Algorithmic Trading, Artificial Intelligence and the Politics of Cognition

Armin Beverungen

In this chapter I focus on the changes in algorithmic trading in financial markets brought about by developments in machine learning and artificial intelligence (AI). Financial trading has for a long time been dominated by highly sophisticated forms of data processing and computation in the dominance of the "quants". Yet over the last two decades high-frequency trading (HFT), as a form of automated, algorithmic trading focused on speed and volume rather than smartness, has dominated the arms race in financial markets. I want to suggest that machine learning and AI are today changing the cognitive parameters of this arms race, shifting the boundaries between "dumb" algorithms in high-frequency trading (HFT) and "smart" algorithms in other forms of algorithmic trading. Whereas HFT is largely focused on data internal and dynamics endemic to financial markets, new forms of algorithmic trading enabled by AI are enlarging the ecology of financial markets through ways in which automated trading draws on a wider set of data such as social data for analytics such as sentiment analysis. I want to suggest that to understand the politics of these shifts it is insightful to focus on cognition as a battleground in financial markets, with AI and machine learning leading to a further redistribution and new temporalities of cognition. A politics of cognition must grapple with the opacities and temporalities of algorithmic trading in financial markets, which constitute limits to the democratization of finance as well as its social regulation.

Consciousness and Capitalism

Financial markets arguably are at the forefront of a battle around cognition in contemporary capitalism. If capitalism today is marked both by the way in which finance serves as a primary means to exert violence on and to extract value from life, and by the way in which capital amasses and appropriates cognitive capacities to sustain this extraction (Fumagalli/Mezzadra 2010), then financial markets

are bound to play a key role in this financial and cognitive capitalism (Beverungen 2018). Financial markets might appear then as a "collective capitalist brain" through which capital cognitively organizes the extraction of value, only hampered by "occasional and random catastrophe" associated with high-frequency trading (HFT) (Terranova 2013: 66). And HFT might be understood as the "high frontier of cybernetic innovation" in a war of capital against its enemies and the working class in which computers are "weapons wielded by advanced capital" (Dyer-Witheford 2016: 51, 35). While a closer look at artificial intelligence (AI) and algorithmic trading will yield a complex picture in which a collective capitalist brain is far from perceptible, and class war is perhaps less visible than competition between individual capitals, this is an important frame of analysis to be kept in mind as my analysis proceeds.

That finance is concerned with the extraction of value can however be taken for granted. That premise is also apparent from the perspective of the financial trader, where the question of how to extract value from financial markets becomes one of making the right trade. As Beunza and Stark argue, "What counts?" is the question which "expresses most succinctly the challenge facing securities traders in the era of quantitative finance" (2008: 253), and presumably all other financial traders as well, including high-frequency traders. The task is primarily one of information, with traders "immersed in a virtual flood of information", where "the challenge for traders is not faster, higher, stronger—as if the problem of the volume of data could be solved by gathering yet more—but selecting what counts and making sense of the selection" (Beunza/Stark 2008: 253). The "calculative practices" that traders deploy to respond to the question of "what counts?" are "distributed across persons and instruments" (Beunza/Stark 2008: 254). Beunza and Stark here presume a certain problem of information, where the task is to select relevant information that can be made to count in financial trading which yields a surplus. We can see already how AI and its key advance today—artificial neural networks—may be very helpful.[1] Below I will explore how different types of AI have been deployed in financial trading, and note how these have shifted the parameters of the challenge Beunza and Stark describe.

Before I proceed, though, I would like to historicize Beunza and Stark's premises and expand on their analysis, which will also allow me later to come back to the more abstract political analysis of financial and cognitive capitalism. First of all, it is important to note that Beunza and Stark's market characterize as being characterized by information flows and by the cognitive challenge of filtering

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1   Somewhat amusingly, the futurist and "world leader in pattern recognition techniques" Ray Kurzweil has since 1999 operated a company called "FatKat" which builds "industry-leading tools for quantitatively based investing". Little is known about this company, and its website (www.fatkat.com) is still dated 2001. See Patterson 2012: 306.

information in order to yield information useful for a successful trade, is not a historical given. It took a while for the market to be understood as an information processor and for it to be designed to that end. Mirowski and Nik-Khah (2017) have extensively explored the influence of Hayek's evolving conceptions of markets on the discipline of economics and the practice of market design. They identify at least three stages in Hayek's work in which markets, knowledge and information are understood differently (Nik-Khah/Mirowski 2019: 38-44). First, knowledge is understood as something hard to amass, a task only markets can achieve. Then knowledge becomes something tacit, and therefore something only markets can bring to the fore. Finally, knowledge becomes information, something suprapersonal, residing within the market: "a new virtual kind of *information*" (Nik-Khah/Mirowski 2019: 43; emphasis in original).

Nik-Khah and Mirowski demonstrate that these conceptions of markets have influenced different schools of market design, in which economists act as engineers of markets, such as financial markets. I will note below how market designers such as Alvin Roth and others are involved in designing the financial markets in which algorithmic trading takes place and AI is deployed. The important aspect to note, coinciding with the way market design "constitutes the precepts of neoliberalism taken to their logical conclusion" (Nik-Khah/Mirowski 2019: 63), is the way in which human consciousness and cognition become increasingly irrelevant to markets and are ultimately discounted, with a market conceived as a "person-machine system", a "hybrid computational device", "with the thinking offloaded onto things" (Nik-Khah/Mirowski 2019: 53, 61). As Mirowski and Nik-Khah put it: "Agents would be folded into the person-machine system, no longer deemed capable of understanding why they made the decisions that they do. Think of their predicament as Artificial Ignorance." (2017: 238-239). It might seem ironic that this "artificial ignorance" also of financial traders is to be complemented by the artificial intelligence of machines. But as I will show below, the deployment of AI in algorithmic trading exactly follows the premises of the economists and market designers: information resides in the market, and the task of AI is to extract it—the "alpha"—in order to augment trading.

To get a handle on how markets are constituted both as human and as machinic and computational, and on how thinking is "offloaded onto things", I want to draw on Hayles' recent work around nonconscious cognition (Amoore 2019), as it offers a helpful way of making sense of how cognition is distributed in financial markets (see also Beverungen/Lange 2018). Hayles distinguishes between "thinking" and "cognition", suggesting that thinking is human, conscious cognition whereas cognition "is a much broader faculty present to some degree in all biological life-forms and many technical systems" (2017: 14). She defines cognition as "a process that interprets information within contexts that connect it with meaning" (Hayles 2017: 22), one that can also take place nonconsciously. She offers to replace

the distinction between human and nonhuman with the distinction "cognizers" and "noncognizers", where humans, biological life but also technical systems such as those deploying AI are part of the first category (Hayles 2017: 30). Importantly, this allows us to understand the make-up of financial markets as constituted by a number of cognizers (both human and machinic), to consider how cognition is distributed between these cognizers (both as conscious and nonconscious cognition), and to explore what kinds of autonomy is given to machines in algorithmic trading in "pockets within which technical systems operate autonomously" in a "punctuated agency" (Hayles 2017: 32).

Hayles (2017: 142-177) offers her own analysis of finance and HFT, and suggests that HFT may be "regarded as an evolutionary milieu in which speed, rather than consciousness, has become a weapon in the nonconscious cognitive arms race—a weapon that threatens to proceed along an autonomous trajectory in a temporal regime inaccessible to direct conscious intervention" (2017: 165). In the following sections, I want to build on Hayles and on earlier work with Lange (Beverungen/Lange 2017; 2018) to explore how this "nonconscious cognitive arms race" is shaped by AI. I will suggest that AI offers a different weapon—smartness—in a trade-off with speed in this race, one which shifts the temporal and cognitive parameters of financial markets, which can be made further sense of if discussions around financial and cognitive capitalism are kept in mind.

High-Frequency and Quantitative Trading

Prior to the automation of trading platforms of financial markets, the "cacophony of the marketplace and apparent randomness of trade" was coordinated mostly through human sociality; today, that is a matter of "managing the punctuated electronic signals that encode the orders from masses of anonymous investors", achieved by "toying with the nimble algorithms, sophisticated computer processors, hacked routers, and specialized telecommunication systems that are the material foundations of the contemporary stock exchange" (Pardo-Guerra 2019: 23). Manual trading still exists, although all orders have to be executed via automated platforms, and algorithmic trading constitutes the large majority of trading in financial markets. Kirilenko and Lo define algorithmic trading as "the use of mathematical models, computers, and telecommunications networks to automate the buying and selling of financial securities" (2013: 52). Over the last two and a half decades, its rise has been facilitated by the ways in which the financial system has become more complex, by "a set of breakthroughs in the quantitative modeling of financial markets", and by the "almost parallel set of breakthroughs in computer technology" (Kirilenko/Lo 2013: 53). Markets have been automated, trading strategies are computer-driven, and trade is executed largely by algorithms.

Financial markets, even before the introduction of automated trading platforms, offered opportunities for trading strategies based both on speed and on smartness, and implied certain forms of cognition. The introduction of the ticker tape, as discussed by Preda (2006), for example, changed the temporal regime of the stock market, offering a continuous data flow of price variations, for all means and purposes in real time: the "ragged time structure of paper slips was replaced by the smooth, uninterrupted, unique time of the ticker tape" (Preda 2006: 767). The ticker tape also came with charts and other forms of visualisation, as well as "discursive modes" which "supported the chart as a cognitive instrument, which in its turn conferred authority upon the stock analyst as the only one skilled enough to discover the truth of the market in the dotted lines" (Preda 2006: 770). The speed of the ticker tape alone did not lead to a competitive advantage; the smartness of the stock analyst was required to access the truth of the market and to act on it. This economy of speed and smartness would develop further, for example with the introduction of the Reuters Stockmaster price retrieval service in 1964 or the launch of the first automatic quotation system NASDAQ in 1972 (see Mirowski 2007: 216), and would result in a differentiation of strategies in algorithmic trading.

The ticker tape, and the development of market infrastructures such as telegraph lines spanning the globe, already foreshadows the kinds of infrastructural investments required for HFT, as a form of algorithmic trading characterized by high speed and high volume trading. HFT played a key role in the automation of financial markets since the late 1980s. For example, Mackenzie and Pardo-Guerra (2014) recount the role of Island, a new electronic trading platform launched in 1995, how it challenged existing trading platforms which had not fully automated, and how it already introduced key aspects of automated trading platforms such as ultrafast matching engines, fine-grained pricing or co-location. They also recount how symbiotic the relationship was between Island and Automated Trading Desk, one of the first HFT companies which commenced trading in 1989, and quickly became its biggest client. MacKenzie details how, through bricolage, Automated Trading Desk succeeded in becoming a HFT company, among other things playing a "causal role" in the introduction of all-to-all markets, pushing the computerization of trading, and developing the business model of HFT based on high volume and special market rates (MacKenzie 2016: 175, 180). MacKenzie summarizes: "The use of algorithms helped create markets materially better suited to algorithms" (2016: 190). The ensuing HFT "arms race" has become a "constant of the market design" of financial markets today (Budish et al. 2015: 1553).

Through infrastructural investments in things such as fiber-optic or microwave connections between trading venues, co-location centers and even computer architecture optimized for HFT (Zook/Grote 2017; MacKenzie et al. 2012), the design and temporal regime of markets has come to produce information asym-

metries that enable trading strategies based on high speed, operating in in milli-, micro- and even nanoseconds (Markoff 2018) and on "gaming the plumbing" of financial markets (Toscano 2013). In HFT, speed ultimately trumps smartness. As a consequence, trading algorithms are rather "dumb": speed requires low latency, and all information processing takes time. HFT algorithms therefore need to be kept as simple as possible in order to respond quickly to information changes and to automatically enact a trade, and therefore require constant human supervision (Beverungen/Lange 2018: 86-91). As Arnoldi (2016: 46) puts it, leaving "trading to 'naïve' algos may […] be a choice of economic necessity for high frequency traders […]. Crudely put, algos get faster but not smarter." HFT, in exploiting the plumbing of financial markets, is focused on internal market dynamics and information asymmetries, and it operates on temporal advantages of micro- or by now nanoseconds, and can therefore not afford to give time to complex computation such as that necessary for AI. The "punctuated agency" of algorithms, i.e. the space in which they "draw inferences, analyze contexts, and make decisions in milliseconds" (Hayles 2017: 142) simply doesn't leave time for AI.

That is not to say that AI could not inform HFT strategies. For example, at Automated Trading Desk, basic AI such as linear regression equations were used to predict prices: its machine would calculate an "'adjusted theoretical value' of the stock in question, a prediction of its price 30 seconds in the future", based on market data such as "'the size of the [best] bid relative to the size of the [best] offer', along with 'a short-term trend variable in the transaction prices of the stock'" (MacKenzie 2017: 182-186). That would hardly count as AI today, but it provides an early example of what kinds of models and calculations went into the design of HFT algorithms. In fieldwork conducted by Ann-Christina Lange, high-frequency traders reported that it would take years before AI would become relevant for HFT, with its use only at an experimental stage (Beverungen/Lange 2018: 89). Recent academic work developing approaches to HFT based on reinforcement learning, deep neural networks or convoluted neural networks (e.g. Kearns/Nevmyvaka 2013; Arévalo et al. 2016; Ganesh/Rakheja 2018) similarly suggests that there is a lot of experimentation but little implementation. A recent industry report argues that whereas HFT is "about speed, machine learning is about depth and breadth of insight", and while speed still matters, "it's a different kind of speed" than HFT (McCauley 2016: 4, 7).

Even though the title of Scott Patterson's book *Dark Pools: The Rise of A.I. Trading Machines and the Looming Threat to Wall Street* (2012) would suggest that HFT is largely based on AI, it is not always clear what is considered AI, and his examples either deal with trading strategies more associated with quantitative finance or with examples such as Trading Machines, which in the late 2000s operated an automated trading strategy built on expert systems but which was "a lumbering turtle compared with the rising new breed of speed Bots in the stock market"

(Patterson 2012: 38). In quantitative finance more broadly, developments such as portfolio optimization theory, the capital asset pricing model, and—perhaps most importantly—the Black-Scholes option pricing formula (Kirilenko/Lo 2013: 53-55), have offered calculative devices for deciding which financial assets to invest in, how to devise risk strategies and how to price financial assets such as options. This has allowed the "quants" to conquer Wall Street (Patterson 2010), mostly as part of hedge funds, from the 1980s onwards, and to shape financial markets in the image of their financial models (MacKenzie 2006). Quantitative trading is buy now also algorithmic, i.e. order execution is automatic and much of the trading decisions are also made by algorithms. While many hedge funds also specialize in fast trading in microseconds, in contrast to HFT the focus is on smartness rather than merely speed, and on exploiting not so much the plumbing of financial markets in high volume, high speed trading as on exploiting information asymmetries in trade that operates with holding times of hours, days or weeks rather than seconds.

Although hedge funds and their quantitative traders are extremely secretive, some instances of the deployment of AI are known and point to more recent widespread use. For example, Renaissance Technologies, one of the largest and "considered by many to be the most successful hedge fund in the world" (Patterson 2012: 107), also called "finance's blackest box" (Burton 2016), heavily recruited its staff from cryptographers from the US government and the speech recognition program at IBM (Patterson 2012: 107-117). One of their experts was Robert Mercer, who had worked on Brown clustering as part of Frederick Jelinek's speech recognition team in the 1970s.[2] Or take Haim Bodek, who worked at Hull Trading, a quantitative algorithmic trading firm, from 1997 until it was bought by Goldman Sachs in 1999 (Patterson 2012: 28-30). Bodek had previously worked in fraud detection, and used his machine learning skills at Hull (Patterson 2012: 28), later setting up Trading Machines, which operated from 2007 to 2011 as one of the first fully automated and higher frequency trading outfits (Patterson 2012: 32-60).[3] There are also more recent examples in Patterson's *Dark Pools*, for example Apama, a "complex event processing" engine founded in 1999 and taken over by Software AG in 2013 (Patterson 2012: 62), which already points to the ways in which quantitative trading is embracing a wider set of "alternative" data beyond market and

2   Robert Mercer is now notorious for his engagement in right-wing politics, such as his support for Donald Trump and for Brexit, and for his involvement in the Cambridge Analytica scandal. He resigned from Renaissance in 2017 following political pressure. See Cadwalladr 2017.

3   Haim Bodek is perhaps the most famous whistleblower of Wall Street, because he revealed a secret order type used by high-frequency traders, which was destroying Bodek's own trading strategies at Trading Machines. Bodek is the main character of the documentary *The Wall Street Code* (2013).

trading data—in particular news and social data—for analysis and feedback into trading strategies.

There are three broad current developments related to AI in algorithmic trading relevant to my discussion. First, there is a movement towards automating quantitative trading, that is using computation both for placing orders and for calculating strategies, much like HFT is already automated. Some companies seem to support this strategy by purchasing HFT outfits, such as Citadel buying Automated Trading Desk in 2016. Rebellion Research was perhaps the first fully automated hedge fund, with its "Star" algorithm based on Bayesian networks trading autonomously since 2005 and the updated "Star 2.0" launched in December 2016 (Patterson 2012: 323-335; Metz 2016). Another recent example is Aidyia, another fully automated AI hedge fund that draws "on multiple forms of AI, including one inspired by genetic evolution and another based on probabilistic logic" (Metz 2016). To what extent trading here is really automated remains questionable, however, and the industry seems to have recognized the danger of an over-reliance on and "misplaced confidence" in AI and the need for humans-in-the-loop (McCauley 2016: 14, 16). As in the case of HFT, where traders are unlikely to leave their algorithms unsupervised (Beverungen/Lange 2018), the cases here might be similar to that of Trading Machines, where Bodek also constantly supervised his algorithms operating in a volatile market: "Bodek preferred to trust his own brain. While he used AI methods such as expert systems to build his algos, he preferred to maintain control throughout the trading day. That's why he never left his seat, not even for a bathroom break." (Patterson 2012: 38; see also Satariano/Kumar 2017). Nonetheless, this automation points to a further shift towards a machine-machine ecology in financial markets.

Second, while Aidyia and Rebellion Research are comparatively small, the large majority also of the large hedge funds today claim to work with AI (see e.g. Satariano/Kumar 2017 on Man Group), and there is a significant amount of exchange between companies and research institutes currently developing AI and hedge funds. David Ferruci, developer of IBM's Watson, moved from IBM to become Senior Technologist at Bridgewater Associates in 2012 (Vardi 2016). Li Deng moved from his position as Chief Scientist of Artificial Intelligence at Microsoft to Citadel in 2017 to become Chief Artificial Intelligence Officer. Pedro Domingos, author of *The Master Algorithm* (2015) and expert in markov logic networks, joined D.E. Shaw in 2018 to lead its Machine Learning Research Group. These high-profile movements suggest that hedge funds will play a key role in the development and politics of AI in the coming decades, also through institutions such as the Oxford-Man Institute of Quantitative Finance, and it suggests that the various kinds of AI for which these researchers have expertise will be deployed extensively in algorithmic trading. That is not to say, however, that the application of AI in algorithmic trading will be simple or straight-forward. For example, Li Deng suggests

that there are at least three challenges: low signal-to-noise ratios in the information analyzed to recognize patterns; strong non-stationary with a lot of fake data that needs to be eliminated; and a diversity of data, from speech to text to images, which needs to be amalgamated and analyzed (Deng 2018; see also Frontiers A.I. 2018). Still, this constitutes a significant shift in the cognitive ecology of financial markets, with AI used to make trade both faster and smarter.

Third, there is a significant expansion of the data sources with which algorithmic trading operates and from which it seeks to extract patterns offering trading opportunities, leading to a differentiation of trading strategies (McCauley 2016: 4). In HFT data sources are limited to a clear set of market data mostly related to the order books of the trading platforms in which high-frequency traders operate, and other algorithmic trading relies on a relatively limited set of market and economic data supplied by companies such as Reuters or Bloomberg. Today, however, data sources are multiplying, and so are the companies which offer data streaming and analytics services to algorithmic trading, in particular in relation to social media. Hedge funds such as BlackRock peruse social media and monitor search engines to assist in their investment decisions (De Aenlle 2018), and there are companies such as EquBot which work with proprietary AI and IBM's Watson to parse "millions of articles and news sources to uncover catalysts and events to maximize the probability of market appreciation" ('Artificial Intelligence (AI) and the Technology behind EquBot'), including market sentiment analysis (De Aenlle 2018; McCauley 2016: 8). There are also companies such as Quandl, RavenPack, Eagle Alpha or DataMinr which offer data analytics services for algorithmic trading. DataMinr, for example, specialises in "alternative data" such as "social media, satellite imagery, weather data, and more" ('Alt Data Tips for Traders | Dataminr') and suggests that nearly 80% of traders now use such "alternative" data ('Report: Investors Embrace Alternative Data | Dataminr').[4] This expansion of the data ecology of algorithmic trading calls for AI for pattern recognition, and it would be impossible for a human cognizer to take all of this information into account.[5]

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4 The big data analytics company Palantir Technologies, notorious for its involvement in the Cambridge Analytica scandal, also offers services to finance via Palantir Foundry, which however is largely used for fraud detection. On how Palantir operates, see Munn 2018: 27-56.

5 Critical art projects such as Rybn's ADM Trading Bot (see http://www.rybn.org/ANTI/ADM8/) and Derek Curry's hacktivist, tactical media project *Public Dissentiment* (see http://www.publicdissentiment.org/) seek to disrupt financial markets and to raise "awareness of how social media is now interconnected with stock trading" (Curry 2018: 108).

Shifting Cognitive Ecologies

It is perhaps no surprise that AI has been a central aspect of algorithmic trading, and that more recent developments in AI, such as varieties of deep learning, are being adapted in algorithmic trading. If markets have been designed to not put a premium on human cognition, and to assume that the truth lies in the information processor that is the market itself, then it is no surprise that human cognition is further sidestepped by the nonconscious cognition exercised by artificially intelligent machines. What is perhaps more surprising is that conscious, human cognition still plays a central role *in situ* for all algorithmic trading except its most automated variants. In HFT the "nonconscious cognitive arms race" (Hayles 2017: 165) meant that human conscious cognition was superseded by the *speed* of machinic nonconscious cognition, yet the "costs of consciousness" (Hayles 2017: 41-45)—slow response times, the bounded rationality of humans, and so on—had to be balanced against the "costs of nonconscious cognition" (Beverungen/Lange 2018: 80) which could prove financially disastrous. Investments in AI and machine learning have decidedly shifted the cognitive ecology of financial markets towards a premium put not only on *speed*, with HFT still exploiting the plumbing of financial markets, but also on *smartness*—an artificial smartness which further challenges human cognition. Now human consciousness can keep up neither with the speed in which high-frequency algorithms trade, nor with the smartness by which artificially intelligent machines interpret data and find patterns benefitting trading strategies. The costs of this different kind of nonconscious cognition—that of the various AIs at play in algorithmic trade—remain to be enumerated.

It seems a safe bet to assume that one of the costs of the cognitive ecology produced by algorithmic trading is market volatility. There are already plenty of examples of the ways in which both quantitative and HFT have produced crashes (see Kirilenko/Lo 2013: 60-67 for an incomplete list). For quantitative trading, the most serious event was the "quant quake" of August 2007, in the middle of the then emerging financial crisis. Despite seemingly little market pressure, hedge funds were involved in concerted forced liquidations and subsequent de-leveraging, which lead to huge losses for the hedge funds (Kirilenko/Lo 2013: 61-62). For HFT, the most famous example is the flash crash of 6 May 2010, in which the Dow Jones Industrial Average "experienced its biggest one-day point decline on an intraday basis in its entire history and the stock prices of some of the world's largest companies traded at incomprehensible prices", all largely due to high-frequency algorithms negatively interacting with one another (Kirilenko/Lo 2013: 62-63; Borch 2016). The flash crash was not a singular event though: Johnson et al. identified more than 18.000 "ultrafast extreme events" within a five-year period, which they see as consistent with the observation of an "emerging ecology of competitive machines featuring 'crowds' of predatory algorithms" (2013: 1). Furthermore, one

example of the volatility caused by the expanded data ecology of financial markets has been described by Karppi and Crawford (2016) as the "hack crash", in which a false news announcement on Twitter led to a jitter in financial markets caused by automated trading algorithms fed by DataMinr. These examples suggest that the "enigma of exceptional situations, rare events, and black swans"—already associated with derivatives and other aspects of financial markets—remains, and that the "terrain of a dark and confused empiricism" (Vogl 2015: 15) that characterizes financial markets is only exacerbated by AI.

All of these examples furthermore demonstrate that much of the volatility stems from the interaction of (both "dumb" and "smart") automated trading algorithms in financial markets. These automated agents significantly contribute to the ways in which financial markets are marked by interactive dynamics such as imitation (e.g. Borch 2016; Lange 2016). Yet we are "still far from having a robust understanding of how trading algorithms interact", even though how an algorithm "materially acts is shaped by interaction" so that algorithms "need to be understood relationally" (MacKenzie 2019a: 55). The "machine-machine ecology of automated trading" (Hayles 2017: 175) escapes both the understanding and control of humans as it ultimately escapes that of artificially intelligent agents. One could perhaps imagine a fruitful, symbiotic interaction between "smart" trading algorithms, and within the market design field there is certainly still the ambition and hope that multi-agent AI systems including their rules of interaction could be designed from scratch and bring forth a kind of *machina economicus* (Parkes/Wellmann 2015: 272). However, despite market design the AI trading algorithms largely operate independently, and, in that regard, financial markets also do not constitute a "collective capitalist brain" (Terranova 2013: 66); rather, the smart agents compose a sum of small capitalist brains in competition with each other.

This state of affairs is exacerbated by the multiple opacities that are pervasive in financial markets. Burrell suggests that some of the opacities of machine learning algorithms are unsurmountable and a fundamental part of how machine learning operates in terms of its architectures and scales (Burrell 2016: 4-5). Strategies such as explainable AI also currently do not deliver on reducing opacities (Sudmann 2018: 187-191). Yet these opacities of AI are only the latest addition to the other opacities of financial markets, and they are exacerbated by the secretive strategies of algorithmic traders already mentioned above. I already noted how high-frequency traders exploit the plumbing and the information asymmetries of financial markets. Since these constitute a competitive advantage they are as far as possible kept secret; only revelations such as those by Bodek mentioned above or those of Michael Lewis in *Flash Boys* (2014) have led to the microstructure of financial markets becoming more publicly known. There are also the dark pools (MacKenzie 2019b) which largely operate—as their name suggests—in the dark, with order books and many other features of their platforms largely inaccessible

to the public. Lange (2016) also recounts how the setup of HFT prop-shops produces a kind of organizational ignorance, wherein barriers between traders and coders are established which are meant to avoid imitation but can also lead to detrimental side-effects.

To politically challenge the opacities and black boxes of algorithmic trade would therefore require a serious upheaval in financial markets. Attempts at regulation have only addressed these opacities in a limited way, for example by demanding that HFT algorithms be identifiable (e.g. Coombs 2016). Other attempts at changing the design of markets in order to decrease opacities also exist. For example, the Investors Exchange (IEX) is a trading platform celebrated by Lewis (2014) as fighting HFT: a coil of a 61 km long cable around the data center adds around 7 milliseconds to the "round trip" of the algorithms and effectively excludes HFT from being operable on the platform. IEX also has a much more transparent fee structure and offers "fairer" trading conditions. Another suggestion comes from Budish et al. (2015), who suggest to replace continuous limit order books—currently the way trading platforms organize order matching—with batch auctions, which could take place every second and would thereby also largely deny high-frequency traders their temporal advantages (see also Hayles 2017: 165-169). Roth, a key proponent of market design and a teacher of Budish, supports these suggestions (2015: 81-100). Mirowski and Nik-Khah (2008), in a different context, warn against taking on this constructivist perspective of market design, with its neoliberal tint. While there are other nuanced considerations of the politics of algorithmic trading (see e.g. Lange et al. 2016), none of these suggestions address the opacities of AI in algorithmic trading.

It would also be unclear to what extend these changes would lead to a democratization of algorithmic trading and AI. As MacKenzie and Pardo-Guerra reflect in relation to Island, whose order book was open, "allowing anyone real-time sight of its order book", in contrast to all current trading venues: "information might have wanted to be free, but capitalism had other priorities" (2014: 171). Particularly the developments around the expanding data ecologies of financial markets discussed above suggest that rather than democratization, these developments in algorithmic trading and AI lead to a further financialization of daily life (Martin 2002). The social life recorded on social media and elsewhere can now feed into "financial Social Machines, which integrate the innovative high-speed network, social media information, and trading decisions of individuals to provide more accurate price predictions leading to improved financial market integration" (Ma/ McGroarty 2017: 245). Here the "great promise" of deep learning, which is "not only to make machines understand the world, but to make it predictable in ever so many ways: how the stock market develops, what people want to buy, if a person is going to die or not, and so on" (Sudmann 2018: 193), is enrolled in what Hayles calls

"vampiric capitalism" (2017: 159) and what I discussed above in terms of financial and cognitive capitalism.

A focus on "the infra-medial conditions of modern AI technology and their political dimension" (Sudmann 2018: 185), as they present themselves in relation to financial markets, and the "shifting our analytical focus toward infrastructures" of financial markets (Pardo-Guerra 2019: 31), as attempted in this contribution, reveals how thoroughly algorithmic trading and the more recent deployment of AI as part of it are enthralled to financial and cognitive capitalism. To get to grips with the politics of AI in algorithmic trading requires an analysis of how AI is enrolled in the service of the extraction of value, most recently from social life as it is recorded on social media and elsewhere. The outline above demonstrates that the politics of AI are increasingly closely entangled with finance and the cognitive ecologies in which it operates. As part of an expanded understanding of the politics of operations (Mezzadra and Neilson 2019), AI deployed as part of finance reveals how it partakes, through financialization, in an extraction of value which it would take more than some tweaks of market design to break out of. Most immediately, the politics of AI in financial markets appears as a politics of cognition, one in which currently the "nonconscious cognitive arms race" (Hayles 2017: 165) is decidedly shifting towards a terrain in which AI is complicit with neoliberal finance capital. This calls for a politics of cognition which thinks through the ways in which AI maybe be extracted from this complicity and be put to other ends not necessarily so congruent with financial and cognitive capitalism.

Acknowledgments

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