1. Introduction

The financial world has witnessed a skyrocketing volume of algorithmic (bot) trading since the beginning of the 2000s. Today most transactions in financial markets are executed by automated trading systems. According to Treleaven et al. (2013), algorithmic trading already accounted for more than 70% of US stocks' trading volume in 2011. Flash crashes, which until May 6, 2010, were unprecedented phenomena of extreme short-term volatility triggered by high-frequency algorithmic trading (Kirilenko et al. 2017), prominently demonstrate that algorithms have radically changed the financial market environment. It seems fair to say that today, without understanding the impact of algorithmic trading, a thorough understanding of market behavior would become almost impossible.

To understand the market behavior, we need answers to many questions. For example, what are the impacts of the usage of trading algorithms on market quality, what would be the return to such algorithms, and how will they affect human traders' performance and behavior? How do humans, especially individual investors, respond to trading in markets dominated by algorithms; does interaction with algorithmic traders generate emotional or psychological responses in human traders that impact market sentiment and thus price fluctuations? What type or features of algorithms are either helpful or rather harmful to investors; what kind of regulation is sensible?

We contribute to this research by reviewing the answers given to some of these questions by the experimental literature focusing on the interaction between algorithms and humans in laboratory markets.

Related literature reviews discuss algorithmic trading in the real-world financial marketplace. Kirilenko and Lo (2013) provide an initial review of algorithmic trading in the real-world financial marketplace. The authors acknowledge types of automated trading, including passive strategies like market-making, arbitrage trading, and more aggressive high-frequency trading. They recount important historical events in the age of machine trading, including the 2010 flash crash and cases of high-frequency trading manipulation such as spoofing. Finally, they reflect on potential regulatory measures, particularly in view of the presence of high-frequency trading algorithms, including speed bumps and Tobin taxes. Goldstein et al. (2014) provide a literature survey on algorithmic trading, including theory and studies based on real-world data. Miller and Shorter (2016) survey recent developments in high-frequency trading strategies, focusing on recent efforts in regulatory measures. Beckhardt et al. (2016) provide a broad survey on high-frequency trading strategies, including simulation analyses of profitability. We refer the interested reader to the literature reviews mentioned above as these issues go beyond the scope of the current review, which is limited to controlled laboratory studies. A related area of interest is agent-based modeling, that is, computer simulations where algorithms interact with algorithms. Duffy (2006) provides an excellent survey. He summarizes the literature on zero-intelligence agents, learning, and evolutionary algorithm models of agent behavior. Duffy also reviews the literature that compares human laboratory results with simulation results. Brewer (2008) and De Luca et al. (2011) also review zero-intelligence agents and their extensions. In the following section, we review some relevant algorithms for the interaction with humans discussed in that literature. Closer to us in terms of coverage, March (2019) provides a broad literature review on the interaction of computer players with human subjects, including experiments on strategic reasoning, social dilemmas, markets, auctions, bargaining and negotiation, among other topics. Naturally, this literature review has some overlaps with March's review, notably with his section on market experiments. Nevertheless, our focused approach allows a more detailed report of the studies in question and we also include unpublished work. This chapter provides an overview of the experimental literature on algorithmic trading in experimental financial markets, focusing on human-robot interaction.2 The reported research is interdisciplinary. The interaction of man and machine is of general interest to the behavioral sciences and the computer sciences. The findings of this research can have implications for regulation. That said, the laboratory research that we report here is nascent. Based on the literature survey, we propose, without the ambition of being conclusive, some interesting questions for future research in this area and possible policy implications. The remainder of the chapter is organized as follows. Section 2 reviews the literature on experimenter-induced algorithms that concentrate on the profitability of algorithms versus human traders, studies that look at market quality, the behavioral effects of algorithm response speed, manipulation, arbitraging activity, and the question of subjects' aversion to interacting with algorithms. In section 3, we review studies in which the experimenter leaves in human subjects' hands the decision to employ algorithms for trading. In section 4, we finally conclude and discuss future directions.

2 Algorithms in the hands of the researcher.

Algorithmic trader - Main features

Zero intelligence (ZI) - Algorithm randomly submits orders subject to minimal budget constraint without profit maximization (Gode and Sunder 1993).

Kaplan's Sniping Agent - The algorithmic sniper seller (buyer) sends a limit order to sell (buy) at the market best bid (offer) if at least one of three conditions is met; the best bid (offer) is at least as good or better as the high (low) transaction price of the previous period; the bid-offer spread is small while the expected profit is more than a minimum profit factor ; few instances of time left until the closing of the market period (Rust et al., 1994).

Zero intelligence plus (ZIP) - ZI algorithms with adaptive profit margin which is defined as the difference between the target price and the submitted price. The profit margin is increased/decreased by the algorithm after successful/failed transactions (Cliff and Bruten 1997).

Gjerstad/Dickhaut - GD agent - Algorithm submits orders to the market that maximize its expected surplus based on an updated belief distribution. The GD agent forms a belief about an offer or bid being accepted at price p based on the recent market history of accepted and unaccepted (including inframarginal and extramarginal) orders at that price (Gjerstad and Dickhaut 1998).

Arbitrage trader - Algorithm risklessly exploits mispricing across markets of perfectly correlated assets (e.g, Angerer et al. 2019).

Spoofing - Algorithm aims at manipulating market sentiment by placing a huge limit order (which is not attempted for transaction and which is quickly cancelled upon attempt) while simultaneously trading in the opposite direction (e.g., Leal and Hanaki 2018).

Manipulator - Algorithm, aimed at manipulating demand and supply, repeatedly buys shares by overbidding the best outstanding bid and subsequently sells the shares by undercutting the best offer (Veiga and Vorsatz 2009; 2010)

Market-maker - Algorithm submits bid-offer spreads around the target price (e.g., Aldrich and Lopez Vargas 2020)

Reactionary bot - Algorithm reacts to a (range of) specified limit orders by submitting a market order as soon as a specified order enters the market (Asparouhova et al. 2020)

2.1 Comparison of algorithms in simulations with human traders in experimental markets

Text -

The early experimental studies involved no interaction between algorithms and human subjects. These studies compare the outcomes of interactive experiments with human subjects to the ones of interacting algorithms in the continuous double auction (hereafter CDA) markets. The focus of these studies is typically on market efficiency or trader performance. The documented academic research on algorithms in asset markets seemingly started in the late 1980s. Shyam Sunder (2003, p. 10f) recounts his approach: the press blamed the stock market crash of 1987 on algorithmic trading. Skeptical of this claim, Sunder designed and taught a course at Carnegie Mellon University on algorithmic trading to learn about the structure of trading strategies and the behavior of the CDA market. Being challenged by the students in the course, he and Dan Gode programmed a random algorithm -later labeled ‘zero intelligence or ZI traders (Gode and Sunder 1993), which adheres to a budget constraint. The chosen CDA market environment followed the one in Smith (1962), with induced values and costs. ZI traders provide liquidity to the market by repeatedly submitting orders; ZI buyers submit random bids between 0 and the experimenter induced value; ZI sellers submit random offers between the upper bound of the cost distribution and the induced cost level. Since traders have zero intelligence, they do not profit-maximize, remember or learn. In Gode and Sunder (1993), a ZI transaction occurs whenever the best bid exceeds the best offer (each for one unit), the transaction price being equal to the earlier submitted one of the two. The result was that ZI agents achieved an allocative efficiency of 99% across different sessions, comparable to the one found in data from experiments with human subjects. Gode and Sunder (1993, p. 134) conclude that “the high allocative efficiency of double auctions is [caused by] market discipline imposed on traders” and not by profit maximization, learning, and intelligence. This study in particular and more generally the literature on zero-intelligence traders (summarized in Duffy 2006; De Luca et al., 2011) provides a very important step towards a micro-foundation of general equilibrium theory by showing that market efficiency does not rely on perfect individual rationality and utility maximization behavior. Nonetheless, the trajectories of equilibrium market prices with human subjects are relatively flat, whereas those with ZI agents produce continued volatility around the equilibrium price. Cliff and Bruten (1997) show that with ZIP agents, which are ZI agents with an adaptive profit margin (see section 2.2.), the market price convergence trajectories are similar to human behavior. In a more complex CDA market design with a multi-period lived asset, which frequently generates bubbles and crashes in laboratory studies (i.e., the design of Smith et al. 1988), Duffy and Ünver (2006) also report price and volume paths similarities of their enhanced “near” ZI-trader markets with the human-trader experimental results of Smith et al. (1988). In particular, the authors are able to reproduce bubble and crash patterns in the simulated “near ZI” market. Different from the ZI of Gode and Sunder (1993), the “near ZI” trader’s bids and offers are not purely random but are biased towards the past period’s average price. Arifovic (1996) finds in an experimental macroeconomic setting that the market price behavior of human experimental subjects shares similarities to that of a genetic algorithm. The genetic algorithm selects a decision rule which is updated from one generation to the next using the three genetic operations in offspring generation; reproduction, crossover, and mutation. Rust et al. (1994) report on the Santa Fe Institute double auction tournament -SFDAT in 1990/91. For the SFDAT, 30 colleagues submitted the strategies of profit-maximizing algorithms, including quite complex ones, to trade with another in the Smith (1962) CDA market. To their surprise, the tournament winner involved relatively simple liquidity absorbing (profit-making) strategy -later labeled Kaplan’s Sniping Agent. The Sniper seller (buyer) sends a limit order to sell (buy) at the market best bid (offer) if at least one of three conditions is met. They are, firstly, the best bid (offer) is at least as good or better as the high (low) transaction price of the previous period; secondly, the bid-offer spread is small while the expected profit is more than a minimum profit factor; and thirdly, few instances of time left until the closing of the market period. Later simulation studies highlighted that this Kaplan’s sniper could only be profitable if few agents apply it, as this trading strategy does not play a best response against itself. In conclusion, markets inhabited with algorithmic traders, even with the simplest algorithms, show convergence to the equilibrium similar to the one in the markets of human traders only. This conclusion validates the robustness of the continuous double auction market institution in terms of price discovery and equilibration. However, in the real world, algorithms interact not only with other algorithmic traders, but also with human traders, and the interaction of humans and algorithms in hybrid markets can lead to frictions. The remainder of the chapter focuses on hybrid experimental markets in which algorithms and human subjects transact assets and cash.

Summary :

Summary of Early Experimental Studies on Algorithmic Trading

Focus: Market efficiency and trader performance in continuous double auction (CDA) markets.

Start: Late 1980s, driven by skepticism about the role of algorithmic trading in the 1987 stock market crash.

Key Studies:

- **Zero Intelligence (ZI) Traders (Gode & Sunder, 1993):**
    - Randomly submit orders within budget constraints.
    - Achieve high allocative efficiency (99%) similar to human traders.
    - Suggested market efficiency comes from market discipline, not individual rationality.
    - Price paths show more volatility than with humans.
- **Zero Intelligence Plus (ZIP) Traders (Cliff & Bruten, 1997):**
    - ZI with adaptive profit margins.
    - Price convergence trajectories become more similar to human behavior.
- **Near ZI Traders (Duffy & Ünver, 2006):**
    - Bids/offers biased towards past average price.
    - Reproduce bubble and crash patterns observed with human traders.
- **Genetic Algorithm (Arifovic, 1996):**
    - Market behavior of human subjects similar to a genetic algorithm.

- **Kaplan's Sniping Agent (Rust et al., 1994):**
    - Simple, profitable strategy based on specific market conditions.
    - Not profitable if widely used (doesn't play a best response against itself).

Conclusion:

- Algorithmic traders, even simple ones, can achieve similar market efficiency as humans in CDA markets.
- This validates the robustness of CDA markets for price discovery and equilibrium.
- However, real-world markets involve human-algorithm interaction, which can introduce frictions.

CDA refers to **Continuous Double Auction** in this context.

It's a type of market where buyers and sellers can submit bids and offers for an asset continuously throughout the trading day. Orders are automatically matched based on price, with the highest bid being matched with the lowest offer at a specific price point. This process continues until there are no more matching bids and offers.

The CDA market structure is known for its efficiency in price discovery, meaning it helps establish a fair market price for the asset being traded.

2.2. .Performance of algorithmic and human traders in hybrid experimental markets

Text -

Das et al. (2001) study how agent-human interaction influences human traders' market outcome and trading performance in a hybrid experimental asset market setting within a CDA environment with induced values (Smith 1962). In each of their experimental markets, there are 6 human traders and 6 algorithmic traders (3 buyers and 3 sellers each). Depending on the treatment, the algorithmic trader may adopt one of two types of adaptive trading strategies: (1) the “zero intelligence plus (ZIP)” algorithm (Cliff and Bruten 1997) provides liquidity to the market, similarly to ZI. Still, its orders involve a private profit margin updated over time if a limit order either fails to transact or transacts immediately. When a trade takes place, all agents adjust their bids towards the transaction price. If no trade occurs in t seconds, all agents adjust their bids to improve the best existing bid. (2) The GD algorithm (Gjerstad and Dickhaut 1998) submits orders to the market that maximize its expected surplus based on an updated belief distribution. The GD agent forms a belief about an offer or bid being accepted at price p based on the recent market history of accepted and unaccepted (including inframarginal and extramarginal) orders at that price. Das et al. (2001) find that compared to CDA markets with all-human design or all-algorithm design, the market price shows slower convergence to the equilibrium price in their experimental hybrid market. Meanwhile, human traders underperform algorithms by about 20% in trading surplus. Gjerstad (2007) studies how different market structures and paces of submitting bids and offers influence the trading performance of humans and the GD algorithm in a CDA market with induced values (Smith 1962). There are 6 buyers and 6 sellers in the experimental market. In the hybrid markets involving interaction between human and GD agents. The experiment involves both unbalanced markets (with 6 algorithmic traders on one side and 6 human traders on the other side) and balanced markets (where 3 human buyers/sellers and 3 automated buyers/sellers are on each side of the market). Interested in submission pace, the author differentiates treatments between “patient” and “impatient” algorithmic traders regarding waiting time before submitting a new order. Patient traders submit bids and offers at a slower pace than impatient ones. The result of the paper shows that all markets achieve a very high level of efficiency (usually more than 99.5%). Meanwhile, impatient algorithmic traders’ profitability seems to be lower compared to the patient ones. If algorithmic buyers/sellers are too actively submitting new limit orders, the price moves up/down quickly thus adversely impacting their profits. In general, the profit of patient algorithmic traders is highest, followed by the impatient ones, and human traders’ profit is lowest. The latter result is impacted by the low performing human sellers; human buyers and automated buyers have a similar performance. Unbalanced markets result in greater differences between the performance of humans and agents than balanced markets. Peng et al. (2020) study balanced, unbalanced and uncompetitive markets with “fast” and “slow” ZIP agents. The authors confirm the result of Das et al. (2001) that algorithms outperform human traders in the “fast” treatment in a balanced market. The result seems to be due to “fast” ZIP buyers benefitting from low-priced offers faster than human buyers. In all other conditions, contrary to the result of Das et al. (2001), Peng et al. report that human traders outperform “fast” algorithmic traders. Again, these results are obtained for the simplistic CDA market with induced values (Smith 1962). In a more complex environment, in which earnings depend on the share price at period end, Feldman and Friedman (2010) study human-algorithm interaction in a hybrid experimental CDA market. The studied algorithmic traders are adaptive optimizers adjusting their portfolio composed by a riskless asset and a risky asset in accordance with their changing payoff expectation. Their experimental treatments vary in the composition and the size of markets. Human traders interact with algorithmic traders in large markets (1 human and 29 robots or 5 human and 25 robots) and small markets (5 human traders and 5 robots). The key findings of their study include: (1) the average trading gain of human traders is generally smaller than of algorithmic traders, but human traders may outperform algorithmic traders in market crashes; (2) human traders tend to destabilize small markets and neither stabilize nor destabilize large markets; (3) human traders respond to the payoff gradient similarly as the algorithmic trader. In their study, it is interesting to note that human traders earned higher profits during crashes (i.e., lose less with extreme market volatility) and tend to sell faster after experiencing a loss, although generally exhibiting similar trading behavior as the algorithms. Tai et al. (2018) let one human subject interact in CDA markets populated with ZI traders or with adaptive algorithmic traders of SFDAT, including Kaplan's Sniper, GD, and ZIP. Surprisingly, subjects' earnings are higher in the treatment with adaptive algorithmic traders than with ZI traders. The authors conjecture that subjects' cognitive working memory capacity impacts their trading acuity and test this hypothesis in asymmetric and symmetric CDA markets of Smith (1962) type. The result confirms the hypothesis; subjects with high elicited working memory capacity earn higher profits than those with low elicited working memory capacity; the difference is pronounced in the more complex environments, i.e., asymmetric markets and adaptive agents. Akiyama et al. (2017) implement an algorithm that trades on fundamentals in a Smith et al. (1988) call-auction asset-market design involving belief elicitation on future prices. The authors propose two treatments to study the question of strategic uncertainty as a cause for bubbles and crashes: treatment with 6 human subjects and treatment with 1 human trader and 5 algorithmic traders committing transactions at fundamental value. In the second scenario, strategic uncertainty is eliminated while participants have perfect information about the algorithm's presence and its performed strategy. The results of Akiyama et al. (2017) suggest that strategic uncertainty might partly explain observed mispricing in this market. Using the same experimental setting, Hanaki et al. (2018) show that traders' performance is negatively correlated with their confidence in their short-term price forecast. In a related study, Ahrens et al. (2019) also use this experimental design with the fundamentalist algorithm to investigate subjects' overconfidence in their price forecast to find that the level of overprecision (i.e., the narrowness of the predicted confidence interval) may be endogenously determined or influenced by the observed market price dynamics. It tends to go up (down) when the asset price goes up (down). To conclude, experiments in hybrid markets shed light on the limitations of both algorithmic and human traders. On average, algorithmic traders gain higher profits than humans particularly in early trading phases, but human traders may learn and adapt more quickly to extreme volatility and more complex market environments than simple algorithms. Most of the reported results were achieved in a convergent environment (Smith 1962). It is an open question for further research, how "near ZI" traders (Duffy and Ünver 2006), GD traders or snipers would perform in a more complex hybrid CDA market design such as in Smith et al. (1988), which is known for mispricing. It would be interesting to see if such algorithmic traders would rather have a stabilizing or destabilizing effect on the market.

Summary -

Summary of Human-Algorithm Interaction in Algorithmic Trading

Focus: How interaction between human and algorithmic traders affects market outcomes and performance in CDA markets.

Studies:

- **Das et al. (2001):**
    - Hybrid market with human and ZIP/GD algorithms.
    - Slower price convergence to equilibrium compared to all-human or all-algorithm markets.
    - Humans underperform algorithms in trading surplus.
- **Gjerstad (2007):**
    - Human vs. GD algorithm performance in balanced/unbalanced markets.
    - Patient algorithmic traders achieve highest profits (followed by impatient ones, then humans).
    - Unbalanced markets lead to larger performance differences between humans and algorithms.
- **Peng et al. (2020):**
    - Balanced, unbalanced, and uncompetitive markets with fast/slow ZIP agents.
    - Confirm Das et al. (2001) findings for fast ZIP in balanced markets (humans underperform).
    - In other conditions, humans outperform fast algorithms.
- **Feldman & Friedman (2010):**
    - Human-algorithm interaction in large/small CDA markets.
    - Algorithmic traders generally outperform humans, but humans may do better in crashes.

    - Humans tend to destabilize small markets.
    - Human trading behavior is similar to algorithms, but humans react better to crashes.
- **Tai et al. (2018):**
    - Humans interact with ZI or adaptive algorithmic traders (Kaplan's Sniper, GD, ZIP).
    - Humans earn more with adaptive algorithms than ZI traders.
    - Higher cognitive working memory capacity leads to higher human profits (more in complex markets).
- **Akiyama et al. (2017):**
    - Humans vs. algorithm trading on fundamentals.
    - Strategic uncertainty might contribute to bubbles and crashes.
- **Hanaki et al. (2018):**
    - Trader performance negatively correlates with short-term price forecast confidence.
- **Ahrens et al. (2019):**
    - Overconfidence in price forecasts may be influenced by market dynamics.

Conclusions:

- Algorithmic traders often outperform humans, especially early in trading.
- Humans may adapt better to extreme volatility and complex markets.
- Most studies used a simple market design (Smith 1962).
- Future research: How do algorithms perform in more complex markets (e.g., Smith et al. 1988)?

Overall: Hybrid markets present a complex interaction between human and algorithmic traders, with both limitations and potential benefits on each side.

2.3 Algorithm Speed

Text -

Faster than human response speed to profit from trading has been one of the main reasons for the adoption of algorithmic trading in asset markets, and therefore, it has been an innate research question how much algorithmic traders' profit from low latency, i.e., the minimal response delay. In the previous section, we have already suggested that fast algorithmic traders do not necessarily outperform slower algorithmic traders. Gjerstad (2007) found that patient GD agents perform better than impatient GD agents, and both perform better than human traders in the hybrid market. Das et al. (2001) vary the ZIP algorithm's response speed, introduced by a "sleep-wake cycle", to examine the interaction between humans and algorithmic traders. The "fast" algorithm would be idle for t = 1 second and become active when a new quote or trade is made. The "slow" algorithm would be idle for t = 5 seconds and only become active when a trade is made. When active, the algorithm would update its orders by submitting a new order or updating the existing order. Das et al. (2001) observe more transactions in the "fast" than in the "slow" ZIP treatment. In both treatments, algorithmic traders tend to trade among themselves first before trading with human traders and price trajectories converge to the competitive equilibrium. Das et al. (2001) suggest that algorithmic ZIP traders may outperform their human counterparts in a balanced human-algorithm market, but there are too few observations to draw any conclusion on the performance effect of speed. Contributing data to this point, Cartlidge and Cliff (2013) study the effect of algorithm response speed in the hybrid market involving a further enhanced ZIP agent (called "aggressive adaptive strategy"). They consider four different sleep-wake cycle treatments including the two time-cycles of Das et al. (2001) and two extreme ones; t = {0.1, 1, 5, 10}. The data seem to suggest that the average algorithmic trader earns a lower positive margin over humans in the "fast" treatment (t = 1) than in the "slow" treatment (t = 5). However, the positive marginal gain of algorithmic traders over humans is not a monotonous function of sleep time t, as superhuman speed (t = 0.1) earns a high margin and the very slow speed (t = 10) a low one. Peng et al. (2020) follow up on Das et al. (2001) to investigate the role of ZIP response speed in different market structures involving symmetric and asymmetric demand-supply schedules and balanced and unbalanced markets. Human traders outperform "fast" ZIP traders in all conditions other than the balanced market, and humans outperform "slow" ZIP traders in all balanced and unbalanced competitive markets, i.e., where the number of buyers equals the number of sellers. "Slow" ZIP traders outperform human traders and "fast" ZIP traders in situations of market power. Peng et al. report interesting convergence patterns to the competitive equilibrium; the trajectories seem biased in favor of the trader side that has market power or patience or both. For instance, if there is only one human seller and 6 "slow" ZIP buyers, price trajectories approach the equilibrium from above; or if there are 6 "fast" ZIP sellers and 6 human buyers, price trajectories approach the equilibrium from below. Cartlidge et al. (2012) conduct a series of laboratory experiments assessing the role of algorithms' super-human speed in market efficiency and their performance in an environment where human traders and algorithms interact in the market. They find that the purely simulated market inhabited by slower algorithms, whose trading speed resembles the speed of human traders, seems to converge closer to a competitive equilibrium with enhanced market efficiency. Also, in a hybrid experimental market where human traders interact with algorithms, Cartlidge and Cliff (2013; 2018) investigate the impact of the millisecond-by-millisecond speed of the stock price movement. They argue that there is a price-movement-speed threshold above which human traders can still engage in market transactions and trade with human and algorithmic traders. Below the threshold, latency is too low for human traders to react, so humans can no longer participate in the market. Essentially, the threshold is a tipping point that creates a phase transition from a mixed human-algorithm phase to a algorithm-algorithm phase so that algorithmic traders interact with other algorithms instead of algorithmic traders interacting with human traders. Cartlidge and Cliff (2013; 2018) coined this as a robot-phase transition or market disintegration. They also find that very fast algorithmic traders can cause lower market efficiency besides market disintegration. To sum up, the effects of the algorithm's response speed are mixed depending on the timing of the sleep-wake cycle, on the strategy of the algorithmic traders and the market structure. Algorithmic traders that trade at the response time of humans may perform better than algorithms that respond faster or slower. The robot-phase transition described by Cartlidge and Cliff (2012; 2013; 2018) poses interesting questions for further research. The lower market efficiency observed by the authors in the market disintegration case contrasts with the results obtained in the previous studies without interactions between algorithmic and human traders. Thus, it seems that the inclusion of fast algorithms into the experiment might help to explain flash crashes happening in real-world markets. Another interesting direction marked by the existing research is the adaptability of human and algorithmic traders to the market conditions: increased volatility, unbalanced or uncompetitive markets or non-converging markets, and, of course, to multiple simultaneous markets.

Summary -

Summary of Algorithm Speed in Algorithmic Trading

Focus: How speed of algorithmic trading affects profitability and market efficiency.

Key Points:

- Faster response time isn't always better. Patient algorithms can outperform impatient ones (Gjerstad, 2007).
- Algorithmic traders often trade among themselves before interacting with humans (Das et al., 2001).

- Studies show mixed results on the impact of speed on human vs. algorithm performance:
    - "Fast" ZIP traders outperform humans in balanced markets, but not others (Das et al., 2001, Peng et al., 2020).
    - Algorithmic traders with human-like speed may perform better than very fast or very slow ones (Cartlidge & Cliff, 2013).
- Algorithmic speed can impact market convergence:
    - Slow algorithms may lead to price trajectories favoring patient traders (Peng et al., 2020).
    - Very fast algorithms might cause market disintegration, where humans cannot participate (Cartlidge et al., 2012, 2013, 2018).
- Faster algorithms may contribute to real-world flash crashes (Cartlidge et al., 2012, 2013, 2018).

Open Questions:

- How do humans and algorithms adapt to complex market conditions (volatility, imbalance, etc.)?
- How does speed affect performance in multiple markets simultaneously?

Overall: Algorithmic speed is a complex factor with various effects on profitability, market efficiency, and human participation.

2.4. Arbitrage Algorithms

Text -

In real-world exchanges, financial assets are traded in fragmented markets because the regulatory authorities seek to enforce competition among exchanges to avoid monopoly fees for transactions. Market fragmentation can lead to situations in which an identical asset is demanded or offered at different prices at different venues, thus creating an arbitrage opportunity (e.g., see Figure 1a). Algorithms can also provide arbitrage price discrepancies between an exchange-traded index fund and the assets that compose the index. Similar price discrepancies can arise with two or several different exchange-traded funds based on the same index or between a derivative financial contract and the underlying asset. Automation is usually much faster at exploiting arbitrage opportunities than manual transmissions and, therefore, arbitrage algorithms have been among the most frequently applied algorithmic traders in financial markets (Kirilenko and Lo 2013). Harrison (1992) studies an 8-period lived asset with imperfect payoff information. Including two one-period-ahead futures markets, for period 4 and period 8, he implements an algorithm that arbitrages between spot and futures CDA market (in treatment 4). Harrison (1992) concludes that arbitrageurs could be crucial for ensuring the spot market's informational efficiency and help to constrain the length of any mispricing in spot prices in the study. Angerer et al. (2019) study algorithmic arbitrage in the setting of Charness and Neugebauer (2019), which allows for trading in twin markets of the Smith et al. (1988) type. The dividends in the two markets A and B are perfectly correlated modulo a shift, i.e., the B-share pays in each period the same dividend as the A-share plus a fixed payment of 24 cash units. The authors investigate two liquidity absorbing algorithmic arbitrage traders called FastBot and SlowBot, the liquidity providing algorithmic arbitrage trader LiqBot, and two control treatments, i.e., NoBot (in which the potential participation of an algorithm is announced, but no algorithm participates) and Control (with no announcement and no algorithm). The FastBot arbitrage trader immediately exploits arbitrage opportunities in real-time when they arise, while the SlowBot arbitrage trader trades with a delay. The study suggests that algorithmic arbitrage traders moderate the extent of mispricing. The algorithmic arbitrage traders help to approximate the law of one price and marginally amend the discovery of the fundamental value. The market quality is generally enhanced. Volatility is lower, transaction volume higher, and, particularly in the LiqBot treatment, liquidity is enhanced relative to the NoBot treatment. The arbitrage traders reap some earnings from human subjects upon transaction by design. Nonetheless, subjects' earnings are not significantly lower compared to the treatments without algorithms. Interestingly, the SlowBot algorithm amends market efficiency similar to the other two algorithms, although it earns only a fraction of what the other algorithms earn. Finally, the authors find no announcement effect (see the following subsection) comparing the treatments Control and NoBot Neugebauer et al. (2020) test the Modigliani-Miller theorem of dividend policy irrelevance involving a FastBot algorithmic arbitrager (as in Angerer et al. 2019) and the trading of two 4-period lived assets in a complete asset market. Each asset pays a dividend at the end of the period, which is drawn without replacement from a set of four dividends. After the four regular dividends, shareholders receive a liquidating dividend which is high or low with equal probability. Owed to the fact that the remaining regular dividends are known, the difference in the fundamental value of the two assets is known in each period. Hence, if order in one market crosses the spread in the other market, an arbitrage opportunity arises. In the treatment with the algorithmic arbitrager, such arbitrage opportunities are immediately exploited. The result of the study is that the law of one price (and thus dividend policy irrelevance) holds with and without arbitrager if dividend streams of both assets are identical. If dividends are not identical, the Modigliani-Miller theorem of dividend policy irrelevance can only be supported in the presence of (and must be rejected without) the algorithmic arbitrager. Hence, the result of the study adds laboratory evidence that an algorithmic arbitrage traders may amend mispricing. Rietz (2005) studies index arbitrage in a 15-times repeated one-period CDA setting. At the beginning of each period, subjects are endowed with green and blue assets in a prediction market. One of the assets generates a dividend of $0.50 and the other a dividend of $0.00. The dividendpaying asset is determined by drawing from a bag with 14 green and 6 blue balls at the end of the trading period. Hence, the fundamental dividend value for the green asset is $0.35 and $0.15 for the blue asset, and predicted relative prices are $0.15/$0.35. During the period, subjects trade green and blue assets for cash, and subjects can buy a bundle containing one green and one blue asset from the experimenter or sell the bundle to the experimenter for the bundle's dividend value of $0.50 in cash. Arbitrage opportunities arise whenever the sum of bids (offers) for the two assets totals more (less) than the bundle value. If such an opportunity arises, the arbitrage trader exchanges the bundle for the two assets. In the treatment with the arbitrage trader, subjects are informed about its functioning in the instructions. The results of the study are as follows: the arbitrage trader is involved in most of the transactions, and transaction volume and volatility increase significantly; prices drop relative to the treatment without arbitrage trader, where prices usually are above fundamentals; but relative prices are driven away from their predicted value, with prices of blue assets above and green assets below their fundamentals; and individuals holding less diversified portfolios. Hence, this evidence suggests that the arbitrager supports the law of one price but not always aids market quality and the price discovery of single asset fundamentals. Grossklags and Schmidt (2006) also study arbitrage in a prediction CDA market. Differing from Rietz (2005), where the bundle involves two securities, Grossklags and Schmidt's bundle involves five securities and increased complexity. The algorithmic arbitrage trader is involved in about every fifth transaction. Surprisingly, mispricing in terms of the law of one price is not enhanced with algorithmic arbitrage. Even more surprising, in one treatment, the algorithmic arbitrage trader's presence is not announced, and in that treatment, mispricing is significantly worse than without the participation of the arbitrage trader. Berger et al. (2020) study latency arbitrage in a repeated CDA market for a one-period lived asset with induced values, hence similar to Smith (1962) but with challenges to price discovery. In this setting, an algorithmic "HFT" trader, that is not announced, basically front-runs incoming orders to book an immediate gain. The first one, labeled directional trading algorithm, realizes an immediate gain via the submission of two orders within the queue when a subject submits a market order; for example, if two offers to sell are outstanding at 100 and 101 and a market buy order is submitted, the algorithm buys at the best offer of 100 front-running the market buy order to which it sells at 100.9 just a point below the second-best offer price. The second one, labeled arbitrage algorithm, front-runs any incoming limit order that crosses the spread realizing an immediate gain (such as PB – PA in Figure 1a, but within one market) through two transactions. For example, if one offer to sell is outstanding at 100 and a bid at 101 is submitted to the market, the algorithm buys at the best offer of 100 and sells to the incoming bid at its limit of 101, thus realizing an immediate gain of 1 cash unit. Berger et al. (2020) report market quality enhancements, including an increase in transaction volume and bid-depth of the order book, in the human-algorithm hybrid experimental market relative to the baseline market with human subject only. In conclusion, most existing studies on algorithmic arbitrage in experimental markets suggest that algorithmic arbitrage traders enhance mispricing. However the question of the social cost of arbitrage activity requires further research; particularly, if arbitrage is rather detrimental or beneficial for the market participants and the society. Exploitation of temporary arbitrage opportunities is the business of institutional investment including algorithmic trading companies; including but not limited to stock, index, or foreign exchange arbitrage. The industry evidently extracts value from investors. Therefore, a careful evaluation of this activity is needed to see if the industry should be further regulated. A relevant application of algorithmic arbitrage is theory testing, as financial economic theories are frequently built on the assumption that no arbitrage opportunity should exist in the market. Since experimental subjects seem not aware of arbitrage opportunities without being shown, algorithmic arbitrage can help to test theories built on no arbitrage assumptions in the laboratory. The observed unawareness of arbitrage opportunities is a matter of financial illiteracy and thus another question for further research.

Summary -

Algorithmic Arbitrage in Markets

Summary:

- Exploits price discrepancies between fragmented markets (e.g., different exchanges) or between derivative contracts and underlying assets.
- Generally improves market efficiency by reducing mispricing.
- May have some unintended consequences:
  - Increased volatility (Rietz, 2005)
  - Decreased price discovery accuracy for individual assets (Rietz, 2005)
  - Less diversified portfolios for human traders (Rietz, 2005)
- Latency arbitrage (front-running orders) can improve market liquidity (Berger et al., 2020).
- Unannounced arbitrage bots might worsen mispricing (Grossklags & Schmidt, 2006).
- Algorithmic arbitrage helps test financial theories based on "no arbitrage" assumptions.
- Human unawareness of arbitrage opportunities highlights financial illiteracy.

Open Questions:

- Social cost of arbitrage activity: beneficial or detrimental to society?

- Regulation of algorithmic arbitrage?

Overall: Algorithmic arbitrage plays a complex role in markets, generally improving efficiency but with potential downsides. Further research is needed on its social impact and potential regulation.

2.5. Manipulation

Text -

Market manipulations have always been a concern of market participants. Putniņš (2012) surveys manipulative practices in real-world exchanges, the theoretical and empirical literature. A great advantage of laboratory experiments on market manipulations compared to real-world discovery is that the experimenter can unequivocally identify manipulation in real-time and its effects of price distortion relative to fundamentals. Leal and Hanaki (2018) address the HFT practice of market-making and the manipulative practice of spoofing in a CDA market with long-lived assets (Smith et al. 1988). "'Spoofing' involves intentionally manipulating prices by placing an order to buy or sell a security and then canceling it shortly thereafter, at which point the spoofer consummates a trade in the opposite direction of the canceled order" (Kirilenko and Lo 2013, p. 66). Leal and Hanaki (2018) do not concentrate their analysis on the direct effects of spoofing and market-making but report the effects on subjects' beliefs of the potential presence of such an algorithm. We report their experimental design and results in the following subsection. Veiga and Vorsatz (2009; 2010) investigate the impact on price distortions from manipulation (similar to a "pump-and-dump" scheme, i.e., an attempt to boost the price of the stock to sell it high) performed through an algorithm in an experimental hybrid market. Veiga and Vorsatz (2009) set up an experimental CDA market for an asset that generates a high or low payoff with equal probabilities to study information dissemination similar to Plott and Sunder (1982). The authors consider two treatments. In the control treatment and manipulation treatment, one-third of the 12 market participants are privately informed with certainty about the asset value, whereas the others are uninformed, i.e., have only prior information. In the manipulation treatment, subjects know about the presence of the algorithm but not its strategy. The manipulator algorithm is programmed to buy 10 shares out of 24 after the market is open for 25 seconds and subsequently to sell them back to the market until 50 seconds before market closing. To buy, the algorithmic manipulator overbids the best outstanding bid by a random number drawn from a small positive interval, thus pushing up the price. To sell, similarly, the algorithmic manipulator undercuts the best outstanding offer. After each transaction the algorithm removes all its outstanding orders and after a delay of a few seconds continues with the placing of a new order. The authors find that the algorithmic manipulator distorts price discovery when the asset's actual value is low. When the actual asset value is high, the algorithmic manipulator does not seem to distort price discovery. Also, the algorithmic manipulator usually loses money as it is not programed for profitability. In the follow-up study, Veiga and Vorsatz (2010) investigate manipulation in a CDA market with partially informed traders as in Plott and Sunder (1988) to study the impact of their algorithmic manipulator on information aggregation. In this set-up, the participants trade one asset, taking three possible values x, y or z with equal probabilities. In the first treatment, all participants are partially informed about the asset's value. There is no aggregate uncertainty as 6 subjects are informed that it is not x and the other 6 subjects are told that it is not y when the actual asset value is z. In the second treatment, 6 subjects are partially informed (no aggregate uncertainty), while the other 6 are uninformed. Finally, in the third treatment, similarly to Veiga and Vorsatz (2009), 1/3 of the participants are perfectly informed, while the others are uninformed. The authors report that manipulation has a lasting effect on price discovery only with perfectly informed insiders when the asset's actual value is low. Also, unlike in Veiga and Vorsatz (2009) the algorithmic manipulator earns at least a positive average payoff across human traders. Veiga and Vorsatz's (2009; 2010) two laboratory experiments provide an argument in favor of the regulation obliging market insiders to disclose their transactions. Other experimental studies on manipulation do not use algorithmic traders but offer incentives to subjects to distort market prices (Hanson et al., 2006; Comerton-Forde and Putniņš, 2011). In summary, manipulation in financial markets is an important issue. Since manipulation of market prices is illegal, real-world data on the effects of manipulation are difficult to obtain. There are only few experimental market studies addressing the effects of market manipulation and the mixed evidence of these effects raises questions. Why is the price discovery of low values affected in Veiga and Vorsatz (2009; 2010), but not the price discovery of intermediate or high values after a run up in the price? Does the application of a pump-and-dump manipulation rather lead to inflated prices, or do inflated prices follow from the experimental design as short-sales are banned or because subjects do not know about the strategy of the algorithm? Would human traders be able to counteract and to return the prices to fundamentals if they were familiar with the manipulator's strategy? Under what conditions can an algorithmic manipulator achieve profitability? How would a perhaps more sophisticated, profit-oriented algorithm implement a pump-and-dump manipulation, and what effect would it have on the market? These questions deserve further exploration. Generally, it is surprising that experimental research on market manipulation is scarce. We think that this area of experimental research is very relevant and should attract more interest of experimental finance researchers. The laboratory seems to be a good place to study algorithmic manipulation.

Strategy -

Algorithmic Manipulation in Markets

Focus: How manipulation in the markets affects trading.

Key Points:

- Market manipulation is a concern, but real-world studies are difficult due to its illegality.
- Lab experiments offer a controlled environment to study manipulation.

Algorithmic Spoofing:

- Leal and Hanaki (2018) examine how the **potential presence** of a spoofing algorithm affects human beliefs, not its direct effects.

Algorithmic Price Distortion:

- Veiga and Vorsatz (2009, 2010) use an algorithm to simulate a "pump-and-dump" scheme.
    - The algorithm distorts prices of low-value assets but not high-value ones (Veiga & Vorsatz, 2009).
    - The impact on price discovery is more pronounced with perfectly informed insiders (Veiga & Vorsatz, 2010).
    - The profitability of the manipulation algorithm is unclear (Veiga & Vorsatz, 2009, 2010).

Open Questions:

- Why does manipulation affect low-value prices more?
- Can human traders counteract manipulation?
- How can algorithmic manipulation be made more profitable?
- How would a more sophisticated manipulation algorithm work?

Overall:

- Algorithmic manipulation in markets is under-researched but offers valuable insights due to the controlled environment of lab experiments.

- More research is needed to understand the effectiveness and profitability of different manipulation techniques.

2.6. Announcement effect

Text -

Today, a person committing transactions in the financial market should reasonably expect an algorithmic trader as his or her counterparty. At the same time, the impact of an algorithm's presence or the possibility of its presence on humans' actions and expectations might be nontrivial. Thus, an important question regarding investor psychology is whether the possibility of interacting with an algorithm has a measurable influence on human behavior and the market. The evidence is mixed. As pointed out above, Grossklags and Schmidt (2006) study a prediction market with an algorithmic arbitrager. The paper suggests that the announcement of the presence of algorithms facilitates price discovery raising the rate of price convergence to the equilibrium relative to the setting where the algorithm is present, but this presence is not announced. Within the experiment, three treatments are investigated: no algorithm and no announcement (baseline); algorithm and no announcement; algorithm and announcement. Overall, announcement leads to the increased informational efficiency, defined as deviations between prices and fundamental values, but at the same time, the algorithm's presence without announcement results in a decrease in the convergence rate in comparison to the baseline treatment. The authors explain that arbitrage algorithms tend to decrease the trading opportunities for humans, which results in a lower number of trades and distortion of the information aggregation process. However, when the presence of the algorithms is announced, subjects adapt their behavior by switching to more conservative trading strategies bidding closer to the fundamentals. Farjam and Kirchkamp (2018) also suggest a positive announcement effect. Their subjects seem to behave more rationally following the announcement, bringing transaction prices closer to the fundamental value than without the announcement. The experimental design involves a six-subjects CDA market with one multi-period lived asset (Smith et al. 1988). The study compares price deviations from the fundamental value across the two treatments: either subject is told that the algorithm may be present in their market or that the algorithm is not present. Meanwhile, no algorithm participates in the experiment. The authors align subjects' expectations by asking early participants to describe the algorithm and then sharing the prepared wordle with the other subjects claiming that the algorithm is programmed based on this description. Leal and Hanaki (2018) suggest no announcement effect on prices but find an effect on the elicited first-period beliefs. The experiment involves three treatments that differ in the instructions only. The treatment human-only (HO) makes no reference to algorithmic traders. In the instructions to the treatments spoofing (SP) and market-making (MM), subjects receive the information that they may interact with an algorithmic trader in the market, and the general strategy of the algorithms MM and SP are explained. SP is supposed to be taking advantage of human traders, while MM is supposed to provide more liquidity to the market. Surprisingly, the result of the experiment shows little difference between the two types of market. The results suggest that in MM and SP, relative to HO, initial average price forecasts are higher and more volatile. Initial orders are submitted later. Besides these effects, the market price in MM and SP deviates more from the fundamental value than in HO. Finally, as pointed out above, Angerer et al. (2019) find no announcement effect and no pricing difference relative to fundamentals in the CDA market study with two perfectly correlated assets. The authors compare their control treatment without the announcement of potential algorithm participation with their NoBot treatment in which the potential participation is announced, but no algorithm participates. Different from the studies above, no information is disclosed on the strategy of the algorithm. To sum up, there is mixed evidence. A psychological phenomenon as the announcement effect seems to be dependent on the design of the experiment, including the format and the framing of the announcement, and possibly on the subject pool. For example, simplified visual forms, as for example wordle, possibly have a different impact on the subjects than verbal descriptions of the algorithm's strategy. Subjects' background or experience with algorithms may lead to a different response. For further research, it may be interesting to investigate the impact of various formats and framing of the announcement on the presence of algorithmic traders to market participants, and the development of the announcement effect over time in the laboratory.

Summary -

Announcement Effect on Algorithmic Trading

Key Points:

- The presence of algorithmic traders can influence human behavior in markets.
- Studies show mixed results on the "announcement effect" of algorithmic traders:
    - Announcements can improve market efficiency (Grossklags & Schmidt, 2006; Farjam & Kirchkamp, 2018).
    - Announcement may have no effect on prices (Leal & Hanaki, 2018) or fundamental value alignment (Angerer et al., 2019).
- Announcement effect might depend on:
    - Announcement format (verbal vs. visual)
    - Subject pool (experience, background)

Open Questions:

- How do different announcement formats and framing affect market participants?
- Does the announcement effect change over time?

Overall: The announcement effect of algorithmic traders is a complex phenomenon requiring further research on how announcement design and subject characteristics influence market behavior.

3. Algorithms in the hands of the subject

Text -

While many experiments sought to treat human traders independently from algorithmic traders, Aldrich and López Vargas (2020) and Asparouhova et al. (2020) allowed their subjects to choose to employ algorithmic traders in market experiments. Aldrich and López Vargas (2020) asked subjects to choose a predefined market maker or sniper algorithm or to exit the market to trade a single asset. In the former two cases, subjects also decide on costly improvement in roundtrip-messaging latency to and from the exchange. The market maker algorithm submits the subject's chosen, symmetric bid-offer spread around the fundamental value to transact with algorithmic noise traders that place market-orders at random times to buy or sell one asset. The sniper is a predator algorithm that takes advantage of a market maker's delayed response to changes in fundamentals. At random times the fundamental value jumps and market maker and sniper algorithms adapt to random jumps in fundamental value at established latency. With a large jump, the outstanding spread of a market maker is shortly mispriced. The sniper algorithm attempts to take advantage of the mispricing transacting before and after the spread is readjusted. Aldrich and López Vargas (2020) consider two market environments: the CDA market and the frequent batch auction (FBA) format. The FBA refers to a clearing house mechanism where traders submit orders in continuous time and a call auction clears at uniform price all crossing orders in discrete time intervals. The purpose of the study is to see if FBA, compared to CDA, leads to less wasteful investment in low-latency technology and less predatory behavior, measured by the number of snipers in the market. The authors conclude that FBA induces higher liquidity, price efficiency and less volatility than the CDA. Furthermore, FBA shows fewer snipers present in the market and causes a lower investment in low-latency technology than CDA. In the CDA market, the algorithms produce permanent mispricing, and the authors report flash crashes in the first period. Asparouhova et al. (2020) allow subjects to trade manually or deploy algorithms, and they are assumed to be aware of the potential presence of traders employing algorithms. The trading environment is a CDA market with the declining fundamental value of the underlying asset used in Smith et al. (1988). The algorithms either act as a market-maker or a reactionary robot. The market-maker robot provides liquidity by submitting a buy order (market-maker buyer) for one unit of an asset at 5 cents below or a sell order (market-maker seller) for one unit of an asset at 5 cents above the subject's target price, or both. The reactionary bot is a sniper that takes liquidity; it submits a buy order for one unit at the subject's target price when a sell order arrives at 5 cents below the subject's target price and submits a sell order at the subject's target price when there is a buy order submission at 5 cents above the subject's target price. Asparouhova et al. (2020) report that subjects utilize algorithms frequently, and roughly between 67%-80% of trades employed algorithms. They are interested in evaluating whether putting algorithms in the hands of subjects reduces the extent of asset mispricing but find no evidence to that effect. Price bubbles occur as frequently as without algorithms in the market. Further, they show that subjects who use algorithms do not earn higher earnings than manually trading subjects, and the use of algorithms causes a higher frequency of price surges in the first rounds of trading. In summary, subjects received an opportunity to employ algorithms for trading in the experimental market. Existing experimental evidence shows that human traders utilize the algorithms when they are available to them. Depending on the social cost of algorithmic trading, the regulator can consider the implementation of speed bumps or batch auctions as alternative trading mechanisms to the CDA. Further research shall investigate the impact of other types of algorithmic traders beyond market-making and reactionary algorithms within the framework used in Asparahouva et al. (2020). Generally, the interactions between algorithmic traders and human traders deserve further investigation by considering also other trading strategies and market designs. Designing and teaching a course on algorithmic trading could be a good starting point.

Summary -

Algorithms as Trading Tools for Humans

Summary:

- Experiments allowed human traders to choose and use algorithmic trading tools (Aldrich & López Vargas, 2020; Asparouhova et al., 2020).
- Algorithmic options included market makers, snipers, and reactionary bots.

Impact on Market Efficiency:

- **Frequent Batch Auction (FBA):**
  - Higher liquidity, price efficiency, and less volatility (Aldrich & López Vargas, 2020).

    - Fewer predatory "sniper" algorithms present.
    - Lower investment in low-latency technology (Aldrich & López Vargas, 2020).
- **Continuous Double Auction (CDA):**
    - Permanent mispricing and potential flash crashes (Aldrich & López Vargas, 2020).
    - More frequent use of sniper algorithms.

Human Use of Algorithms:

- Humans frequently use available algorithmic tools (Asparouhova et al., 2020).
- Algorithm use doesn't necessarily reduce mispricing (Asparouhova et al., 2020).
- Algorithm use doesn't lead to higher earnings (Asparouhova et al., 2020).
- Algorithm use may increase price surges initially (Asparouhova et al., 2020).

Open Questions:

- How do other algorithm types affect market dynamics?
- How can human-algorithm interaction be improved through different trading strategies or market designs?
- Could educational resources like algorithmic trading courses be beneficial?

Overall: Giving humans control over algorithmic tools offers mixed results. Further research is needed on the impact of different algorithm types and market designs on human-algorithm interaction.

Explanation -

This passage discusses experiments where human traders were given algorithmic tools to use for trading in a controlled market environment.

Here's a breakdown of the key points:

- **Prior Experiments:** Traditionally, experiments kept human and algorithmic traders separate.

- **New Approach:** Aldrich and López Vargas (2020) and Asparouhova et al. (2020) allowed subjects to choose to use algorithmic trading tools.

  - **Aldrich & López Vargas (2020):**

    - Subjects could pick a pre-made "market maker" or "sniper" algorithm, or exit the market.
    - Market maker: Places buy/sell orders around a central price to facilitate trading.
    - Sniper: Exploits brief price discrepancies to make quick profits.
    - They compared two market formats:
      - **CDA (Continuous Double Auction):** Orders flow continuously.
      - **FBA (Frequent Batch Auction):** Orders are collected and priced at intervals.
    - FBA resulted in:
      - Higher liquidity (ease of buying/selling)
      - More accurate prices
      - Less volatility (price swings)
      - Fewer sniper algorithms used
      - Less investment in super-fast communication technology

- **Asparouhova et al. (2020):**
    - Subjects could trade manually or use "market maker" or "reactionary" algorithms.
    - Market maker: Similar to Aldrich & López Vargas' version.
    - Reactionary bot: Responds to other traders' orders to try to get a good deal.
    - Key findings:
        - Subjects used the algorithms frequently (67-80% of trades).
        - Using algorithms didn't necessarily reduce price inaccuracies.
        - Algorithm users didn't earn more money than manual traders.
        - Algorithm use led to more price spikes early in trading.

Overall:

- Humans tend to use algorithmic tools when available.
- The impact of these tools on market efficiency depends on the algorithm type and market design.
- More research is needed on different algorithms and market structures.
- Educating people about algorithmic trading could be beneficial.

Additional points:

- The passage mentions "flash crashes" in the CDA market, which are sudden, sharp price drops.
- The authors suggest alternative market mechanisms like "speed bumps" (slowing down trading) to potentially address concerns about algorithmic trading.

```
➜  intro-code ./cpu-print | grep hello &
[1] 531 532
➜  intro-code ps -a
  PID TTY          TIME CMD
    1 hvc0     00:00:00 init(Ubuntu)
    6 hvc0     00:00:00 init
  531 pts/0    00:00:03 cpu-print
  532 pts/0    00:00:00 grep
  537 pts/0    00:00:00 ps
➜  intro-code ls -l /proc/531/fd
total 0
lrwx------ 1 vdroid1331 vdroid1331 64 Apr  8 10:05 0 -> /dev/pts/0
l-wx------ 1 vdroid1331 vdroid1331 64 Apr  8 10:05 1 -> 'pipe:[364]'
lrwx------ 1 vdroid1331 vdroid1331 64 Apr  8 10:05 2 -> /dev/pts/0
➜  intro-code ls -l /proc/532/fd
total 0
lr-x------ 1 vdroid1331 vdroid1331 64 Apr  8 10:05 0 -> 'pipe:[364]'
lrwx------ 1 vdroid1331 vdroid1331 64 Apr  8 10:05 1 -> /dev/pts/0
lrwx------ 1 vdroid1331 vdroid1331 64 Apr  8 10:05 2 -> /dev/pts/0
➜  intro-code
```