Google Search Volume and Individual Investor Trading

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ABSTRACT

In this study, we relate Google search volumes to individual investor trading. We follow Da, Engelberg, and Gao (2015) and construct a daily sentiment index ($FEARS$) based on search volumes of negative terms in Google for the German market. We match $FEARS$ with a dataset of individual investor trades from a large German discount brokerage for the period July 2005 through June 2015. We find that when $FEARS$ is high (sentiment is low), individual investors trade more; conditional on trading, when $FEARS$ is high, investors trade out of risky assets. Effects are particularly strong for less sophisticated investors.

JEL classification: D03, D14, G02; G11

Keywords: individual investor; trading behavior; investor sentiment

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1 Introduction

Research has produced ample evidence that investor sentiment has an impact on financial market outcomes. Prime examples are the papers by Baker and Wurgler (2007), Tetlock (2007) and Da, Engelberg, and Gao (2015). Baker and Wurgler (2007) construct a monthly investor sentiment index with market-based measures such as trading volume, number of IPOs or closed-end fund discounts and show that this index predicts market returns. Tetlock (2007) finds a significant relationship between the negativity in columns published in the Wall Street Journal and the stock market. A closely related strand of literature examines how asset prices are affected by non-economic events such as sports (Edmans, Garcia, and Norli (2007)), aviation disasters (Kaplanski and Levy (2010)), weather (Hirshleifer and Shumway (2003)) and seasonal affective disorder (Kamstra, Kramer, and Levi (2003). These results are interpreted as being consistent with theories of noise trading (De Long et al. (1990)).

Da, Engelberg, and Gao (2015) propose a daily sentiment index based on Google search queries ($FEARS$), measuring economic expectations or concerns of millions of households. They show that $FEARS$ significantly affects stock market outcomes. A natural extension is to directly test for a relationship between investor sentiment, as measured by economic expectations or concerns, and individual investors' trades. According to the noise trader hypothesis, one would expect retail investors to be the ideal group to test for the existence of this relationship, because they are commonly considered most susceptible to sentiment (Lee, Shleifer, and Thaler (1991), Kumar and Lee (2006))[2]. By directly testing for effects of $FEARS$ on a micro level and differentiating investors by their sophistication level and other socio-demographic characteristics, we find economic expectations or concerns to significantly affect individual investor trading: When expectations are bad, investors trade more and rather sell securities. We find the effects to be particularly pronounced for less sophisticated investors. When additionally taking weather into account, we find weather and $FEARS$ to be uncorrelated. However, both effects turn out to be significant. Economically, the effects for the direction of trading are comparable whereas the effect for the trading volume is about 50% larger for $FEARS$.

We closely follow Da, Engelberg, and Gao (2015) to construct a German version of the $FEARS$ index. $FEARS$ is based on negative search term volumes such as "financial crisis," "recession"

[2] Greenwood and Nagel (2009) suggest that young mutual fund managers are more likely to exhibit trend-chasing behavior. Kumar and Lee (2006) and Barber, Odean, and Zhu (2009) document individual investor herding. These papers use micro-level data and find results that could be consistent to investor sentiment theory as well.

or “bankruptcy”. Thus, it is a pessimism index. In behavioral finance literature, there have been several attempts to construct an optimal investor sentiment index. We decide to use $FEARS$ rather than another measure because of three reasons: First, it is available at a daily frequency. Second, it is more likely to appropriately capture investor sentiment.[3] Third, because it is shown to robustly predict stock market outcomes in a way that is consistent to investor sentiment theory (Da, Engelberg, and Gao (2015)).

We then combine the German $FEARS$ index, which is available from July 2005 to June 2015 with daily trading records of retail investors. This data is from a collaboration with a large German discount brokerage. Another important feature of this database is that it allows us to focus on the trades of self-directed clients only. To do so, we exclude all trades that have not been initiated by the customer him- or herself, but got merely executed on a specific day (e.g., saving plan transactions or limit orders). Hence, the sample is only comprised of the discretionary trades of investors. Moreover, we obtain data on investor demographics such as academic titles, gender or age, as well as detailed information on traded securities, such as asset class, or risk class.

We employ panel regressions with investor fixed effects. We use two measures of (excess) purchases relative to sales and one measure of (excess) overall trading activity. The inclusion of various investor-, market-, and calendar-specific control variables, as well as month and year fixed effects provides a safeguard against spurious correlations and helps to differentiate between novel and already known effects. Additionally, we find our results to be robust to various clustering strategies of standard errors, such as clusters by person or by zip-codes.

We find a significant relation between private investors’ trading and investor sentiment. On days with high $FEARS$, investors appear to trade more, particularly selling rather than buying assets. In addition, when $FEARS$ is high, retail investors trade out of risky assets. To further analyze whether the impact of investor sentiment is particularly strong for unsophisticated investors, we estimate the differences in the effects of $FEARS$ between sophisticated and unsophisticated investors. We use three different proxies of investor sophistication: investors’ diversification measured by the Herfindahl-Hirschmann Index (HHI) as a proxy for investment mistakes; academic titles as a proxy for intelligence and education; and gender as woman have been found to generally make more patient and less overconfident investment decisions (Barber

[3] For a more extensive discussion about this, refer to Da, Engelberg, and Gao (2015).

and Odean (2001)). The degree of diversification is a good measure of financial sophistication, because it directly measures an investment mistake (Calvet, Campbell, and Sodini (2009)). Let alone, the academic title and gender are imperfect proxies for sophistication, but good additional tests. The results we obtain suggest that the effect of investor sentiment is more pronounced for less sophisticated investors.

The results do not depend on our choices regarding the minimum number of trades per year and investor in order to be included in the dataset. In our main analysis, we set the minimum number of trades to one. Setting this threshold to five or ten trades per year and investor yields qualitatively comparable results. Our results neither depend on the construction of the excess trading variables, as we find our results to be robust to an alternative demeaning procedure, which rules out a potential look-ahead bias. Moreover, the results regarding the trading activity also hold if we apply a linear probability model, suggesting that if sentiment is low, the probability to trade significantly increases. Additionally, controlling for weather conditions (air pressure) or particularly focusing on financial crises does not alter results either. In fact, during financial crises the impact of investor sentiment on the trading behavior of individual investors is even larger. Finally, we show that our findings are not subject to concerns about reverse causality, as market outcomes do not drive $FEARS$.

Most closely related to our paper is Da, Engelberg, and Gao (2015) and Schmittmann et al. (2014). The contributions of our paper are distinctly different from each of these papers: Our first contribution is that investor sentiment, measured as expectations or concerns about the economic perspective, drives individual investor trading. Quite in contrast to our study, Da, Engelberg, and Gao (2015) examine the impact of $FEARS$ on the market level. They include a short and minor test of equity and bond mutual funds and find that $FEARS$ also influences the flows of these assets. They further argue that individual investors might be more likely to hold mutual funds and therefore, this analysis provides ”[…] a more direct test of the “noise trading” hypothesis […]”. While the mutual fund flow analysis by Da, Engelberg, and Gao (2015) might well be a more direct test of the noise trader hypothesis than their main market test, our paper, to the best of our knowledge, is the first study that tests this hypothesis by directly exploring more than 23 million trades of individual investors with assets of all types. Beyond using micro level data, instead of aggregate market data, we are able to distinguish between various investor groups. With respect to Schmittmann et al. (2014), who show that weather induced mood is a factor that influences retail investor trading, our paper differs in that it investigates the impact of $FEARS$—that is, the impact of expectations or concerns about the economic perspective—

on individual investor trading. The effect of $FEARS$ is beyond and distinctly different from the weather-effects found in the literature. We show this in multiple ways: First, the correlation between $FEARS$ and the weather is -0.008 and statistically not different from zero. Second, when controlling for weather, our results remain fully unchanged both in terms of magnitude as well as statistical significance. Third, we show that weather has no causal impact on $FEARS$. Our second contribution is that we empirically show the sentiment theory prediction that unsophisticated investors are more prone to sentiment than sophisticated investors. To the best of our knowledge, neither Da, Engelberg, and Gao (2015) nor Schmittmann et al. (2014) nor any other study of the existing literature provide such a direct test.

Our paper also adds to the literature on exploring why investors trade. These studies show that private investors trade because a security has attracted their attention through news (Barber and Odean (2008)), because the past day's returns were large (Barber and Odean (2008), Grinblatt and Keloharju (2001)), because the weather is bad (Schmittmann et al. (2014)) or because of superstition (Bhattacharya et al. (2016)). Our study is a natural expansion of this strand of literature, as we find that sentiment drives individual investor trading and particularly unsophisticated investors.

The remainder of this paper proceeds as follows: In Section 2, we provide an overview of our dataset and detail how we construct $FEARS$ for Germany. Section 3 develops hypotheses and discusses our empirical approach. Section 4 presents the effects of $FEARS$ on retail investors. Section 5 contains various additional tests and robustness checks. We conclude in Section 6.

2 Data

In this section, we describe our data and discuss all calculated measures. We start with the construction of the $FEARS$ index, as this is the main variable of interest in this study.

2.1 Construction of the $FEARS$ index

In constructing the $FEARS$ index for the German market, we closely follow Da, Engelberg, and Gao (2015). Our first step is to identify all relevant German words that are associated with expectations about economic conditions. Text analytics literature in finance usually uses the Harvard IV-4 Dictionary and the Lasswell Value Dictionary (Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008)). These Dictionaries classify words as "positive" or "negative". Moreover, they classify words into other categories such as "economic". Since Da, Engelberg, and Gao (2015) are interested in the sentiment of households towards the economy, they chose to analyze all words that are labeled as "economic" and as either "positive" or "negative". However, to the best of our knowledge, there are no such dictionaries for the German language available. Therefore, we translate the English words that are used by Da, Engelberg, and Gao (2015) with four major German-English dictionaries—Langenscheidt Routeledge Fachwörterbuch Wirtschaft, Elsevier's Economics Dictionary, Gablers Wirtschaftswörterbuch and Dictionary of Legal Commercial and Political Terms. We use the translation that is obtained most often. Additionally, a translation is only used, if it has a common linguistic usage. This is tested by checking examples in Linguee (http://www.linguee.de/).

Since $FEARS$ is supposed to measure investor sentiment through Google searches, Da, Engelberg, and Gao (2015) check how people search for these words. Accordingly, we use Google Trends, which provides for each entered word ten related "top search". For instance, if one checks the English word "deficit", Google Trends comes up with related searches such as "budget deficit," "attention deficit," "attention deficit disorder" or "federal deficit". By collecting all related search terms, we get a list of 1.062 search terms. After removing all search terms that have no economic relevance, we are left with 289 words.[4]

In a next step, we download the daily search volume index (SVI) for the period January 2005 through December 2015 of all search terms that have sufficient daily data available and do not include German umlaut, because words that include umlaut cannot be downloaded. The final number of downloaded SVI is 198. We restrict the downloads to Germany, because we are interested in a German investor sentiment index, as we analyze German individual investors. Following Da, Engelberg, and Gao (2015), we define the change in SVI of search term j as:

$$\Delta SVI_{j,t} = \ln(SVI_{j,t}) - \ln(SVI_{j,t-1}) \tag{1}$$

In order to account for any outliers, we winsorize each $\Delta SVI_{j,t}$ time series at the 5%-level (2.5% in the lower and 2.5% in the upper tail). Da, Engelberg, and Gao (2015) shows that seasonality might be an issue when analyzing Google search volumes. Therefore, we regress each $\Delta SVI_{j,t}$ on day-of-the-week and month-of-the-year dummy variables and keep the residuals. Finally, to make all $\Delta SVI_{j,t}$ comparable and to ease combining time series, we standardize them by dividing each time series by its standard deviation. In order to keep consistency with Da,

[4] For a more extensive discussion on how Google Trends works see Da, Engelberg, and Gao (2015).

Engelberg, and Gao (2015), we denote the resulting adjusted (winsorized, deseasonalized and standardized) log-changes of SVI by $\Delta ASVI_{j,t}$.

Then, for each period, we identify which search terms are most relevant for the market returns. Specifically, we run expanding backward rolling regressions (every 180 days (half year) the window expands by 180 days) and regress contemporaneously the CDAX on one out of 198 $\Delta ASVI_{j,t}$ at a time.[5] CDAX is a German composite stock market index that captures all stocks tradeable on German's Frankfurt stock exchange. Then, for each period, we keep the 30 search terms with the most negative t-statistics and use them to calculate $FEARS$ for the next 180 days.[6,7] For example, we run a regression from January 3, 2005 through July 1, 2005, we keep the 30 terms with most negative t-statistics and use them to calculate $FEARS$ for the period July 2, 2005 through December 28, 2005.

Finally, we construct the $FEARS$ index at day t as the average $\Delta ASVI$ on that day of the words with the most negative t-statistics of the regressions covering the period January 2005 through the most recent 180-day period:

$$FEARS_t = \frac{1}{30}\sum_{i=1}^{30} R^i\left(\Delta ASVI_t\right) \tag{2}$$

$R^i(\Delta ASVI_t)$ is the $\Delta ASVI_t$ of the search term with the rank i in the corresponding regression. Since this procedure needs 180 days of initial data to calculate $FEARS$, our sample period begins in July 2005. Keep in mind that all choices made in the construction of $FEARS$ are to ensure consistency with the $FEARS$ index of Da, Engelberg, and Gao (2015).[8]

2.2 Investor Data

In cooperation with a large German discount broker, we obtain a large dataset of daily account information for the trades and portfolio holdings of investors. We match these data with our $FEARS$ index for the German market from July 2005 through June 2015. One important characteristic of our investor data is that we are able to identify self-directed investors. In order

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[5] Consequently, the first period covers 180 days, the second period covers 360 days (= 2 x 180), the third period covers 540 days (= 3 x 180) and so on.

[6] Da, Engelberg, and Gao (2015) decide to use thirty words, because thirty is usually considered as the minimum number of observations to diversify away the idiosyncratic noise of a variable.

[7] Tetlock (2007) as well as Da, Engelberg, and Gao (2015) find that negative words are more likely to capture investor sentiment.

[8] For a more detailed discussion why choices are made this way, see Da, Engelberg, and Gao (2015).

to ensure that we are looking at their self-driven behavior, we exclude all investors who use financial advice and are hence not self-directed. Further, we exclude transfers among personal accounts, saving plans, and trades from limit orders[9], because this type of transaction does not reflect the current trading decisions of investors.[10] We keep only private investors that reside in Germany, as their trading decisions should be directly affected by German investor sentiment. In online brokerage, silent attribution is a common phenomenon, as usually having an account is free of charge. Therefore, in order not to analyze the accounts of investors who stopped trading, we require that they make at least one trade per year. Requiring five or ten instead of one trade per year does not change our results qualitatively. Table I shows that these restrictions leave us with a sample of 103,093 investors and approximately 23.3 million trades, with a transaction value of € 154.1 billion. For all the trades, 54.1% are buys (approximately 12.6 million trades and € 83.2 billion), whereas 45.9% are sales (approximately 10.7 million trades and € 70.9 billion). The average age of investors is 53 and the median age is 52. 16.9% of our sample is female and 83.1% is male.

[Insert Table I about here]

2.3 Trading variables

Following Schmittmann et al. (2014), we calculate three trading variables that help us to describe the trading patterns of investors. We calculate all trading variables on a daily basis. Since we want to detect abnormal trading behavior, we form excess rather than absolute measures. We use two measures for purchases relative to sales. The first variable, as shown in Equation (3), measures the excess buy-sell imbalance regarding the number of transactions, whereas the second variable, shown in Equation (4), measures the excess buy-sell imbalance on the basis of transaction values. For the sake of maximized transparency and robustness, both measures should be considered.[11] We define the excess buy-sell imbalance of investor *i* at day *t* as the buy-sell imbalance of this investor at this date minus her average buy-sell imbalance in the corresponding year *y*:

[9] See Linnainmaa (2010).
[10] Saving plan transactions and trades from limit orders do represent trading decisions. However, these decisions are made in the past or are influenced from other sources than the daily sentiment, which we are analyzing.
[11] Buy-sell imbalances measured by values could be driven by just a few huge orders. Similarly, the results of buy-sell imbalances measured by the number of trades are not necessarily economically relevant, if, for example, the underlying value is too small.

$$ExBS^{\#} = \frac{Buy_{i,t}^{\#}}{Buy_{i,t}^{\#} + Sell_{i,t}^{\#}} - \frac{Buy_{i,y}^{\#}}{Buy_{i,y}^{\#} + Sell_{i,y}^{\#}} \tag{3}$$

$$ExBS^{EUR} = \frac{Buy_{i,t}^{EUR}}{Buy_{i,t}^{EUR} + Sell_{i,t}^{EUR}} - \frac{Buy_{i,y}^{EUR}}{Buy_{i,y}^{EUR} + Sell_{i,y}^{EUR}} \tag{4}$$

The third variable measures the excess overall trading activity. We calculate the log excess trading volume (Equation (5) by subtracting the natural logarithm of the average trading volume of investor *i* of the corresponding year *y*, measured in number of trades, from the natural logarithm of trading volume of the same investor at day *t*, also measured by number of trades.[12]

$$ExTr^{\#} = \ln\left(Tr_{i,t}^{\#}\right) - \ln\left(Tr_{i,y}^{\#}\right) \tag{5}$$

2.4 Security Riskiness

In order to gain further insights into the effects of investor sentiment on the trading behavior of households, we distinguish between trading in risky and less risky assets. The German Security Trading Act makes it mandatory for financial institutions to classify each security on a five-point scale (1 through 5) based on each asset's riskiness. Very save investments such as AAA-rated government bonds are labeled with 1. Very risky securities such as options or futures are labeled with 5. This information needs to be made salient to investors. Therefore, the risk perception of our investors regarding an asset's risk level depends on the risk class according to the German Security Trading Act, which we are provided with. We use these risk classes to differentiate between trades with risky and less risky assets. Table II presents the distribution of transactions across risk levels.

[Insert Table II about here]

Using this classification, we define the buy-sell imbalance for risky (Equation (6) and Equation (7)) and less risky (Equation (8) and Equation (9)) assets similar to Equation (3) and Equation (4), by only considering purchases for risky or less risky assets in the numerators, respectively.

[12] We transform every component of Equation (5) by applying the natural logarithm, because the number of trades is highly skewed.

We define an asset as risky if it belongs to risk level 4 and above and as less risky if it belongs to risk level 3 and below.[13]

$$ExBS^{\#}_{Risky} = \frac{Buy^{\#,Risky}_{i,t}}{Buy^{\#}_{i,t} + Sell^{\#}_{i,t}} - \frac{Buy^{\#,Risky}_{i,y}}{Buy^{\#}_{i,y} + Sell^{\#}_{i,y}} \tag{6}$$

$$ExBS^{EUR}_{Risky} = \frac{Buy^{EUR,Risky}_{i,t}}{Buy^{EUR}_{i,t} + Sell^{EUR}_{i,t}} - \frac{Buy^{EUR,Risky}_{i,y}}{Buy^{EUR}_{i,y} + Sell^{EUR}_{i,y}} \tag{7}$$

$$ExBS^{\#}_{Less\ Risky} = \frac{Buy^{\#,Less\ Risky}_{i,t}}{Buy^{\#}_{i,t} + Sell^{\#}_{i,t}} - \frac{Buy^{\#,Less\ Risky}_{i,y}}{Buy^{\#}_{i,y} + Sell^{\#}_{i,y}} \tag{8}$$

$$ExBS^{EUR}_{Less\ Risky} = \frac{Buy^{EUR,Less\ Risky}_{i,t}}{Buy^{EUR}_{i,t} + Sell^{EUR}_{i,t}} - \frac{Buy^{EUR,Less\ Risky}_{i,y}}{Buy^{EUR}_{i,y} + Sell^{EUR}_{i,y}} \tag{9}$$

2.5 Control variables

We include several control variables in our panel regression of different trading variables on $FEARS$. We do so to avoid picking up effects that have already been found in previous studies. In this section, we discuss all our control variables. Table III list all control variables.

[Insert Table III about here]

The first group of controls consists of variables that generally explain trading patterns of private investors. Previous stock market returns may affect the trading behavior of households (Gervais, Kaniel, and Mingelgrin (2001), Barber and Odean (2008), Grinblatt and Keloharju (2001)). In addition, Garcia (2013) shows that investors react to news with a certain time lag. Thus, momentum could play a role in the decision making of households. Therefore, we include three momentum control variables to the right hand side of our regressions. First, a preceding-one-day realized market return variable, second a squared preceding-one-day realized market return variable, and third a preceding-three-month realized market return variable. Since our investor data cover German retail investors (see Section 2.2) we use the CDAX. Including the

[13] Results are robust regarding cut off points for definition of risky and less risky.

preceding-one-day market return and the squared preceding-one-day market return, implicitly provides control for macroeconomic announcements and earnings announcements.

Wealth plays a major role in decision making of households (Carroll (2002), Carroll , Wachter and Yogo (2010)). For instance, Carroll (2002) generates evidence that risk aversion decreases in wealth. In order to account for wealthy investors' trading patterns and to not allow a few huge orders of wealthy investors to drive our results, we control for wealth. We measure wealth as the natural logarithm of the sum of all assets an investor holds at the end of the preceding month.

Our second group of control variables is related to calendar dates, such as holidays, public holidays, and months. School holidays may also impact trading behavior of private investors. Indeed, Hong and Yu (2009) show that during school holidays, trading volume is significantly lower. Therefore, we add a holiday dummy that varies across states, as different states in Germany have different holiday periods. In order to control for abnormal trades just before going on vacation or just after arriving from vacations[14], we insert two more dummy variables: one for the last trading day before vacation and one for the first trading day after vacation. Since public holidays could also have the same effect as school holidays, we include three additional dummy variable: one for public holidays, one for the last trading day before public holidays and one for the first trading day after public holidays.

In our sample, investors trade predominantly on German exchanges. It could be that on days with no trading at Deutsche Börse investors trade significantly less. To control for this effect, we append a dummy variable for days with no trading at Deutsche Börse.

Previous studies find anomalies on capital markets that are associated with the turn of the month (Ariel (1987), Lakonishok and Smidt (1988)) and the turn of the year (Rozeff and Kinney (1976), Reinganum (1983), Jones, Pearce, and Wilson (1987), Ritter (1988), Ritter and Chopra (1989)). Therefore, we add dummy variables for the first and last trading day of the month and year. Likewise, French (1980), Lakonishok and Maberly (1990), Gibbons and Hess (1981), Keim and Stambaugh (1984), Rogalski (1984) find anomalies on Mondays and Fridays. Thus, we insert two more dummy variables that control for Mondays and Fridays.

[14] One could for instance sell all risky positions just before going on vacation and rebuy risky positions right after returning from vacations, because of limited access to her account or simply because of other personal reasons such as forgetting about daily stress.

Other well-known anomalies are related to human biorhythms (Kamstra, Kramer, and Levi (2000), Kamstra, Kramer, and Levi (2003), Pinegar (2002)). Therefore, we control for the seasonal affective disorder (SAD). We measure SAD as in Kamstra, Kramer, and Levi (2003). Further we include two dummy variables for Mondays following changes in day light saving time: one for advancing clocks and one for adjusting them backwards.

Lastly, we incorporate month fixed effects and year fixed effects into the regressions. This ensures that our results are not driven by single months-of-the-year or years-of-the-period (for example, extreme years for the German financial market, such as 2008), or any other slow-moving seasonality effects. In addition, months fixed effects control for the tax-induced trading behavior of retail investors (Rozeff and Kinney (1976), Keim (1983), Roll (1983), Grinblatt and Keloharju (2001)).

3 Hypotheses and Empirical Approach

In this section, we develop our three main hypotheses. We also discuss our empirical approach. Baker and Wurgler (2007) define investor sentiment, as the "…belief about future cash flows and investment risks…". Baker and Wurgler (2006) define investor sentiment as "…optimism or pessimism...". According to these definitions, when $FEARS$ is high—that is, when investor sentiment is low—people tend to be more pessimistic about future cash flows and asset prices in general. Hence, they would rather place sell instead of buy orders. This leads us to posit the following hypothesis:

Hypothesis 1 (H1): When $FEARS$ is high, individual investors purchase less.

We test *H1* using our two excess buy-sell imbalance trading variables (Equation (3) and Equation (4)). Further, we expect low investor sentiment, as measured by high $FEARS$, to reduce risk-prone trading. This statement is in line with the Affect Infusion Model, which posits that negative affect increases the degree of risk-aversion (Forgas (1995), Bassi, Colacito, and Fulghieri (2013)). Therefore, we hypothesize:

Hypothesis 2 (H2): When $FEARS$ is high, individual investors trade out of risky assets.

We validate *H2* using our four risky and less risky asset excess buy-sell imbalance variables (Equation (6) – Equation (9)). With respect to the trading activity, two hypotheses are reasonable. Both are already backed by empirical studies on the market level. First, we posit that when $FEARS$ is high—that is, when people worry about the economic perspective—they might see more need to change their portfolios. It is important to note that we are measuring excess trading. That means that, given an investor is currently trading—that is, given an investor is currently thinking about her portfolio—she actively decides to change more, when investor sentiment is bad.[15] This hypothesis is consistent with Da, Engelberg, and Gao (2015), who find that $FEARS$ temporary increases market volatility.[16] Therefore, we conjecture to observe more trading activity on days where $FEARS$ is high. Consequently, we hypothesize:

Hypothesis 3a (H3a): When $FEARS$ is high, individual investors trade more.

Second, sentiment theory also suggests that extreme sentiment values—that is, very high or very low values of $FEARS$—induce trading. This is consistent with Tetlock (2007), who find that high absolute sentiment levels drive market volume. Hence, we also hypothesize:

Hypothesis 3b (H3b): When $FEARS$ is extreme, individual investors trade more.

We test *H3a and H3b* by examining the excess overall trading activity (Equation (5). Since the noise trader hypothesis suggests that unsophisticated investors are more prone to investor sentiment, we expect all effects to be more pronounced for the less sophisticated part of our sample (De Long et al. (1990)). We test these hypotheses by performing investor fixed effects panel regressions that look as follows:

$$TM_{i,t} = \alpha + \beta FEARS_t + \gamma C_{i,t} + \varepsilon_{i,t} \tag{10}$$

TM represents the trading measure. $FEARS$ is our Financial and Economic Attitudes Revealed by Search index, which proxies investor sentiment in the German market. C is a vector of variables including all control variables discussed in Section 2.5. i stands for an individual investor and t stands for a certain trading day. The effect we are interested in is β. If our hypotheses hold, β should have the expected sign and be statistically significant. We use clustered standard errors at the level of individual investors, in order to account for heteroscedasticity and autocorrelation in the residuals. An alternative would be to cluster at the zip code level, to reflect regional commonalities in the portfolios of investors due to the local

[15] In a robustness test, we also check the validity of this hypothesis unconditional on trading. This means that we check whether the probability to trade is higher, when investor sentiment is low.

[16] It has long been known that volatility and volume are driven by the same factors (Lamoureux and Lastrapes (1990)). Hence, it is not surprising that a sizable literature has documented a robust positive contemporaneous relation between volatility and volume for risky market assets (Andersen (1996), Harris (1987), Harris (1986), Upton and Shannon (1979), Rogalski (1978), Clark (1973), Cornell (2000)).

bias (Ivković and Weisbenner (2005)) or the word-of-mouth effect (Hong, Kubik, and Stein (2004)). Using zip code clusters does not qualitatively affect the significance reported.

We perform regressions in the manner of Equation (10) in several ways. In order to test our four hypotheses, we run these regressions with different trading measures. We use six buy versus sell measures. Two measures for all the assets in our data (Equation (3) and Equation (4)), two for risky assets (Equation (6) and Equation (7)) and two for less risky assets (Equation (8) and Equation (9)) to test *H1* and *H2*. We test *H3a and H3b* by using the excess overall trading activity (Equation (5)). In Section 4.2, we test whether our results are driven by sophisticated or unsophisticated investors. We do this by defining three proxies for financial sophistication and estimating the differences in the effects of $FEARS$ depending on these sophistication proxies.

4 Results

In this section, we present the main results of this paper. In a first step, we show the main effects of $FEARS$ on the trading behavior of the average investor. Next, we analyze how these effects differ across investors of different sophistication levels.

4.1 The effects of investor sentiment on the average investor

Table IV shows coefficient estimates for $FEARS$ of our panel regressions.[17] Panel A of Table IV shows the effects for our excess buy-sell imbalance measures both based on number of trades, as well as on the euro-value of the trades. Panel B displays results for our excess trading measure.

[Insert Table IV about here]

We first focus on trading activity (Panel B). We find strong evidence that when $FEARS$ is high—that is, when investor sentiment is low—private investors trade more (column 1 and 2). For instance, when $FEARS$ increases by one unit, the excess trading volume of the average investor increases by 0.00687. We are able to comfortably reject the null hypothesis that the change of excess trading equals to zero at less than the 1%-level. The coefficient on $FEARS$ diminishes a bit once we include the control variables, year fixed effects and month fixed effects, but the significance remains unchanged. Consistent with *H3a*, when investors worry

[17] Table A.I and Table A.II in the Appendix present coefficient estimates of all control variables.

about the economic outlook, they see more need to change their portfolios and therefore trade significantly more.[18] To test *H3b*, we distinctly analyze the impact of low (smaller than the mean) and high (larger than the mean) $FEARS$ (column 3 to 6). If *H3b* were true, the coefficients of the low $FEARS$ regressions should be negative and the coefficients for the high $FEARS$ regressions should be positive. Instead, we find all coefficients to be positive and significantly different from zero. This rejects *H3b* and strengthens *H3a* even more, which means that individual investors trade most, when sentiment is very low and less, when sentiment is very high.

Turning to the excess buy-sell imbalances (Table IV, Panel A), we also find strong evidence for *H1* and *H2*. By looking at all securities (column 1 through 4), we see that $FEARS$ negatively affects excess buy-sell imbalances no matter what the calculation basis is (number of trades or euro-value of trades). An increase in $FEARS$ is associated with a significant (at the 1%-level) negative excess buy-sell imbalance, which means that retail investors sell rather than buy assets. This evidence provides support for *H1*, where we posit that when investor sentiment is low, people's beliefs about future asset prices in general are overly pessimistic. In detail, when $FEARS$ increases by one unit, the excess buy-sell ratio (based on euro-values of trades) decreases by 0.00915. Again, once we include all control variables as well as year and month fixed effects, coefficients diminish, but significances remain unchanged at the 1%-level.

An important issue is which type of securities drives the observed effect. We expect that when sentiment is low (i.e., $FEARS$ is high), investors sell risky assets (*H2*). We test this prediction by splitting our dataset according to Section 2.4 into two groups: risky and less risky assets.

In fact, columns 5 through 8 of Panel A show that when sentiment is low, private investors trade out of risky securities. Again, the results do not depend on whether trading measures are based on the number or euro-values of trades or on the inclusion of controls as well as year and month fixed effects. Moreover, all coefficient estimates are significant at the 1%-level. For example, when $FEARS$ increases by one unit, the excess buy-sell imbalance (based on number of trades) of risky securities decreases by 0.00891. Apparently, bad sentiment notably drives the average investor out of risky investments. These results are totally in line with *H2*.

[18] In an additional test, we find that when $FEARS$ is high, the probability to trade is higher. This is an additional indication that investors change their portfolios more, when they are pessimistic about the future economic conditions. A more extensive discussion about this analysis and the results are provided in Section 5.3.

Additionally, we find that investors also reduce their exposure to less risky securities, when sentiment is low. Our split between risky and less risky securities is mutually exclusive and collectively exhaustive. Hence, simultaneously selling risky and less risky securities is equivalent to decreasing the risky asset share of a portfolio.

In summary, we find strong evidence for all but one ($H3b$) hypotheses: When $FEARS$ is high—that is, when investor sentiment is low—individual investors trade more; when they trade, they rather sell than buy; and they sell risky as well as less risky assets, which decreases the risky asset share of their portfolios.

4.2 The effects of investor sentiment on sophisticated and less sophisticated investors

Following De Long et al. (1990), we expect less sophisticated investors to be more susceptible to sentiment than sophisticated investors. To test this prediction, we estimate the difference of the effect of $FEARS$ on our main trading variables between sophisticated and unsophisticated investors. We define sophistication in three different ways.

First, we proxy financial sophistication by the level of diversification. Underdiversification has been shown to be a common investment mistake (Calvet, Campbell, and Sodini (2007), Goetzmann and Kumar (2008)). Since financial sophistication is broadly defined as the ability of households to avoid making investment mistakes (Calvet, Campbell, and Sodini (2009)), the level of diversification is a direct and therefore very good proxy for financial sophistication. In order to determine the average diversification level of an investor's portfolio, we calculate the Herfindahl-Hirschman-Index (HHI).[19,20] The lower the value of this measure, the higher the degree of diversification. Then, for each month, we partition the data into deciles according to the HHI level. We assume investors who understand the concept of diversification to actually hold diversified portfolios. If a portfolio is not highly diversified, we consider it as underdiversified. Therefore, we define investors with a mean decile below 3 as sophisticated. Consequently, we define investors with a mean decile above 3 as unsophisticated.[21] We construct an indicator variable for well diversified investors (HHI) and include to our main specification the interaction of $FEARS$ and HHI. This coefficient picks up the difference of the

[19] The HHI is a widely-used measure of diversification in finance literature (Ivković, Poterba, and Weisbenner (2005), Dorn, Huberman, and Sengmueller (2008), Ivković, Sialm, and Weisbenner (2008)).
[20] Following Dorn, Huberman, and Sengmueller (2008), investment funds are counted as 100 different securities.
[21] Using a mean decile of 2 or 4 as cut off point does not change results qualitatively.

impact of $FEARS$ between the two groups (well diversified versus poorly diversified investors). Table V, Panel A displays the coefficient estimates of this difference.[22]

[Insert Table V about here]

The effect of $FEARS$ on both excess buy-sell imbalance measures is smaller for investors with well diversified portfolios. For example, for well diversified investors, the effect of a one unit increase in $FEARS$ is on average 0.00569 smaller than for poorly diversified investors. This difference is statistically significant at the 5%-level. The degree of diversification has a similar effect on the excess trading variable. If an investor holds a diversified portfolio, than, on average, the impact of $FEARS$ on the excess trading is 0.00899 smaller. This difference is statistically different from zero at the 1%-level. We interpret these results as strong evidence that less sophisticated investors are more vulnerable to sentiment fluctuations than sophisticated investors.

In order to test the robustness of our findings we also use other, maybe imperfect, proxies for sophistication. Grinblatt, Keloharju, and Linnainmaa (2012) find that intelligent investors make less investment mistakes. Calvet, Campbell, and Sodini (2009) and Calvet, Campbell, and Sodini (2007) show that education might be a proxy for financial sophistication. The best education (or intelligence) measure in our data is information about the academic title "Dr." or "Prof.", which shows higher education. Therefore, our second proxy for sophistication is the academic title. 6.67% (5,429 investors) of our sampled investors have either the academic title "Dr." or "Prof.". We construct a dummy variable that takes the value one, if an investor bears the academic title "Dr." or "Prof." (sophisticated investors) and zero otherwise (unsophisticated investors) and rerun all regressions with the interaction terms again. Table V, Panel B depicts the coefficient estimates for this model.[23]

Similar to our first sophistication test, we find that the impact of $FEARS$ on our trading variables is smaller for investors with a title, as all coefficients have the expected signs. The largest and most significant difference we obtain for the excess trading. When investors have the academic title "Dr." or "Prof.", the effect of a one unit increase in $FEARS$ on excess trading is 0.008 smaller. This difference is statistically different from zero at the 5%-level. The difference of 0.00441 for the excess buy-sell imbalance based on euro-values is marginally statistically

[22] Table A.III in the Appendix presents coefficient estimates of all control variables.
[23] Table A.IV in the Appendix presents coefficient estimates of all control variables.

significant (p-value: 0.102). These results provide additional evidence that unsophisticated investors might be more prone to sentiment than sophisticated investors.

Our third proxy for sophistication is gender. For instance, Barber and Odean (2001) find that male investors are more overconfident than female investors. Overconfidence is a predisposition that has been shown to be connected to overtrading, which is an irrational behavior in financial markets. Consistent with behavioral finance literature, we expect women to act more rational in financial markets than men. Therefore, we conjecture that men (unsophisticated investors) are more prone to investor sentiment than women (sophisticated investors). Again, we use a dummy for females and interact this variable with $FEARS$. Table V, Panel C shows the results. None of the estimated differences (between females and males) of the impact of $FEARS$ on our trading measures is statistically different from zero.[24]

In sum, we use one direct measure for financial sophistication—level of diversification—and two additional proxies—academic title and gender—to test how the level of financial sophistication influences the reaction of households to swings in the aggregate sentiment. We conclude that less sophisticated investors are more sensitive to sentiment than sophisticated investors.

5 Additional Tests and Robustness Checks

To test the robustness of the impact of $FEARS$ on individual investor trading, we run additional robustness checks. We start with an analysis that takes crises into account. This is followed by a test whether our results still hold, when we look at the unconditional trading activity. Further, we control for other sample definitions, address concerns of a potential look-ahead bias in our dependent variables and check whether weather drives our results. Finally, we alleviate concerns about reverse causality by showing that $FEARS$ cannot be predicted by market outcomes.

5.1 The effect of investor sentiment during the European sovereign debt crisis

We check the robustness of our main results by investigating the effect of investor sentiment on private investors trading during the euro sovereign debt crisis, primarily driven by Greece, Portugal, Spain, Ireland, Italy and partly France. Specifically, we explore whether our main results are solely due to the euro sovereign debt crisis and check how they depend on the level

[24] Table A.V in the Appendix presents coefficient estimates of all control variables.

of the crisis. Common measures for the level of this crisis are sovereign bond yield spreads. We collect daily sovereign 10-year-bond yields of Portugal, Spain, Ireland, Italy, France and Germany from April 2002 through May 2016. Then, we calculate the spreads between Germany, which is considered as the safe haven, and Portugal, Spain, Ireland, Italy and France. Finally, we perform a principal component analysis and keep the first principal component, in order to get one representative market-based euro sovereign debt crisis measure with a daily frequency. We choose to exclude Greece from the principal component analysis, because the sovereign bond yields of Greece may be regarded as too extreme during that crisis and therefore may not be representative for the euro zone as a whole.

We match this debt crisis measure with our individual investor data and use it as a continuous variable in our panel regressions. Specifically, we redo our main analysis, but include the variables $Debt\ Crisis$ and $FEARS\ x\ Debt\ Crisis$. $Debt\ Crisis$ is the debt crisis measure described above and $FEARS\ x\ Debt\ Crisis$ is the interaction between $FEARS$ and $Debt\ Crisis$. Table VI shows the coefficient estimates of $FEARS$, $Debt\ Crisis$ and $FEARS\ x\ Debt\ Crisis$.[25]

[Insert Table VI about here]

The investor sentiment effects we find seem not to be driven by the crisis, as all signs and significances of the $FEARS$-coefficients remain basically unaltered, when we include $Debt\ Crisis$. When $FEARS$ is high, individual investors trade more; and when they trade, they sell all risky market securities, no matter whether they are classified as rather risky or less risky. Moreover, all estimates remain significant at the 1%-level. Additionally, this analysis reveals how private investors behave during crises. We find that when the crisis is more severe, individual investors trade more and, on average, when they trade, they sell securities. The latter effect is more a risky asset effect, as during the crisis, investors seem to buy rather than sell less risky securities. Perhaps the most striking finding of this analysis is the significant interaction between investor sentiment and the crisis measure. We find that the effect of investor sentiment on all our trading measures is more pronounced, when the crisis is more serious. For instance, when $Debt\ Crisis$ increases by one unit—that is, when the crisis becomes more severe—than, the effect of a one-unit increase in $FEARS$ on the excess trading variable significantly (at the 1%-level) increases by 0.00176, which means that investors trade even more.

[25] Table A.VI and Table A.VII in the Appendix present coefficient estimates of all control variables.

5.2 The effect of investor sentiment during the financial crisis

During our sample period there is also the sub-prime crisis[26]. As a further robustness test, we explore whether our main results are solely due to the financial crisis. We use the National Bureau of Economic Research (NBER) business cycle reference dates of that time period to define the beginning and the end of the crisis. Accordingly, we define the period of the financial crisis as December 2007 through June 2009.

In this robustness test, we rerun the panel regressions of our main analysis, but include two variables: $Financial\ Crisis$ and $FEARS\ x\ Financial\ Crisis$. $Financial\ Crisis$ is an indicator variable taking the value one, if the observation lies in the period December 2007 to June 2009 and zero otherwise. $FEARS\ x\ Financial\ Crisis$ is the interaction of our investor sentiment proxy and the financial crisis indicator. Table VII shows the results of $FEARS$, $Financial\ Crisis$ and $FEARS\ x\ Financial\ Crisis$ on all our trading measures.[27]

[Insert Table VII about here]

Again, our main results seem not to be driven by the financial crisis. All signs and significances for the sentiment effect remain unchanged, when we include $Financial\ Crisis$. Similar to our first robustness check, we find that the effects of $FEARS$ are amplified by $Financial\ Crisis$: When a crisis is looming, the effect of sentiment on individual investor trading is even larger.

5.3 Trading activity unconditional on trading

Our excess trading measure introduced in Section 2.3 and tested in Section 4.1 (Table IV, Panel B) investigates the trading activity conditional on trading—that is, it tests the excess trading activity, given that an investor is trading. In this robustness check, we test whether investors trade more (when sentiment is low) unconditional on trading. Put differently: We check whether investors are more likely to trade, when sentiment is low. We set up the following linear probability model:

$$Trading_{i,t} = \alpha + \beta FEARS_t + \gamma C_{i,t} + \varepsilon_{i,t} \qquad (11)$$

$Trading$ is a dummy variable, indicating whether or not investor i traded on day t. We code trading with one and non-trading with zero. The right hand side of the equation is identical to

[26] By sub-prime crisis we refer to the recent international bank crisis, which is also commonly called financial crisis.

[27] Table A.VIII and Table A.IX in the Appendix present coefficient estimates of all control variables.

model (10). Table VIII depicts the coefficient estimates of this linear probability model on $FEARS$.[28]

[Insert Table VIII about here]

We find that when $FEARS$ is high, the probability to trade significantly increases. Similar to the conditional trading analysis, this effect is significant at the 1%-level. The result is robust to the inclusion of month and year fixed effects as well as the inclusion of control variables. This investigation provides further evidence for *H3a*, which posits that when investors worry about the economic conditions, they see more need to change their current portfolios.

5.4 Alternative data processing

The individual investor data processing requires some filtering rules in order to ensure a reasonable analysis. Therefore, in our main analysis we exclude transactions among personal accounts, saving plan transactions and limit order trades. Additionally, we require the sampled investors to reside in Germany and to execute at least one trade each year. Considering the letter requirement, our sample might include investors who trade little and therefore might not be regarded as active traders. Moreover, one might argue that requiring one trade per year is a random choice that might influence our results.

In order to ensure that the analyzed investors are frequent enough traders and our results are not due to this choice, we modify the required number of trades per year to five and ten and redo our main analysis. The restriction of ten trades per year leaves us with approximately 7,700 investors, which is only 7.5% of the original sample. Table IX displays the results for the new sample.[29]

[Insert Table IX about here]

All results are consistent to our main analysis. Sings and significances are identical. The magnitudes of the coefficient estimates for the excess buy-sell imbalance variables decrease, while the magnitudes for the excess trading variable increase. The results remain qualitatively

[28] Table A.X in the Appendix presents coefficient estimates of all control variables.
[29] Table A.XI and Table A.XII in the Appendix present coefficient estimates of all control variables.

the same, when we require five instead of ten trades per year.[30] We conclude that our results do not hinge on our choice of requiring at least one trade per year.

5.5 Alternative excess trading measures

When calculating excess measures, a benchmark value of the measure of interest is needed. Thus, to get excess measures of our trading variables, we demean each variable by the average value of the corresponding variable in the corresponding calendar year. For example, when we calculate the excess buy-sell imbalance of investor i on June 1, 2010, we subtract the average imbalance of this investor in 2010 from her imbalance on June 1, 2010. In doing so, we use information that is not yet available, because the trades from June 2, 2010 through December 31, 2010 are not available on June 1, 2010. Therefore, one might be concerned that our trading variables incorporate a certain look-ahead bias. Yet, it is common in the literature to calculate excess measures of individual behavior in this way. Furthermore, we neither use these variables for forecasting, nor we build any trading strategies that rely on information that is not available. Hence, for our setting and for our purpose, it is not clear why using only past information must be the better approach. Nonetheless, to check the robustness of our results with regard to this choice, we use an alternative excess measure, which is not subject to any look-ahead bias. Specifically, we demean our variables by the average preceding-12-month value of the corresponding variable. Continuing in the example above, we demean the imbalance of investor i on June 1, 2010 by her average imbalance during the period June 1, 2009 through May 31, 2010.

The correlations between the new and old excess trading variables are very high. For instance, the correlation between the new and old excess buys-sell imbalance based on number of trades is 0.95. This is a first sign that only little changes, when we use this alternative demeaning procedure. Table X highlights the coefficient estimates of the panel regressions based on the new excess trading variables.[31] In fact, all but one coefficients increase and statistical significance remains unaltered.

[Insert Table X about here]

[30] These results are not reported, but available upon request.
[31] Table A.XIII and Table A.XIV in the Appendix present coefficient estimates of all control variables.

5.6 Controlling for weather

It is well documented that weather plays a major role in financial markets. Saunders (1993) and Hirshleifer and Shumway (2003), for instance, find a relationship between weather conditions and stock market returns. Recent studies show that weather also directly affects decision making of individuals in financial markets (Schmittmann et al. (2014), Bassi, Colacito, and Fulghieri (2013)).

Researchers might worry that we are just picking up a weather effect. A plausible rationale for this could be that weather affects the mood of individuals and mood fluctuations might impact the economic attitude of individuals, which we observe by looking at what people search for in Google. In our last robustness check, we address this question by incorporating a proxy for weather—$Air\ Pressure$—in the panel regression setting of our main analysis (10). $Air\ Pressure$ is the barometric air pressure. The higher the air pressure, the better is the weather. We choose to use air pressure as a proxy for weather, because it has been shown to be a robust and good indicator (Schmittmann et al. (2014)).

We collect data about the barometric air pressure in Germany for our entire sample period (July 2005 through June 2015) from the Deutscher Wetterdienst, which is publicly available. We collect this data on weather station level (45 weather stations). We follow Schmittmann et al. (2014) step-by-step in order to compute our weather proxy consistent to the literature. First, we exclude weather stations at extreme locations or with only few observations (Fichtelberg, Zugspitze, Brocken, Kahler Asten, Helgoland, Rheinstetten), then we calculate the demeaned air pressure and use it as our weather proxy.[32]

The correlation of $FEARS$ and $Air\ Pressure$ is -0.008 and statistically insignificant. This means that weather and the expectations about the economic conditions are not correlated. This is a first indication that our results should not be driven by the weather.

Table XI presents the coefficient estimates on $FEARS$ and $Air\ Pressure$ of our panel regressions.[33] This examination provides two key findings: First, coefficient estimates on $Air\ Pressure$ are in line with finance literature. When the weather is good, individual investors trade less (because of opportunity costs) and when they trade, they buy rather than sell (because of optimism). This is strong evidence that we created a proper proxy for weather conditions.

[32] Specifically, we demean the time series by subtracting the mean of the corresponding year.
[33] Table A.XV and Table A.XVI in the Appendix present coefficient estimates of all control variables..

Second, coefficients on $FEARS$ do not alter. Sings, magnitudes and significances are very similar to our main results. Consequently, our results are not due to the weather.

[Insert Table XI about here]

5.7 The causality between $\boldsymbol{FEARS}$ and market outcomes or weather

In our main analysis, we regress $FEARS$ on the contemporaneous trading measures. Therefore, researchers might worry that our findings are subject to reverse causality, because market outcomes could drive what people search for in Google. In all our regressions, we control for market outcomes in a very conservative way, as we include several market return variables: preceding-one-day market return, squared preceding-one-day market return, and preceding-three-month market return. Although this procedure ensures that our results are beyond the effects of market returns on individual investor trading, in this section, we provide a direct test on reverse causality. More precisely, we use the methodology of Tetlock (2007) and set up vector autoregressions (VARs) of the following form:

$$FEARS_t = \alpha_1 + \beta_1 L5(FEARS_t) + \gamma_1 L5(DAX_t) + \lambda_1 C_{t-1} \tag{12}$$

DAX is the daily DAX return. $L5$ is an operator that transforms any variable X_t into the following vector: $(X_{t-1}, X_{t-2}, X_{t-3}, X_{t-4}, X_{t-5})'$. C is a vector of the following control variables: First, five lags of an equity market volume measure. In order to keep consistency with Tetlock (2007), we calculate it as the detrended logarithm of the daily DAX volume.[34] Second, five lags of an equity market volatility measure. This is calculated as the detrended squared DAX residuals.[35] Third, two sets of calendar control variables: Day-of-the-week dummy variables and a January dummy variable.[36]

We are interested in the vector of coefficients γ_1. Table XII depicts the coefficient estimates. Colum 4 shows the estimates of model (12), which is identical to Tetlock (2007). No DAX return lag significantly explains $FEARS$. Column 1 to 3 are other, less conservative specifications of model (12). None of these specifications provide statistical significant coefficients either. In column five we expand model (12) by adding five lags of our weather

[34] As the trend, we use the rolling average of the past 60 days of log volume.
[35] First, we calculate the demeaned DAX returns. Then, we obtain the resulting residuals and square these residuals. Finally, we subtract the past 60-day moving average of the squared residuals.
[36] Using VARs with ten instead of five lags does not change results qualitatively. In order to keep consistency with Tetlock (2007), we choose to stick with five lags.

variable—$Air\ Pressure$. Similar to the DAX returns, weather seems not to influence $FEARS$. This provides yet another indication of the fact that $FEARS$ and weather are fundamentally different indices that measure something distinctively different. We conclude that reverse causality is not an issue in our study.

[Insert Table XII about here]

6 Conclusion

In this study, we relate Google search volumes to individual investor trading. Specifically, we construct a daily sentiment measure—$FEARS$—for the German market based on Google search volumes, which was initially proposed by Da, Engelberg, and Gao (2015). $FEARS$ is built upon negative search terms and is therefore to be interpreted as pessimism. Then, we link $FEARS$ to daily trading records and socio-demographic information of German private investors. To the best of our knowledge, we are the first who directly relate private investors' trading to investor sentiment, measured as expectations about future economic conditions, on a daily basis.

Controlling for investor-, calendar- and market-specific factors, we find that $FEARS$ has a significantly positive effect on the trading activity of households. Conditional on trading, when $FEARS$ is high, investors tend to sell rather than buy securities of all types, which is equivalent to participate less in the entire risky asset market. Further, we show that investor sentiment is driving unsophisticated investors significantly more than sophisticated investors, suggesting that sophisticated investors act more rational. Our results are robust to alternative filtering rules in the data processing, to an alternative trading activity measure, to an alternative computation of our excess trading variables, to alternative standard error clustering strategies, to weather conditions, and to financial crises. Financial crises even enhance the effects of sentiment on the trading behavior of our investors. This evidence is broadly consistent with behavioral finance and particularly with investor sentiment and noise trading theory.

We add to the growing literature on investor trading. Specifically, our study helps to understand why and how investors trade. Our main contribution is straightforward: Individual investors factor in their economic expectations as expressed by search queries when making trading decisions. This effect is stronger for less sophisticated investors. Search queries might also be used to explain other financial decisions of households, such as taking out a loan for example. We leave these additional investigations for future research.

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Tables

Table I. Investor data description

This table presents summary statistics for our retail investor data. Data are obtained from one of the largest German discount brokerages. We exclude investors who are not self-directed, do not reside in Germany, and execute less than 1 trade per year. Further, we exclude transfers among personal accounts, saving plans, and bonus shares.

Panel A: Individual Investors and Transactions	
Number of individual investors	103,093
Total number of trades	23.3 million
Total number of buys	12.6 million (54.08%)
Total number of sales	10.7 million (45.92%)
Total transaction value	154.1 billion EUR
Total value of buys	83.2 billion EUR (53.99%)
Total value of sales	70.9 billion EUR (46.01%)
Panel B: Individual Investor Characteristic	
Number of male investors	85,627 (83.06%)
Number of female investors	17,466 (16.94%)
Average age	52.6 years
Age (1. Quartile)	44 years
Age (Median)	52 years
Age (3. Quartile)	61 years

Table II. Distribution of transactions across risk levels

This table presents the distribution of transactions across risk levels. Data originates from a large German discount broker. We exclude investors who are not self-directed, do not reside in Germany and execute less than 1 trade per year. Further, we exclude transfers among personal accounts, saving plans and bonus shares. Risk levels are defined according to the German Security Trading Act. Assets in risk class 1 are considered as not risky, whereas assets in risk class 5 are considered as very risky. Securities in risk class 0 are unclassified.

		Share of Trades in Risk Class				
		1	2	3	4	5
Panel A: Euro Value of Trades						
Purchases	83.2 billion EUR	1.91%	1.08%	21.88%	22.84%	52.16%
Sales	70.9 billion EUR	1.23%	0.57%	23.70%	23.55%	50.92%
Overall	154.1 billion EUR	1.60%	0.84%	22.71%	23.17%	51.59%
Panel B: Number of Trades						
Purchases	12.6 million	0.16%	0.27%	12.18%	18.18%	69.48%
Sales	10.7 million	0.14%	0.30%	12.13%	19.07%	68.72%
Overall	23.3 million	0.15%	0.28%	12.16%	18.59%	69.13%

Table III. List of control variables

This table lists and gives a short description of all control variables used in our main specification. All these control variables are included in the panel regression of our trading variables on $FEARS$. Panel A lists all calendar variables; Panel B lists all market specific variables; Panel C lists all investor specific variables.

Variable	Description
Panel A: Calendar Related Variables	
School vacation	Dummy variable, indicating school vacations.
First trading day before school vacation	Dummy variable, indicating days before school vacations.
First trading day after school vacation	Dummy variable, indicating after before school vacations.
Public holidays	Dummy variable, indicating public holidays.
First trading day after public holidays	Dummy variable, indicating days before public holidays.
Last trading day before public holidays	Dummy variable, indicating after before public holidays.
First trading days of month	Dummy variable, indicating first tradingdays of the month.
Last trading days of month	Dummy variable, indicating last tradingdays of the month.
Monday	Dummy variable, indicating Mondays.
Friday	Dummy variable, indicating Fridays.
Deutsche Börse Frankfurt closed	Dummy variable, indicating days on which the Deutsche Börse is closed.
Day light saving time change (forward)	Dummy variable, indicating Mondays following changes in day light saving for advancing clocks.
Day light saving time change (backward)	Dummy variable, indicating Mondays following changes in day light saving for backward adjusting clocks.
SAD	Measures the seasonal affective disorder as number of hours from sunrise through sunset minus 12, for trading days in the fall or winter and zero otherwise.
Year Fixed Effects	10 Dummy variables, for every year in our sample omitting 2015.
Month Fixed Effects	11 Dummy variables, for every month-of-the-year omitting December.
Panel B: Market Related Variables	
CDAX 1-day-return	Preceding-one-day log realized return of CDAX.
CDAX2 1-day-return	Squared preceding-one-day log realized return of CDAX.
CDAX 3-months-return	Preceding-three-month log realized return of CDAX.
Panel C: Investor Related Variables	
Log wealth	Natural logarith of the sum of all assets an investor holds.
Investor Fixed Effects	Control for individual investors through investor fixed effects panel regressions.

Table IV. The effect of sentiment on the average investor

This table presents results from investor fixed effects panel regressions on *FEARS* for the average investor. Panel A uses excess buy-sell imbalances and Panel B uses log excess number of trades as the dependent variable. Within Panel A, "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. Control variables include: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. Control variables are not displayed, but tables with the full set of variables are available in the Appendix. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Excess Buy-Sell Imbalance												
	All Securities				Risky Securities				Less-Risky Securities			
	#		EUR		#		EUR		#		EUR	
FEARS	-0.00915***	-0.00507***	-0.00921***	-0.00504***	-0.00891***	-0.00428***	-0.00975***	-0.00440***	-0.0138***	-0.00940***	-0.0110***	-0.00781***
	(0.000648)	(0.000657)	(0.000669)	(0.000676)	(0.000684)	(0.000694)	(0.000707)	(0.000715)	(0.00147)	(0.00148)	(0.00151)	(0.00151)
Control Variables	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Year Fixed Effects	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Month Fixed Effects	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES
Panel B: Excess Trading												
			Low FEARS		High FEARS							
FEARS	0.00687***	0.00477***	0.0154***	0.0197***	0.0316***	0.00845***						
	(0.000908)	(0.000906)	(0.00202)	(0.00206)	(0.00217)	(0.00222)						
Control Variables	NO	YES	NO	YES	NO	YES						
Year Fixed Effects	NO	YES	NO	YES	NO	YES						
Month Fixed Effects	NO	YES	NO	YES	NO	YES						

Table V. The effect of sentiment conditional on the sophistication of investors

This table presents results from investor fixed effects panel regressions on $FEARS$ conditional on a sophistication measure. Panel A displays the effect of $FEARS$ conditional on HHI. For each month, we partition the data into deciles according to the HHI level. HHI is a dummy variable taking the value one, if the mean decile of an investor is below 3. Panel B displays the effect of $FEARS$ conditional on $Academic\ Title$. $Academic\ Title$ is a dummy variable taking the value one, if an investor has either the title "Dr." or "Prof.". Panel C displays the effect of $FEARS$ conditional on $Female$. $Female$ is a dummy variable taking the value one, if an investor is female. "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. Control variables are not displayed, but tables with the full set of variables are available in the Appendix. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Well Diversified versus Poorly Diversifed Investors

	Excess Buy-Sell Imbalance		Excess Trading
	#	EUR	
FEARS	-0.00549***	-0.00549***	0.00544***
	(0.000684)	(0.000703)	(0.000949)
FEARS x HHI	0.00569**	0.00605**	-0.00899***
	(0.00238)	(0.00250)	(0.00314)
Control Variables	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Month Fixed Effects	YES	YES	YES

Panel B: Investors With versus Without Academic Title

	Excess Buy-Sell Imbalance		Excess Trading
	#	EUR	
FEARS	-0.00529***	-0.00533***	0.00530***
	(0.000680)	(0.000698)	(0.000933)
FEARS x Academic Title	0.00338	0.00441	-0.00800**
	(0.00257)	(0.00269)	(0.00387)
Control Variables	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Month Fixed Effects	YES	YES	YES

Panel C: Female versus Male Investors

	Excess Buy-Sell Imbalance		Excess Trading
	#	EUR	
FEARS	-0.00502***	-0.00492***	0.00486***
	(0.000698)	(0.000718)	(0.000967)
FEARS x Female	-0.000440	-0.00106	-0.000794
	(0.00199)	(0.00207)	(0.00280)
Control Variables	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Month Fixed Effects	YES	YES	YES

Table VI. The effect of sentiment during the European sovereign debt crisis

This table presents results from investor fixed effects panel regressions on $FEARS$, $Debt\ Crisis$ and $FEARS\ x\ Debt\ Crisis$. $Debt\ Crisis$ is the first principle component of the sovereign bond yield spreads of Portugal, Spain, Ireland, Italy and France to Germany. $FEARS\ x\ Debt\ Crisis$ is the interaction of $FEARS$ and $Debt\ Crisis$. Panel A uses excess buy-sell imbalances and Panel B uses log excess number of trades as the dependent variable. Within Panel A, "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. Control variables are not displayed, but tables with the full set of variables are available in the Appendix. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Excess Buy-Sell Imbalance

	All Securities				Risky Securities				Less-Risky Securities			
	#		EUR		#		EUR		#		EUR	
FEARS	-0.00509***	-0.00526***	-0.00507***	-0.00528***	-0.00419***	-0.00442***	-0.00432***	-0.00458***	-0.00995***	-0.00976***	-0.00841***	-0.00818***
	(0.000657)	(0.000658)	(0.000676)	(0.000677)	(0.000694)	(0.000694)	(0.000715)	(0.000716)	(0.00148)	(0.00148)	(0.00151)	(0.00152)
Debt Crisis	0.000694***	0.000736***	0.00106***	0.00111***	-0.00400***	-0.00396***	-0.00383***	-0.00379***	0.0161***	0.0161***	0.0175***	0.0175***
	(0.000258)	(0.000258)	(0.000272)	(0.000272)	(0.000270)	(0.000271)	(0.000289)	(0.000289)	(0.000605)	(0.000605)	(0.000620)	(0.000620)
FEARS x Debt Crisis		-0.00239***		-0.00287***		-0.00190***		-0.00218***		-0.00104		-0.00124
		(0.000345)		(0.000356)		(0.000363)		(0.000376)		(0.000757)		(0.000775)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Excess Trading

FEARS	0.00463***	0.00476***
	(0.000907)	(0.000908)
Debt Crisis	0.00578***	0.00575***
	(0.000686)	(0.000687)
FEARS x Financial Crisis		0.00176***
		(0.000477)
Control Variables	YES	YES
Year Fixed Effects	YES	YES
Month Fixed Effects	YES	YES

Table VII. The effect of sentiment during the financial crisis

This table presents results from investor fixed effects panel regressions on $FEARS$, $Financial\ Crisis$ and $FEARS\ x\ Financial\ Crisis$. $Financial\ Crisis$ is a dummy variable taking the value one, if the observation lies in the period December 2007 to June 2009 and zero otherwise. $FEARS\ x\ Financial\ Crisis$ is the interaction of $FEARS$ and $Financial\ Crisis$. Panel A uses excess buy-sell imbalances and Panel B uses log excess number of trades as the dependent variable. Within Panel A, "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. Control variables are not displayed, but tables with the full set of variables are available in the Appendix. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Excess Buy-Sell Imbalance

	All Securities				Risky Securities				Less-Risky Securities			
	#		EUR		#		EUR		#		EUR	
FEARS	-0.00507***	-0.00382***	-0.00504***	-0.00345***	-0.00428***	-0.00365***	-0.00440***	-0.00352***	-0.00940***	-0.00467**	-0.00781***	-0.00416*
	(0.000657)	(0.000983)	(0.000676)	(0.00101)	(0.000694)	(0.00103)	(0.000715)	(0.00105)	(0.00148)	(0.00237)	(0.00151)	(0.00244)
Financial Crisis	-0.0256***	-0.0255***	-0.0268***	-0.0268***	-0.0220***	-0.0220***	-0.0329***	-0.0329***	-0.0589***	-0.0589***	-0.0389***	-0.0389***
	(0.00159)	(0.00159)	(0.00181)	(0.00181)	(0.00170)	(0.00170)	(0.00197)	(0.00197)	(0.00391)	(0.00391)	(0.00404)	(0.00404)
FEARS x Financial Crisis		-0.00237*		-0.00302**		-0.00123		-0.00171		-0.00794**		-0.00614*
		(0.00135)		(0.00139)		(0.00142)		(0.00146)		(0.00311)		(0.00319)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Excess Trading

FEARS	0.00477***	0.00315**
	(0.000906)	(0.00133)
Financial Crisis	0.0358***	0.0358***
	(0.00408)	(0.00408)
FEARS x Financial Crisis		0.00308*
		(0.00186)
Control Variables	YES	YES
Year Fixed Effects	YES	YES
Month Fixed Effects	YES	YES

Table VIII. The effect of sentiment on the trading activity unconditional on trading

This table presents results from investor fixed effects panel regressions. On the left hand side of the regression equation we use a dummy variable that is one if trading occurs and zero otherwise. Control variables include: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. Control variables are not displayed, but tables with the full set of variables are available in the Appendix. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

FEARS	0.000187**	0.000823***	0.00126***	0.000606***
	(8.13e-05)	(8.14e-05)	(8.17e-05)	(8.80e-05)
Control Variables	NO	NO	NO	YES
Year Fixed Effects	NO	YES	YES	YES
Month Fixed Effects	NO	NO	YES	YES

Table IX. The effect of sentiment for alternative filtering rule

This table presents results from investor fixed effects panel regressions on $FEARS$ for the average investor who executes at least 10 trades per year. Panel A uses excess buy-sell imbalances and Panel B uses log excess number of trades as the dependent variable. Within Panel A, "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. Control variables are not displayed, but tables with the full set of variables are available in the Appendix. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Excess Buy-Sell Imbalance

	All Securities		Risky Securities		Less-Risky Securities	
	#	EUR	#	EUR	#	EUR
FEARS	-0.00362***	-0.00410***	-0.00268**	-0.00324**	-0.00312	-0.00349
	(0.00127)	(0.00130)	(0.00136)	(0.00139)	(0.00291)	(0.00298)
Control Variables	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES

Panel B: Excess Trading

FEARS	0.00736***
	(0.00200)
Control Variables	YES
Year Fixed Effects	YES
Month Fixed Effects	YES

Table X. The effect of sentiment for alternative excess measure

This table presents results from investor fixed effects panel regressions on *FEARS* for the average investor. Panel A uses excess buy-sell imbalances and Panel B uses log excess number of trades as the dependent variable. The average yearly values of the trading measures that are subtracted from the corresponding observed daily trading measure are the values of the preceding-12-month period. Within Panel A, "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. Control variables are not displayed, but tables with the full set of variables are available in the Appendix. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Excess Buy-Sell Imbalance

	All Securities		Risky Securities		Less-Risky Securities	
	#	EUR	#	EUR	#	EUR
FEARS	-0.00541***	-0.00548***	-0.00453***	-0.00475***	-0.0111***	-0.0110***
	(0.000710)	(0.000728)	(0.000744)	(0.000764)	(0.00166)	(0.00172)
Control Variables	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES

Panel B: Excess Trading

FEARS	0.00455***
	(0.000937)
Control Variables	YES
Year Fixed Effects	YES
Month Fixed Effects	YES

Table XI. The effect of sentiment controlling for weather

This table presents results from investor fixed effects panel regressions on $FEARS$ and $Air\ Pressure$ for the average investor. Panel A uses excess buy-sell imbalances and Panel B uses log excess number of trades as the dependent variable. Within Panel A, "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. Control variables are not displayed, but tables with the full set of variables are available in the Appendix. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Panel A: Excess Buy-Sell Imbalance

	All Securities		Risky Securities		Less-Risky Securities	
	#	EUR	#	EUR	#	EUR
FEARS	-0.00502***	-0.00498***	-0.00425***	-0.00436***	-0.00929***	-0.00768***
	(0.000657)	(0.000676)	(0.000694)	(0.000715)	(0.00148)	(0.00152)
Air Pressure	0.000154***	0.000163***	0.000132***	0.000139***	0.000204***	0.000233***
	(1.33e-05)	(1.37e-05)	(1.41e-05)	(1.45e-05)	(2.96e-05)	(3.03e-05)
Control Variables	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES

Panel B: Excess Trading

FEARS	0.00475***
	(0.000907)
Air Pressure	-6.72e-05***
	(2.09e-05)
Control Variables	YES
Year Fixed Effects	YES
Month Fixed Effects	YES

Table XII The causality between $FEARS$ and market outcomes and weather

This table presents OLS estimates for the coefficients γ_1 of Equation (12) depending on different specifications (column 1 to 4). Column five presents the results for an extended model by adding five lags of the weather variable $Air\ Pressure$. Volatility controls include five lags of the detrended squared DAX residuals. Volume controls include five lags of the detrended logarithm of the daily DAX volume. Calendar controls include day-of-the-week dummies and a January dummy. We use Newey and West (1987) standard errors that are robust to heteroscedasticity and autocorrelation up to five lags. We report p-values in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
	$FEARS_t$	$FEARS_t$	$FEARS_t$	$FEARS_t$	$FEARS_t$
DAX_{t-1}	-0.175	-0.159	-0.131	-0.116	-0.131
	(0.275)	(0.270)	(0.277)	(0.277)	(0.277)
DAX_{t-2}	0.0159	0.0668	0.0921	0.117	0.116
	(0.254)	(0.256)	(0.258)	(0.260)	(0.260)
DAX_{t-3}	-0.269	-0.289	-0.259	-0.257	-0.255
	(0.268)	(0.267)	(0.270)	(0.270)	(0.271)
DAX_{t-4}	-0.111	-0.155	-0.239	-0.273	-0.282
	(0.284)	(0.284)	(0.284)	(0.279)	(0.280)
DAX_{t-5}	0.181	0.0600	0.0526	0.0305	0.0247
	(0.277)	(0.280)	(0.275)	(0.275)	(0.276)
$Air\ Pressure_{t-1}$					-0.000546
					(0.000498)
$Air\ Pressure_{t-2}$					-0.000390
					(0.000570)
$Air\ Pressure_{t-3}$					9.83e-05
					(0.000573)
$Air\ Pressure_{t-4}$					0.000229
					(0.000660)
$Air\ Pressure_{t-5}$					-3.46e-05
					(0.000519)
Volatility Controls	NO	YES	YES	YES	YES
Volume Controls	NO	NO	YES	YES	YES
Calendar Controls	NO	NO	NO	YES	YES

Appendix

Table A.I. The effect of sentiment on excess buy-sell imbalances for the average investor (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$ for the average investor. The dependent variables are excess buy-sell imbalances. "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities		Risky Securities		Less-Risky Securities	
	#	EUR	#	EUR	#	EUR
FEARS	-0.00507***	-0.00504***	-0.00428***	-0.00440***	-0.00940***	-0.00781***
	(0.000657)	(0.000676)	(0.000694)	(0.000715)	(0.00148)	(0.00151)
Log wealth	-0.0122***	-0.0116***	-0.0104***	-0.00981***	-0.0205***	-0.0202***
	(0.000154)	(0.000156)	(0.000150)	(0.000156)	(0.000400)	(0.000403)
CDAX 1-day-return	-0.0574***	-0.0625***	0.226***	0.237***	-0.722***	-0.760***
	(0.0192)	(0.0196)	(0.0179)	(0.0182)	(0.0343)	(0.0351)
$CDAX^2$ 1-day-return	-3.107***	-2.951***	-4.711***	-4.994***	-6.413***	-5.805***
	(0.262)	(0.269)	(0.280)	(0.291)	(0.468)	(0.479)
CDAX 3-months-return	-0.0156***	-0.0170***	-0.00304***	-0.00362***	-0.0456***	-0.0464***
	(0.000532)	(0.000555)	(0.000535)	(0.000560)	(0.00123)	(0.00127)
School vacation	-0.00304***	-0.00272***	-0.00315***	-0.00254***	-0.00385***	-0.00352***
	(0.000401)	(0.000447)	(0.000428)	(0.000480)	(0.000977)	(0.00102)
Public holidays	0.0212***	0.0216***	0.0210***	0.0211***	0.0150***	0.0178***
	(0.00140)	(0.00144)	(0.00146)	(0.00151)	(0.00325)	(0.00334)
First trading day before school vacation	0.00429***	0.00362***	0.00511***	0.00486***	0.00605**	0.00364
	(0.00131)	(0.00135)	(0.00138)	(0.00142)	(0.00305)	(0.00312)
First trading day after school vacation	-0.00212*	-0.00226*	-0.00245*	-0.00250*	-0.000261	0.000575
	(0.00120)	(0.00124)	(0.00127)	(0.00131)	(0.00270)	(0.00278)
SAD	0.00213***	0.00249***	0.00280***	0.00303***	0.000952	0.00193*
	(0.000479)	(0.000493)	(0.000504)	(0.000521)	(0.00111)	(0.00113)
Deutsche Börse Frankfurt closed	0.147***	0.160***	0.196***	0.232***	-0.0330	-0.133***
	(0.0101)	(0.0104)	(0.0106)	(0.0112)	(0.0212)	(0.0194)
First trading day after public holidays	0.00586***	0.00565***	0.00314**	0.00286*	0.00991***	0.0128***
	(0.00147)	(0.00151)	(0.00156)	(0.00160)	(0.00309)	(0.00320)
Last trading day before public holidays	0.00523***	0.00677***	-0.000459	0.000358	-0.0116***	-0.0143***
	(0.00160)	(0.00164)	(0.00169)	(0.00174)	(0.00329)	(0.00336)
First trading days of month	0.000137	-0.000232	0.00189***	0.00165***	-0.00699***	-0.00903***
	(0.000533)	(0.000549)	(0.000558)	(0.000575)	(0.00121)	(0.00123)
Last trading days of month	0.00221***	0.00212***	0.00121**	0.00115**	0.0111***	0.00958***
	(0.000522)	(0.000535)	(0.000545)	(0.000560)	(0.00120)	(0.00123)
Monday	0.00738***	0.00805***	0.00777***	0.00792***	-0.00556***	-0.00349***
	(0.000478)	(0.000489)	(0.000504)	(0.000516)	(0.000910)	(0.000937)
Friday	-0.00929***	-0.0103***	-0.00986***	-0.0107***	-0.00345***	-0.00476***
	(0.000451)	(0.000460)	(0.000474)	(0.000483)	(0.000927)	(0.000946)
Day light saving time change (forward)	0.0144***	0.0147***	0.0133***	0.0146***	0.0314***	0.0322***
	(0.00264)	(0.00270)	(0.00278)	(0.00284)	(0.00621)	(0.00634)
Day light saving time change (backward)	0.00236	0.00210	-0.00243	-0.00241	0.00931*	0.00710
	(0.00238)	(0.00245)	(0.00255)	(0.00263)	(0.00501)	(0.00515)
Constant	0.0892***	0.105***	0.101***	0.122***	0.353***	0.349***
	(0.00292)	(0.00307)	(0.00301)	(0.00321)	(0.00727)	(0.00736)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES

Table A.II. The effect of sentiment on excess trading for the average investor (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$ for the average investor. The dependent variable is log excess number of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

FEARS	0.00477***
	(0.000906)
Log wealth	-0.00160***
	(0.000265)
CDAX 1-day-return	-0.954***
	(0.0188)
CDAX^{2} *1-day-return*	21.21***
	(0.449)
CDAX 3-months-return	-0.0193***
	(0.00128)
School vacation	0.00417***
	(0.000870)
Public holidays	-0.00405*
	(0.00239)
First trading day before school vacation	-0.0119***
	(0.00187)
First trading day after school vacation	0.00296*
	(0.00171)
SAD	0.000203
	(0.000806)
Deutsche Börse Frankfurt closed	-0.321***
	(0.0169)
First trading day after public holidays	0.00630***
	(0.00221)
Last trading day before public holidays	0.0179***
	(0.00258)
First trading days of month	0.00416***
	(0.000759)
Last trading days of month	-0.00121
	(0.000754)
Monday	0.00163**
	(0.000813)
Friday	0.00214***
	(0.000685)
Day light saving time change (forward)	-0.0211***
	(0.00364)
Day light saving time change (backward)	0.00871**
	0.00838***
Constant	-0.311***
	(0.00565)
Year Fixed Effects	YES
Month Fixed Effects	YES

Table A.III. The effect of sentiment conditional on the level of diversification (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$ conditional on HHI. For each month, we partition the data into deciles according to the HHI level. HHI is a dummy variable taking the value one, if the mean decile of an investor is below 3. The dependent variables are excess buy-sell imbalances and log excess number of trades. "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Excess Buy-Sell Imbalance		Excess Trading
	#	EUR	
FEARS	-0.00549***	-0.00549***	0.00544***
	(0.000684)	(0.000703)	(0.000949)
FEARS x HHI	0.00569**	0.00605**	-0.00899***
	(0.00238)	(0.00250)	(0.00314)
Log wealth	-0.0122***	-0.0116***	-0.00159***
	(0.000154)	(0.000156)	(0.000265)
CDAX 1-day-return	-0.0573***	-0.0624***	-0.955***
	(0.0192)	(0.0196)	(0.0188)
$CDAX^2$ 1-day-return	-3.107***	-2.951***	21.21***
	(0.262)	(0.269)	(0.449)
CDAX 3-months-return	-0.0156***	-0.0170***	-0.0193***
	(0.000532)	(0.000555)	(0.00128)
School vacation	-0.00304***	-0.00272***	0.00417***
	(0.000401)	(0.000447)	(0.000870)
Public holidays	0.0212***	0.0216***	-0.00405*
	(0.00140)	(0.00144)	(0.00239)
First trading day before school vacation	0.00429***	0.00362***	-0.0119***
	(0.00131)	(0.00135)	(0.00187)
First trading day after school vacation	-0.00212*	-0.00226*	0.00296*
	(0.00120)	(0.00124)	(0.00171)
SAD	0.00214***	0.00249***	0.000201
	(0.000479)	(0.000493)	(0.000806)
Deutsche Börse Frankfurt closed	0.147***	0.160***	-0.321***
	(0.0101)	(0.0104)	(0.0169)
First trading day after public holidays	0.00586***	0.00564***	0.00631***
	(0.00147)	(0.00151)	(0.00221)
Last trading day before public holidays	0.00522***	0.00676***	0.0180***
	(0.00160)	(0.00164)	(0.00258)
First trading days of month	0.000138	-0.000231	0.00416***
	(0.000533)	(0.000549)	(0.000759)
Last trading days of month	0.00221***	0.00212***	-0.00121
	(0.000522)	(0.000535)	(0.000754)
Monday	0.00738***	0.00805***	0.00164**
	(0.000478)	(0.000489)	(0.000813)
Friday	-0.00929***	-0.0103***	0.00213***
	(0.000451)	(0.000460)	(0.000685)
Day light saving time change (forward)	0.0144***	0.0147***	-0.0211***
	(0.00264)	(0.00270)	(0.00364)
Day light saving time change (backward)	0.00236	0.00210	0.00871**
	(0.00238)	(0.00245)	(0.00340)
Constant	0.0892***	0.105***	-0.311***
	(0.00292)	(0.00307)	(0.00565)
Year Fixed Effects	YES	YES	YES
Month Fixed Effects	YES	YES	YES

Table A.IV. The effect of sentiment conditional on academic title (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$ conditional on $Academic\ Title$. $Academic\ Title$ is a dummy variable taking the value one, if an investor has either the title "Dr." or "Prof.". The dependent variables are excess buy-sell imbalances and log excess number of trades. "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Excess Buy-Sell Imbalance		Excess Trading
	#	EUR	
FEARS	-0.00529***	-0.00533***	0.00530***
	(0.000680)	(0.000698)	(0.000933)
FEARS x Academic Title	0.00338	0.00441	-0.00800**
	(0.00257)	(0.00269)	(0.00387)
Log wealth	-0.0122***	-0.0116***	-0.00160***
	(0.000154)	(0.000156)	(0.000265)
CDAX 1-day-return	-0.0574***	-0.0625***	-0.954***
	(0.0192)	(0.0196)	(0.0188)
CDAX^2 1-day-return	-3.107***	-2.951***	21.21***
	(0.262)	(0.269)	(0.449)
CDAX 3-months-return	-0.0156***	-0.0170***	-0.0193***
	(0.000532)	(0.000555)	(0.00128)
School vacation	-0.00304***	-0.00272***	0.00417***
	(0.000401)	(0.000447)	(0.000870)
Public holidays	0.0212***	0.0216***	-0.00405*
	(0.00140)	(0.00144)	(0.00239)
First trading day before school vacation	0.00429***	0.00362***	-0.0119***
	(0.00131)	(0.00135)	(0.00187)
First trading day after school vacation	-0.00212*	-0.00226*	0.00296*
	(0.00120)	(0.00124)	(0.00171)
SAD	0.00213***	0.00249***	0.000204
	(0.000479)	(0.000493)	(0.000806)
Deutsche Börse Frankfurt closed	0.147***	0.160***	-0.321***
	(0.0101)	(0.0104)	(0.0169)
First trading day after public holidays	0.00586***	0.00565***	0.00630***
	(0.00147)	(0.00151)	(0.00221)
Last trading day before public holidays	0.00523***	0.00677***	0.0179***
	(0.00160)	(0.00164)	(0.00258)
First trading days of month	0.000137	-0.000232	0.00416***
	(0.000533)	(0.000549)	(0.000759)
Last trading days of month	0.00221***	0.00212***	-0.00121
	(0.000522)	(0.000535)	(0.000754)
Monday	0.00738***	0.00805***	0.00163**
	(0.000478)	(0.000489)	(0.000813)
Friday	-0.00929***	-0.0103***	0.00213***
	(0.000451)	(0.000460)	(0.000685)
Day light saving time change (forward)	0.0144***	0.0147***	-0.0211***
	(0.00264)	(0.00270)	(0.00364)
Day light saving time change (backward)	0.00236	0.00210	0.00870**
	(0.00238)	(0.00245)	(0.00340)
Constant	0.004	0.004	0.004
	81,241	81,240	81,241
Year Fixed Effects	YES	YES	YES
Month Fixed Effects	YES	YES	YES

Table A.V. The effect of sentiment conditional on gender (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$ conditional on $Female$. $Female$ is a dummy variable taking the value one, if an investor is female. The dependent variables are excess buy-sell imbalances and log excess number of trades. "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	Excess Buy-Sell Imbalance		Excess Trading
	#	EUR	
FEARS	-0.00502***	-0.00492***	0.00486***
	(0.000698)	(0.000718)	(0.000967)
FEARS x Female	-0.000440	-0.00106	-0.000794
	(0.00199)	(0.00207)	(0.00280)
Log wealth	-0.0122***	-0.0116***	-0.00160***
	(0.000154)	(0.000156)	(0.000265)
CDAX 1-day-return	-0.0574***	-0.0625***	-0.954***
	(0.0192)	(0.0196)	(0.0188)
CDAX^2 1-day-return	-3.107***	-2.951***	21.21***
	(0.262)	(0.269)	(0.449)
CDAX 3-months-return	-0.0156***	-0.0170***	-0.0193***
	(0.000532)	(0.000555)	(0.00128)
School vacation	-0.00304***	-0.00272***	0.00417***
	(0.000401)	(0.000447)	(0.000870)
Public holidays	0.0212***	0.0216***	-0.00405*
	(0.00140)	(0.00144)	(0.00239)
First trading day before school vacation	0.00429***	0.00362***	-0.0119***
	(0.00131)	(0.00135)	(0.00187)
First trading day after school vacation	-0.00212*	-0.00226*	0.00296*
	(0.00120)	(0.00124)	(0.00171)
SAD	0.00213***	0.00249***	0.000203
	(0.000479)	(0.000493)	(0.000806)
Deutsche Börse Frankfurt closed	0.147***	0.160***	-0.321***
	(0.0101)	(0.0104)	(0.0169)
First trading day after public holidays	0.00586***	0.00565***	0.00630***
	(0.00147)	(0.00151)	(0.00221)
Last trading day before public holidays	0.00523***	0.00678***	0.0179***
	(0.00160)	(0.00164)	(0.00258)
First trading days of month	0.000137	-0.000233	0.00416***
	(0.000533)	(0.000549)	(0.000759)
Last trading days of month	0.00221***	0.00212***	-0.00121
	(0.000522)	(0.000535)	(0.000754)
Monday	0.00738***	0.00805***	0.00163**
	(0.000478)	(0.000489)	(0.000813)
Friday	-0.00929***	-0.0103***	0.00214***
	(0.000451)	(0.000460)	(0.000685)
Day light saving time change (forward)	0.0144***	0.0147***	-0.0211***
	(0.00264)	(0.00270)	(0.00364)
Day light saving time change (backward)	0.00236	0.00210	0.00871**
	(0.00238)	(0.00245)	(0.00340)
Constant	0.004	0.004	0.004
	81,241	81,240	81,241
Year Fixed Effects	YES	YES	YES
Month Fixed Effects	YES	YES	YES

Table A.VI. The effect of sentiment on excess buy-sell imbalances during the European sovereign debt crisis (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$, $Debt\ Crisis$ and $FEARS\ x\ Debt\ Crisis$. $Debt\ Crisis$ is the first principle component of the 10-year-bond yield spreads of Portugal, Spain, Ireland, Italy and France (relative to Germany). $FEARS\ x\ Debt\ Crisis$ is the interaction of $FEARS$ and $Debt\ Crisis$. The dependent variables are excess buy-sell imbalances. "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities		Risky Securities		Less-Risky Securities	
	#	EUR	#	EUR	#	EUR
FEARS	-0.00526***	-0.00528***	-0.00442***	-0.00458***	-0.00976***	-0.00818***
	(0.000658)	(0.000677)	(0.000694)	(0.000716)	(0.00148)	(0.00152)
Debt Crisis	0.000736***	0.00111***	-0.00396***	-0.00379***	0.0161***	0.0175***
	(0.000258)	(0.000272)	(0.000271)	(0.000289)	(0.000605)	(0.000620)
FEARS x Debt Crisis	-0.00239***	-0.00287***	-0.00190***	-0.00218***	-0.00104	-0.00124
	(0.000345)	(0.000356)	(0.000363)	(0.000376)	(0.000757)	(0.000775)
Log wealth	-0.0122***	-0.0116***	-0.0105***	-0.00984***	-0.0204***	-0.0200***
	(0.000154)	(0.000156)	(0.000150)	(0.000156)	(0.000400)	(0.000404)
CDAX 1-day-return	-0.0576***	-0.0625***	0.222***	0.232***	-0.706***	-0.743***
	(0.0192)	(0.0195)	(0.0179)	(0.0182)	(0.0341)	(0.0350)
$CDAX^2$ 1-day-return	-3.124***	-2.983***	-4.483***	-4.774***	-6.883***	-6.312***
	(0.262)	(0.270)	(0.280)	(0.291)	(0.468)	(0.479)
CDAX 3-months-return	-0.0152***	-0.0164***	-0.00478***	-0.00527***	-0.0376***	-0.0377***
	(0.000546)	(0.000569)	(0.000547)	(0.000573)	(0.00126)	(0.00130)
School vacation	-0.00307***	-0.00276***	-0.00298***	-0.00238***	-0.00483***	-0.00458***
	(0.000401)	(0.000447)	(0.000428)	(0.000480)	(0.000978)	(0.00102)
Public holidays	0.0215***	0.0220***	0.0213***	0.0214***	0.0145***	0.0173***
	(0.00140)	(0.00144)	(0.00146)	(0.00151)	(0.00325)	(0.00334)
First trading day before school vacation	0.00428***	0.00361***	0.00516***	0.00491***	0.00576*	0.00332
	(0.00131)	(0.00135)	(0.00138)	(0.00142)	(0.00305)	(0.00312)
First trading day after school vacation	-0.00220*	-0.00237*	-0.00244*	-0.00251*	-0.000773	1.86e-05
	(0.00120)	(0.00124)	(0.00127)	(0.00131)	(0.00270)	(0.00278)
SAD	0.00208***	0.00242***	0.00270***	0.00292***	0.000973	0.00195*
	(0.000479)	(0.000493)	(0.000504)	(0.000521)	(0.00111)	(0.00113)
Deutsche Börse Frankfurt closed	0.147***	0.160***	0.195***	0.231***	-0.0307	-0.131***
	(0.0101)	(0.0104)	(0.0106)	(0.0112)	(0.0212)	(0.0193)
First trading day after public holidays	0.00599***	0.00578***	0.00364**	0.00336**	0.00805***	0.0108***
	(0.00147)	(0.00151)	(0.00156)	(0.00160)	(0.00310)	(0.00321)
Last trading day before public holidays	0.00487***	0.00630***	7.31e-05	0.000832	-0.0148***	-0.0178***
	(0.00160)	(0.00164)	(0.00169)	(0.00175)	(0.00329)	(0.00335)
First trading days of month	7.41e-05	-0.000314	0.00198***	0.00172***	-0.00759***	-0.00967***
	(0.000534)	(0.000549)	(0.000559)	(0.000576)	(0.00121)	(0.00123)
Last trading days of month	0.00225***	0.00215***	0.00152***	0.00147***	0.00982***	0.00823***
	(0.000523)	(0.000536)	(0.000546)	(0.000561)	(0.00120)	(0.00123)
Monday	0.00801***	0.00880***	0.00832***	0.00855***	-0.00562***	-0.00352***
	(0.000486)	(0.000497)	(0.000513)	(0.000525)	(0.000927)	(0.000953)
Friday	-0.00950***	-0.0105***	-0.0101***	-0.0110***	-0.00337***	-0.00468***
	(0.000453)	(0.000461)	(0.000476)	(0.000485)	(0.000929)	(0.000948)
Day light saving time change (forward)	0.0143***	0.0147***	0.0127***	0.0140***	0.0329***	0.0337***
	(0.00264)	(0.00270)	(0.00278)	(0.00284)	(0.00620)	(0.00633)
Day light saving time change (backward)	0.00180	0.00139	-0.00217	-0.00224	0.00738	0.00500
	(0.00238)	(0.00245)	(0.00255)	(0.00263)	(0.00501)	(0.00516)
Constant	0.0890***	0.105***	0.103***	0.124***	0.345***	0.341***
	(0.00292)	(0.00307)	(0.00302)	(0.00322)	(0.00729)	(0.00738)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES

Table A.VII. The effect of sentiment on excess trading during the European sovereign debt crisis (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$, $Debt\ Crisis$ and $FEARS\ x\ Debt\ Crisis$. $Debt\ Crisis$ is the first principle component of the 10-year-bond yield spreads of Portugal, Spain, Ireland, Italy and France (relative to Germany). $FEARS\ x\ Debt\ Crisis$ is the interaction of $FEARS$ and $Debt\ Crisis$. The dependent variable is log excess number of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

FEARS	0.00476***
	(0.000908)
Debt Crisis	0.00575***
	(0.000687)
FEARS x Debt Crisis	0.00176***
	(0.000477)
Log wealth	-0.00156***
	(0.000265)
CDAX 1-day-return	-0.948***
	(0.0187)
CDAX^2 1-day-return	20.90***
	(0.448)
CDAX 3-months-return	-0.0167***
	(0.00126)
School vacation	0.00392***
	(0.000869)
Public holidays	-0.00429*
	(0.00239)
First trading day before school vacation	-0.0120***
	(0.00187)
First trading day after school vacation	0.00291*
	(0.00171)
SAD	0.000326
	(0.000806)
Deutsche Börse Frankfurt closed	-0.320***
	(0.0169)
First trading day after public holidays	0.00557**
	(0.00221)
Last trading day before public holidays	0.0171***
	(0.00259)
First trading days of month	0.00402***
	(0.000759)
Last trading days of month	-0.00164**
	(0.000756)
Monday	0.00108
	(0.000824)
Friday	0.00238***
	(0.000687)
Day light saving time change (forward)	-0.0204***
	(0.00364)
Day light saving time change (backward)	0.00818**
	(0.00340)
Constant	-0.314***
	(0.00564)
Year Fixed Effects	YES
Month Fixed Effects	YES

Table A.VIII. The effect of sentiment on excess buy-sell imbalances during the financial crisis (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$, $Financial\ Crisis$ and $FEARS\ x\ Financial\ Crisis$. $Financial\ Crisis$ is a dummy variable taking the value one, if the observation lies in the period December 2007 to June 2009 and zero otherwise. $FEARS\ x\ Financial\ Crisis$ is the interaction of $FEARS$ and $Financial\ Crisis$. The dependent variables are excess buy-sell imbalances. "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities		Risky Securities		Less-Risky Securities	
	#	EUR	#	EUR	#	EUR
FEARS	-0.00382***	-0.00345***	-0.00365***	-0.00352***	-0.00467**	-0.00416*
	(0.000983)	(0.00101)	(0.00103)	(0.00105)	(0.00237)	(0.00244)
Financial Crisis	-0.0255***	-0.0268***	-0.0220***	-0.0329***	-0.0589***	-0.0389***
	(0.00159)	(0.00181)	(0.00170)	(0.00197)	(0.00391)	(0.00404)
FEARS x Financial Crisis	-0.00237*	-0.00302**	-0.00123	-0.00171	-0.00794**	-0.00614*
	(0.00135)	(0.00139)	(0.00142)	(0.00146)	(0.00311)	(0.00319)
Log wealth	-0.0122***	-0.0116***	-0.0104***	-0.00981***	-0.0205***	-0.0202***
	(0.000154)	(0.000156)	(0.000150)	(0.000156)	(0.000400)	(0.000403)
CDAX 1-day-return	-0.0575***	-0.0627***	0.226***	0.237***	-0.722***	-0.761***
	(0.0192)	(0.0196)	(0.0179)	(0.0182)	(0.0343)	(0.0351)
$CDAX^2$ 1-day-return	-3.100***	-2.943***	-4.707***	-4.990***	-6.398***	-5.793***
	(0.262)	(0.269)	(0.280)	(0.291)	(0.468)	(0.479)
CDAX 3-months-return	-0.0156***	-0.0170***	-0.00303***	-0.00361***	-0.0456***	-0.0464***
	(0.000532)	(0.000555)	(0.000535)	(0.000560)	(0.00123)	(0.00127)
School vacation	-0.00304***	-0.00271***	-0.00314***	-0.00253***	-0.00384***	-0.00351***
	(0.000401)	(0.000447)	(0.000428)	(0.000480)	(0.000977)	(0.00102)
Public holidays	0.0213***	0.0217***	0.0211***	0.0211***	0.0152***	0.0180***
	(0.00140)	(0.00144)	(0.00146)	(0.00151)	(0.00325)	(0.00334)
First trading day before school vacation	0.00429***	0.00362***	0.00511***	0.00486***	0.00607**	0.00365
	(0.00131)	(0.00135)	(0.00138)	(0.00142)	(0.00305)	(0.00312)
First trading day after school vacation	-0.00211*	-0.00226*	-0.00245*	-0.00250*	-0.000233	0.000597
	(0.00120)	(0.00124)	(0.00127)	(0.00131)	(0.00270)	(0.00278)
SAD	0.00214***	0.00249***	0.00280***	0.00303***	0.000954	0.00193*
	(0.000479)	(0.000493)	(0.000504)	(0.000521)	(0.00111)	(0.00113)
Deutsche Börse Frankfurt closed	0.147***	0.160***	0.196***	0.232***	-0.0331	-0.133***
	(0.0101)	(0.0104)	(0.0106)	(0.0112)	(0.0212)	(0.0194)
First trading day after public holidays	0.00587***	0.00565***	0.00315**	0.00286*	0.00993***	0.0128***
	(0.00147)	(0.00151)	(0.00156)	(0.00160)	(0.00309)	(0.00320)
Last trading day before public holidays	0.00515***	0.00667***	-0.000501	0.000300	-0.0118***	-0.0145***
	(0.00160)	(0.00164)	(0.00169)	(0.00175)	(0.00329)	(0.00336)
First trading days of month	0.000145	-0.000222	0.00190***	0.00165***	-0.00695***	-0.00900***
	(0.000533)	(0.000549)	(0.000558)	(0.000575)	(0.00121)	(0.00123)
Last trading days of month	0.00222***	0.00213***	0.00121**	0.00116**	0.0111***	0.00961***
	(0.000522)	(0.000535)	(0.000545)	(0.000561)	(0.00120)	(0.00123)
Monday	0.00755***	0.00827***	0.00785***	0.00804***	-0.00501***	-0.00307***
	(0.000489)	(0.000500)	(0.000516)	(0.000528)	(0.000937)	(0.000964)
Friday	-0.00934***	-0.0104***	-0.00989***	-0.0108***	-0.00363***	-0.00490***
	(0.000452)	(0.000461)	(0.000475)	(0.000485)	(0.000930)	(0.000949)
Day light saving time change (forward)	0.0143***	0.0146***	0.0132***	0.0145***	0.0312***	0.0320***
	(0.00264)	(0.00270)	(0.00278)	(0.00284)	(0.00621)	(0.00634)
Day light saving time change (backward)	0.00214	0.00181	-0.00254	-0.00257	0.00855*	0.00651
	(0.00239)	(0.00245)	(0.00256)	(0.00263)	(0.00502)	(0.00516)
Constant	0.115***	0.132***	0.123***	0.155***	0.411***	0.388***
	(0.00250)	(0.00260)	(0.00255)	(0.00270)	(0.00622)	(0.00635)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES

Table A.IX. The effect of sentiment on excess trading during the financial crisis (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$, $Financial\ Crisis$ and $FEARS\ x\ Financial\ Crisis$. $Financial\ Crisis$ is a dummy variable taking the value one, if the observation lies in the period December 2007 to June 2009 and zero otherwise. $FEARS\ x\ Financial\ Crisis$ is the interaction of $FEARS$ and $Financial\ Crisis$. The dependent variable is log excess number of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

FEARS	0.00315**
	(0.00133)
Financial Crisis	0.0358***
	(0.00408)
FEARS x Financial Crisis	0.00308*
	(0.00186)
Log wealth	-0.00160***
	(0.000265)
CDAX 1-day-return	-0.954***
	(0.0188)
$CDAX^2$ 1-day-return	21.20***
	(0.449)
CDAX 3-months-return	-0.0193***
	(0.00128)
School vacation	0.00416***
	(0.000870)
Public holidays	-0.00414*
	(0.00239)
First trading day before school vacation	-0.0119***
	(0.00187)
First trading day after school vacation	0.00296*
	(0.00171)
SAD	0.000200
	(0.000806)
Deutsche Börse Frankfurt closed	-0.321***
	(0.0169)
First trading day after public holidays	0.00629***
	(0.00221)
Last trading day before public holidays	0.0180***
	(0.00258)
First trading days of month	0.00415***
	(0.000759)
Last trading days of month	-0.00122
	(0.000754)
Monday	0.00141*
	(0.000829)
Friday	0.00220***
	(0.000687)
Day light saving time change (forward)	-0.0210***
	(0.00364)
Day light saving time change (backward)	0.00900***
	(0.00341)
Constant	-0.347***
	(0.00436)
Year Fixed Effects	YES
Month Fixed Effects	YES

Table A.X. The effect of sentiment on the trading activity unconditional on trading (including the full set of control variables)

This table presents results from investor fixed effects panel regressions. On the left hand side of the regression equation we use a dummy variable that is one if trading occurs and zero otherwise. Control variables include: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

FEARS	0.000187**	0.000823***	0.00126***	0.000606***
	(8.13e-05)	(8.14e-05)	(8.17e-05)	(8.80e-05)
Log wealth				0.00430***
				(0.000234)
CDAX 1-day-return				-0.0903***
				(0.00149)
CDAX ^{2} 1-day-return				3.197***
				(0.0657)
CDAX 3-months-return				0.00109***
				(6.33e-05)
School vacation				-7.71e-05
				(5.02e-05)
Public holidays				-0.0107***
				(9.63e-05)
First trading day before school vacation				-0.00139***
				(0.000146)
First trading day after school vacation				-0.000468***
				(0.000157)
SAD				-0.000690***
				(5.72e-05)
Deutsche Börse Frankfurt closed				-0.0224***
				(9.95e-05)
First trading day after public holidays				-0.00231***
				(0.000174)
Last trading day before public holidays				-0.00658***
				(0.000145)
First trading days of month				0.000969***
				(6.13e-05)
Last trading days of month				-0.00173***
				(5.81e-05)
Monday				0.00151***
				(4.73e-05)
Friday				0.000161***
				(4.52e-05)
Day light saving time change (forward)				-0.00406***
				(0.000411)
Day light saving time change (backward)				0.000947**
				(0.000376)
Year Fixed Effects	NO	YES	YES	YES
Month Fixed Effects	NO	NO	YES	YES

Table A.XI. The effect of sentiment on excess buy-sell imbalances for alternative filtering rules (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on *FEARS* for the average investor who executes at least 10 trades per year. The dependent variables are excess buy-sell imbalances. "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities		Risky Securities		Less-Risky Securities	
	#	EUR	#	EUR	#	EUR
FEARS	-0.00362***	-0.00410***	-0.00268**	-0.00324**	-0.00312	-0.00349
	(0.00127)	(0.00130)	(0.00136)	(0.00139)	(0.00291)	(0.00298)
Log wealth	-0.00733***	-0.00697***	-0.00751***	-0.00728***	-0.00811***	-0.00859***
	(0.000207)	(0.000212)	(0.000227)	(0.000234)	(0.000496)	(0.000509)
CDAX 1-day-return	-0.0291	-0.0279	-0.0264	-0.0228	0.263***	0.240***
	(0.0463)	(0.0471)	(0.0468)	(0.0477)	(0.0619)	(0.0639)
CDAX^2 1-day-return	-2.953***	-2.922***	-3.892***	-3.743***	-5.729***	-6.383***
	(0.553)	(0.565)	(0.560)	(0.574)	(1.431)	(1.470)
CDAX 3-months-return	-0.00514***	-0.00540***	-0.00225**	-0.00269**	0.00125	0.00184
	(0.00103)	(0.00105)	(0.00107)	(0.00109)	(0.00273)	(0.00277)
School vacation	-0.00258***	-0.00248***	-0.00272***	-0.00268***	-0.000350	-0.000101
	(0.000747)	(0.000792)	(0.000792)	(0.000836)	(0.00203)	(0.00207)
Public holidays	0.0154***	0.0151***	0.0179***	0.0177***	0.0115*	0.0110
	(0.00265)	(0.00270)	(0.00277)	(0.00283)	(0.00662)	(0.00680)
First trading day before school vacation	0.00271	0.00218	0.00377	0.00330	0.00122	0.00184
	(0.00252)	(0.00256)	(0.00263)	(0.00269)	(0.00618)	(0.00631)
First trading day after school vacation	-0.00198	-0.00320	-0.00155	-0.00223	-0.00357	-0.00772
	(0.00235)	(0.00240)	(0.00242)	(0.00248)	(0.00589)	(0.00600)
SAD	0.000667	0.000975	0.000375	0.000656	0.00396	0.00425*
	(0.000904)	(0.000921)	(0.000947)	(0.000964)	(0.00241)	(0.00245)
Deutsche Börse Frankfurt closed	0.117***	0.125***	0.128***	0.139***	0.208**	0.197**
	(0.0292)	(0.0290)	(0.0308)	(0.0309)	(0.0896)	(0.0880)
First trading day after public holidays	0.00246	0.00210	0.00341	0.00325	-0.00126	-0.00380
	(0.00296)	(0.00298)	(0.00310)	(0.00314)	(0.00688)	(0.00690)
Last trading day before public holiday	-0.00730**	-0.00862***	-0.00782**	-0.00934***	-0.00997	-0.00849
	(0.00327)	(0.00333)	(0.00346)	(0.00352)	(0.00787)	(0.00801)
First trading days of month	0.000831	0.00116	-5.31e-05	0.000324	0.00214	0.00245
	(0.00102)	(0.00105)	(0.00107)	(0.00110)	(0.00247)	(0.00252)
Last trading days of month	0.000461	0.000413	0.000762	0.000668	0.00105	0.000943
	(0.00101)	(0.00103)	(0.00105)	(0.00108)	(0.00239)	(0.00243)
Monday	0.00889***	0.00973***	0.00916***	0.00995***	2.54e-06	0.000863
	(0.00104)	(0.00106)	(0.00105)	(0.00108)	(0.00213)	(0.00220)
Friday	-0.0108***	-0.0111***	-0.00974***	-0.0100***	-0.00820***	-0.00836***
	(0.000964)	(0.000971)	(0.000984)	(0.000995)	(0.00197)	(0.00201)
Day light saving time change (forward)	0.00884*	0.00769	0.00807	0.00617	0.0109	0.0182
	(0.00506)	(0.00515)	(0.00531)	(0.00543)	(0.0119)	(0.0123)
Day light saving time change (backward)	-0.00137	-0.00143	0.00198	0.00166	-0.0152	-0.0143
	(0.00472)	(0.00483)	(0.00490)	(0.00499)	(0.0126)	(0.0129)
Constant	0.0594***	0.0829***	0.0747***	0.0995***	0.180***	0.179***
	(0.00512)	(0.00531)	(0.00539)	(0.00558)	(0.0373)	(0.0367)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES

Table A.XII. The effect of sentiment on excess trading for alternative filtering rules (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$ for the average investor who executes at least 10 trades per year. The dependent variable is log excess number of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

FEARS	0.00736***
	(0.00200)
Log wealth	0.00191***
	(0.000550)
CDAX 1-day-return	-1.346***
	(0.0494)
CDAX^2 1-day-return	29.63***
	(1.171)
CDAX 3-months-return	-0.0343***
	(0.00320)
School vacation	0.00614***
	(0.00223)
Public holidays	-0.0148***
	(0.00571)
First trading day before school vacation	-0.0221***
	(0.00429)
First trading day after school vacation	0.00435
	(0.00398)
SAD	-0.00117
	(0.00186)
Deutsche Börse Frankfurt closed	-0.263***
	(0.0600)
First trading day after public holidays	-0.0141***
	(0.00533)
Last trading day before public holiday	-0.0467***
	(0.00670)
First trading days of month	0.00504***
	(0.00171)
Last trading days of month	-0.00432**
	(0.00173)
Monday	-0.0132***
	(0.00228)
Friday	0.00320*
	(0.00184)
Day light saving time change (forward)	-0.0233***
	(0.00820)
Day light saving time change (backward)	0.0134*
	0.00476
Constant	-0.407***
	(0.0132)
Year Fixed Effects	YES
Month Fixed Effects	YES

Table A.XIII. The effect of sentiment on excess buy-sell imbalances for alternative excess measure (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$ for the average investor. The dependent variables are excess buy-sell imbalances. The average yearly values of the trading measures that are subtracted from the corresponding observed daily trading measure are the values of the preceding-12-month period. "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities		Risky Securities		Less-Risky Securities	
	#	EUR	#	EUR	#	EUR
FEARS	-0.00541***	-0.00548***	-0.00453***	-0.00475***	-0.0111***	-0.0110***
	(0.000710)	(0.000728)	(0.000744)	(0.000764)	(0.00166)	(0.00172)
Log wealth	-0.0175***	-0.0178***	-0.0140***	-0.0136***	-0.0292***	-0.0309***
	(0.000234)	(0.000245)	(0.000214)	(0.000221)	(0.000650)	(0.000703)
CDAX 1-day-return	-0.0862***	-0.0826***	0.256***	0.272***	-0.826***	-0.863***
	(0.0204)	(0.0207)	(0.0190)	(0.0192)	(0.0373)	(0.0382)
$CDAX^2$ 1-day-return	-2.873***	-2.959***	-4.762***	-5.470***	-6.747***	-5.905***
	(0.292)	(0.299)	(0.307)	(0.317)	(0.544)	(0.559)
CDAX 3-months-return	-0.0169***	-0.0176***	-0.00562***	-0.00551***	-0.0435***	-0.0433***
	(0.000594)	(0.000619)	(0.000601)	(0.000629)	(0.00139)	(0.00143)
School vacation	-0.00372***	-0.00351***	-0.00360***	-0.00314***	-0.00537***	-0.00548***
	(0.000454)	(0.000492)	(0.000481)	(0.000526)	(0.00114)	(0.00118)
Public holidays	0.0242***	0.0245***	0.0235***	0.0231***	0.0145***	0.0178***
	(0.00150)	(0.00154)	(0.00155)	(0.00160)	(0.00360)	(0.00373)
First trading day before school vacation	0.00394***	0.00294**	0.00521***	0.00464***	0.00555	0.00421
	(0.00142)	(0.00145)	(0.00148)	(0.00151)	(0.00342)	(0.00354)
First trading day after school vacation	-0.00282**	-0.00317**	-0.00295**	-0.00319**	0.000113	0.000640
	(0.00131)	(0.00134)	(0.00137)	(0.00141)	(0.00306)	(0.00317)
SAD	0.00228***	0.00263***	0.00296***	0.00326***	-0.000951	-0.000796
	(0.000524)	(0.000536)	(0.000546)	(0.000561)	(0.00126)	(0.00129)
Deutsche Börse Frankfurt closed	0.156***	0.163***	0.199***	0.223***	-0.0204	-0.129***
	(0.0111)	(0.0113)	(0.0114)	(0.0118)	(0.0236)	(0.0219)
First trading day after public holidays	0.00478***	0.00354**	0.00254	0.00167	0.0160***	0.0141***
	(0.00161)	(0.00165)	(0.00169)	(0.00172)	(0.00362)	(0.00372)
Last trading day before public holidays	0.00947***	0.0105***	0.00413**	0.00420**	-0.0102***	-0.00625
	(0.00179)	(0.00183)	(0.00187)	(0.00192)	(0.00385)	(0.00400)
First trading days of month	-0.000652	-0.000757	0.00155***	0.00153**	-0.00874***	-0.00885***
	(0.000575)	(0.000591)	(0.000598)	(0.000614)	(0.00136)	(0.00140)
Last trading days of month	0.00315***	0.00320***	0.00215***	0.00208***	0.0148***	0.0142***
	(0.000565)	(0.000578)	(0.000585)	(0.000600)	(0.00135)	(0.00139)
Monday	0.00783***	0.00844***	0.00873***	0.00898***	-0.00610***	-0.00417***
	(0.000510)	(0.000522)	(0.000535)	(0.000547)	(0.00103)	(0.00106)
Friday	-0.00992***	-0.0104***	-0.0100***	-0.0104***	-0.00465***	-0.00519***
	(0.000480)	(0.000489)	(0.000501)	(0.000510)	(0.00103)	(0.00106)
Day light saving time change (forward)	0.0169***	0.0170***	0.0158***	0.0167***	0.0318***	0.0300***
	(0.00284)	(0.00290)	(0.00297)	(0.00304)	(0.00707)	(0.00732)
Day light saving time change (backward)	0.00339	0.00257	0.000111	-0.000607	0.00187	-0.000333
	(0.00258)	(0.00265)	(0.00274)	(0.00281)	(0.00566)	(0.00584)
Constant	0.150***	0.172***	0.143***	0.162***	0.466***	0.485***
	(0.00367)	(0.00384)	(0.00363)	(0.00380)	(0.00983)	(0.0104)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES

Table A.XIV. The effect of sentiment on excess trading for alternative excess measure (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$ for the average investor. The dependent variable is log excess number of trades. The average yearly values of the trading measures that are subtracted from the corresponding observed daily trading measure are the values of the preceding-12-month period. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

FEARS	0.00455***
	(0.000937)
Log wealth	0.00969***
	(0.000324)
CDAX 1-day-return	-1.048***
	(0.0195)
CDAX^2 1-day-return	24.21***
	(0.469)
CDAX 3-months-return	-0.0171***
	(0.00138)
School vacation	0.00298***
	(0.000858)
Public holidays	0.000725
	(0.00244)
First trading day before school vacation	-0.0125***
	(0.00193)
First trading day after school vacation	0.000849
	(0.00178)
SAD	-0.000765
	(0.000844)
Deutsche Börse Frankfurt closed	-0.310***
	(0.0174)
First trading day after public holidays	0.00318
	(0.00229)
Last trading day before public holidays	0.0246***
	(0.00279)
First trading days of month	0.00399***
	(0.000789)
Last trading days of month	-0.00218***
	(0.000780)
Monday	0.00343***
	(0.000840)
Friday	0.00108
	(0.000701)
Day light saving time change (forward)	-0.0228***
	(0.00376)
Day light saving time change (backward)	0.00293
	0.0289***
Constant	-0.0279***
	(0.00622)
Year Fixed Effects	YES
Month Fixed Effects	YES

Table A.XV. The effect of sentiment on excess buy-sell imbalances controlling for weather (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$ and $Air\ Pressure$ for the average investor. The dependent variables are excess buy-sell imbalances. "#" stands for measures calculated based on number of trades, whereas "EUR" stands for measures calculated based on euro-values of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	All Securities		Risky Securities		Less-Risky Securities	
	#	EUR	#	EUR	#	EUR
FEARS	-0.00502***	-0.00498***	-0.00425***	-0.00436***	-0.00929***	-0.00768***
	(0.000657)	(0.000676)	(0.000694)	(0.000715)	(0.00148)	(0.00152)
Air Pressure	0.000154***	0.000163***	0.000132***	0.000139***	0.000204***	0.000233***
	(1.33e-05)	(1.37e-05)	(1.41e-05)	(1.45e-05)	(2.96e-05)	(3.03e-05)
Log wealth	-0.0122***	-0.0116***	-0.0104***	-0.00981***	-0.0205***	-0.0202***
	(0.000154)	(0.000156)	(0.000150)	(0.000156)	(0.000400)	(0.000403)
CDAX 1-day-return	-0.0583***	-0.0635***	0.226***	0.236***	-0.723***	-0.762***
	(0.0192)	(0.0196)	(0.0179)	(0.0182)	(0.0343)	(0.0351)
$CDAX^2$ 1-day-return	-3.122***	-2.967***	-4.725***	-5.009***	-6.418***	-5.810***
	(0.262)	(0.269)	(0.280)	(0.291)	(0.468)	(0.479)
CDAX 3-months-return	-0.0158***	-0.0171***	-0.00317***	-0.00375***	-0.0460***	-0.0467***
	(0.000532)	(0.000555)	(0.000535)	(0.000560)	(0.00123)	(0.00127)
School vacation	-0.00300***	-0.00267***	-0.00311***	-0.00249***	-0.00379***	-0.00345***
	(0.000401)	(0.000447)	(0.000428)	(0.000480)	(0.000977)	(0.00102)
Public holidays	0.0214***	0.0218***	0.0212***	0.0213***	0.0153***	0.0181***
	(0.00140)	(0.00144)	(0.00146)	(0.00151)	(0.00325)	(0.00334)
First trading day before school vacation	0.00414***	0.00346**	0.00499***	0.00473***	0.00581*	0.00336
	(0.00131)	(0.00135)	(0.00138)	(0.00142)	(0.00305)	(0.00312)
First trading day after school vacation	-0.00209*	-0.00224*	-0.00244*	-0.00249*	-0.000140	0.000714
	(0.00120)	(0.00124)	(0.00127)	(0.00131)	(0.00270)	(0.00278)
SAD	0.00214***	0.00250***	0.00281***	0.00304***	0.000969	0.00195*
	(0.000479)	(0.000493)	(0.000504)	(0.000521)	(0.00111)	(0.00113)
Deutsche Börse Frankfurt closed	0.146***	0.159***	0.195***	0.231***	-0.0349*	-0.135***
	(0.0101)	(0.0104)	(0.0106)	(0.0112)	(0.0212)	(0.0194)
First trading day after public holidays	0.00565***	0.00542***	0.00292*	0.00262	0.00990***	0.0128***
	(0.00147)	(0.00151)	(0.00156)	(0.00160)	(0.00309)	(0.00320)
Last trading day before public holidays	0.00412**	0.00560***	-0.00142	-0.000653	-0.0130***	-0.0160***
	(0.00160)	(0.00164)	(0.00170)	(0.00175)	(0.00330)	(0.00336)
First trading days of month	0.000229	-0.000135	0.00197***	0.00173***	-0.00680***	-0.00881***
	(0.000533)	(0.000549)	(0.000558)	(0.000575)	(0.00121)	(0.00123)
Last trading days of month	0.00238***	0.00230***	0.00135**	0.00131**	0.0112***	0.00978***
	(0.000522)	(0.000535)	(0.000546)	(0.000561)	(0.00120)	(0.00123)
Monday	0.00749***	0.00816***	0.00786***	0.00801***	-0.00545***	-0.00336***
	(0.000478)	(0.000489)	(0.000504)	(0.000516)	(0.000910)	(0.000937)
Friday	-0.00928***	-0.0103***	-0.00985***	-0.0107***	-0.00345***	-0.00475***
	(0.000451)	(0.000460)	(0.000474)	(0.000483)	(0.000927)	(0.000946)
Day light saving time change (forward)	0.0136***	0.0139***	0.0126***	0.0139***	0.0302***	0.0307***
	(0.00264)	(0.00270)	(0.00278)	(0.00285)	(0.00621)	(0.00634)
Day light saving time change (backward)	0.00232	0.00205	-0.00248	-0.00247	0.00944*	0.00725
	(0.00238)	(0.00245)	(0.00255)	(0.00263)	(0.00501)	(0.00515)
Constant	0.0778***	0.0931***	0.0914***	0.112***	0.338***	0.332***
	(0.00307)	(0.00322)	(0.00317)	(0.00338)	(0.00759)	(0.00770)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES

Table A.XVI. The effect of sentiment on excess trading controlling for weather (including the full set of control variables)

This table presents results from investor fixed effects panel regressions on $FEARS$ and $Air\ Pressure$ for the average investor. The dependent variable is log excess number of trades. All regressions are controlled for calendar- and market-specific factors through the following variables: wealth, measured by the natural logarithm of preceding month's asset holdings; preceding-one-day realized market return (CDAX); preceding-three-month realized market return (CDAX); seasonal affective disorder, measured as in Kamstra, Kramer, and Levi (2003); dummies for school vacations, public holidays, trading days before school vacations, trading days after school vacations, trading days for closed exchange, first trading days of the months, last trading days of the months, first trading days of the years, last trading days of the years, Mondays, Fridays, Mondays following forward changes in daylight saving time, and Mondays following backward changes in daylight saving time. All regressions incorporate month and year fixed effects. We use clustered standard errors on the level of individual investors that are robust to heteroscedasticity and autocorrelation and report them in parentheses. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

FEARS	0.00475***
	(0.000907)
Air Pressure	-6.72e-05***
	(2.09e-05)
Log wealth	-0.00160***
	(0.000265)
CDAX 1-day-return	-0.954***
	(0.0188)
$CDAX^2$ 1-day-return	21.22***
	(0.449)
CDAX 3-months-return	-0.0193***
	(0.00128)
School vacation	0.00415***
	(0.000870)
Public holidays	-0.00414*
	(0.00239)
First trading day before school vacation	-0.0119***
	(0.00187)
First trading day after school vacation	0.00295*
	(0.00171)
SAD	0.000200
	(0.000806)
Deutsche Börse Frankfurt closed	-0.320***
	(0.0169)
First trading day after public holidays	0.00639***
	(0.00221)
Last trading day before public holidays	0.0184***
	(0.00259)
First trading days of month	0.00412***
	(0.000759)
Last trading days of month	-0.00128*
	(0.000754)
Monday	0.00158*
	(0.000813)
Friday	0.00213***
	(0.000685)
Day light saving time change (forward)	-0.0207***
	(0.00364)
Day light saving time change (backward)	0.00873**
	(0.00340)
Constant	-0.306***
	(0.00587)
Year Fixed Effects	YES
Month Fixed Effects	YES