Human vs. Machine: Disposition Effect Among Algorithmic and Human Day-traders

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Abstract

Can humans achieve rationality, as defined by the expected utility theory, by automating their decision making? We use millisecond-stamped transaction-level data from the Copenhagen Stock Exchange to estimate the disposition effect – the tendency to sell winning but not losing stocks – among algorithmic and human professional day-traders. We find that: (1) the disposition effect is substantial among humans but virtually zero among algorithms; (2) this difference is not fully explained by rational explanations and is, at least partially, attributed to prospect theory, realization utility and beliefs in mean-reversion; (3) the disposition effect harms trading performance, which further deems such behavior irrational.

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1. Introduction

Human efforts to raise productivity, marked by the technical progress (e.g. Rosenberg and Nathan, 1982), has brought the world to the Fourth Industrial Revolution (Schwab, 2017). Today's industries increasingly automate not only physical tasks but also decision making, which will likely contribute to the productivity and economic growth (Acemoglu and Restrepo, 2018), raising inequality (Berg et al., 2018) and the disruption of labor markets (Autor, 2015). In the long-run, technological changes may shape institutional frameworks, cultural norms, mental models of reality of individuals and their decision-making (North, 1994).[1] Therefore, it is important to understand the advantages and disadvantages of decisions implemented by algorithms over on-the-spot decisions made by humans. This understanding would help anticipate which industries are the most subject to change and how, and what type of behavior future generations may learn from their environments. Importantly, by comparing humans and machines, we may learn about humans' decision making, which is crucial for economic theory, mostly centered around the rationality assumption (Hogarth and Reder, 1987; Hirshleifer, 2001; Thaler, 2016).

An ideal setting for making this comparison is the stock market, where both professional human and algorithmic day-traders make frequent high-stake buy and sell decisions under uncertainty in an attempt to profit from short term price movements. In this paper we ask: do machines make more rational[2] decisions than humans, and if so, does that help them perform better? We focus on one of the most extensively documented puzzles in behavioral finance – the disposition effect – the tendency to sell winning stocks too early and to hold losing stocks for too long (Shefrin and Statman, 1985). We use the millisecond-frequency transaction-level data from January 2016 to December 2017 provided by NASDAQ OMX Copenhagen Stock Exchange and track all trades executed by every trader. We observe if a trader was a human or an algorithm[3], if it acted as a broker or traded on its proprietary account, if a trade provided or removed liquidity, the trade execution time, stock name, stock price and the traded number of shares. We focus our analysis on the most frequently trading human and algorithmic day-traders, which makes the two groups comparable in terms of their trading activity, namely, trading frequency, turnover, portfolio size, trading horizon and the selection of the most traded stocks. Our findings reveal a substantial disposition effect among professional human stock day-traders but virtually no disposition effect among algorithmic traders. The difference is not fully explained by rational motives such as private information, portfolio rebalancing, contract-induced incentives or transaction costs. Meanwhile, we find support for less rational explanations, namely, the prospect theory, realization utility and

[1] E.g. If people born in the future will be constantly exposed to automated decision making (e.g. self-driving cars), it seems plausible that such an environment might teach them to make more machine-like decisions.

[2] We call a behavior "rational" if it complies with the expected utility theory, axiomatized by von Neumann and Morgenstern (1947): a representative rational agent is risk averse and makes choices that maximize expected utility derived from wealth levels (see, e.g., Machina 1987) (For other definitions, measures and interpretations of rationality see e.g. Marschak, 1950; Simon, 1978; Apesteguia and Ballester, 2015; Nagel, 2016)

[3] NASDAQ OMX Copenhagen requires its members to register their trading accounts as "Personal" if the account is used for manual trading (user ID typically indicating the first few letters of traders' first and last names), and as "Algo" (user ID starting with PTRxxx, AUTDxx or LPSxxx) if the account is used by algorithms with no human involvement, i.e. "a computer algorithm automatically determines individual parameters of orders such as whether to initiate the order, the timing, price or quantity of the order or how to manage the order after its submission". (Nasdaq, 2018)

beliefs in mean-reversion. We also find that the disposition effect harms the already poor performance of human traders, which further supports the irrational explanations. This suggests that human behavior systematically violates the expected utility theory, and implies that algorithms have an advantage of making more optimal trading decisions.

It has been argued that algorithms make decision-making more cost-effective and less noisy, i.e. more consistent (Kahneman et al., 2016). In addition, there is evidence that trading algorithms benefit from their speed advantage (Brogaard et al., 2015; Budish et al., 2015; Baron et al., 2018) and better access to information (Chordia et al., 2018; Biais et al., 2015). Do algorithms also make more rational decisions? Interviews suggest that programmers attempt to curb emotions and behavioral biases when coding trading algorithms (Borch and Lange, 2017). This is consistent with the conventional wisdom among trading professionals who use discipline, e.g. stop-loss strategies (Henderson et al., 2018), to minimize costs from irrational behavior (Locke and Mann, 2005). However, algorithms may suffer from certain biases too, inherited either from developers or from biased training data (see e.g. Cowgill and Tucker, 2019). Thus, it is not clear whether programmers manage to achieve the claimed discipline. To our knowledge, this is the first paper to compare humans and algorithms in terms of trading behavior and performance, and to provide evidence that algorithms in fact do trade more rationally and more successfully.

There has been an ongoing debate between rationalists and behavioralists on the “correct” way of economic modeling (see, e.g., Hogarth and Reder, 1987). The expected utility theory, axiomatized by von Neumann and Morgenstern (1947), characterized how a representative rational agent should make risky choices and became central to modern economic modeling. Kahneman and Tversky (1979) demonstrated that people systematically violate the rationality axioms and proposed an alternative descriptive theory of risky choice – the prospect theory. It predicts, in contrast to the expected utility theory, that people (1) assign different weights to probabilities of outcomes, (2) maximize utility drawn from gains and losses rather than from final wealth, (3) are risk-averse when facing gains and risk-seeking when facing losses, and (4) suffer from losses more than they enjoy adequate gains. This spurred the debate on rationality further (Thaler, 2016).

The prospect theory paired with mental accounting (Thaler, 1985) have provided a long-standing preference-based explanation of the disposition effect (e.g. Shefrin and Statman, 1985; Odean, 1998; Weber and Camerer, 1998; Henderson et al., 2018): if investors view every stock as a separate mental account, and are risk-seeking when facing losses but risk-averse when facing gains, they would prefer to continue gambling with losing investments and to sell winning investments in order to lock in gains. Another preference-based theory – realization utility (Barberis and Xiong, 2009, 2012; Ingersoll and Jin, 2013; Frydman et al., 2014) claims that utility, i.e. pleasure and pain, is drawn directly from the realization of gains and losses. Pleasure and pain can be explained by a number of elements: e.g. cognitive dissonance, i.e. psychological costs of admitting to mistakes (Chang et al., 2016), pride and regret (Shefrin and Statman, 1985; Strahilevitz et al. 2011; Frydman and Camerer, 2016), self-control problems, i.e. planner-doer conflict whereby a doer (but not a planner) experiences the urge to postpone regret and hasten pride of past decisions (Shefrin and Statman, 1985; Fischbacher et al., 2017), the salience of the stock purchase price (Frydman and Wang, 2019; Dierick et al., 2019; Frydman and Rangel, 2014) and affect, i.e. “hot” immediate reaction to recent events (Loewenstein, 2005). Since both preference-based explanations view outcomes, i.e. gains and losses, relative to a reference point, they contradict the rational agent of the expected utility theory.

Beliefs offer alternative (rational and irrational) explanations of the disposition effect (see e.g. Ben-David and Hirshleifer, 2012). For example, investors may believe in mean-reversion and, thus, keep stocks when prices fall and sell stocks when prices rise. Similarly, investors may believe they have private information, which has not been incorporated into the stock price yet. If the stock price falls, investors may either rationally or due to overconfidence believe that it is just a temporary setback and continue to hold losing investments until the market incorporates that private information. If the stock price rises, investors may believe that the private information has been incorporated as expected, and thus sell the investments at a gain. An opposite effect, whereby a gain (loss) reinforces (hurts) confidence in the private information and urges to buy more (to sell) stock, is also possible (Ben-David and Hirshleifer, 2012). However, empirically, both belief-based explanations found little support in the literature (Weber and Camerer, 1998; Odean, 1998; Kaustia, 2010). Moreover, even if they do drive the disposition effect, such beliefs have been shown to be irrational, due to past winners persistently outperforming past losers (Odean, 1998; Frazzini, 2006; Strahilevitz et al., 2011).

The literature on the disposition effect also considers the following rational explanations. (1) Portfolio rebalancing (Odean, 1998; Kaustia, 2010): gains (losses) increase (decrease) the weight of certain stocks in a portfolio, and to restore the well-diversified balance investors may sell a part of the winning stocks (keep or buy more losing stocks). (2) Mechanics of limit orders (Linnainmaa, 2010): if an investor sold a stock using a limit order, the counterparty must have crossed the bid-ask spread and pushed the price up, which makes it more likely that the sold stock was a winner than a loser. (3) Earnings management or contract-induced incentives (Beatty and Harris, 1999): e.g. banks, enabled by accounting rules, were found to smooth their reported taxable earnings by strategically realizing gains and losses from securities. (4) Transaction costs (Odean, 1998): low-priced stocks may have relatively higher transaction costs; thus, investors are reluctant to trade stocks after their prices decrease. (5) Tax considerations (Lakonishok and Smidt, 1986; Odean, 1998): investors have incentives to realize losses in order to reduce taxable income and, in turn, tax payable, but this would generate the reverse disposition effect.

All these rational and irrational theories potentially could explain why we observe a substantial disposition effect among human traders but virtually no disposition effect among algorithms. Firstly, human traders make on-the-spot decisions under stress while developers have time to “think slow” (Kahneman, 2011) and to calmly pass on their deliberate logic to algorithms, keeping in mind that their coded principles would be used for multiple buy and sell decisions in the future. By “thinking slow”, i.e. using System 2, they may avoid behavioral biases, heuristics and other cognitive features of System 1 such as attachments to reference points and loss aversion, which are at the heart of the prospect theory (Kahneman, 2011). Secondly, at the moment of coding, developers are unlikely to feel any pleasure or pain from defining selling decisions, which makes algorithms less dependent on realization utility and other related elements such as cognitive dissonance, pride and regret, and salience of the purchase price. Also, by coding, algorithmic traders effectively pre-commit to their future buy and sell decisions and thus avoid self-control problems and “hot” reactions. Thirdly, algorithmic traders, equipped with better access to information (Chordia et al., 2018; Biais et al., 2015) and the ability to continuously analyze market data, may have different beliefs than humans in mean-reversion and private information. Fourthly, algorithmic traders may use fundamentally different trading strategies than human traders and thus might care less about the portfolio rebalancing. For instance, market making and cross-market arbitrage strategies, once carried out by humans, have been replaced by algorithms (Danish FSA, 2016). Fifthly, if algorithms use relatively less limit orders than humans, this could, at least partially, explain the difference in the disposition effect. Sixthly, human traders may have different career concerns and compensation schemes than programmers of trading algorithmic, and depending on accounting rules, may have stronger incentives to report realized gains (losses) as large (small) as possible. Seventhly, market venues compete to attract algorithmic traders by offering favorable transaction costs (Danish FSA, 2016), which might make algorithms less sensitive to them. We argue that if there are other rational motives to realize gains and losses, that are equally relevant to both algorithms and humans, e.g. taxes, developers should take them into account when coding trading algorithms, and thus, they should not cause the observed difference in the disposition effect between humans and algorithms.

Results. Our estimates of the substantial disposition effect among humans and the virtually zero disposition effect among algorithms remain similar when considering (1) only long daily positions, (2) only short daily positions, (3) only those positions that are short (long) from a daily perspective but long (short) from a two-year perspective, and (4) when considering only full but not partial closures of existing positions. Furthermore, we find that humans use relatively more market orders and less limit orders than algorithms. As argued in the “Results” section, these findings suggest that the aforementioned rational motives fail to explain the large difference in the disposition effect between humans and algorithms. Meanwhile, we find evidence supporting the less rational explanations, namely, the realization utility, the prospect theory and beliefs in mean-reversion. Specifically, we find that (1) humans but not algorithms trade more aggressively, i.e. use disproportionally more market orders, when realizing losses, as if they were nervous and trying to “get over it quickly”, (2) the disposition effect among humans but not among algorithms reacts to the exogenous factor – the weather, and (3) humans but not algorithms tend to open new long (short) positions after stock price drops (hikes). Finally, we find that if a human (algorithmic) trader had been forced to stop trading at any point of the day, 8 trading hours later, his frozen daily positions would have lost EUR 435 (gained EUR 259) on average. This superior performance of algorithmic traders cannot be attributed to the execution speed advantage and suggests that algorithms are better at predicting price movements over the next 8 trading hours. The 8-hour profits would have been significantly higher (lower) for both humans and algorithms, if they were forced to realize all their paper losses (gains) just before freezing their portfolios. The fact that humans persistently realize more gains than losses despite this behavior harming their performance further suggests the irrationality of the disposition effect (Odean, 1998).

Literature and contribution. Our paper contributes to a few lines of research, including (1) algorithmic trading, (2) disposition effect, (3) weather effects on financial markets, (4) algorithmic bias and (5) the debate on the rationality assumption in economics.

The literature on algorithmic trading so far has focused on studying algorithmic traders' speed (Budish et al., 2015; Baron et al., 2018) and informational (Chordia et al., 2018; Biais et al., 2015) advantages, trading strategies (Hagströmer and Nordén, 2013; Menkveld, 2013; Malinova et al., 2014; O'Hara, 2015), and impact on market quality (Hendershott et al., 2011), especially, liquidity (Hendershott and Riordan, 2013; Brogaard et al., 2015; Ait-Sahalia and Saglam, 2017; Brogaard et al., 2018;), volatility (Hasbrouck and Saar, 2013; Kirilenko et al., 2017), and price efficiency (Carrion, 2013; Brogaard et al., 2014; Chaboud et al., 2014; Brogaard et al., 2019; Conrad et al. 2015; Weller, 2017). We contribute by demonstrating that rationality, or lack of behavioral biases, is another economically significant advantage of algorithmic traders. Algorithmic trading has been proliferating across financial markets (Kirilenko and Lo, 2013), which suggests that these markets on average have been becoming more rational. Furthermore, to our knowledge, this is the first paper to compare the behavior and performance between algorithmic and human traders.

The literature on the disposition effect has documented the effect in different markets, e.g. stocks (Odean, 1998), stock options (Heath et al., 1999), futures of currencies and commodities (Locke and Mann, 2005), and real estate (Genesove and Mayer, 2001), and among different market participants, e.g. individual investors (Odean, 1998), institutional investors (Grinblatt and Keloharju, 2001), mutual funds (Cici, 2012) and professional futures' day-traders (Locke and Mann, 2005). A long-standing explanation of the disposition effect has been the prospect theory (Shefrin and Statman, 1985; Odean, 1998; Weber and Camerer, 1998; Henderson 2012; Li and Yang, 2013; Henderson et al., 2018; Meng and Weng, 2018), however, more recently, a particular focus has been set on identifying other explanations theoretically (Barberis and Xiong, 2009; Barberis and Xiong, 2012; Ingersoll and Jin, 2013) and empirically (Kaustia 2010; Weber and Welfens, 2011; Ben-David and Hirshleifer, 2012; Frydman et al., 2014; Frydman and Rangel, 2014; Chang et al., 2016; Frydman and Camerer, 2016; Fischbacher et al., 2017; Frydman et al., 2017; Frydman and Wang, 2019; Dierick et al., 2019). Other papers examine the impact of the disposition effect on asset prices (Grinblatt and Han, 2005; Frazzini, 2006; An, 2015; Birru, 2015). We contribute by documenting, for the first time, the (lack of) disposition effect among algorithmic traders – an important group of traders that constituted roughly half of trading volume at Nasdaq Copenhagen in the beginning of our data sample period (Danish FSA, 2016). To the best of our knowledge, this is also the first paper to document the disposition effect among professional stock day-traders at the intraday horizon. Furthermore, we contribute by identifying irrational explanations of the disposition effect using novel strategies such as the exogenous effect of the weather and the use of liquidity absorbing orders.

This paper also contributes to the behavioral finance literature studying how the weather affects financial markets. For instance, weather has been shown to affect stock returns (Hirshleifer and Shumway, 2003; Goetzmann et al., 2014), behavior of individual (Schmittmann et al., 2014) and institutional (Goetzmann et al., 2014) investors, and behavior and performance of loan-officers (Cortés et al., 2016). We contribute with evidence that weather affects the disposition effect.

We also add to the literature on algorithmic bias and fairness (Cowgill and Tucker, 2019). For instance, algorithms have been shown to make biased and discriminatory decisions in lending (Bartlett et al., 2019), criminal sentencing (Dressel and Farid, 2018) and ad targeting (Datta et al., 2015). We provide the first evidence that algorithms can make more rational decisions, as defined by von Neumann and Morgenstern (1947), and that this leads to a better performance.

Finally, by providing novel evidence of subrational behavior of human traders, we contribute to the debate on the rationality assumption in economics (Hogarth and Reder, 1987; Hirshleifer, 2001; Thaler, 2016).

2. Data

We use the millisecond-stamped transaction-level trade data from 9 am., i.e. the stock market's opening time, January 1, 2016 to 5 pm, i.e. the stock market's closing time, December 31, 2017 provided by the NASDAQ OMX Copenhagen Stock Exchange. We observe the following information about every trade executed by every approved member of the stock exchange: (1) the execution date and time at millisecond precision, (2) the name of the traded stock, (3) the indicator of whether shares were bought or sold, (4) the share price of the traded stock, (5) the number of shares traded, (6) the indicator of whether a trade added or removed liquidity, (7) the indicator of whether a trade was executed on a trader's own proprietary account or on behalf of the trader's client (i.e. a trader acted as a broker) (8) the name of a trader's institution, i.e. a member of the stock exchange, (9) the indicator of whether a trader's account is used by a human or an algorithm, (10) the user account name (first three letters of a trader's name and surname for humans and PTRxxx, AUTDxx or LPSxxx for algorithms), and (11) the name of a counterparty's organization. Conveniently, very trade enters the dataset twice, treating each counterparty as a primary one. The name of an organization in combination with the user account name provides a unique trader's id.

While we do not know how exactly trading algorithms are coded, what strategies every of them follows and how complex they are, e.g. if they are self-learning and adjust depending on their trading experience, we do know that they are programmed to make the following decisions without human involvement: "whether to initiate the order, the timing, price or quantity of the order or how to manage the order after its submission" (Nasdaq, 2018). These are the requirements of the NASDAQ Copenhagen when issuing "Algo"-type accounts starting with PTRxxx, AUTDxx or LPSxxx to its members. For an overview of the algorithmic trading on the NASDAQ Copenhagen, refer to the report of the Danish Financial Supervisory Authority released in February 2016 – at the beginning of our sample period (Danish FSA, 2016). The report summarizes algorithms' trading strategies, algorithms' benefits and risks to the market, the recent trends in trading volume of algorithms and humans, regulations, etc.

In total, our dataset contains 102,553,306 transactions. Since we cannot identify traders that access the stock market through the brokerage services provided by the exchange's members, we focus only on the proprietary trades of the exchange members. This leaves us with 39,740,156 transactions in 159 different stocks: 32,243,301 transactions executed by 91 algorithmic trading accounts from 33 member institutions and 7,496,855 transactions executed by 597 human trading accounts from 54 member institutions. The trading frequency across both human and algorithmic traders is very heterogenous (see Figure 1). In this paper, we focus on day-traders that trade with the highest frequency possible for three reasons. Firstly, to the best of our knowledge, this is the first paper to analyze the intraday disposition effect in the stock market. Secondly, most of the algorithms in our database trade frequently throughout the day. For instance, more than two thirds of algorithms (63 of 91) trade on average at least once in every 10 minutes (i.e. 48 times per day). Thirdly, we want to identify algorithms that are the least likely to be affected by the direct human intervention. For instance, a seldomly trading algorithm might be launched by a human only when a he desires to trade particular stocks, while continuously trading algorithms allow less time for a human to intervene.

In order to identify day-traders, in the default setting, we consider only those human and algorithmic traders that on average execute at least 1 trade in every two minutes (at least 240 trades per day). However, our results are qualitatively similar if we use different thresholds, e.g. at least 1 trade in every 10 minutes (48 trades per day) or at least 1 trade in every 1 minute (480 trades per day) (See Appendix A). Moreover, the most frequently trading human executes 1,523 trades per day on average, thus, in order to make the two groups of traders comparable, we exclude algorithmic traders that trade more frequently than 1,530 times per day on average. In the default setting, this leaves us with 11,097,306 transactions: 5,899,279 of them executed by 31 algorithmic traders from 14 member institutions and 5,198,027 trades executed by 34 human day-traders from 13 member institutions.

How comparable are these two groups of traders? For each trader-day, we estimate (1) total number of trades per day; (2) total turnover; (3) portfolio size, calculated as an average stock inventory (grossing both long and short stock positions) valued at 5-minute intervals throughout a day at original purchase (selling, for short positions) prices; and (4) trading horizon in days, calculated similarly to “Inventory days”: a ratio of average portfolio size over the total value of shares sold (repurchased, for short positions) throughout a day valued at purchase (selling, for short positions) prices. Also, for each trader-day, we identify (1) 10 most traded stocks in terms of total turnover, (2) the member institution type, e.g. international bank, local bank etc., and (3) the city of its headquarters. As shown in Table 1.A, humans and algorithms trade similarly. Humans on average execute 695 trades per day, while algorithms execute 68 trades more. This difference is not statistically significant. An average daily turnover of a human trader is EUR 5.7 m and is not statistically different from an average turnover of an algorithm (EUR 5.1 m). The difference between an average portfolio size of a human (EUR 1.4 m) and of an algorithm (EUR 1.1 m) is also not statistically significant. For both humans and algorithms, it would take almost 3 (2.7 for humans and 2.8 for algorithms) days on average to close their positions opened throughout a day. Finally, humans on average generate 90% and algorithms 86% of turnover by trading 10 favorite stocks of a day. This difference is not statistically significant. Table 1.B shows that humans and algorithms trade the same stocks. The table presents the list of the 10 most popular stocks for both humans and algorithms. It is based on the number of times that every stock enters an individual trader’s top 10 in terms of daily turnover. Most (22 of 34 for humans and 24 of 31 for algorithms) of the analyzed proprietary day-traders are employed by large international banks such as BNP Paribas, Barclays, Credit Suisse, Deutsche Bank, Goldman Sachs, Merrill Lynch, Citigroup, Societe Generale, Nordea, Danske Bank, SEB, HSBC and JP Morgan. The rest of traders work for small investment banks or local commercial banks. Algorithmic traders are located in London (20), Paris (7), Stockholm (2), Copenhagen (1) and Dublin (1), while human traders are based in London (8), Randers (7), Paris (6), Copenhagen (6), Stockholm (3), Silkeborg (2) and Aabenraa (2).

3. Results

In the default setting, we consider 31 algorithmic and 34 human day-traders that trade on their proprietary accounts, and make between 240 and 1530 trades per day on average.[4] In line with Locke and Mann (2005), Coval and Shumway (2005), Baron et al. (2018), we assume that traders start with zero inventory every day[5] and by trading build up their long and short positions throughout a day.[6] Having a timeline of all trades in the market, and using a volume-weighted average purchase price (WAPP) as a reference purchase price[7], we calculate total gain for every trader-stock position at every point in time. Total gain consists of cumulative realized gain and outstanding paper gain. Outstanding paper gain is calculated by multiplying the number of shares outstanding by the difference between the last observed stock price in the market and WAPP. Realized gain occurs when traders either fully or partially close their position, and is calculated by multiplying the number of shares sold (or repurchased, in case of short positions) by the difference between the selling (repurchasing) price and WAPP. Cumulative realized gain is calculated by accumulating realized gains throughout a day. Following Odean (1998), we measure the disposition effect at every point of time for every trader as the proportion of gains realized (PGR) minus the proportion of losses realized (PLR). PGR (PLR) equals trader's cumulative realized gains above (below) zero summed up across all trader-stock positions divided by total gains above (below) zero summed up across all trader-stock positions.[8]

Figure 2.A shows PGR and PLR at the end of every hour throughout the day, averaged across traders and days within both groups, i.e. humans and algorithms. The graph shows that by the end of the day, algorithms realize on average 32% of gains and 32% of losses, while humans realize 35% of gains but only 20% of losses. Due to the assumption of zero starting inventory, these gains and losses can be interpreted as incrementally caused by actions taken throughout the day. Table 2 Panel A shows that the average disposition spread, i.e. the average difference between PGR and PLR across all traders, days and hours, is 1 pp and not statistically significant from zero for algorithms, and 12 pp and statistically significant at 1% level for humans.[9] Figure 2.B (2.C) and Table 2 Panel B (C) shows that when considering only long (short) positions, the disposition spread

[4] As argued in "Data" section, in this way we focus on the comparable algorithmic and human day-traders. Our results are robust to including algorithms that trade more frequently than 1,530 per day on average and to using other minimum thresholds instead of 240, e.g. 48 or 480 trades per day (i.e. at least 1 trade in every 10 or in every 1 minute, respectively). As a robustness check, in Appendix A, we present the main results from Table 2 but using these different thresholds.

[5] Our results are qualitatively similar if we assume zero starting inventory on the first day and accumulate inventories, gains and losses over the two-year sample period.

[6] Although in the default setting, we use both long and short positions, we show that our results hold for both long and short positions separately.

[7] The results are robust if we use first-in-first-out method to determine the reference purchase price (see Appendix B).

[8] Originally, Odean (1998) measures the disposition effect for long term investors who trade less frequently. Realized gains (losses) are counted daily as a number of different stocks sold at a gain (loss) and paper gains (losses) are counted daily as a number of different stocks held at a gain (loss) but not sold. To get closer to the original measure, we calculate for every trader hourly PGR (PLR) as a number of shares sold at a gain (loss) within a given hour divided by the total number of winning (losing) shares held in that hour, i.e. the shares sold at a gain (loss) within a given hour plus the winning (losing) shares remaining at the end of the hour. Our results are qualitatively similar when using this alternative measure of PGR and PLR.

[9] In order to account for autocorrelation within trader's observations, standard errors are clustered at the trader level.

is 1 pp (1 pp) and not statistically significant for algorithms and 15 pp (13 pp) and statistically significant at 1% level for humans. Finally, Figure 2.D and Table 2 Panel D shows that human day-traders do but algorithms do not realize significantly more gains than losses when considering long-term portfolios, i.e. when we assume zero starting inventory on the first trading day and accumulate inventories throughout the whole two-year sample period. The average disposition spread is 1 pp and not statistically significant for algorithms, and 13 pp and statistically significant at 1% level for humans.

Rational explanations. Firstly, in order to examine if the "portfolio rebalancing" story drives our results, we re-run the main analysis using only those realizations of gains and losses that close the position entirely and not just partially. According to Odean (1998), "investors who are rebalancing will sell a portion, but not all, of their shares of winning stocks. A sale of the entire holding of a stock is most likely not motivated by the desire to rebalance". After eliminating the partial realizations, which might be motivated by rebalancing, our results remain qualitatively similar to the default setting (see Figure 2.E and Table 2 Panel E).

Secondly, it is plausible that accounting rules paired with career concerns or compensation schemes incentivize human traders to realize their gains and losses differently from algorithmic traders. For instance, banks have been shown to manage, e.g. smooth, their reported earnings by strategically realizing gains and losses from securities (see e.g. Dong and Zhang, 2017; Beatty and Harris, 1999; Ahmed and Takeda, 1995). To test this possibility, we consider those gains and losses that occur mentally, but are not reported in any way – i.e. missed opportunities to gain and lose. For instance, suppose a trader owns 100 shares and sells one. If the price goes up (down), the actual and reportable value of the portfolio increases (decreases), but the trader may consider the missed opportunity to earn (lose) money on the sold share as a loss (gain). The trader can "realize" this "loss" ("gain") by repurchasing the sold share at the new higher (lower) price, but this "realization" would not be reflected in the actual profits. Our estimates of the disposition effect for both humans and algorithms are robust when considering only these mental "gains" and "losses" (See Figure 2.F and Table 2 Panel F). This result is consistent with Strahilevitz et al. (2011) who study how regret affects the repurchase of stocks previously sold. Specifically, we calculate cumulative inventories of every trader-stock position over the two-year period, and use only those trader-stock-days in which a long-term position, i.e. cumulative from day 1, remains long (short) throughout the whole given day, but the short-term position, i.e. cumulative from the beginning of the given day, is short (long). In this case, an upward (downward) price move brings gains (losses) from the long-term portfolio perspective, but losses (gains) from the narrower daily portfolio perspective. Thus a "daily" loss (gain) is not an actual loss (gain) that can be reported but a missed opportunity to gain (lose).

Thirdly, it is plausible that after losing, compensation schemes incentivize human traders to take extra risks, and if investors believe that low-priced stocks are more volatile than high-priced stocks (e.g. Ohlson and Penman, 1985; Dubofsky, 1991), they might prefer to hold on to stocks that recently decreased in price and caused losses. Similarly, it is possible that a low stock price makes traders reluctant to trade due to relatively high transaction costs. However, these explanations are plausible only when considering long positions, since with short positions they predict a reverse disposition effect. As can be seen in Figures 2.B and 2.C and Table 2 Panels B and C, long and short positions exhibit very similar disposition effects.

Fourthly, if human traders used relatively more limit orders than algorithms, especially when closing their positions to realize gains and losses, this could explain the difference of the disposition effect between the two groups (Linnainmaa, 2010). However, Figure 3.A shows that in fact humans use relatively less limit orders and more market (liquidity taking, aggressive) orders than algorithms when deepening positions and even more so when closing positions to realize gains and losses.

Less rational explanations. Firstly, Figure 3.B and Table 3 show that humans trade particularly aggressively, i.e. use relatively more liquidity absorbing market orders, when realizing losses as compared to when realizing gains or when deepening positions (i.e. not realizing either gains or losses). Meanwhile, algorithms trade almost equally aggressively when realizing losses and when deepening positions. This suggests that human traders are more nervous when realizing their losses as predicted by realization utility theory. Since the realization of losses is a painful procedure, human traders might urge to "get over it" quickly, and, thus, use more liquidity taking market orders. Following the argumentation of Linnainmaa (2010), if one sells a stock to realize a gain or a loss using an aggressive market order, one has to cross the bid-ask spread and thus the stock is more likely to be sold at a loss and less likely at a gain. These simple mechanics explain why for algorithms in Figure 3.B the line representing the aggressive loss (gain) realization is slightly above (below) the line of non-realization. For humans, however, the loss realization line is far above other lines, which suggest there are other forces explaining why human traders use relatively more aggressive orders when realizing losses than when realizing gains or when not realizing either.

Secondly, we test if the gap between PGR and PLR is sensitive to the weather. Table 4 Panel A shows that human traders exhibit a larger disposition spread during sunny hours than on cloudy hours, while algorithms show no reaction to the weather (Table 4 Panel B). This result can be explained by the prospect theory. During sunny hours, human traders might be more distracted from work and thus rely more on System 1, which is subject to cognitive features such as attachments to reference points and loss aversion (Kahneman, 2011). These results, however, should be treated with caution, as they lack economical significance and are not very robust to different fixed effects and error clustering.

Thirdly, if traders believed in mean-reversion they would expect a stock price to increase after seeing it dropping and to decrease after seeing it rising, even if currently they have no position in that stock (Ben-David and Hirshleifer, 2012). We consider only those trades which open, but do not increase or decrease the existing, long or short daily trader-stock positions, assuming that every day starts with zero inventory. Figure 4 shows that humans, but not machines, tend to open their daily positions by selling recent (previous 60 minutes) winners and buying recent losers. This suggests that humans but not algorithms tend to believe in mean-reversion, which may contribute to the disposition effect. In fact, algorithms tend to do the opposite – to buy recent winners and to sell recent losers, which suggest that they prefer trend following strategies.

Performance. Our evidence suggests that rational explanations such as portfolio rebalancing, contract-induced incentives, transaction costs and limit order mechanism cannot fully explain the large difference in disposition effect between humans and algorithms. Meanwhile, we find evidence that less rational explanations such as the prospect theory, the realization utility theory and beliefs in mean-reversion contribute to the difference. Independently on whether preferences or beliefs drive the disposition effect, if such behavior helps traders perform better, it would be justified and rational (Odean, 1998). However, if traders continue to exhibit disposition effect despite persistent evidence that it hurts their performance, this behavior would be irrational (Odean, 1998). In order to estimate the harm/benefit of the disposition effect we do the following exercise for the same groups of traders as before: 31 algorithmic and 34 human day-traders.

As before, we assume zero starting inventories every day and construct portfolios for every trader considering trades that they executed throughout the day. At the end of every trading hour we freeze portfolios' compositions (we call them the "Actual portfolios") and use stock prices prevailing 8 trading hours later to calculate how much profits every trader would have made over those next 8 trading hours had they not executed any more trades. Then, for every trader, at every moment of the freeze, we construct a hypothetical "Realization portfolio", which is formed by trades that would be necessary in order to realize all existing paper losses. Assuming constant compositions of "Realization portfolios" we calculate profits over the same next 8 trading hours. Adding up the "Actual portfolio" and the "Realization portfolio" gives us a "Combined portfolio" – a hypothetical portfolio that a trader would be holding at the moment of the freeze had he just realized all paper losses.

Figure 5.A shows profits earned within the next 8 trading hours by the "Actual", "Realization" and "Combined" portfolios frozen at various times of the day averaged across traders and days. Figure 5.A and Table 5 suggests that human traders on average would persistently make losses (on average 404 euros) over the next 8 trading hours if they stopped trading at any point of the day. Yet, on average they would earn more than that (421 euros) and break-even over the same 8 trading hours if they realized all their losses. The best time to realize all losses appears to be at around 1 pm since the "Realization portfolio" would have earned 596 euros on average over the next 8 trading hours. Realization of losses would allow human traders to avoid persistent losses since the "Combination portfolio" would earn on average 63 euros over the 8-hour period. Figure 5.B and Table 5 Panel B shows that algorithms are better at choosing stocks than humans as their "Actual portfolio" on average earns positive (even though not statistically significant) profits of 134 euros over the 8 hours[10]. However, they would benefit from realizing more losses too as their "Combined portfolio" would earn 271 euros on average. Interestingly, these findings suggest that algorithms can predict better than humans, which stocks will be profitable during the next 8 trading hours. This difference in performance cannot be explained by algorithms' execution speed advantage, which is only in the matter of milliseconds.

Results are different in magnitude but similar qualitatively when instead of 8-hour horizon we use 1,2,4,16 and 24 hours: the "Realization portfolio" always generates gains and helps both humans

[10] When including algorithms that trade more frequently than 1,530 times per day on average, algorithms' "Actual portfolio" earns 260 euros on average - a positive profit statistically significant at 10%.

to offset their loses and algorithms to increase their gains. We see a similar picture (Figure 5.C for humans and 5.D for algorithms) when looking at returns, i.e. when we divide portfolio profits by the initial portfolio values at the time of freezing. As shown in Table 5, both profits and returns of "Realization portfolio" are positive and statistically different from zero.

Using the same logic, we form "Realization portfolios" with trades that would realize all gains instead of losses (Table 6 and Figure 6.A for humans and 6.B for algorithms). In this case the "Realization portfolio" incurs negative profits – on average -173 euros for human and -283 euros for algorithms in the next 8 hours. This leads to "Combined portfolio" performance being worse than "Actual portfolio" performance on average. The same applies when analyzing returns instead of profits (Figure 6.C for humans and 6.D for algorithms). All in all, this evidence suggests that both realization of gains and non-realization of losses are detrimental to the trading performance, which suggests the disposition effect to be irrational behavior. In addition, since algorithms' average performance over the intraday horizon is always better than humans', independently on what time the portfolios are frozen, this serves as evidence that algorithms, either due to informational advantage or due to rationality, are better at picking stocks for day trading and would outperform humans even without their execution speed advantage.

4. Conclusion

In this paper we ask: do machines make more rational decisions, as defined by the expected utility theory, than humans, and if so, does that help them perform better? We use two years of transaction-level millisecond-stamped trade data from the NASDAQ OMX Copenhagen Stock Exchange to compare the disposition effect between two groups of proprietary day-traders, namely algorithms and humans. In order to ensure the comparability between the two groups in terms of trading frequency, turnover, portfolio size, trading horizon and favorite stocks, and in order to minimize the likelihood that a human could directly impact trading decisions of algorithms, we focus our analysis on traders that trade the most frequently, namely the 31 algorithms and 34 humans that on average execute between 240 and 1530 trades per day. We also show that our results are qualitatively similar when changing the lower bound from 240 to 48 and 480 trades per day.

We find a substantial disposition effect among humans but virtually no disposition effect among algorithms. This difference cannot be fully explained by the popular rational explanations, such as private information, portfolio rebalancing, contract-induced incentives or transaction costs. However, we find evidence that it is at least partially explained by less rational explanations such as the prospect theory, realization utility and beliefs in mean-reversion. The evidence of the irrationality of the disposition effect is reinforced by our finding that the realization of gains and the non-realization of losses systematically hurt future performance of both humans and algorithms. Finally, we find that algorithms have a better ability than humans to predict the stock price movements in the next 1,2,4,16 and 24 hours, which suggests that algorithms would outperform humans even without their advantage of execution speed.

These results suggest that professional human day-traders do not behave fully rationally as defined by the expected utility theory, even though rationality would be profitable. Our findings also suggest that rationality can be achieved by automating the decision-making process. For example, by "thinking slow" (using System 2) programmers can avoid behavioral biases and heuristics. Also, while programming their decisions, which may or may not be executed in the future, depending on future situations, programmers can minimize their pleasure and pain derived from these decisions. Furthermore, by pre-committing to the future decisions, programmers can avoid self-control problems and "hot" reactions.

This grants an additional advantage to algorithms, which have already been shown before to make faster, better-informed, less noisy and more cost-effective decisions. In turn, this advantage may widen the scope of industries that could benefit from and be changed by the automation of decision-making. In the long run, future generations, surrounded by more rational decision making executed by machines, might learn to behave in a more rational manner as well. Whether this is something worth striving for is a matter of ethics and depends on what machines are programmed to optimize, e.g. shareholders' profits, consumers' happiness, well-being of the society as whole etc.

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FIGURE 1

Number of traders and total turnover ordered by traders' average trading frequency

Figure 1 shows the distribution of 91 algorithmic and 597 human traders ordered by their average trading frequency per day (blue columns, lhs). For example, a large part of both algorithmic (28) and human (427) traders trade relatively seldomly – less than 48 times per day (i.e. less than 1 trade in every 10 minutes) on average. The orange line (rhs) shows the aggregate turnover in euros generated by traders in each trading frequency category throughout the two-year sample period.

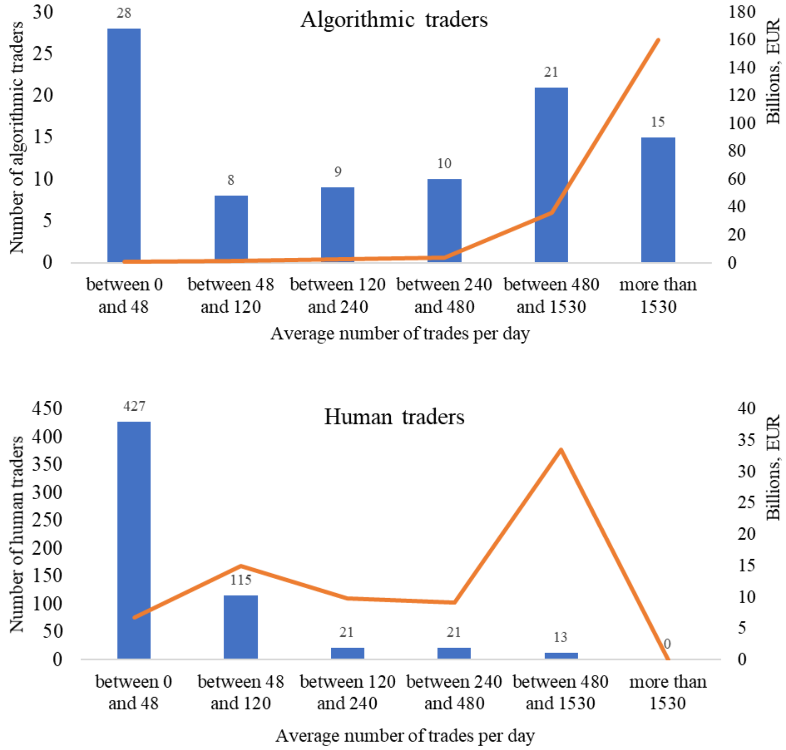

FIGURE 2.A

Realization of gains and losses throughout a day – default setting

Figure 2.A shows the proportion of gains realized (PGR) and the proportion of losses realized (PLR) at the start of every hour of a day, averaged across trading days and across traders in the two groups, i.e. humans and algorithms. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. Individual PGR and PLR for every trader are calculated as follows. Traders are assumed to start every day with zero inventory (at 9 am) and by trading to build their long and short positions in stocks throughout a day. For every trader-stock position at every point of time we calculate *total gain*, which consist of *cumulative realized gain* and *outstanding paper gain*. *Outstanding paper gain* is calculated by multiplying remaining inventory by the difference between the last observed stock price and the volume-weighted average purchase price (WAPP). *Realized gain* is calculated by multiplying the number of shares sold (or repurchased, in case of short positions) by the difference between the selling (repurchasing) price and WAPP. *Cumulative realized gain* is calculated by accumulating *realized gains* throughout a day. At any point of time, a trader's PGR (PLR) equals *cumulative realized gains* above (below) zero summed up across trader-stock positions divided by *total gains* above (below) zero summed up across trader-stock positions.

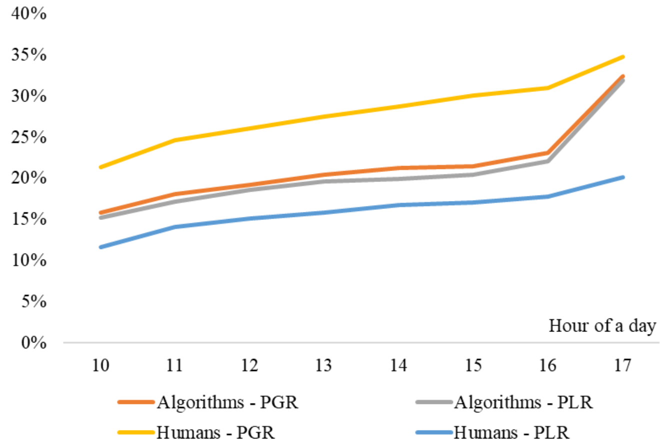

FIGURE 2.B

Realization of gains and losses throughout a day – only long positions

Figure 2.B shows the proportion of gains realized (PGR) and the proportion of losses realized (PLR) at the start of every hour of a day, averaged across trading days and across traders in the two groups, i.e. humans and algorithms. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. Individual PGR and PLR for every trader are calculated as follows. Traders are assumed to start every day with zero inventory (at 9 am) and by trading to build their long and short positions in stocks throughout a day. **In this chart we only consider long positions**. For every trader-stock position at every point of time we calculate *total gain*, which consist of *cumulative realized gain* and *outstanding paper gain*. *Outstanding paper gain* is calculated by multiplying remaining inventory by the difference between the last observed stock price and the volume-weighted average purchase price (WAPP). *Realized gain* is calculated by multiplying the number of shares sold by the difference between the selling price and WAPP. *Cumulative realized gain* is calculated by accumulating *realized gains* throughout a day. At any point of time, a trader's PGR (PLR) equals *cumulative realized gains* above (below) zero summed up across trader-stock positions divided by *total gains* above (below) zero summed up across trader-stock positions.

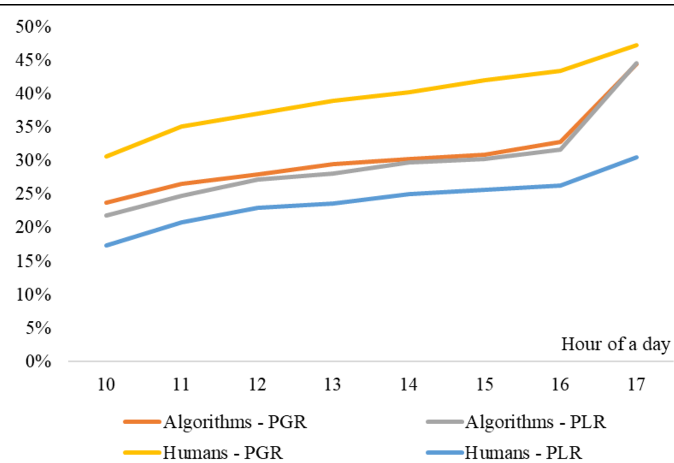

FIGURE 2.C

Realization of gains and losses throughout a day – only short positions

Figure 2.C shows the proportion of gains realized (PGR) and the proportion of losses realized (PLR) at the start of every hour of a day, averaged across trading days and across traders in the two groups, i.e. humans and algorithms. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. Individual PGR and PLR for every trader are calculated as follows. Traders are assumed to start every day with zero inventory (at 9 am) and by trading to build their long and short positions in stocks throughout a day. **In this chart we only consider short positions**. For every trader-stock position at every point of time we calculate *total gain*, which consist of *cumulative realized gain* and *outstanding paper gain*. *Outstanding paper gain* is calculated by multiplying remaining inventory by the difference between the last observed stock price and the volume-weighted average purchase price (WAPP). *Realized gain* is calculated by multiplying the number of shares repurchased by the difference between the repurchase price and WAPP. *Cumulative realized gain* is calculated by accumulating *realized gains* throughout a day. At any point of time, a trader's PGR (PLR) equals *cumulative realized gains* above (below) zero summed up across trader-stock positions divided by *total gains* above (below) zero summed up across trader-stock positions.

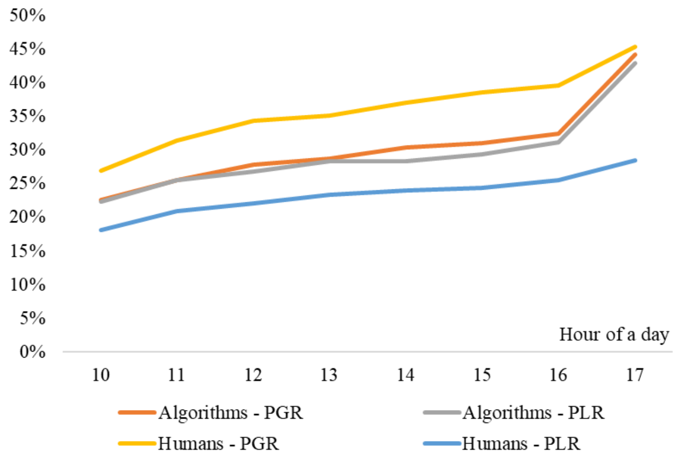

FIGURE 2.D

Realization of gains and losses throughout the two years sample period

Figure 2.D shows the proportion of gains realized (PGR) and the proportion of losses realized (PLR) at the end of every quarter, averaged across traders in the two groups, i.e. humans and algorithms. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. Individual PGR and PLR for every trader are calculated as follows. Traders are assumed to start with zero inventory on the first trading day and to build their long and short positions in stocks by trading throughout the two years. For every trader-stock position at every point of time we calculate *total gain*, which consist of *cumulative realized gain* and *outstanding paper gain*. *Outstanding paper gain* is calculated by multiplying remaining inventory by the difference between the last observed stock price and the volume-weighted average purchase price (WAPP). *Realized gain* is calculated by multiplying the number of shares repurchased by the difference between the repurchase price and WAPP. *Cumulative realized gain* is calculated by accumulating *realized gains* throughout the two years. At any point of time, a trader's PGR (PLR) equals *cumulative realized gains* above (below) zero summed up across trader-stock positions divided by *total gains* above (below) zero summed up across trader-stock positions.

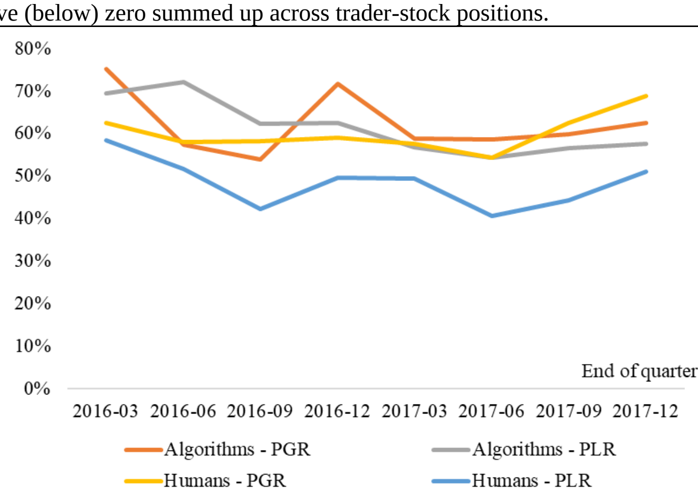

FIGURE 2.E

Realization of gains and losses throughout a day – without partial realizations

Figure 2.E shows the proportion of gains realized (PGR) and the proportion of losses realized (PLR) at the start of every hour of a day, averaged across trading days and across traders in the two groups, i.e. humans and algorithms. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. Individual PGR and PLR for every trader are calculated as follows. Traders are assumed to start every day with zero inventory (at 9 am) and by trading to build their long and short positions in stocks throughout a day. For every trader-stock position at every point of time we calculate *total gain*, which consist of *cumulative realized gain* and *outstanding paper gain*. *Outstanding paper gain* is calculated by multiplying remaining inventory by the difference between the last observed stock price and the volume-weighted average purchase price (WAPP). *Realized gain* is calculated by multiplying the number of shares sold (or repurchased, in case of short positions) by the difference between the selling (repurchasing) price and WAPP. **In this chart we consider only those sales (repurchases), which completely closed trader-stock positions**. *Cumulative realized gain* is calculated by accumulating *realized gains* throughout a day. At any point of time, a trader's PGR (PLR) equals *cumulative realized gains* above (below) zero summed up across trader-stock positions divided by *total gains* above (below) zero summed up across trader-stock positions.

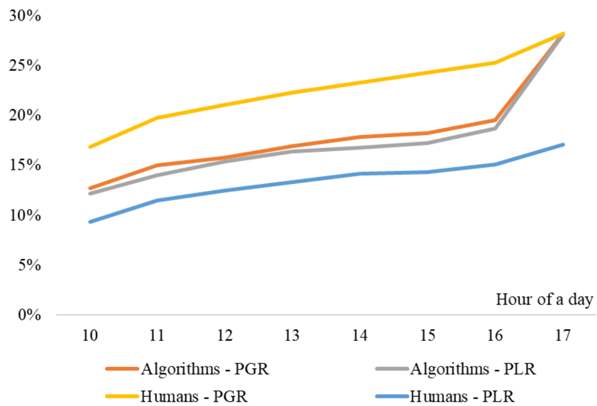

FIGURE 2.F

Realization of gains and losses throughout a day – mental "gains" and "losses"

Figure 2.F shows the proportion of gains realized (PGR) and the proportion of losses realized (PLR) at the start of every hour of a day, averaged across trading days and across traders in the two groups, i.e. humans and algorithms. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. Individual PGR and PLR for every trader are calculated as follows. Traders are assumed to start every day with zero inventory (at 9 am) and by trading to build their long and short positions in stocks throughout a day. **We call these positions "daily" positions.** For every trader-stock position at every point of time we calculate *total gain*, which consist of *cumulative realized gain* and *outstanding paper gain*. *Outstanding paper gain* is calculated by multiplying remaining inventory by the difference between the last observed stock price and the volume-weighted average purchase price (WAPP). *Realized gain* is calculated by multiplying the number of shares sold (or repurchased, in case of short positions) by the difference between the selling (repurchasing) price and WAPP. *Cumulative realized gain* is calculated by accumulating *realized gains* throughout a day. At any point of time, a trader's PGR (PLR) equals *cumulative realized gains* above (below) zero summed up across trader-stock positions divided by *total gains* above (below) zero summed up across trader-stock positions. **We also calculate "overall" trader-stock positions assuming zero inventory at 9 am of day 1, and accumulating inventories throughout the two years. In this chart we only consider those trader-stock positions, which are either long throughout the whole day from the "overall" perspective and short from the "daily" perspective or short throughout the whole day from the "overall" perspective and long from the "daily" perspective. Thus, "daily" losses (gains) are not actual losses (gains) but missed opportunities to gain (lose) "overall".**

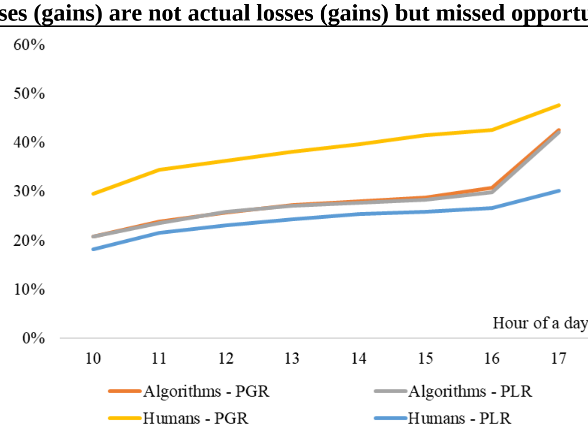

FIGURE 3.A

Aggressiveness of trades – realization and non-realization trades

Figure 3.A shows the average ratio of trader's hourly turnover that was executed with market orders over the sum of hourly turnover executed using both market and limit orders. The ratio is averaged across trading days and across traders in the two groups, i.e. humans and algorithms. We consider separately (1) trades that opened or deepened existing positions, i.e. non-realization trades, and (2) trades that closed (partially or fully) existing positions, i.e. realization trades. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day.

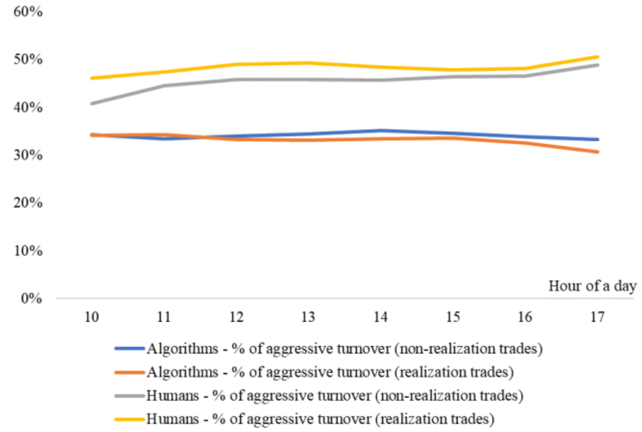

FIGURE 3.B

Aggressiveness of trades – loss realization, gain realization and non-realization trades

Figure 3.B shows the average ratio of trader's hourly turnover that was executed with market orders over the sum of hourly turnover executed using both market and limit orders. The ratio is averaged across trading days and across traders in the two groups, i.e. humans and algorithms. We consider separately (1) trades that opened or deepened existing positions, i.e. non-realization trades, (2) trades that closed (partially or fully) existing positions at a loss, i.e. trades realizing losses and (3) trades that closed (partially or fully) existing positions at a gain, i.e. trades realizing gains. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day.

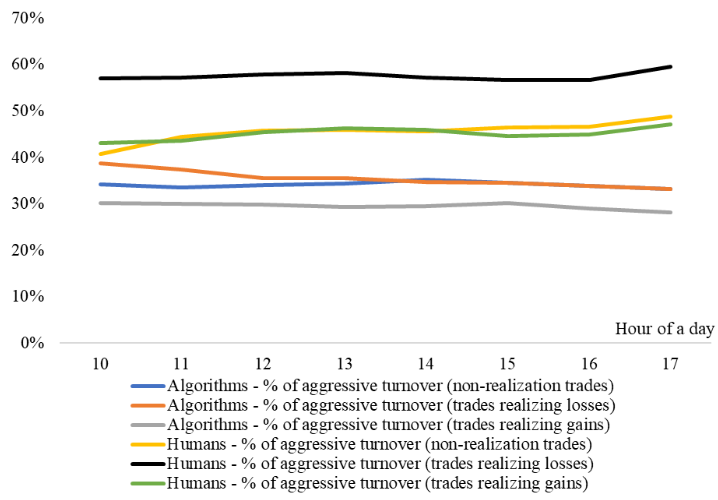

FIGURE 4

Opening daily positions by buying and selling recent winners and losers

Figure 4 shows the average number of times per day that traders opened their daily positions (assuming zero starting inventory every day) by buying and selling recent winners, i.e. stocks that increased in price during the previous 60 minutes, and recent losers, i.e. stocks that decreased in price during the previous 60 minutes. The black lines are 95% confidence intervals. The graph shows that human traders tend to open their positions by selling recent winners and buying recent losers, which is in line with the beliefs in mean-reversion. Algorithms tend to do the opposite – open their positions by buying recent winners and selling recent losers, which is in line with trend following. However, the result for algorithms is not statistically significant, as all the confidence intervals overlap.

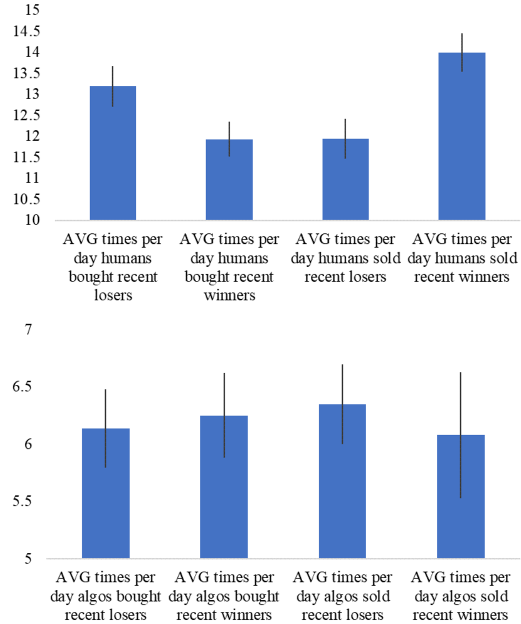

FIGURE 5.A

Gains of frozen portfolios of human traders over the next 8 hours – case of loss realization

Figure 5.A shows average profits in euros earned over the next 8 hours by three types of portfolios frozen at different times of the day. The average is calculated across human traders and trading days. Dashed lines of corresponding colors represent confidence intervals. Individual trader's "Actual portfolio" is constructed by assuming zero starting inventory every day and executing actual trades up to the moment of the freeze. The composition of the "Actual portfolio" is frozen at every hour of a trading day. Individual trader's "Realization portfolio" is a hypothetical portfolio constructed by executing trades necessary to realize all existing paper losses at the moment of the freeze. Individual trader's "Combined portfolio" is a combination of both "Actual portfolio" and the "Realization portfolio", thus, it is a hypothetical portfolio that a trader would hold at the moment of the freeze had he just realized all paper losses. The gain of every portfolio is calculated by comparing stock prices at the moment of the freeze and eight trading hours later, holding the portfolios' compositions constant. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day.

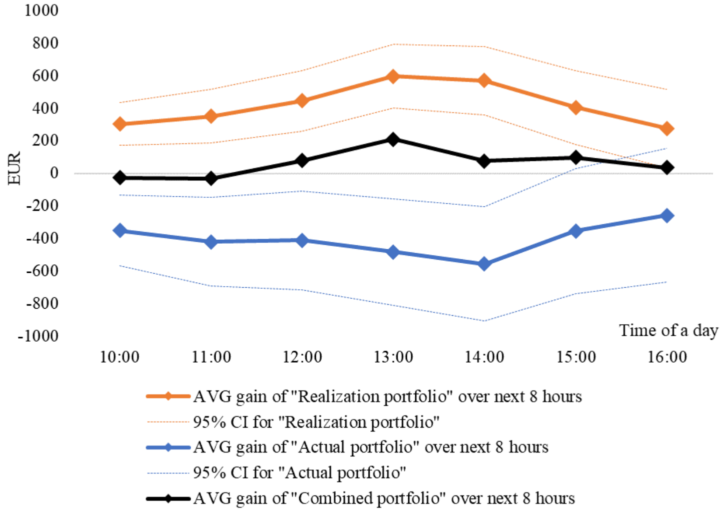

FIGURE 5.B

Gains of frozen portfolios of algorithmic traders over the next 8 hours – case of loss realization

Figure 5.B shows average profits in euros earned over the next 8 hours by three types of portfolios frozen at different times of the day. The average is calculated across algorithmic traders and trading days. Dashed lines of corresponding colors represent confidence intervals. Individual trader's "Actual portfolio" is constructed by assuming zero starting inventory every day and executing actual trades up to the moment of the freeze. The composition of the "Actual portfolio" is frozen at every hour of a trading day. Individual trader's "Realization portfolio" is a hypothetical portfolio constructed by executing trades necessary to realize all existing paper losses at the moment of the freeze. Individual trader's "Combined portfolio" is a combination of both "Actual portfolio" and the "Realization portfolio", thus, it is a hypothetical portfolio that a trader would hold at the moment of the freeze had he just realized all paper losses. The gain of every portfolio is calculated by comparing stock prices at the moment of the freeze and eight trading hours later, holding the portfolios' compositions constant. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day.

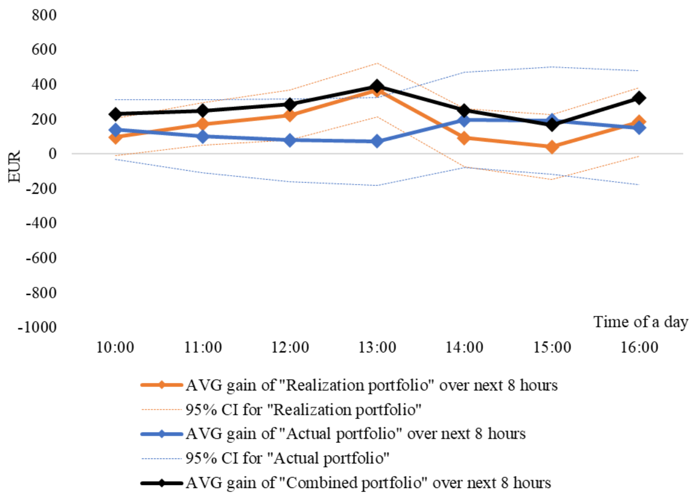

FIGURE 5.C

Returns of frozen portfolios of human traders over the next 8 hours – case of loss realization

Figure 5.C shows average returns earned over the next 8 hours by three types of portfolios frozen at different times of the day. The average is calculated across human traders and trading days. Dashed lines of corresponding colors represent confidence intervals. Individual trader's "Actual portfolio" is constructed by assuming zero starting inventory every day and executing actual trades up to the moment of the freeze. The composition of the "Actual portfolio" is frozen at every hour of a trading day. Individual trader's "Realization portfolio" is a hypothetical portfolio constructed by executing trades necessary to realize all existing paper losses at the moment of the freeze. Individual trader's "Combined portfolio" is a combination of both "Actual portfolio" and the "Realization portfolio", thus, it is a hypothetical portfolio that a trader would hold at the moment of the freeze had he just realized all paper losses. The return of every portfolio is calculated by subtracting the portfolio value at stock prices prevailing at the time of the freeze from the portfolio value at stock prices prevailing 8 trading hours later (holding the portfolios' compositions constant), and dividing the difference by the former portfolio value. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day.

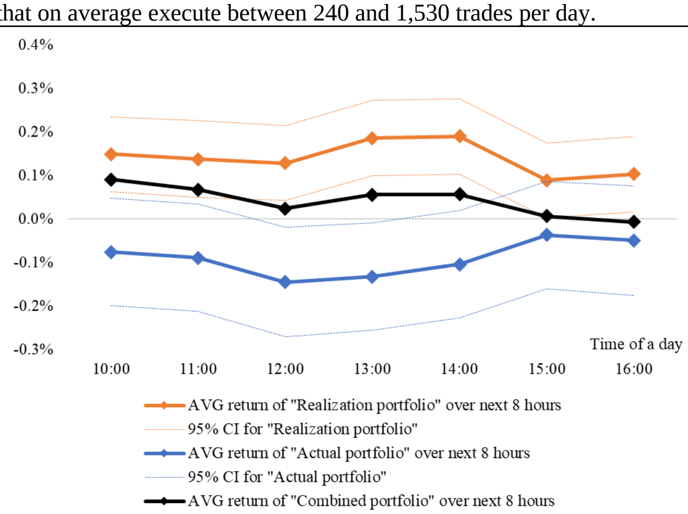

FIGURE 5.D

Returns of frozen portfolios of algorithmic traders over the next 8 hours – case of loss realization

Figure 5.D shows average returns earned over the next 8 hours by three types of portfolios frozen at different times of the day. The average is calculated across algorithmic traders and trading days. Dashed lines of corresponding colors represent confidence intervals. Individual trader's "Actual portfolio" is constructed by assuming zero starting inventory every day and executing actual trades up to the moment of the freeze. The composition of the "Actual portfolio" is frozen at every hour of a trading day. Individual trader's "Realization portfolio" is a hypothetical portfolio constructed by executing trades necessary to realize all existing paper losses at the moment of the freeze. Individual trader's "Combined portfolio" is a combination of both "Actual portfolio" and the "Realization portfolio", thus, it is a hypothetical portfolio that a trader would hold at the moment of the freeze had he just realized all paper losses. The return of every portfolio is calculated by subtracting the portfolio value at stock prices prevailing at the time of the freeze from the portfolio value at stock prices prevailing 8 trading hours later (holding the portfolios' compositions constant), and dividing the difference by the former portfolio value. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day.

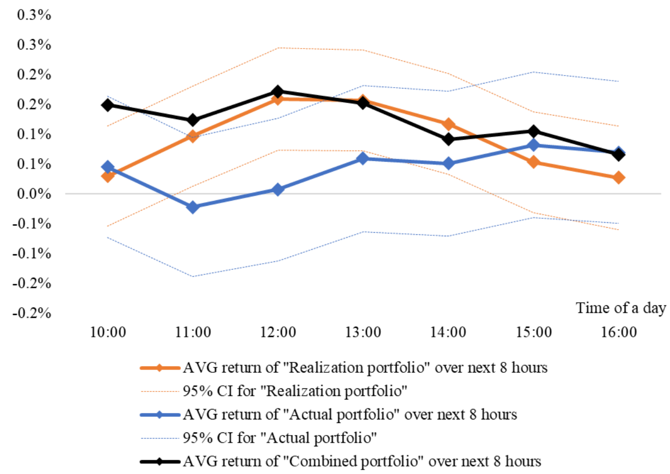

FIGURE 6.A

Gains of frozen portfolios of human traders over the next 8 hours – case of gain realization

Figure 6.A shows average profits in euros earned over the next 8 hours by three types of portfolios frozen at different times of the day. The average is calculated across human traders and trading days. Dashed lines of corresponding colors represent confidence intervals. Individual trader's "Actual portfolio" is constructed by assuming zero starting inventory every day and executing actual trades up to the moment of the freeze. The composition of the "Actual portfolio" is frozen at every hour of a trading day. Individual trader's "Realization portfolio" is a hypothetical portfolio constructed by executing trades necessary to realize all existing paper gains at the moment of the freeze. Individual trader's "Combined portfolio" is a combination of both "Actual portfolio" and the "Realization portfolio", thus, it is a hypothetical portfolio that a trader would hold at the moment of the freeze had he just realized all paper gains. The gain of every portfolio is calculated by comparing stock prices at the moment of the freeze and eight trading hours later, holding the portfolios' compositions constant. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day.

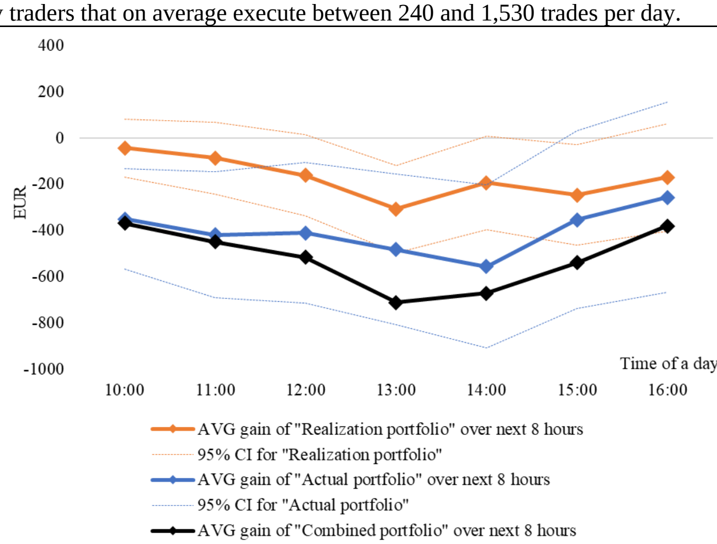

FIGURE 6.B

Gains of frozen portfolios of algorithmic traders over the next 8 hours – case of gain realization

Figure 6.B shows average profits in euros earned over the next 8 hours by three types of portfolios frozen at different times of the day. The average is calculated across algorithmic traders and trading days. Dashed lines of corresponding colors represent confidence intervals. Individual trader's "Actual portfolio" is constructed by assuming zero starting inventory every day and executing actual trades up to the moment of the freeze. The composition of the "Actual portfolio" is frozen at every hour of a trading day. Individual trader's "Realization portfolio" is a hypothetical portfolio constructed by executing trades necessary to realize all existing paper gains at the moment of the freeze. Individual trader's "Combined portfolio" is a combination of both "Actual portfolio" and the "Realization portfolio", thus, it is a hypothetical portfolio that a trader would hold at the moment of the freeze had he just realized all paper gains. The gain of every portfolio is calculated by comparing stock prices at the moment of the freeze and eight trading hours later, holding the portfolios' compositions constant. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day.

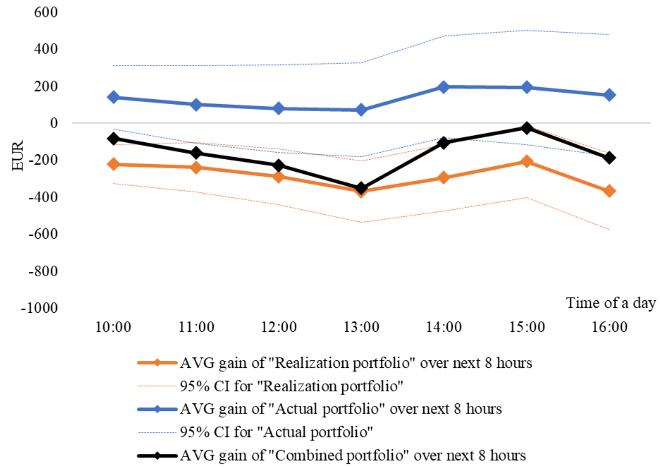

FIGURE 6.C

Returns of frozen portfolios of human traders over the next 8 hours – case of gain realization

Figure 6.C shows average returns earned over the next 8 hours by three types of portfolios frozen at different times of the day. The average is calculated across human traders and trading days. Dashed lines of corresponding colors represent confidence intervals. Individual trader's "Actual portfolio" is constructed by assuming zero starting inventory every day and executing actual trades up to the moment of the freeze. The composition of the "Actual portfolio" is frozen at every hour of a trading day. Individual trader's "Realization portfolio" is a hypothetical portfolio constructed by executing trades necessary to realize all existing paper gains at the moment of the freeze. Individual trader's "Combined portfolio" is a combination of both "Actual portfolio" and the "Realization portfolio", thus, it is a hypothetical portfolio that a trader would hold at the moment of the freeze had he just realized all paper gains. The return of every portfolio is calculated by subtracting the portfolio value at stock prices prevailing at the time of the freeze from the portfolio value at stock prices prevailing 8 trading hours later (holding the portfolios' compositions constant), and dividing the difference by the former portfolio value. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day.

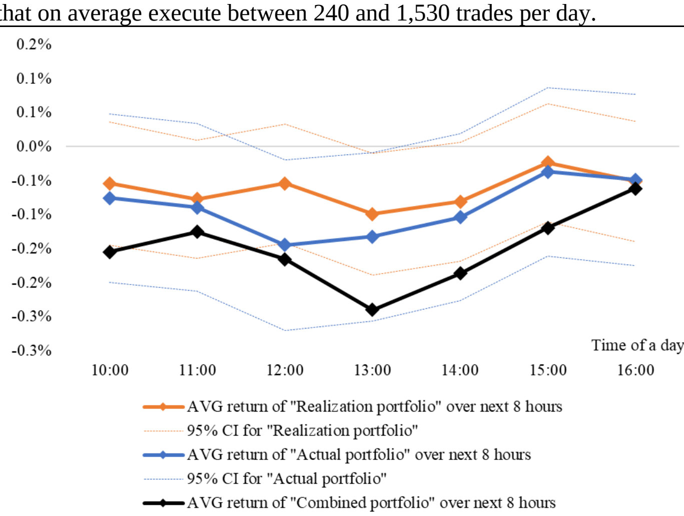

FIGURE 6.D

Returns of frozen portfolios of algorithmic traders over the next 8 hours – case of gain realization

Figure 6.D shows average returns earned over the next 8 hours by three types of portfolios frozen at different times of the day. The average is calculated across algorithmic traders and trading days. Dashed lines of corresponding colors represent confidence intervals. Individual trader's "Actual portfolio" is constructed by assuming zero starting inventory every day and executing actual trades up to the moment of the freeze. The composition of the "Actual portfolio" is frozen at every hour of a trading day. Individual trader's "Realization portfolio" is a hypothetical portfolio constructed by executing trades necessary to realize all existing paper gains at the moment of the freeze. Individual trader's "Combined portfolio" is a combination of both "Actual portfolio" and the "Realization portfolio", thus, it is a hypothetical portfolio that a trader would hold at the moment of the freeze had he just realized all paper gains. The return of every portfolio is calculated by subtracting the portfolio value at stock prices prevailing at the time of the freeze from the portfolio value at stock prices prevailing 8 trading hours later (holding the portfolios' compositions constant), and dividing the difference by the former portfolio value. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day.

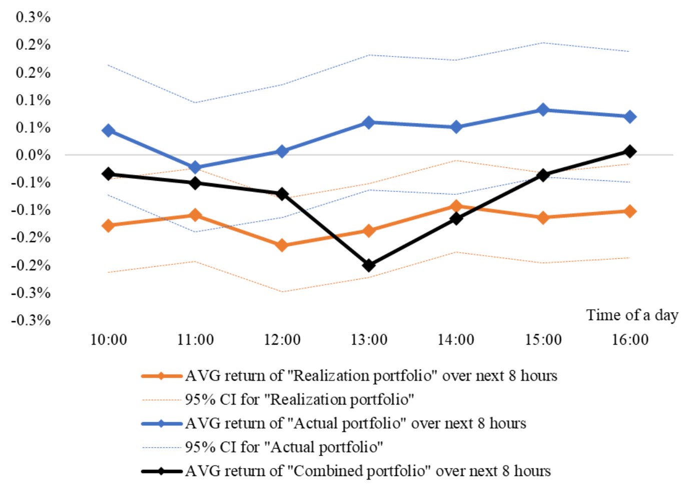

TABLE 1.A

Comparison of trading activity between algorithms and humans

Table 1.A shows the results of regressing trader-day level observations of five different variables on a constant and a dummy *Algorithm*, which is equal to one if a trader is an algorithm and zero if it is a human. We consider 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1530 trades per day. The four dependent variables are calculated as follows: (1) “N of trades” is a total number of trades that a trader executed in a given day; (2) “Turnover” is a total turnover in euros traded by a trader in a given day; (3) “Portfolio size”, measured in euros, is calculated by assuming that every trader starts every day with zero inventory and builds long and short stock positions by trading throughout the day. Every 5 minutes, i.e. 96 times per day, we calculate values of every short and long trader-stock position by multiplying the outstanding number of shares by the original purchase (selling, for short positions) price, and sum up gross values of all positions to arrive at 96 daily observations for each trader. “Portfolio size” is an average across the 96 daily observations. (4) “Inventory days”, measured in days, is calculated by dividing “Portfolio size” by the total value of shares sold (repurchased, for short positions) during a given day valued at purchase (selling, for short positions) prices. (5) “Turnover top10” is a ratio of daily turnover in the most traded 10 stocks throughout the day over the total daily turnover. The table suggests that the differences between humans and algorithms are not statistically significant in any of these four categories.

	Dependent variable:				
	N of trades	Turnover	Portfolio size	Inventory days	Turnover top10
Algorithm	67.9	-598,733	-346,552	0.1	-0.040
	(0.566)	(0.616)	(0.102)	(0.948)	(0.148)
Constant	694.5***	5,710,481***	1,416,845***	2.7***	0.902***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	121,720	121,720	121,720	112,832	121,552

P-values in parentheses. Standard errors are clustered at trader's level

*** p<0.01, ** p<0.05, * p<0.1

TABLE 1.B

Comparison of trading activity between algorithms and humans

Table 1.B presents the list of the 10 most popular stocks for both humans and algorithms. It is based on the number of times that every stock enters an individual trader’s top 10 in terms of daily turnover.

Humans		Algorithms	
Number of times that a stock is among trader's top 10 in terms of daily turnover	Stock name	Number of times that a stock is among trader's top 10 in terms of daily turnover	Stock name
5159	NOVO B	6072	NOVO B
4794	VWS	5099	VWS
4588	GEN	4725	DANSKE
4582	PNDORA	4374	PNDORA
4421	DANSKE	4327	GEN
3627	MAERSK B	4076	MAERSK B
2832	DSV	3904	DSV
2736	CARL B	3617	CARL B
2545	COLO B	3414	COLO B
2419	NZYM B	3242	NZYM B

TABLE 2

Realization of gains and losses

Table 2 shows the results of regressing hourly (end of hour) trader-level observations of the spread between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) on a constant and a dummy *Algorithm*, which is equal to one if a trader is an algorithm and zero if it is a human. When regressing the spread on a constant only, we split the sample into two groups – humans and algorithms. Standard errors are clustered at a trader level. We consider 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. Individual PGR and PLR for every trader at the end of every hour are calculated as follows. In Panels A, B, C, E and F traders are assumed to start every day with zero inventory and by trading to build their long and short positions in stocks throughout a day. In Panel D, traders are assumed to start the first trading day with zero inventory and to accumulate inventory throughout the full two-year sample period. For every trader-stock position at every point of time we calculate *total gain*, which consist of *cumulative realized gain* and *outstanding paper gain*. *Outstanding paper gain* is calculated by multiplying remaining inventory by the difference between the last observed stock price and the volume-weighted average purchase price (WAPP). *Realized gain* is calculated by multiplying the number of shares sold (or repurchased, in case of short positions) by the difference between the selling (repurchasing) price and WAPP. *Cumulative realized gain* is calculated by accumulating *realized gains* over time. At any point of time, a trader's PGR (PLR) equals *cumulative realized gains* above (below) zero summed up across trader-stock positions divided by *total gains* above (below) zero summed up across trader-stock positions. The dependent variable is the difference between PGR and PLR. Panels A and D consider both long and short trader-stock positions, while Panels B and C consider only long and short positions, respectively. Panel E is similar to Panel A, but considers only those realizations of gains and losses that fully closed positions, i.e. it ignores those stock sales (or repurchases, in case of short positions) which realized only part of a gain or a loss. Panel F considers only those trader-stock positions, which are either long throughout the whole day from the 2-year perspective and short from the daily perspective or short throughout the whole day from the 2-year perspective and long from the daily perspective.

Dependent variable: PGR-PLR spread

	Panel A: all daily positions			Panel B: long daily positions			Panel C: short daily positions		
Subsample:	Algorithms	Humans	Both	Algorithms	Humans	Both	Algorithms	Humans	Both
Algorithm			-0.112***			-0.145***			-0.118***
			(0.002)			(0.001)			(0.004)
Constant	0.009	0.121***	0.121***	0.009	0.154***	0.154***	0.011	0.129***	0.129***
	(0.620)	(0.000)	(0.000)	(0.694)	(0.000)	(0.000)	(0.630)	(0.000)	(0.000)
Observations	57,982	54,674	112,656	51,803	47,912	99,715	51,921	48,981	100,902

	Panel D: all 2-year positions			Panel E: only full realizations			Panel F: only "mental" gain and loss		
Subsample:	Algorithms	Humans	Both	Algorithms	Humans	Both	Algorithms	Humans	Both
Algorithm			-0.118**			-0.087***			-0.140***
			(0.030)			(0.004)			(0.001)
Constant	0.011	0.129***	0.129***	0.007	0.093***	0.093***	0.003	0.143***	0.143***
	(0.762)	(0.003)	(0.002)	(0.658)	(0.001)	(0.000)	(0.883)	(0.000)	(0.000)
Observations	95,990	107,225	203,215	57,982	54,673	112,655	51,747	48,090	99,837

P-values in parentheses. Standard errors are clustered at trader's level

*** p<0.01, ** p<0.05, * p<0.1

TABLE 3

Aggressiveness of trades when realizing losses

Table 3 shows the results of regressing hourly calculated trader-level %ALRT-%ANRT spread on a constant and a dummy *Algorithm*, which is equal to one if a trader is an algorithm and zero if it is a human. When regressing the spread on a constant only, we split the sample into two groups – humans and algorithms. Standard errors are clustered at a trader level. We consider 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. %ALRT (proportion of aggressive loss realization turnover) is equal to a trader's hourly turnover that was executed when realizing losses (i.e. partially or fully closing losing positions) using market orders divided by the hourly turnover executed when realizing losses using both market and limit orders. %ANRT (proportion of aggressive non-realization turnover) is equal to a trader's hourly turnover that was executed when opening new or deepening existing positions using market orders divided by the hourly turnover executed when opening new or deepening existing positions using both market and limit orders. The table shows that algorithms trade virtually equally aggressively when realizing losses and when opening or deepening positions, while humans are more likely to use market orders when realizing losses than when opening or deepening positions.

	Dependent variable: %ALRT-%ANRT spread		
Subsample:	Algorithms	Humans	Both
Algorithm			-0.059***
			(0.005)
Constant	-0.002	0.057***	0.057***
	(0.826)	(0.004)	(0.003)
Observations	40,530	28,110	68,640

P-values in parentheses. Standard errors are clustered at trader's level

*** p<0.01, ** p<0.05, * p<0.1

TABLE 4

Disposition effect sensitivity to the weather

Table 4 shows the results of regressing hourly (end of hour) trader-level observations of the spread between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) on weather variables. The PGR-PLR spread is defined as in Table 1. In these regressions we consider only those observations where PGR-PLR spread is positive, i.e. we test if the disposition effect is sensitive to the weather provided that there is a disposition effect. The hourly trader-specific (depending on the city in which a trader is located) variable of interest is "sunshine duration" (minutes of sunshine during a given hour), and "sunshine dummy" which is equal to 1 if a variable is larger than its monthly average and zero otherwise. We also use three other similarly constructed weather dummy variables as controls: (1) temperature (in Celsius at the beginning of a given hour), (2) precipitation (milliliters of water per square meter of surface), and (4) air pressure (average hectopascal at sea level during a given hour). We use other weather controls in columns 3-6. In columns 1-3 we control for trader fixed effects and time (i.e. date-hour) fixed effects. In columns (4-6) we control for time fixed effects and trader x hour fixed effects in order to account for the possibility that the time of the day may be correlated with both the weather and traders' tiredness of some traders. Robust standard errors are unclustered in columns 1-4, clustered at a trader's level in column 5 and clustered at trader x date level in column 6. Panel A (B) considers 34 human (31 algorithmic) proprietary traders that on average execute between 240 and 1530 trades per day.

	Dependent variable: PGR-PLR spread (percentage points)					
	Panel A: Humans					
	(1)	(2)	(3)	(4)	(5)	(6)
sunshine dummy		0.793**	0.919**	1.016***	1.016*	1.016*
		(0.038)	(0.019)	(0.009)	(0.078)	(0.053)
sunshine duration (minutes)	0.015**					
	(0.044)					
Constant	31.844***	31.849***	31.368***	31.453***	31.453***	31.453***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature, precipitation and pressure controls			Yes	Yes	Yes	Yes
Trader fixed effects	Yes	Yes	Yes			
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Trader x hour fixed effects				Yes	Yes	Yes
Observations	32,022	32,022	32,022	32,018	32,018	32,018
Adjusted R-squared	0.190	0.190	0.190	0.195	0.194	0.195
	Panel B: Algorithms					
	(7)	(8)	(9)	(10)	(11)	(12)
sunshine dummy		0.274	0.299	0.125	0.125	0.125
		(0.676)	(0.656)	(0.852)	(0.882)	(0.886)
sunshine duration (minutes)	0.005					
	(0.661)					
Constant	21.903***	21.914***	22.757***	22.961***	22.961***	22.961***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Temperature, precipitation and pressure controls			Yes	Yes	Yes	Yes
Trader fixed effects	Yes	Yes	Yes			
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Trader x hour fixed effects				Yes	Yes	Yes
Observations	26,466	26,466	26,466	26,465	26,465	26,465
Adjusted R-squared	0.162	0.162	0.162	0.172	0.172	0.172

P-values in parentheses. Robust standard errors are unclustered in columns 1-4, clustered at trader's level in column 5 and clustered at trader x hour leve in column 6

*** p<0.01, ** p<0.05, * p<0.1

TABLE 5

Average profits and returns of frozen portfolios over the 8-hour period – case of loss realization

Table 5 shows the results of regressing (only on a constant) hourly trader-level observations of profits (Panels A and B) and returns (Panels C and D) over the following 8-hour period earned by frozen “Realization” (column 1), “Actual” (column 2) or “Combined” (column 3) portfolios. Panels A and D consider human traders and Panels B and E consider algorithms. Standard errors are clustered at a trader level. We consider 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. The frozen “Realization”, “Actual” and “Combined” portfolios are constructed in the following way. Individual trader’s “Actual portfolio” is constructed by assuming zero starting inventory every day and executing actual trades up to the moment of the freeze. The composition of the “Actual portfolio” is frozen at the end of every hour of a trading day. Individual trader’s “Realization portfolio” is a hypothetical portfolio constructed by executing trades necessary to realize all existing paper **losses** at the moment of the freeze. Individual trader’s “Combined portfolio” is a combination of both “Actual portfolio” and the “Realization portfolio”, thus, it is a hypothetical portfolio that a trader would hold at the moment of the freeze had he just realized all paper **losses**. The gain of every portfolio is calculated by comparing stock prices at the moment of the freeze and eight trading hours later, holding the portfolios’ compositions constant. The return of every portfolio is calculated by subtracting the portfolio value at stock prices prevailing at the time of the freeze from the portfolio value at stock prices prevailing 8 trading hours later (holding the portfolios’ compositions constant), and dividing the difference by the former portfolio value.

	Dependent variable: Portfolio profit over the 8-hour period (EUR)					
	Panel A: humans' profit			Panel B: algorithms' profit		
Portfolio type	"Realization"	"Actual"	"Combined"	"Realization"	"Actual"	"Combined"
Constant	420.577***	-403.512**	63.228	168.819***	133.729	271.410**
	(0.000)	(0.026)	(0.522)	(0.003)	(0.401)	(0.018)
Observations	52,381	52,381	52,381	54,124	54,124	54,124

	Dependent variable: Portfolio return over the 8-hour period (%)					
	Panel D: humans' return			Panel E: algorithms' return		
Portfolio type	"Realization"	"Actual"	"Combined"	"Realization"	"Actual"	"Combined"
Constant	0.141***	-0.090**	0.042	0.092**	0.042	0.123***
	(0.000)	(0.030)	(0.158)	(0.028)	(0.513)	(0.004)
Observations	48,656	50,381	49,565	51,039	52,608	51,885

P-values in parentheses. Standard errors are clustered at trader's level

*** p<0.01, ** p<0.05, * p<0.1

TABLE 6

Average profits and returns of frozen portfolios over the 8-hour period – case of gain realization

Table 6 shows the results of regressing (only on a constant) hourly trader-level observations of profits (Panels A and B) and returns (Panels C and D) over the following 8-hour period earned by frozen "Realization" (column 1), "Actual" (column 2) or "Combined" (column 3) portfolios. Panels A and D consider human traders and Panels B and E consider algorithms. Standard errors are clustered at a trader level. We consider 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. The frozen "Realization", "Actual" and "Combined" portfolios are constructed in the following way. Individual trader's "Actual portfolio" is constructed by assuming zero starting inventory every day and executing actual trades up to the moment of the freeze. The composition of the "Actual portfolio" is frozen at the end of every hour of a trading day. Individual trader's "Realization portfolio" is a hypothetical portfolio constructed by executing trades necessary to realize all existing paper **gains** at the moment of the freeze. Individual trader's "Combined portfolio" is a combination of both "Actual portfolio" and the "Realization portfolio", thus, it is a hypothetical portfolio that a trader would hold at the moment of the freeze had he just realized all paper **gains**. The gain of every portfolio is calculated by comparing stock prices at the moment of the freeze and eight trading hours later, holding the portfolios' compositions constant. The return of every portfolio is calculated by subtracting the portfolio value at stock prices prevailing at the time of the freeze from the portfolio value at stock prices prevailing 8 trading hours later (holding the portfolios' compositions constant), and dividing the difference by the former portfolio value.

	Dependent variable: Portfolio profit over the 8-hour period (EUR)					
	Panel A: humans' profit			Panel B: algorithms' profit		
Portfolio type	"Realization"	"Actual"	"Combined"	"Realization"	"Actual"	"Combined"
Constant	-173.020**	-403.512**	-518.472***	-283.064***	133.729	-162.156**
	(0.012)	(0.026)	(0.000)	(0.008)	(0.401)	(0.018)
Observations	52,381	52,381	52,381	54,124	54,124	54,124

	Dependent variable: Portfolio return over the 8-hour period (%)					
	Panel D: humans' return			Panel E: algorithms' return		
Portfolio type	"Realization"	"Actual"	"Combined"	"Realization"	"Actual"	"Combined"
Constant	-0.063***	-0.090**	-0.150***	-0.120***	0.042	-0.071
	(0.005)	(0.030)	(0.000)	(0.003)	(0.513)	(0.105)
Observations	48,890	50,381	49,576	51,299	52,608	51,697

P-values in parentheses. Standard errors are clustered at trader's level

*** p<0.01, ** p<0.05, * p<0.1

Appendix A

TABLE 2 (Trading frequencies 48-1530)

Realization of gains and losses

Table 2 (Trading frequencies 48-1530) shows the results of Table 2 but using a different subsample – those 63 algorithmic and 170 human traders that on average executed between 48 and 1,530 trades per day throughout our two-year sample period.

This table shows the results of regressing hourly (end of hour) trader-level observations of the spread between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) on a constant and a dummy *Algorithm*, which is equal to one if a trader is an algorithm and zero if it is a human. When regressing the spread on a constant only, we split the sample into two groups – humans and algorithms. Standard errors are clustered at a trader level. We consider 63 algorithmic and 170 human proprietary traders that on average execute between 48 and 1,530 trades per day. Individual PGR and PLR for every trader at the end of every hour are calculated as follows. In Panels A, B, C, E and F traders are assumed to start every day with zero inventory and by trading to build their long and short positions in stocks throughout a day. In Panel D, traders are assumed to start the first trading day with zero inventory and to accumulate inventory throughout the full two-year sample period. For every trader-stock position at every point of time we calculate *total gain*, which consist of *cumulative realized gain* and *outstanding paper gain*. *Outstanding paper gain* is calculated by multiplying remaining inventory by the difference between the last observed stock price and the volume-weighted average purchase price (WAPP). *Realized gain* is calculated by multiplying the number of shares sold (or repurchased, in case of short positions) by the difference between the selling (repurchasing) price and WAPP. *Cumulative realized gain* is calculated by accumulating *realized gains* over time. At any point of time, a trader's PGR (PLR) equals *cumulative realized gains* above (below) zero summed up across trader-stock positions divided by *total gains* above (below) zero summed up across trader-stock positions. The dependent variable is the difference between PGR and PLR. Panels A and D consider both long and short trader-stock positions, while Panels B and C consider only long and short positions, respectively. Panel E is similar to Panel A, but considers only those realizations of gains and losses that fully closed positions, i.e. it ignores those stock sales (or repurchases, in case of short positions) which realized only part of a gain or a loss. Panel F considers only those trader-stock positions, which are either long throughout the whole day from the 2-year perspective and short from the daily perspective or short throughout the whole day from the 2-year perspective and long from the daily perspective.

	Dependent variable: PGR-PLR spread								
	Panel A: all daily positions			Panel B: long daily positions			Panel C: short daily positions		
Subsample:	Algorithms	Humans	Both	Algorithms	Humans	Both	Algorithms	Humans	Both
Algorithm			-0.053**			-0.082***			-0.067**
			(0.022)			(0.008)			(0.020)
Constant	0.019	0.072***	0.072***	0.021	0.103***	0.103***	0.022	0.088***	0.088***
	(0.241)	(0.000)	(0.000)	(0.325)	(0.000)	(0.000)	(0.291)	(0.000)	(0.000)
Observations	75,959	113,123	189,082	64,021	85,808	149,829	63,651	85,871	149,522
	Panel D: all 2-year positions			Panel E: only full realizations			Panel F: only "mental" gain and loss		
Subsample:	Algorithms	Humans	Both	Algorithms	Humans	Both	Algorithms	Humans	Both
Algorithm			-0.039			-0.041**			-0.081**
			(0.286)			(0.035)			(0.010)
Constant	0.008	0.048**	0.048**	0.015	0.056***	0.056***	0.017	0.098***	0.098***
	(0.788)	(0.024)	(0.023)	(0.276)	(0.000)	(0.000)	(0.431)	(0.000)	(0.000)
Observations	143,214	472,388	615,602	75,939	113,129	189,068	63,171	83,326	146,497

P-values in parentheses. Standard errors are clustered at trader's level

*** p<0.01, ** p<0.05, * p<0.1

TABLE 2 (Trading frequencies 480-1530)

Realization of gains and losses

Table 2 (Trading frequencies 480-1530) shows the results of Table 2 but using a different subsample – those 21 algorithmic and 13 human traders that on average executed between 480 and 1,530 trades per day throughout our two-year sample period.

This table shows the results of regressing hourly (end of hour) trader-level observations of the spread between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) on a constant and a dummy *Algorithm*, which is equal to one if a trader is an algorithm and zero if it is a human. When regressing the spread on a constant only, we split the sample into two groups – humans and algorithms. Standard errors are clustered at a trader level. We consider 21 algorithmic and 13 human proprietary traders that on average execute between 480 and 1,530 trades per day. Individual PGR and PLR for every trader at the end of every hour are calculated as follows. In Panels A, B, C, E and F traders are assumed to start every day with zero inventory and by trading to build their long and short positions in stocks throughout a day. In Panel D, traders are assumed to start the first trading day with zero inventory and to accumulate inventory throughout the full two-year sample period. For every trader-stock position at every point of time we calculate *total gain*, which consist of *cumulative realized gain* and *outstanding paper gain*. *Outstanding paper gain* is calculated by multiplying remaining inventory by the difference between the last observed stock price and the volume-weighted average purchase price (WAPP). *Realized gain* is calculated by multiplying the number of shares sold (or repurchased, in case of short positions) by the difference between the selling (repurchasing) price and WAPP. *Cumulative realized gain* is calculated by accumulating *realized gains* over time. At any point of time, a trader's PGR (PLR) equals *cumulative realized gains* above (below) zero summed up across trader-stock positions divided by *total gains* above (below) zero summed up across trader-stock positions. The dependent variable is the difference between PGR and PLR. Panels A and D consider both long and short trader-stock positions, while Panels B and C consider only long and short positions, respectively. Panel E is similar to Panel A, but considers only those realizations of gains and losses that fully closed positions, i.e. it ignores those stock sales (or repurchases, in case of short positions) which realized only part of a gain or a loss. Panel F considers only those trader-stock positions, which are either long throughout the whole day from the 2-year perspective and short from the daily perspective or short throughout the whole day from the 2-year perspective and long from the daily perspective.

	Dependent variable: PGR-PLR spread								
	Panel A: all daily positions			Panel B: long daily positions			Panel C: short daily positions		
Subsample:	Algorithms	Humans	Both	Algorithms	Humans	Both	Algorithms	Humans	Both
Algorithm			-0.111**			-0.138**			-0.117**
			(0.020)			(0.018)			(0.020)
Constant	-0.010	0.101**	0.101**	-0.014	0.124**	0.124**	-0.013	0.105**	0.105**
	(0.536)	(0.038)	(0.024)	(0.524)	(0.034)	(0.021)	(0.541)	(0.035)	(0.022)
Observations	47,077	30,657	77,734	44,212	27,781	71,993	44,157	28,308	72,465
	Panel D: all 2-year positions			Panel E: only full realizations			Panel F: only "mental" gain and loss		
Subsample:	Algorithms	Humans	Both	Algorithms	Humans	Both	Algorithms	Humans	Both
Algorithm			-0.166**			-0.092**			-0.138**
			(0.040)			(0.025)			(0.015)
Constant	-0.028	0.138*	0.138**	-0.010	0.082**	0.082**	-0.014	0.124**	0.124**
	(0.472)	(0.067)	(0.050)	(0.448)	(0.049)	(0.034)	(0.519)	(0.030)	(0.017)
Observations	65,949	50,373	116,322	47,078	30,654	77,732	44,343	27,952	72,295

P-values in parentheses. Standard errors are clustered at trader's level

*** p<0.01, ** p<0.05, * p<0.1

Appendix B

FIGURE 2.A (FIFO method)

Realization of gains and losses throughout a day – default setting

Figure 2.A (FIFO method) shows the same result as Figure 2.A but using a first-in-first-out (FIFO) method instead of weighted average purchase price (WAPP) in order to determine the reference purchase (selling, in case of short positions) stock price.

The figure shows the proportion of gains realized (PGR) and the proportion of losses realized (PLR) at the start of every hour of a day, averaged across trading days and across traders in the two groups, i.e. humans and algorithms. The graph considers 31 algorithmic and 34 human proprietary traders that on average execute between 240 and 1,530 trades per day. Individual PGR and PLR for every trader are calculated as follows. Traders are assumed to start every day with zero inventory (at 9 am) and by trading to build their long and short positions in stocks throughout a day. For every trader-stock position at every point of time we calculate *total gain*, which consist of *cumulative realized gain* and *outstanding paper gain*. *Outstanding paper gain* is calculated by multiplying remaining inventory by the difference between the last observed stock price and the original purchase (selling, in case of short positions) price of each stock using the first-in-first-out (FIFO) method. *Realized gain* is calculated by multiplying the number of shares sold (or repurchased, in case of short positions) by the difference between the selling (repurchasing) price and the original purchase (selling, in case of short positions) price of each stock using the first-in-first-out (FIFO) method. *Cumulative realized gain* is calculated by accumulating *realized gains* throughout a day. At any point of time, a trader's PGR (PLR) equals *cumulative realized gains* above (below) zero summed up across trader-stock positions divided by *total gains* above (below) zero summed up across trader-stock positions.