The Good, the Bad, and the Ugly of Automated High-Frequency Trading

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This article discusses the pros and cons of automated high-frequency trading (HFT). There is an ongoing heated debate over the positive and negative effects of HFT on the quality of financial markets.[1] By quality, we mean primarily liquidity, price efficiency, and price discovery–overall, market health. More and more articles studying this topic have been written, but there still appears to be much confusion of whether HFT is "Good," "Bad," or "Ugly." On the one hand, for example Gomber et al. [2011] highlighted the beneficial aspects of HFT and saw the perceived problems to be a largely a result of the U.S. market structure. On the other hand, the SEC (and the regulatory authorities in Europe) was scrutinizing HFT in the fear it was putting "less tech-savvy investors at a disadvantage."[2] Behind that fear lies the perhaps unconscious worry that computers are about to run over humans in investing as they have done in other demanding fields.[3-5]

We review the current literature on HFT and the closely related algorithmic trading (AT), but we do not claim to be comprehensive. We emphasize academic studies, because their views of this topic seem to be the most neutral. Importantly, we do not merely present the evidence but also discuss it from our own point of view. We hope this gives a fresh perspective and brings research in HFT and related fields to the forefront.

DEFINING HFT

Before discussing the pros and cons of HFT, one thing should be cleared up right away: HFT and AT are not the same concepts. Many academic authors consider HFT as a subset of AT, but this practice should be challenged more. We see HFT as a subset of automated (not algorithmic) trading, a view which we share for example with the Markets Committee [2011].[6] Automated trading, in our view, includes both HFT and AT as its subsets. Both require a high level of automation, but for different purposes, which will be explained below. The different definitions of AT and HFT used in the literature are collected in Gomber et al. [2011]. Ignoring the conceptual differences has probably added to the confusion. With AT and HFT being different entities, their pros and cons are not necessarily the same.

Traditionally, an automated trading model (HFT or slower trading) is about determining whether a trade should be placed, while an algorithmic trading (AT) model is about determining how to place a trade in order to minimize execution costs. More explicitly, automated HFT is about profit maximization using trading strategies specifically developed for this task, while AT is about minimizing transaction costs of trading large blocks of assets.[7] A number of authors, for example the SEC [2010] and Brogaard

[2012], listed specific features required of HFT.[8] Simply put, HFT is "fast" profit-maximizing automated trading that avoids taking large positions to any direction. How fast the trading must be depends on the trading strategy. Typically, HFT involves asset-holding times of only minutes, or even seconds, the most technologically savvy trading firms working in the subsecond range (milliseconds, or even faster).

SCOPE OF THIS ARTICLE

Donefer [2010] divided the users of automated trading strategies into four groups: i) liquidity seekers; ii) automated market makers; iii) statistical arbitrage strategy traders, some of whom are gamers or predators; and iv) rebate seekers. In this article, we accept a rather broad definition of HFT: automated trading executed at intradaily intervals, but such that it excludes trading for the purposes of minimizing transaction costs. Our definition of HFT, thus, includes the last three groups and excludes the first.

We focus mostly on the present and, to some extent, the future of HFT. There exist several good articles describing the historical background on HFT. We refer the interested readers to McGowan [2010] for an introduction to the "rise of the machines." Shorter descriptions can found for example in Biais and Woolley [2011] and Vuorenmaa [2012a]. Technological developments are discussed for example in Cliff [2011] and Cliff et al. [2011]. A limitation of our article is that we do not discuss the role of financial market fragmentation or different models of market microstructure in much detail. For the former, we refer the readers to O'Hara and Ye [2011] and Vuorenmaa [2012b] and for the latter to De Jong and Rindi [2009]. Those aspects are usefully intertwined in the theoretical framework of Pagnotta and Philippon [2012], who studied the joint evolution of trading regulations, market fragmentation, and speed, and its effect on welfare.

THE UGLY

We now review and discuss the evidence whether the pros outweigh the cons. In our context, the "Ugly" category includes perhaps the most serious objections raised against HFT. They are certainly the most popularized ones by media.[9]

Flash Crashes

The most well-known and most likely the ugliest argument against HFT is the Flash Crash of May 6, 2010. The U.S. stock market indices, stock-index futures, options, and exchange-traded funds (ETFs) then experienced a sudden and unprecedented increase in volatility. A drop of more than 5% in prices was followed by a rapid rebound—in about 20 minutes—of almost the same magnitude. Although an intraday event, Zigrand, Cliff, and Hendershott [2011] among others argued that it eroded confidence in markets for a considerable time to come and was, thus, not inconsequential. Short popular accounts have appeared in MacKenzie [2011] and several finance industry magazines[10]. A detailed description on what is thought to have taken place on May 6, 2010, can be found in the joint study of CFTC/SEC [2010], commissioned by Joint Advisory Committee on Emerging Regulatory Issues in the United States.[11] The importance of this event is emphasized by the fact that officially commissioned studies are rather rare, although by no means are fast crashes limited to the era of HFT.

Probably the most famous report was commissioned after the 1987 stock market crash. In that crash, the main blame was put on portfolio insurance strategies (see, e.g., Carlson [2006]). Coupled with more standard stop-loss strategies, they created a feedback loop, bearing some resemblance to what apparently happened on May 6, 2010. The Markets Committee [2011] described another—but less well known—event related to stop-losses that took place for Japanese yen on March 17, 2011. Many HFT firms and market makers then reportedly withdrew from the market. Designated market makers did practically the same by submitting unrealistic quotes. There are also parallels to the so-called quant meltdown that took place in August 2007, where "a rapid unwinding of a large equity-market-neutral portfolio may have caused losses in other portfolios using similar strategies" (see Khandani and Lo [2008]). In 2007, however, automated trading was not yet in as dominant a position as it was in 2010.

Who is to blame for the Flash Crash then?[12] Kirilenko et al. [2011] attempted to uncover that by studying the E-mini S&P 500 stock index future data. Their conclusion supports that of CFTC/SEC [2010]: HFT firms did not trigger the crash, but their trading response to the sudden selling pressure by an institutional seller exacerbated the volatility. HFT firms were aggressively trading in the direction of price changes, causing a "hot-potato" effect: a toxic asset changing hands from one to another rapidly. This effect is due to the HFT firms' trading style, which may be quite different from the trading style of designated market makers. Designated market makers are typically less aggressive and accumulate larger inventory positions. HFT firms, on the other hand, avoid taking such positions to minimize market risk.[13] Martinez and Roşu [2011] showed in a theoretical framework that HFT firms can accomplish this by increasing their trading frequency. HFT firms may sometimes compete fiercely for liquidity and so amplify price volatility.[14]

The "doomsday dynamics" of the Flash Crash were apparently set in motion by a "run-on-a-bank" type of self-fulfilling prophecy—a topic famously studied decades ago by sociologist Robert K. Merton (see Merton [1949]). On May 6, 2010, the run seems to have started from an unwinding of a position reportedly executed by volume-based—but not price-contingent—AT methods. HFT firms reacted by increasing their trading, which signaled the algorithm to sell even more. This created a temporary "liquidity black hole" (see Morris and Shin [2004]). The effect was worsened by market makers trying to avoid "catch a falling knife by its point."[15] More research on such feedback loops is clearly warranted as we have limited experience on automated trading that is faster than manually possible (see Zigrand, Cliff, and Hendershott [2011]).

Near catastrophic events are what Perrow [1999] categorized as "normal accidents." Such catastrophes are inevitable consequences of closely coupled processes that typically take place in "high-risk technologies." Catastrophes are a latent feature of "socio-technological systems," large-scale information technology systems supporting critical social and economic functions. They happen because risky events are often misinterpreted as being normal. The risk of catastrophes typically does not materialize until later (see, e.g., Zigrand, Cliff, and Hendershott [2011]). The main problem of socio-technological systems is that failures are hard or impossible to predict. Failures could be controlled to some extent by simulation-based techniques. Gsell [2008] used simulations to demonstrate how AT impacts markets in terms of price formation and volatility. For such a framework to be useful in the sense just described, algorithms should be considered in relation to other algorithms. Similarly, theoretical models like that of Carlin, Lobo, and Viswanathan [2005], which demonstrated how liquidity crises could arise from a breakdown of cooperation among different market participants, are typically simplified equilibrium models. Farmer and Geanakoplos [2008], for example, discussed the limitations of such models.

In line with Perrow's view, Johnson et al. [2012] found novel evidence of "mini flash crashes" that took place in the sub-second range, "at the limits of the monitoring capability of human response times."[16] Although this topic warrants more thorough research, it signals that reasonable control should be exerted over trading at the market microstructure level where sub-seconds and cents matter. For example, the use of special orders and routing practices in the U.S. markets may have played a key role in the perceived problems. Wood, Upson, and McInish [2012] suspected that the use of intermarket sweep orders (ISOs) contributed to the occurrence of the Flash Crash. They found that the amount of ISOs was much higher on May 6, 2010, than normally and were mostly used by informed traders before the crash. This is in line with Gomber et al. [2011] who noted that similar crashes had not taken place in Europe. It would, thus, not make sense to regulate technology excessively. Instead, more efficiently working technology could, in many cases, save exchanges from experiencing message traffic overloading.

Digression: Black Swans and Dragon-Kings

Flash crashes are by their nature surprise phenomena. In the last decade, there has been a strong, renewed interest in extreme event modeling, popularized by Nassim Nicholas Taleb. Building on earlier work in academic literature (see Mandelbrot [1963] and Fama [1965]), Taleb [2007] called surprise extreme events "Black Swans." Mandelbrot often used the term "wild" events, or the more descriptive "Noah-effect" in this context.

The basic underlying theoretical assumption of Black Swans is that events are independent of each other. This means that they cannot be predicted. Does the Flash Crash qualify as a Black Swan in that sense? It depends on what time-scale the event is being observed. In order to clarify this, assume for a moment that we sample some historical data covering May 6, 2010, at a daily frequency. As described before, the prices that experienced a sudden drop recovered after about 20 minutes of trading. Clearly, then, at a daily sampling frequency no Black Swan by this definition took place. Even at an hourly sampling frequency, we would not have evidence of a Black Swan.

But if we sampled the data at a five-minute frequency, we would see the evidence.

One could go further: sample at a second or, better yet, at a sub-second frequency, and the evidence starts to change form again. The changes in prices were not, in fact, independent of each other. There was a feedback loop that accumulated to one large surprise event at a larger time-scale. Clearly, Black Swans are wild events only at certain time-scales. In other words, the blackness or wildness can be "tamed" by moving from one time-scale to another. This is actually a more general phenomenon: the changes of logarithmic prices tend to have probability distributions with heavy-tails when the time-scale is small, but when the time-scale gets larger, the probability distributions start to resemble normal distributions. Having a lighter tail means that there is a lower probability of an extreme event.

We could approach the Flash Crash in yet another way. By not assuming independence, we could let the observations at the highest frequencies be serially dependent. Then a negative price change would be more likely to be followed by another negative price change than a positive one. Using Sornette's [2009] terminology, events that grow extreme and surprising through such a dependent process are called "Dragon-Kings."[17] Events created this way can become more extreme than Black Swans. The advantage of this approach is that the sampling frequency becomes an important dimension in the analysis of extreme events.

In the era of high technology seemingly unrelated processes may become coupled at the very short time-scales, leading to surprising extreme events that could not have been easily predicted using knowledge from older technology. There is some amount of chaotic behavior involved in the sense that small changes in a variable can accumulate to unexpected end results at a large scale. The importance of time (or time-scale) must be a central aspect of the analysis of an extreme event. Probability distributions should be modeled over various time-scales with special focus on the shortest ones if HFT activity is of prime interest.

Front Running and Predatory Trading

Some HFT strategies taking advantage of short-term correlations have earned an especially ugly reputation.[18] In a typical front-running strategy, a high-frequency trader steps in front of a large institutional order and drives the price to a direction that is beneficial for herself. This can be achieved by, for example, co-locating a computer server close to a stock exchange, making it possible to react very fast to incoming orders. Co-locating has become a profitable business to stock exchanges themselves, perhaps limiting their interests to monitor or regulate their clients more efficiently.[19] The situation is similar to what the NYSE specialists were able to do years ago: to see the state of the order book and forecast the direction of short-term price movements with high probability. Speed and competition have replaced their protected status.

Front running is an example of predatory trading. Predatory trading refers to strategically placed trades that hunt prey by first trading in the same direction and then reversing the position and making a "kill." The most well-known example of predatory trading—although not from the HFT world—is the fate of the Nobel Laureate lead hedge fund Long Term Capital Management (LTCM). In the 1990s, LTCM was engaged in convergence arbitrage, a strategy in principle the same as the simpler pairs trading, in which the long-short positions were prepared to be taken for a long term. The weak point of the strategy was that the LTCM positions were highly leveraged and hard to keep as a secret. In 1998, in the aftermath of the Russian debt crisis, the positions of LTCM in certain illiquid assets became well known in many large Wall Street investment banks. Many of those banks then started trading against the known LTCM positions and eventually drove LTCM to the brink of bankruptcy, which was, interestingly, a bit later recapitalized by a consortium of some of the same banks that had been (claimed to be) the predators. Thus, predatory trading is nothing new to Wall Street. The techniques to do it are now different, however, and rely much on technology, speed in particular.

De Luca et al. [2011] reported experimental evidence that speed, and not (artificial) intelligence, is the primary advantage of algorithms over humans. Predatory algorithms, immediate or cancel orders, and dark pool pinging try to determine the state of large institutional orders and use this knowledge to make (almost) risk-free arbitrage by trading on different exchanges in milliseconds or faster. Institutional investors using slower and not-so-smart algorithms lose. The industry standard is to execute large orders based on historical volume using the so-called volume weighted-average price (VWAP) algorithm. Such algorithms are relatively easy to spot and predict by predatory HFT (see Agatonovic, Patel, and Sparrow [2012]), creating a technological adverse selection problem for institutional investors. This was, by some accounts, the key triggering mechanism of the Flash Crash.

Some of the predatory HFT strategies based on speed are called quote stuffing, smoking, and spoofing. Stuffing is arguably the most damaging to market quality by limiting the access of slower traders to markets by submitting a large number of orders and then canceling them very fast. This leads to order congestion, which may create technical trouble and quotes lagging by significant amounts of time. Egginton, Van Ness, and Van Ness [2012] found that over 74% of U.S.-listed equity securities experienced at least one stuffing episode in 2010 based on consolidated data from exchanges in the National Market System (NMS). They also found that during those episodes stocks experienced decreased liquidity, higher trading costs, and increased short-term volatility. The smoking and spoofing strategies, on the other hand, try to manipulate other traders to participate in trading at an unfavorable moment, such as just before the arrival of relevant news.[20] Manipulative techniques are naturally not limited to those three strategies (see BMO Capital Markets [2009]). Most likely, smarter strategies are being developed and the most ingenious ones are kept secret.

Predatory trading may damage liquidity provision. Because of the adverse selection problem, slower traders may not want to supply liquidity for fear of being taken advantage of. However, evidence of predatory trading is still largely anecdotal. We know that high-frequency traders foresee the actions of slower traders to some extent, but it is not clear if this should be labeled predatory. Easley, Lopez de Prado, and O'Hara [2012] stated that it is obvious that the goal of many HFT strategies is to profit from slower traders' mistakes. Hirschey [2011] found a positive correlation between HFT and slower trading not simply due to faster reaction to arriving news. High-frequency traders seem to anticipate the buying and selling pressure of slower traders. McInish and Upson [2012] found that fast traders were able to pick off slower liquidity demanders at prices that were not the best available. They estimated the profit to the faster traders to be more than $233 million annually and explained this trading opportunity arose largely from how the U.S. markets were constructed (the flicker quote exception to Rule 611). But there is also some evidence to the contrary: Aldridge [2012] did not find any sign of HFT "pump-and-dump" gaming in futures.

Theoretical work on predatory trading is accumulating. In the model of Brunnermeier and Pedersen [2005], predatory trading led to price overshooting and illiquidity. This may spill over markets and lead to a growth in systemic risk. Using arbitrage arguments, Jarrow and Protter [2011] argued that HFT can create mispricing disadvantageous to the slower traders. Decreasing profits to the slower traders is also forecasted by Hoffmann [2011] who allowed computers to trade with human traders. The model of Biais, Foucault, and Moinas [2011] forecasted that increasing adverse selection costs leads to an arms race and excessive investment in HFT. Pagnotta and Philippon [2012] found competing on speed to have negative welfare effects, when the default speed reaches a threshold faster than is humanly possible.

We now move to the bit more abstract, but potentially worse, arguments. The stand against HFT is reflected in the opinion of Nobel Laureate Paul Krugman: "It's hard to see how traders who place their orders one-thirtieth of a second faster than anyone else do anything to improve that [capital allocation] social function."[21]

THE BAD

Academic literature on the "Bad" is surprisingly sparse, although it appears to be on the rise especially on the theoretical side. The reason for the lack of evidence may be, as noted in the beginning, that typically studies do not make a distinction between AT and HFT (or other forms of automated trading) and use inaccurate proxies for them.

Volatility

Zhang [2010] studied the long-term effect of HFT on volatility and if HFT aids or hinders the markets in reflecting the true prices, that is, if fundamental news are incorporated in market prices efficiently. According to this study, HFT was responsible for about 78% of the dollar trading volume in 2009 in the United States, while in 1995 it was practically zero.[22] Zhang found that HFT (or its proxy, more exactly) increased long-term (quarterly) stock market volatility. The effect was stronger for the largest 3,000 market capitalization stocks and stocks with high institutional holdings. That finding is in agreement with the argument presented in the "Ugly" section that HFT firms take advantage of institutional investors' large trades. It is also in agreement with the theoretical results of Cartea and Penalva [2012] whose model predicted HFT would increase the price impact of large institutional investors making sizable portfolio changes.

There is also empirical evidence of increased short-term volatility due to HFT. By analyzing an international dataset covering 39 exchanges worldwide, Boehmer et al. [2012] found that short-term volatility was systematically increased by AT and/or HFT, defined and measured following Hendershott, Jones, and Menkveld [2011]. The authors argued that the increase in short-term volatility was hard to explain by faster absorption of news, but did not explicitly consider the possibility that higher trading frequencies could be the cause. More precisely, "flickering" market microstructure noise volatility (e.g., due to bid-ask bouncing) would need to be separated from "bursting," a bit longer term, volatility.

The fact that HFT leads to higher trading volumes cannot be disputed. Empirically, for example, Dichev, Huang, and Zhou [2011] established a positive relationship between volume and volatility. They found that trading, in general, creates its own volatility beyond fundamental changes, consistent with larger market impacts and price overshooting. The theoretical model of Jarrow and Protter [2011] also forecasted higher volatility in the presence of high-frequency traders. But such models make quite radical simplifying assumptions that may not hold in reality. For example, they often assume HFT is about liquidity taking rather than liquidity providing. Similarly, the empirical studies often are not able to convincingly prove causality.

Price Discovery and Transparency

Zhang [2010] also found that HFT was negatively associated with the market's ability to incorporate news about a firm's fundamentals into asset prices. News about firm fundamentals led to stock price overreaction when there was a lot of HFT volume in the markets. HFT firms are typically interested only in short-term dynamics, leaving valuation to fundamental analysts. The overreaction hypothesis gets some theoretical support from Froot, Scharfstein, and Stein [1992] who found that short-term speculators may put too much emphasis on short-term information and not enough on stock fundamental information, leading to a degradation of the informational quality of prices. That may be a problem if the mispricing caught momentum.

More trading volume does not necessarily lead to more precise pricing. Much of this volume is out of reach of ordinary traders, who are simply not fast enough. Grillet-Aubert [2010] reports that order cancellation by HFT firms can take place in less than 10 microseconds and that message-to-trade ratios tended to be extremely high for the most actively traded stocks: 96.5% of three HFT hedge funds' orders were reportedly canceled, accounting for 39.6% of trading in the most liquid French stocks. Similar evidence was presented by Van Kervel [2012], who reported ratios of 31:1 and 51:1 for the London Stock Exchange and the Chi-X, respectively. He found that the liquidity offered of interlinked trading venues may not be realizable, because some HFT market makers duplicated their limit order schedules on several different venues to increase their execution probabilities.

Does the visible state of the order book represent real tradable opportunities or not? If orders appear and disappear so fast that they cannot be reacted to by anyone other than computers—and, more precisely, computers co-located near stock exchanges—it is not clear how to place your buy or sell order to get a fair price in an active trading situation. Market transparency can be argued to be hurt by HFT at least to some extent, because most of the order submission and cancellation activity takes place at or very close to the best bid and ask prices. One might suspect with some good reason that in the era of ultrafast automatized trading, it is more probable that a large order will need to walk in the book to get fully executed.

The feature of large trades being executed at prices significantly different from the top-of-the-book is not really an HFT-specific problem, however. It is rather related to the decrease of the minimum tick size or price change (see Vuorenmaa [2010]). In the United States, the preliminary steps in this direction were taken in the 1990s. In 2001, decimalization was completed by the move to cent-ticks. As a consequence, the sizes of orders decreased noticeably in the U.S. stock markets. The completion of the decimalization process motivated large institutional investors to use AT strategies to minimize their impact on prices and to hide their trading intentions from the others. Retrospectively, the doomsday dynamics were set into motion by regulatory changes—

RegNMS[23] in the United States—and the following decentralization of markets.

More Subtle Changes

Regulatory and technological changes have changed the landscape of trading, and HFT activity has made the change even more dramatic. We categorize the following changes as "Bad" to be conservative and because they may affect the systemic risk as explained below.

The theoretical model of Cvitanic and Kirilenko [2010] demonstrated that in limit-order book markets populated by low-frequency human traders, the introduction of HFT led to a distribution of transaction prices that has more mass around the center and thinner tails. The authors argued that the shape of the transaction price density is consistent with high-frequency traders making positive expected profits by "sniping out" human orders somewhat away from the top-of-the-book. It also led to shorter times between trades and higher volume.

Smith [2010] used wavelet methodology to estimate the Hurst parameter, which reflects the long-memory characteristics of a stochastic process. The author found that the Hurst parameter increased substantially after the wider adoption of HFT in 2005 and that the changes in the prices and volume of some liquid stocks started to present fractal-like self-similarity at increasingly shorter time-scales, especially on the NYSE.[24] While the study made some doubtful arguments,[25] and suffers from obvious data limitations, it is interesting to find that the long-memory characteristics were increasing over time. In practice, this means that the traded volumes have become more predictable. In a related study, Chaboud et al. [2011] showed that AT and HFT strategies were more correlated over time than strategies operated by humans manually. Similarly, Brogaard [2010] found that HFT strategies were more correlated with each other than non-HFT strategies. Thus, HFT could potentially lead to increases in systemic market risk.

In addition to having more correlated asset prices at the intradaily level, there is growing concern of correlation across assets and markets. This heightened correlation manifested itself partly in the Flash Crash, where different asset classes became quickly coupled through hedging attempts. The trend toward higher correlations in financial markets is likely to continue rather than to reverse. Finance Watch [2012] noted that crossmarket arbitrage strategies performed on systematic, automated basis at high speeds might lead to worse contagion effects across markets. Fads in algorithms and inability to protect them intellectually could lead to quant-meltdowns described in Khandani and Lo [2008]. Markets may become overcrowded and the population of algorithms too homogenous. Markets Committee [2011] noted that the adoption of equity market trading technology to FX markets may create a more fertile ground for crashes to flourish there. Debt and interest rate markets could also be dominated by algorithms.

Proposed Policy Recommendations

The Bank of England's director of financial stability, Andrew Haldane, has become known for his strong policy recommendations based on the Flash Crash (see Haldane [2011]).[26] In his view, the most technologically savvy traders have gained an unfair edge over the less sophisticated investors, comparable to being informed of the true value of a stock. The observed increasing correlations and the potentially larger systemic risk is at the heart of these worries. The "race to zero" in terms of speed increases systemic risk and has no winners. This forecast was supported by the theoretical equilibrium prediction of Biais, Foucault, and Moinas [2011], in which large institutions are fast and informed while small institutions are slow and incur adverse selection costs. "Grit in the wheels, like grit on the roads, could help forestall the next crash" was Haldane's policy proposal.

More extensive data analysis on the part of regulators should be feasible if financial data are cleared through central counterparties and trade repositories. Larger datasets would allow regulators to identify the potential troublemakers. For example, the order-imbalance methodology proposed in Easley, Lopez de Prado, and O'Hara [2011a, 2011b] could perhaps be applied to forecast flash crashes to some extent. Stress-testing financial markets by using simulation-based techniques described by Cliff [2010] could also be applied. By changing the initial conditions in simulations and recording the results after each realization, an ensemble forecasting approach could be used to give estimated probabilities of extreme events.

Farmer and Skouras [2011] suggested an ecological perspective to developing real-time warning signals for systemic risk. Their claim was that predator–prey relationships existed in the markets, some of which were beneficial and some of which were not. More generally, agent-based simulations (ABS) could yield useful insight on how heterogeneity among market participants and small changes of parameters affected financial markets (see among others Aloud et al. [2012a, 2012b]). ABS might be combined with experimental economics, a field that studies how human agents operate in electronic markets (see Cliff [2011] and De Luca et al. [2011]).

The critics of HFT see it as necessary to have stricter market making guidelines and circuit breakers. The most radical suggestion appearing in Haldane, among others, is the use of resting rules for trades which presumably would increase quoted bid–ask spreads and decrease liquidity in normal times, but would hopefully save the markets from excessive instabilities. The proposals in Europe however often ignore the fact that many of the observed problems are related to the U.S. market microstructure.

The general idea that high liquidity should not be a top priority is nothing new in the field of economics. Finance Watch [2012] noted that John M. Keynes—one of the most influential economists of all time—himself thought that liquidity can divert the attention from the true value of an asset by creating an incentive for speculation. The high trading volumes experienced today could, thus, be interpreted as proof of more speculative behavior. Finance Watch was quick to note, however, that higher trading volumes should not be confused with higher liquidity. They proposed, for example, that HFT firms provide authorities access to their trading algorithms on a regular basis, an unlikely scenario by today's standards.

The underlying problem discussed above could be stated in the form of two questions. Is the HFT firms' trading behavior mostly speculative and, if so, does it lead to more "Bad" than "Good" overall? It could be argued by many that speculation is acceptable if the "Good" wins the "Bad." Essentially then, does HFT carry out a valuable function, for example, by market making, and this way make the markets function better? The answer by the HFT industry to the latter question is positive and it is backed up by a significant amount of empirical as well as theoretical evidence as we next discuss.

THE GOOD

The HFT industry is biased toward speaking of the "Good" rather than the "Bad" or the "Ugly."[27] For that reason, their arguments must be interpreted with as much caution as the critics speaking of the "Ugly" and "Bad" above. The following presents mostly academic empirical results concerning AT and HFT.

Profitability and Industry View

The view of the HFT industry is a good place to start. Essentially, HFT proprietary firms and hedge funds believe their trading style gives them better risk protection than more traditional trading styles, because of the short intraday holding times. Market risk is further decreased by their extremely fast absorption of news content and by taking minimal overnight positions. In the industry's view, their profit maximizing leads to more efficient markets through lower trading costs (especially quoted spreads), lower volatility, higher liquidity, transaction transparency, price discovery, and more diversified market interactions.[28]

With less risk, HFT firms claim to find better profit opportunities than traditional investors. Brogaard [2010] estimated that HFT generates trading profits of \$2.8 billion annually. The TABB Group [2009] estimated \$7.2 billion in net profits in 2009.[29] Kearns, Kulesza, and Nevmyvaka [2010] put an upper bound to \$21 billion in the U.S. equity markets in 2008, but believed the true profits to be more modest (perhaps a few billion dollars). Some real-world examples, such as Renaissance Technologies have exemplified that extraordinary profits can be made.[30] A large chunk of those HFT firms' revenues is thought to be driven by speed of execution and low-latency capabilities to quote and cancel orders. Moallemi and Saglam [2011] showed mathematically the importance of having low-latency in contemporaneous decision-making situations. Many brokers and exchanges also require large volumes to give better fee structures, so to play the game profitably one must have sufficiently low latency and high volume. Easley, Lopez de Prado, and O'Hara [2012] noted that there might be more to this than just speed, however: in their view, HFT is more about strategic order placing and operating in another clock, not a physical one like the ordinary traders, but a volume-induced clock.[31] This presumed HFT's edge would not disappear by setting speed limits on trading.

Trading volumes have increased dramatically over the last decade. Credit Suisse [2010], for example, reported tripled daily volumes in the U.S. equity markets where the share of HFT of daily volume is typically reported to be in the range of 50% to 70% (see, e.g., TABB Group [2009]), being a bit lower in Europe. Similar HFT participation rates have been documented for Australia as well (see Lepone and Mistry [2010]). Those rates are also in line with recent theory (see, e.g. Martinez and Roşu [2011]). But, high volumes alone cannot be considered "Good," unless they serve a good purpose. The argument is that higher volumes imply faster price discovery and higher liquidity and, thus, better market quality. But as discussed in the "Bad" section above, higher volumes do not necessarily lead to those goals. To solve this apparent contradiction, we must first understand what liquidity is and how to measure it. The problem is that no universally accepted definition of liquidity exists. For the purposes of clarifying problems in liquidity measurement, we take a constructive approach and define liquidity to consist of three dimensions: spread, depth, and resiliency as done in, for example, Linton and O'Hara [2011].

Liquidity

There is overwhelming evidence that quoted bid-ask spreads have declined over the last decade or so. Spreads started to dramatically decline already in the end of 1990s due to decimalization. Trading algorithms have narrowed quoted spreads further (see, e.g., Castura et al. [2010]). Menkveld [2012] found a 50% decrease in quoted spreads on Chi-X Europe. Hasbrouck and Saar [2012] studied low-latency automated trading, which is trading that reacts to market events in milliseconds. They found low-latency automated trading was associated with lower quoted and effective spreads on NASDAQ. Their study highlighted that it was crucial to define and to identify HFT accurately. Hasbrouck and Saar approximated HFT activity by "strategic runs" linked to submissions, cancellations, and executions—the tell signs of HFT.

The fact that spreads have narrowed seems to imply that the costs of trading have lowered as well. In addition to retail investors, institutional traders have most likely benefited from those spread decreases assuming they have kept up with the technological pace. That means using some kind of transaction cost analysis (TCA) and AT to minimize adverse price impacts of large orders, slicing large orders into small child orders, and distributing them over different trading venues. OXERA [2011] found that prices and costs of using infrastructure providers declined, as did the costs of using intermediaries. But, the costs expressed in terms of value of trading have increased on some financial centers. Thus, it cannot be unanimously concluded that trading costs have decreased overall.[32]

Smaller spreads and higher automation have reduced the power of certain privileged groups. The good news is that in the automated world there appears to be less room for manipulation in the form of front running and other predatory strategies. Opinions to the contrary have been suggested as well, though. Zigrand, Cliff, and Hendershott [2011] believed that the greater anonymity of computer-based trading has made predatory trading easier. But that misses the fact predatory trading behavior is typically "penny-picking" requiring substantial technological investments and the field is getting more competitive. It is harder to gain a competitive edge without being technologically savvy.

Theoretically, the observed spread decrease is understandable due to fast quoting and cancellation, which minimizes exposure to asymmetric information risk (adverse selection). The high message-to-trade ratios are instrumental in decreasing the spread to low levels. Fiercer competition should take care of any excessively large market making or HFT returns. Martinez and Roşu [2011] showed that as the number of high-frequency traders increased, they tended to make the markets more efficient and more stable. In the end, one would not expect any particular participant to rise above others. Repeating the success of the early HFT adaptors is going to be much harder unless new significant innovations or regulations change the playing field again.

Depth and resiliency need to be considered as well. Angel, Harris, and Spatt [2010], for example, presented evidence that depth improved in the last decade. While the transparency of the order book may have diminished after decimalization and the rise of automated trading, most empirical studies still find the total effect on depth to be positive. Credit Suisse [2010], for example, reported large increases in quoted sizes after 2004. Hendershott and Riordan [2011] found that automated trading demands liquidity when spreads are narrow and depth is high, but not in the converse situation. HFT firms make a service to markets in supplying liquidity when needed and taking liquidity when not critical. Some HFT firms have also become designated market makers, giving some reassurance that HFT can be trusted to provide liquidity also in trouble.[33]

The third dimension of liquidity, resiliency, is the ability of the price to revert back fast to its original price after an abnormal shift, perhaps due to a large order. This dimension of liquidity is harder to measure accurately because it depends on the time-scale of investigation. Although the Flash Crash is an example of a loss of resiliency, it is in some sense only a temporary one.[34] One common way to measure that is the Amihud illiquidity measure. Using it at a daily frequency, Boehmer et al. [2012] found that AT and/or HFT were associated with decreases in liquidity. Gsell [2008], on the other hand, used a simulation-based technique to find, quite expectedly, that AT increased market impact when larger volumes were being traded. Research concerning resiliency is still however rather scant and more should be conducted.

While not all of the dimensions of liquidity have been exhaustively examined in the literature, numerous studies report increases in overall liquidity due to AT and/or HFT (see Gomber et al. [2011] and Markets Committee [2011]). We briefly mention two often referenced academic studies using wider proxies for AT and HFT. First, using the NYSE quote dissemination change to autoquoting in 2003 as an exogenous instrument, Hendershott, Jones, and Menkveld [2011] showed that trading algorithms improved liquidity and enhanced the informativeness of quotes. One potential weakness of their study was, however, that they cannot observe what trade was actually computer algorithm generated and what was human generated, forcing them to use the rate of electronic message traffic as a proxy. Similarly, Chaboud et al. [2011] resorted to a proxy showing the amount of human- and computer-generated trades and quotes at relatively coarse, fixed time-scales in the FX markets. They did not find any evidence of AT and/or HFT causing liquidity shortages. But, as both empirical studies noted, the periods in their analysis were not truly tumultuous, making it uncertain how automated trading would behave outside of normal times.

Price Efficiency and Price Discovery

There exist several definitions of price efficiency, but the most applied states that there cannot be any predictability in prices because they already reflect all relevant information. This, in turn, means that the true value of an asset is discovered correctly and fast. Increased HFT market making activity should, in principle, increase price efficiency and discovery. Increased predatory trading and manipulation could, however, swamp those benefits, but as noted, for example, by Linton and O'Hara [2011], competition should eliminate most of the adverse effects.

Most of the empirical evidence finds that HFT has an overall beneficial effect on price efficiency (see, e.g., Castura et al. [2010]). In particular, Brogaard, Hendershott, and Riordan [2012] concluded that HFT increases price efficiency by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors. In general, the efficiency-enhancing activities of high-frequency traders appear to play a greater role in trading than the alleged manipulative strategies.

Volatility

That HFT increases liquidity suggests that volatility is dampened. There is in fact a fair amount of empirical evidence showing that volatility and HFT are inversely related to each other: HFT tends to be low with high volatility and high with low volatility. Credit Suisse [2010], for example, reported dampening of short-term volatility "that might otherwise be created by large institutional orders filled during the day." Brogaard [2012] reported that HFT was associated with lower intraday volatility on NASDAQ and BATS. Chaboud et al. [2011] did not find evidence of volatility increases in the FX markets. However, as noted before, they used sporadically sampled data so that increases in microstructure noise might not be so evident. Perhaps most notably, Hasbrouck and Saar [2012] found declined volatility in association with low-latency automated trading in equities.

But do the HFT firms participate only in low-volatility regimes, or do they actually lower volatility by their trading practices? Brogaard [2012] addressed the question econometrically using Granger-causality tests and a dataset that identified several HFT firms, but could not determine the direction of causality. Brogaard did find that reducing HFT activity by the short sale ban effective in 2008 increased intraday volatility, suggesting that if regulations were placed to limit HFT, it might have adverse consequences. In a related study, Gsell [2008] also found that low-latency AT decreases volatility, giving some support to the controversial colocation practice.

The empirical findings concerning "Good" can be criticized by the fact that most of them are found in normal times. In a speech given in May 2010, the chair of SEC, Mary L. Schapiro, questioned whether HFT algorithms were "programmed to operate properly in stressed market conditions."[35] Flash crashes are statistically speaking infrequent so no scientifically convincing evidence is yet available. There is at least some cause for concern as shown by Boehmer et al. [2012], who used an extensive international database. By identifying difficult market-making days, they found that some of the "Good" aspects were decreased and short-term volatility was increased more than in normal times. They, however, resorted to using an inaccurate proxy following Hendershott, Jones, and Menkveld [2011]. The results suggested that HFT firms avoided market-making days that put them at a disadvantage with respect to informed investors. But because of the unreliable proxy this could also describe the behavior of institutional AT instead.

It is possible to increase the statistical significance by analyzing events that are more frequent. Brogaard [2012] did that by studying the effect of macro and company specific news on HFT activity and volatility and found that HFT firms tended to take liquidity after macroeconomic news announcements and supply liquidity after company-specific news. Most of the empirical evidence of Brogaard supported the view that HFT reduced volatility. This would also seem to be consistent with the theoretical predictions of Jovanovic and Menkveld [2011], who found that HFT can increase welfare by quickly updating quotes on news in general and, thereby, decrease adverse selection costs on price quotes.

Proposed Policy Recommendations

While the SEC is currently contemplating how to regulate HFT, it is interesting to note that its former chair, Arthur Levitt Jr., took a strong stand in favor of HFT.[36] HFT was, in his view, only the most recent stage in technological innovation and authorities should, thus, not regulate it out of existence. There is much truth to the claim in that restricting progress has never worked out well. The insights offered by Easley, Lopez de Prado, and O'Hara [2012] support it as well. HFT is not perhaps so much about speed as is believed, but more about strategic order placing. Instead of suggesting stricter speed limits for HFT, they offered solutions to make slower traders harder targets for potentially predatory HFT-algorithms. One could also try to create more detailed datasets for regulators, restricting available order types, and by developing real-time screening techniques based on for example the decomposition of automated trading by Donefer [2010].

Stricter regulations or fee structures on HFT could turn out to be suboptimal. They could lead to substantial welfare losses by shifting HFT from being mainly a liquidity provider to being an aggressive liquidity consumer (see Jovanovic and Menkveld [2011]). Levitt argues that there is nothing wrong in looking for inefficiencies and exploiting them fast, especially if it facilitates liquidity, pricing, and healthy transparent markets.

An introductory book by Aldridge [2010] summarized a few key social benefits of HFT: increased market efficiency, added liquidity, innovation in computer technology, and stabilization of market systems. Those and other benefits are supported by the academic studies reviewed above, although there is some concern on how stable the markets are with HFT. One solution could be to require market makers to always trade. Venkataraman and Waisburd [2007] showed that there were benefits of having designated (but not otherwise privileged) market makers directly compensated by the listing firm. However, history has taught us that even they prefer to stop providing liquidity in difficult times.[37] As a potentially more flexible solution, real-time variable make/take-fees have been suggested to attract liquidity. In times of high market stress, larger rebates would be paid out to liquidity providers to attract them. The theoretical model of Foucault, Kadan, and Kandel [2012] could form a basis for pre-analysis.

Overall, we need to pay more attention to what we are talking about. First, we need a good working definition of HFT and to reach a consensus of how to measure liquidity and other key concepts for HFT. Several characteristics of HFT have been suggested in the literature, but no all-satisfying definition has been found. Pressure to find it is building up among regulators: CFTC Commissioner Scott D. O'Malia has suggested a seven-part test for what constitutes HFT.[38] Second, we need extensive data of HFT covering different periods for better statistical analysis. We need to identify HFT and separate it from other forms of electronic trading, especially institutional AT. Until then, we are mere speculators placing probabilities on "Good," "Bad," and "Ugly." We hope the reader is now at least in a more favorable position to place a bet on her own.

CONCLUSIONS

We have reviewed the literature on "the Good, the Bad, and the Ugly" aspects of HFT. Based on the results of mostly academic studies of both theoretical and empirical nature, we cannot conclude which interpretation is the correct one from a neutral standpoint. It seems, however, that the "Good" aspects have the most weight and dominate the other aspects. That said, evidence on the "Bad" and the "Ugly" is gaining some momentum. Once we have clearer working definitions for HFT and AT and gain better access to more exhaustive datasets, we should be able to make more sound policy recommendations.

To decompose this general conclusion more usefully, we state the main message of each category in turn. First, the main message of the "Ugly" is that speed kills. Flash crashes and other extreme events eventually force financial markets down on their knees by higher systemic risk that is induced by HFT and, in the process, wealth is being redistributed from ordinary traders to predatory-like high-frequency traders. Second, the main message of the "Bad" is that HFT is a Pandora's Box. The seemingly good attributes of HFT are a hoax and market quality in the form of volatility, liquidity, transparency, and price discovery is mutilated and the health of the markets jeopardized. Finally, the main message of the "Good" is that progress should not be denied. HFT is part of the 21st-century trading technology and by acting competitively, it guarantees better performing financial markets in just about every respect imaginable.

To be fair, each of those arguments is excessively pointed. The truth lies somewhere in the midst of the three dimensions. Obviously, the "Bad" and the "Ugly" are closer to each other than the orthogonal "Good." Policy and regulations will play an increasingly large role in the future of financial markets. Looser regulations have allowed the fragmented, competitive structure we see today. Now they have the capacity to reform the financial markets again. HFT, and possibly other forms of automated trading, should present their case clearly, so that when the regulations get changed, the health of the markets is actually improved and not impaired. Technological advancements in the form of better simulation capability and real-time screening could be used as a guideline. Empirical experiences from the United States, Europe, and other parts of the world should be evaluated rigorously and their differences and flaws compared in a commensurate way. There is no turning back to age-old trading practices. Technology is here to stay and we must find means to control it.

ENDNOTES

[1]*Wall Street Journal.* "Does High-Speed Trading Hurt the Small Investor?" October 9, 2011.

[2]MacKenzie, M. "High-Frequency Trading under Scrutiny." *Financial Times*, July 28, 2009.

[3]Salmon, Felix and Jon Stokes. "Algorithms Take Control of Wall Street." *Wired*, December 27, 2010.

[4]BBC. "Quant Trading: How Mathematicians Rule the Markets." September 25, 2011. Available at http://www.bbc.co.uk/news/business-14631547.

[5]Gasparov, G. "The Chess Master and the Computer." New York Review of Books, February 2010. Available at http://www.nybooks.com/articles/archives/2010/feb/11/the-chess-master-and-the-computer/?pagination=false.

[6]To emphasize the view we take, in the title of this article we use "automated HFT" instead of simply "HFT." Some authors use automated and algorithmic interchangeably (see Zhang and Powell [2011]), which is confusing. Some proprietary trading firms propose to use the term "automated professional traders" (see Connell et al. [2010]).

[7]Bertsimas and Lo [1998] studied the dynamic optimization problem of how large positions of assets should be accumulated or liquidated through breaking them into smaller pieces to minimize the expected cost of execution.

[8]"typically is used to refer to professional traders acting in a proprietary capacity who engage in strategies that generate a large number of trades on a daily basis. Other characteristics often attributed to proprietary firms engaged in HFT are: 1) the use of extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders; 2) use of co-location services and individual data feeds offered by exchanges and others to minimize network and other types of latencies; 3) very short time-frames for establishing and liquidating positions; 4) the submission of numerous orders that are cancelled shortly after submission; and 5) ending the trading day in as close to a flat position as possible (that is, not carrying significant, unhedged positions over-night)." (SEC [2010].)

[9]YouTube: Senator Kaufman discusses HFT on MSNBC's Dylan Ratigan Show. Available at http://www.youtube.com/watch?v=eu-e9x_FKp0.

[10]*Automated Trader.* "What Just Happened?" 2010. Available at http://www.automatedtrader.net/articles/risk/50335/what-just-happened.

[11]Bowley, Graham. "Ex-Physicist Leads Flash Crash Inquiry." *New York Times*, September 20, 2010.

[12]Buchanan, Mark. "Flash-Crash Story Looks More Like a Fairy Tale." *Bloomberg*, May 7, 2012.

[13]*Wall Street Journal*. "A Call to Pull Reins on Rapid-Fire Trade." October 2011.

[14]Kirilenko et al. [2011] used a rather unusual definition of liquidity: in their article, they argued that high-frequency traders supply liquidity by executing against the standing limit-orders. This is the opposite to the standard notion of liquidity supplying by placing limit-orders in the book.

[15]Katz, Gary. "Relying on the 'Rules of the Game' in the U.S. Options Market." 2011.

[16]Keim, Brandon. "Nanosecond Trading Could Make Markets Go Haywire." *Wired Magazine*, February 16, 2012.

[17]*MIT Technology Review*. "How Dragon Kings Could Trump Black Swans." August 4, 2009.

[18]Duhigg, Charles. "Stock Traders Find Speed Pays in Milliseconds." *New York Times,* July 23, 2009.

[19]*Wall Street Journal*. "NYSE's Fast-Trade Hub Rises up in New Jersey." July 3, 2009.

[20]For more detail on manipulation techniques, see Biais and Woolley [2011] and Easley, Lopez de Prado, and O'Hara [2012].

[21]Krugman, Paul. "Rewarding Bad Actors." *New York Times*, August 2, 2009.

[22]*Financial Times*. "High-Frequency Trading under Scrutiny." (July 28, 2009).

[23]Regulation National Market System (RegNMS).

[24]ZeroHedge. "Scientific Proof That High Frequency Trading Induces Adverse Changes In Market Microstructure And Dynamics, And Puts Market Fairness Under Question." July 13, 2010. Available at http://www.zerohedge.com/article/scientific-proof-high-frequency-trading-induces-adverse-changes-market-microstructure-and-dy.

[25]It is for example incorrect to state that self-similarity has increased because pure random walk in continuous-time, that is, Brownian motion, is as self-similar as fractional Brownian motion with a higher ($H > 0.5$) Hurst exponent.

[26]Bank of England. "The Race to Zero." News release on a speech by Andrew Haldane, July 8, 2011. Available at http://www.bankofengland.co.uk/publications/Pages/news/2011/068.aspx.

[27]See the recent speech given by Jim Simons, the founder of Renaissance Technologies: video at 48:20. Available at http://www.marketfolly.com/2012/03/rentecs-jim-simons-on-mathematics.html?utm_source=feedburner&utm_medium=feed&utm_campaign=Feed:+MarketFolly+(Market+Folly).

[28]Tradeworx. Public Commentary on SEC Market Structure Concept Release." April 21, 2010. Available at http://www.sec.gov/comments/s7-02-10/s70210-129.pdf.

[29]*Wall Street Journal*. "A Wild Ride to Profits." August 16, 2011. Available at http://online.wsj.com/article/SB10001424053111904253204576510371408072058.html.

[30]Renaissance Technologies' Medallion Fund: Performance Numbers Illustrated. Available at: http://www.marketfolly.com/2010/06/renaissance-technologies-medallion-fund.html.

[31]This idea goes again back to the 1960s: it was Mandelbrot and his authors who suggested using "subordination."

[32]This depends crucially on if costs are transaction or volume based.

[33]*Traders Magazine*. "Designated Market Making Alive and Well at NYSE." December 23, 2011. Available at http://www.tradersmagazine.com/news/market-maker-nyse-trading-109684-1.html.

[34]This opinion, and how it compares to the 1987 market crash, was raised for example by Jim Simons: video at 50:56.

[35]Schapiro, Mary L. "Strengthening Our Equity Market Structure." SEC speech. May 2010.

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