the avatar in directions unforeseen ahead of time” (Abbott 2005, p. 269). Initially, said an interviewee, “people believed that this [the creation of ECN-like trading venues in foreign exchange] was going to force the banks into the new paradigm,” as had happened in share trading. However, the dealer banks “were able to say no and not participate” in developments in trading venues that threatened their interests, and without their support and the large volumes of liquidity they could provide, it was difficult for a new foreign-exchange trading venue to thrive.

So confrontation between the new electronic venues and banks had to give way to collaboration. At one new venue, “the original investors fired the CEO,” said an interviewee, and his replacement “changed the business model … he befriended the banks … and work[ed] with them over the course of the years.” As automation of foreign-exchange trading took place, therefore, it was often shaped by the interests and preferences of the big banks. For example, equivalents of Island’s ultra-fast ITCH datafeed and OUCH order-entry protocol were not adopted widely in foreign exchange. Instead, the protocol mainly used in foreign-exchange trading was and is FIX, which was much slower (the above interviewee described it as “verbose” compared to the “compact, efficient” ITCH and OUCH), but widely used in banking and already familiar to banks’ information-technology departments.

In share trading, the three crucial linked ecologies were HFT, trading venues, and regulation. As HFT began in foreign exchange, often introduced by firms that were already trading shares or futures, its practitioners confronted a different configuration of linked ecologies. The ecology of trading venues seemed similar — two large, established venues (EBS and Reuters); a number of new ECN-like venues; and other venues run by banks — but in foreign exchange the crucial linkages of the ecology of trading venues were not to regulation but to the big dealer banks. As an interviewee said, “when someone calls or we call someone we want to trade on [his venue], we ask them if they have existing bank relationships.” In share trading, HFTs can operate relatively independently; indeed, larger HFTs often become broker-dealers in their own right. In foreign exchange, if an HFT is to operate on any scale, it needs a bank to act as its prime broker, facilitating its trading and especially the settlement of its trades.[34]

In foreign exchange (as, indeed, as elsewhere), banks appear ambivalent about HFT, welcoming the income (such as prime brokerage fees) proprietary trading firms bring them, but anxious about HFTs as competitors in trading. Banks’ organizational structures do not seem conducive to the creation of pared-down, speed-optimized technical systems. In HFT firms, which are (as noted) usually relatively small, privately-held proprietary trading businesses, trading activities and the development of technological systems are intimately interwoven; often, there is no clear organizational distinction between traders and system developers. In a bank, system developers are not normally managed by those responsible for trading, but are part of a separate IT department. “That’s problematic,” says interviewee BF, who has worked in both HFT firms and a bank. Banks’ IT departments have their own preferred technological styles and priorities. In one bank, said BF, the IT department tried to insist that the HFT system had a security firewall. “[G]uess what, that firewall takes 50 milliseconds to go through it. I can’t do that: I’m out of the game.” Another interviewee, a technology specialist, talked about the problem in

[34] HFT firms cannot get full membership, said interviewee BI, of the international Continuous Linked Settlement system in foreign exchange. They therefore have to work through a bank that is a member of the system.

banks of “legacy systems” that “just get ingrained in the very fabric of the organization, … doing it [HFT] in a large investment bank is really hard work.”

The linkages between trading venues in foreign exchange and banks, and the ambivalence of the latter about HFT mean that measures to restrict HFT are more prevalent and harsher in foreign exchange than in share trading. HFTs in foreign exchange that are too profitable — especially those that “pick off” banks’ stale quotes — do not simply face, as in the dark pools discussed in the previous section, admonitory telephone calls or their algorithms being electronically tagged as “opportunistic,” but more brutal sanctions.[35] If they are trading on a bank-owned venue and the bank “figures out what they are doing,” said a foreign-exchange trader it “normally just cuts them off the day they figure it out: ‘that’s it, your account’s closed here, take your money away and don’t come back.’” Even on an ECN-style venue, a HFT whose algorithms are too successful can get frozen out by the larger participants. “ECNs are naturally anonymous,” said interviewee AU, but “most of them if not all provide client ID [a firm’s numerical identifier], and the bank can say: ‘oh, I don’t want to trade with this person because they’re good; let’s turn them off.’”

Attempts to create technical obstacles to HFT are also more prominent in foreign exchange. Share trading venues that create obstacles, such as Light Pool (mentioned in the last section), are “niche” markets rather than large-scale. In foreign exchange, the traditionally biggest venues seek to constrain HFT. Both Reuters and EBS impose a minimum order resting time: on EBS, for example, an order must remain in the electronic order book for a quarter of a second before it can be cancelled. In 2012, EBS reversed an earlier move to reduce minimum price

[35] Expulsions of HFT firms from trading venues do happen in share trading, but are not commonplace: I know of only four that I am confident took place.

increments, increasing the increment five-fold for some currency pairs, and it also then changed its matching algorithm (which was a time-priority algorithm which "queued" orders in essentially the same way as share-trading matching engines do) to an algorithm that collects incoming orders into a batch and then randomizes the order in which it processes them. Speed "is a technology arms race to the bottom, and a huge tax on the industry," said the chief executive of EBS. Its preferred customers "are serious players who come to the market to exchange risk — they do not come to race" (Foley 2013).

Interviewees in the ECN-type venues in foreign exchange were markedly less negative than that about HFT. However, the continuing dependence of those venues on the dealer banks, the biggest players in foreign exchange, has led in most of those venues to the creation of an institution no longer found in automated share trading: "last look." Before a matching engine consummates a trade involving a participant granted last-look privileges (normally, a major dealer bank), the engine sends a message to the participant's trading system giving the latter a period of time ("[a]nywhere from five to ten milliseconds, up to a few hundred milliseconds, sometimes up to a few seconds," reported interviewee AU) in which it can reject the trade. "ECNs don't usually have a choice" in respect to last look, said AU: "that is where the power of the liquidity provider comes in." That provider says to the ECN:

> "if I'm not 'last look,' I'm not going to provide you liquidity." So the ECN gets to a certain point where [the] top 15 people in the world [the major dealer banks that] can provide liquidity are asking for last look and if they don't [grant them last look] they don't get access to liquidity for [the ECN's] clients to take.

The rationale for last look from a dealer bank's viewpoint is that it is continually providing liquidity (posting bids and offers) on multiple foreign-exchange trading platforms. The matching engines on those platforms tend to be slower than in share trading, the banks' systems are usually slower than HFTs' systems, and (as noted) the dominant communications protocol in foreign exchange, FIX, is slower than its counterparts in shares. So the dealer bank faces the risk that all its offers will be lifted simultaneously or its bids hit simultaneously on multiple platforms, or that the prices of those offers and bids will become "stale" and will be picked off before the bank is able to cancel them. A representative of one of the ECN-like venues in foreign exchange thus defends last look as a necessary institution:

> If you're offering the same price at two different venues, you don't really want to deal twice, so one of the main safeguards that last look provides is the ability to validate that the trade is legitimate; that the price is the best you can get at that instant; and, from a risk perspective, that they're not getting taken out on three venues at once and exposing themselves to too much risk. If that happens too many times to the market-maker, they widen out their quotes, which doesn't help anybody. (Smith 2012)

To high-frequency traders who come to foreign exchange from trading shares or futures, "last look" is at best a peculiarity that has to be lived with, at worst a scandal. Interviewee AK took the latter attitude. In trading foreign exchange, he said, "you're a second-class citizen if you're not a bank." His firm had had some success in the high-frequency trading of foreign exchange, but the "last straw" had been when a trade against one of its liquidity-making orders (it was pursuing an electronic market-making strategy) got rejected on “last look” by a participant that had traded against his firm’s passive order:

> When we complained about it, they [the ECN] said, “that’s our structure: these certain participants get last look on everything.” We were, like, we’re done. You can give us back our $100,000 we have on account … and close our accounts and you’ll never see a dime from us again. We’re out.

Other HFTs took a more accommodating attitude. Interviewee BD, whose firm’s background was in futures trading, said that to be successful in HFT in foreign exchange, one had to “develop relationships” with banks, and “to be careful not to be so carnivorous as in the futures.” One had to be “nice,” and to provide “more friendly flow” rather than simply pursuing maximum profits. Similarly, interviewee AU said of the HFT of foreign exchange:

> It’s all about relationships. … You have to build a pretty good relationship to get access to certain things. … FX spot [the trading of foreign exchange for immediate delivery] is an over-the-counter electronically-traded, relationship business. And often some of the electronic players just focus on the first two components but without the relationship.

CONCLUSION

What becomes of economic sociology when markets and most participants in them are computer algorithms? This paper has examined high-frequency trading algorithms: the forms of price prediction on which they rely, their interactions with matching engines and execution algorithms, and the liquidity-making or liquidity-taking actions they take. It has described how some high-frequency traders themselves and some of the venues on which HFTs trade engage in “Zelizerian” boundary-work, seeking to distinguish appropriate from less appropriate or unacceptable algorithmic economic action, but has also shown how that boundary-work is contested. The paper has offered a politically inflected historical sociology of HFT, expressed in Abbott’s (2005) vocabulary of “linked ecologies,” for example contrasting the high-frequency trading of U.S. shares (influenced both historically and in the present by the “hinge” connecting HFT, trading venues, and regulation) with the quite different contingencies confronting HFT in foreign exchange.

The indefinite article in the paper’s title is meant seriously. This particular form of the sociology of algorithms is only one of many that are conceivable. For example, the interviewees’ comments on the importance of “relationships” to the successful high-frequency trading of foreign exchange, and the importance (discussed below) of the circulation of personnel to the diffusion of HFT techniques point to the possibility of a “Granovetterian” network sociology of algorithms. A cultural sociology of algorithms is also clearly possible. Island, say, was as much a cultural project as a economic one (author ref.). The fears about HFT that have fuelled the boundary-work discussed in this paper can plausibly be interpreted as the conjunction of two wider cultural anxieties: about out-of-control technology (for which, see Winner 1977) and out-of-control finance (an anxiety of course greatly strengthened by the 2007-8 crisis).

The plethora of possibilities for the sociology of algorithms should not, however, lead us to imagine that it can simply be “business as usual” for economic sociology. The actor-network extension of the notion of “actor” from humans to non-human entities such as algorithms needs taken seriously, as do phenomenological investigations of how humans, machines, and markets interact, investigations of the kind pioneered in economic sociology by Knorr Cetina. Algorithmic finance is, surely, the perfect terrain for the "meeting" of economic sociology and science and technology studies called for by and exemplified in Pinch and Swedberg (2008).

Amongst the reasons this "meeting" is needed is that, in share trading (although not in foreign exchange), a topological shift has taken place. HFT in shares began in the 1990s largely enfolded within trading venues, and those who conducted HFT generally had to accept the features of those venues as a fixed environment to which HFT had to adapt: "you had to learn to live within the realities that you confronted" (interviewee BF, as quoted above). By 2008, that relationship had reversed: trading venues, faced with fierce competition for market share and even survival, had to adapt to HFT, at least as much as vice versa. Venues needed HFT market-makers to provide the tight spreads that would attract business, and so had to offer those market-makers co-location, a fast matching engine, a direct datafeed, low fees, rebates, etc. In some cases, HFTs helped venues overcome the resultant technical challenges (see author ref.). In other cases, HFTs provided funding for new trading venues, or even themselves launched them. As noted above, the new venue BATS was launched in 2005 by the Kansas City HFT firm, Tradebot. In early 2014, BATS merged with a similar venue, Direct Edge, to form BATS Global Markets, and the new firm is on the brink of becoming the world's largest share-trading venue. Its market share is almost identical to that of NYSE, which has itself been bought by an upstart electronic futures-trading venue, the InterContinental Exchange.

What has triumphed in share trading, therefore, is a set of anonymous, highly competitive, electronic markets in which most action is algorithmic. The outcome may seem (to an economic sociologist) uncomfortably close to the economists' "perfect market." However, the ecology that now largely enfolds trading venues, HFT, remains a *socio*technical domain. For example, although the data for a systematic social network analysis are not available, there were many pointers in the interviews to the importance of network links, both amongst HFTs (such links, as noted above, are a major mechanism by which HFT techniques diffuse) and between HFTs and trading venues. Staff from the latter can be valuable recruits for HFTs, bringing with them detailed understanding of venues' computer systems and also, for example, knowledge of exactly whom at the venue to speak to if, for example, one's connections to the latter seem to be via an unusually slow server.

Above all, there is no teleology to the apparent triumph of "perfect markets." As shown in the discussion of Intermarket Sweep Orders, the current practices of the HFT of U.S. shares are still shaped by the legacy of a specific historical event: the decision in the late 1970s not to adopt a "Hard CLOB," but to follow the preference of most of the exchanges and develop an Intermarket Trading System. Furthermore, the comparison between share trading and foreign exchange shows that the market form that has triumphed U.S. share trading, far from being natural or inevitable, was the result of the particular "hinge" connecting HFT, trading venues, and regulation. Absent that hinge, and with no equivalent of the SEC, foreign exchange trading venues are quite different. In addition, as we have also seen, alongside the apparently "perfect" lit markets in shares, and hosting a growing proportion of trading, are "dark" markets whose operators perform Zelizerian boundary-work. These markets contribute, some high-frequency traders complain, to the lit markets, far from actually being "perfect", becoming full of what interviewee BI called toxic "exhaust."[36]

"[M]arkets are not more or less social," commented Mark Granovetter a decade ago: "They may be more or less personal" (Krippner et al. 2004, p.129). Algorithmic markets in which most actors are themselves algorithms are the most depersonalized of current market forms. Revealing the many ways in which these markets are still social is a major challenge for economic sociology. This paper has identified some of those ways, but I am confident many others remain to be discovered. The sociology of algorithms is still in its infancy, but its growth to maturity will surely be a major aspect of economic sociology in the years to come.

REFERENCES

Abbott, Andrew. 1995. "Things of Boundaries." *Social Research* 62:857-882.

—. 2001. *Time Matters: On Theory and Method Chicago*. Chicago, University of Chicago Press.

—. 2005. "Linked Ecologies: States and Universities as Environments for Professions." *Sociological Theory* 23:245-274.

—. n.d.. V: Ecologies and Fields, Available at http://home.uchicago.edu/aabbott/Papers/BOURD.pdf, accessed February 1, 2014.

Angel, James J., Lawrence E. Harris, and Chester S. Spatt. 2013. Equity Trading in the 21st Century: An Update, June 21. Available at: http://www.knight.com/newsroom/pdfs/researchCommentary06272013.pdf, accessed January 21, 2014.

[36] As noted above, institutional investors typically try first to execute their offers in dark pools, before routing them to lit markets. If a large sell order, say, finds no buyers in dark pools, it probably means that prices are about to fall. The HFT market-making algorithms whose bids are hit when the order reaches the lit markets will thus lose money. "Adverse selection" of this kind seems substantial: at around 0.1 cents per share traded (or perhaps less), HFT profits are lower than rebates (which are, as noted, around 0.3 cents per share traded), indicating that without rebates HFT market-making would on average lose money.

Anon. 2009. Direct Edge Launches Hide Not Slide Order, May 28. Available at http://www.thetradenews.com/print.aspx?id=2597, accessed December 31, 2012.

—. 2010. "It's a Screaming Hold." *Financial Times* October 9-10:24.

Arthur, Brian W. 1984. "Competing Technologies and Economic Prediction." *Options* April:10-13.

Baron, Matthew, Jonathan Brogaard, and Andrei Kirilenko. 2012. The Trading Profits of High Frequency Traders, Typescript, November.

Beunza, Daniel, and David Stark. 2004. "Tools of the Trade: The Socio-Technology of Arbitrage in a Wall Street Trading Room." *Industrial and Corporate Change* 13:369-400.

Beunza, Daniel, and Yuval Millo. 2013. Folding: Integrating Algorithms into the Floor of the New York Stock Exchange, Available at http://ssrn.com/abstract=2265849, accessed December 2, 2013.

Blume, Michael E. 2000. The Structure of the US Equity Markets, Available at http://finance.wharton.upenn.edu/~rlwctr/papers/0017.pdf.

Brogaard, Jonathan A., Terrence R. Henderschott, and Ryan Riordan. 2012. High Frequency Trading and Price Discovery, Available at: http://ssrn.com/abstract=1928510, accessed 14 November 2012.

Budish, Eric, Peter Cramton, and John Shim. 2013. The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response, Available at: http://faculty.chicagobooth.edu/eric.budish/research/HFT-FrequentBatchAuctions.pdf, accessed July 8, 2013.

Çalişkan, Koray, and Michel Callon. 2009. "Economization, Part 1: Shifting Attention from the Economy towards Processes of Economization." *Economy and Society* 38:369-398.

—. 2010. "Economization, Part 2: A Research Programme for the Study of Markets." *Economy and Society* 39:1-32.

CFA Institute. 2012. "Dark Pools, Internationalization, and Equity Market Quality", Charlottesville, VA, CFA Institute.

Chapman, Peter. 2012a. "Barclays Polices Dark Pool," Traders Magazine Online News, April 25. Available at http://www.tradersmagazine.com, accessed April 25, 2012.

Chapman, Peter. 2012b. "Keeping Watch", Traders Magazine Online News, May 7. Available at http://www.tradersmagazine.com, accessed May 7, 2012.

David, Paul A. 1992. "Heroes, Herds and Hysteresis in Technological History: Thomas Edison and 'The Battle of the Systems' Reconsidered." *Industrial and Corporate Change* 1:129-180.

Deleuze, Gilles. 1990. *The Logic of Sense*. New York, Columbia University Press.

Durbin, Michael. 2010. *All About High-Frequency Trading*. New York, McGraw-Hill.

Fligstein, Neil, and Doug McAdam. 2012. *A Theory of Fields*. Oxford, Oxford University Press.

Foley, Stephen. 2013. "HFT Platforms Facing 'Speed Limits'." *Financial Times* April 29:22.

Gieryn, Thomas. F. 1999. *Cultural Boundaries of Science: Credibility on the Line*. Chicago, Chicago University Press.

Hasbrouck, Joel. (2003). "Intrading Price Formation in U.S. Equity Index Markets." *Journal of Finance* 58:2375-2399.

Hasbrouck, Joel, and Gideon Saar. 2010. Low-Latency Trading, Available at http://ssrn.com/abstract=1695460, accessed 25 August 2011.

Hendershott, Terrence, and Charles M. Jones. 2005. "Island Goes Dark: Transparency, Fragmentation and Regulation." *Review of Financial Studies* 18: 743-793.

Hillis, Ken, Michael Petit, and Kyle Jarrett. 2013. *Google and the Culture of Search*. New York, Routledge.

Hirschey, Nicholas H. 2011. Do High-Frequency Traders Anticipate Buying and Selling Pressure?, Available at https://www2.bc.edu/~taillard/Seminar_spring_2012_files/Hirschey.pdf, accessed 13 August 2012.

Johnson, Neil, Guannan Zhao, Eric Hunsader, Jing Meng, Amith Ravinder, Spencer Carrran, and Brian Tivnan. 2012. Financial Black Swans Driven by Ultra Fast Machine Ecology, Available at http://arxiv.org/abs/120z.1448, accessed February 21, 2012.

Knight Capital Group, Inc. 2012. 2011 Annual Report, Jersey City, NJ: Knight Capital Group. Available at http://www.knight.com, accessed December 6, 2012.

Knorr Cetina, Karin. 2005. How are Global Markets Global? The Architecture of a Flow World. *The Sociology of Financial Markets*. K. Knorr Cetina and A. Preda. Oxford, Oxford University Press:38-61.

—. 2007. "Global Markets as Global Conversations." *Text and Talk* 27: 705-734.

—. 2013. Presentation to Panel, Theorizing Numbers, American Sociological Association Annual Meeting, New York, August 9-13.

Knorr Cetina, Karin, and Urs Bruegger. 2002. "Global Microstructures: The Virtual Societies of Financial Markets." *American Journal of Sociology* 107:905-951.

Knorr Cetina, Karin, and Alex Preda. 2007. "The Temporalization of Financial Markets: From Network to Flow." *Theory, Culture and Society* 24/7-8:116-138.

Latour, Bruno. 2005. *Reassembling the Social: An Introduction to Actor-Network Theory*. Oxford, Oxford University Press.

Lenglet, Marc. 2011. "Conflicting Codes and Codings: How Algorithmic Trading is Reshaping Financial Regulation." *Theory, Culture & Society* 28:44-66.

Mackenzie, Adrian. 2006. *Cutting Code: Software and Sociality*. New York, Peter Lang.

MacKenzie, Donald. 2006a. *An Engine, not a Camera: How Financial Models Shape Markets*. Cambridge, MA, MIT Press.

Mackenzie, Michael. 2012. "Calls to Extend Circuit Breakers on Superfast Traders." *Financial Times* August 15:26.

Madhavan, Ananth. 2012. Exchange-Traded Funds, Market Structure and the Flash Crash, Available at http://ssrn.com/abstract=1932925, accessed 30 December 2012.

Massoudi, Arash, and Michael Mackenzie. 2013a. "In Search of a Fast Buck." *Financial Times* February 20:11.

—. 2013b. "Investors Turn to the Dark Side for Trading." *Financial Times* April 26: 30.

McInish, Thomas, and James Upson. 2012. Strategic Liquidity Supply in a Market with Fast and Slow Traders, Available at: http://ssrn.com/abstract=1924997, accessed 21 January 2013.

McInish, Thomas, James Upson, and Robert Wood. 2012. The Flash Crash: Trading Agressiveness, Liquidity Supply, and the Impact of Intermarket Sweep Orders, Available at http://ssrn.com/abstract=1629402, accessed June 3, 2012.

Mehta, Nina. 2011. "Credit Suisse Plans Market for Long-Term Investors." *Bloomberg Businessweek* January 11: Available at http://www.businessweek.com, accessed January 17, 2011.

Muniesa, Fabian. 2003. Des marchés comme algorithmes: Sociologie de la cotation électronique à la Bourse de Paris, PhD thesis: École Nationale Supérieure des Mines.

—. 2005. "Contenir le marché: La transition de la criée à la cotation électronique à la Bourse de Paris." *Sociologie du travail* 47:485-501.

—. 2011. "Is a Stock Exchange a Computer Solution? Explicitness, Algorithms and the Arizona Stock Exchange." *International Journal of Actor-Network Theory and Technological Innovation* 3/1:1-15.

Pardo-Guerra, Juan Pablo 2010a. Computerising Gentlemen: The Automation of the London Stock Exchange, c. 1945-1995, PhD thesis: University of Edinburgh.

—. 2010b. "Creating Flows of Interpersonal Bits: The Automation of the London Stock Exchange, c.1955-90." *Economy and Society* (39):84-109.

Patterson, Scott. 2012. *Dark Pools: High-Speed Traders, A.1. Bandits, and the Threat to the Global Financial System*. New York, Crown.

Patterson, Scott, and Jenny Strasburg. 2012. "Dark Markets: For Superfast Stock Traders, A Way to Jump Ahead in Line." *Wall Street Journal* September 19:A1.

Patterson, Scott, Jenny Strasburg, and Liam Pleven. 2013. "Speedy Traders Exploit Loophole." *Wall Street Journal* May 1: 1-2.

Pinch, Trevor, and Richard Swedberg., Ed. 2008. *Living in a Material World*. Cambridge, MA, MIT Press.

Poon, Martha. 2007. Scorecards as Devices for Consumer Credit: The Case of Fair, Isaac & Company Incorporated. *Market Devices*. M. Callon, Y. Millo and F. Muniesa. Oxford, Blackwell:284-306.

—. 2009. "From New Deal Institutions to Capital Markets: Commercial Consumer Risk Scores and the Making of Subprime Mortgage Finance." *Accounting, Organizations and Society* 34:654-674.

Popper, Nathaniel, and Christopher Leonard. 2012. High-Speed Traders Profit at Expense of Ordinary Investors, a Study Says, *New York Times*, December 3. Available at http://www.nytimes.com, accessed December 5, 2012.

Preda, Alex. 2006. "Socio-Technical Agency in Financial Markets: The Case of the Stock Ticker." *Social Studies of Science* 36:753-782.

—. 2007. Where do Analysts come from? The Case of Financial Chartism. *Market Devices*. M. Callon, Y. Millo and F. Muniesa. Oxford, Blackwell: 40-64.

—. 2009a. "Brief Encounters: Calculation and the Interaction Order of Anonymous Electronic Markets." *Accounting, Organizations and Society* 34:675-693.

—. 2009b. *Framing Finance: The Boundaries of Markets and Modern Capitalism*. Chicago, University of Chicago Press.

—. 2013. "Tags, Transaction Types and Communication in Online Anonymous Markets." *Socio-Economic Review* 11:31-56.

Saavedra, Serguei, Kathleen Hagerty, and Brian Uzzi. 2011. "Synchronicity, Instant Messaging, and Performance among Financial Traders." *Proceedings of the National Academy of Sciences* 108:5296-5301.

Securities and Exchange Commission. 2005. "17 CFR Parts 200, 201, et al.: Regulation NMS; Final Rule." *Federal Register* 70/124 (June 29):37496-37644.

Seligman, Joel. 1982. *The Transformation of Wall Street: A History of the Securities and Exchange Commission and Modern Corporate Finance*. Boston, Houghton Mifflin.

Smith, Robert MacKenzie. 2012. "Has Last Look Had Its Day in FX?" *FX Week* December 10: Available at http://www.fxweek.com/2229300/, accessed October 28, 2013.

Winner, Langdon. 1977. *Autonomous Technology: Technics-out-of-Control as a Theme in Political Thought*. Cambridge, MA, MIT Press.

Zaloom, Caitlin. 2006. *Out of the Pits: Trading and Technology from Chicago to London*. Chicago, Chicago University Press.

Zelizer, Viviana A. 2012. "How I became a Relational Economic Sociologist and What Does That Mean?" *Politics & Society* 40(2):145-174.

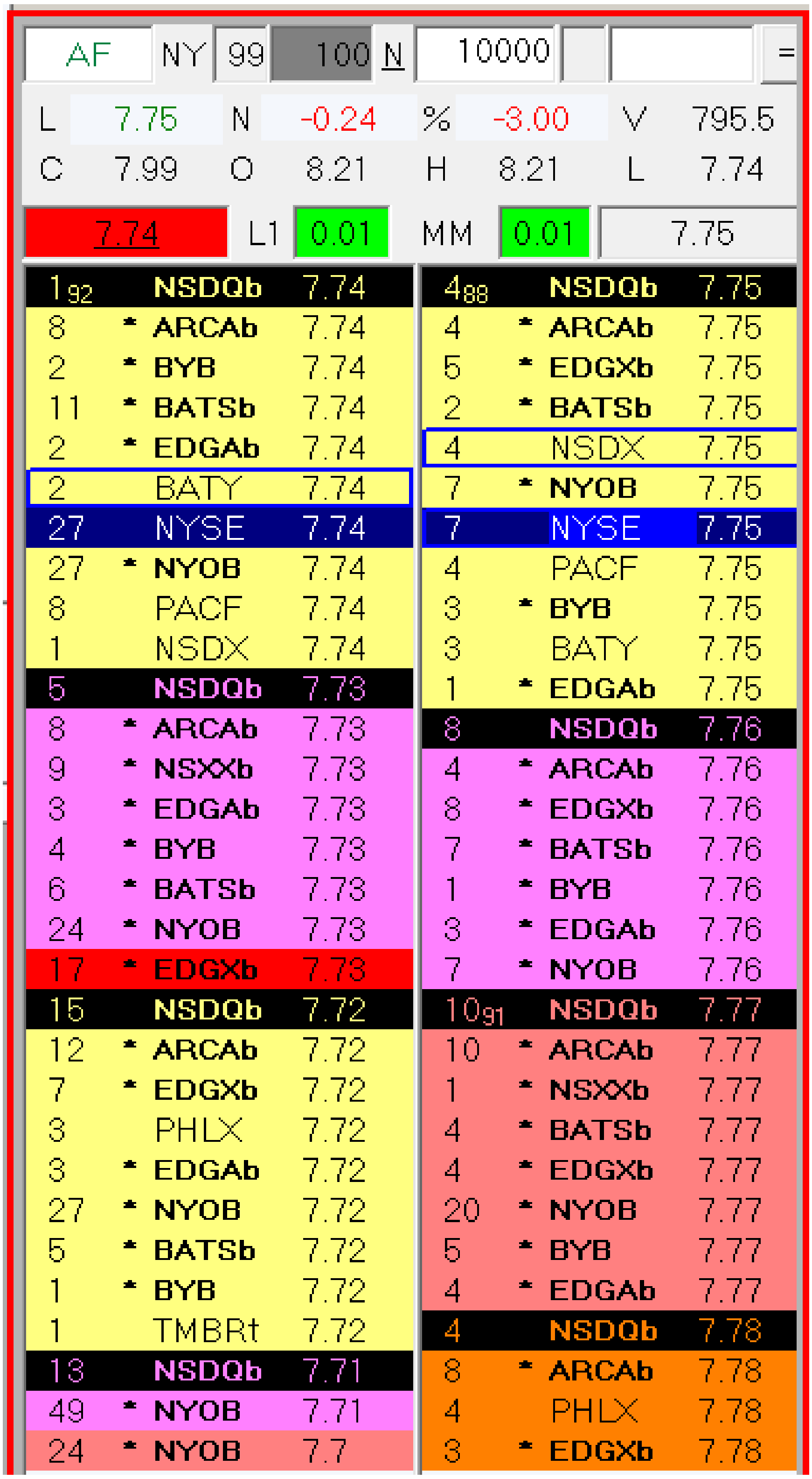
U.S. shares	53%
Global futures	52%
Global foreign exchange	40%
Global fixed income (bonds and bond-like products)	18%

TABLE 1. High-frequency trading as a percentage of all trading in selected markets in 2012. Source: Aite Group estimates; Massoudi and Mackenzie (2013a).

High-frequency traders		39
of which primary area of experience:		
Shares	20	
Futures	9	
Foreign exchange	6	
Other instruments	4	
Exchange/trading venue personnel		36
of which primary area of experience:		
“Lit” share trading	5	
“Dark” share trading	7	
Futures	11	
Foreign exchange	10	
Other instruments	3	
Suppliers/users of execution algorithms		6
Practitioners of other forms of algorithmic trading		5
Manual traders		7
Brokers		3
Suppliers of hardware or services to HFT		10
Market analysts with expertise in HFT		13
Regulator		1
Total		120

TABLE 2. Interviewees.

In total, 104 interviews were conducted, of which 13 were with two people, five with three people, and one with four people. Six people were interviewed twice, and two were interviewed three times. “Lit” and “dark” are explained in the text.



AF	NY	99	100	N	10000	=

L	7.75	N	-0.24	%	-3.00	V	795.5
C	7.99	O	8.21	H	8.21	L	7.74

7.74	L1	0.01	MM	0.01	7.75

1 92	NSDQb	7.74	4 88	NSDQb	7.75
8	* ARCAb	7.74	4	* ARCAb	7.75
2	* BYB	7.74	5	* EDGXb	7.75
11	* BATSb	7.74	2	* BATSb	7.75
2	* EDGAb	7.74	4	NSDX	7.75
2	BATY	7.74	7	* NYOB	7.75
27	NYSE	7.74	7	NYSE	7.75
27	* NYOB	7.74	4	PACF	7.75
8	PACF	7.74	3	* BYB	7.75
1	NSDX	7.74	3	BATY	7.75
5	NSDQb	7.73	1	* EDGAb	7.75
8	* ARCAb	7.73	8	NSDQb	7.76
9	* NSXXb	7.73	4	* ARCAb	7.76
3	* EDGAb	7.73	8	* EDGXb	7.76
4	* BYB	7.73	7	* BATSb	7.76
6	* BATSb	7.73	1	* BYB	7.76
24	* NYOB	7.73	3	* EDGAb	7.76
17	* EDGXb	7.73	7	* NYOB	7.76
15	NSDQb	7.72	10 91	NSDQb	7.77
12	* ARCAb	7.72	10	* ARCAb	7.77
7	* EDGXb	7.72	1	* NSXXb	7.77
3	PHLX	7.72	4	* BATSb	7.77
3	* EDGAb	7.72	4	* EDGXb	7.77
27	* NYOB	7.72	20	* NYOB	7.77
5	* BATSb	7.72	5	* BYB	7.77
1	* BYB	7.72	4	* EDGAb	7.77
1	TMBRt	7.72	4	NSDQb	7.78
13	NSDQb	7.71	8	* ARCAb	7.78
49	* NYOB	7.71	4	PHLX	7.78
24	* NYOB	7.7	3	* EDGXb	7.78

FIG 1. Orders for shares of Astoria Financial Corp. on U.S. venues, c. noon, October 21, 2011.
Source: interviewee.

Bids to buy		Offers to sell	
		↑	
		$7.78	400
		$7.77	1091
		$7.76	800
		$7.75	488
192	$7.74		
500	$7.73		
1500	$7.72		
1300	$7.71		
	↓		

FIG 2. Orders for shares of Astoria Financial Corp. on NASDAQ, c. noon, October 21, 2011.

Source: interviewee.