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Competitive Advantage in Algorithmic Trading:

A Behavioral Innovation Economics Approach

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Abstract:

- **Purpose:** This paper investigates the strategic behavior of algorithmic trading firms from an innovation economics perspective. We seek to uncover the sources of competitive advantage these firms develop to make markets inefficient *for them* and enable their survival.
- **Methodology:** First, we review expected capability, a quantitative behavioral model of the sustainable, or reliable, profits that lead to survival. Second, we present qualitative data gathered from semi-structured interviews with industry professionals as well as from the academic and industry literatures. We categorize this data into first-order concepts and themes of opportunity-, advantage-, and meta- seeking behaviors. Associating the observed sources of competitive advantages with the components of the expected capability model allows us to describe the economic rationale these firms have for developing those sources and explain how they survive.
- **Findings:** The data reveals ten sources of competitive advantages, which we label according to known ones in the strategic management literature. We find that, due to the dynamically complex environments and their bounded resources, these firms seek heuristic compromise among these ten, which leads to satisficing. Their application of innovation methodology that prescribes iterative *ex post* hypothesis testing appears to quell internal conflict among groups and promote organizational survival. We believe our results shed light on the behavior and motivations of algorithmic market actors, but also of innovative firms more generally.
- **Originality:** Based upon our review of the literature, this is the first paper to provide such a complete explanation of the strategic behavior of algorithmic trading firms.
- **Keywords:** High frequency trading, behavioral innovation economics, strategic entrepreneurship, competitive advantage, expected capability theory

[Algorithmic] trading is, first and foremost, the business of innovation (#J).

Firms able to identify opportunities but incapable of exploiting them do not realize their potential ... Similarly, firms with current competitive advantages but without new opportunities identified to pursue and exploit with these advantages expose their stakeholders to an increased risk... Wealth is created only when firms combine effective opportunity-seeking behavior...with effective advantage-seeking behavior (Ireland et al., 2003).

1. Introduction

Financial markets are now ecologies of algorithms (see MacKenzie, 2019). However, that some algorithmic actors earn sustained profits and survive in this environment is inconsistent with classical economic theory's efficient market hypothesis. Building on the behavioral economic theories of Schumpeter (1939) and Simon (1955, 1957), Andrew Lo (2004, 2017) has proposed the adaptive market hypothesis, where evolutionary processes allow for the possibility that some actors survive by adapting successfully to the changing market environment. Such adaptation, however, is done heuristically and not necessarily in an optimal or rational fashion. For the purposes of this paper, we investigate the relevant point of departure, that algorithmic trading is an organizational endeavor. Rational choice may (or may not) be a valid theory of individual actors, but it is not so, we assume, of organizational ones. *Firms*, comprised of groups of traders, quants, IT staff, and management, engage in algorithmic trading (Davis *et al.*, 2013), and according to Cyert and March (1963), conflicts among groups such as these lead to boundedly rational decisions. Yet, survival implies that some firms have acquired competitive

advantage and, furthermore, are able to adapt in ways that make continued competitive advantage possible. Put another way, some firms appear to have developed ways to make financial markets inefficient *for them*.

Farmer and Lo (1999, p. 9992) discusses this:

Another point of view is to extend the definition of efficient markets so that consistent profits are possible to those who acquire...competitive advantage. ...Under this view, financial agents compete and adapt, but they do not necessarily do so in an optimal fashion.

Hasanhodzic et al. (2011, p. 1043) further develops these ideas:

We believe that it does not make sense to talk about market efficiency without taking into account that market participants have bounded resources. ... This allows for markets to be efficient for some investors, but not for others.

In our review, the academic and industry literatures have acknowledged the existence of competitive advantage in algorithmic trading, but have not studied the topic in a structured fashion. In this paper, we provide this structure by considering two research questions:

- 1. What is meant by sustainable, or consistent, or what we call *reliable* profits that lead to survival in an uncertain environment? This is a proxy for a market being inefficient *for them*.
- 2. What are the sources of competitive advantage these firms develop that allow them to generate those reliable profits and survive?

We answer the first question by fully developing expected capability theory (Kumiega *et al.*, 2014; Van Vliet, 2017), a behavioral innovation model of decision-making. We answer the second question by gathering data on the sources of competitive advantage through semi-

structured interviews with industry professionals and a review of the academic and industry literatures. We categorize these data according to known sources of competitive advantage using the methodology of Gioia *et al.* (2013). Then, because competitive advantage positively affects performance (see Ferreira *et al.* 2020), we discuss the links between expected capability and the observed sources of competitive advantage, thus providing a theoretical rationale for their development. As trading firms are exemplary of firms that have a proactive, entrepreneurial orientation—"a propensity to engage in the pursuit of new market opportunities and the renewal of existing areas of operation (Hult and Ketchen, 2001; Ferreira *et al.* 2020)"—we believe the results of this investigation shed light on the behavior and motivations of fintech firms and other highly innovative firms more generally.

The remainder of this paper is organized as follows. Section 2 presents relevant background information on the evolutionary economics, innovation, and strategic entrepreneurship literatures. Section 3 provides an overview of expected capability theory. Section 4 presents representative empirical data and categorizes it according to known sources of competitive advantage. Section 5 discusses how the observed sources contribute to the firm's survival through the expected capability model. Section 6 concludes.

2. Background on Evolutionary Economics, Innovation, and Strategic Entrepreneurship

An ecosystem is an environment where organisms interact. Following Schumpeter's (1939) evolutionary approach, competitive processes in the market ecosystem determine which algorithmic "organisms" of various "species" survive. External factors, such as regulations and exchange rules, determine the structure of the ecosystem and control the rate of internal, competitive processes. Homeostasis occurs when the interdependent organisms coexist in

approximately stable equilibrium (Lo, 2004). As the environment changes, however, organisms must adapt, and this drives trading firms to innovate.

The innovation literature focusses on discovery and exploitation of opportunities in dynamically complex environments (Lumpkin and Dess, 1996; Hitt *et al.*, 2001). Performance in such environments is emergent. It cannot be known *ex ante*. See Daft and Weick (1984), Marshall and Brady (2001), Seddon and Currie (2017), Day (1994), Hoffman (2017), Marshall and Brady (2001), Brady and Hobday (2011), and Hobday (2000). Because of this, actors are boundedly rational (see Simon, 1955, 1957, 1976; Abbot, 2010; Dibb *et al.*, 2020). They intend to make optimal decisions but face incomplete or imperfect information, cognitive limitations, and time and resource constraints, not to mention the internal conflicts that require compromise. For these reasons, they rely on search heuristics, short-cuts that limit the set of decision choices, and settle for satisficing, or "good enough," performance. Which is to say that innovation is a behavioral discipline (Potts, 2017).

We choose the behavioral innovation economics perspective of Baron (1998, 2007), Morrison and Potts (2008), and Potts (2017) because algorithmic trading systems fit the innovation literature's definition of complex product systems (CoPS) [2]. They are "high cost, technology-intensive, customized, capital goods (Hobday, 2000, p. 793)" that firms use to generate revenue in the market ecosystem. As with all CoPS, algorithmic trading systems change their external environment and the environment feeds back in unexpected and non-linear ways, which in turn changes the behavior of these systems (see Gramlich and Oet, 2018). But building and operating successful CoPS requires the internal resources and competences necessary for converting opportunity into organizational survival (see Davies and Brady, 2000).

The literature on strategic entrepreneurship focusses on survival through sustainable profits, which arise from "identifying opportunities ... and then developing competitive advantages to exploit them (Ireland et al., 2003, p. 966)." As a general definition, competitive advantage is a position or state of a firm that allows it to generate better performance than its rivals (Porter, 1980). In the parlance of finance, we might say that a firm has competitive advantage when it has an "edge," which emphasizes its probabilistic nature. Competitive advantage does not guarantee survival but rather shifts the distribution in the firm's favor. Sources of competitive advantage, then, are those specific organizational abilities or strengths that put a firm in such a position or state. This is part of the strategic management literature's resource-based view (see Barney, 1991), which studies how firms deploy their resources and competences-their tangible and intangible assets, such as brands, knowledge, skills, networks, machinery, internal processes, culture, and capital (Wernerfelt, 1984)—to develop those organizational abilities or strengths. In highly dynamic industries, however, the sources of competitive advantage are individually short-lived. As a result, firms "constantly start new strategic initiatives, building and exploiting many transient [sources of] competitive advantage at once (see McGrath, 2013)."

3. Overview of Expected Capability Theory

Expected capability theory is a behavioral innovation economics theory of decisionmaking, where a *capable* innovation is one that succeeds in generating emergent performance above some goal or aspiration level (see Van Vliet, 2020). In this section we fully develop this model's quantitative definitions of opportunity, performance, and probability of survival. This allows us to explain how individual sources of competitive advantage in algorithmic trading increase performance and lead to survival.

3.1 **Opportunity**

An opportunity is a state, or scenario, or set of circumstances, favorable to realizing some benefit (see McMullen and Shepherd, 2006), which for our purposes is along the dimension of financial performance. In algorithmic trading, opportunity lies in the possibility of earning positive expected gross revenues, or trading profits, $E(\pi)$ by satisfying latent market demand for information processing (i.e. removing informational inefficiencies) or liquidity. There is a wide literature equating informational inefficiency with opportunity for profit in markets. See, for example, Kondor (2009), Biais et al. (2011), Hendershott, et al. (2011), and Hoffman (2014). Algorithmic traders that demand liquidity profit by trading quickly on public information, thereby removing informational inefficiencies, while high frequency traders (a subset of algorithmic traders) that supply liquidity profit from the bid-ask spread and both reduce their adverse selection risk and make prices more efficient by updating their limit orders quickly to reflect new information (Chaboud et al., 2014). Following Cooper and Van Vliet (2015), an informational inefficiency O can be captured with some probability C and incurs the bid-ask spread S, either positive or negative, and a variable cost VC, which includes any rebate. Typically, trading strategies supplying only information processing have positive O and a zero or negative S, while those making markets and, therefore, supplying only liquidity have negative O and positive S. (Firms often mix these two types.) These components define opportunity as the expected trading profit per trade equation in (1).

$$E(\pi) = O \cdot C + S - VC \tag{1}$$

While the distribution of trading profits π need not be normal, we only consider its standard deviation σ_{π} .

Trading firms engage in heuristic search for opportunities (i.e. scenarios with positive $E(\pi)$) and new trading systems to exploit them through both deductive learning—primarily backtesting—and inductive learning, typified by three, well-known innovation methodologies— Agile (Beck et al., 2001), Lean Startup/minimum viable product (MVP) (Reis, 2011; also Mansoori et al. 2019), and design thinking (Dunne and Martin, 2006) (Van Vliet, 2020). Rather than ex ante optimization, these methodologies prescribe iterative ex post testing of hypotheses about system design and performance, followed by heuristic adaptation, often called "pivoting." Rather than designing the optimal product prior to launch, these methodologies allow firms to lower search costs while learning their way into a product the market demands.

3.2 Performance

Net present value (NPV) as a measure of future performance is sufficient only if the firm has complete information *ex ante*. In dynamic systems, Bayesian actors get information about future performance from the performance path. For this reason, expected capability proposes the process capability index C_{pl} (see Kane, 1986) as the appropriate measure (Kumiega *et al.*, 2014). Assuming the expectation in (1) is constant across an average of *q* independent trades per day, where *q* is a fairly large number, the distribution of trading profit *per day* π_d should be approximately normal through the central limit theorem with $\pi_d \sim N(E(\pi_d) = E(\pi) \cdot q, \sigma_d = \sigma_{\pi} \cdot \sqrt{q})$. These trading profits must also cover the firm's fixed costs *c* over some reconciliation period of *w* days (say, monthly or quarterly), inclusive of any required rate of return (see Roy, 1952). The average net profit μ_w and its uncertainty, the standard deviation σ_w , over the *w*-day reconciliation period are in the equations in (2).

$$\mu_{w} = w \cdot E(\pi_{d}) - c$$

$$\sigma_{w} = \sigma_{d} \sqrt{w}$$
(2)

Similar to the Sharpe ratio (Sharpe, 1994), but replacing the risk-free rate with the more general *c*, performance is defined as in (3).

$$\zeta_w = \frac{\mu_w}{\sigma_w} \tag{3}$$

In dynamic environments, performance is a statistical test of whether the revenues will cover fixed cost. Performance ζ_w greater than one means that *on average* the firm should be net profitable in each period *w*. However, *on average*, does not define the firm's goal for the level of reliability of those profits. As the measure in (3) is a *t*-statistic, the question of sufficient reliability comes down to what percentage of statistical assurance the firm aspires to. If *z* is the aspiration value for performance, equation (4) needs to be true.

$$\frac{\zeta_w}{z} = \frac{\mu_w}{z\sigma_w} > 1 \qquad \text{or} \qquad \zeta_w = \frac{\mu_w}{\sigma_w} > z \qquad (4)$$

For example, defining the firm's loss-risk tolerance ξ as the α -significance level, if the firm aspires to have only a $\xi = 5\%$ loss-risk in any period of length *w*, then $z = \Phi^{-1}(0.05) = 1.65$, where Φ^{-1} is the inverse normal cumulative distribution function. So, the firm needs performance $\zeta_w > 1.65$ implying the required sustainability, or *reliability*, of profits is $1 - \xi = 95\%$. This is what satisfices.

The firm aims to create trading systems with sustainable, or reliable, *net* profitability, where failure occurs due to serial losses [3] (see Currie and Seddon, 2017). As proprietary trading firms typically operate more than one trading system, the performance of these firms' portfolio of trading systems ζ_p is what ultimately determines survival of the firm itself. In either the case of an individual trading system or the portfolio case, the required probability of survival ψ is related to ζ as in (5).

$$\psi = 1 - \xi^{\theta} \tag{5}$$

where θ is the number of serial losses over periods of duration w that result in failure.

To ease comparison across firms, we annualize both sides of (4) by dividing by the square root of the number of reconciliation periods per year $\tau = \sqrt{(w/252)}$. If the firm's aspiration value for annualized performance ζ or ζ_p is z / τ , then (4) can be restated as the hypothesis test in (6).

$$H_{0}: \frac{\mu}{\sigma} \le \frac{z}{\tau}$$

$$H_{1}: \frac{\mu}{\sigma} > \frac{z}{\tau}$$
(6)

Thus, expected capability quantifies the hypothesis test performed iteratively in the three innovation methodologies previously discussed—*Agile*, *Lean Startup*, and *design thinking*. If the firm can reject the null hypothesis, it can expect its trading system, or its portfolio of trading systems, to generate reliable profits. The market is inefficient *for them*. Relative to maximizing the Sharpe ratio, hypothesis testing is a satisficing concept. Iterative testing of (6) is central to our discussion in section 5 of how trading firms adapt to survive.

3.3 Sensitivities

Considering the *p*-value nature of ξ , increasing performance ζ decreases loss-risk ξ at which H_0 is rejected and increases the probability of survival ψ . The impacts of the variables comprising the left-hand side, performance ζ , in (6) on the probability of survival ψ in the right-hand side are as follows:

- a) the higher O, C, and S, the higher the ζ and ψ .
- b) if $E(\pi) > 0$, the higher q, the higher the ζ and ψ .
- c) the lower the *VC*, *c*, and σ , the higher the ζ and ψ .

From this we expect that firms develop sources of competitive advantage that move the variables in directions that increase ψ .

4. Identifying Sources of Competitive Advantage

To investigate the sources of competitive advantage, we collected two sets of data. The primary data set consists of evidence gathered through semi-structured interviews with 12 Chicago-based professionals in the algorithmic trading industry generously given over a fiveyear period, which allowed ideas to be revisited and updated. In total, 30 interviews occurred each lasting roughly two hours. Table AI in the Appendix breaks down the roles—trader, quant, IT staff, and management—of the interviewees, who are referenced in the paper anonymously as #A through #L. Semi-structured interviews and narrative analysis enable richer data to be collected (Sobolev, 2020) and improve the understanding of the organizational realities at these firms (see Saunders and Townsend, 2016). As open-ended questions provide a useful entry-point for building on key themes (see Denzin and Lincoln, 2005), we began each interview with a framing question—What abilities, or edges, does your firm have that help you exploit opportunities in financial markets?---and added new questions in response to feedback (see Edwards and Holland, 2013). This led to additional discussion about how the interviewees view competitive advantage and allowed us to focus on real-life experiences, minimizing bias and subjectivism (see Flyvbjerg, 2006). The secondary data set consists of evidence gathered from the scholarly and industry literatures regarding sources of competitive advantage. This evidence provides independent corroboration of the interviewees' comments. Essentially, primary and secondary data were collected until they became repetitive, which suggests saturation (see Guest et al., 2006).

We analyzed the data and refined the theoretical concepts as a step toward theory generalization (see Silverman, 2013; Campbell, 1975). Following the methodology of Gioia *et al.* (2013), we extracted first-order concepts, to which we assign descriptors drawn from the

literature. We then group these descriptors into the second-order themes of opportunity-seeking, advantage-seeking, and meta- behaviors, which support the aggregate dimension of competitive advantage (see Corbin and Strauss, 2015). Table I presents representative data from the two data sets. Once structured, the data tell a story (see Carter, 1993) about the interaction between competitive advantage and survival in a highly competitive, innovation-driven industry.

As an introductory observation, we note that the interviewees' comments were peppered with the vocabularies of the three innovation methodologies. Terms such as agile, MVP, pivoting, iteration, hypotheses, lean, and design came up repeatedly. Classical economic theory aside, the people involved in algorithmic trading take an innovation perspective of their work. Also, as an indication of the importance of strategic management in this industry, #K stated:

[Some firms] view [algorithmic trading] as 'I'm going to win on cost' or 'I'm going to win on speed,' but I think the ones that are in the top tier, they place strategic management at a much higher level... because they understand that's what drives their long-term profitability.

Primary Data Secondary Data	First-Order Concept Descriptor	Second-Order Theme	Aggregate Dimension
 "It's more about your execution and position management strategy than the actual signal (#A)." "We're all dealing with a subset of the possible strategieswe are constantly looking for the best ones (#E)." "You don't derive these strategies. They're based on logic about what other market participants will do. If we do this, then they'll do that, and we'll make money (#F)" "You're always years behind with me-too strategies. You're better off stealing your strategies, that's why there's so many NDAs (#F)." "There are groups that make hundreds of millions of dollars a year, year on year on year, and they're not being challenged, because [their strategy] is so specific and idiosyncratic that it does not fall into the concept of a strategy that is singular. The complexity is such that even if I told it to you, [you couldn't] replicate it (#K)." 	Strategic Creativity		
Pisani (2018) describes the "collision" of firms' systematic strategies and its impact on volatility. Aldridge (2013) describes four types of algorithmic trading strategies. Goldstein <i>et al.</i> (2014) reviews algorithmic strategies, some of which "derive profits from the … bid-offer spreads," rebates, and price information. Carrion (2013) studies the profitability of HFT. Serbera <i>et al.</i> (2016) surveys strategies and profits in HFT. Boehmer and Saar (2018) investigate product differentiation in HFT strategies.		Opportunity Seeking	Competitive Advantage
"The most important part of our execution research team was the market impact team. There was no good literature at the time. One of our guys [figured a model out]. It was very successfulThe turning point was when we finally got a good model of market impact. One of the models had 900 inputs. We actually got it down to 84 with the same results (#I)." "If you get the models right, and you're printing money, the market has ups and downs and you can recover and change with it (#I)." "Now you're talking about conventional trading strategies [where] you're assuming risk and you think that you have some kind mathematical way that you can make money (#K)."	Quantitative		
Anderson (2011) discusses how firms hire gifted mathematicians to create formulae to automatically buy and sell according to algorithms. Cartea <i>et al.</i> (2015) states that "the design of trading algorithms requires sophisticated mathematical models." Leshik and Cralle (2012) state that "the major banks and brokerages have recognized quantitative algorithmic trading as one of their major competitive advantages." Huang <i>et al.</i> (2018) state that "the development of sensitive and effective novel technical indicators is a major concern … because they are crucial for the timely discovery of trading opportunities."	ımprovement		

"We use 'quantamental' data to get our proprietary edge (#A)." "Wait, you can read ALL of Twitter? Everyone started doing the math. Traders have figured out this is a whole source of knowledge we've ignored. That's information. We can trade on that all day long. Traders know there's information there. If you don't have it, you're going to get picked off (#F)." "We subscribed to all the data Reuters had for every exchange in the world and did analysis and research on that Just having access to all this data gives the big firms a huge edge over their smaller competitorsHaving any data above and beyond what your competitor has is a huge advantage. We spend \$3 million a year on data. It's all about finding data early (#I)." "[Some] firms are able to harvest their own data and trade their own data. If you can make it your own data, then that has value (#K)." "IT is important in that as much as anything else HFT has become an information processing and data analytics business. Some people fail because the size of the data overwhelms them. There is no room in HFT for people who can't think in terms of large-scale data (#L)."	Data and Analytics	
Eastwood (2017) has an overview of the growing importance of big data and machine learning in financial trading. Nordrum (2017) and Metz (2016) describe how hedge funds are handling the flood of financial data and machine learning. Fang and Zhang (2016) states that "being able to process massive complex events in ultra-fast speed removes the roadblock for promptly capturing market trends and timely managing risks."		
"We don't even try to play in the speed advantage game (#A)." "You had to buy bigger, faster tools in order to compete (#F)." "It becomes a technology game. Whoever has the better technology will win that game. At that point, it's science But then, can they source the talent to continuously maintain that technology advantage (#K)?"	Tachualagiaal	gical Advantage Seeking
Meyer <i>et al.</i> (2018) discusses "latest stage in [the industry's] quest to move financial transactions closer to the speed of light." See also Adler (2012). Osipovich (2020) states that "minuscule fraction[s] of a second can make the difference between profits and losses." Goldstein <i>et al.</i> (2014) note the need to be "faster than other HFT participants" to generate the trading volume necessary for profitability. Baron <i>et al.</i> (2019) show that "relative latency accounts for large differences in HFTs' trading performance."	Speed	
 "If you don't have the cost structure to compete, there's a whole bunch of strategies you don't even consider (#A)." "We have to control costs, or we're all going to be replaced by low-cost systems (#C)." "This is an investment-intensive enterprise. The barrier is that once in the game, you can drive out competitors (#D)." "If you want to compete, you've had to take on these larger fixed costs [e.g. colocations, microwave towers] and it's only made sense to amortize those costs over a larger amount of trading (#F)." 	Cost Leadership	

 "Everyone is watching for [volume] breakpoints in trading costs. [For trading firms that sponsor a lot of trading desks,] the aggregated company takes advantage of those lower trading costs. We'll recognize that edge. (#F)." "We've got our back office pretty lean right now (#H)." "Our report shows here's what it's going to costevery time we do this: commissions, exchange costs, broker costs, and projected market impact. If you get that right, then you're not giving away money (#I)." 	
Meyer <i>et al.</i> (2018) discusses costs, and one CEO's quote that the industry "sees [costs] as a war of attrition." Goldstein <i>et al.</i> (2014) discusses the need for high trading volume to "cover fixed costs." Kumiega <i>et al.</i> (2014) discusses the allocation of fixed costs as a component of profitability. Carrion (2013) discusses how algorithmic traders "fixed costs will be spread over more transactions." Menkveld (2013) talks about the importance of variable costs and fixed costs of HFT.	
 "In HFT, it's a race just to break even (#E)." "If it's only gonna work for four months, and you wait two months, then it's only gonna work for two months. The smart ones recognize that this is a short-term play. If I could freeze time, I could study this, and say this is the optimal strategy. But, you can't freeze time. You ask, am I better off deploying my capital or not? (#F)." "The easy money goes away fast (#I)." "Say [the strategy] life cycle is five years. Say, once discovered maybe three years [are left] Maybe it takes you two years to innovate it, you're still gonna make profit on it (#K)." 	Danid Time 40
Schmerken (2018) reviews a product aimed at speeding "time to market for quant shops." Yesalavich (2010) quotes one industry professional saying "it's mostly a time-to-market issue for these algorithmsAn algorithm might be irrelevant by the time it is available." The author states that "reduced time to market means fewer man hours are needed to get algorithms into traders' hands, which ultimately helps cut costs." Velu (2020) discusses the commercial need for time to market, which may "supersede consideration of rigorous models" or "the need for stability." This shows the trade-off between time to market and quality management. See also Bates and Palmer (2007). Dykes <i>et al.</i> (2019) describe an HFT firm which "purposefully developed a flat organizational structure to speed implementation of good ideas."	Kapia 1ime to Market
"It's like fishing. You pick where to put your hooks in the water. Hopefully, you catch some fish. If you're [a bigger firm], you can put more hooks in the water (#B)." "If I bet the farm on one strategy, and it blows up, then I've lost the value of the fixed assets that I've built up. I can monetize them tomorrow [if I have] other strategies. My game has to be 'don't lose it all on one strategy' because these assets I've built have value (#F)." "[There's a] portfolio effect of trading a broad portfolio. There's money down there in trading the little crummy stocks, even stocks that are less liquid (#I)."	Portfolio Management

"Say that you run a thousand strategies. Each strategy has a product life cycle As long as your funnel is big enough and developed enough, then it warrants that you will continuously make money off that (#K)." "At events when new products were listed, historically I would have run into traders and now, they're not the ones there. It's going to be someone making an appropriate strategic decision, on how to devote resources It's clear where the organizational hierarchy for the firms believe the value is (#K)." "Even if the trader scratches, they are able to get infrastructure assets they are required to have for free or reach transaction limits and use that multiplier effect (#K)."		
A study by Morgan (2008) presents evidence of firms "seeking front-end platforms which have the flexibility to accommodate different trading styles." Chen (2014) describes a portfolio of trading systems as the "path of least resistance to consistent profitability."		
 "Quality is measured in standard deviations [of returns] The firms that survive are gonna be the ones that don't blow themselves up (#C)." "There are plenty of companies out there that will bet the blow up never happens. They only way you survive is to define your blow ups in a safe way (#F)." "Knowing you have a problem in 5 minutes might be 4 minutes and 59 seconds too late. We spent a great deal of time on real time quality control and real time attribution. Every group read daily reports and formed action plans based on them (#L)." Matthews (2012) discusses bugs in trading. See also Bates (2018). The media and academic literature are rife with references to (in particular) the Knight Capital collapse due to technological error, including Goldstein (2014) and Coombs (2016). 	Quality Control	
"You have to be constantly adapting. Otherwise, you just get lost (#B)." "If you're playing a strategy that's worked for years, and it doesn't work anymore, what are you going to do? What do we do with the money we're managing? You say, let's look and see what we can do, and there are start-up costs associated with that. It's a big bet, but there are risk-loving investors out there (#F)." "Getting the right people with the right skills is important and incentivizing them to keep learning. [One firm] lays off 10% of its people every year. A lot of firms aren't able to reinvent themselves (#I)." "As computer technology advances, then the question becomes are they willing to continuously put that money into [sourcing talent] and non-stop innovating versus trying to harvest that P&L? Then the answer is they'll be able to maintain their advantage It used to be just the trader was the talent. Now, the person who sources the talent is the talent The people hiring now have longer non-competes than the people they're hiring (#K)."	Dynamic Capabilities / Absorptive Capacity	Meta-Advantage Seeking

Strategic agility in algorithmic trading has received little attention in the academic literature. Nevertheless, we can observe firms adapting to changing opportunities. Lujan (2017) and Massa (2017) discusses trading firms "pivoting" to enable Bitcoin trading. Also, see D'Antona (2018) for a discussion of one HFT firm switching to the "wholesaling and retail facing business." Woods (2020) uses HFT to demonstrate that to "overcome [new] risk[s] requires enhancing the ability to anticipate and build a readiness-to-respond in advance of challenge events." See also Seddon and Currie (2017). Dykes <i>et al.</i> (2019) also use the HFT firm as an example of the "need to develop and leverage the capability to speed up relevant organizational processes that undergird competitive advantage."		
"People look for new products instead of new strategies. Products that are new, exchanges that are new, you can make a profit on if you're only semi-good. Traders say all the time, 'I have an idea for a new product, I have an idea for a new exchange.' They say, 'there's some residual risk, an arcane thing, I want to trade that. [I] know it will take [the competition] time to gain my expertise. I'll be the first one there to do this. Let's change the rules so we can trade this or that (#F)."" "It didn't work. The market structure wasn't there. Two years later, we said 'it looks like it works now' and we went back and it was successful. Most people just walk away (#I)." "I've been involved in the products related to the LIBOR transition to SOFR (secured overnight financing rate), and in Chicago you've got some people who are very skilled at [creating opportunity through new products or new exchanges]. Some are very vocal about this kind of innovation (#K)" "There are places where the rules are ambiguous or at cross-purposes with each other [and that] also presented opportunities If they are open to interpretation then you interpret them in the most profitable way possible. The interpretation just needs to be defensible. There is always a push to keep the rules as favorable as possible. When an unfavorable change comes your way, you back off and look for another weak place in the regulation [where] you can push. Some of the more aggressive firms lobby (#L)"	Structural Influence	
Structural influence in algorithmic trading has received little attention. However, we can observe trading firms attempting such influence. Javers (2014) discusses the HFT industry's Modern Markets Initiative working together with Bart Chilton and DLA Piper on "regulatory and public policy matters." See also Bain (2017) for a discussion of how regulators have "faced intense pushback from industry" on issues relating to the "robot invasion." Osipovich (2019) describes how trading firms are launching a new exchange MMEX. Sanders states that "the exchanges realized 'they had to cater to the firms that filled their pools with liquidity.' High-frequency traders took advantage of the situation by asking for special order types that would give them an advantage over competing traders." See also Vaananen (2015) and Dolgopolov (2014).		

Table I: Representative Primary and Secondary Data

Focusing on the first-order descriptors in Table I, the first three are grouped into the second-order theme of opportunity-seeking behaviors. These are essentially domain specific forms of Chamberlain's (1933) product differentiation. In Schumpeterian fashion, rare and difficult-to-imitate trading strategies, or ones requiring sophisticated implementations, create temporary monopolies and allow for reliable profits until competition arrives. *Strategic Creativity* was a frequent concept raised with the most common comments being that pure return forecasting was not the best place to search. Multi-instrument arbitrage, statistical arbitrage, and liquidity provision strategies were mentioned as more fertile territory. Moreover, given the vast number of strategies and instruments, assessing where to look for positive $E(\pi)$ and where "not to waste your time" were very important. This supports the idea that firm's use heuristic search. Quantitative Improvement was brought up regarding their firms' demand for master's degrees and Ph.D.'s in quantitative disciplines. The feeling among interviewees was that advanced techniques are often necessary to uncover opportunities that would be unseen by less sophisticated approaches. Data and Analytics describes what Grossman and Stiglitz (1980) argued, that markets cannot be informationally efficient if only because we observe that firms invest capital to acquire information resources, something they would only do if they expected a return on that investment. This appears to be the case in algorithmic trading. Most interviewees discussed their appetite for new or alternative data sets. Further, data filtering and cleaning techniques are important to uncovering positive $E(\pi)$. High frequency trading firms in particular have massive amounts of data on quotes, executed trades, and markets. As interviewee #L said, "If the sample size is 200,000,000 you don't need a statistical test, you just need to know if the effect is profitable." These three first-order concepts show a generalizable truth-to survive, the

firm's search processes require sophisticated strategies, math, data, and analytical techniques to identify and exploit opportunities unseen by rivals.

The next five first-order concepts relate to the second-order theme of advantage-seeking. Technological Speed, akin to response time or delivery time in the literature (see Li and Lee 1994; Shang and Liu, 2011), was identified by a majority of respondents as essential. While not all were concerned with ultra-low latency, being fast enough relative to competitors is important. But speed is not free and understanding where to spend is crucial. The impact of *Technological* Speed on the number of trades q is a primary focus. For liquidity supplying, high frequency trading systems, Technological Speed implies the ability to place limit orders ahead of competitors in the exchange queue, increasing the probability of being matched against an incoming liquidity demanding order and earning S. It also implies the ability to lower risk σ by canceling orders ahead of market-moving trades. As interviewee #L stated regarding high frequency trading, "Risk is measured in microseconds." Cost Leadership (see Porter, 1980), including reducing VCs and controlling fixed costs c associated with technology and data, were cited as highly important goals by virtually all interviewees. Lower exchange fees, for example, open up new opportunities, and the ability to generate sufficient transaction volume q to meet break points was specifically mentioned. (This is appears to be one of the primary drivers of consolidation in the industry.) Further, the ability to amortize fixed costs c over a larger number of trades was repeatedly mentioned. Rapid Time to Market (see Cohen et al., 1996; Kessler, 1996), shortening the time to exploitation, mattered to interviewees because these firms assume opportunities are short-lived. Proprietary implementations of the three iterative innovation methodologies appear to be the foundation of their approach. Interviewee #G stated, "We used to run [multiple versions of] the same strategy with different configurations at the same time with

one lots in a liquid market. Then, we would increase the size on the good ones." Those systems that do not achieve some performance threshold are discarded. This reinforces the idea that algorithmic traders use heuristic search by iteratively testing alternatives until they find a satisficing system (see Van Vliet, 2020). Portfolio Management also came up. Interviewees were sensitive to both the ideas of reducing risk σ_p through uncorrelated returns across multiple systems (see Markowitz, 1952) and of reducing fixed costs c through positively correlated infrastructures firmwide (see Levine, 2005). This adds the project management perspective to *Portfolio Management*. Interviewee #K pointed out that even a money losing trading system can improve portfolio performance ζ_p if it has a sufficiently positive diversification effect or helps the firm achieve an exchange fee breakpoint, which lowers VC and increases the number of available trading systems. Quality Control (Powell, 1995) similarly was important in controlling operational risks and preventing catastrophic failure due to, for example, software bugs. Quite succinctly, not "blowing yourself up" (i.e. losing a large sum of money on an out-of-control system in a very short amount of time), a repeated phrase, is a key to survival. These five firstorder concepts are also generalizable-to survive the firm must develop internal processes that are better, faster, and cheaper than those of competitors.

The last two first-order concepts are categorized as meta-behaviors as they are a level of abstraction above those previous. We use the terms *Dynamic Capability* (see Teece *et al.*, 1997), and *Absorptive Capacity* (see Cohen and Levinthal, 1990) to also include the related concepts of *Strategic Agility* (see Doz and Kosonen, 2010) and Brown and Eisenhardt's (1997) continuous change. All these describe the ability of the firm to adapt its sources of competitive advantage to a changing environment (see Eisenhardt and Martin, 2000). As interviewee #L stated, "The mix of what causes you to make money changes, and it changes fairly often." Interviewee #G stated,

"You have to be constantly adapting. Otherwise, you just get lost." Their proactive orientation leads them to continuously learn new trading strategies, techniques, technologies, data sources, and markets. This is most recognizable in their interest in continuously hiring new talent with whatever new skills are thought needed. Somewhat surprisingly, many interviewees specifically mentioned their human resources department as being a key, front-office resource, rather than simply a back-office cost center. *Structural Influence* refers to the ability to impact the structure of the market ecosystem itself, which is similar to the driving-markets approach of Jaworski *et al.* (2000). Interviewees often discussed their interest in and efforts to invent new markets, financial instruments, technologies, and order types. Essentially, newness in any of these can create or destroy opportunities. Some suggested that influencing the regulatory trajectory is a necessary endeavor, particularly in nascent markets such as cryptocurrencies. These last two first-order concepts are also generalizable—to survive the firm must adapt its organizational abilities quickly and inexpensively to changes in the ecosystem and, to the extent possible, proactively direct how the structure of the ecosystem evolves.

5. Discussion and Implications

Using the expected capability model and the sensitivity analysis in section 2.3, we explain the economic rationale these firms have for developing each source of competitive advantage identified in Table I. For convenience, Table II summarizes the variables introduced in section 2.

Variable	Description
С	Fixed cost over w
С	Capture, the probability of earning O
d	The number of trading days
0	Opportunity present in an informational inefficiency
q	The average number of trades per day
S	The bid-ask spread

VC	Variable cost
W	The firm's waiting time, or reconciliation period
z	The <i>z</i> -score given the firm's loss-risk tolerance ξ
ζ	The measure of performance
θ	The number of periods of length <i>w</i> that may cause bankruptcy
μ	The average annual net profit
۲	The firm's loss-risk tolerance
π	Trading profit exclusive of fixed costs c
σ	Standard deviation of profits
τ	The annualization factor
Ψ	The firm's acceptable probability of survival

Table II: Summary of Variables

Because competitive advantage improves performance, Table III highlights the direction of change in the variables implied by each source of competitive advantage that leads to increased performance ζ , and therefore, probability of survival ψ , as inferred from the data. For clarity, Table III also defines each source of competitive advantage as a specific organizational ability.

Opportunity-Seeking Behaviors	Impact			
Strategic Creativity	$O\uparrow, C\uparrow, \sigma\downarrow, S\uparrow$			
The ability to invent novel rules, logics, or methodologies for transacting in financial markets.				
Quantitative Improvement $O\uparrow, C\uparrow, \sigma\downarrow, S\uparrow$				
The ability to mathematically model the behavior of financial instruments and market phenomena.				
Data and Analytics $O \uparrow, C \uparrow, \sigma \downarrow, S$				
The ability to extract insights from the volume, velocity, and variety of data (see Mikalef, <i>et al.</i> , 2020).				
Advantage-Seeking Behaviors				
Technological Speed	$C\uparrow,q\uparrow,\sigma\downarrow$			
The ability to respond to demand and deliver more quickly than competitors (see Li and Lee, 1994).				
Cost Leadership $VC \downarrow, c \downarrow$				
The ability to satisfy demand at a lower cost than competitors (Porter, 1980).				
Rapid Time to Market $C \uparrow, q \uparrow$				
The ability to develop and deploy new products quickly (see Cohen, et al., 1996).				

Portfolio Management	$c\downarrow,\sigma_p\downarrow$			
The ability to correctly evaluate, select, prioritize, and allocate resources among new and existing projects (see Lerch and Spieth, 2013).				
Quality Control $\sigma \downarrow$				
The ability to reduce risk by improving processes and eliminating defects.				
Meta-Behaviors				
Dynamic Capabilities / Absorptive Capacity $O \uparrow, c \downarrow$				
The ability to adapt the firm's resources, competences, and abilities to the changing environment to sustain competitive advantage.				
Structural Influence	$O\uparrow,\sigma\downarrow,q\uparrow,c\downarrow,S\uparrow$			
The ability to affect or impact the structure of the ecosystem or the roles or behaviors of actors in it to create opportunity or defend a source of competitive advantage.				

Table III: Sources of Competitive Advantage and Their Impact on the Performance

Variables

We also see in the data underlying issues addressed in Cyert and March's (1963) behavioral theory of the firm. Conflicts among the groups that comprise trading firms lead to compromise and heuristic trade-offs that result in organizational behavior that is not necessarily rational. This may explain the prevalence of iterative hypothesis testing methodology as the mechanism of compromise. Interviewee #B alluded to this scenario stating, "You can't find a way to allocate using optimization [in this domain]." We observe heuristic trade-offs when these firms make allocation decisions in and among three portfolios:

1. *Idiosyncratic resource position*, the firm's current portfolio of resources and competences.

The data suggests that trading firms heuristically allocate capital to acquire the resources and competences—people, skills, hardware, software, networks, data, colocation, etc.—necessary to develop the organizational abilities that create competitive advantage. These resources and competences are well-known, but their idiosyncratic resource positions appear to have varying emphases, or "weights."

2. *Idiosyncratic competitive position*, the firm's portfolio of the observed sources of competitive advantage in Table I.

These firms heuristically allocate their resources and competences toward an idiosyncratic competitive position. The data suggests that firms' competitive positions vary widely in their emphases on various sources, with some "weights" near zero. A few interviewees acknowledged allocating fairly few resources to *Quality Control*. One firm appeared to weight very heavily toward *Technological Speed* with little weight on *Data and Analytics*. Interviewee #E stated, "We don't play the speed game." Many firms appear to allocate significant resources to pursuing *Structural Influence*, while one did not "get into that." Several interviewees alluded to these emphases, referring to various firm's reputations as "quant shops" or "high frequency shops" while others are known to focus on creating favorable market structures by, for example, "paying for order flow."

3. *Idiosyncratic product position*, the firm's portfolio of trading systems.

The firms appear to heuristically allocate capital among their portfolio of both existing trading systems and those under development. The firm's product position is what drives its performance and its survival. Interviewee #B stated, "You don't have unlimited risk capital. It's like fishing. You pick where to put your hooks in the water. Hopefully, you catch some fish. If you're [a bigger firm], you can put more hooks in the water." Interviewee #B also stated, "You don't stop doing something that isn't working too soon. You keep improving it until it works out. You don't give up [on a good idea] too early." These statements indicate that resources may be deallocated from working systems and allocated to the development of new ones, while tolerating poorer performance.

The heuristic trade-offs and allocations in and among the three positions just described show up in performance ζ . Allocating capital to acquire the resources and competences necessary to improve one source of competitive advantage may require sacrificing another. This is most clear in the trade-off between Technological Speed and Cost Leadership. Acquiring low latency technology increases fixed costs c but ought to increase C and q and decrease σ so that ζ increases. Likewise, allocating a technology budget to Data and Analytics to increase O, C, and S, may leave fewer resources for *Technological Speed*. Many interviewees described the tradeoff between Quality Control and Rapid Time to Market. They perceive that doing things right detracts from doing things quickly. We can think of many other binary trade-offs. For example, should the firm allocate more resources to Quantitative Improvement to build better models or allocate to more *Data and Analytics* to better calibrate existing models? Or, should the firm allocate more to its existing trading systems or to human resources to better source new traders with new ideas for new systems? Trading-off among all the sources of competitive advantage is even more complex (see Scherer, 1967). Given bounded resources, the performance impact of all possible positions cannot be known ex ante. As interviewee #E stated, "If they build a new microwave tower [to transmit market data more quickly], then the whole trade may change." This implies that the firm would recognize a need to acquire its own new tower (i.e. resource position reallocation) that would enable the *Technological Speed* (i.e. competitive position reallocation) necessary for new trading systems (i.e. product position reallocations) to achieve satisficing performance ζ . The survival imperative is evident, but there is no perfect information about the future performance of these reallocations for optimal decision-making. We suggest that the widespread use of the innovation methodologies in this domain is due to their ability to lower the costs of finding weights for the three portfolios that satisfice.

The firm's idiosyncratic competitive position is also shaped by its ability to assess those of rival firms (see Denrell et al. 2003). Trading firms are keenly aware that once they act to exploit an opportunity, their own market activity will elicit a competitive response. Interview #D stated, "The introduction of any strategy may be met with a counter-strategy...that defeats it." Interviewee #L stated, "The mix [of sources of competitive advantages] can change just because the players change. One guy leaves the market, and now a guy with a different strategy is your main competitor." Particularly in the case of high frequency trading, these firms assess how fast they need to be to beat their rivals. Interviewee #C described how their firm never optimized their Technological Speed, but rather only sought "good enough" latency. That way, if a competitor increased their speed, the firm would have room to respond. Further, interviewees highlighted their firm's interest in learning the competition's data sources, for example through common vendor relationships, and quantitative methods, for example by hiring rival's quants, and in taking pains to hide their own, for example through non-compete contracts and nondisclosure agreements. "Loose lips sink ships," was a repeated phrase. Adapting the firm's competitive position is a rival-aware process.

Internal conflict between groups at trading firms requires compromise. We suggest that this conflict may arise from the inherent correlations between groups and the sources of competitive advantage. That is, some sources can largely be assigned to one group. Traders presumably are responsible for *Strategic Creativity*, quants for *Quantitative Improvement*, IT staff for *Technological Speed*, and management for *Portfolio Management* allocations. However, for the others, there is no such simple correspondence. *Rapid Time to Market* is something all groups appear to contribute to, and the same can be said for *Cost Leadership*, *Quality Management*, and *Dynamic Capabilities*. All groups seek to develop faster, lower costs, increase

work quality, and increase their learning. Nevertheless, how conflicts among the groups described by Cyert and March (1963) may arise is apparent. Each group could justify a demand for additional resources by arguing how the sources of competitive advantages most closely associated with it drive the firm's performance. Any group could claim, "Without the [*insert competitive advantage here*] we create, the firm wouldn't survive." The data collected reveals interconnections between the sources, which obfuscates portfolio allocation outcomes and makes it difficult to order preference options. Algorithmic trading firms appear to quell conflict through the iterative hypothesis test in (6), where heuristic reallocations are quickly evaluated by their performance impact.

5.1 Theoretical Implications

Given that the firm's three idiosyncratic positions are determined heuristically, performance satisficing is a more appropriate description of decision-making in algorithmic trading than is performance maximizing. Allocating requires information regarding the benefits of various decision choices, but gathering information and switching are costly. In the dynamic market environment, gathering information and adapting, or "pivoting," through iterative *ex post* hypothesis testing of (6) appears to accelerate heuristic search and lower costs. Thus, the innovation methodologies discussed are the mechanism by which they achieve McGrath's (2013) "transient advantage," adapting their competitive position while maintaining satisficing performance. Unlike the individual investor who, under the efficient market hypothesis, relies on luck to succeed, the algorithmic trading firm, under the adaptive market hypothesis, depends on its ability to deploy its resource position to develop a competitive position that enables its product position to exploit market opportunities in ways that generate performance sufficient to survive.

Where expected utility theory provides for exact allocations for optimal behavior, expected capability theory provides for a range of possible allocations for acceptable behavior. Thus, two algorithmic trading firms with the exact same resource positions and presented with the same opportunities can develop different competitive positions, and both can survive. Further, both can adapt their resource positions and reallocate toward new, satisficing competitive positions, reflecting their competitive response to the current environment (see Ruben and Capra, 2011). Barney (1991), for example, suggests the existence of efficient resource markets. If trading firms compete in this market, none should generate sustainable profits and survive over the long term. If, however, performance is emergent as we assume, then resource values and NPV cannot be calculated *ex ante*. Because resource values are determined heuristically due to their complex and dynamic contributions to firms' idiosyncratic competitive positions, and therefore performance ζ , survival becomes possible.

In dynamic industries, where opportunities are constantly evolving, windows of opportunity will always exist, but the resources and competences that enable the firm to exploit them stay the same. As interviewee #K stated, "There are always new instruments that need to be priced and need to be priced faster. There are always going to be new markets. There are always going to be some opportunities to profit." What the data in this paper shows is that trading firms are investing in resource positions that allow them to exploit those opportunities and surviving.

5.2 **Practical Implications**

Simply recognizing opportunity is not the same as profitably exploiting it. Many firms may discover an informational inefficiency, for example, but very few may have the competitive position to generate reliable profits from it. Essentially, the firm's idiosyncratic competitive position makes available to the firm trading strategies that competitors find unprofitable. The

challenge for the firm is to assess the opportunities available to it in the current environment and to adapt its competitive position to make more strategies available in the future. Of course, not all sources of competitive advantage will be equally important (Dreyer and Gronhaug, 2004). Management must consider the search costs associated with iteratively assessing performance through *ex post* hypothesis tests. A change to the firm's competitive position will take time to impact the variables driving performance ζ . Heuristic ranking of the sources may focus attention to those with the greatest potential and guide the understanding of switching costs. In quantifying the probability of survival, the expected capability model ought to help management better conceptualize the goal of their portfolio allocations.

Further, understanding the competitive, satisficing behavior of algorithmic market actors ought to promote appropriate regulation. Ensuring firms trade safely in the market ecosystem while satisfying their obligations to stakeholders as they innovate and adapt ought to play a central role in the regulatory structure. Regulations themselves ought to adapt to the evolving species and satisficing organisms that comprise the market ecology if they are to continuously promote market effectiveness—voluntariness, transparency, informational efficiency, and reliability (see Cooper *et al.*, 2020). Regulation cognizant of the evolutionary process ought to focus on the structure of opportunities and the fairness of access to new, satisficing organisms.

6. Conclusion

This paper has drawn upon concepts from the literatures of innovation, strategic entrepreneurship, and behavioral finance to describe the strategic behaviors of algorithmic trading firms. This investigation was motivated by the consistent profits some of these market actors are known to generate. We fully developed expected capability as a model of reliable profits in uncertain environments and presented data regarding the sources of competitive

advantage that algorithmic trading firms develop to generate reliable profits. By linking the observed sources to expected capability, we explain the economic rationale these firms have for developing them. The firm's competitive position is what can make the markets inefficient *for them*, while others see no opportunity.

This research invites further investigation into the relationship between the strategic behavior of algorithmic trading firms and macro-market phenomena, such as market volatility, liquidity, and efficiency. This is a new area of inquiry, but recent contributions examine such relationships. Farboodi and Veldkamp (2020), for example, investigates how improvements in technology (i.e. Data and Analytics and Technological Speed) shape trading strategies, market efficiency, and market liquidity. Min and Borch (2021) investigates "high-reliability practices" (i.e. *Quality Control*) at algorithmic trading firms and their impact on market volatility and systemic risk. We recognize that as a complex adaptive system, the macro-behavior of the algorithmic market ecology may not be directly predictable from the behaviors of the actors that comprise it (see Miller and Page, 2007). Nevertheless, agent-based models may shed light on some of these relationships. We suggest that new markets may exhibit, for example, less efficiency, lower liquidity, and higher volatility than more mature ones. This would be consistent with the view that it takes time for trading firms to learn through *ex post* iterative hypothesis testing the resource positions and then competitive positions and then product positions that generate reliable profits. As trading firms adapt heuristically, there is potential to introduce the behavioral biases in the portfolio allocations and on/off decisions described by Kumiega and Van Vliet (2012). The aggregate result could be markets that are less than effective.

References

- Abbott, R. (2010). "Equity markets and computational intelligence." In 2010 UK Workshop on Computational Intelligence (UKCI), p. 1-6.
- Adler, J. (2012, August 3). "Raging bulls: How Wall Street got addicted to light-speed trading." *WIRED*. Available at: https://www.wired.com/2012/08/ff-wallstreet-trading/
- Aldridge, I. (2013). *High-frequency trading: A practical guide to algorithmic strategies and trading systems*, John Wiley and Sons.
- Anderson, R. (2011, September 26). "Quant trading: How mathematicians rule the markets." *BBC News*. Available at: https://www.bbc.com/news/business-14631547
- Bain, B. (2017, October 20). "Regulators can't keep up with Wall Street's robot invasion." *Bloomberg*. Available at: https://www.bloomberg.com/news/articles/2017-10-20/as-robots-invade-wall-street-slow-footed-regulators-lose-ground
- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), pp. 99-120.
- Baron, M., Brogaard, J., Hagströmer, B., and Kirilenko, A. (2019). "Risk and return in high-frequency trading." *Journal of Financial and Quantitative Analysis*, 54(3), pp. 993-1024.
- Baron, R.A. (1998). "Cognitive mechanisms in entrepreneurship: Why and when entrepreneurs think differently than other people." *Journal of Business Venturing*, 13(4), pp. 275-294.
- Baron, R.A. (2007). "Behavioral and cognitive factors in entrepreneurship: Entrepreneurs as the active element in new venture creation." *Strategic Entrepreneurship Journal*, 1(1-2), pp. 167-182.
- Bates, J., and Palmer, M. (2007). "Next-Generation Algorithmic Trading: A User's Guide." *Trading*, 2007(1), pp. 31-34.
- Beck, K., Beedle, M., van Bennekum, A., Cockburn, A., Cunningham, W., Fowler, M., Grenning, J., Highsmith, J., Hunt, A., Jeffries, R., Kern, J., Marick, B., Martin, R., Mellor, S., Schwaber, K., Sutherland, and J., Thomas, D. (2001). *The agile manifesto*. Available at: https://agilemanifesto.org/
- Biais, B., Foucault, T., and Moinas, S. (2011). Equilibrium high frequency trading. In Proceedings from the Fifth Annual Paul Woolley Centre Conference, London School of Economics.
- Brady, T., and Hobday, M. (2011). Projects and innovation: Innovation and projects. In *The Oxford Handbook of Project Management*. Morris P.W.G., Pinto J.K., and Söderlund, J. (Eds.). Oxford University Press.
- Boehmer, E., Li, D., and Saar, G. (2018). "The competitive landscape of high-frequency trading firms." *Review of Financial Studies*, 31(6), pp. 2227-2276.
- Brown, S. L., and Eisenhardt, K. M. (1997). "The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations." *Administrative Science Quarterly*, pp. 1-34.
- Carrion, A. (2013). "Very fast money: High-frequency trading on the NASDAQ." *Journal of Financial Markets*, 16(4), pp. 680-711.
- Campbell, D.T. (1975). "Degrees of Freedom and the Case Study." *Comparative Political Studies*, 8(1), pp. 178-191.
- Cartea, Á., Jaimungal, S., and Penalva, J. (2015). *Algorithmic and High-frequency Trading*. Cambridge University Press.

- Carter, K. (1993). "The place of story in the study of teaching and teacher education." *Educational Researcher*, 22, pp. 5-12.
- Chaboud, A.P., Chiquoine, B., Hjalmarsson, E., and Vega, C. (2014). Rise of the machines: Algorithmic trading in the foreign exchange market. *Journal of Finance*, 69(5), pp. 2045-2084.
- Chamberlin, E. (1933). *The Theory of Monopolistic Competition: A Re-Orientation of the Theory of Value*. Harvard University Press.
- Chen, T. P. (2014). *Portfolio of trading systems: Path of least resistance to consistent profitability*. Partridge Publishing Singapore.
- Cohen, M. A., Eliasberg, J., and Ho, T. H. (1996). "New product development: The performance and time-to-market tradeoff." *Management Science*, 42(2), pp. 173-186.
- Cohen, W. M., and Levinthal, D. A. (1990). "Absorptive capacity: A new perspective on learning and innovation." *Administrative Science Quarterly*, 35, pp. 128-152.
- Coombs, N. (2016). "What is an algorithm? Financial regulation in the era of high-frequency trading." *Economy and Society*, 45(2), pp. 278-302.
- Cooper, R., and Van Vliet, B. (2015). "Expected return in high-frequency trading." *Journal of Trading*, 10(2), pp. 34-40.
- Cooper, R., Davis, M., Kumiega, A., and Van Vliet, B. (2020). "Ethics for automated financial markets." In *Handbook on Ethics in Finance*, San-Jose, L., Retolaza, J.L., and van Liedekerke, L. (Eds.), pp. 229-246. Springer International Publishing.
- Corbin, J., and Strauss, A. (2015). *Basics of Qualitative Research: Techniques and Procedures* for Developing Grounded Theory, 4rd Ed. Sage Publications
- Currie, W. L., and Seddon, J. J. (2017). "The regulatory, technology and market 'dark arts trilogy'of high frequency trading: a research agenda." *Journal of Information Technology*, 32(2), pp. 111-126.
- Cyert, R. M., and March, J. G. (1963). A Behavioral Theory of the Firm, Prentice Hall.
- Daft R.L., and Weick, K.E. (1984). "Toward a model of organizations as interpretation systems." *Academy of Management Review*, 9, pp. 284-295.
- D'Antona, J. (2018, February 16). "Flashback Friday: Getco buys Knight." *Markets Media*. Available at: https://www.marketsmedia.com/flashback-friday-getco-buys-knight/
- Davies, A., and Brady, T. (2000). Organisational capabilities and learning in complex product systems: towards repeatable solutions. *Research Policy*, 29(7-8), pp. 931-953.
- Davis, M., Kumiega, A., and Van Vliet, B. (2013). "Ethics, finance, and automation: A preliminary survey of problems in high frequency trading." *Science and Engineering Ethics*, 19(3), pp. 851-874.
- Day, R.H. (1994). Complex Economic Dynamics, Volume I: An Introduction to Dynamical Systems and Market Mechanisms. MIT Press.
- Denrell, J., Fang, C., and Winter, S. G. (2003). "The economics of strategic opportunity." *Strategic Management Journal*, 24(10), pp. 977-990.
- Denzin, N.K., and Lincoln, Y.S. (2005). "Introduction: The discipline and practice of qualitative research." In *The Sage Handbook of Qualitative Research*, Denzin, N., and Lincoln, Y. (Eds.), Sage Publishing.
- Dibb, S., Merendino, A., Aslam, H., Appleyard, L., and Brambley, W. (2020) "Whose rationality? Muddling through the messy emotional reality of financial decision-making." *Journal of Business Research*, November.

- Dolgopolov, S. (2014). "High-frequency trading, order types, and the evolution of the securities market structure: One whistleblower's consequences for securities regulation." *University of Illinois Journal of Law, Technology and Policy*, 2014, pp. 145-175.
- Doz, Y. L., and Kosonen, M. (2010). "Embedding strategic agility: A leadership agenda for accelerating business model renewal." *Long Range Planning*, 43(2-3), pp. 370-382.
- Dreyer, B., and Grønhaug, K. (2004). Uncertainty, flexibility, and sustained competitive advantage. *Journal of Business Research*, 57(5), pp. 484-494.
- Dunne, D., and Martin, R. (2006). "Design thinking and how it will change management education: An interview and discussion." *Academy of Management Learning and Education*, 5(4), pp. 512-523.
- Eastwood, G. (2017, June 20). "3 ways big data is changing financial trading." *Bloomberg*. Available at: https://www.bloomberg.com/professional/blog/3-ways-big-data-changing-financial-trading/

Edwards, R., and Holland, J. (2013). What is qualitative interviewing? Bloomsbury Academic.

- Eisenhardt, K.M., and Martin, J.A. (2000). "Dynamic capabilities: what are they?" *Strategic Management Journal*. 21, pp. 1105–1121.
- Fang, B., and Zhang, P. (2016). "Big data in finance." In *Big Data Concepts, Theories, and Applications*, Yu, S., and Guo, S. (Eds.), pp. 391-412. Springer.
- Farboodi, M., and Veldkamp, L. (2020). "Long-run growth of financial data technology." *American Economic Review*, 110(8), pp. 2485-2523.
- Farmer, J. D., and Lo, A. W. (1999). "Frontiers of finance: Evolution and efficient markets." *Proceedings of the National Academy of Sciences*, 96(18), pp. 9991-9992.
- Ferreira, J., Coelho, A., and Moutinho, L. (2020). "Dynamic capabilities, creativity and innovation capability and their impact on competitive advantage and firm performance: The moderating role of entrepreneurial orientation." *Technovation*, 92, 102061.
- Flyvbjerg, B. (2006). "Five misunderstandings about case-study research." *Qualitative Inquiry*, 12(2), pp. 219-245.
- Gioia, D. A., Corley, K. G., and Hamilton, A. L. (2013). "Seeking qualitative rigor in inductive research: Notes on the Gioia methodology." *Organizational Research Methods*, 16(1), pp. 15-31.
- Goldstein, M. A., Kumar, P., and Graves, F. C. (2014). "Computerized and high-frequency trading." *Financial Review*, 49(2), pp. 177-202.
- Gramlich D., and Oet, M.V. (2018). "Systemic financial feedbacks–Conceptual framework and modelling implications." *Systems Research and Behavioural Science*, 35, pp. 22-38.
- Grossman, S. J., and Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review*, 70(3), pp. 393-408.
- Guest, G., Bunce, A., and Johnson, L. (2006). "How many inter-views are enough?" *Field Methods*, 18, pp. 59–82.
- Hasanhodzic, J., Lo, A.W., and Viola, E. (2011). "A computational view of market efficiency." *Quantitative Finance*, 11(7), pp. 1043-1050.
- Hendershott, T., Jones, C.M., and Menkveld, A.J. (2011). Does algorithmic trading improve liquidity? *Journal of Finance*, 66(1), pp. 1-33.
- Hitt, M.A., Ireland, R.D., Camp, S.M., and Sexton, D.L. (2001). "Strategic entrepreneurship: Entrepreneurial strategies for wealth creation." *Strategic Management Journal*, 22(6-7), 479-491.

- Hobday M. (2000). "The project-based organisation: An ideal form for managing complex products and systems?" *Research Policy*, 29, pp. 871-893.
- Hoffmann, P. (2014). A dynamic limit order market with fast and slow traders. *Journal of Financial Economics*, 113(1), pp. 156-169.
- Hoffmann, C.H. (2017). "Towards understanding dynamic complexity in financial systems Structure-based explanatory modelling of risks." *Systems Research and Behavioural Science*, 34, pp. 728-745.
- Huang, B., Huan, Y., Xu, L.D., Zheng, L., and Zou, Z. (2019). "Automated trading systems statistical and machine learning methods and hardware implementation: a survey." *Enterprise Information Systems*, 13(1), pp. 132-144.
- Hult, G.T.M., and Ketchen, D.J. (2001). "Does market orientation matter?: A test of the relationship between positional advantage and performance." *Strategic Management Journal*, 22, pp. 899–906.
- Ireland, R.D., Hitt, M.A., and Sirmon, D.G. (2003). "A model of strategic entrepreneurship: The construct and its dimensions." *Journal of Management*, 29(6), pp. 963-989.
- Javers, E. (2014, August 21). "High-frequency trading critic Chilton joins HFT lobby effort." CNBC. Available at: https://www.cnbc.com/2014/08/21/high-frequency-trading-critic-chiltonjoins-hft-lobby-effort.html
- Jaworski, B., Kohli, A.K., and Sahay, A. (2000). "Market-driven versus driving markets." *Journal of the Academy of Marketing Science*, 28(1), pp. 45-54.
- Kane, V.E. (1986). Process capability indices. Journal of Quality Technology, 18(1), pp. 41-52.
- Kessler, E.H., and Chakrabarti, A.K. (1996). "Innovation speed: A conceptual model of context, antecedents, and outcomes." *Academy of Management Review*, 21(4), pp. 1143-1191.
- Kondor, P. (2009). Risk in dynamic arbitrage: the price effects of convergence trading. *Journal* of *Finance*, 64(2), pp. 631-655.
- Kumiega A., and Van Vliet, B. (2012). "Automated finance: The assumptions and behavioral aspects of algorithmic trading." *Journal of Behavioral Finance*, 13, pp. 51-55.
- Kumiega, A., Neururer, T., and Van Vliet, B. (2014). "Trading system capability." *Quantitative Finance*, 14, pp. 383-392.
- Spieth, P., and Lerch, M. (2014). Augmenting innovation project portfolio management performance: the mediating effect of management perception and satisfaction. *R&D Management*, 44(5), pp. 498-515.
- Leshik, E.A., and Cralle, J. (2011). *An Introduction to Algorithmic Trading*. John Wiley and Sons.
- Levine, H.A. (2005). Project Portfolio Management: A Practical Guide to Selecting Projects, Managing Portfolios, and Maximizing Benefits. John Wiley and Sons.
- Li, L., and Lee, Y.S. (1994). Pricing and delivery-time performance in a competitive environment. *Management Science*, 40(5), pp. 633-646.
- Lo, A.W. (2004). "The adaptive markets hypothesis." *Journal of Portfolio Management*, 30(5), pp. 15-29.
- Lo, A.W. (2017). Adaptive Markets. Princeton University Press.
- Lujan, S. (2017, October 23). "DRW and Other Firms Embrace High-Frequency Bitcoin Trading." *Bitcoin.com*. Available at: https://news.bitcoin.com/drw-and-other-firms-embracehigh-frequency-bitcoin-trading/
- Lumpkin, G.T., and Dess, G.G. (1996). "Clarifying the entrepreneurial orientation construct and linking it to performance." *Academy of Management Review*, 21(1), pp. 135-172.

- MacKenzie, D. (2019). "How algorithms interact: Goffman's 'interaction order'in automated trading." *Theory, Culture & Society*, 36(2), pp. 39-59.
- Mansoori, Y., Karlsson, T., and Lundqvist, M. (2019). "The influence of the lean startup methodology on entrepreneur-coach relationships in the context of a startup accelerator." *Technovation*, 84, 37-47.
- Markowitz, H. (1952). "Portfolio selection." Journal of Finance, 7, pp. 77-91.
- Marshall, N., and Brady, T. (2001). "Knowledge management and the politics of knowledge: illustrations from complex products and systems." *European Journal of Information Systems*, 10, pp. 99-112.
- Massa, A. (2017, November 21). "High-speed traders in search of new markets jump into Bitcoin." *Bloomberg*. Available at: https://www.bloomberg.com/news/articles/2017-11-21/bitcoin-draws-high-speed-traders-seeking-markets-to-transform
- Matthews, C. (2012, August 8). "High frequency trading: Wall Street's doomsday machine?" *Time*. Available at: https://business.time.com/2012/08/08/high-frequency-trading-wall-streets-doomsday-machine/
- McGrath, R.G. (2013). "Transient advantage." Harvard Business Review, 91(6), pp. 62-70.
- McMullen, J., and Shepherd, D. (2006). "Entrepreneurial action and the role of uncertainty in the theory of the entrepreneur." *Academy of Management Review*, 31(1), pp. 132-152.
- Menkveld, A.J. (2013). "High frequency trading and the new market makers." *Journal of Financial Markets*, 16(4), pp. 712-740.
- Metz, C. (2016, January 25). "The rise of the artificially intelligent hedge fund." *WIRED*. Available at: https://www.wired.com/2016/01/the-rise-of-the-artificially-intelligent-hedge-fund/
- Meyer, G., Bullock, N., and Rennison, J. (2018, January 1). "How high-frequency trading hit a speed bump." *Financial Times*. Available at: https://www.ft.com/content/d81f96ea-d43c-11e7-a303-9060cb1e5f44
- Mikalef, P., Krogstie, J., Pappas, I.O., and Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, 57(2).
- Miller, J.H., and Page, S.E. (2007). Complex Adaptive Systems: An Introduction to Computational Models of Social Life. Princeton University Press.
- Min, B. H., and Borch, C. (2021). Systemic failures and organizational risk management in algorithmic trading: Normal accidents and high reliability in financial markets. *Social Studies of Science*.
- Morgan, C. (2008, February 20). "Hedge funds and technology: Automation in the feedback loop." *TABB Group*. Available at: https://research.tabbgroup.com/report/v06-018-hedge-funds-and-technology-automation-and-feedback-loop
- Morrison, K., and Potts, J. (2008). Toward behavioural innovation economics Heuristics and biases in choice under novelty. Discussion Papers Series 379, School of Economics, University of Queensland, Australia.
- Nordrum, A. (2017, June 28). "Hedge funds look to machine learning, crowdsourcing for competitive advantage." *IEEE Spectrum Tech Talk*. Available at: https://spectrum.ieee.org/tech-talk/computing/software/fintech-trends-hedge-funds-look-to-machine-learning-crowdsourcing-for-competitive-advantage
- Osipovich, A. (2019, January 7). "Wall Street firms plan new exchange to challenge NYSE, Nasdaq." *Wall Street Journal*. Available at: https://www.wsj.com/articles/wall-street-firms-

plan-new-exchange-to-challenge-nyse-nasdaq-

11546866121#:~:text=A%20group%20of%20financial%20heavyweights,Inc.%2C%20the%2 0companies%20said.

Osipovich, A. (2020, December 15). "High-frequency traders push closer to light speed with cutting-edge cables." *Wall Street Journal*. Available at: https://www.wsj.com/articles/high-frequency-traders-push-closer-to-light-speed-with-cutting-edge-cables-11608028200

Pisani, B. (2018, February 8). "As market sell-off intensifies, a search for who, or what, to blame." *CNBC*. Available at: https://www.cnbc.com/2018/02/08/as-market-sell-off-intensifies-a-search-for-who-or-what-to-blame.html

Porter, M. (1980). Competitive Strategy. Free Press.

Potts, J. (2017). Behavioral innovation economics. In *Handbook of Behavioral Economics*. Franz, R., Chen, S.H., Dopfer, K., Heukelom, F., and Mousavi, S. (eds.). Routledge.

Powell, T.C. (1995). "Total quality management as competitive advantage: a review and empirical study." *Strategic Management Journal*, 16(1), pp. 15-37.

- Ries, E. (2011). *The Lean Startup: How Today's Entrepreneurs Use Continuous Innovation to Create Radically Successful Businesses*. Crown Books.
- Roy, A.D. (1952). Safety first and the holding of assets. *Econometrica*. 20(3), pp. 431–450.

Rubin, P., and Capra, C. (2011). "The evolutionary psychology of economics." In *Applied Evolutionary Psychology*, Roberts, S. (ed.). Oxford University Press.

Sanders, J. (2016). "High-frequency traders: A plan to eliminate the abuses without losing the benefits." *Wake Forest Law Review*. Available at: wakeforestlawreview.com/2016/04/high-frequency-traders-a-plan-to-eliminate-the-abuses-without-losing-the-benefits/

Saunders, M.N.K., and Townsend, K. (2016). "Reporting and justifying the number of interview participants in organization and workplace research," *British Journal of Management*, 27, pp. 836–852.

Scherer. F.M. (1967). "Research and development resource allocation under rivalry." *Quarterly Journal of Economics*, 81(3), pp. 359–394.

Schmerken, I. (2018, February 19). "Morgan Stanley's trading technology platform speeds time to market for quant shops." *Wall Street and Technology*. Available at: https://www.wallstreetandtech.com/trading-technology/morgan-stanleys-trading-technology-platform-speeds-time-to-market-for-quant-shops/d/d-id/1268609d41d.html?

Schumpeter, J.A. (1939). Business Cycles, McGraw-Hill.

Schumpeter, J.A. (2000). "Entrepreneurship as innovation." In *Entrepreneurship*, Swedberg, R., (Ed.), *Oxford University Press*, 51-75.

Seddon, J.J.M., and Currie, W.L. (2017). "A model for unpacking big data analytics in high-frequency trading." *Journal of Business Research*, 70, pp. 300-307.

Serbera, J.P., and Paumard, P. (2016). "The fall of high-frequency trading: A survey of competition and profits." *Research in International Business and Finance*, 36, pp. 271-287.

Shang, W., and Liu, L. (2011). "Promised delivery time and capacity games in time-based competition." *Management Science*, 57(3), pp.599-610.

Sharpe, W.F. (1994). "The Sharpe ratio." Journal of Portfolio Management, 21(1), pp. 49-58.

Silverman, D. (2013). Doing Qualitative Research, Fourth Edition. Sage Publishing.

Simon, H.A. (1955). "A behavioral model of rational choice." *Quarterly Journal of Economics*, 69, pp. 99-118.

Simon, H.A. (1957). Models of Man: Social and Rational. John Wiley and Sons.

Simon, H.A. (1976). Administrative Behavior, 3rd ed. The Free Press.

- Sobolev, D. (2020). "Insider information: The ethicality of the high frequency trading industry." *British Journal of Management*, 31(1), pp. 101-122.
- Teece, D.J., Pisano, G., and Shuen, A. (1997). "Dynamic capabilities and strategic management." *Strategic Management Journal*, 18(7), pp. 509-533.
- Vaananen, J. (2015). "Dark pools and high frequency trading for dummies." John Wiley and Sons.
- Van Vliet, B. (2017). "Capability satisficing in high frequency trading." *Research in International Business and Finance*, 42, pp. 509-521.
- Van Vliet, B. (2020). "A behavioural approach to the Lean Startup/minimum viable product process: The case of algorithmic financial systems." *International Journal of Innovation Management*, 24(03), 2050029.
- Velu, R. (2020). Algorithmic Trading and Quantitative Strategies. CRC Press.
- Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, 5(2), pp. 171-180.
- Woods, D.D. (2020). "The strategic agility gap: How organizations are slow and stale to adapt in turbulent worlds." In *Human and Organisational Factors*, Journé, B., Laroche, H., Bieder, C., and Gilbert, C. (eds.). Springer. pp. 95-104.
- Yesalavich, D. (2018, February 19). "Coding switch to make algorithmic trading even faster." *Wall Street Journal*. Available at:

wsj.com/articles/SB10001424052702304354104575568550052835646

Notes

- [1] Innovation is "the introduction of new technical methods, products, sources of supply, and forms of industrial organization (Schumpeter, 2000, p. 51)." Largely, "entrepreneurship focuses on newness and novelty in the form of new products, new processes, and new markets as the drivers of wealth creation" (Ireland *et al.*, 2003 p. 965). We use these terms interchangeably.
- [2] "The conventional product vs. process dichotomy is unhelpful in explaining the nature and determinants of innovation in CoPS (Brady and Hobday, 2011, p. 284)." This seems to be true of algorithmic trading and, more generally, of financial innovation.
- [3] Failure in algorithmic trading occurs not just due to serial losses, but (in a more behavioral sense) also because serial losses cause investors to *believe* a leftward shift in $E(\pi)$ has occurred even before statistical proof arrives. Sustainability is about knowing when not only to lose confidence in the distribution but also in the people estimating that distribution (see Kumiega and Van Vliet, 2012).

Appendix

	Role			
Trading Firm	Trader	Quant	IT Staff	Management
1	A (4)			
2				B (2)
3			C (4)	
4		D (3)		
5		E (1)		
6		F (3)		
7	G (2)			
8				H (2)
9	I (2)			
10				J (1)
11				K (3)
12		L (3)		

Table AI: Roles of and Number of Meetings with Interviewees