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Exploring the Key Debates Surrounding Algorithmic Trading

One of the ways in which the finance industry is changing as a result of the use of new algorithmic systems is through the implementation of algorithmic trading. Algorithmic trading is defined as trading in financial markets where a computer algorithm, programmed to follow a pre-determined set of instructions, automatically determines the individual parameters of orders such as the timing, price, quality, and management of the order with little to no human intervention (Gomber and Zimmermann 2). For example, a user could program an algorithm to buy fifty shares of a stock when it is moving above the 50-day moving average or sell when it dips below (Seth 2021). Thus, the trader no longer has to monitor the live share price or place orders manually. Users cite faster and more precise trading, lower costs, and increasing liquid market that contributes to greater market quality. In contrast, critics argue that algorithmic trading is highly unregulated, biased, and volatile, resulting in undesired outcomes where losses can accumulate quickly.

To begin, the first benefit of algorithmic trading is faster trading and a more precise trading design strategy. In a study by Gsell and Gomber from 2009, the two authors focus on the differences in trading patterns between human traders and computer-based traders. They not only found that they could distinguish between algorithmic and human submissions, but that the algorithm's transactions were more frequent and in smaller orders (Gomber and Zimmermann

14). The authors also state that while algorithms are fundamentally different than human traders, “algorithmic trading systems capitalize on their ability to process high-speed data feeds and react instantaneously to market movements by submitting corresponding orders or modifying existing ones” (14). Thus, the algorithm’s speed allows it to be pinpoint-accurate and could result in more profits for the user than doing their transactions manually.

Secondly, the use of algorithmic trading improves the overall market quality for traders. In a 2011 study by Hendershott et al., the authors assessed the New York Stock Exchange’s release of automated quotes from 2003 (15). The authors analyzed the trades before and after the automated quoting update and found that algorithmic trading “lowers the costs of trading and increases the informativeness of quotes” (15). Additionally, another 2011 study from Hendershott and Riordan found that algorithmic trading consumes liquidity when it is cheap and provides liquidity when it is expensive, thereby dampening volatility in unstable market phases (15). An algorithm is programmed to satisfy particular parameters, and so when the market is more volatile, they do not retreat. This results in liquidity even if markets become unstable, and thus “dampen[s] price fluctuations and contribute to the robustness of markets in times of stress” (16). A computer program takes away all of the emotion from investing. Where a human thinks about the impact of trading on their livelihood, a computer sees only numbers, and thus allows them to be much calmer in highly volatile markets. This makes algorithmic trading a useful and more stable option in this type of environment than the average human trader.

With that being said, there are several risks associated with relying on an algorithm to make money in financial markets. One risk that has been identified by the Senior Supervisors Group (SSG) in an Algorithmic Trading Briefing Note from April 2015 states that the internal controls of these algorithms may not be able to keep pace with the speed and complexity of the

market (Senior Supervisors Group 5). For example, the authors emphasize that the risk controls vary widely to keep pace with this type of activity (5). Furthermore, SSG expresses concerns about the amount of risk accumulated without transparency or robust controls (5). Technology failures or an unexpected failure in the algorithm during the day can result in more risk than the firm or individual has originally intended (5). Thus, without proper controls, losses can accumulate and spread much quicker than someone who is controlling their fate. Especially for individuals who are ill-informed about the market or coding, as it is difficult to learn them both individually, let alone together.

Similar to other uses of artificial intelligence, algorithmic trading poses risks associated with bias in the baseline data they receive. In an article from Forbes, Sam Farao, CEO of Banqr, emphasizes that although data is 'neutral' it is not free from conscious or unconscious bias (Brown and Farao 2021). Therefore, data used in an algorithm for trading poses a significant risk of bias in terms of favorable prices under certain conditions. The data used could be from a much more stable moment in the market, but in a more volatile scenario, the same conditions may not provide the same benefit, leading to a loss or a gain much smaller than it could have been.

As with any new technology, the law is much more reactive than proactive. Thus, the government should begin to explore how it could regulate algorithmic trading. From an ethical standpoint and a slightly pessimistic one too, there are a few ways in which algorithmic trading could be used unethically. First, market manipulation is defined by the SEC as "intentional conduct designed to deceive investors by controlling or artificially affecting the market for a security" (Wellman et al. 619). There is a possibility for traders to program an algorithm to pump a certain stock, think Wall Street Bets type, that drives up the price and therefore results in major gains for the trader. In an even worse scenario, traders can use an algorithm to perform a

malicious action. For example, Wellman et al. identify some illegal scenarios such as “denial-of-service or other cyber-attacks on electronic markets, presentation of false credentials, or corruption of critical records” (621).

Thus, I conclude that in a more proactive measure, it would be highly favorable for G7 governments to consider exploring options into regulations and infrastructure that could prevent the forthcoming of these situations. Willman et al. describe it perfectly when they write, “some clarifications will be required in order to maintain financial integrity in the face of autonomous trading agents adept at finding and exploiting loopholes” (621).

Works Cited

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This text is hyperlinked to the Gsell and Gomber 2009 study in the Gomber and Zimmerman piece.

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