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Mood over money

An analysis of the causal link between mood and trading behaviour of Swedish household investors

Abstract: This thesis investigates whether the mood of Swedish online household investors has a causal influence on their trading behaviour, as predicted by decision theory but not empirically established. We also investigate differences in sensitivity to mood within different demographic dimensions. Utilizing panel data on daily volume and value changes for 900 household trading accounts, daily weather forecasts and weather observations across Sweden, and daily blog entries of c.150 000 Swedish blogs, we find a significant and positive causal relationship between mood and an increase in buying/decrease in selling behaviour. Our results are of economic significance for the individual household investor, but not of a magnitude likely to affect asset prices. In addition we develop and test deviations from weather forecasts as a novel continuous mood proxy. Our findings are helpful in explaining the trading behaviour of active online household investors.

Keywords: household investor, trading behaviour, decision making, mood, weather deviations

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I. Introduction

During the last two decades behavioural economists have become increasingly interested in the role of mood and emotions in decision making. Emotions enter into decision making in two distinct ways; through *expected emotions* and *immediate emotions*. Expected emotions play a large role in the traditional expected utility theory where the decision maker weighs expected benefits or expected emotional consequences of alternative choices and subsequently makes the choice that maximises the ratio of positive to negative emotions. Expected emotions are not experienced at the time of decision making, rather they are predictions about what emotions will be experienced in the future (Loewenstein and Lerner, 2003).

Immediate emotions are, unlike expected emotions, experienced at the time of the decision making. They can exert a direct impact on the decision at hand, as well as an indirect impact by altering the individuals' expectations of the probability of outcomes or the desirability of the outcomes.[1] Thus, individuals in a good mood may make too optimistic judgments and individuals in a bad mood make too pessimistic judgments of future prospects (Wright and Bower, 1992; Johnson and Tversky, 1983; Isen et al., 1978; Schwartz and Clore, 1983). Theory and experimental research also posit that emotions carried over from prior and irrelevant situations can bias an unrelated economic decision (Forgas, 1995; Schwarz, 1990; Clore, 1992) and that emotions can bias the interpretation and processing of decision-relevant information (Niedenthal and Setterlund, 1994; Peters, 2006; Goetzmann and Peles, 1997; McFadden, 1974). Furthermore, negative emotions have been suggested to trigger more systematic processing than positive emotions (Schwarz, 1990; Schwarz and Bless, 1991) and a higher tendency to sell current assets than buying new ones (Lerner et al., 2004), while good mood is associated with increased use of simplifying heuristics to aid quick decision making (Forgas, 1998). Loewenstein and Lerner (2003) suggest that the impact of immediate emotions on an individual's decision critically depends on the intensity of the immediate emotion, where emotions with higher intensity exert a higher influence on the behaviour.

Research within social psychology find significant differences in sensitivity, intensity and levels of mood between young and old (Gross et al., 1997; Carstensen et al., 1999; Labouvie-Vief and DeVoe, 1991; Agarwal et al., 2009); men and women (Fujita et al., 1991; Wood et al., 1989; Diener et al., 1999); and wealth groups (Diener et al., 1993; Diener and Biswas-Diener, 2002), thus suggesting differences in decision behaviour within demographic dimensions.

[1] See Appendix A for a detailed framework by Loewenstein and Lerner (2003).

In parallel, empirical research has found that the trading behaviour of household investors[2] differ from what is proposed by standard financial theory. They are frequent traders, hold undiversified portfolios (Barber and Odean, 2000, 2002; Anderson, 2004; Kelly, 1995; Odean, 1999) and are reluctant to repurchase stocks previously sold for a loss and to repurchase stocks that have risen in price subsequent to a prior sale (Strahilevitz et al., 2011). In addition, men trade more frequently than women (Barber and Odean, 2001a), and online traders trade more frequently than offline traders (Barber and Odean, 2001b). To the best of our knowledge, Anderson (2004) represents the only paper on Swedish data. Using data from 1999-2002 he finds that online household investors trade more aggressively and hold less diversified portfolios than non-online household investors.

The observed discrepancies can be attributed to household investors being motivated by emotional drivers to a higher extent than professional investors, as discussed by (Shiller, 1984, 1999; De Long et al., 1990; Daniel et al., 1998; Baker and Wurgler, 2007). However, though promising on theoretical and experimental stages, researchers have been unable to affirm a causal relationship between mood and trading behaviour among household investors using empirical data.

In this paper we attempt to establish a causal relationship between mood and investment behaviour of household investors, harnessing the quantitative strength of three novel datasets. The first dataset contains daily trading account data for 900 anonymous and randomly selected Swedish household investors from an online broker. This allows us to track daily volume and market value changes in individual investors' trading accounts. The second dataset consists of daily blog entries from c.150 000 Swedish blogs. From these blogs we extract mood related words to construct an index that measure the aggregate mood level of the Swedish population. The third dataset consists of daily observed and forecasted weather. We intend to use actual weather observations and deviations from weather forecasts as proxies for mood. Using deviations from weather forecasts as a mood proxy is, to the best of our knowledge, a novel method of capturing mood changes stemming from discrepancies between expectations and actual outcome.

We will limit ourselves to study the behaviour of households that have and frequently use an online broker account. The terms investor, household investor and active household investors will be used interchangeably. The term *emotion* depicts a transient state of feeling at a particular time. The term *mood* is used as a concept of aggregate emotions stretching over a couple of hours.

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[2] Defined as private/non-professional investors

The remainder of this paper is organised as follows. In section II. we formulate our hypotheses. Section III. provides a review of the current literature and section IV. describes the data used and design of variables. In section V. we discuss the method and section VI. presents our results. In Section VII. We discuss implications and limitations of our findings in relation to our hypotheses and previous research. Section VIII. summarises our findings.

II. Hypotheses

Psychological evidence and casual intuition predict that mood has an impact on behaviour. We hypothesise that this extends to the trading behaviour of household investors.

Level of activity

Previous research suggests that a negative mood state (bad mood) is associated with a more pessimistic assignment of probabilities and more systematic processing of information, whereas positive mood states (good mood) is associated with an increased use of simplifying heuristics, aiding quick decision making. Thus, we expect positive mood to increase the level of activity among household investors, while negative mood will have the opposite effect.

H1: Positive mood increases activity

H2: Positive mood increases the level of activity

Direction of activity

Decision theory suggests that people use their current mood state as a piece of information in decision making, implying that individuals in a good mood assign more optimistic probabilities to positive future states than those in a bad mood. Moreover, experimental findings suggest that a bad mood state increases the tendency to sell currently held assets more than taking in new ones. Household investors in a good mood are therefore hypothesised to buy more or sell less than those in a bad mood.

H3: Positive mood will increase buy activity relative to sell activity

H4: Positive mood increases the size of buy activity relative to sell activity

III. A review of the literature

Despite recent years' increased focus on the role of emotions in decision making, there is, to our knowledge, little research that directly ties evidence of emotions' impact on decision making to data on household investors' trading behaviour. Previous research has used actual weather observations as a proxy for mood and finds that stock returns are higher on sunny days, arguing that this effect is related to investors' good mood as a consequence of the sun (Saunders, 1993; Hirshleifer and Shumway, 2003; Kliger and Levy, 2003). Testing the effect of sunshine on intraday stock returns Chang et al. (2008) find a significant impact only for the first 15 minutes of trading, arguing that new information quickly dilutes the impact of emotions induced by sunshine. In addition, stock returns have been found to be lower on days following daylight savings (Kamstra et al., 2000), highlighting the positive effect of sunlight on investor sentiment. Using a detailed dataset on all Finish market transactions, Kaustia and Rantapuska (2011) find that sunshine has a positive although insignificant effect on the demand for stocks, whereas precipitation has a negative effect. In terms of economic significance they conclude that mood changes, proxied by weather, exert a minor influence on investors' trading behaviour. Moreover, Goetzmann and Zhu (2005) find no correlation between increased buying behaviour and sunshine when studying individual investor data. Instead they document a significant impact between liquidity, measured by bid-ask spreads, and sunshine arguing that market makers are those potentially influenced by weather. Chang et al. (2008) fail to find a similar pattern when studying intraday data. Similarly, Loughran and Schultz (2004) fail to find a relationship between weather and stock returns. Bouman and Jacobsen (2002) document a strong seasonal pattern in stock returns but find no evidence of this seasonal pattern being related to mood.

Other than weather, few large scale proxies for mood have been studied. Edmans et al. (2007) propose sports results as a proxy for mood. Using a cross section of 39 countries they find a significant negative impact on next day stock returns following a defeat in international sport games such as the soccer world cup. Kaplanski and Levy (2010) use aviation disasters as a proxy for bad mood and find that disaster are associated with a negative event effect leading to an average market decline of more than 60 times the actual loss, before reverting after two days. Reduced demand for risky assets induced by bad mood, anxiety and fear is proposed as an explanation. Bollen et al. (2011) measure collective mood states using quantitative analysis of micro blog posts (twitter) and find that the accuracy of the Dow Jones Industrial Average predictions can be significantly improved by inclusion of specific public mood dimensions.

IV. Data Description

Three datasets are used to test our hypotheses: (i) data on 900 household investors' trading accounts (ii) data on mood related words in Swedish blogs and (iii) data on actual and forecasted weather. Details of these are outlined below.

Household investor data

Nordnet Bank[3] has provided us with a detailed dataset that includes daily information on closing volume and value of investments in 30 groups of financial products (henceforth instrument groups) for 900 anonymous and randomly selected Nordnet accounts. The dataset allows us to track how household investors allocate their assets and how the allocation changes over time. Furthermore, each investor is labelled with its gender, age and zip code. Using data from 1st July 2009-19st August 2011[4] this gives us 475 976 observations across 529 days.

Investors included in the sample were required to have an account open on the 1st of January 2009, although not required to have an open account by the end of the sample period. In addition, we only consider active households investors, which are defined as those with more than 32 executed trades during our sample period.[5] We exclude 128 observations due to errors related to stock splits (see Appendix B). Excluded observations make up 0.03% of our sample.

Constructed Variables

The variable $Total\ activity$ is a dummy that takes on 1 if the volume has changed in any of the instrument groups between time t and $t-1$. This variable is designed to test Hypothesis 1.

$$Total\ activity_{\,i,t} = \begin{cases} 1\ if\ \Delta Q_{i,t}^{J} \neq 0\ for\ any\ j \\ 0\ if\ \Delta Q_{i,t}^{J} = 0\ for\ all\ j \end{cases} \tag{1}$$

Where $\Delta Q_{i,t}^{J} = \{\, \Delta Q_{i,t}^{1},\ \Delta Q_{i,t}^{2} \dots \Delta Q_{i,t}^{j}, \Delta Q_{i,t}^{J}\}$ is a vector where $\Delta Q_{i,t}^{j}$ is the difference in volume of instrument group j held by investor i between time t and $t-1$.

As we do not have intraday transaction data we can only look at the net changes in volume per instrument group. $Buy_{i,t}$ captures buying activity by taking on 1 if the volume has increased in any of the instrument groups j between t and $t-1$. Analogously, we create $Sell_{i,t}$ signalling

[3] Nordnet is an online based broker with c. 215 000 active household investor accounts www.nordnet.se.
[4] Data for May 2010 is missing. Nordnet affirms that data is missing for random reasons; hence we assume it will not bias our sample.
[5] More specifically, 32 commission generating trades between Jan 2009- Aug 2011, which includes e.g. stocks and ETFs, but not mutual funds. Cut-off corresponds to average trade statistics in Anderson (2004). The sample selection criteria were a consequence of data extraction being limited to 900 accounts. Implications are discussed in section 7. Discussion

a volume decrease. $Net\ activity_{i,t}$ captures the net of buy and sell activities by investor i between time t and $t-1$. This variable is designed to test Hypothesis 3.

$$Buy_{i,t} = \{\begin{matrix} 1\ if\ \Delta Q_{i,t}^{j}\ > 0\ for\ any\ j \\ 0\ if\ \Delta Q_{i,t}^{j}\ <= 0\ for\ all\ j \end{matrix} \quad (2)$$

$$Sell_{i,t} = \{\begin{matrix} 1\ if\ \Delta Q_{i,t}^{j}\ < 0\ for\ any\ j \\ 0\ if\ \Delta Q_{i,t}^{j}\ >= 0\ for\ all\ j \end{matrix} \quad (3)$$

$$Net\ activity_{i,t}\ =\ Buy_{i,t} -\ Sell_{i,t} \quad (4)$$

Where:

$$Net\ activity_{i,t} = \{-1,0,1\}$$

Data on instrument group level does not allow us to disentangle value changes related to buy or sell activity from changes related to market movements. Instead we assume that days where $\Delta Q_{i,t}^{j} \neq 0$ all changes in the value of instrument group j belonging to investor i, between t and $t-1$, is due to trading activity. Thus we disregard value changes related to market movements. We create $B\%P$ and $S\%P$ to measure the absolute change in market value for those instruments that have increased or decreased in quantity from previous period relative to the absolute average portfolio size of investor i. $N\%P$ measures the net change in value due to activity as a percentage of the average portfolio size. This variable is designed to test Hypothesis 4.

$$B\%P_{i,t} = \frac{\sum_{i,j=1}^{J} \left|\Delta V_{i,t}^{j}\right|\ if\ \Delta Q_{i,t}^{j} > 0}{\frac{1}{T}\sum_{t}^{T}\left[\sum_{i,j=1}^{J} |V_{i,t}^{j}|\right]} \quad (5)$$

$$S\%P_{i,t} = \frac{\sum_{i,j=1}^{J} \left|\Delta V_{i,t}^{j}\right|\ if\ \Delta Q_{i,t}^{j} < 0}{\frac{1}{T}\sum_{t}^{T}\left[\sum_{i,j=1}^{J} |V_{i,t}^{j}|\right]} \quad (6)$$

$$N\%P_{i,t} = B\%P_{i,t} - S\%P_{i,t} \quad (7)$$

Where $V_{i,t}^{J}$ is the value and $\Delta V_{i,t}^{J}$ is the difference in value of instrument j held by investor i between time t and $t-1$. T corresponds to the number of days in our sample, 529.

$TS\%P$, is defined as the average of $B\%P_{i,t}$ and $S\%P_{i,t}$, and measures the magnitude of activity, regardless of direction, relative to the absolute average portfolio size of investor i. This variable is designed to test Hypothesis 2.

$$TS\%P_{i,t} = \frac{B\%P_{i,t} + S\%P_{i,t}}{2} \tag{8}$$

The group of four trading behaviour variables will be denoted by Y_v. Table 1 provides summary statistics for $Y_{v,i}$, where v denotes the four constructed trading behaviour variables: $Total\ activity$; $Net\ activity$; $N\%P$; and $TS\%P$, and i denotes investor.

Table 1 – Summary statistics for trading behaviour variables

Table summarises trading behaviour variables, Y_v. Values are averages per houseuhold investor i over the sample period, t=1,…,529. Sample consists of 900 household investors, $i = 1 \ldots 900$. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$ measures net change in value from instrument groups that have changed volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i.

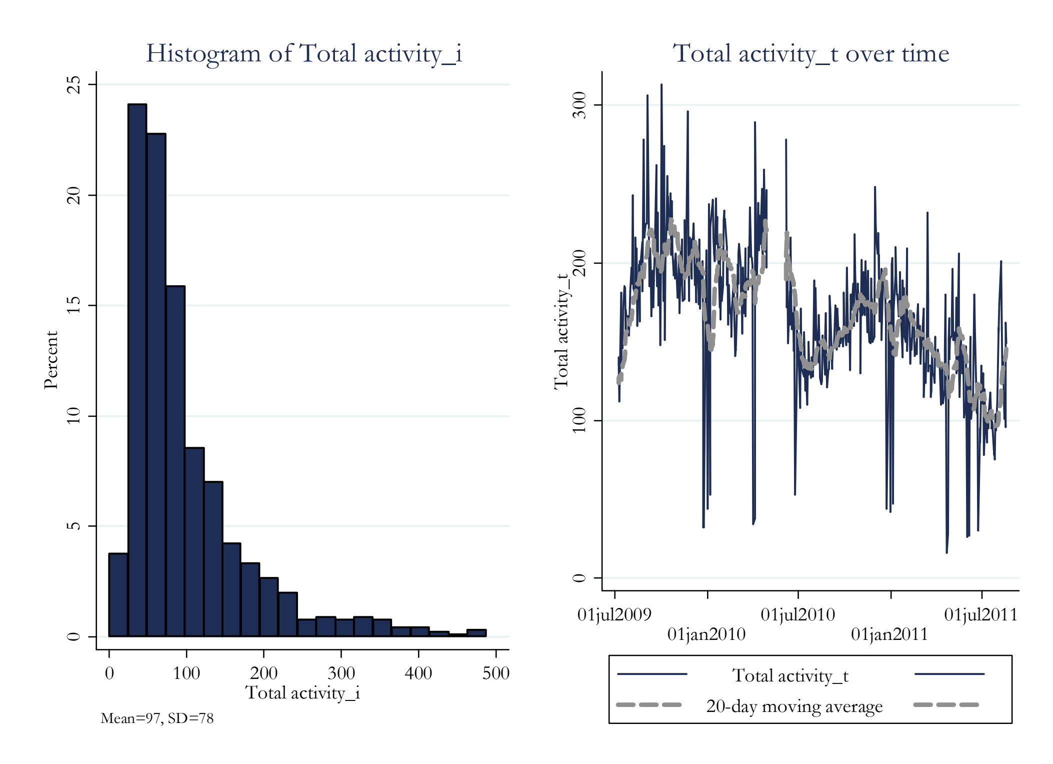
$Y_{v,i}$	Mean	SD	p25	Median	p75
$Total\ activity_i$	0.18	0.15	0.09	0.14	0.23
$Net\ activity_i$	0.02	0.04	0.00	0.02	0.04
$N\%P_i$	0.0%	0.5%	-0.1%	0.0%	0.1%
$TS\%P_i$	2.0%	3.0%	0.5%	1.0%	2.2%

Household characteristics

Figure 1 provides a graphical summary of $Total\ activity$. The average household investor has done c. 100 activities over the 26 months our sample covers, an average of four times per month. Approximately 10% of the household investors are active on more than 200 days and the most active investor is active on 487 days. The 10% least active investors have been active on less than 35 days. Over time we see a downward trend, although with significant variation on a day to day basis. The main slumps in activity relate to public holidays.

Figure 1 – Descriptive statistics for Total activity

Histogram of $Total\ activity_i$ per household investor i. $Total\ activity_i$ is the sum of $Total\ acitivity_{i,t}$ across time period $t = 1 \ldots 529$. Line diagram of $Total\ activity_t$ over time. $Total\ activity_t$ is the sum of $Total\ activity_{i,t}$ per day over all investors $i = 1 \ldots 900$. $Total\ activity_{i,t}$ = 1 if volume has changed in any instrument group from t to $t - 1$ and = 0 otherwise.



Note: Data missing for May 2010

Table 2 summarises demographical dimensions of our data; gender, age and portfolio size[6] (as a proxy for wealth). 86% of the household investors in our sample are male and 79% are above 40 years old. All investors are assigned to one of two portfolio size groups: *small* and *large*. Those investors assigned to small has an average portfolio size below the sample median in a majority of the months, whereas those assigned to large has a portfolio size above the sample median in a majority of the months. Median size for small portfolios is c. 118 000 SEK and for large c. 770 000.

[6] Absolute values are used to account for short positions

Table 2 – Demographic breakdown of household investors

Household investor data split by 3 demographic dimension: Gender, Age and Portfolio size. Portfolio size is calculated as average absolute value across sample period. Small refers to investors that has an average absolute portfolio size below the sample median in a majority of the months in our sample period, investors assigned as large has an average absolute portfolio size above the sample median in a majority of the months.

Dimension	Groups	Description	N	N (%)
Gender	Female		123	14%
	Male		777	86%
Age	Young	Aged 20-39	188	21%
	Not Young	Age≥ 40	712	79%
Portfolio size	Small	Median Portfolio size c.118 TSEK	446	50%
	Large	Median Portfolio size c.770 TSEK	454	50%

Mood data

In order to measure the collective mood states in Sweden we use a database, owned and managed by Kairos Future[7], which stores daily blog posts of Swedish blogs. The database is used to measure the frequency of key words related to mood throughout the Swedish blogosphere on a daily basis between the dates 1 July 2009 – 31 August 2011, equal to 782 days. The blogosphere is suggested to reflect the mood state of the general public (Bollen et al., 2011; O'Connor et al., 2010; Gilbert and Karahalios, 2010 and Balog et al., 2006). This paper uses an approach to measure mood by quantitatively analysing information from social media inspired by methods developed by Bollen et al. (2011), although without the aid of artificial intelligence.

The database consists of c. 150 000 blogs, posting an average of 57 000 posts or 6.7 million words per day. Of the writers of blogs in the data, approximately 30% are students, 30% career pursuers and 25% are parents.[8]

To construct our measure of mood, words are classified into emotion categories based on the *Positive and Negative Affect Schedule* (PANAS), designed by Watson et al. (1988). PANAS consists of 20 adjectives divided into two categories: Positive Affect (PA) containing 10 adjectives such as *Alert* and *Enthusiastic*; and Negative Affect (NA) containing 10 adjectives such as *Afraid* and *Hostile*. Words are translated into Swedish and to adapt the test to today's online language the list is expanded by collecting synonyms of the original PANAS words and as a second step, synonyms of the synonyms. To not distort the meaning of original words we exclude second level synonyms that only occur once.[9] Detailed description of process for selection of words, list of original PANAS words and creation of $Net\ mood$ is available in

[7] Kairos Future, a consultancy. http://www.kairosfuture.com/

[8] Categories not mutually exclusive, classification is based on an algorithm, owned by Kairos Future, analysing topics discussed by bloggers

[9] Tests were also done without this restriction. The results of these tests closely match those with a restriction. See Appendix C.

Appendix D. After removing duplicate words we are left with a list of 549 unique words; 262 words within PA and 287 words within NA. Based on these words we create $RawMood_{d,t}$.

$$RawMood_{d,t} = I_{d,t} \tag{9}$$

Where $I_{d,t} = \{I_{d,t}^1, I_{d,t}^2, \dots, I_{d,t}^n, I_{d,t}^N\}$ is a vector with $I_{d,t}^n$ denoting the frequency at which word n within mood dimension $d = \{PA, NA\}$ is mentioned at time t. Table 3, provides examples of words included in the index and from the context which they were extracted.

Table 3 – Examples of words included in $RawMood$

Examples of words included in $RawMood_{d,t}$ and the blog posts from which they were extracted. Blog posts are extracted from our database capturing daily posts from c. 150 000 blogs. Translations are our own.

Word	**Blog post**
Rädd (Eng. Afraid)	jag blev rädd när jag vaknade imorse… någon annan som blivit dålig av vaccinet för svininfluensan. (Eng. *I was scared when I woke up this morning ... someone else was ill from the swine flu vaccine*)
Arg (Eng. Angry)	Kom precis hem och sitter i soffan och låtsas att jag inte är arg längre, det funkar inte så bra tyvärr. (Eng. *Just got home and I am sitting in the sofa pretending that I am not angry any more, unfortunately it is not working.*)
Exalterad (Eng. Excited)	Nästan på gränsen till orimligt exalterad. Och till den grad att jag förvånar mina kollegor (Eng. *almost on the verge of being unreasonably excited. And to the extent that I surprise my colleagues*)

To capture the increasing blog coverage of the database, resulting in more blogs being added during the investigated period we normalise each $RawMood_{d,t}$ by the total number of words in the database each day. As PA includes more words than NA both measures are rebased to 1 July 2009. Next, we create $Net\ Mood_t$ to capture the ratio of positive to negative mood.

$$Net\ mood_t = \frac{NormRawMoodRebased_{PA,t}}{NormRawMoodRebased_{NA,t}} \tag{10}$$

We only keep $Net\ mood$ data for the 529 days where have data on investor trading behaviour.

Interpreting the net mood index

Values of $Net\ mood$ above 1 indicate an aggregate positive mood state, while values below 1 indicate an aggregate negative mood state. Values at 1 can either signify states of emotional indifference or emotional ambiguity. Thus, we focus on values deviating from 1, enabling us to evaluate the effects on trading behaviour when there is an unambiguous state of positive or negative mood.

Summary statistics for Net mood

Summary statistics for $Net\ mood$ are provided in Table 4.

Table 4 – Summary statistics of $Net\ mood$

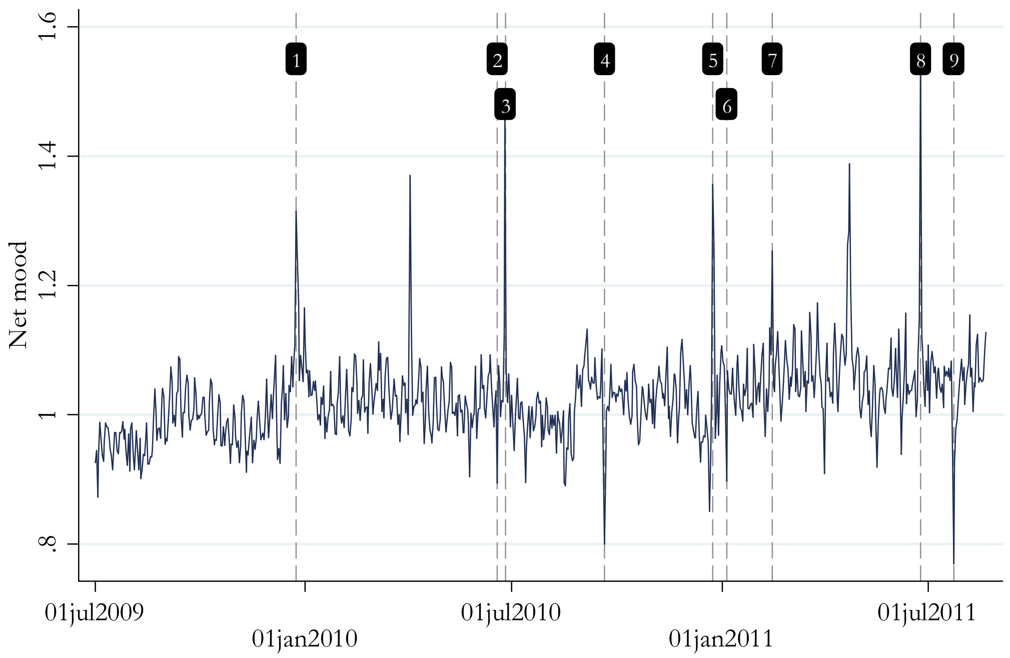
Summary statistics of $Net\ Mood$. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis. The index is constructed by measuring the relative frequency of positive to negative words in blogs. The words used are based on PANAS, Watson et al. (1988) and has been extended to include synonyms of the original words. We only the keep $Net\ mood$ variable for the 529 days where have data on investor trading behaviour.

$Mood$	T	Mean	SD	p25	median	p75
$Net\ mood_t$	529	1.01	0.064	0.98	1.01	1.04

We have cross referenced some of the peaks and lows of $Net\ Mood$ to events that are likely to have affected the majority of the Swedish population, see Figure 2. As observed a high number of peaks and lows can be explained by nationwide events.

Figure 2 - $Net\ mood$ compared to nationwide events

Blue line displays $Net\ mood$ per day over the sample period. Labels identify peaks in the $Net\ mood$. List below explains what event corresponds to the numbered peak or low. Assignment of corresponding events is based on current topics covered by news articles on the day of the peak or low. A few peaks and lows remain unlabelled as we have not been able to distinguish which event it corresponds to. Graph includes weekends and holidays. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

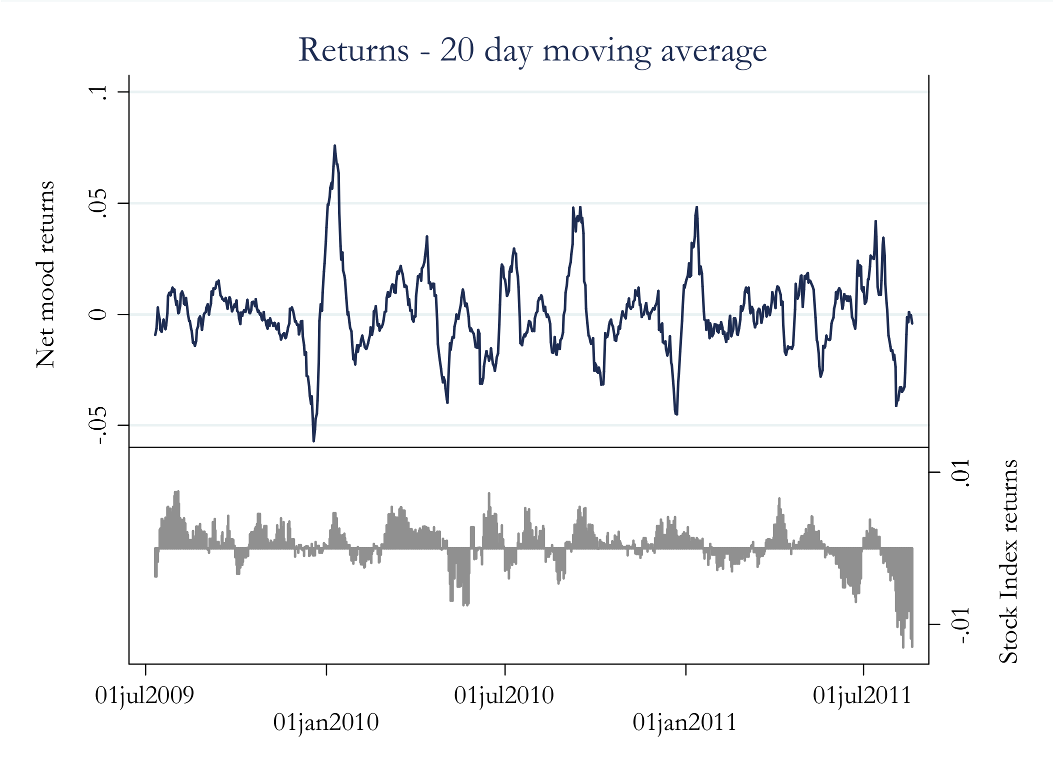


1. Christmas 2009, 24 Dec. 2009
2. The day preceding the royal wedding, 18 Jun. 2010
3. Midsummer 2010, 25-26 Jun. 2010
4. Sweden Democrats are elected into the Swedish Gov.
5. Christmas 2010, 24 Dec. 2010
6. Heavy snowstorms in Sweden and Europe, 5 Jun. 2011
7. Valentine's day, 14 Feb. 2011
8. Midsummer 2011, 24-25 Jun. 2011
9. Shootings in Utöja, 22 Jul. 2011

Figure 3, suggests that there is a positive relationship between stock returns and mood. This gives further support of the N$et\ mood$ index being a relevant measure as it seems to capture nationwide occurrences.

Figure 3 - Daily change of $Net\ mood$ compared to stock returns

The graph compares daily changes (returns) of Net mood (LHS, blue line) and return from OMX all share index (RHS, grey). Both series are 20-day moving average of daily returns. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.



Source: Nasdaq OMX (2011)

Compared to Bollen et al. (2011), we use PANAS rather than the Profile of Mood States test (POMS; McNair et al., 1971). The upside with the PANAS it that it provides an easily interpreted valance based (positive vs. negative) mood scale. A downside is that it does not capture different types of emotions as POMS may do. Nevertheless, Bollen et al. (2011) only find significant relationships for two of the six emotional dimensions in their study. Instead of adding synonyms, Bollen et al. (2011) use an algorithm to analyse and add words that tend to co-occur with the original words on the Internet.

As the Swedish language works as a natural barrier we feel confident in knowing that we only analyse Swedish data, whereas Bollen et al. (2011) cannot affirm that the data relates to the U.S. public as populations in several countries use English as their first language.

Weather data

Data on actual weather and next day forecasts for sun, temperature and precipitation is collected from the Swedish Meteorological and Hydrological Institution (SMHI), which is a government agency under the Ministry of the Environment.

Due to limits in time and resources we are restricted to collect data for five weather stations, located in: Stockholm, Göteborg, Malmö, Örebro and Umeå (see Appendix E for geographical coordinates). These stations, including neighbouring cities, are home to around 45% of the Swedish population (SCB, 2011a) and are located in separate parts of Sweden. Data collected from these stations is used as proxy for the actual weather in surrounding regions, denoted with subscript r. Weather forecasts for sun and temperature for these regions are missing for 14 random days of the sample period. Each investor is assigned to weather stations based on their zip code.

We use temperature at 12 UTC[10], 2 meters above ground. Precipitation is measured as the cumulative precipitation in mm between 6 UTC t to 6 UTC $t+1$. Precipitation below 0.1 mm is counted as 0. Data on sunshine is extracted from SMHI's STRÅNG model (STRÅNG, 2011). STRÅNG enables extraction of sunshine duration data, given in minutes per hour for requested geographical coordinates. SMHI does not forecast sunshine duration directly, but rather percentage of sky covered by clouds. To match our actual sunshine data with forecasts we make two adjustments. First we convert actual sunshine duration into percentage of sunshine during an hour by dividing the number of sunshine minutes by 60. Secondly, we use the complement of forecasted cloud cover at 12 UCT as a proxy for forecasted sunshine duration.

To create deviations from weather forecasts (henceforth weather deviations) we deduct the $t-1$ forecast ($F_{t-1,t,r}$) from the actual weather at time t ($W_{t,r}$), for each region r. A summary of the components of weather variables is found in Table 5. $Weather_w$ will be used to refer to all weather and weather deviation variables.

$$Deviation_{r,t} = W_{t,r} - F_{t-1,t,r} \tag{11}$$

[10] *Coordinated Universal Time hours*. Sweden's local time is UTC+1 during the winter and UTC+2 during the summer. No adjustments have been made for summer and winter time as hours in both seasons have equal probability of sunshine

Table 5 - Definition of weather and weather deviation variables

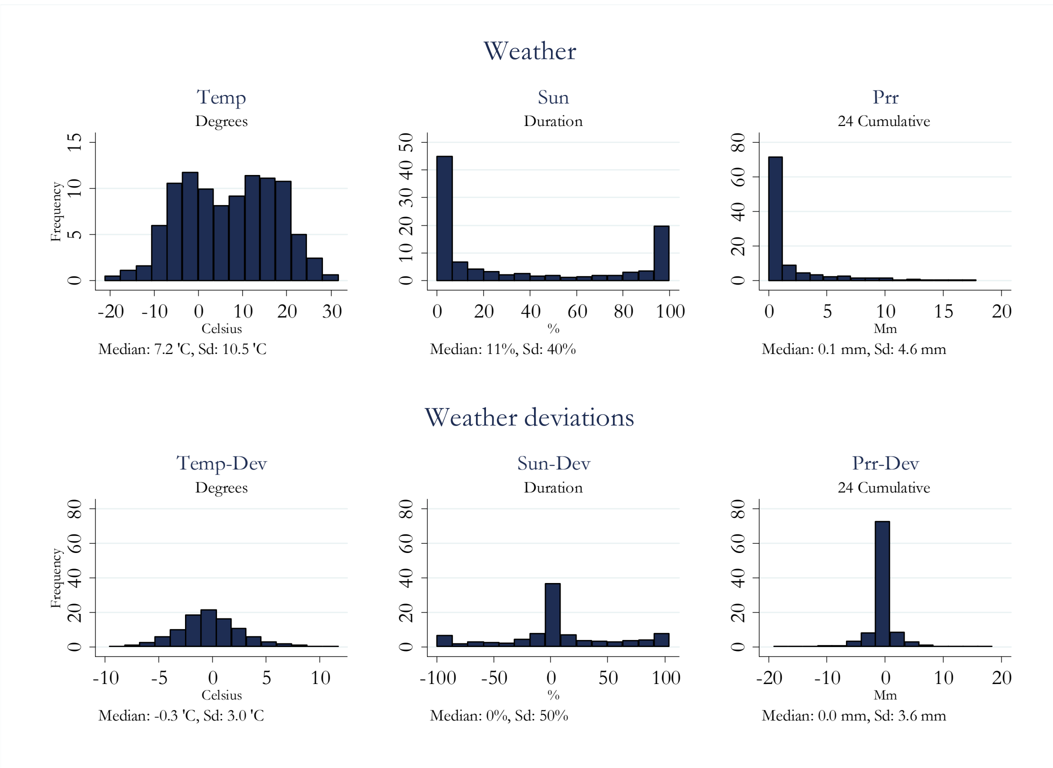
Table displays definitions of actual weather, forecasted weather and weather deviations. Weather deviations are created by deducting the forecast made at time $t-1$ for weather at time t (F), for the actual weather at time t (W). Deviations are created for each day t and region r. UTC refers to *Universal Time hours*. No adjustments have been made to account for daylight savings. $temp$ refers to temperature 2m above ground. $CloudCover_{12UTC}$ is the % of sky forecasted to be covered by clouds at 12 UCT.

$\boldsymbol{type}$	$\boldsymbol{W}$	$\boldsymbol{F}$	$\boldsymbol{Deviation\ (W\ -F\ )}$	**Unit**
$temp_{t,r}$	$°C\ at\ 12\ UTC$	$°C\ at\ 12\ UTC$	$Sun-Dev_{r,t}$	°C
$precipitation_{t,r}$	$\sum_{6\ UCT\ t}^{6\ UCT\ t+1} mm$	$\sum_{6\ UCT\ t}^{6\ UCT\ t+1} mm$	$Prr-Dev_{r,t}$	mm
$sun_{t,r}$	$\frac{1}{60}\sum_{11\ UTC}^{12\ UTC} minutes\ of\ sun$	$(1-CloudCover_{12\ UTC})$	$Sun-Dev_{r,t}$	%

Figure 4 contains histograms of both observed weather and weather deviations for 2010. The median weather deviation is close to 0 for all weather dimensions. Positive and negative weather deviations seem equally likely to occur.

Figure 4 - Descriptive statistics of weather and weather deviation

Weather refers to observed weather at time t. Weather deviations refer to deviations of actual weather from forecast at time $t-1$ for time t. $Temp$ is temperature at 12 UTC. Sun is measured as % of sunlight between 12-13 UTC. Prr is the cumulative precipitation in mm between 6 UCT at t to 6 UCT at time $t+1$. Histograms based on data for 2010. Histograms contain one observation per region (5) and day. Prr and $Prr-Dev$ observations >|20mm| are excluded for convenience of scale.



Note: Data missing for $Sun, Temp, Sun-Dev, Temp-Dev$ on 6 days

Other datasets

We use the Swedish Riksbank's Stress index as a measure of the stress level in Sweden. Data is available for the period 1st July 2009 - 24th November 2010 (Riksbank, 2010).

We use the OMX Stockholm All share index as a broad stock return measure. Data is downloaded from the Nasdaq OMX website (Nasdaq OMX, 2011).

We use the Swedish Consumer Confidence Indicator (CCI) as a measure for the level of confidence in the general public in Sweden. CCI is a monthly index designed to measure consumers' confidence level of their personal finances and the Swedish economy at present and in the next 12 months. Data is downloaded from Statistics Sweden (SCB, 2011b).

V. Method

We have divided our analysis into two sections. The first section establishes the naïve correlation between mood and trading behaviour, followed by an analysis of differences within the demographic dimensions: age, gender and average portfolio size. The second section tests the causal link between mood and trading behaviour. After establishing a link between mood and weather, we employ two different statistical methods to uncover the causal relationship – fixed effects using panel data and an IV regression using time series data.

Unless otherwise stated, standard errors are clustered at both investor level and by day throughout the thesis[11]. This approach, suggested by Thompson (2011) and Cameron et al. (2006), allows for correlations among different investors in the same day and different days for the same investor.

Naïve analysis

In this section we examine if mood correlates with different measures of trading activity. This will be done using both aggregate national data and individual data. At this stage we are not concerned with potential biases due to omitted variables or simultaneous causality.

Naïve regression

We create an aggregate value for each trading behaviour variable and day by taking the average of all investors per day, $\bar{Y}_{v,t}$. We start by visually inspecting the naïve correlation on an aggregate level by plotting the residuals for collected from running regression (12) and (13) each $\bar{Y}_v$.

[11] $Var(\hat{\beta}) = \hat{V}_{investor} + \hat{V}_{day,0} - \hat{V}_{white,0}$ where $\hat{V}_{investor}$ and $\hat{V}_{day,0}$ are the estimate variances from clustering by investor and day respectively, and $\hat{V}_{white,0}$ is the heteroskedasticity-robust OLS variance matrix.

$$Net\ mood_t = \alpha + \sum_{m=1}^{11} \beta_m Month_m + \epsilon_t \tag{12}$$

$$\bar{Y}_{v,t} = \alpha + \sum_{m=1}^{11} \beta_m Month_m + \epsilon_{v,t} \tag{13}$$

Where

$$v = \{Total\ activity, Net\ activity, N\%P, ST\%P\}$$
$$t = day\{1, \ldots, 529\}$$
$$m = month\{1, \ldots, 12\}$$

After visual inspection we run regression specification (14) for each Y_v, to estimate correlation with $Net\ Mood$ on an individual level. Month dummies are used to account for time fixed effects.

$$Y_{v,i,t} = \alpha + \beta_1 Net\ mood_t + \sum_{m=1}^{11} \beta_m Month_m + \epsilon_{v,i,t} \tag{14}$$

Differences in correlation within demographic dimensions

All household investors are grouped by age, gender and portfolio size to investigate if we can observe any differences in behaviour within these dimensions. We use interaction dummies to assess if the behaviour in the groups differ when exposed to the same $Net\ mood$.

Running specification (15) allows us to analyse differences between age groups. We run one regression for each Y_v. For simplicity we have grouped young and old into two different groups, Y$oung$, aged 20-39, and $Not\ young$, aged 40-84.

$$Y_{v,i,t} = \alpha + \beta_1 Net\ mood_t + \beta_2 Young_i + \beta_3 Net\ mood_t * Young_i + \sum_{m=1}^{11} \beta_m Month_m + \epsilon_{v,i,t} \tag{15}$$

Regression specification (16) is used to analyse differences between $Female$ and $Male$ for each Y_v.

$$Y_{v,i,t} = \alpha + \beta_1 Net\ mood_t + \beta_2 Female_i + \beta_3 Net\ mood_t * Female_i + \sum_{m=1}^{11} \beta_m Month_m + \epsilon_{v,i,t} \tag{16}$$

We run specification (17) for each Y_v to test differences between portfolio sizes.

$$Y_{v,i,t} = \alpha + \beta_1 Net\ mood_t + \beta_2 Small_i + \beta_3 Net\ mood_t * Small_i + \sum_{m=1}^{11} \beta_m Month_m + \epsilon_{v,i,t} \tag{17}$$

Causal analysis

Establishing a link between mood and weather

To isolate the causal impact of mood on trading behaviour we use weather and weather deviations. For the causal relationship to be valid weather and weather deviations must be significantly correlated with mood, the *instrument significance condition*[12]. This corresponds to the first stage of an IV regression. In addition, they must be uncorrelated with all factors that have an influence on trading behaviour other than mood and cannot have a causal impact themselves on trading behaviour, *the exclusion restriction*[13].

The use of actual weather conditions is motivated by previous research, which suggests that sunshine has a positive impact on mood (Cunningham, 1979; Schwarz and Clore, 1983; Molin et al., 1996; Lambert et al., 2002) and precipitation to have a negative impact on mood (Keller et al., 2005), whereas the effect of temperature is ambiguous (Cunningham, 1979; Howarth and Hoffman, 1984; Watson, 2000; Goldstein, 1972). Further strengthening the instrument significance condition, we find that ~18% of blog entries include references to either rain, sun or both, and that close to 40% of blog entries include references to weather during some days in the sample period, suggesting that people in Sweden are concerned about weather conditions.

Motivated by principles of prospect theory (Kahneman and Tversky, 1979), we also introduce weather deviations as mood proxy. The logic is that forecasts serve as the reference point from which better weather than expected is considered a utility gain while worse weather than expected a utility loss. Kaustia and Rantapuska (2011) propose that expectations on weather, manifested by forecasts, might affect investors' behaviour. To use deviations from weather forecasts as a proxy for mood are, to the best of our knowledge, a novel approach in this field of study. When constructing our variable we assume that expectations of tomorrow's weather are based on today's forecasts. SMHI is the main source of weather forecast data for all major news outlets in Sweden, and thus it is not unlikely that expectations of coming weather are based on forecasts broadcasted through these outlets. While actual weather can be persistent allowing investors to adjust expectations thereby reacting prior to it, deviations from forecasts are near-random with an expected value close to zero. This suggests that the observed effect of weather deviations should be stronger than the effect of actual weather. Weather is considered to be slightly more difficult to forecast during summer month. To account for this we control for time fixed effects in our regressions.

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[12] $Cov(M_i, Z_i) \neq 0$, where M_i represent the mood measures and Z_i represents instrument variables
[13] $Cov(\eta_i, Z_i) = 0$, where η_i represent all unobserved causal factors that influence trading behaviour Y_i

The exclusion restriction cannot be tested and relies on economic reasoning. Actual weather and weather deviations affect all parts of society, for example transportation or weather sensitive agriculture, and could therefore possibly have a broad impact on economic activity. Yet, the weather seldom deviates on an extreme magnitude, and thus, daily deviations should not affect fundamental stock valuation. Also, agriculture plays a minor role in the Swedish economy, around 1.7% of GDP in 2009 (Utrikespolitiska Institutet, 2011), hence weather resulting in a bad harvest should have a negligible effect on the aggregate stock market on a daily basis. Another potential problem is if investors chose to go to the beach when it is sunnier than expected, decreasing trading activity through decreased access to a trading platform, such as a computer. However, as 76% of investors in our sample are in working age, we believe few have the option to head down to the beach during a working day. In addition, increased use of smartphones[14] allow investors to trade whether in their office or at the beach. Extreme weather or extreme deviations from weather forecasts could also lead to reduced access to trading through power outages or closed down offices. However, these types of extreme weather conditions are rare in Sweden and storms[15] occur on average once per winter.

Reverse causality does not present a problem when interpreting our results as weather is exogenously given and as forecasts are done by computer models with limited human interference we consider weather deviations to be exogenous as well.

Our mood data is on national level while weather data is on regional level. Weather deviations have low correlation across Sweden and are likely to average out over Sweden on a given day, making an analysis on a national level meaningless. We mitigate this problem by proposing two specifications for testing the *instrument significance condition*. In specification (18) we treat Sweden as one unit in terms of weather. Aggregate weather for Sweden is created by taking the average of our 5 weather stations weighted by the number of investors in that region. At this stage we expect actual weather to have an impact on mood, while the effect of weather deviations being indistinct. In specification (19) we select the region with highest impact on the mood index, i.e. the Stockholm region including surrounding regions representing c. 25% of the Swedish population, and test the instrument significance condition. We will test for weak identification of instruments using F-tests.[16] $Weather_w$ variables that pass the instrument significance test will be denoted $MoodProxy_{mp,r}$, where mp denotes the weather or weather deviation and r the region.

[14] Nordnet has a free app for Android and Apple, allowing investors to manage their portfolios using smartphones.
[15] Defined as average wind above 25 meters per second for at least 10 consecutive minutes.
[16] Kleibergen-Paap Wald rk F-statistic which is consistent in presence of heteroskedasticity (Kleibergen and Paap, 2006).

$$Net\ Mood_t = \alpha + \beta_w Weather_{Sweden,w,t} + \sum_{m=1}^{11} \beta_m Month_m + \epsilon_{Sweden,w,t} \tag{18}$$

$$Net\ Mood_t = \alpha + \beta_w Weather_{Sthlm,w,t} + \sum_{m=1}^{11} \beta_m Month_m + \epsilon_{Sthlm,w,t} \tag{19}$$

$$w = \{Sun, Temp, Prr, Sun - Dev, Temp - Dev, Prr - dev\}$$

Isolating the causal impact of mood on trading behaviour

We use two different approaches to isolate the causal impact of mood on trading behaviour. The first involves using $MoodProxy_{mp,r}$ as a proxy for mood, utilizing the panel dimension of the investor and weather data. The second involves using $MoodProxy_{mp}$ as instrumental variables in an IV regression, utilizing the time series dimension of $Net\ mood$.

Fixed effects using panel data

We run specification (20) for each Y_v to test the relationship between $MoodProxy_{mp}$ and Y_v. By including day and investor fixed effects we remove any components that affect all individuals in the same way on the same day, such as changes in GDP, unemployment or stock returns; as well as components that are constant for an individual across time, such as differences in wealth or education. When accounting for day and investor fixed effects we use the algorithm designed by Guimarães and Portugal (2009) for estimating regression models with high dimensional fixed effects.

$$Y_{v,i,t} = \alpha + \beta_{mp} MoodProxy_{mp,r,t} + \sum_{t=1}^{T-1} \beta_t Day_t + \sum_{i=1}^{I-1} \beta_i Investor_i + \epsilon_{v,i,t} \tag{20}$$

$$r = \{Stockholm, Gothenburg, Central\ Sweden, Northern\ Sweden, Southern\ Sweden\}$$

$$mp = \{Weather_w\ variables\ that\ pass\ instrument\ significance\ test\}$$

$$v = \{Total\ activity, Net\ activity, N\%P, ST\%P\}$$

$$i = investor\{1, \dots, 900\}$$

The downside with the fixed effects approach is that we cannot say anything about the magnitude of the causal relationship between trading behaviour and mood in terms of $Net\ mood$.

IV estimation using time series data

The second method used is time series IV estimation. This allows us to estimate the causal impact off mood on investment behaviour in terms of $Net\ mood$. As mood data is on a national level it only allows for a time series IV regression. At this stage we focus on Stockholm as weather deviation variables are non-meaningful on a national level. We convert the individual trading behaviour variables to a Stockholm time series by taking the average across all investors in Stockholm for each time t, $\bar{Y}_{v,sthlm,t}$. The IV regression is operationalized using the 2SLS approach which consists of two stages, specified in (21) and (22). We run the 2SLS estimator for each $\bar{Y}_v$ and each $MoodProxy_{mp,Sthlm}$. Dummies are used to account for month fixed effects.

$$Net\ Mood_t = \alpha_1 + \beta_{1,mp} MoodProxy_{mp,Sthlm,t} + \sum_{m=1}^{11} \beta_m Month_m + \epsilon_{1,v,sthlm,mp,t} \tag{21}$$

$$\bar{Y}_{v,sthlm,t} = \alpha_2 + \beta_{2nd,mp} \left[\hat{\alpha}_1 + \hat{\beta}_{1,mp} MoodProxy_{mp,Sthlm,t} + \sum_{m=1}^{11} \hat{\beta}_m Month \right] + \epsilon_{2,v,mp,sthlm,t} \tag{22}$$

Where the expression in brackets refer to the fitted values from the first stage regression and:

$$mp = \{Weather_w\ variables\ that\ pass\ instrument\ significance\ test\}$$
$$v = \{Total\ activity, Net\ activity, N\%P, ST\%P\}$$
$$sthlm = \{Stockholm\}$$

VI. Results

This section contains the results from implementing the method laid out in section V. Method.

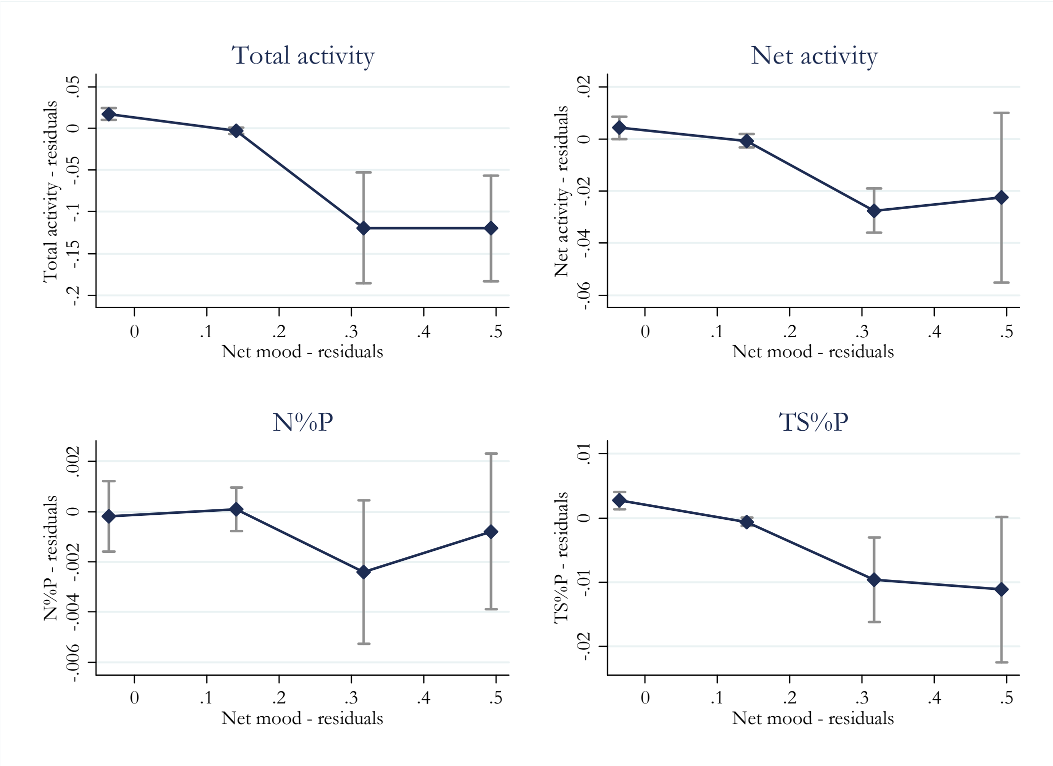
Naïve analysis

Naïve regression

Figure 5 displays the unexplained variation in trading behaviour as a function of the unexplained variation in net mood. We observe a negative correlation between each Y_v and $Net\ mood$, with the least apparent relationship being between $Net\ mood$ and $N\%P$. The negative relationships imply that good mood is associated with household investors trading less, buying less or selling more, and making smaller trades relative to their average portfolio size. Graphs without removed time fixed effects, including test for differences in mean, can be seen in Appendix F.

Figure 5 - Visual display of residuals from naïve regression

Graphs plot residuals after removing time fixed effects from $Net\ mood$ using specification (12) versus residuals after removing time fixed effects using specification (13) for each trading behaviour variable respectively. Graphs are created by grouping the distance between the min and max value of residuals of $Net\ mood$ from regression (12) into four equal sized bins. Mean and standard deviation of corresponding trading behaviour variable is then calculated for values in each bin. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$measures net change in value from instruments group that have changed volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.



Note: Blue diamond indicate mean

Grey lines indicate 95% confidence intervals

To confirm the visual observations from Figure 5 we run regression specification (14), Table 6. The negative trend observed in Figure 5 is manifested by negative and significant coefficient estimates, suggesting that increases in $Net\ mood$ are significantly correlated with all trading behaviour variables. But as suggested by the graph, the relationship is weakest for $N\%P$.

Differences in correlation within demographic dimensions

From Table 7, we notice that the household investors in our sample seem to be a heterogeneous group. There are significant differences in all trading behaviour coefficients between young and old household investors, as well as between household investors with a small trading portfolio and those with large trading portfolios. The least significant differences are between men and women.

Table 6 - Naïve regression results

Table displays results from regression specification (14) looking at naïve correlation between $Net\ mood$ and each trading behaviour variable respectively. Month dummies were used to account for time fixed effects. Estimates for these are omitted from the table. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$ measures net change in value from instrument groups that have changed in volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i.

	Total activity	Net activity	N%P	TS%P
Net mood	-0.339***	-0.091***	-0.006+	-0.040***
	[0.038]	[0.016]	[0.004]	[0.006]
	(-8.87)	(-5.58)	(-1.69)	(-6.58)
Constant	0.541***	0.114***	0.006	0.060***
	[0.040]	[0.018]	[0.004]	[0.007]
	(13.59)	(6.23)	(1.44)	(8.91)
Adj R^2	0.006	0.000	0.000	0.001
N	475 976	475 976	475 976	475 976

Note: T-stats are in parentheses and standard errors in square bracket Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

Standard errors used are clustered at both investor and day dimension

Table 7 - Summary statistics of trading behaviour by demographic dimension

Table displays the mean, standard deviation, differences in means and t-stats for trading behaviour variables of women relative to men, young (20-39 yrs old) relative to old (>39), household investors with small portfolios relative to investors with large portfolios. Small refers to investors that has an average absolute portfolio size below the sample median in a majority of the months in our sample period, investors assigned as large has an average absolute portfolio size above the sample median in a majority of the months. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$ measures net change in value from instrument groups that have changed in volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i.

		Women	Men	Diff. gender (T-stat)	Young	Old	Diff. age (T-stat)
Total activity	Mean	0,173	0,186	-0.013***	0,145	0,194	-0.049***
	SD	0,378	0,389	(-7.97)	0,352	0,396	(-35.59)
Net activity	Mean	0,025	0,027	-0.0013	0,023	0,027	-0.004**
	SD	0,402	0,414	(-0.74)	0,367	0,423	(-2.68)
N%P	Mean	-0,001	0,000	-0,001	0,000	0,000	-0,000
	SD	0,001	0,000	(-0.70)	0,000	0,000	(-0.51)
TS%P	Mean	0,019	0,020	-0,001***	0,013	0,022	-0,009***
	SD	0,000	0,000	(-2.91)	0,000	0,000	(-20.99)
	N	65 051	410 925	475 976	99 440	376 536	475 976

		Small portf.	Large portf.	Diff. portf. (T-stat)
Total activity	Mean	0,148	0,219	-0.071***
	SD	0,355	0,414	(-63.79)
Net activity	Mean	0,020	0,033	-0.012***
	SD	0,372	0,448	(-10.43)
N%P	Mean	0,000	0,000	0.009
	SD	0,001	0,000	(-0.06)
TS%P	Mean	0,024	0,015	0.009***
	SD	0,000	0,000	(27.14)
	N	235 853	240 123	475 976

Note: T-stats are in parentheses Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

We proceed with our analysis by further examination of differences between groups of investors using interaction variables, while controlling for month fixed effects.

By gender

From Table 8 we see that being a female has a positive and significant impact on $N\%P$ and that women are significantly impacted by $Net\ mood$ when deciding level of $N\%P$, whilst men seem not to be. Other coefficients are not significantly different from zero.

Table 8 - Naïve regression by Gender

Table displays results from regression specification (15) of $Net\ mood$ on trading behaviour variables, where household investors are grouped by gender. In addition month dummies are used to account for time fixed effects. Estimates for these are omitted from the table. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$ measures net change in value from instrument groups that have changed in volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Total activity	Net activity	N%P	TS%P
Net mood	-0.349***	-0.094***	-0.004	-0.041***
	[0.039]	[0.017]	[0.004]	[0.006]
	(-8.90)	(-5.51)	(-0.87)	(-6.51)
Female	-0.088	-0.019	0.020*	-0.012
	[0.056]	[0.027]	[0.008]	[0.012]
	(-1.58)	(-0.73)	(2.42)	(-1.07)
Net mood * Female	0.074	0.018	-0.020*	0.011
	[0.048]	[0.025]	[0.008]	[0.010]
	(1.54)	(0.72)	(-2.51)	(1.06)
Constant	0.553***	0.117***	0.003	0.062***
	[0.041]	[0.019]	[0.004]	[0.007]
	(13.48)	(6.16)	(0.70)	(8.68)
Adj R^2	0.006	0.000	0.000	0.001
N	475 976	475 976	475 976	475 976

Note: T-stats are in parentheses and standard errors in square bracket
Standard errors used are clustered at both investor and day dimension

Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

By age

From Table 9 we see that $Total\ Activity$ for young household investors is significantly less sensitive to changes in $Net\ mood$, by a magnitude of 9 pp. or 25% less than that of older household investors. $TS\%P$ also seems to be significantly less affected by changes in $Net\ mood$ for young household investors, by 1.5pp or c. 30% less than that of old household investors.

Table 9 - Naïve regression by Age

Table displays results from regression specification (16) of $Net\ mood$ on trading behaviour variables, where household investors are grouped as $Young$ or $Not\ young$. In addition month dummies are used to account for time fixed effects. Estimates for these are omitted from the table. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$ measures net change in value from instrument groups that have changed in volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Total activity	Net activity	N%P	TS%P
Net mood	-0.358***	-0.095***	-0.007	-0.043***
	[0.040]	[0.017]	[0.004]	[0.007]
	(-8.92)	(-5.55)	(-1.64)	(-6.23)
Young	-0.140***	-0.020	-0.003	-0.024**
	[0.037]	[0.018]	[0.006]	[0.009]
	(-3.81)	(-1.13)	(-0.62)	(-2.72)
Net mood * Young	0.090**	0.016	0.003	0.015+
	[0.032]	[0.016]	[0.005]	[0.008]
	(2.86)	(0.98)	(0.55)	(1.90)
Constant	0.570***	0.118***	0.006	0.065***
	[0.042]	[0.019]	[0.004]	[0.008]
	(13.54)	(6.18)	(1.44)	(8.46)
Adj R^2	0.009	0.000	0.000	0.002
N	475 976	475 976	475 976	475 976

Note: T-stats are in parentheses and standard errors in square bracket Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

Standard errors used are clustered at both investor and day dimension

By Portfolio size

The results from regression specification (17), displayed in Table 10 show that $Net\ activity$ for household investors with small trading portfolios is significantly less sensitive to changes in $Net\ mood$ than investors with large trading portfolios. The difference is 0.03 units or c.30% less than that of large portfolio investors. Moreover, $TS\%P$ for small portfolio investors seems to be significantly more sensitive to $Net\ mood$, by 2.9 pp. or more than twice that of large portfolio investors.

Table 10 - Naïve regression by Portfolio size

Table displays results from regression specification (17) of $Net\ mood$ on trading behaviour variables, where household investors are grouped as small or large. In addition month dummies are used to account for time fixed effects. Estimates for these are omitted from the table. Small refers to investors that has an average absolute portfolio size below the sample median in a majority of the months in our sample period, investors assigned as large has an average absolute portfolio size above the sample median in a majority of the months. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$ measures net change in value from instrument groups that have changed in volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Total activity	Net activity	N%P	TS%P
Net mood	-0.365***	-0.107***	-0.009*	-0.025***
	[0.047]	[0.019]	[0.004]	[0.005]
	(-7.85)	(-5.60)	(-2.50)	(-5.23)
Small	-0.125**	-0.044*	-0.006	0.038***
	[0.042]	[0.019]	[0.007]	[0.010]
	(-2.96)	(-2.26)	(-0.95)	(3.85)
Net mood * Small	0.053	0.031+	0.006	-0.029**
	[0.037]	[0.018]	[0.007]	[0.009]
	(1.41)	(1.72)	(0.95)	(-3.26)
Constant	0.602***	0.136***	0.009*	0.041***
	[0.049]	[0.021]	[0.004]	[0.005]
	(12.29)	(6.39)	(2.22)	(7.52)
Adj R^2	0.014	0.001	0.000	0.002
N	475 976	475 976	475 976	475 976

Note: T-stats are in parentheses and standard errors in square bracket Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

Standard errors used are clustered at both investor and day dimension

Causal analysis

Finding proxies for mood

Table 11 summarises findings from regression specification (18) of national weather on mood. The estimated coefficient for Sun is positive and significant at a 5% level. None of the weather deviations are significant on a national level. The coefficient for Prr is negative but not significant.

Table 11 - Net mood and Weather Sweden

Table displays results from regression specification (18) of all $Weather_w$ on $Net\ mood$ treating Sweden as one unit. In addition month dummies are used to account for time fixed effects. Estimates for these are omitted from the table. Variables ending with $-Dev$ refer to deviations of actual weather at time t from forecast at time $t-1$ for time t. $Temp$ is temperature at 12 UTC. Sun is measured as % of sunlight between 12-13 UTC. Prr is the cumulative precipitation in mm between 6 UCT at t to 6 UCT at time $t+1$. Swedish average weather values are created by taking the value for each region r weighted by the number of investors i in that region. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Net mood					
	Actual weather			Deviation from forecasts		
Sun	0.00024* [0.00011] (2.28)					
Temp		0.00006 [0.00096] (0.07)				
Prr			-0.00117 [0.00097] (-1.21)			
Sun - Dev				0.00011 [0.00007] (1.50)		
Temp - Dev					-0.00002 [0.00140] (-0.01)	
Prr - Dev						-0.00049 [0.00108] (-0.45)
Constant	1.00507*** [0.00498] (201.71)	1.01337*** [0.00968] (104.64)	1.01595*** [0.00318] (319.48)	1.01339*** [0.00273] (371.40)	1.01396*** [0.00274] (370.39)	1.01375*** [0.00266] (381.59)
Adj R^2	0.097	0.088	0.092	0.090	0.088	0.090
N	515	515	529	515	515	528
F-stat	5.208	0.004	1.459	2.248	0.000	0.202

Note: T-stats are in parentheses and standard errors in square bracket Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

Robust standard errors are used

F-stat refers to robust Kleibergen-Paap Wald rk F statistic

For the Stockholm region, Table 12, Sun remains significantly positive, now at a 1% level. $Sun - Dev$ now has a significant positive impact on mood at a 1% significance level while $Prr - Dev$ has a significant negative impact at a 10% level. An increase by one standard deviation of $Sun - Dev$ is associated with a 0.7 pp. increase in net mood, while for $Prr - Dev$ it is associated with a decrease of 0.6 pp. Sun and $Sun - Dev$ have F-statistics at around 8.6 which is close to 10 which is a commonly used rule of thumb when determining the strength of an instrument (Stock et al., 2002). The F-statistic for $Prr - Dev$ is 3.6. When the number of instruments equal the number of endogenous variables, the 2SLS is approximately median unbiased even in the presence of weak instruments. Unless very large standard errors are present in the first stage regression weak instruments should not present a problem (Angrist and Pischke, 2009b). In our case Sun, $Sun - Dev$ and $Prr - Dev$ are all significant in the first stage regression, hence we keep them even though F-stats are below 10.

Table 12 - Net mood and Weather Stockholm

Table displays results from regression specification (19) of all $Weather_w$ on $Net\ mood$ only considering household investors in the Stockholm region. In addition month dummies are used to account for time fixed effects. Estimates for these are omitted from the table. Variables ending with $-Dev$ refer to deviations of actual weather at time t from forecast at time $t-1$ for time t. $Temp$ is temperature at 12 UTC. Sun is measured as % of sunlight between 12-13 UTC. Prr is the cumulative precipitation in mm between 6 UCT at t to 6 UCT at time $t+1$. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Net mood					
	Actual weather			Deviation from forecasts		
Sun	0.00020** [0.00007] (2.94)					
Temp		0.00020 [0.00079] (0.25)				
Prr			-0.00095 [0.00076] (-1.25)			
Sun - Dev				0.00014** [0.00005] (2.93)		
Temp - Dev					0.00014 [0.00108] (0.13)	
Prr - Dev						-0.00153+ [0.00081] (-1.89)
Constant	1.00598*** [0.00386] (260.44)	1.01207*** [0.00826] (122.48)	1.01515*** [0.00292] (348.01)	1.01305*** [0.00266] (381.55)	1.01392*** [0.00271] (374.38)	1.01335*** [0.00264] (383.18)
Adj R^2	0.101	0.088	0.092	0.099	0.088	0.095
N	515	515	529	515	515	528
F-stat	8.614	0.061	1.558	8.593	0.016	3.564

Note: T-stats are in parentheses and standard errors in square bracket Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

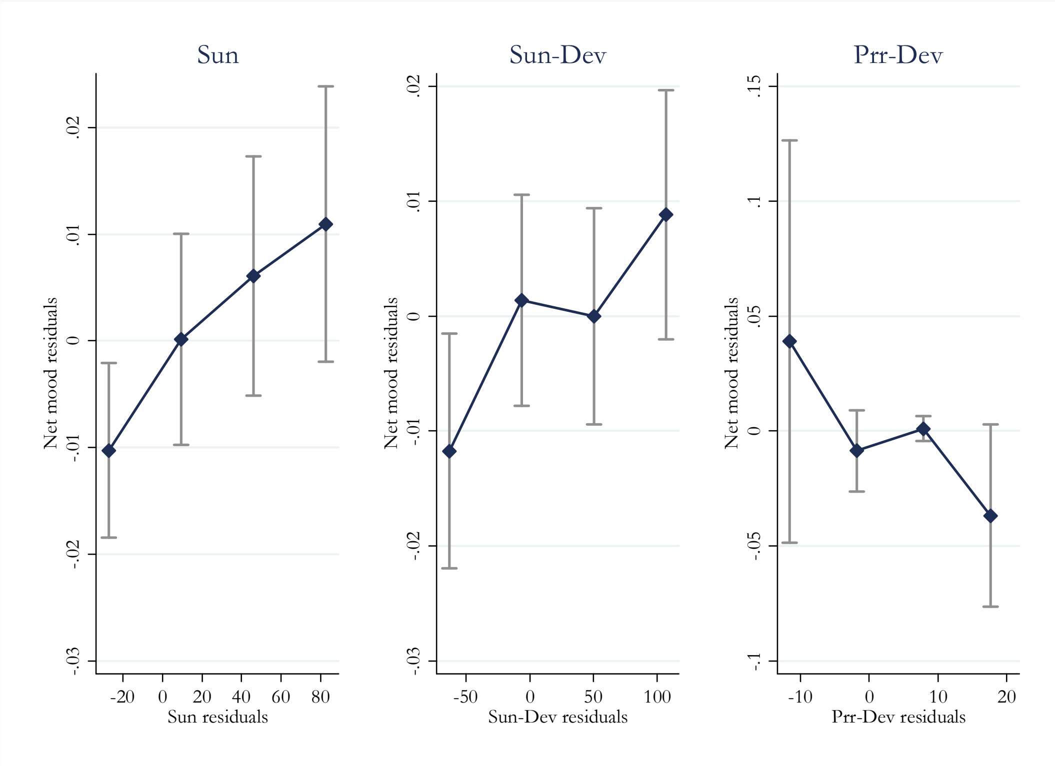
Robust standard errors are used

F-stat refers to robust Kleibergen-Paap Wald rk F statistic

Figure 6 provides a graphical display of the positive relationship between $Net\ mood$ and Sun and $Sun - Dev$ respectively and the negative relationship between Mood and $Prr - Dev$, by plotting residuals after removing time fixed effects.

Figure 6 - Visual display of residuals of $MoodProxies$ and $Net\ mood$

Figure displays plots of residuals after removing time fixed effects from $Net\ mood$, Sun, $Sun - Dev$ and $Prr - Dev$ respectively. Graphs are created by, for each Sun, $Sun - Dev$ and $Prr - Dev$, dividing the distance between min and max value of residual after removing month fixed effects, respectively into 4 equal sized bins. Mean and standard deviation of corresponding trading behaviour variable is then calculated for values in each bin. Sun is measured as % of sunlight between 12-13 UTC. Prr is the cumulative precipitation in mm between 6 UCT at t to 6 UCT at time $t + 1$. Variables ending with $-Dev$ refer to deviations of actual weather at time t from forecast at time $t - 1$ for time t. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.



Note: Blue diamond indicate mean

Grey lines are 95% confidence intervals

Table 13 provides summary statistics for regressions of Sun, $Sun - Dev$ and $Prr - Dev$ against observable causal factors that are likely to influence $Total\ activity$. Historical stock returns, Riksbanken's stress index and the CCI all have a significant impact on $Net\ mood$ at the 0.1% level, while none of the variables have a significant impact on Sun, $Sun - Dev$ or $Prr - Dev$. These findings strengthen our belief that the exclusion restriction is valid.

Table 13 - Correlation of weather and weather deviation on observable economic factors

Table displays results from regression Sun, $Sun - Dev$ and $Prr - Dev$ and $Total\ acitivty$ on economic factors. $Total\ acitivty$ is average per day for all household investors living in the Stockholm region. $Total\ activity$ at the individual level per day equals 1 if volume has changed in any instrument group from $t - 1$ to t and 0 otherwise. Hist. Return is 2 weeks historical moving average return on the OMX Stockholm All share Index. Stress index is an index designed by Riksbanken to measure the stress level in the Swedish financial system. We only have data up to 24 November 2010. CCI is the Consumer Confidence Indicator. Month dummies are used to account for time fixed effects. Estimates for these are omitted from the table. $Total\ activity$ = 1 if volume has changed in any instrument group from t to $t - 1$ and =0 otherwise. Sun is measured as % of sunlight between 12-13 UTC. Prr is the cumulative precipitation in mm between 6 UCT at t to 6 UCT at time $t + 1$. Variables ending with $-Dev$ refer to deviations of actual weather at time t from forecast at time $t - 1$ for time t.

	Total Activity			Sun		
Hist. Return	1.883**			-348.547		
	[0.589]			[415.944]		
	(3.20)			(-0.84)		
Stress Index		0.032***			8.102	
		[0.006]			[5.396]	
		(5.29)			(1.50)	
CCI			-0.001***			-0.012
			[0.000]			[0.209]
			(-6.32)			(-0.06)
Constant	0.180***	0.159***	0.205***	40.140***	25.758***	40.063***
	[0.002]	[0.007]	[0.005]	[1.632]	[7.166]	[3.504]
	(90.82)	(21.34)	(45.19)	(24.60)	(3.59)	(11.43)
Adj R^2	0.288	-0.128	0.288	0.165	0.174	0.163
N	515	515	528	515	328	515

	Sun - Dev			Prr - Dev		
Hist. Return	95.984			-3.243		
	[554.682]			[29.606]		
	(0.17)			(-0.11)		
Stress Index		1.291			0.449	
		[6.836]			[0.596]	
		(0.19)			(0.75)	
CCI			-0.083			-0.013
			[0.280]			[0.021]
			(-0.30)			(-0.62)
Constant	6.536**	4.386	7.906+	-0.288*	-0.710	-0.086
	[2.240]	[9.219]	[4.617]	[0.131]	[0.775]	[0.359]
	(2.92)	(0.48)	(1.71)	(-2.20)	(-0.92)	(-0.24)
Adj R^2	0.025	-0.001	0.025	0.014	0.015	0.015
N	515	328	515	528	336	528

Note: T-stats are in parentheses and standard errors in square bracket Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

Robust standard errors are used

Fixed effects

As Sun, $Sun - Dev$ and $Prr - Dev$ are significantly correlated with $Net\ mood$ and as we argue they do not violate the exclusion restriction we proceed to use Sun and $Sun - Dev$ as proxies for good mood and $Prr - Dev$ as a proxy for bad mood.

Table 14 displays results from specification (20) testing the impact of Sun, $Sun - Dev$ and $Prr - Dev$ on trading behaviour variables after removing investor and day fixed effects. $Prr - Dev$ has a negative impact on T$otal\ activity$ at the 10% significance level while the other mood proxies are insignificant. For $Net\ activity$ $Prr - Dev$ has a negative significant impact at the 1% level. Average $Net\ Activity$ in our sample is 0.027, implying 0.973 sell activities for every buy activity. An increase in $Prr - Dev$ by one standard deviation is associated with a decrease in $Net\ activity$ by 0.002[17] buy activities per sell activity. Neither Sun nor $Sun - Dev$ has a significant impact on $Total\ activity$ or $Net\ activity$ though it provides comfort that the direction of the coefficients are opposite to that of $Prr - Dev$ and t-stats are at c. 1.5.

Table 14 - Fixed effects regression of Mood Proxies and trading behaviour

Table displays results from regression specification (20) of effect of Sun, $Sun - Dev$ and $Prr - Dev$ on trading behaviour variables. Dummies are used to account for investor and day fixed effects. Estimates for these are omitted from table. Coefficient for constant omitted. At the individual level, $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$ measures net change in value from instrument groups that have changed in volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. Sun is measured as % of sunlight between 12-13 UTC. between 6 UCT at time t and 6 UCT at time $t+1$. Variables ending with $-Dev$ refer to deviations of actual weather at time t from forecast at time $t-1$ for time t.

	Total activity			Net activity		
Sun	-0.00002			0.00003		
	[0.00002]			[0.00002]		
	(-1.15)			(1.50)		
Sun - Dev		-0.00002			0.00003	
		[0.00001]			[0.00002]	
		(-1.17)			(1.56)	
Prr - Dev			-0.00026 +			-0.00043 **
			[0.00017]			[0.00016]
			(-1.61)			(-2.67)
Adj R^2	0.15893	0.15893	0.15887	0.01218	0.01218	0.01223
N	463 378	463 378	475 076	463 378	463 378	475 076
	N%P			TS%P		
Sun	0.000008			-0.000002		
	[0.00001]			[0.000007]		
	(0.76)			(-0.32)		
Sun - Dev		0.000006			0.000004	
		[0.00009]			[0.000004]	
		(0.76)			(0.98)	
Prr - Dev			-0.000033			-0.000035
			[0.00010]			[0.000042]
			(-0.34)			(-0.82)
Adj R^2	-0.00096	-0.00096	-0.00101	0.06876	0.06876	0.06710
N	463 378	463 378	475 076	463 378	463 378	475 076

Note: T-stats are in parentheses and standard errors in square bracket. Significance: + $p<0.1$ * $p<0.05$ ** $p<0.01$ *** $p<0.001$

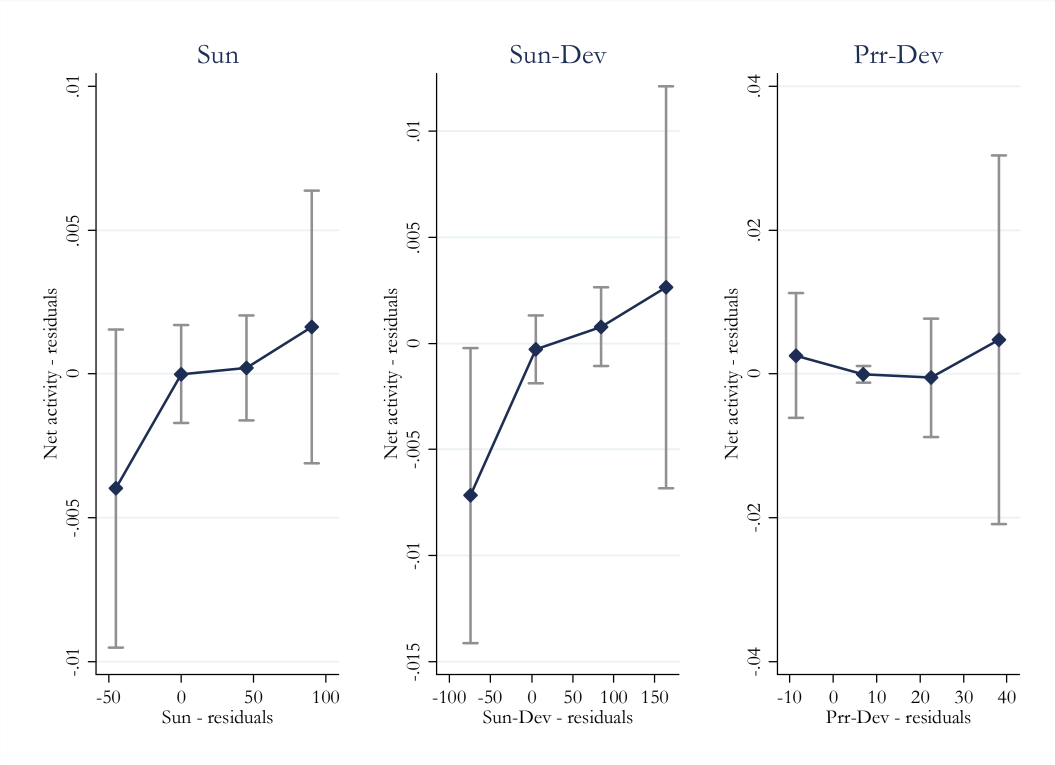
Standard errors used are clustered at both investor and day dimension

[17] $\beta_{Prr-dev} * \sigma_{Prr-dev} = -0.00043 * 3.8444 = -0.002$

Figure 7 provides graphical display of the regression results above for $Net\ activity$. This allows us to see how variation in weather deviations that cannot be explained by investor or time effects are explained by variation in trading behaviour that cannot be explained by investor or time effects. The corresponding graphs for the other trading behaviour variables are available in Appendix G. We can see a clear positive trend for both Sun and $Sun - Dev$, while $Prr - Dev$ is trending downwards but with a positive slope between the two highest bins.

Figure 7 - Visual display of residuals of $MoodProxies$ and $Net\ activity$

Figure displays residuals from regressions on $Net\ activity$, Sun, $Sun - Dev$ and $Prr - Dev$ respectively removing day and investor fixed effects. Graphs are created by, for each Sun, $Sun - Dev$ and $Prr - Dev$, dividing the distance between min and max value of residual after removing month fixed effects, respectively into 4 equal sized bins. Mean and standard deviation of corresponding trading behaviour variable is then calculated for values in each bin. $Net\ activity$ indicates if investor has increased volume in any instrument group (=1), decreased volume in any instrument group $(= -1)$ or both $(= 0)$ from time $t - 1$ to t. Sun is measured as % of sunlight between 12-13 UTC. Prr is the cumulative precipitation in mm between 6 UCT at time t and 6 UCT at time $t + 1$. Variables ending with $-Dev$ refer to deviations of actual weather at time t from forecast at time $t - 1$ for time t. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.



Note: Blue diamond indicate mean

Grey lines indicate 95% confidence intervals

IV estimation

Table 15 displays findings from the second stage IV regression, specification (21) and (22) with Sun, $Sun - Dev$ and $Prr - Dev$ as separate instruments for $Net\ mood$ in the Stockholm region. $Net\ mood$ has a positive and significant impact on $Net\ activity$ at the 10% level, instrumented by $Sun - Dev$. When using Sun and $Prr - Dev$ as instruments the coefficients are still positive but not significant. This suggests a causal and positive impact of $Net\ mood$ on $Net\ activity$. A one standard deviation increase in $Net\ mood$ is associated with 0.943 sell activities for every buy activity compared to 0.973 on average.[18] Using $Prr - Dev$ as instrument for N$et\ mood$ on $Total\ activity$ gives a negative coefficient with a t-statistic of 1.6, while the Sun and $Sun - Dev$ are insignificant and point in opposite directions of each other.

Table 15 - IV regression

Table displays the estimates from 2SLS IV estimate using specification (21) and (22), only including household investors living in Stockholm region. Estimates from the first stage of the IV regression and F-stats can be seen in Table 12. Trading behaviour variables are converted from individual to Stockholm values by taking the average investor i per time t. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$measures net change in value from instrument groups that have changed in volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. Sun is measured as % of sunlight between 12-13 UTC. Prr is the cumulative precipitation in mm between 6 UCT at time t and 6 UCT at time $t+1$. Variables ending with $-Dev$ refer to deviations of actual weather at time t from forecast at time $t-1$ for time t. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Total Activity			Net		
(Instrument)	(Sun)	(Sun - Dev)	(Prr - Dev)	(Sun)	(Sun - Dev)	(Prr - Dev)
Net mood	-0.196	0.195	-0.490	0.396	0.470+	0.419
	[0.261]	[0.340]	[0.307]	[0.244]	[0.279]	[0.340]
	(-0.75)	(0.57)	(-1.60)	(1.62)	(1.69)	(1.23)
Constant	0.381	-0.017	0.683*	-0.387	-0.462	-0.409
	[0.266]	[0.346]	[0.314]	[0.250]	[0.284]	[0.346]
	(1.44)	(-0.05)	(2.18)	(-1.55)	(-1.62)	(-1.18)
Adj R^2	0.288	-0.128	0.288	-0.788	-1.081	-0.857
N	515	515	528	515	515	528

	N%P			TS%P		
(Instrument)	(Sun)	(Sun - Dev)	(Prr - Dev)	(Sun)	(Sun - Dev)	(Prr - Dev)
Net mood	0.033	-0.003	0.045	-0.123+	0.029	-0.115
	[0.117]	[0.090]	[0.098]	[0.071]	[0.064]	[0.072]
	(0.28)	(-0.04)	(0.46)	(-1.73)	(0.46)	(-1.60)
Constant	-0.036	0.001	-0.048	0.145*	-0.010	0.138+
	[0.119]	[0.091]	[0.100]	[0.073]	[0.065]	[0.074]
	(-0.31)	(0.01)	(-0.48)	(2.00)	(-0.15)	(1.87)
Adj R^2	-0.036	-0.012	-0.053	-0.044	-0.115	-0.011
N	515	515	528	515	515	528

Note: T-stats are in parentheses and standard errors in square bracket — Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

Robust standard errors are used

[18] $\beta_{Net\ mood} * \sigma_{Net\ mood} = 0.47 * 0.064 = 0.03$. A positive impact on $Net\ activity$, indicates that more buy activities per sell activity or analogously fewer sell activities per buy activity

VII. Discussion

In this section we discuss the results from section VI. Results. We divide the discussion into two parts, where the first part comments on naïve correlations between N$et\ mood$ and trading behaviour, and the second part comments on the causal relationship between mood and trading behaviour.

Naïve analysis

Results from the naïve regressions point towards a significant and negative relationship between mood and trading behaviour. The results are somewhat surprising as we would expect mood to be positively correlated with all our trading behaviour variables. However, the results are most likely clouded by omitted variable bias and as we see when controlling for time and investor effects the direction of many relationships change, underlining the importance of moving beyond a naïve regression. A lengthier discussion regarding the causal link is found in the second part of this section.

Level of activity (Total activity and TS%P)

The results shown in Table 9 suggest that $Net\ mood$ has a significantly weaker impact on $Total\ activity$ and $TS\%P$ respectively for young investors than for old investors, i.e. young investors are less sensitive to mood levels when deciding whether to trade and deciding the size of the trade. This is in line with Gross et al. (1997) who finds that older people have greater emotional experiences than young people, and are thus more affected by changes in the general mood state. Also, older investors' higher level of activity can be explained by older people experiencing a higher net mood than younger people (Mroczek and Kolarz, 1998). Furthermore, the results partially confirm Agarwal et al. (2008) suggesting that analytical abilities decline with age, in our case resulting in older people relying more on mood than analytical skills when choosing if and how much to trade.

We also see that households with small trading portfolios, table 10, are more sensitive to $Net\ mood$ when determining the size of the trade, $TS\%P$. This could simply be a consequence of small portfolio investors using their trading accounts as cash buffers for rainy days, i.e. as times are bad they are forced to divest a larger portion of their portfolio than large portfolio investors.

Direction of activity (Net activity and N%P)

The results shown in Table 8 suggest that women are significantly more sensitive to $Net\ mood$ changes than men when deciding level of $N\%P$. When mood levels increase women are inclined to sell more relative to buy in terms of value, whilst men's behaviour is not significantly affected by mood. This finding is in line with previous research suggesting that women are more sensitive to mood (Fujita et al., 1991 among others).

Small portfolio household investors seem to be less affected by $Net\ mood$ when deciding level of $Net\ activity$. This could be explained by small investors acting more frequently (although at lower levels relative to portfolio, see $TS\%P$) when in a good mood, and less frequently (although at higher levels relative to portfolio, see $TS\%P$) when in a bad mood.

Conclusion of findings from naïve regressions

We conclude that there seems to exist a correlation between $Net\ mood$ and trading behaviour. In addition, we find differences in the sensitivity to $Net\ mood$ within demographic dimensions; women seem to be more sensitive to mood when deciding the direction of a trade, whereas older investors are more affected by mood than young investors. Though not causal, the findings point in the direction suggested by previous research, which strengthens that our novel measure $Net\ mood$ does capture relevant mood states. In the coming section we examine if mood is the causal driver of trading behaviour. Sadly, we do not have ample depth in our data to determine if there are differences in the causal relationship to mood within demographic dimensions[19], hence we cannot proceed with a causal analysis including demographic variables.

Analysis of a causal impact

We find mixed results when trying to identify a causal relationship between mood and trading behaviour variables. However, supported by both the fixed effects approach, Table 14, and the IV approach, Table 15, we find a significant and positive causal impact of $Net\ mood$ on $Net\ activity$, in line with Hypothesis 3. To the best of our knowledge this represents the first established IV-causal link between emotions and behaviour of individual investors outside an experimental setting.

Net activity

The fixed effects regression tells us that, conditional on effects that are constant for investor i over time, and effects that are common for all investors on the same day, $Prr - Dev$ has a negative and significant impact on $Net\ activity$. In addition, both Sun and $Sun - Dev$ have a positive impact with t-stats close to 1.5. We argue that mood is driving this relationship, supported by the significant correlation between $Prr - Dev, Sun - Dev$ and $Net\ mood$, Table

[19] As we cannot control for investor fixed effects without losing variation in the demographic dimension of interest we would need a vast number of control variables, e.g. educational level and employment, in order to be confident that there is no omitted variable bias. An IV estimation would require panel data on an individual level.

12. An example of this relationship would be an investor experiencing more rain than expected on his way to work. As he did not bring his umbrella he is soaked and his hair a mess when arriving at work, getting him in a bad mood. This bad mood is carried over to decision making activities during the day even though these activities are totally unrelated to the weather (Forgas, 1995; Loewenstein and Lerner, 2002; Schwarz, 1990). Assessing his trading portfolio his bad mood makes him feel more pessimistic about future prospects (Wright and Bower 1992; Johnson and Tversky, 1983; Isen et al., 1978) and when asking himself “how do I feel about my assets?” he weighs in his current bad mood in his subsequent trading decision (Clore, 1992, Schwarz 1990; Schwarz and Clore, 1983), leading to a higher likelihood to sell assets in his portfolio than buy new ones (Lerner et al , 2004).

The causal relationship rests on the assumption that there are no factors significantly correlated with $Prr - Dev$ that also have a significant correlation with $Net\ activity$, and at the same time varies over both investor and day dimensions. An example of one such a factor would be an unexpected storm in the southern region of Sweden. Such a storm could reduce investors' access to trading facilities due to power outages or leave investors stuck in public transportation. In this example it is understandable why $Total\ activity$ would decrease unrelated to the impact of mood, however, there seems to be no straight forward reason to why $Net\ activity$ would be influenced. One the one hand, storms could cause economic damages forcing investors to sell assets to finance repairs. One the other hand such effects, if any, are more likely to be observed when the storm has withdrawn and once damages have been assessed. Hence, this would not explain a higher tendency to sell relative to buy on the day of the storm. In addition, Table 13 show that $Prr - Dev$ is uncorrelated with a number of macroeconomic factors that impact household investors decision making.

Our findings are further supported by the IV estimation for the Stockholm region. We see that there is a positive and causal relationship between $Net\ mood$ on $Net\ activity$ conditional on month fixed effects using $Sun - Dev$ as an instrument. This finding is analogous to the negative impact of $Prr - Dev$ on $Net\ activity$ found in the fixed effects estimation. As our data only allows for an IV time series regression we cannot control for investor or day fixed effects. Hence it is important to note that while the coefficient of $Prr - Dev$ in the fixed effects estimation only captures the incidental bad mood caused by an unexpected rainy day, the coefficients of $Net\ mood$ in the IV estimation captures the effect of changes in public mood levels, and indirectly investor mood levels. Changes in public mood levels can arise from numerous factors besides weather, such as the national soccer team losing a game (see Edmans et al., 2007).

As an example we return to the drenched investor and imagine him finding out that he is being promoted which naturally gets him in to a good mood. This good mood spills over to his investment decision, and he assigns more optimistic probabilities to future prospects of various investment opportunities, and thus decides not to sell but rather to buy more assets.

The positive relationship between $Net\,mood$ and $Net\,acitivity$ found in the causal analysis is opposite to the findings from the naïve analysis, Table 6 and Figure 5. This suggests that the naïve coefficient is negatively biased by factors that are positively correlated with $Net\,mood$ and negatively correlated with $Net\,activity$. Such a factor could be that investors are happy about a public holiday such as Christmas, but has to sell assets to finance it. This effect should however be mitigated by the use of month dummies. Another example of such a factor is that investors' mood may be affected by the act of trading, such as becoming happy when buying a new car, reversing the direction of proposed causality. This problem is removed in the IV regression as weather and weather deviations are exogenously given.

Economic significance

An increase of $Net\,mood$ by one standard deviation implies a change in $Net\,activity$ corresponding to a decrease of 0.03 sell activities per buy activity, per investor and day. To assess the wider economic significance of this relationship we allow ourselves to make some simplifying assumptions. First, we sum the number of household investors with an online broker account at Nordnet, (c.214 700 active accounts) and with the market leader Avanza (c.372 500 active accounts). Our definition of active investors puts us in the top quartile of the Swedish online household population based on a comparison with the dataset used by Anderson (2004), leaving us with a base of c. 150 000 comparable investors. The average investor in our sample buys on at least 21 occasions per year. Extrapolating this to all comparable investors we arrive at a total figure of 3 150 000 buy activities per year. This, multiplied by the 0.03 fewer sell activities per buy activity converts into 94 500 fewer sell activities in total. Multiplied with the average portfolio value change resulting from sell activity in our sample, 8425 SEK, we arrive at a total of c.800 MSEK of less selling or more buying. Initially sounding like an economically significant amount, it is dwarfed by the 3600 BSEK that the OMX All shares Index turns over in a year. Hence, it seems unlikely that emotions are strong enough to drive asset prices. However, on an individual investor level it corresponds to c. 5500 SEK, a small but significant amount.

Interpreting the results for other trading behaviour variables

The results for $TS\%P$, $Total\,activity$ and $N\%P$ show varying levels of significance, and limited consistency between the fixed effects and IV method across mood proxies, hence we find no support for Hypothesis 1, 2 and 4. One plausible explanation for these non-results could be the design of $Net\,mood$. Motivated by the idea of creating a simple and unambiguous measure of emotions we might have reduced the palette of human emotions excessively. Hence $Net\,mood$, being designed as a valance based ratio, is insensitive to levels of the underlying good and bad mood states. Subsequently $Net\,mood$ may be an adequate measure for behaviour related to the inclination towards good or bad mood states such as $Net\,activity$, however, may have a limited ability to explain trading behaviour related to changes in levels or intensities of mood states, such as $N\%P$ and $TS\%P$. Moreover, technical limitations forced us to disregard the scale of emotional intensity, i.e. we made no difference between "happy" and "super happy". Another potential explanation for the ambiguous results of $Net\,mood$'s influence on $Total\,activity$ is that mood, as measured in this thesis with a time horizon of a couple of hours, does not influence the *decision to trade* which may be contemplated during several days. While the decision on *what to trade* is a more spontaneous choice made once front of the computer, as suggested by the causal impact of mood on $Net\,activity$.

Findings in relation to previous studies

Our finding that $Net\,mood$ has a positive influence on $Net\,activity$ is in line with Edmans et al. (2007), who finds that bad mood, proxied by national sport teams' losses, has a negative impact on next day stock returns and Kaplanski and Levy (2010) who document negative stock market overreactions associated with aviation disasters. In contrast to our naïve results, Bollen et al. (2011) document a positive naïve correlation between good mood and increased buying behaviour.

Our results are also in line with previous research that use good weather as a proxy for good mood (Saunders, 1993; Hirshleifer and Shumway, 2003 and Kliger and Levy, 2003) and Kaustia and Rantapuska (2011) who by looking at individual investor data find an increased though insignificant demand for buying on sunny days, and a decreased demand on rainy days. In contrast, our findings contradict those of Goetzman and Zhu (2003), who find no significant relationship between sun and household investors' buying behaviour. Yet neither of these studies are directly comparable to this paper as we use weather deviations in addition to actual weather as our main mood proxy, while previous studies only use actual weather.

Limitations

No return without risk is a fundamental theorem in finance. The same rule applies to research. With this paper we have sought to employ a novel method using new sets and combination of data to identify and measure the causal impact of mood on household investors' trading behaviour. When possible we have sought guidance from previous research but the majority of our methods and variables definitions are our own. This makes it more exciting, but also exposes us to the risk of taking a wrong turn at some point, both in terms of economical and statistical interpretations and relevance. This section aims at highlighting features of this paper that should be considered when determining the internal and external validity of the proposed results.

External validity

Firstly, our sample only consists of active online household investors that are not representative of the population of online household investors. Comparing our dataset with Anderson (2004), investors in our sample would rank in the top activity quartile. If this distribution is still valid it suggests that our findings can be generalised to the quarter most active online household investors in Sweden. For a further comparison between active and inactive investors we refer to Appendix H were we provide a comparison of the 900 active accounts used in this paper and a sample of 100 accounts defined as inactive, also randomly drawn by Nordnet from the same investor population.

Secondly, our data stretches from July 2009 to August 2011. One could argue that the observed trading behaviour is specific to a highly volatile period such as the one studied. These concerns are valid, however, we believe that the observed link between mood and trading behaviour is valid across different macro economical settings – using the words of investor Sir John Templeton "The four most expensive words in the English language are, 'This time it's different.'". Our findings should therefore be applicable to active online investors across different macroeconomic settings.

Thirdly, our IV estimates are based on a sample of investors from Stockholm. We do believe that our results can be generalised across Sweden for reason such as cultural homogeneity and supporting evidence from the fixed effect estimate. However, it is difficult to judge whether results can be generalised to other countries. Judging from the wide body of small scale experimental evidence from different parts of the western world showing consistent results we believe that our results can serve as reference point when researching active household investors in other western countries.

Fourthly, the estimated IV coefficient measures the effect of instruments on those who react when being exposed to weather or weather deviations, but would otherwise have not reacted (Angrist and Krueger, 2001). Based on previous research pointing to the impact of weather and mood as well as Swedes interest in weather, we believe that a large majority of the population is influenced by the instruments. In interpreting the coefficient we have also assumed that there are no contrarian reactions to weather or weather deviation, e.g. people who become happy when it rains more than expected. Of course, we cannot rule out that there are a few people that react in this way, but in our database of 150 000 bloggers such emotions will have limited impact on $Net\ mood$ and hence we assume monotonicity in responses to weather and weather deviations.

Fifthly, online brokerage accounts only include a portion of investors' total wealth (Campbell, 2006). Our findings are therefore limited to the activity related to the online portion of their wealth.

Finally, our findings only apply to online investors as their behaviours differ from offline investors as noted by Barber and Odean (2001b). This being said, the share of online households relative to the total household trading population is likely to have increased since 1991-1996, the time period covered by Barber and Odean (2002) and 1999-2002, the time period covered by Anderson (2004). Thus, our findings should not be directly side-lined by claims of non-generalizability of the online household as an ever increasing portion of the Swedish household investor population is in fact online household investors.

In conclusion, we believe that our results can be generalised to the top quartile of active online household investors in Sweden and across different macro-economic settings. Furthermore, there is a reasonable likelihood of generalizability across other western countries as well as among a larger portion of household investors.

Internal validity

This section aims at discussing potential issues and limitations of the method used to reach our results.

Household investor data

Our sample has been randomly drawn from a large pool of investors and we feel confident that there is no selection bias in our sample other than those imposed through our selection criterion. Furthermore we feel confident that our trading data measures the trading behaviour of household investors in a better way than using stock market indices such as Bollen et al. (2011) and Edmans et al. (2007) as they contain noise from institutional investors and trading robots. Our investor data only allows us to observe net changes per day and instrument group hence our data only captures net of trading behaviour per day. We have also assumed that all portfolio value changes on an active day arise due to transactions, disregarding changes in overall market value. As the market moves on average +/-2% per day[20] we expect the impact of this simplification to be minor.

[20] Average daily return of OMX all share index is 0.1% with a standard deviation of 1.5% during our sample period

We did not observe the random selection of the household investor accounts, nor can we be sure that the data provided by Nordnet is accurate. Recognizing this, we have no reason to suspect that Nordnet has intentionally tampered, and thereby possibly biasing, the provided data. The reliability of the data is considered to be high as the same type of data is used for internal analysis.

Blog data

When constructing $Net\ mood$ we have assumed that people who write blogs express mood through their writing, supported by previous research such as Baron (1987). As we have translated and expanded the original PANAS-test there is a risk that the test's integrity has been compromised. In this case our mood variable will contain uncontrolled for biases invalidating the proposed causal relationship. We address this issue by excluding words that only occur once as synonyms of synonyms for an original word, see Appendix D for a detailed description.

For technical reasons we have also assumed that the PANAS words were not used in negative or ironic connotations to a large extent. Judging from qualitative tests and analysis this seems to occur in a minority of the blog posts, but we have no way of knowing the extent to which this occurs in the full dataset.

We have assumed that the mood expressed in blogs in our database reflect the mood of the general population and in extension each investors in our sample. The link between web based mood and the general public is supported by previous research such as O'Connor et al. (2010), Gilbert and Karahalios (2010) and Balog et al. (2006).[21]

Underlying data for $Net\ mood$ was provided by Kairos Future, a consultancy. We did not have free access to the database, instead we have relied on Kairos Future to provide us with data extractions. Hence, insight into the structure of the database has been limited. We trust the provider in that the dataset includes a representative sample of Swedish blog population. The method used to gather blog data is frequently updated, extending its reach from the most common blog domains to less common ones. This may imply that the dataset is not fully comparable over time. Recognizing these potential biases we still consider the reliability of the data to be high.

Weather data

Due to time and resource constraints weather data was only used for five locations in Sweden and these were then used as proxies for the surrounding regions. The locations of chosen

[21] In addition, surveys from 2011 have shown that 46% of Swedes that use internet read blogs, 51% of men between the ages of 26-35 read blogs occasionally and 10% do so on a daily basis. For men aged 56-65 the corresponding numbers are 31% and 4% respectively (Findahl, 2011).

weather stations cover around 45% of the Swedish population. Nevertheless there is a probability that people inside our defined regions experience different weather or weather deviation than we have in our data.

Constructing our measure of sunshine deviations we converted a continuous measure of actual sunshine duration during an hour to a snapshot value in order to compare it with forecasted data. Although not a perfect match it is important to note that errors stemming from this simplification are likely to be minor and unlikely to induce strong enough emotions for it to affect trading behaviour

We consider the reliability of the weather and forecast data to be high as SMHI is a government funded agency, who is delivering data to most major national newspapers and news programs. Data is available free of charge for research purposes.

Exclusion restriction

Our finding of a causal relationship heavily relies on the assumption that our instruments fulfil the exclusion restriction. Apart from reasoning we have demonstrated that stock returns, Riksbanken's Stress Index and the Consumer Confidence Indicator correlate with both trading behaviour and mood but not with any of our instruments. Nevertheless, it all comes down to if you believe that daily weather and daily weather deviations drive economic activity or investor behaviour in any other way than through mood.

In cases when we are limited to time series data we have controlled for month fixed effects. These tests have been re-run using week fixed effects; see Appendix I, with insignificant changes to our results. Furthermore, if you believe that the weather and weather deviations are randomly assigned there will most likely be no omitted variable bias even though we do not control for fixed effects (Angrist and Pischke, 2009a).

VIII. Conclusion

The starting point for this thesis is the increased interest in the role of mood and emotions in decision making witnessed during the last decade, combined with the lack of studies affirming theoretical and experimental findings in empirical data.

Using a fixed effects approach we are able to isolate a causal impact of investors' bad mood on their tendency to decrease buy activities relative to sell, by proxying bad mood with deviations from precipitation forecasts. Using a time series IV regression for the Stockholm region we were able to isolate a positive causal impact of good mood and an increased tendency to buy relative to sell, measured by our constructed mood index. These findings are in line with evidence from previous studies.

Also in line with previous research, we find that women and old investors are more impacted by emotions in their decision making than male and young investors respectively in some types of financial decision making. However, this relationship could not be established on a causal basis due to data limitations.

In contrast to previous theory, we find no significant causal relationship between mood and size of trading activity. This could be due to the design of our mood measure, synthesizing a vast array of human emotions into a single good versus bad mood index. Additionally, we find no consistent influence of mood on the volume of trading.

We believe that our results can be generalised to the top quartile of active online household investors in Sweden and across different macroeconomic settings. Furthermore, there is a reasonable likelihood of generalizability across other western countries.

Annualizing the impact of an increase in good mood by one standard deviation on $Net\ activity$ and applying the active customer base of Sweden's two largest online retail brokers, this translates into c. 800 MSEK or c. 5500 SEK per active household investor. We hypothesise that this impact is not large enough to impact asset prices at an aggregate level but that it is large enough to be of economically significance at the individual household level.

In conclusion, this paper contributes to research in two distinct ways. Firstly, we develop and test deviations from weather forecasts as a new continuous mood proxy with characteristics that, in theory, captures deviations from expectations. Secondly, we link observed trading behaviour directly to a measure of mood, constructed by quantifying emotions expressed through blogs. The observed positive relationship between mood and an increase buying relative to selling behaviour represents, to the best of our knowledge, the first established causal link between mood and trading behaviour among household investors.

IX. Further research

We believe that research has merely scratched the surface of comprehending the impact of mood and emotions in decision making processes and that the increasing availability of new, frequent and detailed data will continue to drive research forward.

Building on our findings, a natural next step would be to further develop our mood measure allowing it to capture both intensity of experienced emotions at the individual level as well as different types of emotions. Other tests, such as POMS (McNair et al., 1971) or PANAS-X (Watson and Clark, 1994), could potentially provide tools for such analysis on a large scale population. Sweden is especially well-suited for this type of quantitative analysis of blogs as the Swedish language creates a natural barrier from outside influence in combination with Sweden's widespread adoption of reading and writing blogs.

Another next step would be to provide further support to our findings by using regional mood data to benefit from the panel dimension of the investor and weather data allowing for panel IV estimation. This would also enable further research into differences in the sensitivity to mood within demographic dimensions, possibly finding differences in the causal relationship between mood and trading behaviour.

We discussed using traffic delays as a proxy for bad mood but decided not to due to time constraints. Detailed daily data is available from local authorities and we were given access to data for both Stockholm and Gothenburg regions free of charge.

A final suggestion for further research would be to test if the established causal relationship of good mood on the tendency to buy relative to sell is strong enough to drive asset prices by studying volumes or returns on stock indices rather than individual investor data. This could potentially be done in a cross country setting analysing countries with similar climate and culture as Sweden, using weather deviations as an instrument.

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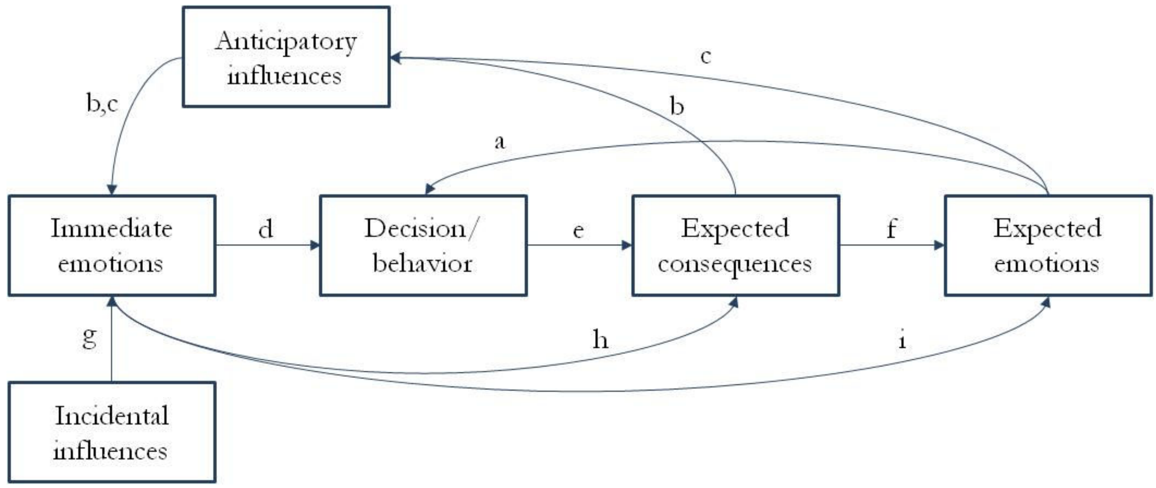
XI. Appendix

Appendix A - The role of emotions in decision making

Here we describe the framework developed by Loewenstein and Lerner (2003), see Figure 8 below for understanding the role of emotions in decision making. In the framework emotions enter into decision making in two distinct ways; through *expected emotions* and *immediate emotions*.

Figure 8 - Framework for role of emotions in decision making

Framework developed by Loewenstein and Lerner (2003) depicting the impact of emotions in decision making. Emotions enter into the decision making in two distinct ways; through expected emotions and immediate emotions. Explanations of framework in text.



Expected emotions

Expected emotions consist of making predictions about the emotional consequences of decision outcomes. They play a large role in the traditional expected utility theory where the decision maker weighs expected benefits or expected emotional consequences of alternative choice and subsequently makes the choice that maximises the ratio of positive to negative emotions. Expected emotions are not experienced at the time of the decision making, rather they are predictions about what emotions will be experienced in the future. Expected emotion enters the decision making framework when an individual attempts to predict the probabilities of potential outcomes (line *e*) and thereafter what emotions the different outcomes would invoke (line *f*). The decision may then be effected by the desire to avoid or attain expected emotions (line *a*). An example would be an investor considering whether to invest funds in a high risk stock. When making this decision the investor attempts to predict the probabilities of losing or gaining money on the investment (line e) as well as how he would feel under different scenarios (line f) [22]. The investor might then not make the investment as he envisions the feeling of regret he would feel

[22] The example is inspired by the one given in Loewenstein and Lerner (2003), p.620

if the stock took a dive as documented by (Shefrin and Statman, 1985). Evidence of such regret avoiding behaviour has been documented in several studies (e.g. Strahilevitz et al, 2011).

Immediate emotions

Immediate emotions are, unlike expected emotions, experienced at the time of the decision making and thus of high relevance in this paper. They can exert a direct impact on the decision (line *d*) or an indirect impact by altering the individuals expectations of the probability of outcomes (line h) or the desirability of the outcomes (line i). Returning to the investor considering whether to invest in a high risk stock, an example of a direct impact (line d) would be that the investor experiences immediate exaltation at the prospect of investing in a high risk stock which might induce him to invest. An example of an indirect influence would be if the investor's pre-existing good mood makes him feel more optimistic about the prospects of the high risk stock (line h) or about the joy he will feel having made a profit from the investment (line i).

Appendix B - Remove observations related to stock splits

In some cases of stock splits the value of the portfolio spiked due to a technical detail in Nordnet's system. As stock splits often occur after markets have closed there is no market price available for the post-split quantity of the share. Instead the system multiplies the post-split quantity of stocks with the pre-split value of stocks causing value to increase substantially which is then reported as the end of day value at investor $i's$ account. As soon as trading commence the next day prices are adjusted.

As we do not have individual security data we cannot identify stock splits explicitly. Instead we remove such observations that fulfil two criteria:

(1) the market value of the portfolio at t belonging to investor i deviates by more than a factor of 3 from the market value at time $t-1$ and $t+1$ for the same investor and (2) the market value of the portfolio of investor i deviates by more than a factor of 3 from the average size of the investor's portfolio. This condition is there to make sure we do not exclude investor who trade frequently, as the average trade will then be large they will not be excluded.

In addition we came across 4 observations that clearly indicated a similar problem with stock splits which were not captured by the two criterions. There were also excluded.

Appendix C - Regression using $Net\ mood$ without dropped synonyms

Table 16 - IV regression using non-adjusted $Net\ mood$

Table displays the estimates from 2SLS IV estimate using specification (21) and (22) of $Net\ mood$ on trading behaviour variables but with a non-adjusted $Net\ mood$ as explained variable. The regression only includes household investors living in the Stockholm region. In this case $Net\ mood$ (unadjusted) include all synonyms of synonyms, ie. we do not exclude those that only occur once. Trading behaviour variables are converted from individual to Stockholm values by taking the average investor i per time t for all investors in the Stockholm region. At the individual level, $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$ measures net change in value from instruments group that have changed volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. Sun is measured as % of sunlight between 12-13 UTC. Prr is the cumulative precipitation in mm between 6 UCT. Variables ending with $-Dev$ refer to deviations of actual weather at time t from forecast at time $t-1$ for time t. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Total Activity			Net		
(Instrument)	(Sun)	(Sun - Dev)	(Prr - Dev)	(Sun)	(Sun - Dev)	(Prr - Dev)
Net mood	-0.259	0.399	-0.833	0.525	0.960	0.712
(unadjusted)	[0.334]	[0.745]	[0.472]	[0.314]	[0.666]	[0.566]
	(-0.78)	(0.53)	(-1.76)	(1.67)	(1.44)	(1.26)
Constant	0.390	-0.137	0.850*	-0.403	-0.752	-0.552
	[0.268]	[0.595]	[0.379]	[0.252]	[0.532]	[0.453]
	(1.46)	(-0.23)	(2.24)	(-1.60)	(-1.41)	(-1.22)
Adj R^2	0.315	-0.287	0.424	-0.618	-1.800	-1.037
N	515	515	528	515	515	528

	N%P			TS%P		
(Instrument)	(Sun)	(Sun - Dev)	(Prr - Dev)	(Sun)	(Sun - Dev)	(Prr - Dev)
Net mood	0.043	-0.007	0.077	-0.163+	0.059	-0.196+
(unadjusted)	[0.154]	[0.183]	[0.161]	[0.086]	[0.136]	[0.112]
	(0.28)	(-0.04)	(0.47)	(-1.90)	(0.44)	(-1.76)
Constant	-0.038	0.003	-0.064	0.150*	-0.028	0.177*
	[0.123]	[0.146]	[0.129]	[0.069]	[0.109]	[0.090]
	(-0.31)	(0.02)	(-0.49)	(2.18)	(-0.26)	(1.98)
Adj R^2	-0.031	-0.012	-0.059	0.175	-0.207	0.108
N	515	515	528	515	515	528

Note: T-stats are in parentheses and standard errors in square bracket Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

Robust standard errors are used

Table 17 - Naïve regression using non-adjusted $Net\ mood$

Table displays results from regression specification (X) looking at naïve correlation between $Net\ mood$ and each trading behaviour variable respectively In this case $Net\ mood$ (unadjusted) include all synonyms of synonyms, ie. we do not exclude those that only occur once. Month dummies were used to account for time fixed effects. Estimates for these are omitted from the table. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$measures net change in value from instruments group that have changed volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Total activity	Net activity	N%P	TS%P
Net mood (unadjusted)	-0.339**	-0.091**	-0.006+	-0.040***
	[0.038]	[0.016]	[0.004]	[0.006]
	(-8.87)	(-5.58)	(-1.69)	(-6.58)
Constant	0.541**	0.114**	0.006	0.060***
	[0.040]	[0.018]	[0.004]	[0.007]
	(13.59)	(6.23)	(1.44)	(8.91)
Adj R^2	0.006	0.000	0.000	0.001
N	475 976	475 976	475 976	475 976

Note: T-stats are in parentheses and standard errors in square bracket Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

Standard errors used are clustered at both investor and day dimension

Appendix D - Creation of mood index

Our mood index is based on the *Positive and Negative Affect Schedule* (PANAS) developed by Watson et al. (1988). PANAS consists of 20 adjectives broken down into two categories: Positive Affect (PA) and Negative Affect (NA). See Table 18 for full list.

Table 18 - Words in original PANAS including translations

List of the 20 words from the original PANAS test (Watson et al., 1988). Translations are our own.

Positive Affect (PA)		**Negative Affect (NA)**	
English	Swedish	English	Swedish
Active	*Aktiv*	Afraid	*Rädd*
Alert	*Alert*	Ashamed	*Skamsen*
Attentive	*Uppmärksam*	Distressed	*Bekymrad*
Determined	*Bestämd*	Guilty	*Skyldig*
Enthusiastic	*Entusiastisk*	Hostile	*Fientlig*
Excited	*Exalterad*	Irritable	*Lättretlig*
Inspired	*Inspirerad*	Jittery	*Skakis*
Interested	*Intresserad*	Nervous	*Nervös*
Proud	*Stolt*	Scared	*Skraj*
Strong	*Stark*	Upset	*Upprörd*

After having translated the original PANAS words to Swedish we create a list of all the synonyms to these original words[23]. These words are referred to as Level 1 words. Thereafter we collect all the synonyms of the Level 1 words, which are referred to as Level 2 words. This gives us a total of 989 unique words[24], containing the original PANAS words, Level 1 words and Level 2 words. To prevent the meaning of the original words from being distorted we exclude Level 2 words that only occur once within each original word, i.e. for a Level 2 word to be included it has to be the synonym of at least two Level 1 words which in turn are synonyms to the same original word, illustrated in Table 19. After dropping these Level 2 words we have removed 55% of the Level 2 words. Examples of words that are dropped by this approach includes “romantisk” (Eng. romantic), which is a synonym to lyrisk (Eng. lyrical) which in turn is a synonym to the original word “entusiastisk” (Eng. enthusiastic).

Table 19 - Method to exclude level 2 synonyms from expanded list of PANAS words

Table displays the method used when excluding level 2 synonyms that do not occur more than once within one original PANAS word. In the example below X is a synonym to A, and E/F/G are synonyms to X. Words G/H/N are dropped as they do not occur twice within the same original word. Level 2 words in brackets represent dropped words.

Original	Level 1	Level 2
A	X	**E**
		F
		[G]
	Y	**E**
		F
		[H]
B	Z	**L**
		M
		[N]
	U	**L**
		M
		[G]

All duplicate words within a mood dimension (PA or NA) are thereafter removed, leaving us with a total of 549 unique words; 262 words within PA and 287 words within NA. Removing duplicates gives each word equal weighting. We create value series, $ood_{j,t}$, using the information from the blog-database.

[23] Using the website www.synonymer.se – a Swedish based online synonym finder

[24] All of which are adjectives. Some words are in fact 2,3 or 4-gram strings, e.g. a synonym to the word *vettskrämd* (Eng. *terrified*) is *skrämd från vettet* (Eng. *frightened out of one's wits*)

$$RawMood_{d,t} = I_{d,t} \quad (23)$$

Where $I_{d,t} = \{I_{d,t}^1, I_{d,t}^2, \dots, I_{d,t}^n, I_{d,t}^N\}$ is a vector with $I_{d,t}^n$ denoting the frequency at which word n within mood dimension $d = \{PA, NA\}$ is mentioned at time t.

To account for the fact that the number of bloggers captured by the database change over time and that blogging behaviour might change due other circumstances we normalise $RawMood_{j,t}$ by $TotalWords_t$.

$$NormalizedRawMood_{j,t} = \frac{RawMood_{j,t}}{TotalWords_t} \quad (24)$$

Where $TotalWords_t$ is the total number of words in the entire database at time t.

As the expanded wordlists contain different amounts of words, we need to index $NormalizedRawMood_{j,t}$ in order to compare the values of the two mood dimensions.

$$MoodIndex_{j,t} = \frac{NormalizedRawMood_{j,t}}{NormalizedRawMood_{j,1}} \times 100 \quad (25)$$

In a final stage we create a net mood index, simply contrasting the two mood dimension index with each other in each t.

$$Net\ Mood_t = \frac{MoodIndex_{PA,t}}{MoodIndex_{NA,t}}$$

Appendix E - List of weather stations

Table 20 - List of weather stations

Weather station used when extracting weather data with corresponding coordinates. Region refers to the region for which observations data from each weather station were extrapolated to proxy.

Weather station	Region	Latitude	Longitude
Stockholm	Stockholm	59.31	18.06
Göteborg	Gothenburg	57.72	12.00
Malmö	Southern Sweden	55.59	13.00
Umeå	Northern Sweden	63.83	20.27
Örebro	Central Sweden	59.28	15.21

Appendix F - Trading behaviour variables grouped by net mood index quartiles

Figure 9 - Trading behaviour variable by quartile of $Net\ mood$

Figure displays Behaviour variables grouped by quartiles of $Net\ mood$, where quartile 4 represents days with highest $Net\ mood$. $TTotal\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$ measures net change in value from instruments group that have changed volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

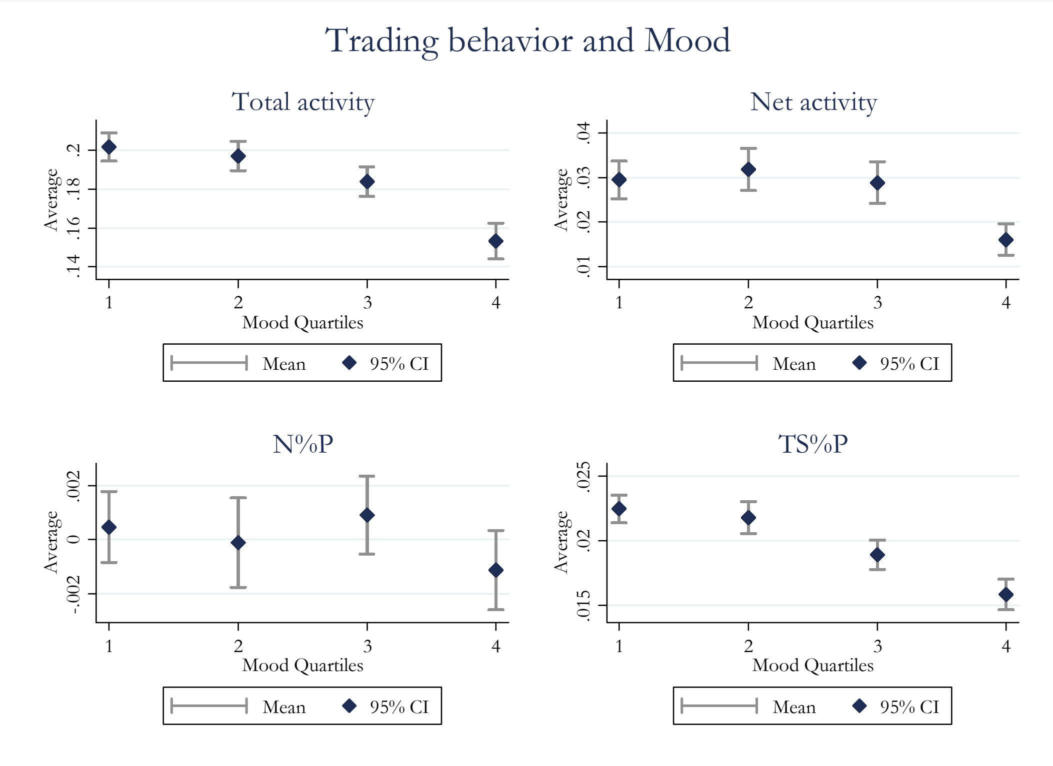


Table 21 - Differences in means trading behaviour variables grouped by quartiles of Net mood

Table means and difference in means by quartile of trading variables grouped by quartiles of $Net\ mood$, where Q4 represents days with highest $Net\ mood$ difference in mean to other quartile. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$measures net change in value from instruments group that have changed volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Total activity				Net activity			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Mean	0.202	0.197	0.183	0.153	0.030	0.032	0.029	0.016
Diff vs								
Q2	-.004595				.002343			
	(1.000)				(1.000)			
Q3	-.0178	-.013204			-.000667	-.003009		
	(0.010)	(0.118)			(1.000)	(1.000)		
Q4	-.048468	-.043873	-.030669		-.013367	-.01571	-.012701	
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	

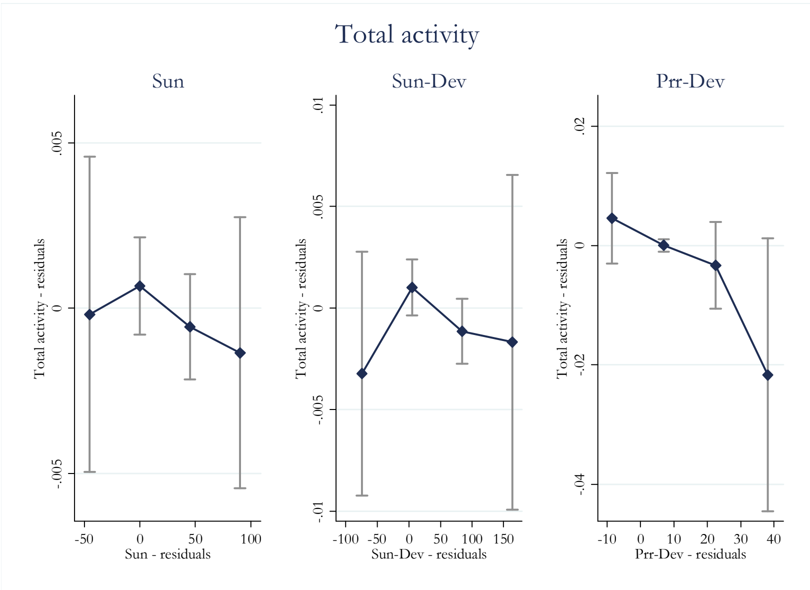
	N%P				TS%P			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Mean	0.0005	-0.0001	0.009	-0.011	0.022	0.022	0.019	0.016
Diff vs								
Q2	-.000581				-.000685			
	(1.000)				(1.000)			
Q3	.000443	.001024			-.003547	-.002861		
	(1.000)	(1.000)			(0.000)	(0.004)		
Q4	-.001594	-.001013	-.002037		-.006635	-.005949	-.003088	
	0.789	(1.000)	0.327		(0.000)	(0.000)	(0.001)	

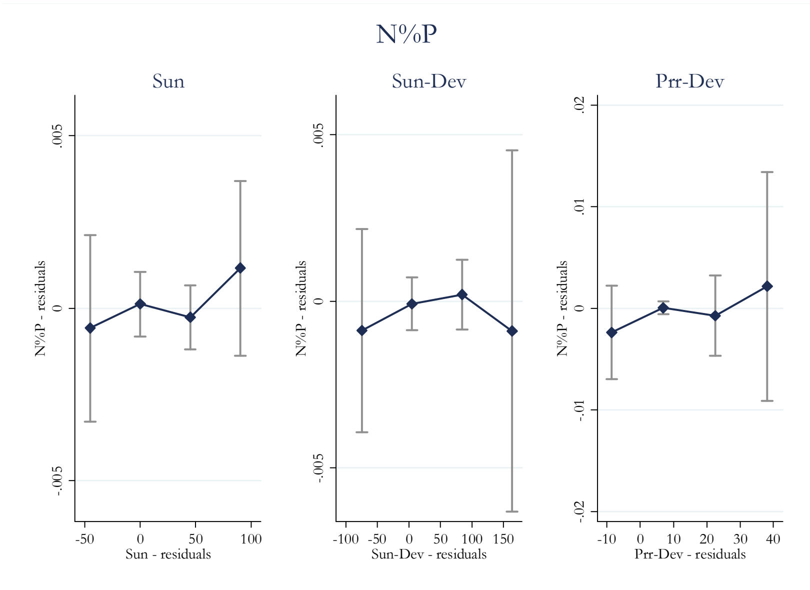
Note: P-values in parentheses

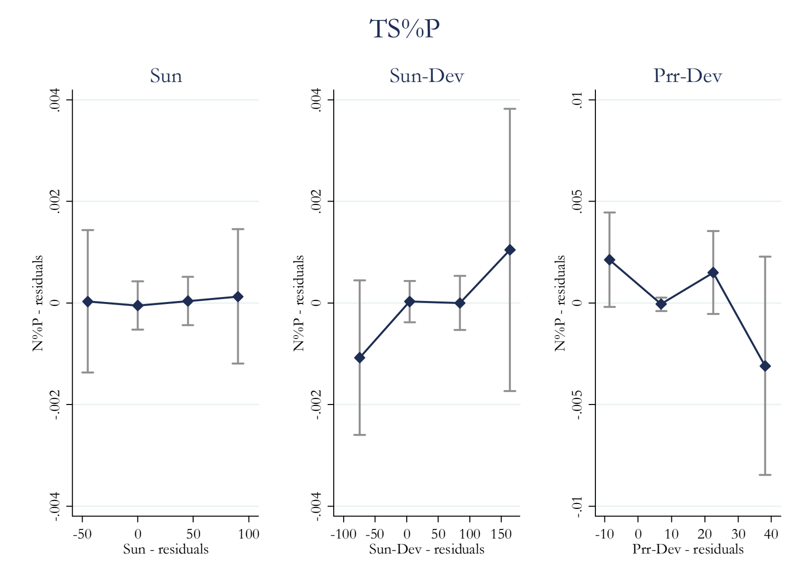
Appendix G - Visual display of residuals from FE regressions

Figure 10 - Visual display of $Weather_w$ and $Net\ activity$ residuals

Table displays residuals from regression specification (X) for $Net\ activity$ and (Y) for $Weather_w$, that did not meet the instrument significance condition, removing day and investor fixed effects. Graphs are created by dividing distance between min and max value of residual Sun, $Sun - Dev$ and $Prr - Dev$ from regression (X) respectively into 4 equal sized bins. Mean and standard deviation of corresponding trading behaviour variable is then calculated for values in each bin. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $N\%P$measures net change in value from instruments group that have changed volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i.Sun is measured as % of sunlight between 12-13 UTC. Prr is the cumulative precipitation in mm between 6 UCT at time t and 6 UCT at time $t+1$. Variables ending with $-Dev$ refer to deviations of actual weather at time t from forecast at time $t-1$ for time t.






TS%P
Sun
Sun-Dev
Prr-Dev
N%P - residuals
.004
.002
0
-.002
-.004
.01
.005
-.005
-.01
-50
0
50
100
Sun - residuals
-100
150
Sun-Dev - residuals
-10
10
20
30
40
Prr-Dev - residuals

Appendix H - Comparison of actual sample and control sample

Figure 11 - Actual vs. Control sample - Total activity per investor histogram

Histogram of $Total\ activity_i$ per household investor i by actual sample and control sample. Actual sample are accounts that have done more than 32 commission generating trades during Jan 2009 Sep 2011. Control sample has done less than 32 commission generating trade during the same period. $Total\ activity_i$ is the sum of $Total\ acitivity_{i,t}$across time period $t = 1$…529. $Total\ activity_{i,t}$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise.

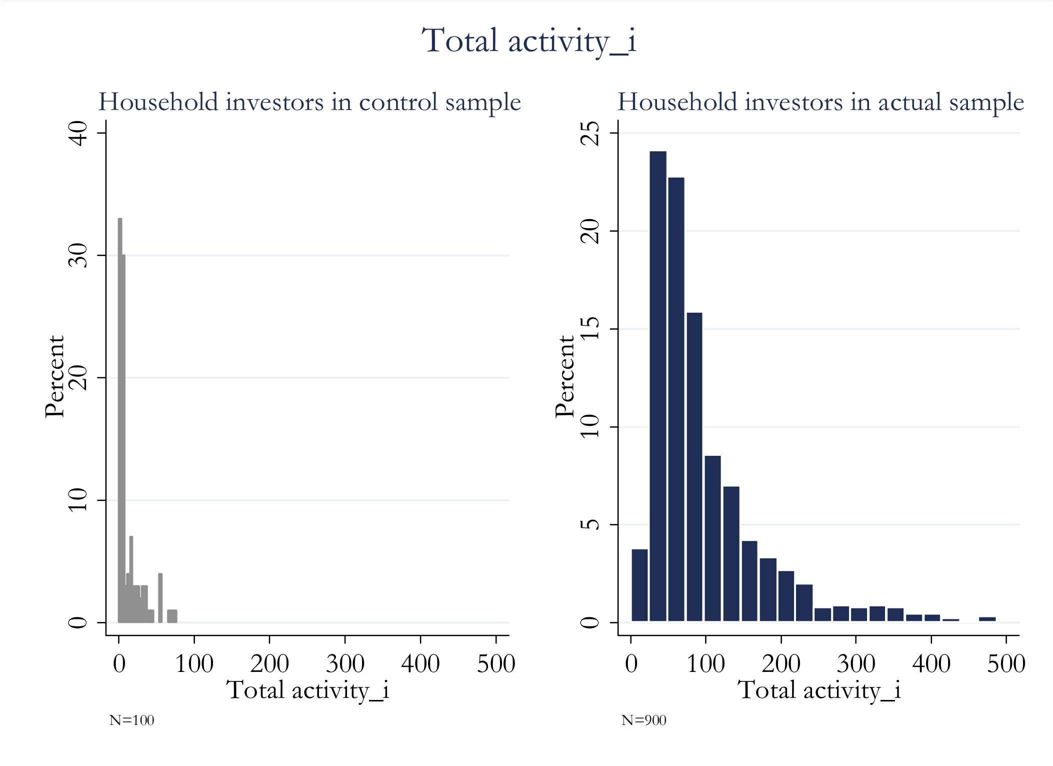


Table 22 - Actual vs. Control sample - Summary stats of trading behaviour

Table summarises trading behaviour variables, Y_v by actual sample and control sample. Actual sample are accounts that have done more than 32 comission generating trades during Jan 2009 Sep 2011. Control sample has done less than 32 comission generating trade during the same period. Values are averages per household investor i over the sample period, T=529. Sample consists of 900 household investor i. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$measures net change in value from instruments group that have changed volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i.

	$Y_{v,i}$	Mean	SD	p25	Median	p75
Actual sample	$Total\ activity_i$	0.18	0.15	0.09	0.14	0.23
	$Net\ activity_i$	0.02	0.04	0.002	0.02	0.04
	$N\%P_i$	0.0%	0.5%	-0.1%	0.0%	0.1%
	$TS\%P_i$	2.0%	3.0%	0.5%	1.0%	2.2%
Control sample	$Total\ activity_i$	0.02	0.033	0.09	0.14	0.23
	$Net\ activity_i$	0.01	0.03	0	0	0.07
	$N\%P_i$	0.0%	0.5%	-0.0%	0.0%	0.0%
	$TS\%P_i$	0.2%	0.5%	0.0%	0.0%	0.1%

Figure 12 - Actual vs. Control sample - Total activity over time

Line diagram of $Total\ activity_t$ over time by actual sample and control sample. Actual sample are accounts that have done more than 32 comission generating trades during Jan 2009 Sep 2011. Control sample has done less than 32 commission generating trade during the same period. $Total\ activity_t$is the sum of $Total\ activity_{i,t}$ per day over all investors $i = 1 \dots 900$. $Total\ activity_{it}$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise.

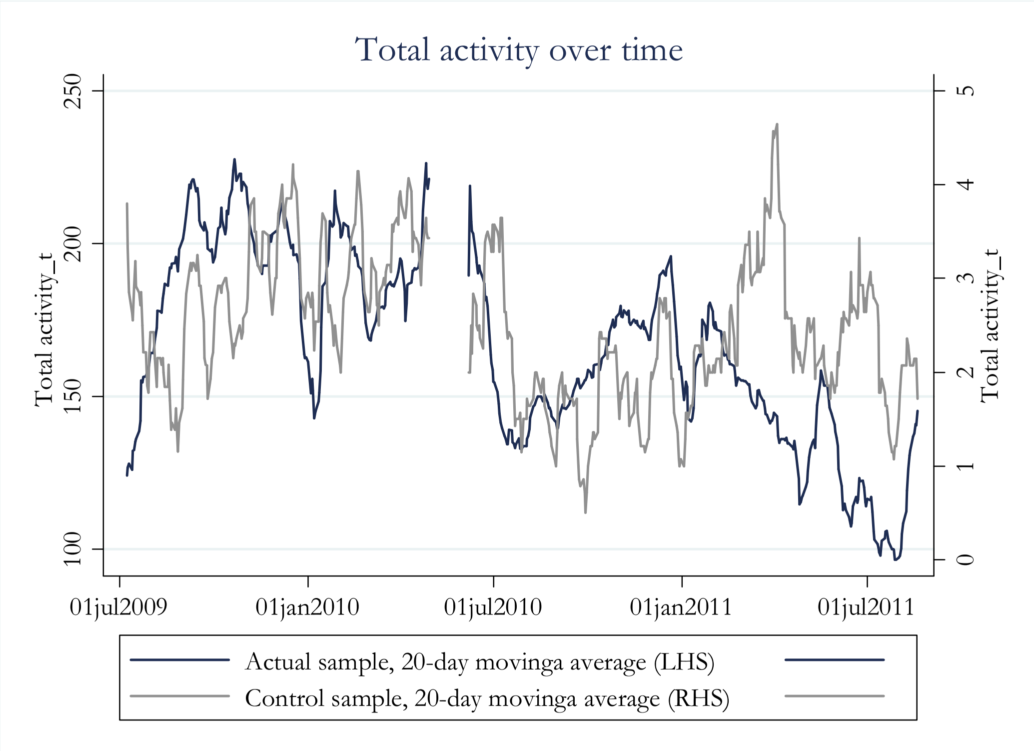
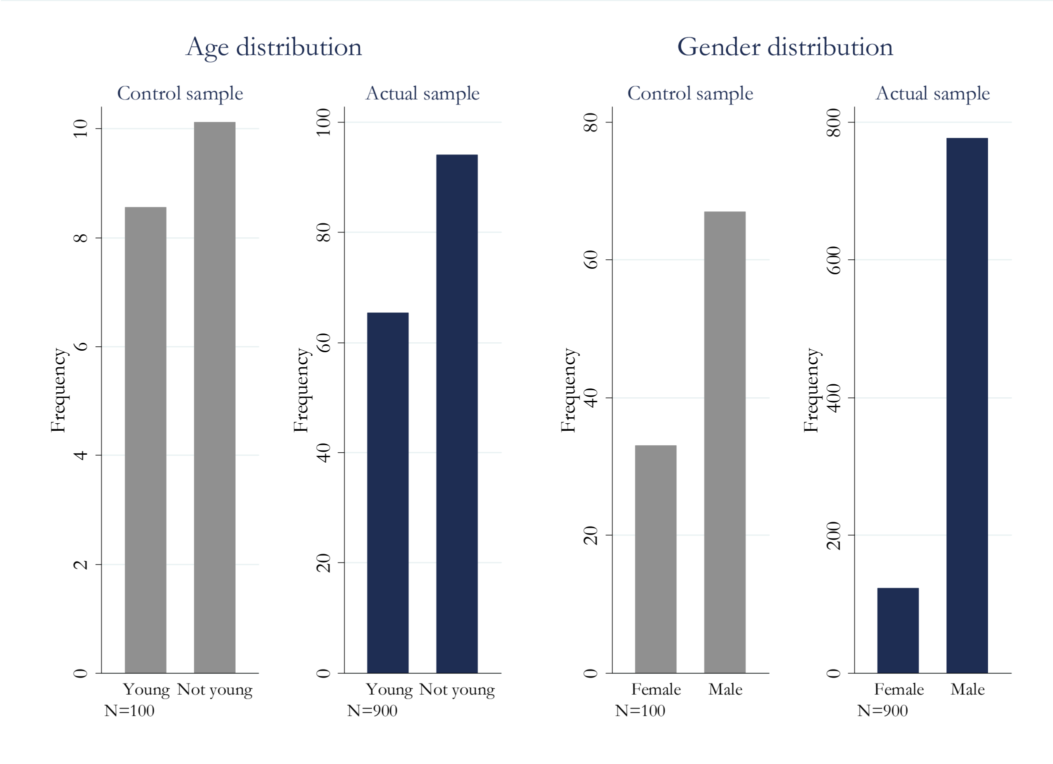
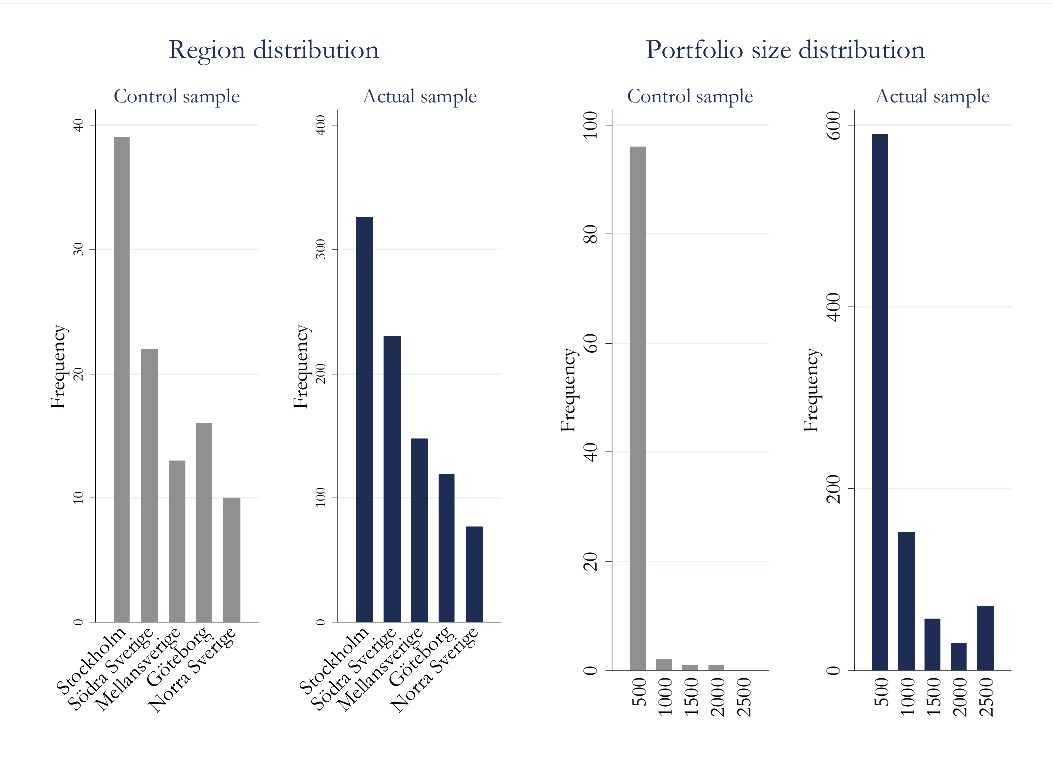


Figure 13 - Actual vs. Control sample - Demographical breakdown

Household investor data split by 4 demographic dimension: Gender, Age, Region and Portfolio size. Data displayed by actual sample and control sample. Actual sample are accounts that have done more than 32 commission generating trades during Jan 2009 Sep 2011. Control sample has done less than 32 commission generating trade during the same period. Portfolio size is calculated as average absolute value across sample period. Region classification is based on zip codes.





Appendix I - IV regression and naïve regression using week dummies

Table 23 - IV regression using week dummies

Table displays the estimates from 2SLS IV estimate using specification (21) and (22) of $Net\,mood$ on trading behaviour variables but with week dummies rather than month dummies to account for time fixed effects. Estimates for these are omitted from the table. The regression only includes household investors living in Stockholm region. Trading behaviour variables are converted from individual to Stockholm values by taking the average investor i per time t for all investors in Stockholm. At the individual level, $Total\,activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\,activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$ measures net change in value from instruments group that have changed volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. Sun is measured as % of sunlight between 12-13 UTC. Prr is the cumulative precipitation in mm between 6 UCT at time t and 6 UCT at time $t+1$. Variables ending with $-Dev$ refer to deviations of actual weather at time t from forecast at time $t-1$ for time t. $Net\,mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Total Activity			Net		
(Instrument)	(Sun)	(Sun - Dev)	(Prr - Dev)	(Sun)	(Sun - Dev)	(Prr - Dev)
Net mood	-0.214	0.026	-0.511	0.331+	0.334+	0.421
	[0.207]	[0.256]	[0.324]	[0.190]	[0.202]	[0.356]
	(-1.03)	(0.10)	(-1.58)	(1.74)	(1.65)	(1.18)
Constant	0.365	0.097	0.697+	-0.362+	-0.365	-0.463
	[0.231]	[0.289]	[0.363]	[0.214]	[0.226]	[0.399]
	(1.58)	(0.33)	(1.92)	(-1.69)	(-1.61)	(-1.16)
Adj R^2	0.316	0.146	0.286	-0.471	-0.478	-0.750
N	515	515	528	515	515	528

	N%P			TS%P		
(Instrument)	(Sun)	(Sun - Dev)	(Prr - Dev)	(Sun)	(Sun - Dev)	(Prr - Dev)
Net mood	0.021	-0.023	0.053	-0.079+	0.014	-0.137+
	[0.077]	[0.072]	[0.098]	[0.048]	[0.052]	[0.076]
	(0.27)	(-0.31)	(0.54)	(-1.65)	(0.27)	(-1.80)
Constant	-0.023	0.026	-0.059	0.103+	-0.000	0.168*
	[0.086]	[0.081]	[0.110]	[0.053]	[0.058]	[0.085]
	(-0.26)	(0.32)	(-0.54)	(1.93)	(-0.00)	(1.98)
Adj R^2	-0.044	-0.042	-0.094	0.131	-0.019	-0.076
N	515	515	528	515	515	528

Note: T-stats are in parentheses and standard errors in square bracket Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

Robust standard errors are used

Table 24 - Naive regression using week dummies

Table displays results from regression specification (X) looking at naïve correlation between $Net\ mood$ and each trading behaviour variable respectively. Week dummies were used to account for time fixed effects. Estimates for these are omitted from the table. $Total\ activity$ equals 1 if volume has changed in any instrument group from $t-1$ to t and 0 otherwise. $Net\ activity$ indicates if investor i has increased volume in any instrument group (=1), decreased volume in any instrument group $(=-1)$ or both $(=0)$ from time $t-1$ to t. $N\%P$measures net change in value from instruments group that have changed volume from time $t-1$ to t as % of average portfolio of household investor i. $TS\%P$ measures the average of absolute value changes from instrument groups that have increased or decreased from time $t-1$ to time t, relative to average portfolio of investor i. $Net\ mood$ captures the ratio of positive mood to negative mood on a daily basis.

	Total activity	Net activity	N%P	TS%P
Net mood	-0.317***	-0.091***	-0.007+	-0.040***
	[0.040]	[0.016]	[0.004]	[0.007]
	(-7.92)	(-5.56)	(-1.67)	(-5.79)
Constant	0.492***	0.106***	0.008	0.060***
	[0.048]	[0.019]	[0.005]	[0.008]
	(10.22)	(5.56)	(1.45)	(7.19)
Adj R^2	0.007	0.001	0.000	0.001
N	475 976	475 976	475 976	475 976

Note: T-stats are in parentheses and standard errors in square bracket — Significance: + p<0.1 * p< 0.05 ** p< 0.01 *** p< 0.001

Standard errors used are clustered at both investor and day dimension