Human vs. Machine: Disposition Effect among Algorithmic and Human Day Traders

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Abstract

This paper studies whether algorithmic traders exhibit one of the most broadly documented behavioral puzzles – the disposition effect – and why or why not. 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 increases significantly on colder mornings, 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 can reduce psychological biases. Considering the global AI adoption, this may have broad implications.

Keywords: disposition effect; algorithmic trading; decision making; financial markets; rationality
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1. Introduction

Artificial intelligence (AI) has been rapidly transforming the financial sector in general and algorithmic trading (AT) in particular (see, e.g., Buchanan, 2019; Bholat and Susskind, 2021; Buckmann et al., 2021). Arguably, one of the benefits of AT is the ability to reduce psychology-related human errors and biases (see, e.g., Borch and Lange, 2017; Buckmann et al., 2021), yet, to our knowledge, there is no evidence on the extent to which AT achieves that.[1] This paper provides such evidence by examining whether algorithmic traders (ATs) exhibit one of the most broadly-documented biases in behavioral finance – the disposition effect, i.e., the tendency to realize gains faster than losses (Shefrin and Statman, 1985) – and why or why not.[2]

By tackling this question we shed light on both the disposition effect and algorithms, and thus our contribution is twofold. First, by exploiting exogenous weather variation and using trading algorithms as a control group, we provide rare causal field evidence that psychology affects the disposition effect. Although the disposition effect challenges rational economic models and appears to be easier explained by psychological biases (Barberis and Thaler, 2003), causal evidence of these biases has started to emerge only recently and primarily from experiments (e.g., Frydman et al., 2014; Chang et al., 2016; Frydman and Camerer, 2016; Fischbacher et al., 2017).[3] Second, despite

[1] E.g., algorithms can inherit biases from programmers and training data (e.g., Cowgill and Tucker, 2019).

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

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

the prevalence of ATs[4], we are the first to estimate the disposition effect for them. If we find automated decisions to be more in line with rational economic models than on-the-spot human decisions, this may have broad implications, given the growing ubiquity of algorithms in society.

We use trade data from the NASDAQ Copenhagen Stock Exchange for the two years 2016-2017 to measure the intraday disposition effect for exchange members' proprietary trading accounts. Around 2/3 of the accounts belong to large international banks, which supports the external validity of our study. For comparability between algorithms and humans, we focus on day-traders that trade at similar frequencies. The data has two important features. First, we see members' addresses and thus use weather data in respective cities to proxy for shocks to traders' psychology. Second, we observe types of trading accounts and thus precisely identify humans and algorithms that trade "with no human involvement" (Nasdaq, 2019). Since algorithms are immune to psychological shocks, we use them as a control group to account for potential weather-induced stock market movements (e.g., Saunders, 1993) that could affect all traders, including algorithms. We find that, on average, the disposition effect for humans is substantial and increases significantly on colder mornings, while for similarly-trading algorithms it is insignificant and insensitive to the weather. This suggests that the disposition effect is at least partially driven by psychology, e.g., by mood and cognition, and that by avoiding these drivers algorithms behave more in line with rational economic models.

The literature mostly uses cloud cover and temperature to test weather effects on trading.[5] Less cloudy weather is found to increase stock returns (Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann et al., 2014), stock market volatility (Symeonidis et al., 2010), risk-taking (Bassi et al.,

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

[5]E.g., 26 of the 35 studies recently reviewed by Muhlack et al. (2022) used cloud cover and 23 used temperature. In the review, temperature is the variable that has the most consistent effect on stock returns.

2013), and a relative propensity to buy stock (Schmittmann et al., 2014; Goetzmann et al., 2014). Higher temperature is also found to increase stock market volatility (Symeonidis et al., 2010) and a relative propensity to buy stock (Schmittmann et al., 2014)[6], but to decrease stock returns (Cao and Wei, 2005). We contribute by testing the impact of weather on the disposition effect. Some studies find little or no evidence of the weather effects on trading (Loughran and Schultz, 2004; Andrikopoulos et al., 2019) and suggest that the correlations found by others might be spurious due to seasonality (Jacobsen and Marquering, 2008) and daylight (Kamstra et al., 2003). Weather effects are also suspicious since trading takes place indoors (Jacobsen and Marquering, 2008). We therefore observe the weather when traders are likely exposed to it due to the commute, i.e., before the market opening at 9 am CET, and test how it affects the disposition effect right after the opening.[7] We suspect overcast to have little impact, since the sun rises relatively late in Northern Europe during a part of the year. We therefore focus on temperature and use other weather variables as controls.

To explain weather effects on trading, the literature commonly resorts to the weather-mood link studied in psychology (see, e.g., Lucas and Lawless, 2013), and the impact of mood on judgement (e.g., Wright and Bower, 1992; Forgas, 1995) and risk tolerance (Bassi et al., 2013). Yet, evidence on the weather-mood link is mixed (Watson, 2000; Denissen et al., 2008), possibly due to small samples (Howarth and Hoffman, 1984) or heterogenous effects that cancel out in aggregate (Klimstra et al., 2011). According to Lucas and Lawless (2013) and Denissen et al. (2008), Keller et al. (2005) is likely the most thorough study that finds consistent weather effects on mood. It finds that more pleasant (higher in spring but lower in summer) air temperature improves mood, which is in line with reducing aggression (Baron and Bell, 1976; Howarth and Hoffman, 1984; Anderson, 1989) and

[6] Liu et al. (2021) find a U-shaped relationship: more comfortable but not necessarily higher temperature is associated with relatively higher retail investors' propensity to buy stock.

[7] To our knowledge, only Chang et al. (2008); Lu and Chou (2012) test intraday weather effects on trading.

increasing altruism (Cunningham, 1979). The study also finds similar effects on cognition, which is in line with Yeganeh et al. (2018) who show in a meta-analysis of 28 experimental studies that cognitive performance worsens if air temperature deviates in either direction from control temperatures set at around 21-23°C on average. In our study, we use only morning temperature observations, 97% of which are below 21°C, and thus we interpret higher temperatures as more pleasant.

Based on these empirical findings and the theory on the disposition effect, we propose three hypotheses how air temperature can affect the disposition effect. First, according to the prospect theory (Kahneman and Tversky, 1979), traders care about gains and losses relative to a reference point, are risk-averse (risk-seeking) when facing gains (losses) and are loss-averse, which can explain the disposition effect. Loss aversion and attachments to reference points are cognitive biases that could be reduced if warmer air improves cognition. Second, according to realization utility (Barberis and Xiong, 2012), the disposition effect occurs because it is pleasant (painful) to realize gains (losses). Such behaviour can thus be seen as a mood-repair technique that could become less relevant if warmer air improves mood.[8] Third, evidence shows that better mood increases overconfidence (e.g., Au et al., 2003; Ifcher and Zarghamee, 2014), and overconfidence is thought to strengthen the disposition effect through beliefs in private information (Ben-David and Hirshleifer, 2012). The first two preference-based explanations predict that higher air temperature would reduce the disposition effect, while the third belief-based explanation predicts the opposite. Our tests therefore shed light on whether air temperature affects the disposition effect primarily through preferences or beliefs.[9]

In line with (Odean, 1998), we define the disposition effect (DE) as the gap between the proportion of gains realized (PGR) and the proportion of losses realized (PLR). First, we regress

[8]Craving for mood-repair has been shown to affect behavior (e.g., Morris and Reilly, 1987; Elliott, 1994). Li et al. (2021) also use mood regulation to explain the link between air pollution and the disposition effect.
[9]Kuhnen and Knutson (2011) find that affect impacts both preferences and beliefs in financial decisions.

trader-day level DE (observed at the end of a day) on a constant for humans and algorithms separately, and then, to test the difference between the two groups, we add a dummy variable that splits between them. We find that the average end-of-day DE for humans is statistically significant and equals 11.5 pp, while for algorithms it is statistically insignificant and equals 1.5 pp. The difference is statistically significant at the 5% level. By the end of the day, humans on average realize 28% of gains and only 17% of losses while algorithms realize 34% of gains and 33% of losses.

To test the impact of temperature, we regress DE observed at 10 am CET on the temperature variable observed between 8 am and 9 am CET. First, we estimate the impact for humans and algorithms separately and then, to test difference between them, we add the dummy variable and its interaction with temperature. For algorithms, we find no significant impact, while for humans, the average DE is found to be 1.5 pp, or 19%, stronger on mornings that are colder than median. The difference between the two groups is significant at the 5% level. The results are similar when controlling for other weather variables, none of which show any significant impact, and when adding trader and time-fixed effects. The effect of temperature remains significant until 10:30 am but fades out thereafter and, in line with evidence in Keller et al. (2005) on the temperature-mood relationship, is most significant when temperatures are moderate, i.e., in spring and autumn. We show that the results are robust to using a three-dimensional panel data setting with trader-time, stock-time, and trader-stock fixed effects, and to a number of different alterations of our baseline setting.

Our results suggest that the disposition effect for humans is at least partially driven by psychology, e.g., by mood and cognition, and that by at least partially avoiding these drivers algorithms behave more in line with rational economic models. Given the ongoing ubiquitous adoption of AI, this may have broad implications for economic theory, financial markets, the real economy and human behavior. With regard to economic theory and financial markets, as humans are replaced by AI, rational economic models, e.g., those based on Bayesian updating of beliefs, the Expected Utility theory (EUT) (von Neumann and Morgenstern, 1947) or Subjective Expected Utility (SEU) (Savage, 1954), might become more accurate in explaining the real world, including financial markets. As for the real economy, industries that require more "rational" decision-making might replace humans with algorithms faster, affecting unemployment, productivity and economic growth.[10] As for human behavior, being constantly surrounded by automated decisions (e.g. of robots, cars, virtual assistants, etc.) that are more "rational", might affect people's "rationality".[11]

In addition to the aforementioned contributions to the literatures on the disposition effect and the weather effects in financial markets, this paper adds to the research (1) on algorithmic trading, which studies ATs' trading strategies (Brogaard et al., 2014), impact on market quality Hendershott et al. (2011), speed advantage (Budish et al., 2015; Baron et al., 2019), access to information (Biais et al., 2015; Chordia et al., 2018), learning capacity Abis (2022), etc., and (2) on algorithmic bias, which documents that algorithms can make biased and discriminatory decisions (Cowgill and Tucker, 2019), e.g., in lending (Bartlett et al., 2022), criminal sentencing (Dressel and Farid, 2018) and ad targeting (Datta et al., 2015). We contribute to both lines of research with novel evidence that ATs can reduce behavioral biases. Moreover, our evidence that automated decisions are more rational, at least as defined by the EUT, than on-the-spot human decisions contributes to the debate on the rationality assumption in economics (Hogarth and Reder, 1987; Hirshleifer, 2001; Thaler, 2016).[12]

The rest of the paper is structured as follows. Section 2 presents the data. Section 3 describes the methodology. Section 4 summarizes and discusses the main results. Section 5 concludes.

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

[11] See, e.g., North (1994)'s lecture on how environments shape people's mental models of reality.

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

2. Data

2.1. Trading data

We use millisecond-stamped transaction-level trade data provided by the NASDAQ OMX Copenhagen Stock Exchange for the period from 1 January 2016, 9 am, i.e., the stock market's opening time, to 31 December 2017, 5 pm, i.e., the stock market's closing time. We observe the following details about every trade executed by every member of the stock exchange: (1) the execution date and time with millisecond precision, (2) the name of the traded stock, (3) the indicator of whether shares were bought or sold, (4) the share price of the traded stock, (5) the number of shares traded, (6) the indicator of whether a trade added or removed liquidity, (7) 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 was used by a human or an algorithm, (11) the user account name (first three letters of a trader's name and surname for humans, and PTRxxx, AUTDxx or LPSxxx for algorithms), and (12) the organization name of a second counterparty. Every trade enters the dataset twice, treating each counterparty as a primary one. The name of a trader's institution combined with the user account name provides a trader's unique id.

NASDAQ Copenhagen issues "Algo" accounts to algorithms that "automatically determine individual parameters of orders such as whether to initiate the order, the timing, price or quantity of the order or how to manage the order after its submission" (Nasdaq, 2019). For example, the exchange specifies that a "PTRxxx account may be used for execution algo flow with no human involvement when placing Child Orders in the market" (Nasdaq, 2019), and an "AUTDxx account <...> is used for purely automated trading for algorithms with no human involvement in the investment decision and order execution" (Nasdaq, 2019). The Danish Financial Supervisory Authority report (Danish FSA, 2016), released in February 2016, i.e., at the beginning of our sample period, provides a broad overview of algorithmic trading activity on the NASDAQ Copenhagen Stock Exchange. The report summarizes ATs' strategies, benefits and risks to the market, the trends in trading volume of both algorithms and humans, relevant regulations, etc.

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 buy and sell 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.[13] In this final dataset, there are 93 human trading accounts (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 Zürich). 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

[13]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.

Suisse, etc., which supports the external validity of our study. Others trade for local banks, small investment banks or proprietary trading firms.

To ensure that humans and algorithms in our regression analyses are as comparable as possible, we estimate every trader's average time gap between trades. Since high-frequency traders (HFTs) are known to have special trading strategies (Hagströmer and Nordén, 2013; Menkveld, 2013; Malinova et al., 2014; Brogaard et al., 2014; O'Hara, 2015; Van Kervel and Menkveld, 2019; Korajczyk and Murphy, 2019), when comparing humans and algorithms, we exclude 14 algorithms that trade more frequently than the most frequently trading human, i.e., every 54 seconds on average, and label them "HFTs". Moreover, since some traders, especially humans, trade very infrequently, e.g., once every hour (and not necessarily the same stock), 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 we include all the remaining traders labeled "infrequent traders". Focusing on "frequent traders" helps to ensure both that we have enough within-trader variation in the disposition effect measured daily at 10 am for the weather impact analysis, and that algorithms and humans are on average similar in terms of other trading patterns.

Table 1 provides summary statistics of these patterns and tests whether they are similar between the two groups. We consider 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;[14] (4) $Inventory\_days_{i,t}$ – trading horizon for trader i in day

[14]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. We sum up absolute values of long and short positions and calculate an average of this sum across the 5-minute intervals.

t, calculated as a ratio of $Portfolio\_size\_EUR_{i,t}$ over the total value of shares sold (repurchased, for short positions) by trader i in day t, valued at purchase prices (sale prices, for short positions); and (5) $Turnover\_top10_{i,t}$ – the turnover generated in the 10 most traded stocks by trader i in day t, divided by total turnover generated by trader i in day t. 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.

Table 1, 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 fewer trades, both humans and algorithms generate around EUR 4.1m daily turnover, average portfolio size is EUR 0.9m for algorithms and EUR 0.1m 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 1, 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 1, 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.

2.2. *Weather data*

We merge the trading data with the hourly weather simulation data, i.e., stored forecasts, provided by Meteoblue in the 12 cities where traders are located: Copenhagen, London, Stockholm, Paris, Amsterdam, Hamburg, Dublin, Zürich, Randers, Silkeborg, Aabenraa and Aalborg.[15] According to the data provider, its weather simulation data is comparable to the measurement data collected by weather stations and has the advantage of often being more complete, more frequent, more detailed, and, if weather stations are relatively remote, more precise than measurement data (Meteoblue, 2022). 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/m2), and (8) wind speed 10 meters above ground (km/h). The hourly data frequency allows us to observe these variables exactly when traders are most likely to be exposed to the weather – on their way to work before the stock market opens. 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 2 provides summary statistics for all the weather variables and the correlation coefficients between temperature and the other weather variables. The median morning temperature across all cities and days in 2016 and 2017 was 9.2 °C. The 1st and 99th percentiles were -3.4 °C and 23.2 °C, respectively. Temperature is most correlated with radiation (correlation coefficient = 0.680). With other variables, the absolute value of the correlation coefficient does not exceed 0.5.

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

3. Methodology

3.1. 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); Baron et al. (2019), and construct traders' intraday stock positions using observed trades. The assumption ensures that our estimated gains and losses are attributed to trading decisions made throughout a day and that the estimated disposition effect results from the asymmetric reversion of those decisions. The assumption also alleviates potential concerns regarding the nonstationarity and the autocorrelation of the daily time series of the disposition effect. We estimate outstanding paper gain for every trader i, in every stock position s, at every point of time t as follows:

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

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 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:

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

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

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

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

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

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

For every trader i at every point of time t, 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[16].

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

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

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

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

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

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 $PLR_{i,t}$:

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

Figure 1 shows average intraday developments for the disposition effect for humans and algorithms. In regression analyses, we use daily observations of $DE_{i,t}$ either at end-of-day, i.e., at 5 pm CET, or, when testing morning weather effects, after the first trading hour, i.e., at 10 am CET.

3.2. Average disposition effect

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

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

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

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

For robustness, we re-estimate the average disposition effect using a specification that exploits the three dimensions of our panel data, and, thus, allows us to control for interactive fixed effects:

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} + FE + \epsilon_{s,i,t} \tag{10}$$

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:

$$PR_{s,i,t} = \frac{cumulative\_realized\_gain_{s,i,t}}{total\_gain_{s,i,t}} \tag{11}$$

and $Gain_{s,i,t}$ is a dummy equal to one if $total\_gain_{s,i,t} \geq 0$ and zero otherwise.[17] 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-time fixed effects.

To test again if the difference in the disposition effect between the two groups is statistically significant, we include the variable $Human_i$ and its interaction with the variable $Gain_{s,i,t}$:

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} + \beta_2 Human_i + \beta_3 Gain_{s,i,t} \times Human_i + FE + \epsilon_{s,i,t} \tag{12}$$

A significant coefficient β_3 would indicate that the difference is statistically significant. In all four regressions, we cluster standard errors at the trader level.

[17] $PR_{s,i,t}$ 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 $PR_{s,i,t} < 0$.

3.3. The impact of air temperature on the disposition effect

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

$$DE_{i,t} = \alpha + \beta_1 Temperature_{i,t} + C + FE + \epsilon_{i,t} \tag{13}$$

$$DE_{i,t} = \alpha + \beta_1 Human_i \times Temperature_{i,t} + V\&I + C + FE + \epsilon_{i,t} \tag{14}$$

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} \times Temperature_{i,t} + V\&I + C + FE + \epsilon_{s,i,t} \tag{15}$$

$$PR_{s,i,t} = \alpha + \beta_1 Gain_{s,i,t} \times Temperature_{i,t} \times Human_i + V\&I + C + FE + \epsilon_{s,i,t} \tag{16}$$

where $Temperature_{i,t}$ is a dummy equal to one if the temperature is above or equal to the median value of the time interval $[t-15; t+15]$ in that city, and zero otherwise; $V\&I$ includes all variables that constitute a specified interaction term and all the possible interactions among those variables; C includes the other seven dummy weather variables and their interactions with the variables that are interacted with $Temperature_{i,t}$; FE includes trader-fixed effects and trading day-fixed effects in the main specifications (13) and (14), and trader-time, stock-time and trader-stock fixed effects in specifications (15) and (16) that are used for checking the robustness. Both dependent variables, i.e., $DE_{i,t}$ and $PR_{s,i,t}$, are observed at 10 am CET, i.e., one hour after the stock market opening. In all four regressions, we cluster standard errors multiway at the city and trading day level.

The coefficient of interest in every regression specification is β_1. In specifications (13) and (15), which are used either for humans or for algorithms separately, the statistical significance of β_1 would indicate that the temperature has an impact on the disposition effect. In specifications (14) and (16), which are used for humans and algorithms jointly, the significance of β_1 would indicate that the impact of temperature differs between the two groups.

4. Results

4.1. Average disposition effect

Table 3 presents estimates of the average disposition effect for humans and algorithms, as well as the average difference in the disposition effect between the two groups. The average end-of-day disposition effect for humans equals 11.5 pp when estimated using specification (8) and 6.6 pp when using specification (10) that controls for trader-time, stock-time and trader-stock fixed effects. In both cases, the results are statistically significant at the 1% level. For algorithms, these estimates equal only 1.5 pp and 1.8 pp, respectively, and are not statistically different from zero. The average difference in the disposition effect between the two groups estimated by specification (9) equals 9.9 pp and is statistically significant at the 5% level. This difference equals 4.6 pp and is statistically significant at the 10% level when using specification (12) with the interactive fixed effects.

Figure 1 presents average intraday developments for the proportion of gains realized (PGR) and the proportion of losses realized (PLR) for humans and algorithms. The gap between PGR and PLR represents the disposition effect. The figure shows that, on average, PGR and PLR gradually and stably increase throughout most of a day for both humans and algorithms, and that both groups realize roughly the same proportion of gains but humans realize a much lower proportion of losses. In the last trading hour, the realization of both gains and losses intensifies, especially for algorithms. By the end of the day, humans on average realize 28.2% of their gains and only 17.4% of their losses, while algorithms realize 34.4% of their gains and 32.9% of their losses. The gap between 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. An average disposition effect at 10 am for humans estimated using the regression specification (8) equals 8.6 pp (p-value = 0.001).

4.2. The impact of air temperature on the disposition effect

Table 4 presents estimates of the impact of air temperature observed between 8 am and 9 am on the disposition effect observed at 10 am for algorithms and humans, as well as the difference in the impact between the two groups. When using regression specification (13) but without weather controls and fixed effects, the coefficient on $Temperature_{i,t}$ equals 0.005 (p-value=0.505) for algorithms and -0.015 (p-value=0.005) for humans. Hence, while for algorithms the disposition effect is not sensitive to the temperature, for humans, the disposition effect is, on average, 1.5 pp, or 19%, stronger on mornings that are colder than median as compared to mornings that are warmer than median.[18] The average difference of -2 pp between algorithms and humans is statistically significant at the 5% level as indicated by the coefficient on the interaction term $Temperature_{i,t} \times Human_i$ from specification (14) presented in column (3). These results remain similar when adding weather controls, none of which show any statistically significant impact on the disposition effect (columns 4 to 6), and when controlling for trader-fixed effects and time-fixed effects (columns 7 to 9). Similarly, when using specifications (15) and (16) with the three-dimensional panel data, weather controls and trader-time, stock-time and trader-stock fixed effects (columns 10 to 12), we find that the disposition effect is 1.2 pp stronger on colder mornings for humans (p-value=0.028), not sensitive to the temperature for algorithms, and the average difference in the impact between the two groups equals -1.4 pp (p-value=0.006).

Having algorithms as a control group helps to assure that the estimated impact of air temperature on the disposition effect for humans is not driven by weather-induced stock market movements (see, e.g., Saunders, 1993; Hirshleifer and Shumway, 2003; Goetzmann et al., 2014), that could affect trading decisions for all traders, including algorithms. For example, if traders (including algorithms) pursue a mean-reversion strategy in which they trade stocks when prices cross certain thresholds, then a positive effect of the weather on stock prices could generate more realized gains, and thus lead to a stronger disposition effect for all traders.

Figure 2 shows how the coefficient on $Temperature_{i,t}$, obtained for humans using specification (13) (see Table 4, column 8 for a baseline result), depends on the time when the disposition effect is observed. On average, a statistically significant coefficient (at the 10% level) can be detected after 30 minutes of trading, i.e., at 9:30 am. The significance peaks at 10 am (more precisely, at 9:50 am as the coefficient estimate reaches -0.029). The coefficient becomes insignificant after 10:30 am.

[18]The constant (not reported for brevity) is 9.4 pp, thus, an average $DE_{i,t}$ on warmer mornings is 7.9 pp.

In line with Keller et al. (2005), who find that higher air temperature improves mood and cognition when temperatures are moderate, i.e., in spring, we find that our results are strongest in spring and autumn. The same coefficient on $Temperature_{i,t}$ from specification (13) for humans is equal to -0.046 (p-value=0.015) in spring months (March, April and May), -0.019 (p-value=0.322) in summer (June, July and August), -0.037 (p-value=0.032) in autumn (September, October, November), and -0.004 (p-value=0.820) in winter (December, January, February). The insignificant coefficients in summer and winter could be explained by diminishing marginal effects of temperature and by a potential avoidance of exposure to uncomfortable temperatures.

Overall, we find that the disposition effect for humans is, on average, significant and increases on colder days, while for algorithms it is insignificant and insensitive to the weather. To check the robustness of these results, Table 5 presents the constant from specification (8) and Table 6 shows the coefficient on $Temperature_{i,t}$ from specification (13), estimated for humans (Panel A) and algorithms (Panel B) under different modifications of our baseline setting. Column (1) in both tables presents the baseline results that match those in Tables 3 and 4, respectively. The alterations of the baseline setting in columns (2) to (5) provide tests for alternative explanations of why humans exhibit the disposition effect while algorithms do not, and are therefore discussed separately in the subsection 4.4 below. The remaining columns show that our results remain similar to the baseline when we estimate realized gains and losses using the first-in-first-out (FIFO) method instead of the WAPP method (column 6), include "infrequent traders" into the sample (column 7), use raw weather variables instead of dummies (column 8), do both include "infrequent traders" and use raw weather variables (columns 9), and leave robust standard errors unclustered (column 10). The statistically significant coefficient of -0.006 (p-value=0.034) in column (8) indicates that, on average, a 1°C lower temperature is associated with a 0.6 pp stronger disposition effect for humans.

4.3. Discussion

Our results show that, on average, algorithmic traders manage to avoid the disposition effect while similarly-trading humans do not. This suggests that the disposition effect is largely driven by unintentional causes specific to humans, e.g., emotions and cognitive biases, rather than by intentional profit-maximizing motives, e.g., portfolio rebalancing, transaction costs, and private information, that would be relevant for algorithms as well. This notion is strengthened by our causal evidence that air temperature, potentially through mood and cognition, affects the disposition effect for humans but not for algorithms. Here we discuss potential explanations of how air temperature might affect the disposition effect for humans and how algorithms might avoid the disposition effect.

How can air temperature affect the disposition effect for humans? More pleasant air temperature has been associated with better mood 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), which may become 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 (Thaler, 1985), they will prefer to continue gambling with losing investments and to sell winning investments. If a higher air temperature improves cognition, this could 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. According to Ben-David and Hirshleifer (2012), the disposition effect can be caused by traders' beliefs in their private information about the stock value,[19] and these beliefs can stem either from genuine information or overconfidence.[20] Since there is evidence that a more pleasant temperature enhances mood (Keller et al., 2005) and that better mood increases overconfidence (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 of our findings, which suggests that air temperature impacts the disposition effect primarily by affecting preferences rather than beliefs.

How can algorithms avoid the disposition effect? First, while humans make on-the-spot decisions under stress, developers have time to polish decision-making principles in their algorithms. By "thinking slow", i.e., using the slow System 2 (Kahneman, 2011), developers may avoid behavioral biases, heuristics and other cognitive features of the fast System 1, such as attachments to reference points and loss aversion, which are at the core of prospect theory (Kahneman and Tversky, 1979; Kahneman, 2011) – the long-standing explanation of the disposition effect. Yet, despite the claimed effort (Borch and Lange, 2017), it is not clear if developers manage to achieve that. For example, algorithms may inherit biases from programmers or training data (Cowgill and Tucker, 2019).

Second, while coding, developers are unlikely to experience feelings related to the realization of

[19] Traders may view price hikes as the incorporation of their private information into the price and price drops as temporary setbacks, and thus sell (hold) stock after price hikes (drops). The opposite may hold if price drops (hikes) make traders lose (gain) confidence in the information (Ben-David and Hirshleifer, 2012).

[20] Overconfidence is a broadly documented cognitive bias that affects beliefs (Barberis and Thaler, 2003).

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

Third, algorithms may serve as a pre-commitment device 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 them to blame someone else.

Other potential explanations of why humans but not algorithms exhibit the disposition effect include belief-based explanations and purely rational explanations such as portfolio rebalancing, career concerns and transaction costs. We test these explanations in the following sections.

4.4. Other robustness checks

In order to test whether transaction costs, career concerns and portfolio rebalancing explain the disposition effect among humans and its absence among algorithms, we re-estimate regression specification (8) using the following four alterations of the baseline setting. We consider (1) only long positions, (2) only short positions, (3) only missed opportunities to gain and lose (i.e., mental gains and losses), and (4) only full realizations of gains and losses. The results are presented as robustness checks in Table 5, columns (2) to (5), Panel A for humans and Panel B for algorithms.

Transaction costs. A stock price decline may relatively increase transaction costs for that stock, and, therefore, cause reluctance to sell a losing position. Algorithms may care less about transaction costs since market venues compete for algorithmic traders by offering favorable terms (Danish FSA, 2016). This could explain the difference in 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. To consider only long positions we set negative $\#\_shares\_outstanding_{s,i,t}$ and negative $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, to zero. Similarly, to consider short positions, we set positive $\#\_shares\_outstanding_{s,i,t}$ and positive $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, to zero. Table 5 shows that for only long and only short positions, the disposition effect is similar to the baseline for both humans and algorithms.

Career concerns. Human traders and programmers of trading algorithms may have different incentives to report realized gains and losses due to potentially different career concerns or compensation schemes. For instance, banks have been shown to manage, e.g., smooth, their reported earnings by strategically realizing gains and losses from securities (see, e.g., Dong and Zhang, 2018; Beatty and Harris, 1999; Ahmed and Takeda, 1995). However, these concerns should affect only reported realized gains and losses but not missed opportunities to gain and lose. For example, consider a trader who is long in 100 shares and sells one of them. If the stock price subsequently increases, the trader gains on the 99 shares, but misses the opportunity to gain on the sold share, which can mentally be perceived as a loss. This mental loss can be realized by repurchasing the share at the higher price.[21] 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. To test this, 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 trading day, or short from the daily perspective but long from the long-term perspective. 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, we set positive $\#\_shares\_outstanding_{s,i,t}$ and positive $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, to zero. If the position from the long-term perspective is short, we set negative $\#\_shares\_outstanding_{s,i,t}$ and negative $\#\_of\_shares\_sold_{s,i,t}$ in equations (1) and (2), respectively, to zero. Table 5, shows that when considering only mental gains and losses, the average disposition effect is similar to the baseline for both humans and algorithms.

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

Portfolio rebalancing. Gains (losses) increase (decrease) the weight of certain stocks in a portfolio and to restore a well-diversified balance, investors may close a portion of their winning positions (increase their losing positions). If algorithmic traders care less about portfolio rebalancing, this could explain the difference in the disposition effect between humans and

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

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 calculate $PGR_{i,t}$ and $PLR_{i,t}$ considering realized gains and losses only of those positions that were fully closed at least once throughout a day. Technically, in the numerator of equations (5) and (6), we set $cumulative\_realized\_gain_{s,i,t}$ to zero for those trader-stock-day positions that were never fully closed throughout the day. Table 5 shows that disposition effect remains significant for humans and insignificant for algorithms.

The results in Table 5 (columns 2 to 5) suggest that neither transaction costs, nor career concerns, nor portfolio rebalancing can explain why, on average, humans exhibit a significant disposition effect while algorithms do not. Table 6 (columns 2 to 5) shows that the impact of temperature on the disposition effect remains statistically significant (at least at the 10% level) for humans and insignificant for algorithms under each of the four alterations of the baseline setting.

4.5. Belief-based explanations

Traders may purchase a stock because they believe they have superior private information about its potential future price. As a result, they may view price hikes as incorporation of their private 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 price hikes and buy it after price drops, which would also lead to the disposition effect. Algorithms, having different access to information (Chordia et al., 2018; Biais et al., 2015), computational power and learning capacity (Abis, 2022) may have weaker "belief" in these price-reversal trading strategies than humans, which would explain the weaker disposition effect.

To test whether humans pursue price-reversal strategies more often than algorithms, we implement the following exercise. First, we estimate the absolute value of the hourly change in the number of shares, $|\Delta inventory_{s,i,t}|$, for every trader i, stock s, day-hour t, and, in order to consider deliberately large movements, find the 90th percentile, $perc90_{s,i}$, of this variable for every trader-stock using only non-zero observations. Second, for every trader i, we count the number N_i of stock-day-hour level observations, where $|\Delta inventory_{s,i,t}| > perc90_{s,i}$ and, similutaneously, 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 the change in inventory, $\Delta inventory_{s,i,t}$, occurred 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:

$$Reversal\_trading\_proportion_i = \frac{N\_reverse_i}{N_i} \tag{17}$$

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 pursue 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 indicates that humans pursue price-reversal trading 56% of the time. The difference is statistically significant at the 5% level and thus helps to explain why humans' disposition effect is stronger.

It is not clear, however, if humans' 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 performance, it would be justified and rational, but if traders exhibit it despite evidence that doing so hurts performance, it 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:

$$r_{i,t} = \frac{\sum_{s=1}^{S} total\_gain_{s,i,t}}{Portfolio\_size_{i,t}} \tag{18}$$

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 Table 1, but not converted to euros. We regress $r_{i,t}$ on a constant, separately for humans and algorithms, and cluster standard errors at the trader level. For humans, the constant equals -0.00033 (p-value = 0.260), which translates to an average annualized return of -11.4%.[22] The negative return is driven by traders that tend to pursue 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). Hence, for humans, price-reversal trading appears to be associated with losses, which suggests that humans' beliefs in their abilities to pursue such strategies are not rational.

For algorithms, the average annualized return equals 17.2%. The return equals 45.2% for algorithms with $Reversal\_trading\_proportion_i$ larger than median (i.e., 0.50) and 2.2% for the rest (all p-values are above 0.1). Hence, algorithms appear to perform better than humans, especially when pursuing price-reversal strategies, which suggests a better ability to purse them.[23]

Finally, to test whether the disposition effect, and in particular the reluctance to realize losses

[22] Average annualized return is calculated as $(1+\text{average\_daily\_return})^{365}$ - 1.

[23] In an unreported analysis of HFTs, we find that most of them systematically exhibit either a significant disposition effect or its inverse, and this can be entirely predicted by HFTs' tendency to purse price-reversal strategies. We find no evidence for HFTs that price-reversal strategies are associated with lower performance.

as suggested by Figure 1, harms the performance of human "frequent traders", we implement the following exercise. 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 "loss 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 the "loss realization portfolio". We regress it on a constant and cluster errors at the trader level. The constant equals 0.0006312 (p-value = 0.026), which translates to an average annualized return of 25.9%. Hence, human 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.

5. Conclusion

This paper studies for the first time whether algorithmic traders exhibit the disposition effect and why or why not, and in this way contributes to a better understanding of both automated decision-making and causes of the disposition effect.

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 show that warmer morning weather reduces the disposition effect for humans but has no impact for algorithms. According to the psychology literature, more pleasant 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 and prospect theory. The belief-based explanation of the disposition effect predicts the opposite of our findings, which suggests that the temperature impacts the disposition effect primarily though preferences rather than beliefs.

We also find that, on average, professional human stock day-traders exhibit a significant disposition effect while similarly-trading algorithms do not. This further suggests that the disposition effect is driven by unintentional, e.g., psychological, causes specific to humans rather than by intentional profit-maximizing motives that would be relevant for algorithms as well. Our robustness checks show that neither transaction costs, nor career concerns, nor portfolio rebalancing practices can fully explain the results. We find some suggestive evidence that the difference in the disposition effect between the two groups could be at least partially explained by humans' irrational beliefs in their ability to pursue prise-reversal strategies.

Overall, our results suggest that the disposition effect for humans is at least partially caused by psychological biases and that by reducing these biases algorithms behave more in line with rational economic models. Due to the rapid global adoption of AI, these results may have broad implications for the real economy, financial markets, economic theory and human behavior. As for the real economy, industries that need more rational decisions might replace humans with algorithms faster, affecting unemployment, productivity and economic growth. With regard to economic theory and financial markets, as algorithms become more ubiquitous, rational economic models might become more accurate in explaining both the economy and financial markets. Finally, being surrounded by more rational decision-making might affect humans and human behavior in multiple ways. We suggest that testing these implications is an important direction for future research.

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TABLE 1

Trading patterns of algorithms and humans

Panels A and B show the results of regressing five trader-day-level variables on a constant and a dummy *Human$_i$*, which is equal to 1 for humans and 0 for algorithms. The five dependent variables are: (1) *N_of_trades$_{i,t}$* – total number of trades executed by trader *i* in day *t*; (2) *Turnover_EUR$_{i,t}$* – total turnover expressed in euros generated by trader *i* in day *t*; (3) *Portfolio_size_EUR$_{i,t}$* – average portfolio size expressed in euros for trader *i* throughout day *t* (see the "Data" section for the detailed variable definition); (4) *Inventory_days$_{i,t}$* – trading horizon for trader *i* in day *t*, calculated as a ratio of *Portfolio_size_EUR$_{i,t}$* over the total value of shares sold (repurchased, for short positions) by trader *i* in day *t*, valued at purchase prices (sale prices, for short positions); and (5) *Turnover_top10$_{i,t}$* – the turnover generated in the 10 most traded stocks by trader *i* in day *t*, divided by total turnover generated by trader *i* in day *t*. Panel A considers "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 2

Summary statistics of morning weather variables

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

Variable	1st percentile	25th percentile	median	75th percentile	99th percentile	mean
Air temperature 2 meters above ground (°C)	-3.4	4.4	9.2	15.0	23.2	9.5
Relative humidity 2 meters above ground (%)	46.5	73.0	82.5	90.0	97.0	80.3
Mean sea level pressure (hPa)	983.6	1007.7	1014.9	1021.9	1039.7	1014.4
Precipitation (mm)	0	0	0	0	1.35	0.074
Cloud cover (% of the sky area)	0	25	100	100	100	68.6
Sunshine duration (minutes)	0	0	0	30.4	60	16.3
Shortwave radiation (W/m2)	0	16.9	120.6	277.2	514.4	162.7
Wind speed 10 meters above ground (km/h)	1.8	10.5	16.6	23.5	45.0	17.7

Correlation coefficient between air temperature and:						
Relative humidity 2 meters above ground (%)	Mean sea level pressure (hPa)	Precipitation (mm)	Cloud cover (% of the sky area)	Sunshine duration (minutes)	Shortwave radiation (W/m2)	Wind speed 10 meters above ground (km/h)
-0.493	-0.072	0.017	-0.160	0.286	0.680	-0.217

TABLE 3

Average disposition effect

Table 3 presents estimates of the average disposition effect for algorithms (columns 1 and 4) and humans (columns 2 and 5), as well as the average difference in the disposition effect between the two groups (columns 3 and 6). The average disposition effect is estimated by the constant in columns (1) and (2) and by the coefficient on $Gain_{s,i,t}$ in columns (4) and (5). The average difference in the disposition effect is estimated by the coefficient on $Human_i$ in column (3) and by the coefficient on $Human_i \times Gain_{s,i,t}$ in column (6). The top of the table indicates for every column the dependent variable, i.e., either $DE_{i,t}$ (disposition effect) or $PR_{s,i,t}$ (proportion of either a gain or a loss realized), the sample, i.e., either algorithms or humans or both, and the regression specification used. The dependent variables are observed daily at 5 pm CET. Subscripts *s*, *i* and *t* represent *stock*, *trader* and *trading day*, respectively. $Human_i$ equals 1 for humans and 0 for algorithms. $Gain_{s,i,t}$ equals 1 for non-losing positions and 0 for losing ones. Fixed effects include stock-time, trader-time and trader-stock fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	$DE_{i,t}$ (disposition effect)			$PR_{s,i,t}$ (proportion realized)		
Sample:	Algos	Humans	Both	Algos	Humans	Both
Regression specification:	8	8	9	10	10	12
Constant	0.015	0.115***	0.015	0.416***	0.257***	0.331***
	(0.571)	(0.000)	(0.565)	(0.000)	(0.000)	(0.000)
$Human_i$			0.099**			
			(0.011)			
$Gain_{s,i,t}$				0.018	0.066***	0.019
				(0.307)	(0.000)	(0.314)
$Gain_{s,i,t} \times Human_i$						0.046*
						(0.062)
Fixed effects				Yes	Yes	Yes
Observations	8,159	9,847	18,006	167,524	182,043	359,630
Adjusted R-squared	0.000	0.000	0.020	0.291	0.224	0.279

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

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

TABLE 4

The impact of air temperature on the disposition effect

Table 4 presents estimates of the impact of temperature measured at 8-9 am on the disposition effect observed at 10 am for algorithms and humans, as well as the difference in the impact between the two groups. Every column indicates the dependent variable, i.e., either $DE_{i,t}$ (disposition effect) or $PR_{s,i,t}$ (proportion of either a gain or a loss realized), the sample, i.e., either algorithms or humans or both, and the specification used. Subscripts *s*, *i* and *t* represent *stock*, *trader* and *trading day*, respectively. Weather variables are dummies equal to 1 when a corresponding raw variable (see Table 2) is above or equal to its median of the time interval [t-15; t+15] in the trader *i*'s city. $Human_i$ equals 1 for humans and 0 for algorithms. $Gain_{s,i,t}$ equals 1 for non-losing positions and 0 for losing ones. Fixed effects include trader and time-fixed effects in columns (7) to (9) and stock-time, trader-time and trader-stock fixed effects in columns (10) to (12). For brevity, we do not report the constant and the coefficients on $Human_i$ (columns 3 and 6), $Gain_{s,i,t}$ (columns 10 to 12) and $Gain_{s,i,t}$ × $Human_i$ (column 12).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable:	$DE_{i,t}$ (disposition effect)			$DE_{i,t}$ (disposition effect)			$DE_{i,t}$ (disposition effect)			$PR_{s,i,t}$ (proportion realized)		
Sample:	Algos	Humans	Both	Algos	Humans	Both	Algos	Humans	Both	Algos	Humans	Both
Regression specification:	13	13	14	13	13	14	13	13	14	15	15	16
$Temperature_{i,t}$	0.005	-0.015***	0.005	0.005	-0.016**	0.005	0.020	-0.024**	-0.003			
	(0.505)	(0.005)	(0.463)	(0.541)	(0.010)	(0.505)	(0.305)	(0.019)	(0.851)			
$Temperature_{i,t}$ × $Human_i$			-0.020**			-0.021**			-0.016*			
			(0.014)			(0.014)			(0.061)			
$Cloud\_cover_{i,t}$				-0.002	-0.014	-0.002	-0.021	-0.002	-0.007			
				(0.848)	(0.362)	(0.836)	(0.197)	(0.880)	(0.518)			
$Precipitation_{i,t}$				-0.015	-0.008	-0.015	-0.023	0.001	-0.008			
				(0.234)	(0.458)	(0.180)	(0.224)	(0.936)	(0.589)			
$Sunshine\_duration_{i,t}$				-0.016	-0.011	-0.016	-0.041	-0.002	-0.031*			
				(0.148)	(0.410)	(0.101)	(0.183)	(0.895)	(0.076)			
$Humidity_{i,t}$				-0.000	-0.007	-0.000	0.012	-0.027*	-0.012			
				(0.973)	(0.501)	(0.971)	(0.714)	(0.053)	(0.546)			
$Pressure_{i,t}$				-0.006	-0.007	-0.006	-0.002	-0.012	-0.001			
				(0.137)	(0.179)	(0.114)	(0.924)	(0.269)	(0.889)			
$Radiation_{i,t}$				-0.003	-0.024	-0.003	-0.011	-0.021*	-0.009			
				(0.646)	(0.205)	(0.623)	(0.291)	(0.089)	(0.349)			
$Wind\_speed_{i,t}$				0.001	0.010	0.001	0.013	0.002	-0.005			
				(0.893)	(0.142)	(0.346)	(0.369)	(0.867)	(0.353)			
$Cloud\_cover_{i,t}$ × $Human_i$						-0.012			-0.002			
						(0.445)			(0.883)			
$Precipitation_{i,t}$ × $Human_i$						0.006			-0.002			
						(0.750)			(0.892)			
$Sunshine\_duration_{i,t}$ × $Human_i$						0.005			0.018			
						(0.763)			(0.294)			
$Humidity_{i,t}$ × $Human_i$						-0.007			-0.007			
						(0.613)			(0.666)			
$Pressure_{i,t}$ × $Human_i$						-0.001			-0.007			
						(0.889)			(0.498)			
$Radiation_{i,t}$ × $Human_i$						-0.022			-0.013			
						(0.243)			(0.235)			
$Wind\_speed_{i,t}$ × $Human_i$						0.009			0.013			
						(0.346)			(0.353)			
$Gain_{s,i,t}$ × $Temperature_{i,t}$										0.000	-0.012**	0.002
										(0.909)	(0.028)	(0.341)
$Gain_{s,i,t}$ × $Human_i$ × $Temperature_{i,t}$												-0.014***
												(0.006)
Controls				Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects							Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,975	7,266	14,241	6,975	7,266	14,241	6,975	7,266	14,241	97,589	73,626	178,383
Adjusted R-squared	0.000	0.000	0.011	0.000	0.001	0.011	0.069	0.113	0.101	0.270	0.166	0.242

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

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

TABLE 5

Robustness tests – average disposition effect

Table 5 presents estimates of the average disposition effect for humans (Panel A) and algorithms (Panel B) obtained using regression specification (8), where the trader-day level dependent variable $DE_{i,t}$ (disposition effect) is regressed on a constant. Column (1) presents the baseline estimates, which match Table 3, and the remaining columns present estimates obtained by modifying the baseline setting in ways indicated at the top of the table. Column (2) uses only long positions, column (3) – only short positions, column (4) – only positions that are either long from the long-term perspective but short from the daily perspective or short from the long-term perspective but long from the daily perspective, column (5) – only positions that were fully closed at least once throughout the day, column (6) uses the first-in-first-out method instead of the WAPP method to estimate realized gains and losses, column (7) includes "infrequent traders" in the sample.

Panel A: humans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	$DE_{i,t}$ (disposition effect)						
Change in the baseline setting:	Baseline	Long positions	Short positions	Mental gains and losses	Full realization	FIFO method	Include infrequent traders
Constant	0.115***	0.126***	0.112***	0.123***	0.079***	0.094***	0.079***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Observations	9,847	8,602	8,228	8,345	9,847	9,955	18,826
Adjusted R-squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: algorithms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	$DE_{i,t}$ (disposition effect)						
Change in the baseline setting:	Baseline	Long positions	Short positions	Mental gains and losses	Full realization	FIFO method	Include infrequent traders
Constant	0.015	0.015	0.031	0.023	0.010	0.022	0.019
	(0.571)	(0.569)	(0.258)	(0.381)	(0.673)	(0.321)	(0.385)
Observations	8,159	7,209	7,249	7,267	8,159	8,268	10,286
Adjusted R-squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000

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

TABLE 6

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

Table 5 presents estimates of the impact of temperature measured at 8-9 am on the disposition effect measured at 10 am for humans (Panel A) and algorithms (Panel B) obtained using regression specification (13), where the trader-day level dependent variable $DE_{i,t}$ (disposition effect) is regressed on eight weather dummies equal to 1 when a corresponding raw weather variable (see Table 2) is above or equal to its median of the time interval [t-15; t+15] in the trader *i*'s city. The regression also includes trader-fixed effects and time-fixed effects. For brevity, only the coefficient on $Temperature_i$ is reported. Column (1) presents the baseline estimates, which match Table 4, and the remaining columns present estimates obtained by modifying the baseline setting in ways indicated at the top of the table. Column (2) uses only long positions, column (3) – only short positions, column (4) – only positions that are either long from the long-term perspective but short from the daily perspective or short from the long-term perspective but long from the daily perspective, column (5) – only positions that were fully closed at least once throughout the day, column (6) uses the first-in-first-out method instead of the WAPP method to estimate realized gains and losses, column (7) includes "infrequent traders" in the sample, column (8) uses raw weather variables (see Table 2) instead of dummies, column (9) does both includes "infrequent traders" and uses raw weather variables, column (10) uses the baseline setting but leaves robust standard errors unclustered.

Panel A: humans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	$DE_{i,t}$ (disposition effect)									
Change in the baseline setting:	Baseline	Long positions	Short positions	Mental gains and losses	Full realization	FIFO method	Include infrequent traders	Raw weather variables	(7) + (8)	No error clustering
$Temperature_{i,t}$	-0.024**	-0.024*	-0.031**	-0.032**	-0.018*	-0.023**	-0.012*	-0.006**	-0.004*	-0.024**
	(0.019)	(0.076)	(0.038)	(0.027)	(0.058)	(0.047)	(0.092)	(0.034)	(0.050)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,266	5,439	5,627	5,547	7,266	7,270	11,594	7,266	11,594	7,266
Adjusted R-squared	0.113	0.117	0.093	0.070	0.102	0.070	0.102	0.113	0.102	0.113

Panel B: algorithms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	$DE_{i,t}$ (disposition effect)									
Change in the baseline setting:	Baseline	Long positions	Short positions	Mental gains and losses	Full realization	FIFO method	Include infrequent traders	Raw weather variables	(7) + (8)	No error clustering
$Temperature_{i,t}$	0.020	0.008	0.029	-0.003	0.008	0.018	0.023	0.003	0.003	0.020
	(0.305)	(0.538)	(0.158)	(0.916)	(0.639)	(0.318)	(0.103)	(0.444)	(0.311)	(0.184)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,975	5,692	5,631	5,586	6,975	6,978	7,988	6,975	7,988	6,975
Adjusted R-squared	0.069	0.115	0.112	0.050	0.068	0.044	0.057	0.069	0.057	0.069

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

FIGURE 1

Intraday average disposition effect

Figure 1 plots average intraday developments for the proportion of gains realized (PGR, dotted lines) and the proportion of losses realized (PLR, solid lines) observed at the end of every trading hour for human and algorithmic "frequent traders". Every data point in the chart is an average of variables $PGR_{i,t}$ and $PLR_{i,t}$ across traders (i) and days (t).

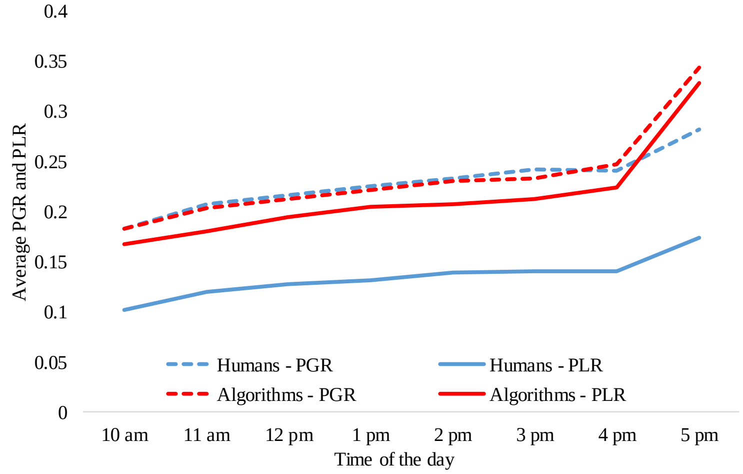

FIGURE 2

The impact of morning temperature on the humans' disposition effect measured at different times

Figure 2 plots coefficient estimates on dummy $Temperature_{i,t}$ obtained for humans using the regression specification (13) with controls and fixed effects, and using observations of the dependent variable $DE_{i,t}$ (disposition effect) at different times throughout the day (x-axis). The grey dotted lines represent the upper and lower bounds of the 90% confidence interval. The estimate at 10 am equals -0.024 and matches the baseline result presented in column (8) of Table 4 and column (1) of Table 6. The graph indicates that the effect of morning air temperature on the disposition effect is detectable between 9:30 and 10:30 but fades out after that.