RATIONALITY AND DISPOSITION EFFECT IN ALGORITHMIC TRADING*

Karolis Liaudinskas[a]

[a]*Norges Bank, Bankplassen 2, 0151 Oslo, Norway; +4740557981; karolis.liaudinskas@norges-bank.no*

Abstract

This article examines the economic rationality of algorithmic decision-making. I use data from the NASDAQ Copenhagen Stock Exchange to study whether algorithmic traders exhibit the disposition effect, i.e., realize gains faster than losses. I find that 17% of algorithms do so but that can be explained by contrarian (mean reversion) trading. These algorithms are profitable and thus not deemed irrational. For algorithms as a group the disposition effect, on average, is not significant while for human traders it is. The difference increases on colder mornings, which evidences psychological causes of the disposition effect and algorithms' ability to avoid psychological biases.

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1. Introduction

Various cognitive biases challenge the rationality assumptions used in economic models (see, e.g., Hogarth and Reder, 1987; Hirshleifer, 2001; Barberis and Thaler, 2003; Thaler, 2016). For example, Kahneman and Tversky (1979) demonstrate how people violate rationality axioms defined by von Neumann and Morgenstern (1947) for the Expected Utility Theory (EUT).[1] Today, decision-making is increasingly automated, and algorithms are shown to inherit unfairness and biases from humans (e.g., Cowgill and Tucker, 2019; Cowgill et al., 2020; Ludwig and Mullainathan, 2021), but, to my knowledge, there is no evidence if algorithms inherit cognitive biases studied in economics. This article contributes to the literature by providing the first such evidence. This is important for the economy and economic theory. For example, if algorithms behave more in line with rational economic models (e.g. those based on Bayesian updating of beliefs or the EUT) than humans do, as algorithms proliferate, these models may become better at explaining and predicting the world. Meanwhile, industries that need more rational decisions may replace humans faster, affecting unemployment, productivity, and economic growth.[2]

An ideal setting for studying rationality is provided by a stock market due to the clear objective of participants - profit maximization. I examine if fully automated algorithmic traders (ATs) exhibit one of the most broadly-documented biases in behavioral finance – the disposition effect, i.e., the tendency to sell winning stocks too early and keep losing

[1] See, e.g., Machina (1987); Marschak (1950); Simon (1978); Apesteguia and Ballester (2015) for other definitions of rationality.

[2] See, e.g., Autor (2015); Acemoglu and Restrepo (2018); Berg et al. (2018) for effects of automation.

stocks for too long (Shefrin and Statman, 1985). If traders do so, their utility appears to depend on a reference point, i.e., past purchase price, which contradicts the rationality defined by the EUT. I measure the disposition effect (DE) as the gap between the proportion of gains realized (PGR) and the proportion of losses realized (PLR), which is broadly in line with Odean (1998). I use trade data from the NASDAQ Copenhagen Stock Exchange for the two years 2016-2017 to estimate DE for every trading account of every member of the exchange at every point in time.[3] Around 2/3 of accounts belong to large international banks, which supports the external validity of the study. The dataset indicates traders' addresses and whether trading accounts are used by humans or ATs that trade "with no human involvement" (Nasdaq, 2019). First, I estimate the average end-of-day DE for ATs and humans. Then, I use exogenous city-hour level variation in weather conditions to test if psychology at least partially causes the difference in DE between the two groups. I also implement robustness checks to test if the difference can be explained by common rational explanations. Finally, I examine whether any individual ATs show positive DE and why.

ATs may exhibit positive DE either due to rational reasons, e.g., portfolio rebalancing, or due to psychological biases that can be either inherited from programmers or learned from data (Cowgill and Tucker, 2019; Cowgill et al., 2020). ATs in my sample period were likely based on fixed rules, which allows me to rule out the machine-learning channel and

[3] As most algorithms trade relatively frequently, I focus on day traders, i.e., those that buy and sell the same stock within a day, and, in line with Locke and Mann (2005); Coval and Shumway (2005); Baron et al. (2019), I assume daily zero starting inventories. As a result, my estimated gains and losses are attributed to trading decisions made throughout the day, and DE can be interpreted as a stronger willingness to reverse those decisions that turned out to be profitable. I show that the main results are similar for both "long" and "short" positions, as well as when assuming zero starting inventories only on the first trading day.

identify the programmer's channel.[4] If ATs in my sample exhibit no biases but future research finds biases among AI-based ATs, this would suggest that biases are learned from data. Why would programmers code the disposition effect? Psychological causes of the disposition effect are still debated and have different plausibilities to affect programmers. Since programmers do not experience the realization of gains and losses, they are unlikely to experience realization utility (Barberis and Xiong, 2012), pride and regret (Muermann and Volkman Wise, 2006) or cognitive dissonance (Chang et al., 2016), but their coding decisions might be affected by loss aversion, attachments to reference points (two biases of the prospect theory (Kahneman and Tversky, 1979) that help explain the disposition effect), and unjustified or overconfident beliefs in mean reversion of stock prices (Odean, 1998; Grinblatt and Keloharju, 2001; Kaustia, 2010; Ben-David and Hirshleifer, 2012). Even if informed, programmers might be insufficiently disciplined or incentivized to control their biases, e.g., if algorithms trade profitably anyway.[5]

I find that 25 out of 146 ATs do systematically realize more gains than losses and this can be fully explained by their contrarian trading strategies, but these ATs are on average profitable (and at least as profitable as other ATs), which suggests that their beliefs in mean reversion are justified. For comparison, humans' DE is not explained by contrarian trading, and humans with positive DE on average perform significantly worse than other humans. For

[4]Even in 2019, only around 35% of the UK banks used machine-learning algorithms for trading (BoE-FCA, 2019).

[5]The usage of stop-loss orders is shown to reduce and even reverse the disposition effect (Nolte, 2012; Fischbacher et al., 2017), which may suggest that automated trading should be bias-free, but this evidence is conditional on endogenous self-selection into the usage, and the usage is relatively low (e.g., only for 20% of position closures in the FX market (Nolte, 2012)). This suggests that investors' motivation to control biases matters even when automation tools are available.

ATs as a group, the average end-of-day DE is not statistically significant while for humans it is. The results are similar in the full sample (146 ATs and 1,151 humans), in the baseline setting with proprietary human and algorithmic traders matched on their average trading frequency (52 ATs and 126 humans), and when using trader-day-level observations tightly matched between humans and ATs on the same day and on five trading characteristics: the number of trades, turnover, portfolio size, trading horizon, and the concentration of turnover in the 10 most traded stocks (59 ATs and 116 humans). For example, in the baseline setting, by the end of the day, ATs on average realize 32% of gains and 30% of losses. The average end-of-day DE equals 2 pp and is not statistically significant. In contrast, humans realize 22% of gains and only 14% of losses. The average DE equals 8.9 pp and is statistically significant at the 1% level. The average difference in DE between humans and ATs of 7.0 pp is significant at the 5% level. Robustness tests show that rational explanations such as transaction costs, career concerns, and portfolio rebalancing, cannot explain the difference.

To understand if this difference is at least partially caused by psychology, I test if DE depends on the weather. Finance literature (e.g., Hirshleifer and Shumway, 2003; Goetzmann et al., 2014) commonly explains the link between the weather and trading behavior by the weather-mood link studied in psychology (e.g., Keller et al., 2005), and the impact of mood on either judgment (e.g., Forgas, 1995) or risk tolerance (Bassi et al., 2013). Keller et al. (2005) is referred to as one of the most thorough studies on the weather-mood link (e.g., by Denissen et al., 2008) and the strongest study to find consistent weather effects on mood (e.g., by Lucas and Lawless, 2013). It finds that more pleasant air temperature improves both mood and cognition. Based on this and the leading theories on the disposition effect, I hypothesize three links between the weather and DE. First, a more pleasant temperature, and thus better mood, can increase overconfidence (Au et al., 2003; Ifcher and Zarghamee, 2014), and overconfidence can strengthen the disposition effect through beliefs in private information (Ben-David and Hirshleifer, 2012). Second, the disposition effect can be explained by the prospect theory (Kahneman and Tversky, 1979), according to which traders care about gains and losses relative to a reference point, are risk-averse (risk-seeking) when facing gains (losses), and are loss-averse. Loss aversion and attachments to reference points are cognitive biases that could be reduced if cognition is improved by a pleasant temperature. Third, according to realization utility (Barberis and Xiong, 2012), the disposition effect occurs because it is pleasant (painful) to realize gains (losses). Such behavior can be viewed as a mood-repair technique that becomes less necessary if mood is improved by a pleasant temperature.[6] The first belief-based explanation predicts that a more pleasant air temperature would increase the disposition effect while the latter two preference-based explanations predict the opposite.[7]

High-frequency data allows me to zoom into the moment when traders are most likely exposed to the weather - on the way to work - and to analyze their trading immediately after the exposure - in the first trading hour (from 9 to 10 am CET). Yeganeh et al. (2018) show in a meta-analysis of 28 experimental studies that cognition worsens if air temperature

[6]Craving for mood-repair has been shown to affect behavior (e.g., Morris and Reilly, 1987; Elliott, 1994). Li et al. (2021) also use mood regulation to explain the link between air pollution and the disposition effect.

[7]Kuhnen and Knutson (2011) find that affect impacts both preferences and beliefs in financial decisions.

deviates from around 21-23°C on average. Since I use only morning temperatures, 97% of which are below 21°C, I interpret higher temperatures as more pleasant.

I find that DE is stronger on colder mornings for humans but not sensitive to the weather for ATs, which supports the two preference-based explanations linking air temperature and DE. The results are similar in the full sample, the baseline setting with the matched traders, and the setting with the tightly matched trader-day-level observations. For example, in the baseline setting, the average DE at 10 am CET for humans is stronger by 1.5 pp, or 21%, on mornings that are colder than the city-time-specific median. The difference in the impact of temperature on DE between humans and ATs is significant at the 1% level. The results are similar when controlling for trader-fixed effects, time-fixed effects, and other weather variables, none of which show robust evidence of impact on DE.[8] Although the impact of the morning temperature is significant and robust to different alterations of the baseline setting, it is not long-lasting. It remains statistically significant until 10:30 am but fades out thereafter. In line with evidence in Keller et al. (2005) on the weather-mood relationship, the results are the most significant when temperatures are moderate, i.e., in spring and autumn.

Overall, this paper shows that DE is, on average, significant for humans, insignificant for ATs (and even when it is significant for individual ATs, this is explained by profitable, and thus not irrational, contrarian trading), and the difference is at least partially caused by psychology. This suggests that programmers manage to avoid coding known psychological

[8]Besides temperature, sunshine (or cloudiness) is also a popular variable in the finance literature. For example, 26 of the 35 studies reviewed by Muhlack et al. (2022) used cloudiness while 23 used temperature. However, in Northern Europe, where most traders in my sample are located, during a part of the year, the sun rises late (sometimes after 9 am) and most days are cloudy with little variation, which helps to explain why the impact of sunshine is insignificant in my setting.

biases into algorithms, and, as a result, algorithmic decisions resemble rational economic models more than on-the-spot human decisions do.

Besides the debate on the rationality assumptions in economics, this paper contributes to the large literature on the disposition effect.[9] First, the paper estimates, for the first time, the disposition effect for algorithmic traders - one of the most prevalent groups of traders.[10] Second, the paper shows that the disposition effect for algorithms can be explained by their profitable contrarian trading. Third, by using exogenous weather variation the paper provides rare field evidence that the disposition effect is at least partially caused by psychology. Causal evidence of psychological biases has started to emerge relatively recently and primarily from experiments (e.g., Frydman et al., 2014; Chang et al., 2016; Frydman and Camerer, 2016; Fischbacher et al., 2017).[11]

The paper also adds to the literature exploring the weather effects on trading. Less cloudy weather is found to increase stock returns (Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann et al., 2014), stock market volatility (Symeonidis et al., 2010), risk-taking (Bassi

[9] Barber and Odean (2013) review the disposition effect literature, which provides explanations for the effect and documents it for various asset classes and investor types. The asset classes include stocks (Odean, 1998), stock options (Heath et al., 1999), commodity and currency futures (Locke and Mann, 2005), real estate (Genesove and Mayer, 2001), while investors include individuals (Odean, 1998), mutual funds (Cici, 2012), and day-traders of futures (Locke and Mann, 2005). The explanations include the prospect theory of Kahneman and Tversky (1979) (e.g., Weber and Camerer, 1998; Kaustia, 2010; Henderson, 2012; Li and Yang, 2013; Henderson et al., 2018; Meng and Weng, 2018), the realization utility of Barberis and Xiong (2009, 2012) (e.g., Ingersoll and Jin, 2013; Frydman et al., 2014), regret aversion and self-control issues (Shefrin and Statman, 1985), beliefs in mean reversion or private information (Ben-David and Hirshleifer, 2012), the nature of limit orders (Linnainmaa, 2010), earnings management (Beatty and Harris, 1999), transaction costs and portfolio rebalancing (Odean, 1998).

[10] Algorithms generated around half of the trading volume in my dataset from the Copenhagen Stock Exchange in 2016-2017. See SEC (2010) for the prevalence of HFT in the US and ESMA (2014) in Europe.

[11] Using field data, Heimer (2016) finds peer effects, Frydman and Wang (2020) find salience effects and Li et al. (2021) find air pollution effects on the disposition effect.

et al., 2013), and propensity to buy stock (Schmittmann et al., 2014; Goetzmann et al., 2014). Higher temperature is also found to increase stock market volatility (Symeonidis et al., 2010) and propensity to buy stock (Schmittmann et al., 2014), but to decrease returns (Cao and Wei, 2005). This paper contributes by testing the weather's impact on the disposition effect.

This paper adds to the research on algorithmic trading, which studies ATs' trading strategies (Brogaard et al., 2014), impact on market quality Hendershott et al. (2011), speed advantage (Budish et al., 2015; Baron et al., 2019), access to information (Biais et al., 2015; Chordia et al., 2018), learning capacity Abis (2022), etc. It also adds to the research on algorithmic bias, which documents that algorithms make biased and discriminatory decisions (Cowgill and Tucker, 2019), e.g., in lending (Bartlett et al., 2022), criminal sentencing (Dressel and Farid, 2018) and ad targeting (Datta et al., 2015). This paper adds to both lines of research by showing that ATs avoid known cognitive biases.

In the rest of the paper, section 2 presents the data, section 3 describes the methodology, section 4 summarizes and discusses the results, and section 5 concludes.

2. Data

2.1. Trading data

I use millisecond-stamped transaction-level trade data provided by the NASDAQ OMX Copenhagen Stock Exchange for the period from 1 January 2016, 9 am, i.e., the stock market's opening time, to 31 December 2017, 5 pm, i.e., the stock market's closing time. I observe the following details about every trade executed by every member of the stock exchange: (1) the execution date and time with 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) trading capacity (i.e., the indicator of whether a trade was proprietary or executed 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 member's address, (10) the indicator of whether a trader's account was used by a human or an algorithm, (11) the user account name (first three letters of a trader's name and surname for humans, and PTRxxx, AUTDxx or LPSxxx for algorithms), and (12) the organization name of a second counterparty. Every trade enters the dataset twice, treating each counterparty as a primary one. The name of a trader's institution combined with the user account name and trading capacity provides a trader's unique id.

NASDAQ Copenhagen issues "Algo" accounts to algorithms that "automatically determine 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, 2019). For example, the exchange specifies that a "PTRxxx account may be used for execution algo flow with no human involvement when placing Child Orders in the market" (Nasdaq, 2019), and an "AUTDxx account <...> is used for purely automated trading for algorithms with no human involvement in the investment decision and order execution" (Nasdaq, 2019). The Danish Financial Supervisory Authority report (Danish FSA, 2016), released in February 2016, i.e., at the beginning of my sample period, provides a broad overview of algorithmic trading activity on the NASDAQ Copenhagen Stock Exchange.

The report summarizes ATs' strategies, benefits and risks to the market, the trends in trading volume of both algorithms and humans, relevant regulations, etc.

The dataset contains 102,160,854 (double-counted) transactions in all 159 stocks listed in the exchange throughout the sample period. Most of the transactions, i.e., 51,541,584, were executed by 146 algorithmic trading accounts belonging to 43 members while 15,981,833 transactions were executed by 1,151 human trading accounts belonging to 67 members. I exclude the rest of the transactions since they were executed by accounts that directly connect members' clients with the exchange and thus it is not clear if they are used by algorithms or humans. There are two main challenges associated with using the full dataset of algorithms and humans. First, I cannot identify traders that use the exchange members as brokers. Second, humans and algorithms may have different trading strategies, and this could explain potential differences in the disposition effect. Most algorithms can be considered to be day traders as they buy and sell the same stock within a day and thus tend to realize at least some gains and/or losses by the end of the day. In contrast, most humans trade infrequently, e.g., a few times per day or even per month, and therefore generate many end-of-day observations of the disposition effect that are either missing or equal to zero.[12]

Therefore, in the baseline setting, I focus on members' proprietary trades that constitute roughly half (50.1 m) of all trades in the dataset, and, for comparability between humans and algorithms, I analyze traders that had more than one non-missing and non-zero end-of-day observation of the disposition effect and that matched at least one trader of the opposite

[12] The measure of the disposition effect is defined in the "Methodology" section as the gap between the proportion of gains realized and the proportion of losses realized.

type in terms of trading frequency. An algorithm was matched to a human if the algorithm's average time gap between trades was within the +-5% window around the human's average time gap between trades. In this way, I focus on day traders and exclude both the most frequently trading algorithms, e.g., high-frequency traders (HFTs) that are known to have special trading strategies (Hagströmer and Nordén, 2013; Menkveld, 2013; Malinova et al., 2014; Brogaard et al., 2014; O'Hara, 2015; Van Kervel and Menkveld, 2019; Korajczyk and Murphy, 2019), and the least frequently trading humans.

This baseline setting contains 14,802,064 transactions: 9,149,783 executed by 52 algorithms belonging to 27 members located in 7 cities (24 accounts in London, 13 in Paris, 6 in Stockholm, 3 in Copenhagen, 3 in Hamburg, 1 in Oslo, 1 in Zürich and 1 in New York) and 5,652,281 transactions executed by 126 humans belonging to 29 members located in 10 cities (57 in London, 16 in Copenhagen, 14 in Paris, 11 in Stockholm, 6 in Amsterdam, 2 in Oslo and 20 in other Danish cities). More than 2/3 of traders (89 of 126 humans and 36 of 52 algorithms) trade for large international banks such as Goldman Sachs, J.P. Morgan, UBS etc., which supports the external validity of the study. Others trade for local banks, small investment banks or trading firms.

Table 1 provides summary statistics of trading patterns for algorithms and humans, and tests if these patterns are similar between the two groups. It includes the following trader-day-level variables: (1) $N\_of\_trades_{i,t}$ – the total number of trades executed by trader i in day t; (2) $Turnover\_EUR_{i,t}$ – total turnover expressed in euros generated by trader i in day t; (3) $Portfolio\_size\_EUR_{i,t}$ – average portfolio size expressed in euros for trader i

throughout day t;[13] (4) $Inventory\_days_{i,t}$ – trading horizon for trader i in day t, calculated as a ratio of $Portfolio\_size\_EUR_{i,t}$ over the total value of shares sold (repurchased, for short positions) by trader i in day t, valued at purchase prices (sale prices, for short positions); and (5) $Turnover\_top10_{i,t}$ – the turnover generated in the 10 most traded stocks by trader i in day t, divided by total turnover of trader i in day t. I regress these variables on a constant and a dummy $Human_i$ equal to 1 for humans and 0 for algorithms. Errors are clustered at the trader level.

Table 1, Panel A shows that when using the full sample, humans and algorithms on average trade very differently as the dummy $Human_i$ is statistically significant at the 1% level for every dependent variable. On average, algorithms execute 1,603 trades per day, while humans execute 172 trades (1,431 fewer). Algorithms generate around EUR 10.6m daily turnover, while humans generate less than EUR 1.9 m. The average portfolio size is EUR 1.6 m for algorithms and EUR 0.4 m for humans. On average it would take 5 days to close all positions for algorithms and 9 days for humans. On average algorithms generate 89% of their turnover in their 10 most-traded stocks, while humans generate 97%. The list of 10 most-traded stocks in terms of aggregate turnover is the same for humans and algorithms. Table 1, Panel B shows that when using the baseline setting with proprietary traders matched on their average trading frequency, humans and algorithms trade more similarly, yet the differences remain significant mostly at the 5% level. Panel C considers

[13]For every trader, I assume zero daily starting inventories and, based on trades, estimate long and short stock positions valued at purchase prices (sale prices, for short positions) at 5-minute intervals. I sum up absolute values of long and short positions and calculate an average of this sum across the 5-minute intervals.

only those trader-day-level observations that were matched between humans and algorithms on the same five variables (within the +- 30% window) and on the same day. In this case, the average differences in trading patterns between algorithms and humans are not significant. Although this setting includes observations from 59 algorithms and 116 humans, the total number of trader-day-level observations is only 2,120. I, therefore, use this setting only as a robustness check for the main results.

2.2. Weather data

I merge the trading data with the hourly weather simulation data, i.e., stored forecasts, provided by Meteoblue in the 12 cities where traders are located: Copenhagen, London, Stockholm, Paris, Amsterdam, Hamburg, Oslo, Zürich, Randers, Silkeborg, Aabenraa and Aalborg.[14] According to the data provider, its weather simulation data is comparable to the measurement data collected by weather stations and has the advantage of often being more complete, more frequent, more detailed, and, if weather stations are relatively remote, more precise than measurement data (Meteoblue, 2022). The dataset includes the following weather variables: (1) air temperature (°C) two meters above ground, (2) relative humidity (%) two meters above ground, (3) mean sea level pressure (hPa), (4) precipitation (mm), (5) cloud cover (% of the sky area), (6) sunshine duration (minutes), (7) shortwave radiation (W/m2), and (8) wind speed 10 meters above ground (km/h). The hourly data frequency allows to observe these variables exactly when traders are most likely to be exposed to the

[14]For a few traders that were located in small Danish towns, I use weather data from the closest of the following five Danish cities: Copenhagen, Randers, Silkeborg, Aabenraa and Aalborg. I exclude New York (one trader) due to a very different time zone.

weather – on their way to work before the stock market opens. I thus construct city-day-level weather variables by taking an average of two data points: at 8 am and at 9 am CET. Table 2 provides summary statistics for all the weather variables and the correlation coefficients between temperature and the other weather variables. The median morning temperature across all cities and days in 2016 and 2017 was 9.0 °C. The 1st and 99th percentiles were -4.2 °C and 23.2 °C, respectively. Temperature is most correlated with radiation (correlation coefficient = 0.690). With other variables, the absolute value of the correlation coefficient does not exceed 0.5.

3. Methodology

3.1. The measure of the disposition effect

The baseline setting focuses on day traders that normally assess their trading decisions within the same day. Therefore, I assume zero starting inventories every day for every trader, which is in line with e.g., Locke and Mann (2005); Coval and Shumway (2005); Baron et al. (2019), and construct traders' intraday "long" and "short" stock positions using observed trades. In this way, my estimated gains and losses are attributed to trading decisions made throughout the same day and the disposition effect occurs from the asymmetric reversion of those decisions. The assumption alleviates potential concerns regarding the nonstationarity and the autocorrelation of the daily time series of the disposition effect. I estimate outstanding paper gain for every trader i, in every stock position s, at every point of time t as follows:

$$\begin{aligned} outstanding\_paper\_gain_{s,i,t} = \#\_shares\_outstanding_{s,i,t} \times \\ \times (stock\_price_{s,t} - WAPP_{s,i,t}) \end{aligned} \quad (1)$$

where $\#\_shares\_outstanding_{s,i,t}$ is the number of shares outstanding in stock s held by trader i at time t, $stock\_price_{s,t}$ is the stock price in the latest transaction of stock s observed in the market up to time t, and $WAPP_{s,i,t}$ is the volume-weighted average purchase price paid for outstanding shares in stock s held by trader i at time t. $WAPP_{s,i,t}$ is updated every time when shares are bought and stays the same when shares are sold. For short positions, $\#\_shares\_outstanding_{s,i,t}$ is negative and $WAPP_{s,i,t}$ is replaced by the corresponding weighted average selling price $WASP_{s,i,t}$.

Every time trader i closes stock position s either fully or partially, I observe a realization of a gain (or a loss, if negative). At that time t, the realized gain is calculated as follows:

$$realized\_gain_{s,i,t} = \#\_of\_shares\_sold_{s,i,t} \times (selling\_price_{s,i,t} - WAPP_{s,i,t}) \quad (2)$$

where $\#\_of\_shares\_sold_{s,i,t}$ is the number of shares sold by trader i in stock s at time t (for short positions - repurchased, hence, $\#\_of\_shares\_sold_{s,i,t}$ is negative), and $selling\_price_{s,i,t}$ is the selling price of those shares (for short positions - repurchasing price). For short positions, $WAPP_{s,i,t}$ is replaced by $WASP_{s,i,t}$.

I accumulate all realized gains up to time t for every trader in every stock:

$$cumulative\_realized\_gain_{s,i,t} = \sum_{n=0}^{t} realized\_gain_{s,i,n} \tag{3}$$

Total gain consists of outstanding paper gain and cumulative realized gain:

$$total\_gain_{s,i,t} = outstanding\_paper\_gain_{s,i,t} + cumulative\_realized\_gain_{s,i,t} \tag{4}$$

For every trader i at every point of time t, I aggregate $total\_gain_{s,i,t}$ across stock positions considering only those with $total\_gain_{s,i,t} > 0$. I also aggregate $cumulative\_realized\_gain_{s,i,t}$ across stock positions considering only those with $cumulative\_realized\_gain_{s,i,t} > 0$. I divide these aggregated positive cumulative realized gains by the aggregated positive total gains to estimate the proportion of gains realized $PGR_{i,t}$ for trader i at time t, and winsorize it if it exceeds one[15].

$$PGR_{i,t} = \frac{\sum_{s=1}^{S}(cumulative\_realized\_gain_{s,i,t} \times j_{s,i,t})}{\sum_{s=1}^{S}(total\_gain_{s,i,t} \times k_{s,i,t})} \tag{5}$$

where $j_{s,i,t}$ is equal to one if $cumulative\_realized\_gain_{s,i,t} > 0$ and zero otherwise, and $k_{s,i,t}$ is equal to one if $total\_gain_{s,i,t} > 0$ and zero otherwise.

Similarly, I estimate the proportion of losses realized $PLR_{i,t}$:

$$PLR_{i,t} = \frac{\sum_{s=1}^{S}(cumulative\_realized\_gain_{s,i,t} \times m_{s,i,t})}{\sum_{s=1}^{S}(total\_gain_{s,i,t} \times n_{s,i,t})} \tag{6}$$

[15] $PGR_{i,t} > 1$ is possible if, e.g., a trader had realized all gains but then re-opened the position and experienced some paper losses. The winsorization ensures that $PGR_{i,t} \in [0; 1]$.

where $m_{s,i,t}$ is equal to one if $cumulative\_realized\_gain_{s,i,t} < 0$ and zero otherwise, and $n_{s,i,t}$ is equal to one if $total\_gain_{s,i,t} < 0$ and zero otherwise.

Following Odean (1998), the disposition effect is the gap between $PGR_{i,t}$ and $PLR_{i,t}$:

$$DE_{i,t} = PGR_{i,t} - PLR_{i,t} \tag{7}$$

In regression analyses, I use daily observations of $DE_{i,t}$ either observed at end-of-day, i.e., at 5 pm CET, or, when testing morning weather effects, after the first trading hour, i.e., at 10 am CET.

3.2. Average disposition effect

I estimate the average end-of-day disposition effect (DE) separately for humans and algorithms by regressing the variable $DE_{i,t}$ on a constant and clustering standard errors at the trader level:

$$DE_{i,t} = \alpha + \epsilon_{i,t} \tag{8}$$

To test whether the difference in the disposition effect between the two groups is statistically significant I include a dummy variable $Human_i$ that equals one for humans and zero for algorithms and run the following regression for both groups jointly.

$$DE_{i,t} = \alpha + \beta_1 \times Human_i + \epsilon_{i,t} \tag{9}$$

3.3. *The impact of air temperature on the disposition effect*

To estimate the impact of weather conditions on the disposition effect, I extend both regression specifications (8 and 9) with the eight city-day-level weather variables observed between 8 am and 9 am CET (see "Data" section and Table 2). To reduce the effects of seasonality and to simplify the interpretation of regression coefficients, I transform these variables into dummies. A dummy equals one if a corresponding raw weather variable on day t in trader $i's$ city is above or equal to the median value of the time interval $[t-15; t+15]$ in that city, and zero otherwise.[16] I show in a robustness test that the results remain similar if I use raw weather variables. Finance literature mostly uses cloud cover (or sunshine) and temperature variables to test weather effects on financial markets (see, e.g., Muhlack et al., 2022), but, in this study, the impact of cloud cover and sunshine might be limited since, in the Northern Europe, in a part of the year, the sun rises relatively late (especially to reach a meaningfully high level above the horizon, e.g., above buildings). Moreover, Table 2 shows that there is relatively little variation in cloud cover, sunshine duration and precipitation, as most of the mornings are not rainy but completely cloudy with zero sunshine. I therefore first focus on the effect of the temperature, then include the other weather variables as controls (C), and then add fixed effects (FE). The regressions are specified as follows:

$$DE_{i,t} = \alpha + \beta_1 \times Temperature_{i,t} + C + FE + \epsilon_{i,t} \quad (10)$$

[16] The results would be similar when using a past time interval $[t - 30; t]$ but using it would bias the dummy values depending on a season, e.g., towards one in spring as the temperature gets gradually higher and towards zero in autumn as the temperature gets gradually lower.

$$DE_{i,t} = \alpha + \beta_1 \times Human_i + \beta_2 \times Temperature_{i,t} + \\ + \beta_3 \times Human_i \times Temperature_{i,t} + C + FE + \epsilon_{i,t} \tag{11}$$

where $Temperature_{i,t}$ is a dummy equal to one if the temperature (observed daily between 8 am and 9 am CET) in trader $i's$ city on day t is above or equal to the median value of the time interval $[t-15; t+15]$ in that city, and zero otherwise; C includes the other seven dummy weather variables and their interactions with the variable $Human_i$; FE includes trader-fixed effects and trading day-fixed effects. The dependent variable $DE_{i,t}$ is observed at 10 am CET, i.e., one hour after the stock market opening. In both regressions, standard errors are clustered multiway at the city and trading day level.

In specification (10), which is used for humans and algorithms separately, the statistical significance of β_1 would indicate that the temperature has an impact on the disposition effect. In specification (11), which is used for humans and algorithms jointly, the significance of β_3 would indicate that the impact of temperature differs between the two groups.

4. Results

4.1. Average disposition effect

Table 3 presents the average end-of-day DE estimated using specification (8) for humans and algorithms separately as well as the average difference in DE between the two groups estimated using specification (9). In the full sample (columns 1 to 3), the disposition effect for algorithms equals 1.3 pp and is not statistically significant, while for humans it equals 4.5 pp and is statistically significant at the 1% level. The difference of 3.2 pp is statistically significant at the 5% level. When using the baseline setting with proprietary traders matched on trading frequency (columns 4 to 6), DE for algorithms equals 2.0 pp and is not statistically significant, while for humans it equals 8.9 pp and is statistically significant at the 1% level. The average difference in DE between the two groups equals 7.0 pp and is statistically significant at the 5% level. When using the tightly matched trader-day-level observations (columns 7 to 9), DE for algorithms equals 2.7 pp and is not statistically significant, while for humans it equals 11.7 pp and is statistically significant at the 1% level. The average difference in DE between the two groups equals 9.0 pp and is statistically significant at the 5% level.

By the end of the day, in the full sample, algorithms on average realize 30% of losses and 31% of gains, while humans realize 10% of losses and 14% of gains. In the baseline setting, algorithms realize 30% of losses and 32% of gains, while humans realize 14% of losses and 22% of gains. In the setting with the tight daily matching, both algorithms and humans realize around 36% of gains but algorithms realize 34% of losses while humans realize only 24%.

When assuming zero starting stock inventories only on the first day of the sample and accumulating inventories, gains and losses throughout the whole two-year sample period based on the observed trades, by the end of the sample period, in the full sample, algorithms realized 58% of gains and 59% of losses, while humans realized 50% of gains and 40% of losses.

4.2. The impact of air temperature on the disposition effect

Table 4 presents estimates of the impact of the morning air temperature on DE observed at 10 am for algorithms and humans, as well as the difference in the impact between the two groups. The table shows the results for the baseline setting but, as shown in the robustness tests (see Table 6 columns 7 and 8), the main results are similar in the full sample and when using the tight daily matching. When using regression specification (10) but without weather controls and fixed effects (columns 1 to 3), the coefficient on $Temperature_{i,t}$ for ATs equals 0.005 and is not statistically significant while for humans it equals -0.015 and is statistically significant at the 1% level. Hence, while for ATs DE is not sensitive to the temperature, for humans, DE is, on average, 1.5 pp, or 21%, stronger on mornings that are colder than city-time-specific median.[17] The average difference of 2 pp between ATs and humans is statistically significant at the 1% level as indicated by the coefficient on the interaction term $Temperature_{i,t} \times Human_i$ in column (3). The results remain similar after including weather controls (columns 4 to 6), and adding trader-fixed effects and trading day-fixed effects (columns 7 to 9).

The effect of the morning temperature on the disposition effect is relatively short-lived. The coefficient on $Temperature_{i,t}$, obtained for humans using specification (10) (see Table 4, column 8 for a baseline result), is negative and statistically significant (at least at the 5% level) when using DE observations between 9:30 am and 10:30 am. By using 15-minute intervals I find that the absolute value of the coefficient peaks at 9:45 am and becomes

[17]The constant (not reported for brevity) is 8.5 pp, thus, an average DE on warmer mornings is 7.0 pp.

statistically insignificant by 10:45 am.

In line with Keller et al. (2005), who find that higher air temperature improves mood and cognition when temperatures are moderate, i.e., in spring, I find that the results are strongest in spring and autumn. The same coefficient on $Temperature_{i,t}$ from specification (10) for humans is equal to -0.043 (p-value=0.009) in spring months (March, April and May), -0.015 (p-value=0.311) in summer (June, July and August), -0.042 (p-value=0.003) in autumn (September, October, November), and -0.003 (p-value=0.878) in winter (December, January, February). The insignificant coefficients in summer and winter could be explained by diminishing marginal effects of temperature and by a potential avoidance of exposure to uncomfortable temperatures.

4.3. Discussion

The results show that, on average, DE is insignificant for ATs but substantial for similarly-trading humans. This serves as suggestive evidence that DE is driven by unintentional causes specific to humans, e.g., emotions and cognitive biases, rather than by intentional profit-maximizing motives, e.g., portfolio rebalancing, transaction costs, and private information, which would be relevant for algorithms as well. This is supported by the causal evidence that air temperature affects DE for humans but not for algorithms. The negative relationship between air temperature and DE supports the two preference-based hypotheses: (1) that warmer weather improves mood and makes realization utility less demanded, and (2) that warmer weather improves cognition and alleviates cognitive biases (such as loss aversion and attachments to reference points) which define the prospect theory and explain the disposition effect. My results contradict the belief-based hypothesis, i.e., that warmer weather increases the disposition effect by boosting mood, overconfidence, and thus beliefs in private information. This suggests that air temperature impacts the disposition effect primarily through preferences rather than beliefs.

In my data sample from 2016-2017, algorithms were likely based on fixed rules rather than on machine learning, which means that algorithms could inherit psychological biases from programmers but would not learn them from data. My findings, therefore, suggest that programmers manage to code algorithms that a free of cognitive biases, at least well-documented ones, and, as a result, algorithms behave more in line with rational economic models than humans do. Below I discuss how algorithms may avoid the disposition effect.

First, while humans make on-the-spot decisions under stress, developers have time to polish decision-making principles in their algorithms. By "thinking slow", i.e., using the slow System 2 (Kahneman, 2011), developers may avoid behavioral biases, heuristics and other cognitive features of the fast System 1, such as attachments to reference points and loss aversion, which are at the core of prospect theory (Kahneman and Tversky, 1979; Kahneman, 2011) – the long-standing explanation of the disposition effect.

Second, while coding, developers are unlikely to experience feelings related to the realization of gains and losses. This arguably makes algorithms less affected by realization utility (Barberis and Xiong, 2012), i.e., pleasure and pain drawn from the realization of gains and losses, and by other related psychological mechanisms that help explain the disposition effect such as pride and regret (Muermann and Volkman Wise, 2006; Strahilevitz et al., 2011; Frydman and Camerer, 2016), the salience of the stock purchase price (Frydman and Wang, 2020) and affect (Loewenstein, 2005).

Third, algorithms may serve as a pre-commitment device that eliminates time-inconsistent behavior stemming from self-control problems associated with the disposition effect. For example, Fischbacher et al. (2017) find that an option to pre-commit to a realization of losses using an automatic selling device reduces the disposition effect.

Fourth, coding can arguably be viewed as a delegation of trading decisions to an algorithm, which creates distance between the trading decisions and developers and, thus, reduces the cognitive dissonance associated with the realization of losses. Chang et al. (2016) finds that the delegation of trading decisions, e.g., to mutual funds, is associated with a lower – and even reversed – disposition effect. According to the authors, this can be explained by cognitive dissonance: investors dislike admitting past mistakes, but delegation allows them to blame someone else.

Other explanations can be rational and related to, e.g., portfolio rebalancing, career concerns and transaction costs. These explanations are tested in the following subsection.

4.4. Robustness checks

The main results show that DE for humans is, on average, significant and increases on colder days, while for ATs it is insignificant and insensitive to the weather. To further check the robustness of these results, Table 5 presents the constant from specification (8) and Table 6 presents the coefficient on $Temperature_{i,t}$ from specification (10), estimated for humans

(Panel A) and algorithms (Panel B) under different modifications of the baseline setting. Column (1) in both Table 5 and Table 6 presents the baseline results that match those in Table 3 and Table 4, respectively. Robustness checks presented in columns (2) to (5) of Table 5 test whether transaction costs, career concerns, and portfolio rebalancing explain positive DE among humans and its insignificance among algorithms.

Transaction costs. A stock price decline may relatively increase transaction costs for that stock, and, therefore, cause reluctance to sell a losing position. Algorithms may care less about transaction costs since market venues compete for algorithmic traders by offering favorable terms (Danish FSA, 2016). This could explain the difference in DE between humans and algorithms, but only for long positions. I test this explanation by comparing DE between long positions, short positions and the baseline setting, which includes both. To consider only long positions I set negative $\#\_shares\_outstanding_{s,i,t}$ and negative $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, to zero. To consider short positions, I set positive $\#\_shares\_outstanding_{s,i,t}$ and positive $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, to zero. Columns (2) and (3) of Table 5 show that for long and short positions, respectively, DE is similar to the baseline for both humans and algorithms. This suggests that transaction costs cannot explain why, on average, humans exhibit a significant DE while algorithms do not.

Career concerns. Human traders and programmers of trading algorithms may have different incentives to report realized gains and losses due to potentially different career concerns or compensation schemes. 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, 2018; Beatty and Harris, 1999; Ahmed and Takeda, 1995). However, these concerns should affect only reported realized gains and losses but not missed opportunities to gain and lose. For example, consider a trader who is long in 100 shares and sells one of them. If the stock price subsequently increases, the trader gains on the 99 shares, but misses the opportunity to gain on the sold share, which can mentally be perceived as a loss. This mental loss can be realized by repurchasing the share at the higher price.[18] If DE for these mental gains and losses is similar to the baseline, this would suggest that the main results are not driven by contract-induced incentives to realize gains and losses. To test this, I consider positions that are either long from the daily perspective, i.e., when assuming zero starting inventory every day, but short from the long-term perspective, i.e., when assuming zero starting inventory only on the first trading day, or short from the daily perspective but long from the long-term perspective. Technically, I first select trader-stock-day positions that from the long-term perspective are either long or short throughout the whole day. Then, if a position from the long-term perspective is long, I set positive $\#\_shares\_outstanding_{s,i,t}$ and positive $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, to zero. If the position from the long-term perspective is short, I set negative $\#\_shares\_outstanding_{s,i,t}$ and negative $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, to zero. Column (4) of Table 5 shows that when considering only mental gains and losses, average DE is similar to the baseline for both humans and algorithms. This suggests that career concerns

[18] Similarly, Strahilevitz et al. (2011) study how regret affects the repurchase of stocks previously sold.

cannot explain why DE is significant among humans but not among ATs.

Another potential explanation related to career concerns could be that after a stock price decline and an associated loss, human traders may be incentivized to take extra risks, e.g., gamble for resurrection, and if low-priced stocks are more volatile than high-priced stocks (see, e.g., Ohlson and Penman, 1985; Dubofsky, 1991), traders might prefer to hold on to losing stocks. However, this holds only for long positions. Table 5 shows that the results are similar for long and short positions.

Portfolio rebalancing. Gains (losses) increase (decrease) the weight of certain stocks in a portfolio and to restore a well-diversified balance, investors may close a portion of their winning positions (increase their losing positions). If algorithmic traders care less about portfolio rebalancing, this could explain the difference in DE between humans and algorithms. 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". To test the portfolio rebalancing explanation, I check if the results remain similar to the baseline when I calculate $PGR_{i,t}$ and $PLR_{i,t}$ considering realized gains and losses only of those positions that were fully closed at least once throughout a day. Technically, in the numerator of equations (5) and (6), I set $cumulative\_realized\_gain_{s,i,t}$ to zero for those trader-stock-day positions that were never fully closed throughout the day. Column (5) of Table 5 shows that DE remains significant for humans and insignificant for algorithms. This suggests that portfolio rebalancing cannot explain this difference between the two groups.

Other robustness checks. The last column (6) in Table 5 shows that the results remain similar to the baseline when using the first-in-first-out (FIFO) method instead of the WAPP to estimate realized gains and losses.

Columns (2) to (6) of Table 6 show that the impact of temperature on DE is statistically significant (at least at the 10% level) for humans and insignificant for ATs under all five alterations of the baseline setting discussed above. The remaining columns show that the impact of temperature remains similar to the baseline when using trader-day level observations that are tightly matched between humans and algorithms on their trading patterns (column 7), using the full sample (column 8), using raw weather variables instead of dummies (column 9), and leaving standard errors unclustered (column 10).

4.5. Why do some ATs exhibit positive DE?

Although average DE for ATs as a group is not statistically significant, it might be significant for some individual ATs. To understand how many such ATs are in my sample and why, I estimate α from equation (8) for every AT separately. I find that out of 146 ATs, α is positive and statistically significant at the 1% level for 25 ATs while it is negative with the same significance for 18 ATs. To understand why, I zoom into their trading patterns during the first ten days of my sample. Figure 1 shows that stock inventories aggregated across the 30 most traded stocks and across all ATs that exhibit a negative and significant average DE evolve broadly in line with the stock price (averaged across the 30 stocks). The pattern is inverse for ATs that exhibit a positive and significant average DE. This suggests that the former group follows momentum trading strategies while the latter one tends to engage in contrarian (or mean reversion) trading strategies.

These strategies can explain the positive and negative average DE. For example, in contrarian trading, traders bet on mean reversion by selling stock after its price increases and buying it after its price decreases. If traders are long (short) in a stock position, selling after a price increase coincides with the realization of gains (the doubling-down on losses) while buying after a price decrease coincides with the doubling-down on losses (the realization of gains). By following such a strategy, one always either realizes gains or doubles down on losses and thus generates positive DE.[19] The disposition effect, however, is not defined by doubling down on losses - only by the relative avoidance of realizing them. Hence, if positive DE is generated by contrarian trading, it should be explained equally well by the tendency to realize gains and the tendency to double down on losses, but if DE is generated by the genuine disposition effect, it should be better explained by the tendency to realize gains than by the tendency to double down on losses.

To test this, I estimate a ratio for the doubling down on losses $RDDL_{i,t} = DDL_{i,t}/(DDL_{i,t} + DDG_{i,t})$, where $DDL_{i,t}$ ($DDG_{i,t}$) is the number of trades executed by trader i during day t to increase stock positions, either long or short, which at the moment of trading had unrealized losses (gains), and a ratio for the realization of gains $RRG_{i,t} = RG_{i,t}/(RG_{i,t} + RL_{i,t})$, where $RG_{i,t}$ ($RL_{i,t}$) is the number of trades executed by trader i during day t to realize any amount of gains (losses).

[19] Similarly, the momentum strategy generates negative DE.

Then I run the following regression and compare coefficients β_1 and β_2.

$$DE_{i,t} = \alpha + \beta_1 \times RDDL_{i,t} + \beta_2 \times RRG_{i,t} + FE + \epsilon_{i,t} \tag{12}$$

FE includes trader-fixed effects and trading day-fixed effects. Standard errors are clustered at the trader level. The results are presented in Table 7. Both coefficients β_1 and β_2 are positive and statistically significant, and, as indicated by the Wald test at the bottom of the table, the difference between them is not significant for ATs (either when using all ATs or only ATs that exhibit positive average DE) but significant for humans. This suggests that DE for ATs is explained equally well by the tendency to realize gains and the tendency to double-down on losses, and thus is associated with contrarian trading. For human traders, and especially those that exhibit positive average DE, β_2 is significantly higher than β_1, which suggests that DE is associated with a genuine disposition effect.

According to Odean (1998), if traders exhibit the disposition effect despite evidence that doing so hurts performance, this would be irrational. I find that, on average, ATs that do not exhibit a positive average DE earn around EUR 900 per day (p-value=0.017) while ATs that do exhibit it earn around EUR 1,300 per day (p-value=0.002). This suggests that the trading strategies of the latter are not irrational. For comparison, human traders that do not exhibit a positive DE lose around EUR 90 per day (p-value=0.219) while humans that do exhibit it lose around EUR 700 per day (p-value=0.000). The difference between the two groups of human traders is statistically significant at 1% level, which suggests that for humans the disposition effect is associated with larger losses and thus irrational behavior.

5. Conclusion

This paper studies whether algorithmic decisions resemble rational economic models more than on-the-spot decisions made by humans. In particular, it examines if ATs exhibit the disposition effect and why or why not. In this way, the paper contributes to a better understanding of both algorithmic decision-making and the causes of the disposition effect.

I find that, on average, trading algorithms do not exhibit a significant disposition effect, while similarly-trading humans do. This suggests that the disposition effect is driven by unintentional, e.g., psychological, causes specific to humans rather than by intentional profit-maximizing motives that would be relevant for algorithms as well. The robustness checks show that neither transaction costs, nor career concerns, nor portfolio rebalancing practices can fully explain these results. Some algorithms, however, do tend to realize more gains than losses but this can be explained by their contrarian trading strategies. These algorithms on average are at least as profitable as the remaining ones and thus are not deemed irrational.

By using exogenous weather variation, I provide a novel identification of the impact of human psychology on the disposition effect. Specifically, I show that warmer morning weather (possibly, by improving mood and cognition) reduces the disposition effect for humans but has no impact for algorithms.

Overall, the results suggest that the disposition effect for humans is at least partially caused by psychological biases and that by suppressing these biases programmers make algorithms behave more in line with rational models. Due to a rapid automation of decision-making, these results may have broad implications for the economy and economic theory.

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TABLE 1

Trading patterns of algorithms and humans

Panels A, B and C show the results of regressing five trader-day-level variables on a constant and a dummy $Human_i$, which is equal to 1 for humans and 0 for algorithms. The five dependent variables are: (1) $N\_of\_trades_{i,t}$ – total number of trades executed by trader *i* in day *t*; (2) $Turnover\_EUR_{i,t}$ – total turnover expressed in euros generated by trader *i* in day *t*; (3) $Portfolio\_size\_EUR_{i,t}$ – average portfolio size expressed in euros for trader *i* throughout day *t* (see the "Data" section for the detailed variable definition); (4) $Inventory\_days_{i,t}$ – trading horizon for trader *i* in day *t*, calculated as a ratio of $Portfolio\_size\_EUR_{i,t}$ over the total value of shares sold (repurchased, for short positions) by trader *i* in day *t*, valued at purchase prices (sale prices, for short positions); and (5) $Turnover\_top10_{i,t}$ – the turnover generated in the 10 most traded stocks by trader *i* in day *t*, divided by total turnover generated by trader *i* in day *t*. Panel A considers the full sample, i.e., 1151 human and 146 algorithmic trading accounts. Panel B considers the baseline sample including 126 humans and 52 algorithms that were matched on their average trading frequency (within the +-5% window around the average time gap between trades). Panel C considers trader-day-level observations that were matched between humans and algorithms on the same five variables (within the +-30% window) reported in this table. Standard errors are clustered at the trader level and reported in parentheses.

Panel A: Full sample - 1151 humans and 146 algorithms

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$N\_of\_trades_{i,t}$	$Turnover\_EUR_{i,t}$	$Portfolio\_size\_EUR_{i,t}$	Inventory $days_{i,t}$	$Turnover\_top10_{i,t}$
$Human_i$	-1,431***	-8,765,083***	-1,151,458***	3.559***	0.074***
	(347)	(2,140,773)	(212,816)	(0.948)	(0.012)
Constant	1,603***	10,634,374***	1,597,980***	4.965***	0.893***
	(347)	(2,130,201)	(208,286)	(0.760)	(0.011)
Observations	124,777	124,777	124,777	60,530	124,120

Panel B: Baseline setting - 126 humans and 52 algorithms

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$N\_of\_trades_{i,t}$	$Turnover\_EUR_{i,t}$	$Portfolio\_size\_EUR_{i,t}$	Inventory $days_{i,t}$	$Turnover\_top10_{i,t}$
$Human_i$	-436***	-2,239,215**	-336,297**	2.320**	0.043**
	(144)	(976,198)	(156,483)	(1.144)	(0.018)
Constant	682***	4,472,328***	845,871***	4.141***	0.902***
	(137)	(877,615)	(134,876)	(0.672)	(0.017)
Observations	36,399	36,399	36,399	22,742	36,382

Panel C: Tight daily matching - 116 humans and 59 algorithms

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	$N\_of\_trades_{i,t}$	$Turnover\_EUR_{i,t}$	$Portfolio\_size\_EUR_{i,t}$	Inventory $days_{i,t}$	$Turnover\_top10_{i,t}$
$Human_i$	-52	-53,447	18,731	0.181	0.012
	(181)	(1,334,250)	(232,385)	(0.281)	(0.027)
Constant	796***	5,364,266***	1,267,654***	1.695***	0.880***
	(116)	(891,639)	(162,980)	(0.197)	(0.021)
Observations	2,218	2,218	2,218	2,218	2,218

Robust standard errors are clustered at the trader level and reported in parentheses

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

TABLE 2

Summary statistics of morning weather variables

Table 2 provides summary statistics of the morning weather variables and correlation coefficients between the temperature and the other weather variables. All weather variables are constructed at the city-day level by taking an average of two data points: at 8 am and 9 am CET in every city. The data includes every daily observation in the years 2016 and 2017 from the following 12 cities: Copenhagen, London, Stockholm, Paris, Amsterdam, Hamburg, Oslo, Zürich, Randers, Silkeborg, Aabenraa and Aalborg. There are 8,772 observations for each variable.

Variable	1st percentile	25th percentile	median	75th percentile	99th percentile	mean
Air temperature 2 meters above ground (°C)	-4.2	4.0	9.0	15.2	23.2	9.4
Relative humidity 2 meters above ground (%)	42.5	71.5	82.0	90.0	97.0	79.6
Mean sea level pressure (hPa)	983.5	1007.4	1014.6	1021.6	1039.9	1014.2
Precipitation (mm)	0	0	0	0	1.35	0.07
Cloud cover (% of the sky area)	0	22.5	100	100	100	68.4
Sunshine duration (minutes)	0	0	0	32.9	60	16.7
Shortwave radiation (W/m2)	0	18.7	125.9	286.58	516.6	167.4
Wind speed 10 meters above ground (km/h)	1.74	10.3	16.15	23.2	45.3	17.4

Correlation coefficient between air temperature and:						
Relative humidity 2 meters above ground (%)	Mean sea level pressure (hPa)	Precipitation (mm)	Cloud cover (% of the sky area)	Sunshine duration (minutes)	Shortwave radiation (W/m2)	Wind speed 10 meters above ground (km/h)
-0.478	-0.061	0.011	-0.164	0.287	0.690	-0.225

TABLE 3

Average disposition effect

Table 3 presents the average disposition effect (DE) estimated by a constant in specification (8) for algorithms (columns 1, 4 and 7) and humans (columns 2, 5 and 8) separately, as well as the average difference in DE between the two groups estimated by the coefficient on dummy variable $Human_i$ (equal to one for humans and zero for algorithms) in specification (9) (columns 3, 6 and 9). The trader-day level dependent variable $DE_{i,t}$ observed at 5 pm CET is defined as the gap between the proportion of gains realized and the proportion of losses realized (see equation 7). The top of the table indicates the setting used, i.e., either the full sample (1151 humans and 146 ATs), or the baseline setting that uses proprietary human and algorithmic traders (126 humans and 52 ATs) matched on their average trading frequency, or the setting that uses trader-day level observations tightly matched between humans and algorithms (116 humans and 59 ATs) on their trading patterns.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	$DE_{i,t}$ (disposition effect)								
	Full sample			Baseline setting			Tight daily matching		
Sample:	Algos	Humans	Both	Algos	Humans	Both	Algos	Humans	Both
Regression specification:	8	8	9	8	8	9	8	8	9
Constant	0.013	0.045***	0.013	0.020	0.089***	0.020	0.027	0.117***	0.027
	(0.285)	(0.000)	(0.282)	(0.353)	(0.000)	(0.346)	(0.293)	(0.000)	(0.287)
$Human_i$			0.032**			0.070**			0.090**
			(0.031)			(0.018)			(0.021)
Observations	27,470	46,604	74,074	11,211	13,790	25,001	1,057	1,063	2,120
Adjusted R-squared	0.000	0.000	0.002	0.000	0.000	0.010	0.000	0.000	0.013

Standard errors are clustered at the trader level; p-values are reported in parentheses

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

TABLE 4

The impact of morning air temperature on the disposition effect

Table 4 presents estimates of the regression specification (10) for ATs (columns 1, 4 and 7) and humans (columns 2, 5 and 8) separately as well as estimates of the regression specification (11) for both groups jointly (columns 3, 6 and 9). The trader-day level dependent variable $DE_{i,t}$ observed at 10 am CET is defined as the gap between the proportion of gains realized and the proportion of losses realized (see equation 7). Weather variables are dummies equal to 1 when a corresponding raw weather variable observed between 8 am and 9 am CET (see Table 2) is above or equal to its median of the time interval [t-15; t+15] in the trader *i*'s city. The dummy variable $Human_i$ equals 1 for humans and 0 for algorithms. Columns 1 to 3 include only one weather variable – $Temperature_{i,t}$. Columns 3 to 6 control for all the remaining weather variables. Columns 7 to 9 add trader-fixed effects and trading day-fixed effects. All regressions are estimated using the baseline setting with proprietary human and algorithmic traders (126 humans and 52 ATs) matched on their average trading frequency. For brevity, only the weather variables and their interaction with the dummy variable $Human_i$ are reported.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	$DE_{i,t}$ (disposition effect)								
Sample:	Algos	Humans	Both	Algos	Humans	Both	Algos	Humans	Both
Regression specification:	10	10	11	10	10	11	10	10	11
$Temperature_{i,t}$	0.005	-0.015***	0.005	0.004	-0.015***	0.004	0.017	-0.025**	0.001
	(0.428)	(0.001)	(0.399)	(0.626)	(0.003)	(0.607)	(0.225)	(0.011)	(0.923)
$Temperature_{i,t}$ × $Human_i$			-0.020***			-0.019**			-0.020**
			(0.008)			(0.016)			(0.015)
$Cloud\_cover_{i,t}$				0.000	-0.016	0.000	-0.008	-0.002	0.001
				(0.995)	(0.118)	(0.995)	(0.520)	(0.805)	(0.904)
$Precipitation_{i,t}$				-0.005	-0.007	-0.005	-0.012	0.007	-0.002
				(0.734)	(0.488)	(0.722)	(0.433)	(0.522)	(0.855)
$Sunshine\_duration_{i,t}$				-0.010	-0.018**	-0.010	-0.021	-0.005	-0.018
				(0.285)	(0.045)	(0.257)	(0.250)	(0.713)	(0.172)
$Humidity_{i,t}$				-0.005	-0.007	-0.005	-0.005	-0.020*	-0.015
				(0.696)	(0.511)	(0.680)	(0.826)	(0.058)	(0.340)
$Pressure_{i,t}$				-0.005	-0.007*	-0.005	0.005	-0.009	0.003
				(0.123)	(0.091)	(0.113)	(0.762)	(0.311)	(0.787)
$Radiation_{i,t}$				-0.012*	-0.023	-0.012*	-0.014	-0.013	-0.011
				(0.086)	(0.177)	(0.059)	(0.171)	(0.221)	(0.139)
$Wind\_speed_{i,t}$				0.003	0.012**	0.003	0.004	0.007	-0.002
				(0.549)	(0.045)	(0.178)	(0.781)	(0.411)	(0.287)
$Cloud\_cover_{i,t}$ × $Human_i$						-0.016			-0.010
						(0.163)			(0.296)
$Precipitation_{i,t}$ × $Human_i$						-0.002			-0.001
						(0.917)			(0.967)
$Sunshine\_duration_{i,t}$ × Huma						-0.007			0.006
						(0.561)			(0.658)
$Humidity_{i,t}$ × $Human_i$						-0.002			0.000
						(0.873)			(0.976)
$Pressure_{i,t}$ × $Human_i$						-0.002			-0.008
						(0.756)			(0.256)
$Radiation_{i,t}$ × $Human_i$						-0.012			-0.002
						(0.434)			(0.834)
$Wind\_speed_{i,t}$ × $Human_i$						0.010			0.010
						(0.178)			(0.287)
Controls				Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects							Yes	Yes	Yes
Observations	8,797	8,379	17,176	8,797	8,379	17,176	8,797	8,365	17,162
Adjusted R-squared	0.000	0.000	0.006	0.000	0.002	0.007	0.054	0.110	0.087

Standard error are clustered multiway at the city and trading day levels; p-values are reported in parentheses

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

TABLE 5

Robustness tests – average disposition effect

Table 5 presents estimates of the average disposition effect for humans (Panel A) and algorithms (Panel B) obtained using regression specification (8), where the trader-day level dependent variable $DE_{i,t}$ (disposition effect) is regressed on a constant. Column (1) presents the baseline estimates, which match Table 3 (columns 4 and 5), and the remaining columns present estimates obtained by modifying the baseline setting in ways indicated at the top of the table. Column (2) uses only long positions, column (3) – only short positions, column (4) – only positions that are either long from the long-term perspective but short from the daily perspective or short from the long-term perspective but long from the daily perspective, column (5) – only positions that were fully closed at least once throughout the day, and column (6) uses the first-in-first-out method instead of the WAPP method to estimate realized gains and losses.

Panel A: humans

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$DE_{i,t}$ (disposition effect)					
Change in the baseline setting:	Baseline	Long positions	Short positions	Mental gains and losses	Full realization	FIFO method
Constant	0.089***	0.111***	0.089***	0.104***	0.063***	0.072***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	13,790	10,717	10,336	10,215	13,790	14,375
Adjusted R-squared	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: algorithms

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$DE_{i,t}$ (disposition effect)					
Change in the baseline setting:	Baseline	Long positions	Short positions	Mental gains and losses	Full realization	FIFO method
Constant	0.020	0.016	0.032	0.022	0.015	0.022
	(0.353)	(0.414)	(0.142)	(0.292)	(0.451)	(0.184)
Observations	11,211	9,355	9,345	9,401	11,211	11,356
Adjusted R-squared	0.000	0.000	0.000	0.000	0.000	0.000

Standard error are clustered at the trader level; p-values are reported in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 6

Robustness tests – the impact of air temperature on the disposition effect

Table 6 presents estimates of the impact of temperature measured at 8-9 am on the disposition effect measured at 10 am for humans (Panel A) and algorithms (Panel B) obtained using regression specification (10), where the trader-day level dependent variable $DE_{i,t}$ (disposition effect) is regressed on eight weather dummies equal to 1 when a corresponding raw weather variable observed between 8 am and 9 am CET (see Table 2) is above or equal to its median of the time interval [t-15; t+15] in the trader *i*'s city. The regression also includes trader-fixed effects and time-fixed effects. For brevity, only the coefficient on $Temperature_i$ is reported. Column (1) presents the baseline estimates, which match Table 4 (columns 7 and 8), and the remaining columns present estimates obtained by modifying the baseline setting in ways indicated at the top of the table. Column (2) uses only long positions, column (3) – only short positions, column (4) – only positions that are either long from the long-term perspective but short from the daily perspective or short from the long-term perspective but long from the daily perspective, column (5) – only positions that were fully closed at least once throughout the day, column (6) uses the first-in-first-out method instead of the WAPP method to estimate realized gains and losses, column (7) considers trader-day-level observations that were matched between humans and algorithms on the five variables (within the +-30% window) reported in Table 1, column (8) considers the full sample (due to the inclusion of inactive traders, the full sample is dominated by missing or zero observations of DE at 10 am, thus, in this setting, I use observations where traders realized at least some gains and losses. This sample includes 1095 humans and 144 algorithms), column (9) uses raw weather variables (see Table 2) instead of dummies, column (10) uses the baseline setting but leaves robust standard errors unclustered.

Panel A: humans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	$DE_{i,t}$ (disposition effect)									
Change in the baseline setting:	Baseline	Long positions	Short positions	Mental gains and losses	Full realization	FIFO method	Tight daily matching	Full sample	Raw weather variables	No error clustering
$Temperature_{i,t}$	-0.025**	-0.026*	-0.031**	-0.039***	-0.018*	-0.025**	-0.089**	-0.032**	-0.005*	-0.025***
	(0.011)	(0.074)	(0.022)	(0.004)	(0.055)	(0.027)	(0.034)	(0.015)	(0.057)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,365	5,713	6,023	5,794	8,365	8,371	706	6,607	8,365	8,365
Adjusted R-squared	0.110	0.116	0.087	0.063	0.095	0.067	0.100	0.070	0.110	0.110

Panel B: algorithms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	$DE_{i,t}$ (disposition effect)									
Change in the baseline setting:	Baseline	Long positions	Short positions	Mental gains and losses	Full realization	FIFO method	Tight daily matching	Full sample	Raw weather variables	No error clustering
$Temperature_{i,t}$	0.017	0.007	0.032	-0.001	0.011	0.013	0.076	0.007	0.003	0.017
	(0.225)	(0.570)	(0.121)	(0.967)	(0.292)	(0.320)	(0.329)	(0.694)	(0.384)	(0.124)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,797	6,886	6,741	6,742	8,797	8,806	751	13,010	8,797	8,797
Adjusted R-squared	0.054	0.131	0.121	0.042	0.054	0.025	0.076	0.072	0.054	0.054

Standard error are clustered multiway at the city and trading day levels (except column 10); p-values are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 7

Testing if contrarian trading explains DE

Table 7 presents estimates of the regression specification (12) that tests for whether DE is explained by contrarian (price mean-reversion) trading. The trader-day level dependent variable $DE_{i,t}$ (disposition effect) is regressed on a constant and two trader-day level ratios: $RDDL_{i,t}$ – a number of trades that expand losing stock positions over the sum of this number and a number of trades that expand winning stock positions, and $RRG_{i,t}$ – a number of trades that realize gains over the sum of this number and a number of trades that realize losses. The regressions include trader-fixed effects and trading day-fixed effects. The bottom three rows present the results of a Wald test for the coefficients on the two ratios being equal: the F-statistic, its degrees of freedom, and its p-value (Prob>F). Column (1) considers all ATs, column (2) considers ATs that exhibit positive average DE, column (3) considers all human traders and column (4) considers human traders that exhibit positive average DE.

	(1)	(2)	(3)	(4)
Dependent variable:	$DE_{i,t}$ (disposition effect)			
Sample:	Algos	Algos with positive DE	Humans	Humans with positive DE
$RDDL_{i,t}$	0.376***	0.358***	0.207***	0.089**
	(0.000)	(0.005)	(0.000)	(0.016)
$RRG_{i,t}$	0.332***	0.496***	0.333***	0.371***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.358***	-0.364***	-0.215***	-0.116***
	(0.000)	(0.000)	(0.000)	(0.000)
Trader-fixed effects	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes
Observations	21,278	7,633	19,328	9,047
Adjusted R-squared	0.141	0.073	0.131	0.132
Test $RDDL_{i,t}$=$RRG_{i,t}$				
Degrees of freedom	**F(1, 105)**	**F(1, 24)**	**F(1, 261)**	**F(1, 61)**
F-statistic	**0.35**	**1.08**	**6.45**	**46.23**
Prob>F	**0.554**	**0.308**	**0.012**	**0.000**

Standard error are clustered at the trader level; p-values are in parentheses
*** p<0.01, ** p<0.05, * p<0.1

FIGURE 1

Trading pattern of the first ten days for ATs that exhibit positive and negative disposition effect

Figure 1 plots stock inventories aggregated across the 30 most traded stocks and across all ATs that exhibit a significantly (at 1% significance level) negative (black solid line) and positive (red solid line) average DE (lhs axis). Inventories are assumed to start at zero on the first trading day and are accumulated based on trades observed throughout the ten days. Before aggregating across stocks, all inventories are weighted (i.e., multiplied) by the first observed prices of respective stocks. The dotted line (rhs axis) represents the average stock price (averaged across the 30 most traded stocks).