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

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Abstract

This paper studies whether and why algorithmic traders exhibit one of the most broadly-documented behavioral puzzles – the disposition effect. We use trade data from the NASDAQ Copenhagen Stock Exchange merged with the weather data. We find that on average, the disposition effect for humans is substantial and decreases significantly on warmer days, while for similarly-trading algorithms, it is insignificant and insensitive to the weather. This provides causal evidence of the link between human psychology and the disposition effect, and suggests that algorithms have the ability to reduce psychology-related human errors. Considering the ongoing AI adoption, this may have broad implications.

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1. Introduction

Artificial intelligence (AI) has been rapidly transforming the financial sector in general and algorithmic trading (AT) in particular (Buchanan, 2019; Bholat et al., 2020; Bholat and Susskind, 2021). Arguably, one of the benefits of AT is the ability to reduce psychology-related human errors (Borch and Lange, 2017; Buchanan, 2019; Buckmann et al., 2021), yet, to our knowledge, there is no evidence on the extent to which AT actually achieves that.[1] This paper provides such evidence by examining whether and why algorithmic traders (ATs), including high frequency traders (HFTs), exhibit one of the most robust and broadly-documented puzzles in behavioral finance – the disposition effect, i.e., the tendency to realize gains faster than losses (Shefrin and Statman, 1985).[2]

This paper bridges the behavioral finance literature with the AT and HFT literature, and makes a twofold contribution. First, psychological biases help explain why investors behave differently than predicted by rational economic models (Barberis and Thaler, 2003), yet, evidence of the causal link between psychology and the disposition effect has started to emerge only recently and primarily from experimental studies (e.g., Frydman et al., 2014; Chang et al., 2016; Frydman and Camerer, 2016; Fischbacher et al., 2017).[3] We provide novel identification of this causal link by using field trading data, exogenous weather variation and algorithms as a control group. More generally, we contribute by suggesting how algorithms can be used as a control group to help identify effects of human psychology. We also provide suggestive evidence on the link between psychology and the disposition effect by simply comparing the levels of the disposition effect among algorithms

[1] E.g., algorithms may inherit various biases from developers or training data (e.g. Cowgill and Tucker, 2019).
[2] Barber and Odean (2013) review the literature that provides potential explanations for the disposition effect and documents it for different 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), the real estate (Genesove and Mayer, 2001), while investors include individual (Odean, 1998) and institutional (Grinblatt and Keloharju, 2001) investors, mutual funds (Cici, 2012), and professional day-traders of futures (Locke and Mann, 2005). The explanations include the prospect theory of Kahneman and Tversky (1979), the realization utility theory of Barberis and Xiong (2012), regret aversion and self-control issues (Shefrin and Statman, 1985), beliefs in mean-reversion or in private information (Ben-David and Hirshleifer, 2012), portfolio rebalancing and transaction costs (Odean, 1998).
[3] Using field data, Heimer (2016) finds causal peer effects, Frydman and Wang (2019) find causal salience effects and Li et al. (2021) find causal air pollution effects on the disposition effect.

and humans. If the disposition effect is driven primarily by emotions and cognitive biases rather than by rational reasons such as informed trading, portfolio rebalancing or transaction costs, we would expect to observe it for humans but less so for algorithms. Second, despite the prevalence of ATs and HFTs,[4] the literature is silent on the disposition effect among them. We document for the first time the disposition effect for HFTs and examine which trading strategies it is associated with. This contributes to a better understanding of both the disposition effect and HFT.[5]

We use two years, 2016-2017, of trade-level data from the NASDAQ Copenhagen Stock Exchange to measure the disposition effect as a percentage of gains realized (PGR) minus a percentage of losses realized (PLR) for every proprietary trading account of every member at every point in time. We focus on day-traders for comparability between algorithms and humans, and, in line with, e.g., Locke and Mann (2005), Coval and Shumway (2005), Baron et al. (2018), assume zero starting inventories every day. The data has two unique features. First, we see members' addresses, which allows matching the data with the hourly weather data in traders' locations, and thus, similarly to Goetzmann et al. (2014), to proxy for traders' mood. Second, we observe the types of trading accounts issued by the exchange and thus can precisely identify humans and algorithms that trade "with no human involvement" (Nasdaq, 2019). Since algorithms are immune to mood shocks, we use them as a control group to account for weather-induced stock market movements (e.g., Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann et al., 2014) that could potentially affect trading decisions for all traders, including algorithms. To further strengthen the identification, we control for interactive fixed effects, i.e., trader-day, stock-day and trader-stock fixed effects.

Results. First, we find that by the end of the day, human traders realize 28% of gains (PGR) and only 17% of losses (PLR) on average. The average end-of-day disposition effect, i.e., PGR-PLR gap, equals 11 pp and is statistically different from zero at 1% significance level. For similarly-

[4] Algorithms generated around half of the trading volume in our dataset from the NASDAQ Copenhagen Stock Exchange in years 2016-2017. See SEC (2010) for the prevalence of HFT in the US and ESMA (2014) in Europe.
[5] See, e.g., O'Hara (2015) and Menkveld (2016) for the literature reviews on HFT.

trading algorithms,[6] the disposition effect equals 1 pp and is not statistically significant (PGR=34% and PLR=33% on average). This suggests that the disposition effect is likely driven by unintentional causes specific to humans, e.g., emotions and cognitive biases, rather than by intentional profit-maximizing motives that would be relevant for algorithms as well.

Second, we find that warmer weather between 8 am and 9 am CET i.e., when traders travel to work and thus are the most likely to be exposed to the weather, reduces the disposition effect in the first trading hour. For human traders, the disposition effect at 10 am CET on average equals 7.1 pp on mornings that are warmer than monthly median and 10.2 pp, i.e., 43% more, on mornings that are colder than monthly median. The difference is statistically significant at 1% level. The result remains similar when using different fixed effects and error clustering, measuring temperature in degrees instead of the “higher-than-median” dummy, and controlling for other weather variables: sunshine duration, cloud cover, precipitation, air pressure, humidity, radiation and wind speed. No other weather variable shows such significant and robust effect. The effect of morning air temperature remains significant by 11 am but fades out by noon and, in line with Keller’s et al. (2005) evidence on the temperature-mood relation, is the most significant when temperatures are moderate, i.e., in spring and autumn. We find no impact of weather on the disposition effect for algorithms.

Due to a well-documented link between the weather and human psychology (see, e.g., Denissen et al., 2008; Klimstra et al., 2011; Harley, 2018), we interpret these results as evidence of the causal effect of psychology on the disposition effect. Our setting does not allow for the identification of the precise psychological mechanism, but since warmer air is found to improve both mood (Cunningham, 1979; Howard and Hoffman, 1984; Keller et al., 2005) and cognition (Keller et al., 2005; Yeganeh et al., 2018), our results can be explained by both major preference-based theories on the disposition effect – realization utility (Barberis and Xiong, 2012) and prospect theory (Kahneman and Tversky, 1979). Firstly, according to realization utility, the disposition effect occurs

[6] For comparability, we exclude algorithms that trade more frequently than the most frequently trading human.

because it is pleasant to realize gains and painful to realize losses. Realizing more gains than losses can thus be seen as a mood-repair technique, which becomes less relevant as the mood is improved by warmer weather.[7] Secondly, if warmer weather improves cognition, this can help reduce cognitive biases that potentially cause the disposition effect, e.g., loss aversion and attachments to reference points which are at the heart of prospect theory (Kahneman and Tversky, 1979; Kahneman, 2011). Alternatively, the weather could impact the disposition effect through beliefs rather than preferences. There is evidence that better mood increases overconfidence (e.g., Au et al., 2003; Nofsinger, 2005; Ifcher and Zarghamee, 2014), and overconfidence is thought to strengthen the disposition effect through stronger beliefs in private information (Ben-David and Hirshleifer, 2012). Yet, we find a weaker disposition effect, which suggests that it is affected more through preferences than beliefs.

Third, we find that 11 of the 22 most frequently trading algorithms (those with an average gap between trades of less than 100 seconds) persistently exhibit a strong disposition effect and this can be very well predicted by their engagement into price-reversal trading strategies. For every algorithm, we count stock-hour observations when a trader either increased or decreased a stock position significantly (by more than trader-stock average) and the stock price has either increased or decreased for two consecutive hours, i.e., during the same hour and one hour before. Then we calculate in how many of these cases a trader engaged in price-reversal trading, i.e. either purchased stock as the price decreased or sold stock as the price increased. All 11 algorithms with a significant disposition effect engaged in price-reversal trading more than 50% of the time, while 10 of the remaining 11 algorithms engaged in price-reversal trading less than 50% of the time. This provides evidence that beliefs in mean-reversion or private information may create the disposition effect (Ben-David and Hirshleifer, 2012) for HFTs and helps to better understand directional HFT strategies (Brogaard et al., 2014; Van Kervel and Menkveld, 2019; Korajczyk and Murphy, 2019).

[7] Craving for mood-repair has been shown to significantly affect behavior (see 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.

Overall, our results suggest that apart from the HFTs that favor price-reversal strategies, ATs on average avoid the disposition effect while similarly-trading humans do not, and this difference can at least partially be explained by psychology-related human errors that ATs manage to reduce. Given the ongoing ubiquitous adoption of AI, this may have broad implications for economic theory, financial markets, the real economy, and, potentially, the future of human behavior. For economic theory, our results suggest that decisions automated by algorithms are more consistent with rational economic models than on-the-spot decisions made by humans. Hence, as humans get replaced by AI, rational economic models, e.g., those based on Bayesian updating of beliefs, the Expected Utility theory (von Neumann and Morgenstern, 1947) or Subjective Expected Utility (Savage, 1964), might become more accurate in explaining the real world. Similarly, as human traders get replaced by algorithmic traders (see, e.g., Kirilenko and Lo, 2013), financial markets might become easier to explain with rational models. For the real economy, our evidence of algorithms' ability to reduce psychology-related human errors may help to predict which industries will be affected more by the automation of decision-making.[8] Finally, if people will be surrounded by automated decision-making (e.g. self-driving cars) that is more "rational", they may either learn to behave more "rationally" or their "rationality" may atrophy due to the reliance on machines.[9]

The rest of the paper is structured as follows. Section 2 highlights our contribution to the related literature. Section 3 presents the data. Section 4 describes the methodology. Section 5 summarizes and discusses the results. Section 6 concludes.

2. Literature and contribution

This paper contributes to a few lines of literature, including on (1) AT and HFT, (2) the disposition effect, (3) weather effects on financial markets, (4) the algorithmic bias and (5) the debate on the rationality assumption in economics.

[8] See, e.g., Autor (2015), Acemoglu and Restrepo (2018), Berg et al. (2018) for effects of automation on economy.
[9] See, e.g., North's (1994) lecture on how environments shape people's mental models of reality, and, in the long run, through collective learning, affect the behavior of future cultures.

First, the literature on AT so far has focused on studying ATs' speed advantage (Budish et al., 2015; Baron et al., 2018), informational advantage (Biais et al., 2015; Chordia et al., 2018), 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 impact on market quality, namely, liquidity (Hendershott et al., 2011; 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; Conrad et al. 2015; Weller, 2017; Brogaard et al., 2019). In a related paper, Abis (2022) finds evidence that algorithmic portfolio managers benefit from a higher learning capacity but suffer from a lower flexibility during recessions as compared to human portfolio managers. We contribute with evidence that besides other advantages, e.g., speed, informational, and, potentially, accuracy (see Kahneman et al., 2016), AT has the ability to reduce behavioral biases.

Second, the literature on the disposition effect has documented the effect in different markets, e.g. stocks (Odean, 1998), options (Heath et al., 1999), currency and commodity futures (Locke and Mann, 2005), the real estate (Genesove and Mayer, 2001), and for different investors, 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). Our first contribution is to document the disposition effect for the widespread group of traders – ATs, including HFTs.

Our second contribution is on the identification of causes of the disposition effect. The prospect theory (Kahneman and Tversky, 1979) paired with mental accounting (Thaler, 1985) provide a long-standing preference-based explanation of the disposition effect (e.g. Shefrin and Statman, 1985; Odean, 1998; Weber and Camerer, 1998; Henderson 2012; Li and Yang, 2013; Henderson et al., 2018; Meng and Weng, 2018): if investors view stocks as separate mental accounts, and are risk-seeking when facing losses but risk-averse when facing gains, they would prefer to gamble with losing investments and to sell winning investments. Realization utility theory (Barberis and Xiong, 2009, 2012; Ingersoll and Jin, 2013; Frydman et al., 2014) provides another preference-based explanation, whereby investors draw utility, e.g., pleasure and pain, directly from the realization of gains and losses. Recent empirical, mostly experimental, studies find evidence that the disposition effect is caused by specific psychological elements such as cognitive dissonance (Chang et al., 2016), pride and regret (Strahilevitz et al. 2011; Frydman and Camerer, 2016), self-control problems (Fischbacher et al., 2017), the salience of the stock purchase price (Frydman and Rangel, 2014; Frydman and Wang, 2019; Dierick et al., 2019), mental accounting (Frydman et al., 2017), peer pressure (Heimer, 2016), mood regulation (Li et al., 2021) and affect (Loewenstein, 2005). The disposition effect can be potentially explained also by beliefs in mean-reversion or private information (see Ben-David and Hirshleifer, 2012), portfolio rebalancing (Odean, 1998; Kaustia, 2010), transaction costs (Odean, 1998), the nature of limit orders (Linnainmaa, 2010), and earnings management (e.g., Beatty and Harris, 1999). We contribute with a novel identification of the causal link between psychology and the disposition effect, using field trading data, exogenous weather variation, and algorithms as a control group. Other related papers on the disposition effect examine its impact on asset prices (Grinblatt and Han, 2005; Frazzini, 2006; An, 2015; Birru, 2015).

Third, this paper relates to the literature studying how the weather affects financial markets. For instance, the weather has been shown to affect stock returns (Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann et al., 2014), the behavior of individual (Schmittmann et al., 2014) and institutional (Goetzmann et al., 2014) investors, and the behavior and performance of loan-officers (Cortés et al., 2016). We contribute with evidence that the weather affects the disposition effect for human traders. This adds to the psychology literature studying how the weather affects mood (Cunningham, 1979; Howard and Hoffman, 1984; Denissen et al., 2008; Klimstra et al., 2011) and cognition (Keller et al., 2005). For example, Keller et al. (2005) find that higher air temperature improves both mood and cognition but only in spring, when people spend more time outside and the air temperature is neither too low nor too high. The link between air temperature and cognition is also studied in the engineering literature (for a review, see Yeganeh et al., 2018).

Fourth, the paper also relates to the literature that studies algorithmic biases (Cowgill and Tucker, 2019). For instance, algorithms have been shown to make biased and discriminatory decisions in lending (Bartlett et al., 2022), criminal sentencing (Dressel and Farid, 2018) and ad targeting (Datta et al., 2015). We contribute with evidence that algorithms reduce behavioral biases.

Finally, our evidence that decisions made by algorithms are more consistent with rational economic models than on-the-spot decisions made by humans contributes to the debate on the rationality assumption in economics (Hogarth and Reder, 1987; Hirshleifer, 2001; Thaler, 2016).[10]

3. Data

We use millisecond-stamped transaction-level trade data spanning from January 1, 2016, 9 am., i.e. the stock market's opening time, to December 31, 2017, 5 pm, i.e. the stock market's closing time, provided by the NASDAQ OMX Copenhagen Stock Exchange. We observe the following details about every trade executed by every 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 member's address, (10) the indicator of whether a trader's account is 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

[10] For various definitions, measures and interpretations of rationality see e.g. Machina (1987), Marschak (1950), Simon (1978), Apesteguia and Ballester (2015).

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 provides a unique trader's 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 our sample period, provides a broad overview of the algorithmic trading activity on the NASDAQ Copenhagen Stock Exchange. The report summarizes ATs' strategies, benefits and risks posed to the market, the trends in trading volume of both algorithms and humans, relevant regulations, etc.

Our dataset contains 102,160,854 (double-counted) transactions in all 159 stocks listed in the exchange throughout our sample period. Since we cannot identify traders that use the exchange members as brokers, we focus only on the proprietary trades of the members. This leaves us with 39,703,660 transactions: 32,243,301 executed by 91 algorithmic trading accounts belonging to 33 members and 7,460,359 executed by 597 human trading accounts belonging to 54 members. Throughout the 503 trading days in our sample, an average algorithm executed 704 trades per day, while an average human – less than 25. For comparability between the two groups, we focus on day traders, i.e., those that trade the same stock multiple times per day and, therefore, by the end of the day tend to realize some gains and/or losses. We keep traders with at least 30 non-zero end-of-day observations of the disposition effect.[11] In this final dataset, there are 93 human trading accounts

[11] 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.

(6,581,144 transactions) belonging to 26 members located in nine cities (32 accounts in London, 21 in Copenhagen, 11 in Stockholm, 8 in Paris, 5 in Amsterdam, and 16 in other Danish cities) and 52 algorithmic trading accounts (31,512,711 transactions) belonging to 24 members located in seven cities (28 accounts in London, 12 in Paris, 5 in Stockholm, 3 in Hamburg, 2 in Copenhagen, 1 in Dublin, and 1 in Zurich). Around 2/3 of traders (60 of 93 humans and 36 of 52 algorithms), trade for large international banks such as BNP Paribas, Deutsche Bank, Credit Suisse, etc. Others trade for local banks, small investment banks or proprietary trading firms. We provide summary statistics of trading patterns for humans and algorithms in the beginning of the "Results" section.

We merge the trading data with the hourly weather simulation data, i.e., stored forecasts, provided by Meteoblue in the twelve cities where traders are located: Copenhagen, London, Stockholm, Paris, Amsterdam, Hamburg, Dublin, Zurich, Randers, Silkeborg, Aabenraa and Aalborg.[12] According to the data provider, their weather simulation data is comparable to the measurement data collected by weather stations and has advantages of often being more complete, more frequent, more detailed, and, if weather stations are relatively remote, more precise than measurement data (Meteoblue, 2022). Our 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/m^2), and (8) wind speed 10 meters above ground (km/h). The hourly data frequency allows us to observe these variables exactly when traders are the most likely to be exposed to the weather – on their way to work before the opening of the stock market. We thus construct city-day-level weather variables by taking an average of two data points: at 8 am and at 9 am CET. Table 1 provides summary statistics for temperature – the variable that we find to have the most significant and robust impact on the disposition effect – and its

[12] For a few traders that were located in small Danish towns we use weather data from the closest one of the following five Danish cities: Copenhagen, Randers, Silkeborg, Aabenraa and Aalborg.

correlation with the other weather variables that we use as controls. The median morning temperature across all cities and days in 2016 and 2017 was 9.2 °C. The 1st and 99th percentiles were -3.4 °C and 23.2 °C, respectively. Temperature is the most correlated with radiation (correlation coefficient = 0.680). With other variables, the absolute value of the correlation coefficient does not exceed 0.5.

4. Methodology

4.1. The measure of the disposition effect

To estimate the disposition effect, we assume zero starting inventories every day for every trader, which is in line with e.g. Locke and Mann (2005), Coval and Shumway (2005), and Baron et al. (2018), and construct traders' intraday stock positions using observed trades. We estimate outstanding paper gain for every trader *i*, in every stock position *s*, at every point of time *t* as follows:

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

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 weighted average selling price $WASP_{s,i,t}$.

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

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

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 $WASP_{s,i,t}$.

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

$$cumulative\_realized\_gain_{s,i,t} = \sum_{n=0}^{t} Realized\ gain_{s,i,n} \quad (3)$$

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

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

For every trader *i* at every point of time *t*, we aggregate $total\_gain_{s,i,t}$ across stock positions considering only those with $total\_gain_{s,i,t} > 0$. We also aggregate $cumulative\_realized\_gain_{s,i,t}$ across stock positions considering only those with $cumulative\_realized\_gain_{s,i,t} > 0$. We 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[13]:

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

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

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

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 $PLR_{i,t}$:

[13] $PGR_{i,t} > 1$ 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 $PGR_{i,t} \epsilon [0; 1]$.

$$DE_{i,t} = PGR_{i,t} - PLR_{i,t} \quad (7)$$

We graphically depict an average intraday development of the disposition effect for humans and algorithms but in all regression analyses, we use daily observations either at end-of-day, i.e., at 5 pm CET, or, when testing morning weather effects, after the first hour of trading, i.e., at 10 am CET.

4.2. Average disposition effect

Separately for humans and algorithms, we estimate average end-of-day disposition effect (DE), proportion of gains realized (PGR) and proportion of losses realized (PLR) by regressing these trader-day-level variables on a constant and clustering standard errors at the trader level:

$$PGR_{i,t} = \alpha + \epsilon_{i,t} \quad (8)$$

$$PLR_{i,t} = \alpha + \epsilon_{i,t} \quad (9)$$

$$DE_{i,t} = \alpha + \epsilon_{i,t} \quad (10)$$

For robustness, we also estimate the following regression specification which exploits all three dimensions of our panel data, and, thus, allows controlling for interactive fixed effects:

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} + FE + \epsilon_{i,t} \quad (11)$$

where $PR_{s,i,t}$ is the proportion of either a gain or a loss realized in a stock position *s* held by trader *i* at the end of day *t*, and is calculated as:

$$PR_{s,i,t} = \frac{cumulative\_realized\_gain_{s,i,t}}{total\_gain_{s,i,t}} \quad (12)$$

and $Gain_{s,i,t}$ is a dummy equal to one if $total\_gain_{s,i,t} \geq 0$ and zero otherwise.[14] Coefficient β_1 represents an average difference in $PR_{s,i,t}$ when gains are realized as opposed to losses, and thus measures the disposition effect. FE includes bank-stock, bank-time, and stock-day fixed effects.

4.3. The impact of air temperature on the disposition effect

[14] $PR_{s,i,t}$ is winsorized if it exceeds 1. If $PR_{s,i,t} < 0$ while $cumulative\_realized\_gain_{s,i,t} > 0$, this suggests that a trader was eager to realize gains (while it was gaining) but lost overall. To reflect his eagerness to realize gains but not losses, in such cases, we replace $PR_{s,i,t}$ with 1 and $Gain_{s,i,t}$ with 1. Similarly, if $PR_{s,i,t} < 0$ and $cumulative\_realized\_gain_{s,i,t} < 0$, we replace $PR_{s,i,t}$ with 1 and $Gain_{s,i,t}$ with 0. Our results remain almost identical if instead we winsorize the variable $PR_{s,i,t}$ below zero or if we drop observations where $PR_{s,i,t} < 0$.

To estimate the impact of weather conditions on the disposition effect we extend regressions (8)-(11) with the eight city-day-level weather variables defined in "Data" section and Table 1, where every observation is an average of two data points in every city: at 8 am and 9 am CET. Since we find only temperature to have a significant and robust impact on the disposition effect, we denote the temperature variable separately by $T_{i,t}$ and treat the other seven weather variables as controls denoted by $C_{i,t}$. Specifically, $T_{i,t}$ is equal to an average temperature (°C) between 8 am and 9 am CET of day *t* in trader's *i* city. To reduce the effects of yearly seasonality in temperature, in our regressions we primarily use a dummy variable $T\_dummy_{i,t}$ equal to one if $T_{i,t}$ is above that month's median in that city and zero otherwise, but we show that our results remain robust if we use variable $T_{i,t}$ instead. The regressions are specified as follows:

$$PGR_{i,t} = \alpha + \beta_1 T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \tag{13}$$

$$PLR_{i,t} = \alpha + \beta_1 T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \tag{14}$$

$$DE_{i,t} = \alpha + \beta_1 T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \tag{15}$$

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} + \beta_2 T\_dummy_{i,t} + \beta_3 Gain_{s,i,t} \times T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \tag{16}$$

All four trade-day-level dependent variables are observed at 10 am CET. The coefficient of interest in regression specification (16) is β_3 on the interaction term. Its statistical significance would show that an average disposition effect measured by β_1 in specification (11) depends on temperature. FE represents trader-fixed effects and day-fixed effects in specifications (13) to (15) and trader-day, stock-day and trader-stock fixed effects in specification (16).

4.4. The difference between humans and algorithms

All regressions specified above are run for humans and algorithms separately. In order to test whether the disposition effect and the impact of temperature differ significantly between humans and algorithms, we extend specifications (10), (11), (15) and (16) with a dummy variable $Human_i$ equal to one if trader *i* is a human and zero if an algorithm, and run the regressions for all traders jointly. Effectively, this splits traders into a treatment group (treated by the weather) and a control group:

$$DE_{i,t} = \alpha + \beta_1 Human_i + \epsilon_{i,t} \tag{17}$$

$$DE_{i,t} = \alpha + \beta_1 Human_i + \beta_2 T\_dummy_{i,t} + \beta_3 Human_i \times T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \tag{18}$$

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} + \beta_2 Human_i + \beta_3 Gain_{s,i,t} \times Human_i + FE + \epsilon_{i,t} \tag{19}$$

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} \times T\_dummy_{i,t} \times Human_i + V\&I_{s,i,t} + C_{i,t} + FE + \epsilon_{i,t} \tag{20}$$

$V\&I_{s,i,t}$ denotes the three variables that constitute the triple interaction term in specification (20) and the three possible interactions among them. The dependent variables in specifications without weather variables, i.e., (17) and (19), are observed at 5 pm CET, while in the other two specifications – at 10 am CET. The coefficients of interest in regressions (18) and (19) are β_3 on the interaction terms, and, in regression (20), β_1 on the triple interaction term.

5. Results

5.1. Comparability between human and algorithmic traders

To ensure that humans and algorithms in our regression analysis are comparable, first we examine trader heterogeneity. Figure 1 plots an average disposition effect on the y-axis for every trader in our sample, i.e., 93 humans and 52 algorithms that have at least 30 non-zero end-of-day observations of variable $DE_{i,t}$. Traders are sorted along the x-axis by a major dimension of heterogeneity – an average trading frequency, which is calculated for every trader as an average time gap (in seconds) between trades executed throughout the sample period. The disposition effect is estimated for every trader by regressing the variable $DE_{i,t}$ (observed daily at 5 pm) on a constant with robust standard errors. Blue and red circles represent humans and algorithms, respectively. If the disposition effect is statistically different from zero at 99% significance level, the circles are colored.

The figure shows that traders differ significantly in their average trading frequency, e.g. some algorithms trade once every few seconds, while some humans trade once every hour (not necessarily the same stock). For comparability between humans and algorithms, we exclude 14 algorithms that trade more frequently than the most frequently trading human, i.e., every 54 seconds, from our regression analysis and label them "HFTs". Moreover, to ensure enough within-trader variation in the disposition effect measured daily at 10 am for the weather impact analysis, as a baseline we consider "frequent traders", i.e., 44 humans and 30 algorithms with an average gap between trades smaller than 10 minutes. The 10-minute threshold is chosen arbitrarily but we show that our main results remain robust when including all the remaining traders labeled "infrequent traders".

Figure 1 suggests that humans tend to exhibit a much larger disposition effect than algorithms that trade at similar frequencies, even though the share of traders that exhibit a statistically significant disposition effect equals one third for both groups (when disregarding HFTs). Interestingly, among algorithms that trade more frequently than once every 100 seconds, a large share, 11 out of 22, exhibit a significant disposition effect while 7 exhibit a significant inverse disposition effect. In section 6 we examine if this heterogeneity can be explained by trading strategies that HFTs pursue.

To compare humans and algorithms in terms of other trading patters besides the disposition effect, we construct 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;[15] (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 10 most traded stocks by trader i in day t, divided by total turnover generated by trader i in day t. We regress these five variables on a constant and a dummy $Human_i$ equal to 1 for humans and 0 for algorithms. We cluster errors at the trader level.

[15] For every trader, we 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 throughout a day. We sum up absolute values of long and short positions, and calculate an average of this sum across the 5-minute intervals.

Table 2, Panel A shows that among "frequent traders", i.e., our baseline sample, humans and algorithms trade similarly as the dummy $Human_i$ is not statistically significant for any of the five dependent variables. On average, algorithms execute 604 trades per day while humans execute 119 trades less, both humans and algorithms generate around EUR 4.1 m daily turnover, average portfolio size is EUR 0.9 m for algorithms and EUR 0.1 m more for humans, on average it takes 3.3 days to close all daily positions for algorithms and 1 day more for humans, and on average algorithms generate 87% of their turnover in their 10 most-traded stocks, while humans generate 4% more. The list of 10 most-traded stocks in terms of aggregate turnover is the same for humans and algorithms. Table 2, Panel B reports that when adding "infrequent traders" to the sample, turnover and portfolio size remains similar between algorithms and humans, but humans tend to trade significantly less frequently, with longer horizon, and with more concentration in favorite stocks than algorithms. To compare algorithms from our baseline sample with HFTs, we redo the analysis with dummy HFT_i instead of $Human_i$. HFT_i equals 1 for HFTs and 0 for algorithms in the "frequent traders" group. Table 2, Panel C shows that HFTs are significantly different. They trade with more frequency, more turnover, larger portfolios, shorter horizons and less concentration on favorite stocks.

5.2. Average disposition effect

To estimate an average disposition effect for humans and algorithms we run the regression specifications (8) to (11) for each group separately. Table 3 presents the results for humans in Panel A and for algorithms in Panel B. Odd columns consider only "frequent traders" and even columns include "infrequent traders". On average, by the end of the day, human "frequent traders" realize 28.2% of their daily gains and only 17.4% of their daily losses. The average disposition effect, i.e., the gap between PGR and PLR, equals 11.5 pp and is statistically different from zero at 1% significance level. When using the regression specification (11) saturated with trader-day, stock-day and trader-stock fixed effects, the average disposition effect drops to 6.6 pp but remains statistically significant at 1% level. All these figures become somewhat smaller but remain statistically significant at 1% level when including "infrequent traders" in the even columns. Algorithmic "frequent traders" realize 34.4% of their daily gains and 32.9% of their daily losses by the end of the day on average. The average disposition effect is only 1.5 pp and is not statistically significant (p-value=0.571). It remains insignificant when using the regression specification (11) saturated with fixed effects and when including "infrequent traders".

Figure 2 shows an average intraday development of PGR and PLR measured at the end of every hour for human and algorithmic "frequent traders". The data points at 5 pm match the estimates from Table 3 described above. The figure shows that on average PGR and PLR gradually and stably increases throughout a day for both humans and algorithms. In the last trading hour, the realization of both gains and losses particularly intensifies, especially for algorithms. The gap between average PGR and PLR remains stable at around 2 pp throughout a day for algorithms but gradually and slightly increases for humans from 8.1 pp at 10 am to 10.8 pp at 5 pm. The graph suggests that the disposition effect for human "frequent traders" at 10 am is substantial and comparable to the end-of-day measure. We, therefore, use it in the analysis of the impact of the morning weather. An average disposition effect at 10 am for human "frequent traders" measured using the regression specification (10) equals 8.6 pp (p-value = 0.001).

5.3. The impact of air temperature on the disposition effect

To evaluate the impact of air temperature on the disposition effect, we estimate regression specifications (13) to (16) using the dependent variables $PGR_{i,t}$, $PLR_{i,t}$, $DE_{i,t}$, and $PR_{s,i,t}$ observed daily at 10 am. Table 4 presents the results for humans in Panel A and for algorithms in Panel B. Columns (1) and (2) indicate that human "frequent traders" realize on average 18.7% of gains and 9.8 % of losses on mornings that are colder than the median of that city-month. On mornings that are warmer than the median, PGR is on average lower by 0.9 pp (i.e., by 5%) and PLR is on average higher by 0.7 pp (i.e., by 7%). Both differences are statistically significant at 10% level and point towards a lower overall disposition effect. Column (3) shows that an average disposition effect for human "frequent traders" equals 9.6 pp on mornings that are colder than the median, and 2.1 pp less (i.e., 22% less) on mornings that are warmer than the median. The difference is statistically significant at 1% level. The estimated impact of temperature is stronger in column (4) when controlling for the other seven weather variables described in "Data" section and Table 1, and even stronger in column (5) when adding trader-fixed effects and day-fixed effects. When extending the sample with "infrequent traders" in column (6), the coefficient on $T\_dummy_{i,t}$ equals -2.1 pp again and is statistically significant at 5% level. When replacing $T\_dummy_{i,t}$ with $T_{i,t}$, the coefficient equals -0.4 pp and is statistically significant at 5% level, which suggests that a 1 °C higher morning air temperature is associated with a 0.4 pp weaker disposition effect on average. In most specifications, including the latter, coefficients on the other weather variables are insignificant.

The results are similar in columns (8) to (10) with three-dimensional panel data. Column (8) shows that the disposition effect for human "frequent traders" measured by the coefficient on $Gain_{s,i,t}$ in specification (11) is lower by 1.6 pp on mornings that are warmer than the median. This result is statistically significant at 1% level. The regression controls for the other weather variables and trader-day, stock-day and trader-stock fixed effects. The result becomes somewhat weaker but remains statistically significant at 1% level in column (9) which includes "infrequent traders". When replacing $T\_dummy_{i,t}$ with $T_{i,t}$ in column (10), the coefficient equals -0.1 pp and is statistically significant at 10% level.

Table 4, Panel B shows that there is no statistically significant impact of air temperature on the disposition effect for algorithms. Having algorithms as a control group reassures that the estimated impact of the weather on the disposition effect for humans is not driven by weather-induced stock market movements (e.g., Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann et al., 2014), that would likely affect trading decisions for all traders, including algorithms. For example, if an algorithm is programmed to pursue a mean-reversion strategy in which it trades stocks when prices cross certain thresholds, then a positive effect of the weather on the stock prices could generate more realized gains, and thus, lead to a stronger disposition effect for the algorithm.

For human "frequent traders", the impact of morning air temperature on the disposition effect remains significant by 11 am but fades out by noon. For example, re-estimating column (3) of Table 4 with the variable $DE_{i,t}$ observed daily at 11 am returns the coefficient on $T\_dummy_{i,t}$ equal to -1.1 pp (p-value = 0.057). The coefficient becomes equal to -1.7 pp (p-value = 0.007) when adding weather control variables (i.e., like in column (4)) and -2.6 pp (p-value = 0.039) when further adding trader-fixed effects and day-fixed effects (i.e., like in column (5)). The coefficient becomes insignificant if the variable $DE_{i,t}$ is observed at 12 pm or later.

In line with Keller's et al. (2005) evidence on the temperature-mood relation, we find that the impact on the disposition effect is the most significant when temperatures are moderate, i.e., in spring and autumn. For example, re-estimating column (3) of Table 4 with observations for March, April and May returns the coefficient on $T\_dummy_{i,t}$ equal to -2.7 pp (p-value = 0.076), and for September, October and November – -3.6 pp (p- value = 0.030). For June, July, August the coefficient equals -1.4 pp (p-value = 0.335), and for December, January and February – only -0.7 pp (p-value = 0.534). These insignificant results could be explained by temperatures becoming uncomfortably high in summer and by a potential avoidance of weather exposure in winter.

5.4. The difference between humans and algorithms

To test if the differences in the results between humans and algorithms in subsections 5.2 and 5.3 are statistically significant, we estimate differential effects using a dummy variable $Human_i$ in regression specifications (17) to (20). Table 5 presents the coefficients of interest for "frequent traders". Column (1) shows that the disposition effect is on average larger by 9.9 pp for humans than for algorithms and the difference is statistically significant at 5% level. In column (2), the coefficient on the interaction term between $T\_dummy_{i,t}$ and $Human_i$ is negative and statistically significant at 10% level, which suggests that a higher morning air temperature reduces the disposition effect for humans significantly more than for algorithms. This differential effect becomes stronger and statistically significant at 5% level when including weather controls in column (3) and somewhat weaker but still statistically significant at 10% level when further adding trader-fixed effects and day-fixed effects in column (4).

The results are similar with the three-dimensional panel data. Column (5) reports a positive and statistically significant coefficient at 10% level on the interaction term between $Gain_{s,i,t}$ and $Human_i$, which suggests that the disposition effect measured by β_1 coefficient on variable $Gain_{s,i,t}$ in specification (11) is significantly larger for humans than for algorithms. Columns (6) and (7) show a negative and statistically significant coefficient at 5% level on the triple interaction term between $Gain_{s,i,t}$, $T\_dummy_{i,t}$ and $Human_i$ with and without trader-day, stock-day and trader-stock fixed effects. This suggests that the impact of air temperature on the disposition effect measured by the negative coefficient β_3 on the $Gain_{s,i,t} \times T\_dummy_{i,t}$ interaction term in specification (16) is significantly stronger for humans than for algorithms.

5.5. Discussion

The results indicate that on average algorithmic day-traders manage to avoid the disposition effect while similarly-trading human day-traders do not. This serves as suggestive evidence that the disposition effect is largely driven by unintentional causes specific to human traders, e.g., emotions and cognitive biases, rather than by intentional profit-maximizing motives, e.g., portfolio rebalancing, transaction costs, and private information, that would be relevant for algorithms as well. This notion is further strengthened by our causal evidence that an air temperature, potentially through mood and cognition, significantly affects the disposition effect for humans but not for algorithms.

Here we discuss potential explanations of how air temperature can affect the disposition effect for humans and how algorithms can avoid the disposition effect.

How can air temperature affect the disposition effect for humans? The psychology literature documents the link between the weather and human psychology (see, e.g., Denissen et al., 2008; Klimstra et al., 2011; Harley, 2018). In particular, higher air temperature is found to improve both mood (Cunningham, 1979; Howard and Hoffman, 1984; Keller et al., 2005) and cognition (Keller et al., 2005; Yeganeh et al., 2018). We therefore argue that our results can be explained by two major preference-based theories on the disposition effect – realization utility (Barberis and Xiong, 2012) and prospect theory (Kahneman and Tversky, 1979). First, according to realization utility, the disposition effect occurs because it is pleasant to realize gains and painful to realize losses. Realizing more gains than losses can thus be seen as a mood-repair technique (see, e.g., Morris and Reilly (1987), Elliott (1994) for theory and other examples of mood-repair techniques), which becomes less relevant as the mood is improved by warmer weather. Li et al. (2021) use the same mood-regulation argument to explain the link between air pollution and the disposition effect.

Second, according to prospect theory, investors draw utility from gains and losses relative to a reference point, are risk-averse when facing gains but risk-seeking when facing losses, and experience losses more severely than equivalent gains, i.e., are loss averse (Kahneman and Tversky, 1979). Hence, if investors view every stock as a separate mental account (see Thaler, 1985), they would prefer to continue gambling with losing investments and to sell winning investments. If higher air temperature improves cognition, this can help reduce cognitive biases such as loss aversion and attachments to reference points, which would reduce the disposition effect.

The weather may also impact the disposition effect through beliefs rather than preferences. For example, Goetzmann et al. (2014) find that the weather-induced mood affects traders' beliefs and behavior. According to Ben-David and Hirshleifer (2012), the disposition effect can be caused by traders' beliefs in their private information about the stock value,[16] and these beliefs can stem either from genuine information or overconfidence.[17] Since there is evidence that higher temperature enhances mood and that better mood increases overconfidence (e.g., Au et al., 2003; Nofsinger, 2005; Ifcher and Zarghamee, 2014), one could expect warmer weather to strengthen the disposition effect. This prediction, however, is the opposite from our findings, which suggests that morning air temperature impacts the disposition effect primarily by affecting preferences rather than beliefs.

The direct effects of the weather can potentially be amplified through social interactions, since mood is found to be contagious (Neumann and Strack, 2000).

How can algorithms avoid the disposition effect? First, while human traders make on-the-spot decisions under stress, developers have time to "think slow" (Kahneman, 2011) and deliberately polish decision-making principles in their algorithms. By "thinking slow", i.e. using the slow System 2, 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. However, despite claims (see, e.g., Borch and Lange, 2017), it is not obvious that developers manage to eliminate effects of mood, emotions and cognitive biases from their codes. For example, algorithms may inherit biases from biased developers or training data (Cowgill and Tucker, 2019). This can help explain why some algorithms in Figure 1 do exhibit a significant disposition effect.

Second, while coding, developers are unlikely to experience feelings associated with the on-the-spot 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, respectively, and by other related psychological mechanisms that help explain the disposition

[16] Traders may view price hikes as the incorporation of their information into the price and price drops as temporary setbacks, and thus sell (hold) stock after price hikes (drops). Yet, the opposite may hold too: after price drops (hikes) traders may lose (gain) confidence in their information and sell (buy more) stock (Ben-David and Hirshleifer, 2012).
[17] Overconfidence is an extensively documented cognitive bias that affects beliefs (Barberis and Thaler, 2003).

effect such as pride and regret (Muermann and Volkman, 2006; Frydman and Camerer, 2016), the salience of the stock purchase price (Frydman and Wang, 2019) and affect (Loewenstein, 2005).

Third, algorithms may serve as a pre-commitment device which can eliminate time-inconsistent behavior stemming from, for example, 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 significantly 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 blaming someone else.

Other potential explanations for the difference in the disposition effect between humans and algorithms include belief-based explanations and purely rational explanations such as portfolio rebalancing, career concerns and transaction costs. We test these explanations in the next section as part of the robustness checks for our main results.

5.6. Robustness checks

We re-estimate regression specifications (10) and (15) under five different assumptions. Namely, we consider only long positions, only short positions, only missed opportunities to gain and lose (i.e., mental gains and losses), and only full realizations of gains and losses. We also use the FIFO method instead of WAPP to estimate real gains and losses. Table 6 shows the results for human and algorithmic "frequent traders" separately. Besides providing robustness checks for our results, these alterations of the baseline setting test whether transaction costs, career concerns and portfolio rebalancing explain the difference in the average disposition effect between humans and algorithms.

Transaction costs. A stock price decline may relatively increase transaction costs for that stock, and, therefore, cause reluctance to sell losing positions. 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 the disposition effect between humans and algorithms, but only for long positions. We test this explanation by comparing the disposition effect between long positions, short positions and our baseline setting which includes both.

Assumption 1: we consider only long positions (see results in Table 6, columns (1) and (2)). Technically, if $\#\_shares\_outstanding_{s,i,t}$ and $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, are negative, we set them to zero.

Assumption 2: we consider only short positions (see results in Table 6, columns (3) and (4)). Technically, if $\#\_shares\_outstanding_{s,i,t}$ and $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, are positive, we set them to zero.

Career concerns. Human traders and developers 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, 2017; Beatty and Harris, 1999; Ahmed and Takeda, 1995). However, these concerns should affect only reported 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 subsequently the stock price increases, the trader gains on the 99 shares, but misses the opportunity to gain on the sold one, which can mentally be perceived as a loss. This loss can be realized by repurchasing the share at the higher price.[18] If the average disposition effect for these mental gains and losses is similar to the baseline, this would suggest that our main results are not driven by contract-induced incentives to realize gains and losses.

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

Assumption 3: we 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 day, or short from the daily perspective but long from the long-term perspective (see Table 6, columns (5) and (6)). Technically, we 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, while $\#\_shares\_outstanding_{s,i,t}$ and $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, are positive, we set them to zero. If a position from the long-term perspective is short, while $\#\_shares\_outstanding_{s,i,t}$ and $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, are negative, we set them to zero.

Another explanation related to career concerns could be that after a stock price decline and an associated loss, human traders (more than algorithmic traders) may be incentivized to take extra risks, 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. This explanation, however, again holds only for long positions, and, therefore can be tested by comparing the results for long and short positions in columns (1) and (3), respectively.

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 the disposition effect 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, we check if the results remain similar to the baseline when we consider only full realization of gains and losses.

Assumption 4: consider the realization of gains and losses only for those trader-stock-day positions that were completely closed at least once throughout a day (see Table 6, columns (7) and (8)). Technically, in the numerator of equations (5) and (6), we set $cumulative\_realized\_gain_{s,i,t}$ to zero for those trader-stock-day positions that were never closed throughout the day.

Finally, we check if our results are affected by the estimation method of real gains and losses.

Assumption 5: use first-in-first-out (FIFO) method, instead of WAPP, to calculate realized gains and losses (see Table 6, columns (9) and (10)).

The estimated constant in the odd columns of Table 6 indicate that under each of the five assumptions, the average disposition effect for humans remains similar and statistically significant at 1% level, while for algorithms it is never statistically different from zero. This suggests that neither transaction costs, nor career concerns, nor portfolio rebalancing alone can fully explain the difference in the average disposition effect between humans and algorithms. The estimated coefficient on $T\_dummy_{i,t}$ in the even columns show that under every assumption, the impact of air temperature on the disposition effect for humans remains similar and statistically significant at least at 10% level, while for algorithms it is never statistically significant. This strengthens the robustness of our results.

5.7. Belief-based explanations

Traders may purchase a stock because they believe to have superior information about its potential future price. As a result, they may view price hikes as incorporations of their information into the price (and thus sell) and price drops as temporary setbacks (and thus hold or buy more), which would create the disposition effect (Ben-David and Hirshleifer, 2012). Similarly, traders may believe in the mean-reversion of the stock price, and thus sell stock after the price hikes and buy it after the price drops, which would also lead to the disposition effect. Algorithms, having better access to information (Chordia et al., 2018; Biais et al., 2015), more computational power and learning capacity (Abis, 2022), and, possibly, being less subject to overconfidence, may have weaker beliefs in these price-reversal trading strategies than humans, which would explain the lower disposition effect on average.

To test whether humans pursue price-reversal strategies more often than algorithms, we implement the following exercise. First, we estimate the absolute value of hourly change in the number of shares, $|\Delta inventory_{s,i,t}|$, for every trader i, stock s, day-hour t, and find the 90th percentile of this variable for every trader-stock, $perc90_{s,i}$, considering only non-zero observations. Second, for every trader i, we count the number of stock-day-hour level observations, N_i, where $\left|\Delta inventory_{s,i,t}\right| > perc90_{s,i}$ and the stock price $S_{s,t}$ has either increased or decreased for the second consecutive hour, i.e., either $(\Delta S_{s,t} > 0\ and\ \Delta S_{s,t-1} > 0)$ or $(\Delta S_{s,t} < 0\ and\ \Delta S_{s,t-1} < 0)$. Third, among these observations, we count the number of cases, $N\_reverse_i$, where a large change in inventory, $\Delta inventory_{s,i,t}$ was in the opposite direction from $\Delta S_{s,t}$, i.e., either $(\Delta inventory_{s,i,t} > 0\ and\ \Delta S_{s,t} < 0\ and\ \Delta S_{s,t-1} < 0)$ or $(\Delta inventory_{s,i,t} < 0\ and\ \Delta S_{s,t} > 0\ and\ \Delta S_{s,t-1} > 0)$. Finally, we estimate a proportion of stock-day-hours spent on price-reversal trading for every trader as:

$$Reversal\_trading\_proportion_i = \frac{N\_reverse_i}{N_i} \qquad (21)$$

We regress this variable on a constant and a dummy $Human_i$ equal to 1 for human and 0 for algorithmic "frequent traders", and use robust standard errors. The constant equals 0.504 (p-value = 0.000) and indicates that algorithms on average purse price-reversal and momentum trading equally often, i.e., 50% of the time. The coefficient on the dummy $Human_i$ equals 0.056 (p-value = 0.023) and suggests that humans pursue price-reversal trading significantly more often than algorithms, which helps explain why they exhibit a stronger disposition effect.

It is not obvious, however, if the price-reversal trading, and the associated disposition effect, are rational or not (e.g. driven by overconfidence). According to Odean (1998), if the disposition effect helps perform better, it would be justified and rational, but if traders continue to exhibit it despite persistent evidence that doing so hurts their performance, this behavior would be irrational.

To measure the performance of human and algorithmic "frequent traders" we estimate every trader's i return at the end of every day t:

$$r_{i,t} = \frac{\sum_{s=1}^{S} total\_gain_{s,i,t}}{Portfolio\_size_{i,t}} \tag{22}$$

where $total\_gain_{s,i,t}$ is defined in equation (4), $\sum_{s=1}^{S} total\_gain_{s,i,t}$ is the sum of end-of-day profits across all stocks held by trader i in day t, and $Portfolio\_size_{i,t}$ is calculated in the same way as $Portfolio\_size\_EUR_{i,t}$ defined in "Data" section and Table 2, but not converted to euros. We regress this variable on a constant separately for human and algorithmic "frequent traders", and cluster standard errors at the trader level. For humans, the constant equals -0.0033 (p-value = 0.260), which translates to an average annualized return of -11.3%.[19] The negative return is driven by traders that purse price-reversal strategies: for humans with $Reversal\_trading\_proportion_i$ larger than median (i.e., 0.54), the average annualized return equals -31.2% (p-value = 0.011), while for the rest it is 20.1% (p-value = 0.214). Similarly, for humans that on average exhibit a significant disposition effect, as shown in Figure 1, and for those who do not, the average annualized return equals -22.5% (p-value = 0.051) and 0.1% (p-value = 0.994), respectively. Hence, both the price-reversal trading and the disposition effect are associated with significant losses for human traders, which suggests that beliefs of human traders in price-reversal strategies are mostly not rational.

For algorithms, the average annualized return equals 17.2% (p-value = 0.244). For traders with $Reversal\_trading\_proportion_i$ larger than median (i.e., 0.50) the average annualized return equals 45.2%, while for the rest it is 2.2% (both p-values above 0.1). Similarly, for those that on average exhibit a significant disposition effect, as shown in Figure 1, the average annualized return equals 49.2%, while for the rest it is 1.7% (both p-values above 0.1). Hence, algorithms perform

[19] Average annualized return is calculated as (1+average_daily_return)^365 – 1

better than humans on average, and particularly when pursuing price-reversal strategies, which suggests that their "beliefs" in price-reversal strategies might be mostly rational.

Finally, to test whether the disposition effect has a causal effect on performance, we implement the following exercise. First, for every trader we observe the portfolio composition daily at 1 pm, i.e., in the middle of a trading day, and create a hypothetical "realization portfolio", which, if acquired, would cancel out all losing positions, and thus, would realize all unrealized losses. At the end of a trading day, i.e., at 5 pm, we estimate the return on this "realization portfolio". Second, we regress this trader-day level return on a constant separately for four groups of "frequent traders": humans and algorithms that do and do not exhibit a significant average disposition effect, as shown in Figure 1. We cluster errors at the trader level. Assuming zero transaction costs and zero price impact, the estimated constant can be interpreted as an average daily return not earned due to not realizing one's losses in the middle of a trading day. For humans that exhibit a disposition effect, this constant equals 0.000929 (p-value = 0.046), which translates to an average annualized return of 40.3%. Hence, these traders would have benefited significantly from a full realization of losses daily at 1 pm, which suggests that the disposition effect for them was harmful and not driven by rational causes. For the other three groups, the estimated constant is positive but not statistically significant.

6. The disposition effect for high-frequency traders

Figure 1 shows that 18 out of the 22 algorithms that on average trade more frequently than once every 100 seconds, on average exhibit either a significant disposition effect or a significant inverse disposition effect. We explore if this can be explained by trading strategies of these HFTs.

SEC (2010) describes four broad categories of HFT strategies, namely, (1) passive market making, (2) arbitrage, e.g., exploiting price inefficiencies across products or markets, (3) structural, e.g., exploiting co-location arrangements to increase the speed of data delivery, and (4) directional, e.g., price-reversal or price momentum strategies. As discussed in subsection 5.7, price-reversal strategies can generate the disposition effect, hence, trading in the opposite direction, i.e., pursuing price momentum strategies, can create its inverse. Since HFTs have been shown to pursue directional trading in both directions (see, e.g., Brogaard et al., 2014; Van Kervel and Menkveld, 2019; Korajczyk and Murphy, 2019), we suspect that being persistently biased towards either one of the two directions may explain the observed patterns of disposition effect for HFTs.

Figure 3, shows an example of a price-reversal trading pattern for an HFT that, according to Figure 1, on average exhibits a significant disposition effect, and a momentum trading pattern for an HFT that on average does not exhibit one. The figure plots, for the first ten days of our sample, hourly (end-of-hour) observations of the stock price of Pandora, one of the most traded stocks in the Copenhagen stock exchange, and inventory of Pandora stock held by the two different HFTs. We assume zero starting inventory on the first day. The price and inventory appears to correlate negatively for the HFT that exhibits the disposition effect and positively for the HFT that does not.

To check how well the engagement in price-reversal strategies can predict the disposition effect among HFTs, we estimate a trader-level variable $Reversal\_trading\_proportion_i$, defined in sub-section “5.7. Belief-based explanations”, equation (21). The variable measures a proportion of stock-day-hours spent on price-reversal trading, i.e., either significantly increasing stock inventory as the price has decreased for the second consecutive period, or significantly decreasing stock inventory as the price has increased for the second consecutive period. Figure 4 plots a distribution of this variable across the 22 algorithms that, according to Figure 1, on average trade more frequently than once every 100 seconds. The red columns represent algorithms that, according to Figure 1, on average exhibit a statistically significant disposition effect, and white columns represent HFTs that do not. The histogram shows that all the algorithms with $Reversal\_trading\_proportion_i > 0.5$ on average exhibit the disposition effect, while all the rest do not. This suggests that the engagement in price-reversal strategies can very well predict whether an HFT would exhibit the disposition effect.

In order to check whether the disposition effect among HFTs is associated with a lower performance, and, thus, irrational explanations, we estimate every trader's daily return $r_{i,t}$ defined in equation (22), and regress it on a constant separately for HFTs that on average exhibit the disposition effect and for HFTs that do not. We cluster standard errors at the trader level. The constant equals 0.00073 (p-value = 0.007) and 0.00087 (p-value = 0.028) for the two groups, respectively. These average daily returns translate to average annualized return of 30.5% and 37.3%, respectively. The difference between them is not statistically significant as measured by a dummy variable splitting the data into the two groups. This suggests that for HFTs, the disposition effect is not associated with a lower performance and, thus, with irrational beliefs. In our dataset, we observe cases where two HFT algorithms belong to the same institution, and one algorithm exhibits a significant disposition effect while the other one exhibits a significant inverse disposition effect. This suggests that multiple algorithms are deliberately designed to purse opposite directional trading strategies, possibly for diversification purposes.

7. Conclusion

This paper studies whether and why algorithmic traders exhibit the disposition effect. First, by using exogenous weather variation and algorithms as a control group, we provide a novel identification of the impact of human psychology on the disposition effect. We find that warmer weather reduces the disposition effect for human traders but has no impact for algorithmic traders. This suggests that the disposition effect for humans is at least partially caused by psychological biases, and that algorithms can at least partially avoid these biases.

According to the psychology literature, higher air temperature improves both mood and cognition, therefore, our results can be explained by the two major preference-based explanations of the disposition effect: realization utility (when traders' mood is worse, they may regulate it more by seeking pleasure and avoiding pain from the realization of gains and losses, respectively) and prospect theory (better cognition may help avoid cognitive biases such as loss aversion and the attachment to reference points). The belief-based explanation predicts the opposite: better mood may boost overconfidence, beliefs in private information and the disposition effect. This suggests that the weather impacts the disposition effect primarily though preferences rather than beliefs.

Second, we find that on average human traders exhibit a significant disposition effect while similarly-trading algorithms do not, and that the difference between the two groups is statistically significant. Our robustness tests show that this cannot be explained by different transaction costs, career concerns and portfolio rebalancing practices between the two groups. This could be explained, however, by different beliefs in mean-reversion and private information as humans on average tend to rely on price-reversal strategies more than similarly-trading algorithms. Yet, we find that for humans, both the price-reversal trading and the disposition effect are associated with significant trading losses, which suggests that such beliefs are irrational. This supports the results of the weather impact analysis by providing suggestive evidence that the disposition effect for humans is driven by psychological biases, and that algorithms can at least partially avoid these biases. Essentially, one could argue that if the disposition effect was rational, it would be programmed in algorithms as well.

Both sets of our results, i.e., on the average disposition effect and on the weather impact, are robust to including maximum fixed effects, using different error clustering, including the least frequently trading human and algorithmic day-traders, defining the temperature variable both as a higher-than-median dummy and as an actual temperature, controlling for other weather variables, and using specifications that exploit the three dimensions of our panel data, which allows adding trader-time, stock-time and trader-stock fixed effects. Moreover, the results remain similar when using only long positions, only short positions, only mental gains and loses (i.e., missed opportunities to gain and lose), only full (not partial) realizations of gains and losses, and the FIFO method instead of WAPP to estimate realized gains and losses.

Third, we find a high heterogeneity of the average disposition effect among the most frequently trading algorithms, HFTs, and that it can be very well predicted by their tendency to engage in price-reversal strategies. Unlike for human traders, we do not find evidence for HFTs that their price-reversal trading, and, thus, the disposition effect is associated with lower trading profits. This suggests that for HFTs, the disposition effect is not associated with irrational beliefs.

Overall, we find evidence that algorithms make decisions that are more consistent with rational economic models than on-the-spot decisions made by humans. Given the speed and scale of adoption of AI around the world, these results may have broad implications for the real economy, financial markets and economic theory. For example, industries that require more rational decision-making might replace humans with algorithms faster, affecting unemployment, productivity and economic growth. As the global reliance on algorithms increases, rational economic models might become more accurate in explaining financial markets and economy.

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TABLE 1

Summary statistics of morning air temperature

Table 1 provides summary statistics of the temperature variable and correlation coefficients between the temperature and 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 years 2016 and 2017 from the following 12 cities: Copenhagen, London, Stockholm, Paris, Amsterdam, Hamburg, Dublin, Zurich, Randers, Silkeborg, Aabenraa and Aalborg.

Number of observations	1^{st} percentile	25^{th} percentile	median	75^{th} percentile	99^{th} percentile	mean
8,772	-3.4 °C	4.4 °C	9.2 °C	15.0 °C	23.2 °C	9.5 °C

Correlation coefficient between 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)
-0.493	-0.072	0.017	-0.160	0.286	0.680	-0.2167

TABLE 2

Comparison of trading patterns between algorithms and humans

Panels A and B show the results of regressing five different 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 10 most traded stocks by trader *i* in day *t*, divided by total turnover generated by trader *i* in day *t*. Panel A considers "frequent traders", i.e., 44 humans and 30 algorithms with an average gap between trades ranging from 54 seconds (the most frequently trading human) to 10 minutes. Panel B includes "infrequent traders" and, thus constitutes 93 humans and 38 algorithms with an average gap between trades larger than 54 seconds. Panel C compares two types of algorithms and thus replaces the *Human*$_i$ dummy with a dummy *HFT*$_i$, equal to 1 for algorithms with an average gap between trades smaller than 54 seconds and 0 for algorithms assigned to the "frequent traders" group. Standard errors are clustered at the trader level and reported in parentheses.

Panel A: "frequent traders" - 44 humans and 30 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$_i$	-119	-86,352	97,037	0.983	0.041
	(100)	(966,293)	(196,820)	(1.004)	(0.025)
Constant	604***	4,165,230***	895,525***	3.308***	0.874***
	(61)	(558,959)	(134,983)	(0.739)	(0.023)
Observations	20,315	20,315	20,315	16,516	20,313

Panel B: "frequent traders" + "infrequent traders" - 93 humans and 38 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$_i$	-199**	-948,756	-155,442	1.803**	0.046**
	(81)	(664,781)	(144,859)	(0.899)	(0.02)
Constant	459***	3,232,470***	706,042***	3.899***	0.902***
	(67)	(512,296)	(117,588)	(0.658)	(0.019)
Observations	37,355	37,355	37,355	25,640	37,344

Panel C: 14 HFT algorithms and 30 algorithms from "frequent traders"

	(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$_{i,t}$
HFT$_i$	4,800***	29,621,417***	2,442,565***	-2.462***	-0.087***
	(1647)	(9,880,467)	(623,033)	(0.79)	(0.028)
Constant	604***	4,165,230***	895,525***	3.308***	0.874***
	(61)	(558,959)	(134,983)	(0.739)	(0.023)
Observations	13,560	13,560	13,560	12,563	13,560

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

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

TABLE 3

Average disposition effect

Table 3 presents estimates of average proportion of gains realized ($PGR_{i,t}$), proportion of losses realized ($PLR_{i,t}$), and disposition effect ($DE_{i,t}$) for humans (Panel A) and algorithms (Panel B) obtained with regression specifications (8) to (11):

$$PGR_{i,t} = \alpha + \epsilon_{i,t} \quad (8)$$
$$PLR_{i,t} = \alpha + \epsilon_{i,t} \quad (9)$$
$$DE_{i,t} = \alpha + \epsilon_{i,t} \quad (10)$$
$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} + FE + \epsilon_{i,t} \quad (11)$$

Variables are observed daily at 5 pm CET. Subscripts *s*, *i* and *t* represent *stock*, *trader* and *day*, respectively. In specification (11), which uses three-dimensional panel data, a proportion of either a gain or a loss realized $PR_{s,i,t}$ is regressed on a dummy variable $Gain_{s,i,t}$ equal to 1 for non-losing positions and 0 for losing positions. Coefficient β_1 estimates the disposition effect. Detailed descriptions of all variables are provided in section 4 "Methodology". FE represents stock-day, trader-day and stock-trader fixed effects. Odd columns consider only "frequent traders" and even columns include "infrequent traders".

Panel A: humans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Depentent variable:	$PGR_{i,t}$		$PLR_{i,t}$		$DE_{i,t}$		$PR_{s,i,t}$	
Regression specification:	(8)		(9)		(10)		(11)	
$Gain_{s,i,t}$							0.066***	0.052***
							(0.000)	(0.000)
Constant	0.282***	0.223***	0.174***	0.150***	0.115***	0.079***	0.257***	0.227***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects							Yes	Yes
Include "infrequent traders"		Yes		Yes		Yes		Yes
Observations	10,504	21,452	10,478	21,368	9,847	18,826	182,043	266,476
Adjusted R-squared	0	0	0	0	0	0	0.224	0.238
Number of traders	44	93	44	93	44	93	44	93

Panel B: algorithms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Depentent variable:	$PGR_{i,t}$		$PLR_{i,t}$		$DE_{i,t}$		$PR_{s,i,t}$	
Regression specification:	(8)		(9)		(10)		(11)	
$Gain_{s,i,t}$							0.018	0.019
							(0.307)	(0.261)
Constant	0.344***	0.321***	0.329***	0.304***	0.015	0.019	0.416***	0.398***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.571)	(0.385)	(0.000)	(0.000)
Fixed effects							Yes	Yes
Include "infrequent traders"		Yes		Yes		Yes		Yes
Observations	8,468	11,042	8,454	11,008	8,159	10,286	167,524	183,980
Adjusted R-squared	0	0	0	0	0	0	0.291	0.297
Number of traders	30	38	30	38	30	38	30	38

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

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

TABLE 4

The impact of air temperature on the disposition effect

Table 4 shows an estimated impact of air temperature on the proportions of gains ($PGR_{i,t}$) and losses ($PLR_{i,t}$) realized and the disposition effect ($DE_{i,t}$) for humans (Panel A) and algorithms (Panel B). We report coefficients of interest for specifications:

$$PGR_{i,t} = \alpha + \beta_1 T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \quad (13)$$

$$PLR_{i,t} = \alpha + \beta_1 T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \quad (14)$$

$$DE_{i,t} = \alpha + \beta_1 T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \quad (15)$$

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} + \beta_2 T\_dummy_{i,t} + \beta_3 Gain_{s,i,t} \times T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \quad (16)$$

Dependent variables are observed daily at 10 am CET. Temperature $T_{i,t}$ and other weather variables $C_{i,t}$ used as controls are observed daily between 8 am and 9 am. $T\_dummy_{i,t}$ equals 1 if $T_{i,t}$ was higher than median of that city-month. Subscripts *s*, *i* and *t* represent *stock*, *trader* and *day*, respectively. In specifications (13)-(15), FE represents trader-fixed effects and day-fixed effects. In specification (16), $PR_{s,i,t}$ is a proportion of either a gain or a loss realized, $Gain_{s,i,t}$ is a dummy variable equal to 1 for non-losing positions and 0 for losing positions, and FE represents stock-day, trader-day and stock-trader fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: humans										
Dependent variable:	$PGR_{i,t}$	$PLR_{i,t}$	$DE_{i,t}$					$PR_{s,i,t}$		
Regression specification:	(13)	(14)	(15)					(16)		
$T\_dummy_{i,t}$	-0.009*	0.007*	-0.021***	-0.028***	-0.038***	-0.021**				
	(0.051)	(0.075)	(0.001)	(0.000)	(0.001)	(0.014)				
$T_{i,t}$							-0.004**			
							(0.027)			
$Gain_{s,i,t} \times T\_dummy_{i,t}$								-0.016***	-0.011***	
								(0.002)	(0.004)	
$Gain_{s,i,t} \times T_{i,t}$										-0.001*
										(0.095)
Constant	0.187***	0.098***	0.096***	0.423	0.808	0.123	0.199	0.140***	0.115***	0.115***
	(0.000)	(0.000)	(0.000)	(0.413)	(0.384)	(0.823)	(0.733)	(0.000)	(0.000)	(0.000)
Weather controls				Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects					Yes	Yes	Yes	Yes	Yes	Yes
Include infrequent traders						Yes	Yes		Yes	Yes
Observations	7,843	7,707	7,101	7,101	7,101	11,325	11,594	71,778	99,145	101,745
Adjusted R-squared	0.000	0.000	0.001	0.008	0.114	0.101	0.102	0.168	0.166	0.166
Number of traders	44	44	44	44	44	93	93	44	93	93
Panel B: algorithms										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	$PGR_{i,t}$	$PLR_{i,t}$	$DE_{i,t}$					$PR_{s,i,t}$		
Regression specification:	(13)	(14)	(15)					(16)		
$T\_dummy_{i,t}$	-0.004	0.001	-0.004	-0.006	0.006	0.013				
	(0.469)	(0.846)	(0.578)	(0.392)	(0.674)	(0.350)				
$T_{i,t}$							0.003			
							(0.180)			
$Gain_{s,i,t} \times T\_dummy_{i,t}$								-0.002	-0.001	
								(0.656)	(0.850)	
$Gain_{s,i,t} \times T_{i,t}$										-0.001
										(0.542)
Constant	0.185***	0.167***	0.021	0.294	0.384	0.875	0.688	0.217***	0.211***	0.211***
	(0.000)	(0.000)	(0.244)	(0.554)	(0.644)	(0.223)	(0.322)	(0.000)	(0.000)	(0.000)
Weather controls				Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects					Yes	Yes	Yes	Yes	Yes	Yes
Include infrequent traders						Yes	Yes		Yes	Yes
Observations	7,359	7,284	6,847	6,847	6,846	7,837	7,988	95,596	101,100	103,186
Adjusted R-squared	-0.000	-0.000	-0.000	0.000	0.067	0.055	0.057	0.270	0.273	0.273
Number of traders	30	30	30	30	30	38	38	30	38	38

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

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

TABLE 5

The difference between humans and algorithms

Table 5 shows an estimated difference in the disposition effect and an estimated difference in the impact of air temperature on the disposition effect between human and algorithmic “frequent traders”. We report coefficients of interest for specifications:

$$DE_{i,t} = \alpha + \beta_1 Human_i + \epsilon_{i,t} \quad (17)$$

$$DE_{i,t} = \alpha + \beta_1 Human_i + \beta_2 T\_dummy_{i,t} + \beta_3 Human_i \times T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \quad (18)$$

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} + \beta_2 Human_i + \beta_3 Gain_{s,i,t} \times Human_i + FE + \epsilon_{i,t} \quad (19)$$

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} \times T\_dummy_{i,t} \times Human_i + V\&I_{s,i,t} + C_{i,t} + FE + \epsilon_{i,t} \quad (20)$$

Subscripts *s*, *i* and *t* represent *stock*, *trader* and *day*, respectively. $Human_i$ is a dummy variable equal to 1 for humans and 0 for algorithms. $DE_{i,t}$ is the disposition effect measured as the difference between a proportion of gains realized and a proportion of losses realized by trader *i* in day *t*. In specification (18), FE represents trader-fixed effects and day-fixed effects. In specifications (19) and (20), $PR_{s,i,t}$ is a proportion of either a gain or a loss realized, $Gain_{s,i,t}$ is a dummy variable equal to 1 for non-losing positions and 0 for losing positions, and FE represents stock-day, trader-day and stock-trader fixed effects. Dependent variables in specifications without weather variables, i.e., (17) and (19), are observed at 5 pm CET, while in the other two specifications – at 10 am. Temperature $T_{i,t}$ and other weather variables $C_{i,t}$ used as controls are observed daily between 8 am and 9 am. $T\_dummy_{i,t}$ equals 1 if $T_{i,t}$ was higher than median of that city-month. $V\&I_{s,i,t}$ denotes the three variables that constitute the triple interaction term in specification (20) and the three possible interactions among them.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Depentent variable:	$DE_{i,t}$				$PR_{s,i,t}$		
Regression specification:	(17)	(18)			(19)	(20)	
$Human_i$	0.099**	0.075**	0.129			-0.990*	
	(0.011)	(0.017)	(0.855)			(0.063)	
$Temp\_dummy_{i,t} \times Human_i$		-0.017*	-0.022**	-0.015*		0.008	
		(0.071)	(0.027)	(0.089)		(0.174)	
$Gain_{s,i,t} \times Human_i$					0.046*	-0.317	-0.484
					(0.062)	(0.426)	(0.191)
$Gain_{s,i,t} \times Temp\_dummy_{i,t} \times Human_i$						-0.014**	-0.013**
						(0.023)	(0.019)
Constant	0.015	0.021	0.294	0.591	0.331***	0.985**	0.180***
	(0.565)	(0.234)	(0.547)	(0.276)	(0.000)	(0.012)	(0.000)
Weather controls			Yes	Yes		Yes	Yes
Fixed effects				Yes	Yes		Yes
Observations	18,006	13,948	13,948	13,948	359,630	182,275	174,603
Adjusted R-squared	0.020	0.011	0.015	0.100	0.279	0.014	0.243
Number of traders	74	74	74	74	74	74	74

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

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

TABLE 6

Robustness checks

Table 6 presents an average disposition effect ($DE_{i,t}$) in odd columns (estimated by the constant) and an impact of temperature on the disposition effect ($DE_{i,t}$) in even columns (estimated by coefficient β_1 on variable $T\_dummy_{i,t}$) for human (Panel A) and algorithmic (Panel B) "frequent traders" obtained using regression specifications (10) and (15):

$$DE_{i,t} = \alpha + \epsilon_{i,t} \quad (10)$$

$$DE_{i,t} = \alpha + \beta_1 T\_dummy_{i,t} + C_{i,t} + FE + \epsilon_{i,t} \quad (15)$$

Variable $DE_{i,t}$ is observed daily at 5 pm CET for specification (10) and at 10 am for specification (15). Temperature $T_{i,t}$ and other weather variables $C_{i,t}$ used as controls are observed daily between 8 am and 9 am. $T\_dummy_{i,t}$ equals 1 if $T_{i,t}$ was higher than median of that city-month. Subscripts *i* and *t* represent *trader* and *day*, respectively. FE represents trader-fixed effects and day-fixed effects. We estimate the results under five different assumptions specified in row "Robustness check":

1) Columns (1) and (2) consider only long positions, i.e., assume that gains and losses in short positions were zero.
2) Columns (3) and (4) consider only short positions, i.e., assume that gains and losses in long positions were zero.
3) Columns (5) and (6) consider positions that are either long from the daily perspective (assuming every day starts with zero inventory) but short from the long-term perspective (assuming only the first day starts with zero inventory) or short from the daily perspective but long from the long-term perspective.
4) Columns (7) and (8) consider the realization of gains and losses only for those trader-stock-day positions that were completely closed at least once throughout a day.
5) Columns (9) and (10) use first-in-first-out (FIFO) method, instead of WAPP, to calculate realized gains and losses.

Panel A: humans

Depentent variable: $DE_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Robustness check:	Only long positions		Only short positions		Mental gains/losses		Only full realizations		FIFO method	
Regression specification:	(10)	(15)	(10)	(15)	(10)	(15)	(10)	(15)	(10)	(15)
$T\_dummy_{i,t}$		-0.032**		-0.030*		-0.040***		-0.025**		-0.025**
		(0.030)		(0.097)		(0.010)		(0.020)		(0.020)
Constant	0.126***	0.772	0.112***	0.652	0.123***	1.529	0.079***	0.748	0.079***	0.748
	(0.000)	(0.500)	(0.000)	(0.696)	(0.000)	(0.293)	(0.001)	(0.408)	(0.001)	(0.408)
Weather controls		Yes		Yes		Yes		Yes		Yes
Fixed effects		Yes		Yes		Yes		Yes		Yes
Observations	8,602	5,315	8,228	5,501	8,345	5,421	9,847	7,101	9,847	7,101
Adjusted R-squared	0	0.119	0	0.089	0	0.069	0	0.101	0	0.101
Number of traders	44	44	44	44	44	44	44	44	44	44

Panel A: algorithms

Depentent variable: $DE_{i,t}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Robustness check:	Only long positions		Only short positions		Mental gains/losses		Only full realizations		FIFO method	
Regression specification:	(10)	(15)	(10)	(15)	(10)	(15)	(10)	(15)	(10)	(15)
$T\_dummy_{i,t}$		0.001		-0.001		-0.031		-0.005		-0.005
		(0.967)		(0.949)		(0.284)		(0.679)		(0.679)
Constant	0.015	1.360	0.031	1.548	0.023	1.039	0.010	0.801	0.010	0.801
	(0.569)	(0.379)	(0.258)	(0.266)	(0.381)	(0.416)	(0.673)	(0.229)	(0.673)	(0.229)
Weather controls		Yes		Yes		Yes		Yes		Yes
Fixed effects		Yes		Yes		Yes		Yes		Yes
Observations	7,209	5,585	7,249	5,523	7,267	5,485	8,159	6,846	8,159	6,846
Adjusted R-squared	0	0.115	0	0.108	0	0.051	0	0.068	0	0.068
Number of traders	44	44	44	44	44	44	44	44	44	44

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

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

FIGURE 1

Disposition effect for individual humans and algorithms sorted by trading frequency

Figure 1 plots on the y-axis an average disposition effect estimated separately for every trader in our sample, i.e., 93 humans and 52 algorithms that have at least 30 non-zero end-of-day observations of disposition effect variable $\text{DE}_{i,t}$. Variable $\text{DE}_{i,t}$ is defined as the gap between the proportion of gains realized (PGR) and the proportion of losses realized (PLR) by trader i at time t (for more details, see "Methodology" subsection 4.1 "The measure of the disposition effect"). The average disposition effect is estimated for every trader by regressing the variable $\text{DE}_{i,t}$ (observed daily at 5 pm) on a constant and using robust standard errors. Traders are sorted along the x-axis by an average trading frequency, which is calculated for every trader as an average time gap (in seconds) between trades executed throughout the sample period. Blue and red circles represent humans and algorithms, respectively. Colored circles represent estimates of the disposition effect that are statistically different from zero at 99% significance level. Algorithms that trade more frequently than the most frequently trading human, i.e., every 54 seconds on average, are labeled "HFTs". Traders that trade less frequently than every 600 seconds on average are labeled "infrequent traders". The remaining traders in between are labeled "frequent traders".

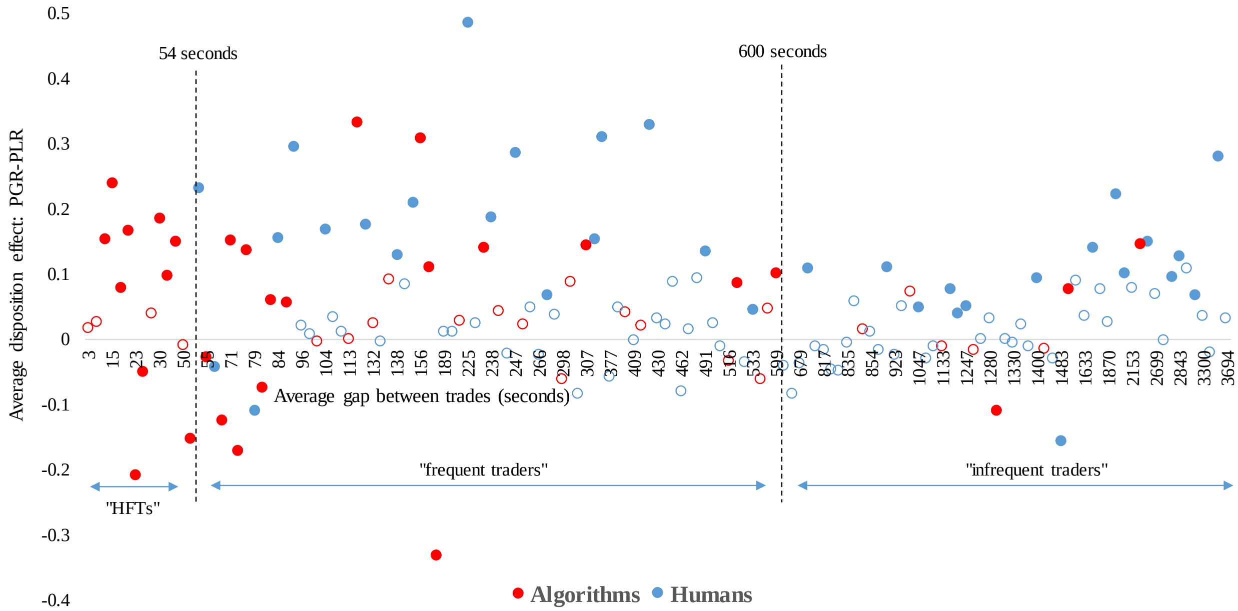

FIGURE 2

Intraday proportion of gains realized (PGR) and proportion of losses realized (PLR)

Figure 2 plots an average intraday development of variables $PGR_{i,t}$ and $PLR_{i,t}$ observed at the end of every trading hour for human and algorithmic "frequent traders". Every data point is an average across traders (i) and days (t). Variables $PGR_{i,t}$ and $PLR_{i,t}$ are described in detail in section 4 "Methodology". The PGR-PLR gap provides an estimate of the disposition effect.

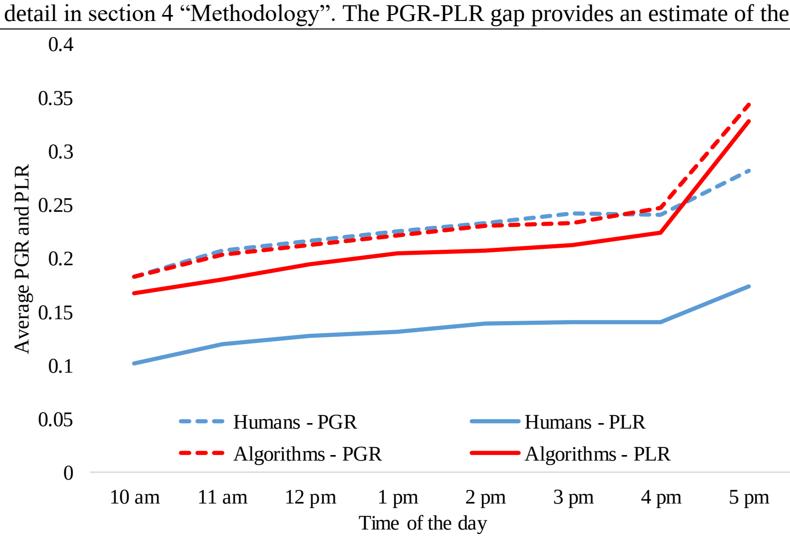

FIGURE 3

An example of price-reversal and momentum trading patterns for HFTs

Figure 3 plots, for the first 10 days of our sample, hourly (end-of-hour) observations of the stock price (solid line, rhs) of Pandora, one of the most traded stocks in terms of average daily turnover, and inventory (dotted line, lhs) of Pandora stock held by two different HFTs: one that, according to Figure 1, exhibits a significant disposition effect on average (Panel A) and one that does not (Panel B). We assume zero starting inventory on the first day. In Panel A, the price and inventory appears to be correlated negatively, which hints towards a price-reversal trading strategy, while in Panel B, the correlation appears to be positive, which suggests a momentum trading strategy.

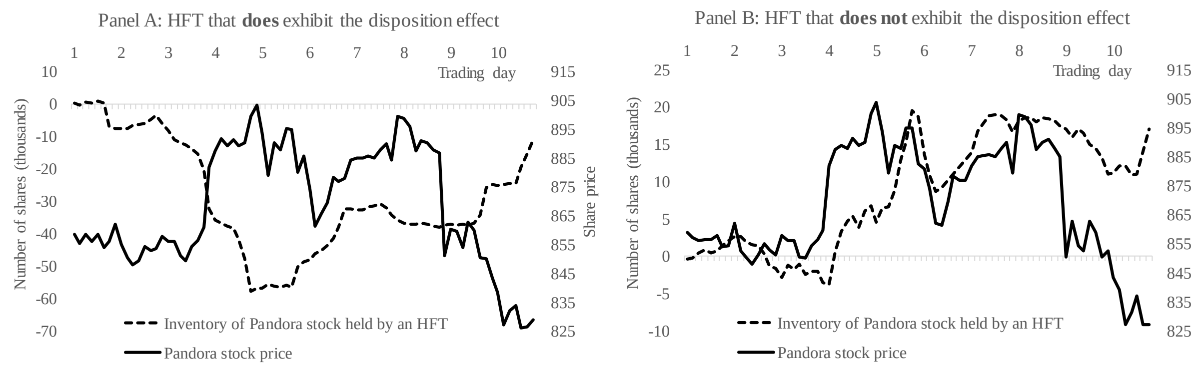

FIGURE 4

Price-reversal trading and the disposition effect among HFTs

Figure 4 plots the distribution of a trader-level variable $Reversal\_trading\_proportion_i$, defined in sub-section "5.7. Belief-based explanations", equation (21), across HFTs. The variable measures a proportion of stock-day-hours spent on price-reversal trading, i.e., either significantly increasing stock inventory as the price has decreased for the second consecutive period, or significantly decreasing stock inventory as the price has increased for the second consecutive period. The red columns represent HFTs that, according to Figure 1, on average exhibit a statistically significant disposition effect, and white columns represent HFTs that do not. We consider 22 algorithms that on average trade more frequently than once every 100 seconds (see Figure 1).