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Social media, Financial Algorithms, and the Hack Crash

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Abstract:

“@AP: Breaking: Two Explosions in the White House and Barack Obama is injured.” So read a tweet sent from a hacked Associated Press Twitter account @AP, which affected financial markets wiping out \$136.5bn of the Standard & Poor’s 500 index’s value. While the speed of the Associated Press hack crash event and the proprietary nature of the algorithms involved make it difficult to make causal claims about the relationship between social media and trading algorithms, we argue that it helps us to critically examine the volatile connections between social media, financial markets, and third parties offering human and algorithmic analysis. By analyzing the commentaries of this event, we highlight two particular currents: one formed by computational processes that mine and analyze Twitter data, and the other being financial algorithms that make automated trades and steer the stock market. We build on sociology of finance together with media theory and focus on the work of Christian Marazzi, Gabriel Tarde and Tony Sampson to analyze the relationship between social media and financial markets. We argue that Twitter and social media are becoming more powerful forces, not just because they connect people or generate new modes of participation, but because they are connecting human communicative spaces to automated computational spaces in ways that are affectively contagious and highly volatile.

Keywords: Affect, data, digital, financial markets, Marazzi, Tarde, technological culture, time, new media

‘@AP: Breaking: Two Explosions in the White House and Barack Obama is injured.’

This message appeared on Tuesday April 23, 2013 at 1.07PM on the official *Associated Press* Twitter account @AP. It quickly received over 4,000 retweets and a number of favorites. Within seconds, according to the Reuters data, the Dow Jones Industrial Average dropped 143.5 points, and nearly \$136.5bn of the Standard & Poor’s 500 index’s value was wiped out (Selyukh, 2013). But soon after the tweet was published, people began to question its veracity. The tweet was revealed as the result of a malicious hack of the Associated Press Twitter account. [1] The recovery of the markets was rapid. Just as quickly as the announcement of the explosions had lead to a precipitous drop, the market had returned to its former position. The entire event happened in less than five minutes.

Explanations of this event, which we call a ‘hack crash’, differ markedly. Detailed information is very difficult to obtain due to the speed, uncertainty and proprietary nature of the algorithms involved. What is clear is that Twitter, and social media in general, has become an influential actor in the operations of financial markets. For this paper, we are interested in the thick lines of

connection that run between social media spaces, intermediate human and algorithmic actors, and financial markets. Following N. Katherine Hayles (2013: 13-14), we argue that these systems are fundamentally interlinked, and it has become impossible to think of the global economy without taking into account the ‘self-organizing ecology of ultrafast machine algorithms.’ This is underscored by estimates that ‘as much as two-thirds of all stock trades in the U.S. from 2008 to 2011 were executed by high-frequency firms’ (Phillips, 2013); and today about half of total equity trading in the US is being driven by proprietary algorithms (Phillips, 2013b; Jeff, 2009). These algorithms are themselves embedded in a wider algorithmic culture of connectivity of co-existing human and non-human operators (Cf. van Dijck, 2013).

Scholars doing research in this area have recognized the importance of finding ways to research these systems, but this is increasingly difficult, especially with high-frequency trading (Lenglet, 2011: 49; Hendershott et al., 2011: 6). As Neil Johnson et al. (2013) observe, without actual exchange data it is impossible to know for sure how certain trading events transpired, particularly given the complexity and speed of the many high-frequency trading systems. But for us, this black-boxed condition is exactly the reason why we need to give deeper attention to these systems. Instead of ‘fetishizing algorithms’ (Crawford, 2013a: 6), or computational processes in general, we need to develop theories that address and analyse the broader sweep their operations and impact as well as their social, political and institutional contexts. Instead of focusing on particular devices or platforms, an alternative approach is to analyze ‘the systems of power they mobilize’ (Galloway, 2012: 18). One way to see these powers in operation is to focus on moments when systems fail. In the Associated Press hack crash financial experts and journalists saw failures in various different levels of security, interpretation, automation, algorithms, credibility, and value. Thus, cases like the Associated Press hack crash may open up a brief moment when we can see which actors are involved in these operations, what relations they evoke, and how their actions are understood.

Christian Marazzi has argued that there is a profound overlap between money and language, evidenced in the communicative nature of monetary policy where central banks issue monthly reports that not merely describe market realities, but create them (2014, 13). Further, the monetary regime so relies on ‘communicative experiments’ as to have a created a system that needs to be understood through the critical humanities as much as by economics: “Central bankers now operate in an area where linguists, psychologists – and even anthropologists – know as much as economists” (Tett quoted in Marazzi, 2014: 16). While Marazzi’s focus is on the engines of monetary policy, the gold standard, and state-led mechanisms of maintaining liquidity, here we look at the affective relationship between Twitter posts and human and algorithmic trading. This paper addresses three observable themes: the use of big data, and the roles of micro-temporality and affective contagion. In specific, we examine the different media discussions where the Associated Press hack crash and its consequent effects on the financial market were addressed in order to elaborate on the broader social debates about the relationship between different human and algorithmic spaces. We begin by asking: 1) how is the relation between social media systems and financial market systems understood in the mainstream media,

and 2) what does this financial-social relation tell us about the wider imaginaries of the emerging ecology of algorithms?

To inform our investigation, we conducted a textual analysis of a corpus of discussions where people tried to make sense of the Associated Press hack crash: including news stories, financial blogs, corporate videos and Twitter messages. We gathered over 100 published commentaries within the timeframe of April 23, 2013 to April 30, 2013. The sample consists of articles, blog posts, interviews and news reports collected by the LexisNexis database on the Associated Press hack crash as well as our own web searches. Fourteen of these items were used for close analysis as they specifically addressed concerns about algorithmic trading: these consisted of twelve news articles and two videos. Six of the news articles are from newspapers or news sites intended for general public such as *the Guardian* and *the Telegraph*, with the remaining six from financial newspapers such as the *Wall Street Journal* and *Bloomberg Businessweek*. If we accept the ‘linguistic turn’ of the economy, as Marazzi (2014), Butler (2010) and MacKenzie (2007) have argued, then this public ‘talk’ about the hack crash is both revealing and productive. It puts things in motion by creating its own truths about how financial algorithms are understood and how we expect them to behave.

We argue that Twitter and social media are becoming more powerful forces, not just because they connect people or generate new modes of participation, but because they are connecting human communicative spaces to automated computational spaces in ways that are affectively contagious and highly volatile. For example, Patti Domm (2013) in CNBC Market Insider website describes how the hack crash was produced by computers operating autonomously without human involvement:

The rapid fire trading also highlights the role of computers and algorithmic trading on Wall Street. “That goes to show you how algorithms read headlines and create these automatic orders – you don’t even have time to react as a human being,” said Kenny Polcari of O’Neill Securities [...]

In short, Twitter affects not only human traders but the whole stock market system structured with people, code and computers. And some of those systems operate at a speed faster than human reaction time. As a research subject, the Associated Press hack crash brings together social media and modern finance, two fields that are closely related but seldom researched together. Here we bring together critical data studies, the social studies of finance and theories of social media in order to understand their relation. Our focus is on the ways in which both social media platforms and economic models do not just describe but rather transform their objects (Mackenzie, 2007; 2009; Didier, 2007: 281). We argue that the Associated Press hack crash is a powerful example of what Marazzi (2014: 21) describes as ‘a new incarnation of capitalism where the most natural and *common* qualities possessed by the linguistic animal (such as linguistic faculty, communicative-relational capacity, capacity to react to unforeseen circumstances, etc) are *put to work*, controlled by value mining devices which reach across the sphere of production.’

Financial Big Data and the History of Prediction

Financial operators follow Twitter and use it for predicting movements in financial markets. For example, trader Jonathan Corpina (2013) illustrates how Twitter has become the dominant platform for breaking news within the financial world: ‘Back in the day people watched the news feeds and they’d watch the rolling news feeds... now we watch Twitter for information.’ [2] CNN journalist Heather Kelly (2013) notes that ‘real tweets have the power to end careers, cause diplomatic tensions, fuel a revolution and find a kidney. Fake tweets can have the same ripple effect.’ Similarly Peter Chow-White notes in an interview about the AP hack crash how social media has become an important actor in defining how we perceive and define our reality especially during the time of crisis:

All of a sudden you've got social media in there, it creeps in and becomes part of our everyday information gathering patterns with information about loved ones, about international events and everything in between. During a crisis, communication is very quick and untrue reports can quickly take on an air of legitimacy, simply through the number of times they are repeated. The repetition starts to create a sense of truth, or a potential truth around it. (Shaw, 2013)

The Associated Press hack crash demonstrates the unexpected consequences of the interplay of market data and social media data, and the ways in which these signals are used to form assumptions, create predictions and act accordingly. But it is also an exemplar of the current tendency to try to model and understand the desires of people and meaning of events in the world by mining social media data. Conducting analyses and making predictions based on social media data is a large and growing industry. Big data techniques, by which we mean large-scale data mining, predictive analytics and machine learning, are being deployed in attempts to understand everything from human behavior to stock market tendencies. With this accumulation of data and the development of new tools to analyse and connect large data sets, we have seen a growing ‘data fundamentalism’ (Crawford, 2013b), a neo-positivist epistemology in which correlation is sufficient rather than causation, and massive data sets and predictive analytics are taken for objective truth. Social media-based predictions that draw on millions of messages and observe the changing nature of social graphs have only recently become computationally possible to store and analyse at speed. But despite all that data, predictions based on social media are still a form of conjecture, often based on shaky assumptions regarding sentiment, meaning, and representativeness (boyd and Crawford, 2012).

While analyzing and exploiting social media data may be a phenomenon of this decade, the fields of finance, economic data and statistics have played a role in predicting stock market movements for well over a century. At the turn of the 20th century Gabriel Tarde noted a popular interest in following the happenings of stock markets printed in daily newspapers (Barry and Thrift, 2007: 516). Tarde (2000: 22) argued that stock-exchange statistics expressed the ‘variations of public

confidence regarding the success of certain enterprises' and 'changes in public desires and interests.' Sampson (2011) explains that Tarde's economics were based on the idea of people's 'periodically linked desires' and the economic appropriation of these desires by social inventions; for instance, peoples daily habits such as eating and drinking were commercialized and turned into profitable actions.

For Tarde, statistics were the 'sense organs of society' (Barry and Thrift, 2007: 516-517). Thus, the numbers at the stock market demonstrated not just information about the current state of financial affairs but, in a broader sense, the tendencies and desires of people (Tarde, 2000: 22; Tarde 2010). As Bruno Latour and Vincent Lepinay note (2009: 22-23) Tarde was arguing for the need to go beyond the focus on economic operations in order to understand the collective desires at work. In the 2010s, stock-exchange statistics are only one possible source to make these observations. As Barry and Thrift (2007: 517) note:

[A] multiplicity of information that can be statistically manipulated is now available, from official statistics which are pored over by multiple agencies (such as those concerning interest rates or inflation) through the rise of large corporate databases which precisely try to track and trace the flow of consumer desires by using geodemographic and other consumer classifications, to the myriad pieces of information about individual consumer choice which circulate on the internet and can be aggregated in ways that attempt to trace the dynamics of the "inter-psychological."

This flow of consumer feelings, however, is only part of the story. Computational financial systems are themselves responding in ways that are described as having their own emotional currents. When analyzing the AP hack crash for *the Wall Street Journal* Geoffrey Rogow and Telis Demos (2013) describe that financial markets were 'alarmed' by the third party social data providers that processed and amplified the Associated Press tweet:

When the words "explosions" and "White House" popped up Tuesday on a verified Associated Press Twitter account, computers in the bare-bones offices of a New York City startup sprang into action. The computers, housed in the Madison Avenue headquarters of a company called Dataminr, sent alerts to clients like hedge funds and government agencies about the apparent news. Shortly thereafter, the Dow Jones Industrial Average tumbled 145 points in seconds.

Rogow and Demos do not merely speculate on the computational power of this event but also name a particular system which was being used to analyze social media feeds. The Associated Press tweet was read by the Dataminr software, which mines Twitter's 'firehose' [3] and delivers what is deemed relevant into the hands of traders:

Dataminr combs through 340 million daily tweets on Twitter and its algorithms quickly seize on abnormal and actionable signals that can be analyzed and confirmed as a relevant event for a client. This could be anything from an assassination or general instability in certain countries to government sanctions, natural disasters or on-the-

ground chatter about products or trends. Dataminr uses available Twitter metadata along with other contextual factors such as historical and concurrent data to create a mathematical signature for an event, ultimately deciding on the fly whether an event is valuable for decision-making purposes. [...] previous technologies that tried to look at Internet data relied on things like sources and the authority of sources or keyword frequency. Dataminr is very focused on the now and deriving instant value from the flow of tweets online. (Kim, 2013.)

The role of Dataminr in the Associated Press hack crash case has been widely acknowledged in the financial press (Rogow & Demos, 2013; Vlastelica, 2013). Dataminr alerted traders to the White House explosions as soon as the AP tweet was published, and the markets immediately began to drop. Minutes later, Dataminr determined that the Associated Press hacked tweet was a hoax by analyzing the authoritativeness of the tweets that denied an attack had happened (Akhtar, 2013).

Dataminr is not the only software offering these services. *RavenPack*, *Gnip*, *DataSift*, and *Topsy* are the names for different third-party software applications that also access the Twitter firehose and interpret that data for different trading companies. Like Dataminr, these software packages are complex and do not interpret only texts or keywords, but as journalist Michelle Price (2013) explains in *the Financial News*, also interpret ‘relationships’ of these words and the expressed ‘emotions’:

The underlying software identifies the emotion in a text by scoring the relationship between key modifier words, such as adjectives and adverbs; concepts such as, for example, apprehension surrounding whether a country will leave the Eurozone; and the object of the sentence, such as a currency. According to Thomson Reuters, the software can identify and understand the grades of emotions expressed in news and social media at a highly nuanced – almost human – level.

However, such software does more than simply produce a sentiment analysis of Twitter data. As Rogow and Demos (2013) note, ‘Dataminr looks at dozens of variables about each tweet, such as the influence of the user, the geo-location of where the tweet is sent from, and how tweets are clustered together’. Meaning is found in the authoritativeness and volume of the tweet – who tweets it, how many times it is retweeted, who by, and how it spreads.

Dataminr is connected to a larger trend that Latour and Lepinay (2009: 61-63) describe as the attempt to technologically rationalize the stock market and make it more predictable. It is a part of ‘psychological passage *from uncertainty to probability*’ which is ‘facilitated, amplified, simplified, and formatted, by the spread of accounting instruments and calculating devices’ (Ibid.: 63). According to an interview with WSJ reporter Telis Demos (2013) Dataminr uses social media data to make predictions and give trading advantage:

On Wall Street it is pretty simple when somebody has a trading advantage of a some kind, when they might know something ahead of somebody else, there is a network effect.

Because if the one guy thinks that the other guy might know something you know few minutes ahead of him they kinda want in on it. And so that's how they've grown very quickly on Wall Street. A word is sort of gotten out that you know if you subscribe to Dataminr which is a kind of a web-based platform you pay like a license for each person of the company who uses it and so you know if you have the Dataminr subscription you might hear something. [4]

Dataminr is an example of technological passage from uncertainty to probability where psychology becomes replaced with machine learning and algorithmic operations. Dataminr offers to sort massive amounts of data and bring the results for the subscribers in real time.

“Essentially what we're doing is predicting the present,” [Dataminr] founder Ted Bailey tells Fast Company, quoting Google's Hal Varian. “[We're] giving people just a better sense of what's happening right now, and a greater confidence in the understanding of a particular situation or breaking information.” (Subbaraman, 2013.)

Through real-time analysis of Twitter data, software packages like Dataminr assess emotion, importance and social meaning in order to ‘predict the present’ and thus transforming social media signals into economic information and value.

Algorithmic Trading and Affect

Donald MacKenzie (2007) quite famously notes that economics are performative. Economics do not just reflect or analyze the flows of money but different economic models change the ways finance operates. This ability to produce effects is dependent on different economic agencements and their capacities (Callon, 2007: 320). Consequently, Sampson (2011) notes that the ‘spreading of the recent financial crisis is linked to the growth of automated networks and so called algotrading.’ Rather than making arguments in favor of technological determinism, we are more interested in the general principles of how these technologies affect and become affected by each other. This stance is inspired by Brian Massumi's (1995: 109) notion that ‘the ability of affect to produce an economic effect more swiftly and surely than economics itself means that affect is itself a real condition, an intrinsic variable of the late-capitalist system, as infrastructural as a factory.’ For Parikka (2014: 11) the notion of affective capitalism explains the technological and communicative practices of harnessing our cognitive and affective capacities as a part of value creation in capital within network culture: ‘Affective capitalism is not so much an entity to be resisted, as it is an apparatus of capture, as Deleuze and Guattari defined it. Indeed, it is in this sense a logic of power, or an abstract machine, for cultivation and capture of affective worlds.’ Following these propositions, we will track how financial markets capture Twitter data, and how it could be turned into value by technological mechanisms such as high-frequency trading.

On the surface, the Associated Press hack crash looks like a simple event: an otherwise reliable source of information on social media was hacked, and incorrect information was used to make

stock market transactions. If we switch the register from social media studies to the field of sociology of finance, one way to model the relation between the hacked Associated Press tweet and financial markets would be through the concept of the ‘self-fulfilling prophecy’, which is often used to explain economic crises. A traditional example of a self-fulfilling prophecy would be a false rumor leading to a ‘bank run’, where people withdraw their money and thus eventually causing the bank to become unsound (Merton, 1949; Mackenzie, 2001: 128; Goldstein, 2013). Journalist Michelle Price (2013) reporting on the hack crash in the *Financial News* argued that the event highlights that the ‘truth’ in stock market is a ‘relative concept’ and ‘traders have long sold stock on bad “news” regardless of whether they believe it to be true or not as the weight of trading will move markets regardless of what has inspired it.’ But this is an inadequate framework for our purposes, as self-fulfilling prophecies center on the human subject and their beliefs and expectations (Callon, 2007: 322). What happened during the hack crash exceeds the anthropocentric frame.

Several journalists and commentators raised concerns that the events of April 23 were triggered by financial algorithms scanning Twitter and then automatically trading stocks (Moore & Roberts, 2013; Clarkson, 2013; Lauricella, et al., 2013; Foxtan 2013).

A fake tweet has triggered a dramatic 143-point fall in the Dow, highlighting just how vulnerable the world’s financial markets are to misinformation on social media. [...] Now it must be stressed that the Dow recovered as soon as it became apparent that the tweet was fake, but it has raised massive concerns over how the immediacy of social media can so dramatically influence financial markets. In this particular instance, one of the main reasons for the sell-off was the impact of the numerous trading algorithms, which basically search all news and execute trades almost immediately in response. (Clarkson, 2013)

Experts like Corpina (2013) agreed that the Associated Press hack crash was caused by automated algorithmic trading systems triggered by the false tweet:

And take that another step with the computers that trade and trade off of headlines and look for negative keywords that are out there and then those computers start trading off of that information. That is exactly what we saw yesterday that was all computer trading ‘algorithms’ just chasing after each other trying to beat each other to the next bid that was trying to head down. Bids were being cancelled and before humans could make the right decision the computers already made bad decisions.

These arguments are based on the idea that trading algorithms are scanning Twitter data using forms of text and sentiment analysis, and then immediately placing trades (Philips, 2013a). Bloomberg Businessweek journalist Matthew Philips (2013a) in his interview with RavenPack CEO Gonzales criticizes some firms for doing this:

Gonzalez [RavenPack CEO] says some of his clients have told him that a handful of high-frequency trading firms forgo filtering and pour Twitter data directly into their

algorithms. “There are a few HFT firms that have, I would argue, irresponsibly added raw Twitter feeds into their systems,” says Gonzalez.

While opinions differ on how much high-frequency trading algorithms draw on Twitter data, it is clear that Twitter now has considerable power to produce effects in the market. But some Twitter accounts have more power than others. This capacity for certain Twitter accounts depends on their legitimacy as a ‘speaker’ – in Marazzi’s terms ‘it depends on the power and the legal designation of whoever “speaks monetarily”’ (2014: 43). Associated Press has legitimacy as an official news source that can influence markets, and so it can be set up as a ‘trusted’ source of data for financial algorithms. Furthermore, the @AP Twitter account had more than 1.9 million followers making it a powerful operator in disseminating news on social media (Bradshaw et al., 2013).

The debates that connect the tweet with financial algorithms highlight an important aspect of how the labor of trading has changed, where human agents are increasingly marginalized while computational processes operate autonomously or semi-autonomously. To emphasize this change in agency, Tiziana Terranova (2013: 10) notes that ‘techno-social economic decision-making in the stock markets enacts not so much the aggregate behavior of individual economic agents, but also affective contagion and the inhuman speed of digital technologies.’

The connection of Twitter information and financial markets opens up a way to explore the role of affect in computers and automation.[5] For Massumi (Massumi N.D.) affect is a way to discuss ‘that margin of manoeuvrability, the “where we might be able to go and what we might be able to do” in every present situation.’ Affect, for Massumi, is not characteristic only to humans but it involves all bodies interacting together. Thus computer-driven market activity indicates affect and affectivity as a phase change or transition in capacity.

Financial algorithms are built to affect and become affected by the surrounding information (price changes, phase changes of other algorithms for example) and they can do it in fractions of a second. According to Hendershott and Moulton (2011: 569), ‘the automation and speed of the trading process have long been important dimensions of financial market design, and the growth of electronic trading in recent years has intensified the emphasis on these dimensions.’ Algorithmic trading is a critical part of this development. Algorithms are used to ‘find prices and match buy-and-sell orders’ but also as noted by Marc Lenglet (2011: 45), to “decide” when and how to send orders without direct human intervention.’ Algorithmic trading ‘slices and dices orders,’ keeping the trade undetected and submerged until the trade has already transpired (Seigworth & Tiessen, 2012: 66-67). Some of these algorithms can even ‘automatically read and interpret economic data releases, generating trading orders before economists have begun to read the first line’ (Chaboud et al, 2009: 1). Thus, financial algorithms have become what Knorr Cetina and Preda (2007: 126) call scoping systems; they are systems ‘of observation and projection that assembles on one surface dispersed and diverse activities, interpretations and representations which in turn orient and constrain the response of an audience.’

The switch from human trading to computerized trading can be understood as a symptom of the fragmentation and globalization of financial markets (Menkveld, 2013: 1). Computers can obtain 24/7 global access to different markets and thus operate on the fragmented level of the globalized economy, and they are cheaper to maintain than the vast network of human traders that would be required to do the same operations (Hendershott, et al., 2011: 1, 31). Furthermore, they are able to respond to changes faster than humans do – they base their calculations on huge amounts of financial data (Aldridge, 2010). Donald MacKenzie describes the birth of automated trading by analyzing the evolution of Chicago Merchantile Exchange. According to MacKenzie (2012: 25) the first mechanical trading systems such as Globex and Aurora relied on the assumption that ‘automated trading would involve a human being inputting orders into a computer terminal.’ Automated trading systems were built to assist traders in responding to the fast pace of pit trading, following the ‘first in first out’ logic where ‘if there were, for example, multiple bids at the same price, the first to be executed (i.e., matched with an offer at the same price) would be the bid that had been first to arrive at Globex’s “matching engines”’ to a more complicated algorithmic processes that mimicked also the informal actions of the traders’ (MacKenzie, 2012: 24, 32-33).

Automated trading is not an anomaly. In 2012 roughly 50 % of the US equity trading volume was accounted by high-frequency trading (HFT) firms which use complex algorithmic processes to trade securities (Philips, 2013b). According to the observations of Andrei Kirilenko et al. (Kirilenko, et al., 2011: 23) the trading activity of high frequency traders is based on three premises:

First, HFTs seem to anticipate price changes (in either direction) and trade aggressively to profit from it. Second HFTs seem to submit resting orders in the direction of the anticipated price move. Third, HFTs trade to keep their inventories within a target level. The inventory-management trading objective of HFTs may interact with their price-anticipation objective. In other words, at times, inventory management considerations of HFTs may lead them to aggressively trade in the same direction as the prices are moving, thus, taking liquidity.

The belief in the effectiveness of HFT is premised on brute computational power to handle massive amounts of data. For instance Aldridge (2010) notes that

At the heart of HFT is a simple idea that properly programmed computers are better traders than humans. Computers can easily read and process amounts of data so large it is inconceivable to humans. For example, frequently traded financial securities such as EUR/USD exchange rate can produce well over 100 distinct quotes each second. Each quote, or "tick," carries unique information about concurrent market conditions. And while a dedicated team of human traders may be able to detect some tradable irregularities in such fast-paced data over time, human brains are no match for computers that can accurately resolve and act upon all minute information infusions in the markets.

Automated trading, then, functions via the dissection of a single moment into tiny fractions of time, creating micro-temporal operations. [6] Micro-temporal operations in financial markets involve the computational division of time into ever-smaller instants, and manipulation of those fractional moments to gain trading advantage and influence future prices on levels that are almost invisible to human perception. Johnson et al. (2013) illustrate that, the competition for even a millisecond of trading advantage has driven the creation of a range of technologies, such as the iW-eCute purpose-built chip, which prepares trades in 740 nanoseconds (1 nanosecond is 10^{-9} seconds). Meanwhile, the quickest a human can notice potential danger and physically react is 1 second, and it takes a chess grandmaster approximately 650 milliseconds to realize they are in trouble (Johnson et al., 2013).

Computational invocation at this speed denotes the non-human side of affect in relation to modern finance. It is driven by the desire to make profits by responding to information faster than anyone or anything else. High-frequency trading (HFT) systems located near the stock markets operate in micro-seconds, which are ungraspable for human traders. Just as Dataminr claims to be able to predict the present by giving real-time information from the Twitter firehose, HFT seeks to predict the future with high-speed trading operations. Presumably, algorithms and other actors respond to sudden changes in financial markets which are then imitated and repeated; when someone or something begins to sell in earnest, other entities follow (Borch, 2007: 554-557). These operations are so fast that the future, rather than being accurately predicted, is in fact invoked as 'the now' (Cf. Elmer and Opel, 2013: 12). [7] Arguably then, in the hack crash the futurity of crisis became present, not because it was falsely predicted but because the interplay of social media and financial markets had the capability to invoke it into being.

Conclusion: Possible futures?

Mackenzie Wark (2014) argues that the role of media theory is speculative, but 'not so much to fabulate futures as to describe in concepts what practices of relation, of pasts into presents and toward futures, could be.' The debates around Associated Press hack crash reveal the fault lines in the very organization of time, from who (and what) can perceive and act in a micro-temporal frame within the complex terrain that connects social media platforms, human traders and trading algorithms. In fact, while the Associated Press hack crash has been widely understood as a 'failure' of these connections, in many ways it was an example of algorithms working according to their design. In the case of the Associated Press hack crash we saw a tweet spreading and creating patterns of repetition. These processes of imitative repetition moved and adapted from one system to another. Human and non-human traders responded to what appeared to be an authoritative news message, a performative utterance with monetary legitimacy. The discourses around Associated Press hack crash reveal the power of networked social and financial systems to connect autonomously and to produce a present without human oversight or governance. But what kind of possible futures does it portend?

In an article published in 2013, Neil Johnson et al. describe the results of a large-scale study of the financial system that indicated "an abrupt transition to a new all-machine phase characterized by large numbers of subsecond extreme events" that escalated in the build up to the onset of the financial collapse of 2008. The study concludes that there is an "emerging ecology of competitive machines featuring 'crowds' of predatory algorithms." Johnson et al. argue there is now an urgent need for a new theory of subsecond financial phenomena. Following Marazzi, we agree that a new theory is needed, but one that draws on affect theory and media studies as well as finance and economics. The case study of the Associated Press hack crash points to a highly imbricated system that draws on affective contagions of networked social activity as well as financial data.

The rise of a subsecond, predatory algorithmic ecology seems a troublingly literal manifestation of Paul Virilio's vision that 'the history of the world is not only about the political economy of riches, that is, wealth, money, capital, but also about the political economy of speed (Armitage 1999, 35).' But speed is being traded for other capacities. As Robert Jackson (2013) notes, algorithms are always compromises between the complexity of decision-making and the speed of automation. With simple affect-based decision-making models, we risk what Sampson (2011) describes as "occasional monstrous aperiodic shock events" – a propensity towards repeated crises, even if they are, like the hack crash, 'micro-crisis events.'

The algorithmic ecology has intensified the three linguistic-monetary affordances that we have considered in this paper: big data use, micro-temporality and affective contagion. If we are to consider the future of this ecology, what will be the role of humans? As Johnson et al. (2013) observe, trades are already operating beyond the speed of human thought. Perhaps then, there is no place for humans at all in this new ecology – competitive trading will all be automated, and any governance system would have to be similarly fast or faster. That would result in algorithms monitoring algorithms, and designers would be optimizing not just for speed but for escaping detection.

But is the idea of 'governance' even relevant here? Marazzi suggests that "the crisis of contemporary financial capitalism requires that we question the *limits* of the linguistic nature of money" (2014, 6), but the closely interwoven nature of social media and trading systems discussed in this paper may indicate that there is, as yet, *no limit*. Or, at least, no limit within what we currently recognise as official economic systems. The drive to create what Marazzi calls "parallel horizontal economies" (such as bitcoins) are driven by an idealism to "escape from the empire of the monetary system" (2014, 46). Yet these systems, paradoxically, always entail the establishment of a different kind of empire, often with their own unstable algorithmic ecologies. The Associated Press hack crash case underscores the *connectedness of the relation* between systems of communication and monetary value – systems of humans and algorithms, which are now tightly bound within 'microrelational forces of imitative encounters' (Sampson, 2012: 19).

BIOGRAPHICAL NOTES

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ENDNOTES

[1] Syrian Electronic Army has taken credit for the hack (Fisher, 2013). Their involvement in the AP hack case would open an interesting discussion to the interconnectedness of social media, economy and politics, however that is not our focus in this paper.

[2] Transcribed from the video by authors.

[3] Twitter uses the term 'firehose' for complete access to its social media data.

[4] Transcribed from the video by authors.

[5] Much has been written about the various meanings and uses of affect, but we are here following Brian Massumi (1995) and Andrew Murphie (2010) among others, who define affect as intensity. Intensity is a relation between two things that takes place when two things or bodies interact or impinge upon each other. It is the passage between two things that can lead to transformations when it becomes amplified or dampened (Massumi 1995, 86).

[6] As Jussi Parikka (2011: 55, 57) has explained, the idea of micro-temporality helps us to understand the information processing, calculation and sequential operations of algorithmic culture on levels that are often invisible or difficult to grasp.

[7] One of the discussions around HFT deals with the volatility of markets; HFT has been connected to the sudden emergence of flash crashes. For example, the Flash Crash of May 6, 2010 is complex event involving many factors of which HFT was one. For more details about the May 6 Flash Crash see a joint report by the U.S. Securities and Exchange Commission and the Commodity Futures Trading Commission (2010).

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