Economy and Society ›

Volume 47, 2018 - Issue 4

Open access

6,901 Views | 54 CrossRef citations to date | 4 Altmetric

Listen

Articles

'Making', 'taking' and the material political economy of algorithmic trading

Donald MacKenzie

Pages 501-523 | Published online: 27 Nov 2018

Cite this article https://doi.org/10.1080/03085147.2018.1528076 Check for updates

Abstract

Drawing upon interviews with 72 practitioners of automated, ultrafast high-frequency trading (HFT), this paper identifies the most salient divide within HFT: between algorithms, trading groups and firms that specialize in 'making' (in adding bids to buy and offers to sell to exchanges' electronic order books) and those that specialize in 'taking' (in executing against existing bids and offers in those order books). The paper explores how 'making' and 'taking' algorithms interact, emphasizing the materiality of that interaction (including, e.g. the surprising effect on it of rain), and suggesting the importance of the 'material political economy' of algorithmic trading: the shaping of that trading, in economically consequential ways, by material orderings that could be different.

Keywords:

In many of the world's most important financial markets, most trading is now by algorithms.[1] The trading pits of the nineteenth and twentieth centuries, crowded with human beings, are now almost all closed. Humans still trade with keyboard and mouse, but in many markets most trading is now by computer algorithms, especially ultrafast high-frequency trading (HFT) algorithms. The transformation is still being digested. There is a growing literature in economics on HFT (most recently reviewed by Menkveld, 2016), and a smaller but vigorous sociological literature, the best collection of which is in the May 2016 special issue of this journal, 'Cultures of high-frequency trading' (Lange et al., 2016).

This paper makes four contributions to the sociological literature on HFT. The first is to highlight the diversity of HFT practices. While the special issue and the insightful examination of algorithmic cultures in Seyfert and Roberge (2016) are careful to invoke 'cultures' in the plural, the best existing treatment of diversity (Seyfert, 2016) compares the epistemic regime of high-frequency traders with those of regulators and of market analysts who are critics of HFT, rather than probing differences among the practices of HFT firms. In contrast, this paper discusses the single most important divide within HFT and, simultaneously, examines the two main 'species' of HFT algorithm. The divide is between HFT firms, trading groups and algorithms that specialize in 'making' or 'providing liquidity' (which means entering into exchanges' computer systems bids to buy and offers to sell that cannot immediately be executed) and firms, groups and algorithms that specialize in 'taking liquidity': in entering orders that can be executed straightaway against existing bids and offers.

The divide between 'making' and 'taking' sounds like a narrow technicality, but is actually both fascinating and important: for example, it is felt by some practitioners of automated trading to have an affective, even a moral, aspect. Above all, analysis of the divide helps us understand how HFT algorithms interact, which is – as Borch points out, also in this journal – a pivotal topic for today's economic sociology (Borch, 2016). When

standard parts of sociology's disciplinary repertoire could be applied to trading (as, e.g. in the classic application of social network analysis by Baker, 1984). What, however, might it mean – theoretically, methodologically – to apply economic sociology to algorithms trading with other algorithms? In the wake of Callon's and Latour's actor-network theory (with its major influence on economic sociology via the work of Muniesa and many others: see, e.g. Callon et al., 2007; MacKenzie et al., 2007), it hardly seems satisfactory to say that we sociologists will study the human beings who program and supervise the algorithms, while leaving to others the investigation of the algorithms themselves and of how they interact – even if, as noted below, that investigation involves methodological difficulties. The second contribution of the research reported here is thus its identification of four distinct styles of algorithmic 'taking', each associated with a distinctive form of making/taking interaction. Only one of these forms of interaction – the 'picking-off' of 'stale quotes': see below – has previously been researched in any depth (by Budish et al., 2015).

The paper's third contribution is its empirical investigation of the material nature of making/taking interaction. Although the authors of the May 2016 special issue would all agree that HFT algorithms interact materially, attention to materiality in the existing sociological literature on HFT has been limited. (The researcher on HFT most sensitive to materiality is the anthropologist, publisher and graphic designer Alexandre Laumonier, with his remarkable work documenting the paths followed in Europe by HFT's microwave links.[2]) Because the materiality of HFT is crucial to the success of HFT firms, it is a sensitive topic in interviewing, and building the necessary trust and technical understanding takes time. (For example, it was only after several years that I came to understand the impact of rain on making/taking interaction.) Materialism comes, of course, in many flavours, ranging from Marxism to, for instance, anthropological perspectives (e.g. Miller, 2005) or media theory (e.g. Parikka, 2015). One example, however, of a helpful theorization is the materialism of what one might call 'late actor-network theory' or 'late ANT', from around 2000–2002 onwards (the years of de Laet and Mol's [2000] study of the Zimbabwe bush pump and Mol's The body multiple [2002]). 'Late ANT' materialism makes fully explicit that materiality is not given or fixed, but processual and enacted: 'late ANT' is, to paraphrase Law (2010), a materialism of verbs, not nouns. Of course, the enactment of materiality need not involve human beings at all, but in almost all actor-network studies it does. The materiality on which ANT scholars actually focus is sociomateriality: practices and

processes, via which materiality takes shape, that involve human beings as well as non-human 'actants'.

An 'enactment materialism' is analytically suitable because it supports this paper's fourth contribution: its investigation of what I will call the 'material political economy' of the interaction of trading algorithms. How HFT algorithms interact materially is strongly shaped by the technological systems within which interaction takes place, and how such a system is designed is 'political' in the sense of, for example, Law and Mol's 'material politics': it involves 'a material ordering of the world … that contrasts with alternative and equally possible modes of ordering' (Law & Mol, 2008, p. 141).[3] Different possible orderings can have substantially differential effects on 'making' and 'taking' (there are, e.g. a number of influential efforts materially to favour 'making' algorithms). Those orderings can be matters of economic 'life or death' for HFT firms, says one interviewee, and are, as argued in the conclusion, of wider importance too. I use the term 'material political economy' here to refer to this issue: economically consequential material orderings to which there are alternatives.[4] The politics of economic life takes a large variety of forms (monetary, ideological, coercive, legal, regulatory, party-political, social movement, and so on), but among them – perhaps increasingly so – are these material orderings. They remain underexplored, even in the actor-network inspired literature on 'performativity': the latter term's origins in the linguistic philosophy of J.L. Austin (1962) makes it seductively easy to conceive of it as a discursive phenomenon, rather than one involving assemblages that are simultaneously discursive and material.

Precisely because the material practices and systems discussed here are 'political' in the above broad sense – they are consequential; they could be different; disputes can take place about them – it is necessary to emphasize that this paper does not take a position in these disputes. The paper's use of the practitioners' terms 'making' and 'taking' does not imply the preference for the former found in other contexts (e.g. Foroohar, 2016),[5] and the paper seeks simply to illustrate the possibility of alternative material orderings, not to promote any of them. The paper's sections are as follows. After this introduction comes a short account of data sources, a brief overall introduction to HFT, and a section discussing 'making'. Next come brief sections on each of the four styles of making and on the technological systems that shape making/taking interaction. I return to material political economy in the final section, the conclusion.

Data sources

As already suggested, it is not straightforward to find high-frequency traders prepared to be interviewed in any depth about HFT's material practices. One of my interviewees, for example, tried unsuccessfully to persuade an acquaintance to speak to me: 'even though he left over a decade ago, he signed paperwork going in and out of the company to keep quiet and also he (nor anyone) wants to get back on [X]'s radar because he has the money and ability to create legal issues for former employees that speak' (email from interviewee MI, 26 June 2017; X is a founder of the HFT firm for which my interviewee's acquaintance had worked). Gradually, however, I identified, primarily via snowballing, 72 practitioners of HFT – mostly in the world's main centres of the activity: Chicago, New York, London and Amsterdam – who were prepared to be interviewed in varying degrees of technical depth (14 on more than one occasion; seven of them three or more times), along with 29 suppliers of technology or communications links to HFT. Other interviewees included exchange staff, regulators, etc. Interviewees are anonymized in what follows via two-letter labels.

Interviewing has limitations when it comes to understanding HFT algorithms and how they interact. When human beings did deals on trading floors, sociologists could not only quiz traders but also listen and watch, but no-one can in any literal sense see algorithms interacting with each other. We can still interview – and, if access can be negotiated, observe – those who program and supervise those algorithms, but their understanding of the latter's actions can be imperfect (as Lange, 2016, documents). For example, I regularly ask interviewees whether their algorithms often identify arbitrage opportunities (in which, e.g. the same shares can be bought on one exchange more cheaply than they can be sold on another). One interviewee (BU) answered 'not really', then corrected himself: 'The truth is … we wouldn't even know … we'd just be making money'. His algorithm's 'valuation' (essentially, its price prediction) 'will move down for some reason', but he did not usually take the time to investigate why.

Fortunately, however, making/taking interaction has an advantage in this respect. In contrast to a possibly opaque change in an algorithm's price prediction, a transaction between a making and a taking algorithm leaves an immediate trace in the form of an electronic notification (a 'confirm') to both parties. However imperfect interviewees' understanding of their algorithms, they can tell, from these 'confirm' messages, when

sell from each other also enables some aspects of this qualitative, sociological enquiry to be checked against the results of quantitative research on HFT by economists.

A brief introduction to high-frequency trading

HFT firms are typically recently established and small. Only a handful date from before 2000, and some firms that have a major presence in HFT have fewer than 150 staff; even an HFT firm with around 50 staff can be a significant player. To my knowledge, only two firms heavily engaged in HFT have more than 1,000 staff, and both also do things other than HFT. Some big banks used to be active in HFT, but their efforts were often less than fully successful: the rapid development of the necessary fast, highly specialized software systems can be difficult in a large, bureaucratic organization. Banks are still active as automated 'market-makers' – see below – in some classes of financial instrument (such as foreign exchange), albeit typically using systems that are slow by HFT standards, but 'taking' strategies in HFT by banks have effectively been ended by the post-crisis constraints on banks' proprietary trading.

The HFT firms I have visited vary widely. Some had offices in bland or even scruffy buildings; others had spectacular views over Lake Michigan, Manhattan or London. Most of their offices could pass for those of a generic dotcom firm, and they usually have something of the relaxed feel of a software start-up. The staff of HFT firms are mostly young and (at least in the roles closest to trading) mostly male. Almost no-one wears a business suit – it is common for me, as the visitor, to be the only person wearing a tie – and the shouting and swearing that used to happen on banks' trading floors is rare. The internal organization of the HFT firms from which my interviewees come varies. Some operate as unified entities, without even the traditional individual 'P&L' (a trader's profit or loss); one firm had a computerized 'signal library' accessible to all its traders and software developers. (What participants call a 'signal' is a pattern of data that informs an algorithm's trading.) Just as Lange (2016) discovered, however, other HFT firms are divided into strictly separate trading teams, with deliberate barriers to communication. One firm, for example, physically separates teams by placing a row of administrative staff between them, and in its main offices even plays white noise between the rows to reduce the chance of members of one team overhearing what is said by members of another. At another compartmentalized firm, said a young trader

(interviewee AC), 'you … could get in trouble for being in the next room talking to someone you're not supposed to talk to'.[6]

High-frequency materially happens not in HFT firms' offices, but in exchanges' computer datacentres.[7] Around two dozen datacentres globally host the vast bulk of the world's financial trading. For example, almost all US financial futures trading happens in the datacentre shown in Figure 1, while nearly all the automated trading of other financial instruments (shares, currencies, Treasury bonds, etc.) takes place in a further seven datacentres in northern New Jersey. Four datacentres in the United Kingdom – in Slough, Basildon, the City of London, and London's Docklands – host major exchanges; a fifth, Interxion's datacentre on London's Brick Lane, is popular with HFT firms because of its central location and proximity to the London Stock Exchange's systems. The most important datacentre for HFT on the Continent is FR2 in Frankfurt am Main. These datacentres are huge warehouses, largely windowless, packed with many thousands of computer servers, powerful cooling systems to extract the heat the servers generate, mile upon mile of cabling, and almost no human beings beyond a few maintenance and security personnel. (Because of tight security, visits to datacentres are hard to arrange, but I have been able to visit two of them.)

Figure 1 The datacentre of the Chicago Mercantile Exchange, the most important in global finance. The microwave dishes via which signals from this datacentre travel to New Jersey and elsewhere, which are currently in a variety of locations close to the datacentre, are being centralized on the pylon under construction on the right of the picture.

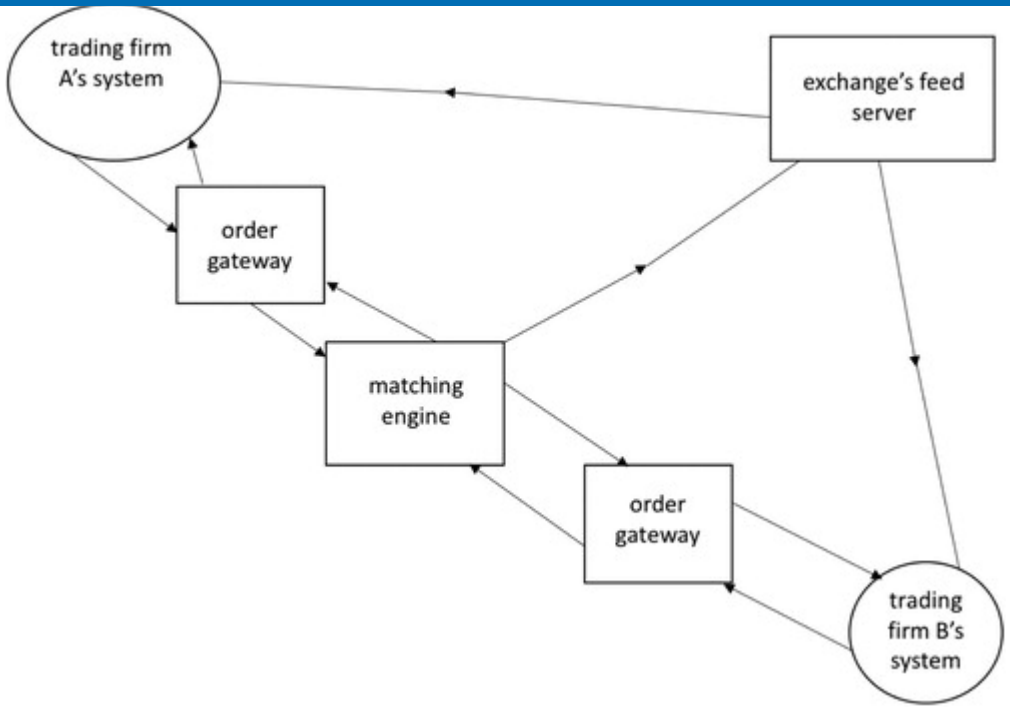
Source: courtesy Bird & Renoult. See http://bird-renoult.net/antenna-gods-us-edition-2018/.



Display full size

Although the internal spatial layout of datacentres varies, there is considerable structural similarity among exchanges' technical systems (see Figure 2). The heart of any modern electronic exchange is its 'matching engines'. These are computer systems that maintain the 'order book' for each financial instrument that the exchange trades. For a 'human-eyes' visual representation of an order book, see Figure 3, but all modern order books are simply data files: ordered lists of all the bids to buy and offers to sell the financial instrument being traded that have not yet been executed. HFT firms normally 'co-locate' their trading servers: install them in the same datacentre as the exchange's matching engines. Bids to buy and offers to sell by the algorithms running on HFT firms' servers (and their cancellations of bids and offers) take the form of electronic messages to the exchange's systems, and arrive at the matching engines via exchange computers known as 'order gateways' (see Figure 2). An exchange's 'feed servers' or 'market data publishers' are computers that receive streams of order-book updates – transactions, new orders, cancellations of orders – from the matching engines, and dispatch them in anonymized form as a datafeed, sold to trading firms, that enables them to synthesize their own constantly updated mirrors of the exchange's order books.

Figure 2 Inside a data centre: highly schematic. Arrows indicate the direction in which electronic messages flow. For example, a trading firm's system sends orders (and cancellations of orders) to an 'order gateway', which in turn sends that system a 'confirm' message when, e.g. one of its orders has been executed. For that system to learn as quickly as possible about transactions (and other 'order book' changes) not involving the firm, the latter has to pay the exchange for the datafeed from, and an ultrafast connection to, its feed servers.



Display full size

Figure 3 An order book.

Source: Author's interviews and observations of trading.



Display full size

Making

Most of the direct and indirect interaction of trading algorithms is mediated by order books – for exceptions, see MacKenzie (forthcoming) – and what differentiates a 'making' from a 'taking' order is its price relative to that of the existing orders in the book. Consider the order book in Figure 3. A bid to buy shares at $29.49 would be a 'making' order. The matching engine cannot execute it immediately, because there are no offers to sell at that price to match it with. Instead, the matching engine would simply add it to the order book's queue of bids at $29.49. In most exchanges, that queue is a time-priority list: a new bid to buy at $29.49 will be executed only when all earlier bids at that price have been executed or cancelled. In contrast, a bid to buy at $29.50 would be a 'taking' order. The matching engine can execute it straightaway (perhaps only partially if it is large), because there are offers to sell at that price. Doing so removes these existing orders from the book: hence the terminology of 'taking'.

In an exchange of the sort in which HFT is prevalent, most 'making' and most 'taking' orders are placed by algorithms. The core mechanism of direct interaction among trading algorithms is this straightforward process of matching: 'taking' orders being matched with (executed against) 'making' orders at the same price. That mechanism is so simple that it is hard to imagine that much pivots on it, and the difference between the prices of a 'making' and a 'taking' order on a modern electronic exchange is normally very small (the one-cent difference in Figure 3 between a bid that 'makes' and a bid that 'takes' is 0.03 per cent of the market price, and differences of roughly that size are typical). Yet this simple mechanism and tiny difference are experienced by some participants as having a moral, affective weight. The words chosen by interviewee BQ are unusually strong, but the underlying sentiment is not unique: 'I tend to want to work at [HFT] companies that are "makers" because I see the inherent evil in the "takers"'.

The 'moral' preference for 'making' rests on the legitimacy of its most systematic form: 'market-making'. This involves an algorithm continually keeping both bids to buy and offers to sell in the order book, at or close to the highest bid price and lowest offer price. In the order book in Figure 3, for example, the first-in-the-queue bid to buy 100 shares at $29.49 and the first-in-the-queue offer to sell 100 shares at $29.50 might both have been entered by the same market-making algorithm. Although the goal is economic (to earn the one-cent difference between those two prices, along with any

inherits the legitimacy of a traditional human role: that of the ‘market-maker’, who constantly stood ready both to buy the financial instrument being traded and to sell it (at a somewhat higher price).

Because other market participants’ bids and offers arrive only sporadically, market-makers – whether human or algorithmic – provide a service to market participants who want to transact immediately. Interviewee OH highlights the continuing potency of that source of legitimacy when she recounts an episode in her algorithmic market-making firm at the height of the global financial crisis of 2007–2008. A software developer had left her firm, saying: ‘I couldn’t look my grandmother in the face anymore and say I worked in finance’. The firm’s chief executive called a trading-room meeting of all its employees, and (as my interviewee recollects) told them, ‘I’m going to explain to you why you should be able to look your grandmother in the face: because we’re market-makers and we provide liquidity’. Another interviewee (OG, who managed to shift another algorithmic market-making firm towards ‘taking’ strategies) describes the resistance he faced from the firm’s traders: ‘ask them, do we market-take? “No, no, no”, as if you asked them if they would stab their sister, really strongly against that. But we had to change’.

Specialists in ‘taking’ reject this ‘moralization’ of making (as indeed do some specialists in the latter). They (e.g. interviewees BY and CU) cite taking’s central role in what economists call ‘price discovery’; its role (via arbitrage, as mentioned above) in keeping prices in different markets aligned; the ‘service’ (interviewee CU) it provides to those who wish to trade using ‘making’ orders (which, other things being equal, is cheaper than ‘taking’); and the plain fact that without ‘taking’ an exchange would have no trading. Furthermore, as OG’s desire for change indicates, legitimacy – being able to ‘look your grandmother in the face’ – does not guarantee economically successful market-making. As AG puts it, ‘you make a little bit of money’, from your algorithm repeatedly selling at a price higher than that at which it buys, but ‘you periodically get run over’: your market-making algorithm buys when prices are about to fall, or sells when prices are about to rise.

The risk of being run over (which can cancel out a long period of repeated small gains) has two implications. First, a market-making algorithm has to keep its ‘inventory’ (its aggregate trading position) reasonably small. ‘[Y]ou have to actively control your inventory’, says AE: if inventory starts to rise, a market-making algorithm will ‘shade’

executed, it will reduce the price of its offers so as to make those more attractive. If that fails, it may begin to ‘take’: in this example, reducing its inventory by executing against existing bids in the order book. (That occasional need for a market-making algorithm to ‘take’ is one of the ways in which the divide between ‘making’ and ‘taking’ is not absolute).

Second, almost all market-making algorithms make predictions of near-future price movements, and use those predictions to minimize the risk of being ‘run over’. As BL says: ‘markets move and you need to know when they’re going to move because [otherwise] you’ll be inventorying at a terrible price’. In all the markets in which HFT is active there are a number of classes of ‘signal’ that algorithms employ to predict price changes: see Table 1 for the main classes used in share trading. These signals need ‘squashed’, as BM put it: to inform how an algorithm trades, they need reduced to a single indicator. Although a variety of mathematical forms of ‘squashing’ are in use, HFT interviewees consistently report that by far the most common is for algorithms to combine signals via what is essentially a linear regression equation, in which a set of predictor variables (here, signals) are each ‘weighted’ so that in combination they best predict the value of a single ‘dependent variable’. In HFT, that variable is a near-term prediction of the price of the financial instrument being traded, based on signals of the kind listed in Table 1. One market-making HFT firm, London-based XTX Markets, even advertises the salience of regression. I assumed its name was one of the quasi-acronyms common in business, but when I read it etched in glass I realized that it was , a pervasive operation in regression analysis (the multiplication of a data matrix by its transpose).

Table 1 The main classes of ‘signal’ used in HFT in shares

Download CSV Display Table

Nothing in principle stops a market-making algorithm from also ‘taking’, and my interviews reveal that there are, e.g. algorithms that ‘make’ if their price prediction is between the highest bid and lowest offer, and ‘take’ if it is sufficiently far outside them. Blending of this kind is, however, far less common than one might expect. It is more usual to find that algorithms, trading groups and firms specialize either in ‘making’ or ‘taking’: ‘it’s almost like two very different strategies and thought processes’

separate trading groups reported that those groups focused either on making or on taking, not both:

> I think there is just something that's so different about having to have an opinion all the time [a market-making algorithm has constantly to be making decisions about its bids and offers] versus occasionally having an opinion [a taking algorithm needs only to identify the intermittent circumstances in which taking will be profitable] … for some reason those two things can't really be married without somehow ruining an aspect of the other one (AG).

The specialization in either making or taking reported by interviewees is confirmed by the literature of financial economics on HFT. There are large differences among firms in the proportions of their algorithms' trades that are making and taking, differences that are broadly stable through time: it is unusual for a firm mostly to 'make' in one month, then mostly 'take' in the next.[8] A preference for 'making' or for 'taking' can indeed be 'hard-wired' into an HFT firm's technical systems. Interviewee CE, for example, reports discovering this when he experimented with implementing 'taking' algorithms in a leading 'making' firm:

> [I]f you're trying to do something different than the system was conceived and built in the first place, you spend an awful lot of time and energy trying to stop it from doing what it wants to do. You get into a position and the first thing it wanted to do was to place an order on the other side [to reduce inventory] … I want to hold [the position] for five minutes. No, you can't do that. It's not that you couldn't, but you'd be trying to rework the code … Very, very, very difficult. (Interviewee CE)

Taking I: 'to gather the world's information in one place' (interviewee CU)

'Taking' is more heterogeneous than 'making' (space constraints prevent discussion of differences in styles of making). All HFT 'taking' strategies involve identifying situations in which it is likely that executing against existing bids and offers in the order book will be profitable, but how that is done varies in important ways, explored in this and the next three sections. One approach is for 'taking' algorithms to process larger amounts

are mathematically more sophisticated. If, by doing this, a ‘taking’ algorithm can improve on ‘making’ algorithms’ price predictions, then there will be profit opportunities. These are not there continuously, but interviewees (e.g. BY) report that when they arise ‘taking’ algorithms typically buy or sell substantially larger quantities of the financial instrument being traded than ‘making’ algorithms do.

Interviewee CU gave the example of a ‘taking’ algorithm trading 10-year US Treasury bond futures in the Chicago Mercantile Exchange’s datacentre, shown in Figure 1. The algorithm will take into account the pattern of bids, offers and trades in those futures, and patterns in the trading of the other Treasury bond and interest-rate futures also traded in that datacentre. The algorithm will receive, via microwave links, data on the buying and selling of the underlying Treasury bonds, which are traded in two datacentres in New Jersey. Via Hibernia Atlantic’s new, ultrafast transatlantic cable, it will receive data on UK gilt futures (traded in the datacentre in Basildon) and German sovereign-bond futures, traded in Frankfurt’s FR2. Data on Japanese government bonds will come from a transpacific cable and yet more microwave links. The algorithm will continuously fuse all this information into a prediction of the price of the futures it is trading, ‘taking’ when it looks profitable to do so.

All of this information is also available to the ‘making’ algorithms of at least the larger market-making firms. The latter’s algorithms, though, have to be ultrafast (and therefore not too complex), because of their need to be at or close to the head of the time-priority queue for executions and the danger of their quotes becoming stale and being picked-off (see the next section). As CB, from a very sophisticated market-making firm, puts it: ‘we add, subtract, multiply and divide really, really well’, in other words very fast indeed. ‘[W]e’re not doing high math and high quant.’ There is, in contrast seldom a queue to ‘take’. ‘Taking’ algorithms, which ‘aren’t fighting for queue position’, therefore ‘maybe have just a little more time to quantitatively evaluate what the market is really saying’, says BY.

That speed can therefore be a less extreme priority in some forms of ‘taking’ than in ‘making’ was, to me, a counterintuitive finding from the interviews, but one consistent with the financial-economics literature (Brogaard et al., 2015). Interviewee CU, however, warns that the lessened priority of speed lasts only until another taking firm ‘begins competing with you’: i.e. discovers and starts to exploit the same predictive pattern. Put more generally, the computationally-complex, quantitatively-sophisticated

‘taking’ discussed in this section is at one end of a spectrum; at the other end is the ‘taking’ discussed in the next section.

Taking II: picking-off stale quotes

The web, touched on in the previous section, through which the world’s financial information flows is strongly structured: some places – some ‘centres of calculation’ in the sense of Latour (1987) – are much more important than others; what happens in them has direct, highly predictable, and largely unidirectional effects. I chose the Chicago Mercantile Exchange’s (CME’s) datacentre for Figure 1 because it is the single most important such place worldwide. For reasons explored in MacKenzie (2018) large transactions on the CME, or significant changes in the contents of its most crucial order books, typically presage changes, both locally in that datacentre and worldwide, that immediately render many market-making algorithms’ bids or offers out-of-date (‘stale’). If that happens, a ‘taking’ algorithm has no need for complex modelling: it can simply ‘pick off’ – profit by trading against – knowably stale bids or offers. The archetype of this simple, ultrafast, form of taking (discussed by many interviewees and by Budish et al., 2015) is when the price of one of the share-index futures traded in the Chicago Mercantile Exchange’s datacentre – especially the most important such future, the ES, which corresponds to the Standard & Poor’s 500 share index – suddenly rises or falls. As discussed in MacKenzie (2018), this is typically followed – less than a hundredth of a second later – by moves in the same direction in the prices of the underlying shares (especially in the prices of the corresponding exchange-traded funds [ETFs], which are composite shares that track the same index). If the algorithms making markets in those shares and ETFs do not cancel their existing bids or offers quickly enough, a ‘taking’ algorithm will pick them off. Substantial changes in the other simple signals universally understood within HFT to have predictive value (see Table 1) give rise to similar ‘picking-off’ opportunities.

‘Picking-off’ creates a speed race between ‘making’ algorithms, seeking to cancel stale bids or offers, and ‘taking’ algorithms trying to execute against those stale quotes. In December 2011, one of my first interviewees (AG) estimated the response time needed from an algorithm engaged in this kind of interaction as below 5 microseconds (millionths of a second); a recent interviewee – CR, in April 2018 – says it is now 300

now feasible.[9] (A nanosecond is a billionth of a second, the time it takes the fastest physically possible signal – light in free space – to travel a mere 30 centimetres.) Picking-off is one of the two most important material drivers of what interviewee CR calls ‘an endless race’ (Budish et al. [2015] call it an ‘arms race’ in speed); the other driver is the competition among ‘making’ algorithms to be at the front of queues. Given the current material arrangements of trading, the speed race imposes unavoidable costs on almost all HFT firms. It requires them, for example, to use microwave, millimetre wave or atmospheric laser links – via which signals travel at almost their speed in free space – rather than fibre-optic cable, the material of which slows light to around two-thirds of its free-space speed.

Hence the influence of rain on the interaction of algorithms. The microwave links that carry futures prices from Chicago Mercantile Exchange’s datacentre to the share-trading datacentres in New Jersey can fail when it rains. Consequent effects on the interaction of HFT algorithms have had two distinct phases. Traces in price data of the first phase, in 2011–2012, were found by economists Shkilko and Sokolov (2016). In that phase, a number of HFT firms had created microwave links between Chicago and New Jersey, and seem to have used them above all for ‘picking-off’ the stale prices of market-making algorithms still dependent on fibre-optic cables. When rain interrupted the microwave links, those ‘making’ algorithms were able to resume market-making without being picked-off, and, as Shkilko and Sokolov demonstrate, standard measures of liquidity temporarily improved.

The second phase began after a communications supplier, McKay Brothers, created a new microwave link between Chicago and New Jersey in 2012, using the fastest available technology and choosing a route very close to the geodesic (the geodesic, or great circle, is the shortest path on the earth’s surface between two given points). McKay has subsequently kept refining the link to keep it at least as fast as any of the privately-owned links. Since 2012, the McKay link (widely used by market-making firms) has given their algorithms a degree of protection from being picked-off. In this second phase, the effect of rain on the interaction of algorithms seems to have reversed. Now, if it rains sufficiently heavily to interrupt the McKay link, market-making firms cannot know for certain that the private links used by ‘taking’ algorithms have also failed. So, reports SJ, market-making algorithms have to ‘widen spreads’, as market participants put it: reduce the prices of their bids and increase the prices of their offers, so lowering the risk of being picked-off (but also reducing one of the standard measures of

Note that – in line with late ANT's 'enactment materialism' – the vulnerability of microwave transmission to rain is not a fixed physical effect: it increases as higher frequencies are used. Of the frequencies available in the United States, microwave engineers prefer the most reliable: 6 GHz. Unfortunately, reports SJ, that band is 'crowded' near the Chicago-New Jersey geodesic (microwave signals at the same frequency can interfere with each other), so keeping close to the geodesic requires use of higher frequencies more vulnerable to rain: 11, 18 and sometimes even 23 GHz. The influence of rain on the interaction of algorithms is, furthermore, not found in Europe. The European analogue of the Chicago-New Jersey geodesic is the microwave route from London to Frankfurt's FR2. (Perhaps fortunately for the generally unappealing prospects for UK finance post-Brexit, Hibernia's undersea cable – via which the fastest signals arrive in Europe from Chicago and the other US datacentres – makes landfall in the United Kingdom, near Brean on the Bristol Channel. The signals arrive in Greater London before transmission to Frankfurt.) McKay Brothers was able to build its London-Frankfurt link using only 6 GHz, so rain has little effect and 'making' algorithms in Europe therefore do not need to widen spreads when it rains as their US counterparts need to (SJ).

Taking III: market-impact trading

The above two forms of 'taking' most likely account for the bulk of the interaction between 'making' and 'taking' HFT algorithms. There are, however, other forms of 'taking' that involve the prediction not just of overall price changes but of the future actions of 'making' algorithms. One is 'market-impact trading', in which an algorithm reflexively exploits the likely influence of its own actions on other algorithms. One version of this, described by interviewees AC and CR, involves identifying situations in which many of the bids or offers in the order book are from small firms that will 'cut their losses' (CR) or 'puke' (AC; i.e. liquidate their positions at an unfavourable price) if prices move against them by more than a certain amount. If a well-capitalized firm's algorithm can detect a 'weak-hand moment' of this kind, it can 'sweep' or 'swipe' (CR) the order book, for example by executing against all the bids at multiple price levels, so driving the market down, forcing 'weak-hand' algorithms to liquidate inventories at temporarily low prices, and profiting – often surprisingly modestly, given the scale of the trade – from the difference between those prices and the average price in the

> It's amazing, you see those swipes and they're huge swipes, millions and millions and millions of dollars underlying value, and if you look at it, the actual profit of one of these trades is $2,000 or something like that. (CR)

Taking IV: cat and mouse

'Swiping' is a crude, aggregate way of exploiting predictable behaviour by other algorithms, but 'taking' algorithms can also do this far more subtly. Predictability can, for example, arise from 'making' algorithms' pervasive use of linear regression equations to combine widely-used signals (of the kind in Table 1) into a price prediction. As interviewee AJ said, 'taking' can involve an algorithm predicting other algorithms' predictions: 'What do you think the [price prediction] will be in a minute, in 30 seconds, in a millisecond, in 10 minutes?' If a taking algorithm can anticipate the typical prediction, it can anticipate how other algorithms will react. If, for example, market-making algorithms are trading the 'ES' (the index future corresponding to the S&P500 share index), they will very likely be receiving 'signals' from the market for the 'NQ' (the index future, also traded in the Chicago Mercantile Exchange's datacentre, corresponding to the Nasdaq-100 share index). A 'taking' algorithm can predict movements in the market for the NQ (for example, by analysis of the balance of bids and offers in the order book for the NQ), and then anticipate how the price predictions of the algorithms making markets in the ES will change in response to those movements. The algorithm can thus sometimes identify a 'coming [order] book imbalance' in the ES, and therefore a predictable shift in price quotations from which it can profit (interviewee CG).

Even more subtle is for a 'taking' algorithm to 'predict what this guy [this specific market-making algorithm] is going to do', and thus profitably play a 'game of cat and mouse' (CG). If, for example, a specific market-making algorithm can be identified, and observed repeatedly, it can be possible to infer when it is approaching an inventory limit and will begin to 'shade' its prices. A sophisticated 'taking' algorithm can then take on a trading position in the anticipation of being able to liquidate it at a profit against those shaded prices. The 'shading', and thus the profitability of the trade, will typically be small (of the order of the minimum price increment: for example, one cent per share, as in Figure 3). If, however, the algorithmic behaviour that has been

A ‘taking’ algorithm successfully playing a ‘game of cat and mouse’ with a specific ‘making’ algorithm is perhaps the most demanding computationally of all the forms of taking. The volumes of data generated by financial markets are huge (and anonymous), and established statistical techniques such as linear regression are not well suited for identifying the ‘signatures’ of specific algorithms in these masses of data: more recent machine-learning techniques are needed. Also required is a powerful grid of multiple computers on which to implement these techniques. This grid can run ‘offline’ (with programs running overnight or at weekends if necessary) when ‘signatures’ are being searched for; the ‘taking’ algorithms that are the result of this research have to be simpler to run – as they have to – on a single computer and fast. They are, however, not very simple. Here, the state-of-the-art technologies that are a result of the speed race are used not to achieve nanosecond reaction times but to permit more complex computation. As CG puts it: ‘speed allows you to do complicated things in the same time’ in which ‘others do simple things’.

The game of algorithmic ‘cat and mouse’ traditionally relied on human intelligence – ‘one of our traders has a friend who works on that [firm’s trading] desk’ (BM) – and the human capacity to spot ‘hints of [order] size, timing, what price levels, how they hedge’ that are characteristic of a firm’s algorithms (BM). More recently, however, machine learning techniques have, as noted above, started being applied to the ‘game’. This is facilitated, reports CG, by technological changes in exchange systems. ‘Most people’s [computer] systems are very deterministic,’ he says. For example, the time taken by an HFT firm’s system to respond to an incoming signal (e.g. by sending the exchange a new order) varies between firms, but for each particular firm it tends to be reasonably constant. This creates a potentially identifiable ‘signature’, but one previously masked by inconsistencies among exchanges in how time is measured and by ‘jitter’ in exchange systems (random fluctuation in the time taken to process orders). Precise atomic-clock synchronization to the global time standard, UTC, and greater determinism in exchange systems (increasingly programmed in C++, which allows fuller control of the material implementation of computational processes) have, however, removed much of that masking.

Alternative material orderings

As far as I can tell, this ‘unmasking’ is an inadvertent material effect, not one sought by those who run exchanges. They are, however, by no means always neutral observers of how ‘making’ and ‘taking’ algorithms interact. When they intervene it is most usually to encourage ‘making’. There is no evidence in my interviews that this is because they regard ‘making’ as ‘more moral’ than ‘taking’. Their fear, rather, is of ‘empty screens’ (interviewee GI) – order books devoid of bids and offers – which make an exchange fatally unattractive to traders and institutional investors. Sometimes, exchanges encourage ‘making’ with economic incentives: for example, small payments (known as ‘rebates’) to those who place ‘making’ orders that subsequently are executed against. Sometimes, too, exchanges protect making algorithms from HFT ‘takers’ by having rules that constrain the latter. For example, the new European stock exchange, Aquis, has a rule banning proprietary trading firms from ‘taking’. Its chief executive told the Financial Times that ‘aggressive predatory trading’ was damaging ‘posted liquidity’, that is, the numbers of ‘making’ orders in its order books (Stafford, 2016).[10]

From the viewpoint of this paper, however, the most interesting intervention by exchanges in making/taking interaction is their use of material devices. The most famous such device (highlighted in Michael Lewis’s 2014 best-seller Flash boys) is a 60-kilometre coil of fibre-optic cable installed by the new US stock exchange, IEX, through which all incoming orders to IEX (and all market data from IEX) have to pass, slowing them down by 350 microseconds. The coil is strikingly reminiscent of Latour’s famous example of material politics, the traffic-slowing ‘sleeping policeman’ (Latour, 1999, pp. 187–188), but it is a less than decisive intervention in the interaction between ‘making’ and ‘taking’ algorithms, because it slows down both categories equally.[11] That did not, however, prevent the coil sparking fierce controversy among market participants in the United States.

Also deeply controversial, although much less well known, was a 2016 proposal from another small exchange, the Chicago Stock Exchange, to install a software-implemented ‘speed bump’ that would slow ‘taking’ orders, while leaving ‘making’ orders and cancellations (by registered market-makers) unaffected. The staff of the US stock market regulator, the Securities and Exchange Commission, initially approved the proposal, but Republican Commissioner Michael Piwowar opposed that decision, which was then put on hold. In April 2018, the Chicago Exchange – also at the centre of a furore around its possible sale to a group including Chinese investors – was bought by the Intercontinental Exchange, owner of the New York Stock Exchange, and it remains

As a result, the introduction of material devices and procedures to shape making-taking interaction has mostly been found in foreign exchange trading, in which there is no need to seek regulatory approval and in which banks, with their slow technical systems, are still important market-makers and retain considerable power and influence. The most sophisticated of these devices is a module, described by interviewee GS, that was added to the Thomson Reuters trading system in 2016. The module examines incoming buy and sell orders for each of the currency pairs being traded, classifies them as either 'taking' or 'making', and adds them to the corresponding buffer.[12] The first order to enter an empty buffer starts a 'timer' that runs for three milliseconds (thousandths of a second), at which point the buffer is emptied by sending the bids or offers it contains to the matching engine in a random order.[13] Randomization stops, e.g. the fastest market-making algorithm always getting to the head of queues, and, crucially, cancellations of orders are not placed in a buffer, but sent to the matching engine immediately. This gives substantial protection to market-making algorithms: if the market moves, they have three milliseconds (a long time, by HFT standards) to cancel their stale quotes before they are picked off.

Conclusion: material political economy

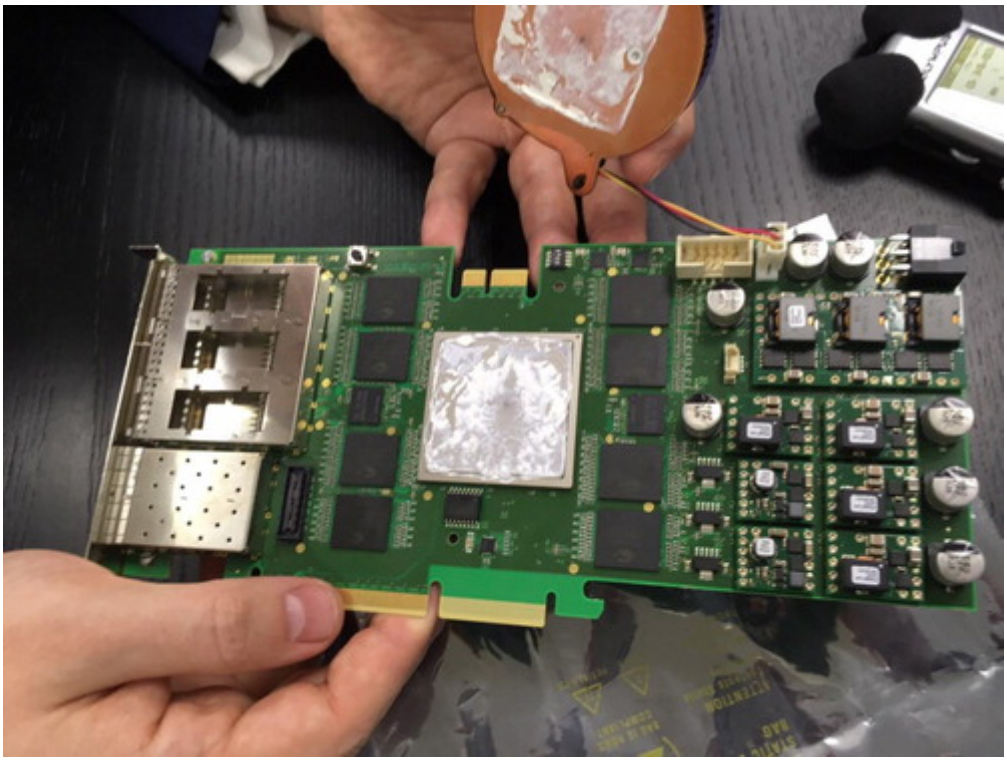
The installation of the Reuters module excited little media interest, but nevertheless exemplifies the phenomenon to which 'material political economy' points: the possibility of alternative material orderings that differ in economically consequential ways. In particular, as just noted, the module is designed to alleviate the arms race in speed in algorithmic trading – though it does not solve it: no modification to any one system could; and other proposals exist.[14]

That arms race sometimes disturbs even those whose business it is. Every so often, my interviews are punctuated by an interviewee spontaneously reflecting on it. For example, the need for nanosecond speeds means that many HFT algorithms are no longer implemented in conventional software but directly in hardware: in specialized silicon chips called 'field-programmable gate arrays' or FPGAs (see Figure 4).[15] In February 2018, a specialist in the use of FPGAs in HFT broke off telling me how sophisticated rejigging of the patterns of connections within FPGAs could 'shave 5–10 nanoseconds' off the time taken to process signals:

> Those engineers that spend day and night on this, it's ridiculous. It's quite ridiculous … mind-numbing … a lot of people with extended training … shaving nanoseconds … you could put that brainpower to something else … something different. (Interviewee UC)

Figure 4 A field-programmable gate array (FPGA) in a 'development kit' for programming and testing. The FPGA is the large central chip with white paste on it.

Source: Author's fieldwork photograph.



Display full size

The net present value of the stakes in even the simplest form of interaction between making and taking algorithms (the picking-off of stale quotes, which is, as noted above, one of the two key drivers of the speed race) may be as high as $100 billion (Budish, 2017). Much of that, however, does not crystallize as profit to HFT firms, but takes the form of otherwise unnecessary spending on technology. While faster FPGAs might conceivably have eventual uses in different spheres, that seems unlikely for other speed-race investments such as marginally speeded-up microwave links. What disturbs some insiders seems to be a nagging sense of scarce resources being wasted: either simply their firm's resources, or (as in the case of interviewee UC) social resources.

Just occasionally, too, the material political economy of HFT erupts into the formal

Kent coast near the little village of Richborough. In 2016, two communications companies owned by HFT firms applied for planning permission to build two huge – 10-foot wide, 1000-foot tall – microwave masts there. (Microwave transmission requires a direct 'line-of-sight' path from source to receiver, and the sea crossing from Richborough to the Continent is sufficiently long that a tall mast is needed. Without the latter, microwave links have to cross further south, where the English Channel is narrower, and that deviation from the geodesic means a transmission time that is around 10 microseconds longer: interviewee SJ.) The economic value of even an apparently minor speeding-up of an important microwave link is indicated by the promise of one of the companies to pay at least £100,000 a year to a community-managed project fund.[16] Considerable opposition was, however, sparked, involving not just those who live close to the proposed masts but also, e.g. Historic England, guardians of the remains of Richborough Fort, an important Roman administrative/military base. After much local debate, Dover District councillors voted in January 2017 to refuse planning permission for the masts.

In the case of the Richborough masts, the material political economy of algorithmic trading would have been all too visible. Such cases, however, are likely to remain rare. We are going to have to dig beneath the surface of the financial system to unearth that material political economy. One of its effects, for example, is what may become a substantial shift in Europe away from exchanges' anonymous order books, which can be 'seen' (at least in technologically mediated ways) by all human and algorithmic participants, towards other, more private, forms of automated trading involving webs of bilateral relationships among firms that disclose their identities to each other. In order books, as many market-making interviewees point out, their algorithms are vulnerable to being picked-off (despite the partial protection offered by the McKay Brothers' links); they suffer losses when order books are 'swept', etc. Such risks are minimized if market-making algorithms are in direct electronic contact with – for instance, receiving electronic 'requests for quotation' from – a firm known to be simply an institutional investor with no interest in or capacity to pick-off stale quotes. This may bring benefits (there is little need for extreme speed; interviewees who are enthusiasts for the shift said that institutional investors can receive better prices in an ongoing bilateral relationship), but it may leave exchanges' order books – the more 'public' form of price formation – depleted and 'toxic' (i.e. populated by orders that could not be executed bilaterally because the risk involved seemed too high: 'the trades that no-one wants'

economy is the growing determinism of exchanges' computer systems, referred to above. As random fluctuations in processing time are reduced, the algorithms of HFT firms without the fastest technology will 'win the trade' less and less often. Deterministic material systems are thus likely to be 'winner-takes-all' systems, with the potential to lead to growing dominance of trading by a diminishing number of ultra-high-tech firms.

The particular material political economy of HFT is new and esoteric. Even other forms of algorithmic trading do not yet manifest the extremity of HFT's speed race, either because slow human beings remain in the loop, or technical systems and material procedures have features that limit the advantages that speed brings.[17] The underlying phenomenon of the importance of material orderings to economic life is, however, not new: slavery, after all, rested upon guns and whips, manacles and slave ships. Nor, indeed, is material political economy a novelty: volume one of Capital, with its detailed attention to the changing material orderings of production, can be read as in this genre (MacKenzie, 1984). As economic life becomes ever more algorithmic, and takes place to an ever-increasing extent in giant datacentres (let us not forget, for example, the elementary but environmentally important fact that datacentres consume huge amounts of electricity), material political economy is a tradition that urgently needs revivified.

Disclosure statement

No potential conflict of interest was reported by the author.

ORCID

Donald MacKenzie http://orcid.org/0000-0002-1860-8116

Additional information

Funding

The research reported here was supported by the UK Economic and Social Research Council, under ESRC grant agreement no. ES/R003173/1; and by the European Research Council, under grant 291733.

Notes on contributors

Donald MacKenzie

Donald MacKenzie is a Professor of Sociology at the University of Edinburgh. His most recent book, written jointly with Diane-Laure Arjaliès, Philip Grant, Iain Hardie and Ekaterina Svetlova, is Chains of finance: How investment management is shaped (Oxford University Press, 2017).

Notes

1 The term ‘algorithm’ is used here to refer not just to a set of instructions sufficiently precise that they can be implemented as a computer program, but to that program running on a physical computer system and having material effects on other systems. For wider research in ‘critical algorithm studies’, which cannot be reviewed here for reasons of space, see the evolving bibliography at https://socialmediacollective.org/reading-lists/critical-algorithm-studies/.

2 See Laumonier’s blog, https://sniperinmahwah.wordpress.com. (Mahwah, NJ, is the location of the New York Stock Exchange’s datacentre.)

3 See also, e.g. the Dingpolitik of Latour (2005) or the subtle reflections in Barry (2002) on how ‘politics’ (in the conventional sense of the word) can have ‘anti-political’ effects in closing down potential contestation.

4 A different aspect of the ‘material political economy’ of HFT is explored in MacKenzie (2017): the influence of processes that are in a broad sense ‘political’ on the ‘signals’ (patterns of data) that are available for price prediction by HFT algorithms.

5 Practitioners’ alternative terms for ‘make/take’ – e.g. ‘add/remove’ or ‘passive/aggressive’ – can also be misread as inherently moralizing, and referring to ‘making’ as ‘passive’ misleads differently, because a making algorithm typically has to

6 Trading teams in compartmentalized firms often welcome the separation, not wanting others, even within the same firm, to profit from ‘their’ ideas. Other reasons for strict compartmentalization include avoiding concentrations of risk caused by teams imitating each other’s trading, and persuading exchanges and regulators to allow one team’s algorithms to trade with another’s. This can easily happen accidentally, and ‘self-trading’ is normally prohibited, because it can be used to create a manipulative ‘false price’.

7 The need to limit this paper’s length means occasional inexact formulations, such as ‘exchange’: not all the trading venues in which HFT is active are registered exchanges, despite having exchange-like roles.

8 See, e.g. Baron et al. (2012); Hagströmer and Nordén (2013); Benos and Sagade (2016). Benos and Sagade, for example, use regulatory data to classify HFT participants in the London Stock Exchange as ‘passive’ (makers), ‘neutral’ or ‘aggressive’ (takers): ‘aggressive HFTs take liquidity 82% of the time, whereas the passive do so only 11% of the time’ (2016, p. 63).

9 These are what in HFT are called ‘wire-to-wire’ or ‘tick-to-trade’ times: the delay between the arrival of a price signal and the dispatch of an order or cancellation.

10 It seems as if the issue was mainly ‘sweeps’ of multiple levels of the order book (interviewee EA), but whether these were ‘market impact trading’ of the kind discussed above is unclear.

11 The main point of the coil is to inhibit a very particular form of ‘taking’. Much trading on IEX is ‘midpoint matching’, in which trades are consummated at the midpoint of the highest bid price and lowest offer price on all the US exchanges. If a ‘taking’ algorithm detected that the midpoint calculated by IEX’s system was out-of-date, it might be able profitably to ‘take’. However, the datafeeds that inform IEX’s calculation of the midpoint do not go through the coil, so the midpoint will be updated before any ‘taking’ order has emerged from the coil.

12 There are separate buffers for ‘making’ orders at different prices.

13 The randomization is by firm: all the orders in the buffer from the same firm are grouped, and only one of them is implemented before the algorithm moves to an order submitted by the next firm in the randomly-ordered list of firms. For more detail on the

14 In particular, Budish et al. (2015) argue that the underlying cause of the arms race is continuous trading, and propose replacing it with frequent but discrete auctions.

15 Even with the best current technology, says CR, it would take far too long (around a microsecond) to send an incoming signal from a network interface card to a conventional computer central processing unit and back again.

16 See http://www.richboroughmast.co.uk/community-benefits/community-benefit-fund, accessed 30 April 2018.

17 For example, the automated advertising auctions triggered by users' Google searches are discrete, single-point-in-time, auctions, in which, e.g. the algorithm that bids first has no advantage. There is an echo here of the material reordering proposed by Budish et al. (2015): see note 14 above.

References

1. Austin, J. L. (1962). How to do things with words. Oxford: Clarendon.

   Google Scholar

2. Baker, W. E. (1984). The social structure of a national securities market. American Journal of Sociology, 89(4), 775–811. doi: 10.1086/227944

   Web of Science ® | Google Scholar

3. Baron, M., Brogaard, J. & Kirilenko, A. (2012). The trading profits of high frequency traders. Typescript.

   Google Scholar

4. Barry, A. (2002). The anti-political economy. Economy and Society, 31(2), 268–284. doi: 10.1080/03085140220123162

   Web of Science ® | Google Scholar

5. Benos, E. & Sagade, S. (2016). Price discovery and the cross-section of high-frequency trading. Journal of Financial Markets, 30, 54–77. doi: 10.1016/j.finmar.2016.03.004

Web of Science ® | Google Scholar

6. Borch, C. (2016). High-frequency trading, algorithmic finance and the flash crash: Reflections on eventalization. Economy and Society, 45(3–4), 350–378. doi: 10.1080/03085147.2016.1263034

Web of Science ® | Google Scholar

7. Brogaard, J., Hagströmer, B., Nordén, L. & Riordan, R. (2015). Trading fast and slow: Colocation and liquidity. Review of Financial Studies, 28(12), 3407–3443. doi: 10.1093/rfs/hhv045

Web of Science ® | Google Scholar

8. Budish, E. (2017). Will the market fix the market? Speech at American Economic Association and American Finance Association. Retrieved from https://www.aeweb.org/conference/webcasts/2017

Google Scholar

9. Budish, E., Cramton, P. & Shim, J. (2015). The high-frequency trading arms race: Frequent batch auctions as a market design response. The Quarterly Journal of Economics, 130(4), 1547–1621. doi: 10.1093/qje/qjv027

Web of Science ® | Google Scholar

10. Callon, M., Millo, Y. & Muniesa, F. (Eds.). (2007). Market devices. Oxford: Blackwell.

Google Scholar

11. de Laet, M. & Mol, A. (2000). The Zimbabwe bush pump: Mechanics of a fluid technology. Social Studies of Science, 30(2), 225–263. doi: 10.1177/030631200030002002

Web of Science ® | Google Scholar

12. Foroohar, R. (2016). Makers and takers: The rise of finance and the fall of American business. New York, NY: Crown.

Google Scholar

13. Hagströmer, B. & Nordén, L. (2013). The diversity of high-frequency traders. Journal of Financial Markets, 16(4), 741–770. doi: 10.1016/j.finmar.2013.05.009

Web of Science ® | Google Scholar

14. Lange, A.-C. (2016). Organizational ignorance: An ethnographic study of high-frequency trading. Economy and Society, 45(2), 230–250. doi: 10.1080/03085147.2016.1220665

Web of Science ® | Google Scholar

15. Lange, A.-C., Lenglet, M. & Seyfert, R. (2016). Cultures of high-frequency trading: Mapping the landscape of algorithmic developments in contemporary financial markets. Economy and Society, 45(2), 149–165. doi: 10.1080/03085147.2016.1213986

Web of Science ® | Google Scholar

16. Latour, B. (1987). Science in action. Cambridge, MA: Harvard University Press.

Google Scholar

17. Latour, B. (1999). Pandora’s hope: Essays on the reality of science studies. Cambridge, MA: Harvard University Press.

Google Scholar

18. Latour, B. (2005). From Realpolitik to Dingpolitik, or how to make things public. In B. Latour & P. Weibel (Eds.), Making things public: Atmospheres of democracy (pp. 14–41). Cambridge, MA: MIT Press.

Google Scholar

19. Law, J. (2010). The materials of STS. In D. Hicks & M. C. Beaudry (Eds.), The Oxford

Google Scholar

20. Law, J. & Mol, A. (2008). Globalisation in practice: On the politics of boiling pigswill. Geoforum, 39(1), 133–143. doi: 10.1016/j.geoforum.2006.08.010

Web of Science ® | Google Scholar

21. Lewis, M. (2014). Flash boys: Cracking the money code. London: Penguin.

Google Scholar

22. MacKenzie, D. (1984). Marx and the machine. Technology and Culture, 25(3), 473–502. doi: 10.2307/3104202

Web of Science ® | Google Scholar

23. MacKenzie, D. (2017). A material political economy: Automated Trading Desk and price prediction in high-frequency trading. Social Studies of Science, 47(2), 172–194. doi: 10.1177/0306312716676900

PubMed | Web of Science ® | Google Scholar

24. MacKenzie, D. (2018). Material signals: A historical sociology of high-frequency trading. American Journal of Sociology, 123(6), 1635–1683. doi: 10.1086/697318

Web of Science ® | Google Scholar

25. MacKenzie, D. (forthcoming). How algorithms interact: Goffman's 'interaction order' in automated trading. Theory, Culture & Society.

Web of Science ® | Google Scholar

26. MacKenzie, D., Muniesa, F. & Siu, L. (Eds.). (2007). Do economists make markets? On the performativity of economics. Princeton, NJ: Princeton University Press.

Google Scholar

27. Melton, H. (2017). Market mechanism refinement on a continuous limit order book venue: A case study. ACM SIGecom Exchanges, 16(1), 72–77. doi:

Google Scholar

28. Menkveld, A. J. (2016). The economics of high-frequency trading: Taking stock. Annual Review of Financial Economics, 8(1), 1–24. doi: 10.1146/annurev-financial-121415-033010

Web of Science ® | Google Scholar

29. Miller, D. (Ed.). (2005). Materiality. Durham, NC: Duke University Press.

Google Scholar

30. Mol, A. (2002). The body multiple: Ontology in medical practice. Durham, NC: Duke University Press.

Google Scholar

31. Parikka, J. (2015). A geology of media. Minneapolis, MN: University of Minnesota Press.

Google Scholar

32. Seyfert, R. (2016). Bugs, predations or manipulations? Incompatible epistemic regimes of high-frequency trading. Economy and Society, 45(2), 251–277. doi: 10.1080/03085147.2016.1213978

Web of Science ® | Google Scholar

33. Seyfert, R. & Roberge, J. (Eds.). (2016). Algorithmic cultures: Essays on meaning, performance and new technologies. London: Routledge.

Google Scholar

34. Shkilko, A. & Sokolov, K. (2016). Every cloud has a silver lining: Fast trading, microwave connectivity and trading costs. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2848562

Google Scholar

35. Stafford, P. (2016, February 3). Aquis Exchange bans ‘predatory’ high-speed trading. Financial Times. Retrieved from https://www.ft.com/content/04944696-c9d9-11e5-a8ef-ea66e967dd44

Google Scholar

Download PDF

Related research

People also read | Recommended articles | Cited by 54

Article contents | Related research

Information for

Authors

R&D professionals

Editors

Librarians

Societies

Open access

Overview

Open journals

Open Select

Dove Medical Press

F1000Research

Opportunities

Reprints and e-prints

Advertising solutions

Accelerated publication

Corporate access solutions

Help and information

Help and contact

Newsroom

All journals

Books

Keep up to date

Register to receive personalised research and resources by email

Sign me up

Copyright © 2026 Informa UK Limited Privacy policy

Cookies Terms & conditions Accessibility

Registered in England & Wales No. 01072954
5 Howick Place | London | SW1P 1WG

Taylor & Francis by informa

Article contents

Related research