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Ambiguity and Investor Behavior

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Ambiguity and Investor Behavior

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ABSTRACT

We relate time-varying aggregate ambiguity (V-VSTOXX) to individual investor trading. We use the trading records of more than 100,000 individual investors from a large German online brokerage from March 2010 to December 2015. We find that an increase in ambiguity is associated with increased investor activity. It also leads to a reduction in risk-taking which does not reverse over the following days. When ambiguity is high, the effect of sentiment looms larger. Survey evidence reveals that ambiguity averse investors are more prone to ambiguity shocks. Our results are robust to alternative survey-, newspaper- or market-based ambiguity measures.

JEL classification: D10; D81; D90; G11; G40

Keywords: ambiguity; uncertainty; individual investor; risk-taking; trading behavior

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1 Introduction

Investment decisions are decisions under uncertainty that are subject to both risk and ambiguity (Knight (1921)). According to Knight (1921), events for which the future outcome is unknown, but the underlying distribution is known, are referred to as “risky.” The Knightian uncertainty or ambiguity as it is called by Ellsberg (1961) and Drechsler (2013) is distinct from risk and describes events for which not only the future outcome but also the underlying distribution is unknown. Thus, risk and ambiguity are conceptually different and may induce different reactions.

Recently, research has focused on the impact of ambiguity on capital markets and asset prices. They found that ambiguity matters (Branger, Schlag, and Thimme (2019)) and that it is distinct from risk as both affect the equity premium (Brenner and Izhakian (2018)). Another strand of literature has researched the impact of ambiguity on individuals’ financial decision making. The most prominent study is Ellsberg (1961), who finds that individuals tend to be ambiguity averse. The paper by Dimmock et al. (2016) derives ambiguity aversion of individuals in a survey and shows that it matters for asset allocation decisions. The higher the ambiguity aversion the lower is the stock market participation of individuals. Bianchi and Tallon (2018) show that ambiguity averse investors exhibit a higher home bias, rebalance their portfolio more actively, and tend to keep their risk exposure constant over time. Thus, there is only cross-sectional evidence for the impact of ambiguity aversion on the behavior of individual investors. In this study, we contribute to the existing literature by investigating the time-varying effect of market-based ambiguity on the trading activity and risk-taking on a large sample of individual investors. We show that over time ambiguity shocks lead investors to trade more and especially trade out of risky securities. This effect is stronger for ambiguity averse investors. Our findings provide complementary evidence to the existing literature by showing that a lower risky share does not only result from initial asset allocation decisions, but also from trading decisions in reaction to ambiguity shocks.

For a measure of time-varying aggregate ambiguity the literature has not yet reached a consensus. Studies are using survey-based measures that build on the dispersion of forecasts of professional forecasters (e.g., Anderson, Ghysels, and Juergens (2009), Drechsler (2013), Andrei and Hasler (2015), Ulrich (2013), David and Veronesi (2013)), newspaper-based measures like the economic policy uncertainty (e.g., Baker, Bloom, and Davis (2016)) and market-based measures like the VIX, the VVIX or those build on high-frequency data. The correlation between these measures is reported to be relatively low (Huang et al. (2020)). Among the market-based measures, the volatility of volatility (examples are the VVIX or V-VSTOXX) represents second-order beliefs, which, according to many theoretical models, are appropriate to capture ambiguity (Klibanoff, Marinacci, and Mukerji (2005), Nau (2006), Segal (1987)). Therefore, it is not surprising that the volatility of volatility is regarded as a good measure for ambiguity and used as such (Baltussen, van Bekkum, and van der Grient (2018), Hollstein and Prokopczuk (2018), Huang et al. (2020), Chen, Chung, and Lin (2014), Bali and Zhou (2016), Bollerslev, Tauchen, and Zhou (2009), Epstein and Ji (2013), Barndorff-Nielsen and Veraart (2012)).

We follow this stream of literature and measure ambiguity using a volatility-of-volatility measure. We use the V-VSTOXX which is the 30-day implied volatility of the VSTOXX. The V-VSTOXX is a daily measure and is the European equivalent to the VVIX and based on the Euro Stoxx index and the regionally closest measure to our investor data. The Euro Stoxx index is a composite stock market index representing the European stock market. Thus, the ambiguity measure we use is the volatility of volatility of the Euro Stoxx. Whereas the VSTOXX measures the expected risk over the following 30 days, the V-VSTOXX measures the expected uncertainty about the future risk over the following 30 days. The uncertainty on the risk or volatility is close to what is generally understood by the term ambiguity. Using this approach provides the additional advantages of a natural, model-free, market-based, and forward-looking measure, which is computed based on liquid securities and daily available and is, thus, the most suitable for our research question. Additionally, this approach allows disentangling risk (implied volatility) and ambiguity (implied volatility of the implied volatility). In the robustness section, we also control for alternative measures of ambiguity. These are volatility-of-volatility of forecaster GDP expectations, newspaper based economic policy uncertainty (EPU) and the recently proposed omega measure by Brenner and Izakhian (2018).

We match the V-VSTOXX to the trading records of more than 100,000 individual investors of a large German online brokerage.[2] The brokerage data cover all time-stamped security transactions for the period from March 2010 through December 2015. They mirror the well-known U.S. transaction data by Barber and Odean (2000). We exclude all individuals who

[2] Because the analog of the VVIX or V-VSTOXX for the German stock market does not exist, we use the V-VSTOXX as a proxy for the German aggregate market ambiguity. The European market measure seems to be a good proxy for German market ambiguity as the correlation between the VSTOXX and the VDAX, the German equivalent of the VSTOXX, is 0.96.

obtain financial advice, because we are interested in the effect of ambiguity on the trading decisions of households and not in the suggestions of financial advisers. Given these data, we conduct a within-person analysis and control for individual average trading behavior, observable time-varying, and observable as well as unobservable time-fixed characteristics of investors.

We first employ an unconditional analysis and test how the aggregate ambiguity (innovations in V-VSTOXX) affects the activity of individual investors along two dimensions: logins[3] and trades. Innovations in ambiguity are associated with higher investor activity both in terms of logins and trades. When ambiguity is high and investors have a hard time assessing risks, stock markets may receive more attention, and hence they deal more with their portfolio as they login more often. Additionally, they seem to be faced with the need to adjust their portfolios, as they then also tend to trade more.

The remainder of this paper analyzes the trading behavior of our investors conditional on trading. That is, given that investors trade as a response to ambiguity shocks, we investigate how exactly they adjust their portfolios. Thereby, we are particularly interested in their risk-taking behavior. We find that ambiguity shocks cause investors to decrease their exposure to the security market by trading out of stocks and similarly risky assets. This effect does not reverse within the following 10 days. This result is broadly in line with theoretical models, predicting that ambiguity shocks can cause investors to reduce their risky asset share or to exit the security market (Mele and Sangiorgi (2015), Garlappi, Uppal, and Wang (2006), Peijnenburg (2018)). This, as well as all other results of the paper, are robust to the inclusion of time-varying aggregate risk (innovations in VSTOXX) in the model. Additionally, we find that when we benchmark the effect of ambiguity (V-VSTOXX) with the effect of risk (VSTOXX), only ambiguity yields statistically significant results in the trading behavior of individual investors. It thus seems that ambiguity matters at least as much as risk for individual investors.

Next, we test a hypothesis that originates from Hirshleifer (2001). He argues that biases should be more severe when ambiguity is high. We test this conjecture using the FEARS index[4], which

[3] A login is counted each time an investor login her account where she does not necessarily have to execute a trade. Thus, logins measure the general tendency to observe the portfolio rather than real activity which is measured by (executed) trades.

[4] FEARS stands for “Financial and Economic Attitudes Revealed by Search” and, in essence, it is the aggregate of Google search volumes of negative economic terms such as “financial crisis,” “bankruptcy,” or “recession.” A German version (Kostopoulos, Meyer, and Uhr (2020)) of the FEARS index is available to us for the period of this paper.

was originally proposed by Da, Engelberg, and Gao (2015). We thereby test if trading reactions to changes in sentiment are different depending on the level of ambiguity. Previous studies investigating the impact of psychology on risky choices of individual investors show that low sentiment is associated with less risk-taking (Kostopoulos, Meyer, and Uhr (2020), Schmittmann et al. (2015), Kaustia and Rantapuska (2016), Kostopoulos and Meyer (2018)). If our conjecture is correct, we should find that in times of high ambiguity, the sentiment effect is stronger than in times of low ambiguity. We observe that sentiment effects are present in days of high and low ambiguity. However, we find evidence that the effect of sentiment looms significantly larger in high ambiguity periods.

Dimmock et al. (2016) show that more ambiguity averse investors are less likely to participate in the ambiguous stock market. In contrast, we show that fluctuations in aggregate ambiguity matter empirically for individual investors' decisions. It seems hence natural to combine the two results and conjecture that more ambiguity averse individuals are also more prone to ambiguity fluctuations. To measure the ambiguity aversion of our investors, we asked the bank to randomly choose 10,000 clients and invite them to participate in a survey. In this survey, we run an Ellsberg-type urn problem and classify the participating investors into ambiguity averse, ambiguity neutral and ambiguity seeking individuals. The total number of investors participating in the survey is 644. From those, 58.7% are ambiguity averse, 12% are ambiguity neutral, and 29.3% are ambiguity seeking. These figures are fully in line with previous studies such as Dimmock et al. (2016) and show that our sample is representative concerning ambiguity preferences. We find that ambiguity averse investors are 4.5 times more vulnerable to innovations in ambiguity than the average investor. That is, we document an interaction between time-varying ambiguity and ambiguity preferences of individuals. Additionally, we find that ambiguity seeking investors, in contrast to ambiguity averse investors, increase their exposure to risk when they experience ambiguity shocks. More technically, the sign of the estimate flips. We interpret this result as strong evidence that changes in V-VSTOXX, indeed, represent innovations in ambiguity.

In this paper, we use the V-VSTOXX as ambiguity measure. Nevertheless, in the robust section, we rerun our analysis and control for three alternative measures of ambiguity. First, we calculate a survey-based measure of ambiguity that builds on the dispersion of forecasts of professional forecasters. Second, we follow the approach by Brenner and Izhakian (2018) and rebuild their measure of ambiguity for the Euro Stoxx. Third, for a newspaper-based measure we control for the economic policy uncertainty using the data from Baker, Bloom, and Davis

(2016).Controlling for these alternative measures of ambiguity does not change our results qualitatively.

2 Measuring ambiguity and investor data

In this study, we measure time-varying ambiguity by the volatility of volatility as a market-based measure. The volatility of volatility (examples are the VVIX or V-VSTOXX) represents second-order beliefs, which, according to many theoretical models, are appropriate to capture ambiguity (Klibanoff, Marinacci, and Mukerji (2005), Nau (2006), Segal (1987)). Therefore, the volatility of volatility is regarded as a good measure for ambiguity and used in empirical work as such (Baltussen, van Bekkum, and van der Grient (2018), Hollstein and Prokopczuk (2018), Huang et al. (2020), Chen, Chung, and Lin (2014), Bali and Zhou (2016), Bollerslev, Tauchen, and Zhou (2009), Epstein and Ji (2013), Barndorff-Nielsen and Veraart (2012)). Because the analog of the VVIX or V-VSTOXX for the German stock market does not exist, we use the V-VSTOXX as a proxy for the German aggregate market ambiguity. We show that the European market measure is a good proxy for German market ambiguity as the correlation between the VSTOXX and the VDAX, the German equivalent of the VSTOXX, is 0.96. We start this section with an introduction of our ambiguity measure, as this is the main variable in this study. Then, we describe our retail investor data. Finally, we present a list of control variables, which we include in all the specifications of this paper.

2.1 Measuring time-varying ambiguity

We use the V-VSTOXX provided and computed by the Stoxx Limited, a subsidiary of the Deutsche Börse AG, that is available from March 23, 2010, onwards. The V-VSTOXX is the 30-day implied volatility of the VSTOXX and is based on VSTOXX real-time option prices. The Euro Stoxx index is a composite stock market index including 50 large Eurozone companies representing the European stock market. That is, the ambiguity measure we use is the volatility of volatility of the Euro Stoxx. Whereas the VSTOXX measures the expected risk over the following 30 days, the V-VSTOXX measures the expected ambiguity over the following 30 days. The VSTOXX is the equivalent of the VIX and the V-VSTOXX is the equivalent of the VVIX. All these measures are computed identically.[5]

[5] The interpretation of these kind of volatility measures is straightforward: For example, a VSTOX value of 40 implies that the annualized expected volatility over the following 30 days is 40%. For a detailed description of the computation of VSTOXX and V-VSTOXX, refer to the STOXX Strategy Index Guide (STOXX Ltd. (2020)).

According to our terminology, both VSTOXX and V-VSTOXX are measures for uncertainty. Whereas the VSTOXX measures the expected risk over the following 30 days, the V-VSTOXX measures the expected ambiguity (= Knightian uncertainty) over the following 30 days. Figure 1 plots the time series of V-VSTOXX and VSTOXX between March 2010 and June 2017. The annotated line graph suggests that V-VSTOXX is a reliable measure of aggregate ambiguity. For each of the peaks in the graphs we can match an event that gives rise to diverging believes about the future of the economy both in terms of expected returns and in terms of the expected volatility.

[Insert Figure 1 about here]

For example, the peak in September 2015 was the day of the announcement of the Volkswagen diesel affair. This marks a point of high ambiguity for the future stock price movements in Germany as the country is heavily relying on the automotive industry. Furthermore, it is interesting to observe that the peak of the V-VSTOXX in May 2010 (124.87) was the starting point of the European sovereign debt crisis. On the other hand, the trough of the V-VSTOXX (51.76) is in June 2014, which was just before the end of the crisis. This may be interpreted as investors became more used to the relatively high level of risk and agreed that it pertained over the next weeks. Then, when investors began to realize that the crisis was probably abating, ambiguity increased again, because investors were again more uncertain about the future level of risk. This evidence is along the line of what Hollstein and Prokopczuk (2018) discuss for the VVIX in the U.S. In particular, aggregate ambiguity in the U.S. was lowest in the crisis year 2009 when investors agreed about the high level of risk during that time. This anecdotal evidence is suggestive of the volatility of volatility being a reasonable proxy for ambiguity.

We are interested in the impact of the aggregate ambiguity on individual investor trading. Thus, our main variable represents the daily innovations in V-VSTOXX, which we denote as $dVVSTOXX$. This is the variation we are working within this study. Since we want to capture the impact of ambiguity beyond the impact of risk, for all employed econometric models we run at least one specification including innovations in VSTOXX, which we denote as $dVSTOXX$.

Table I presents descriptive statistics for the uncertainty measures as well as the return data of the German and European stock markets. The mean of *dVVSTOXX is* close to zero, the standard deviation is 3.99, the minimum is -22.65, and the maximum is 31.29.

[Insert Table I about here]

It is important to understand how representative the V-VSTOXX is as a measure of the aggregate ambiguity in the German market. As of May 31, 2018, 33% of the market capitalization of the Euro Stoxx is attributed to companies also listed in the DAX.[6] These companies represent 50% of the DAX components and their market capitalization represents 74% of the total DAX market capitalization. These figures are stable over time. Hence, it is not surprising that the correlation between the Euro Stoxx and the DAX is high. In Table II, we report the correlation matrix for the uncertainty measures as well as the return data of the German and European stock markets and find that, indeed, the correlation between the Euro Stoxx and the DAX is 0.95. As a result, the VDAX, the German equivalent for the VIX, and the VSTOXX seem also to comove to a large extent, which is presented in Figure 2. The correlation between the VDAX and the VSTOXX is 0.96. Figure 3 shows the same pattern for the VVIX and V-VSTOXX. Additionally, the correlation between innovations in VDAX (*dVDAX*) and innovations in VSTOXX (*dVSTOXX*), which we use throughout the paper to control for innovations in risk, is 0.95 and thus also very high. Campbell and Hentschel (1992), similar to many other asset pricing studies, argue that returns are negatively correlated with future volatility. Columns (2) and (3) of the last two rows of Table II show that innovations in the VDAX and VSTOXX are associated with both, negative DAX returns and negative Euro Stoxx returns. The magnitude of this relationship is highly comparable for all four pairwise correlations, which are all close to -0.8.

[Insert Table II and Figures 2 and 3 about here]

Apart from the appropriateness of the V-VSTOXX to capture the aggregate market ambiguity in Germany, it has several additional appealing features. First, it is computed and provided by STOXX Limited, which belongs to the Deutsche Börse Group. Therefore, it is not subject to any computation of single researchers. Second, the V-VSTOXX is a market-based measure, which is readily available daily. Third, it is a natural and model-free measure. That is, it is not based on any option pricing models. Instead, it is directly derived from real option prices. Fourth, the liquidity of the assets used to derive the V-VSTOXX (options on the VSTOXX) is

[6] The DAX is a German composite stock market index that captures 30 stocks tradeable on the Frankfurt stock exchange and represents the German stock market.

high. For instance, in 2015, more than 6.6 million contracts were traded on the Eurex.[7] This translates to an average monthly volume of approximately €550,000.

2.2 Investor data

The primary data set for this paper comes from a large German online brokerage. These data cover detailed information on trading records of German retail investors. Since the V-VSTOXX is available from March 2010 onwards and our trading records are available up to December 2015, the sample period of this paper is from March 2010 through December 2015. One appealing feature of our data is that they include all security transactions of our investors. We observe the trading in and out of (more and less risky) listed financial securities in all kinds of listed financial securities like stocks, bonds, funds and derivative securities of individual investors. Another important feature of this data set is that it allows us to identify all investors who obtain financial advice. We exclude these investors because we are interested in household financial decision making and not in financial adviser suggestions. We also exclude transactions such as transfers among personal accounts and automated trades such as saving plans, because these kinds of transactions do not represent self-driven trades.

Table III presents descriptive statistics of our investor data. In total, our data set includes 103,113 investors who execute 23.4 million trades. 54% of these trades are purchases and 46% are sells. The overwhelming part of the investors, that is, 84%, are males, and the remaining 16% are females. On average, our investors are 53.17 years old. The median investor is 52 years old and the interquartile range is 45 to 61.

[Insert Table III about here]

With respect to occupation, most investors are employed (48%), while 19% are self-employed, and 13% are already retired. The average investor has been a client of the bank for 15 years and holds a portfolio value of approximately 56,475 Euros. Furthermore, our clients have an average (median) HHI of 35.6% (22.3%) and an average (median) risk class of 3.6 (4) measured on a scale ranging from 1 (indicating lowest risk) to 5 (indicating highest risk). Our data set is highly comparable to the well-known U.S. data set by Barber and Odean (2000). Brokerage clients are generally expected and found to be more sophisticated than the overall population (Dorn and Huberman (2005)). Therefore, it is not surprising that 7% of our investors hold a doctoral

[7] See http://www.eurexchange.com. The Eurex is one of the largest derivatives exchanges in the world.

degree. According to the German Federal Statistical Office, this value is higher than the average of the German population (1.1%; see German Federal Statistical Office (2018b)).

Investor panel data sets based on administrative data are usually subject to the concern that they might only consist of play money accounts. To address this concern, we first compare the average portfolio values to the official statistics. The European central bank reports in its household finance and consumption survey that in 2017, the average portfolio value of German stock market investors was approximately 48,000 Euros (European Central Bank (2017)). This value is comparable to the average values we observe in our sample. Additionally, we compare the portfolio holdings to the self-reported gross annual household incomes for those investors who reported this information. Since income is reported in ranges, we use the midpoint of each range as a proxy for investor income. The mean ratio of the average portfolio value (over the entire sample period) to annual income is 1.3. For comparison, according to the German Federal Statistical Office, the ratio of total financial assets to gross household income in the German population is approximately 1.1 (German Federal Statistical Office (2018c), German Federal Statistical Office (2018a)).

2.3 Control variables

In all specifications of this paper, we include a large set of control variables. We do so to avoid picking up effects that have already been found in previous studies to explain investor trading decisions. In this section, we discuss all our control variables shown in Table IV.

[Insert Table IV about here]

Panel A lists control variables that are related to calendar dates. School holidays may have an impact on the 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. To control for abnormal trading just before going on vacation or just after arriving from vacation, we insert two more dummy variables:[8] one for the last trading day before school vacations begin and one for the first trading day after school vacations end. Since public holidays could also have the same effect as school holidays, we include an additional dummy variable indicating public holidays.

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

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.

Other well-known anomalies are related to human biorhythms (Kamstra, Kramer, and Levi (2003), Kamstra, Kramer, and Levi (2000)). Therefore, we control for seasonal affective disorder (SAD). We measure SAD as in Kamstra, Kramer, and Levi (2003). Furthermore, we include two dummy variables for Mondays following changes in daylight savings time: one for advancing clocks and one for adjusting them backward.

Additionally, we incorporate year fixed effects and month fixed effects into the regressions. This ensures that our results are not driven by single years-of-the-sample-period, months-of-the-year, or any other slow-moving seasonality effects. Besides, month fixed effects control for the tax-induced trading behavior of retail investors (Rozeff and Kinney (1976), Keim (1983), Grinblatt and Keloharju (2001)).

Panel B lists all market-related control variables. All market data in this paper are from Datastream. Previous stock market returns may affect the trading behavior of households (Gervais, Kaniel, and Mingelgrin (2001), Barber and Odean (2008), Grinblatt and Keloharju (2001)). 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, we use the CDAX. CDAX is a German stock market index capturing all stocks that are traded on the Frankfurt stock exchange. Including the preceding-one-day market return and the squared preceding-one-day market return implicitly also provides a control for macroeconomic announcements and earnings announcements.

Panel C lists all investor-related control variables. Wealth plays a major role in the decision making of households. For instance, Carroll (2002) provides evidence that risk aversion decreases in wealth. To account for the trading patterns of wealthy investors and to not allow for 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. Lastly, in all our regressions we include investor fixed effects to account for any observable and unobservable characteristics of investors.

3 Time-varying ambiguity and investor behavior

In this section, we present the empirical approach and the main results of the paper. We start with an unconditional analysis. Specifically, we investigate how the time-varying aggregate ambiguity impacts the activity of individual investors along two dimensions: logins and trades. Next, we explore the risk-taking behavior of our investors conditional on trading. That is, given that an investor trades as a response to ambiguity shocks, we check whether she reduces or increases her exposure to risk. In the last step, we test the conjecture from theory suggesting that the effects of sentiment are more pronounced in times of high ambiguity.

3.1 The effect of ambiguity on investor activity

Ambiguity and investor activity might be related. There are two plausible, but contradicting, possibilities for how this relationship could take shape. The first one is highlighted by a statement in the Minutes of the Federal Open Market Committee (FOMC) on October 2, 2001, right after the 9/11 terrorist attacks: "The events of September 11 produced a marked increase in uncertainty […] fostering an increasingly widespread wait-and-see attitude."

In stark contrast, Daniel, Hirshleifer, and Subrahmanyam (1998) and Daniel, Hirshleifer, and Subrahmanyam (2001) argue that investors tend to be more overconfident when fundamentals are hard to value. At the same time, overconfidence is strongly related to overtrading (Odean (1998), Odean (1999), Barber and Odean (2000), Barber and Odean (2001)). Taken together, when aggregate ambiguity is high, fundamentals are harder to value and hence investors would be more active in financial markets.

Theoretically, Dow and Werlang (1992) link ambiguity aversion to non-participation. In their model, for prices within an interval, investors will optimally choose to hold no quantity of the asset. Hence, the model predicts that an increase in ambiguity can lead an investor holding an asset to sell it and thus relates to more investor activity, i.e. away from the ambiguous assets. To illustrate the general idea, consider an ambiguity averse investor and one risky asset. The investor has an expectation about the value of this asset. If the price of the risky asset is above a certain threshold, she considers the asset as overvalued and thus will sell it (short it). Conversely, if the price of the risky asset is below a certain threshold, she considers the asset as undervalued and thus will buy it. Within the interval of these two thresholds, the investor is neither willing to buy nor to sell the asset—that is, she will not trade. The size of this interval characterizes the perceived ambiguity of the investor. When the aggregate ambiguity is high, the perceived ambiguity is high, too, and vice versa. Thus, when ambiguity increases, this interval of "no trading" increases as well, and trading becomes less likely. Sometimes, this hypothesis is referred to as the "no-trade hypothesis" in the literature.

In this section, we test these two competing theories. Our empirical approach is to investigate the propensity of individual investors to become active in financial markets along two dimensions: logging into their brokerage accounts and trading. Concretely, we analyze the impact of the aggregate ambiguity on the probability to log in and to trade. To formally test this relation, we postulate the following linear probability model with investor fixed effects:

$$Activity_{i,t} = \alpha + \beta \, dVVSTOXX_t + \gamma \, C_{i,t} + \varepsilon_{i,t} \, . \tag{1}$$

Activity is either *Login* or *Trade*. *Login* is a dummy variable taking on the value 1 if and only if a login is observed. *Trade* is a dummy variable taking on the value 1 if and only if a trade is observed.[9] d*VVSTOXX* represents the innovations in aggregate ambiguity. *i* represents an investor and *t* the day. Throughout the paper, *C* is a vector containing all control variables described in Section 2.4. Keep in mind that *C* also includes year and month fixed effects to account for any seasonality. Moreover, throughout the paper, we cluster standard errors at the investor level. All results are robust to clustering at the day or the zip code level.

Table V presents the point estimates β of different specifications from model (1). In columns (1) to (3), we use *Login* as the dependent variable and in columns (4) to (6), we use *Trade* as the dependent variable. Column (1) shows that innovations in ambiguity are associated with an increased probability to log in. To capture the impact of ambiguity beyond the impact of risk, in column (2), we also control for innovations in risk and include *dVSTOXX* to model (1). Even if we control for innovations in risk, the impact of ambiguity on the probability to log in is

[9] The information on logins is only available from 2012 onwards. Therefore, all regressions of this section capture the period from 2012 through 2015.

positive and statistically significant at the 1% level. Specifically, when *dVVSTOXX* increases by one unit, *Login* increases by 0.00132.

[Insert Table V about here]

The skeptical reader might be concerned that uncertainty (ambiguity and risk) and sentiment might be associated with the same underlying factor and that we are thus just picking up a sentiment effect. To ensure that the impact of ambiguity we document is distinct from the already known effect of sentiment on individual investor trading, in column (3), we also include a measure for sentiment (*FEARS*) to model (1). *FEARS* is a well-known and accepted measure for sentiment (Kostopoulos, Meyer, and Uhr (2020)).[10] One has to keep in mind that *FEARS* is based on negative search terms, which means that *FEARS* proxies for pessimism. The pairwise correlation between *FEARS* and *dVVSTOXX* or *dVSTOXX* is 0.09 and 0.36, respectively. This shows that *dVVSTOXX* and *dVSTOXX* comove to some extent with *FEARS* and that sentiment is closer related to risk than to ambiguity. Nevertheless, both ambiguity and risk are conceptually different from sentiment and far away from being identical to sentiment. Column (3) shows that the effect of ambiguity we find is robust to the inclusion of *FEARS*.

To gauge the economic significance of this result, we compare the standardized effect of ambiguity with the ones of other variables from model (1). Specifically, we compare ambiguity with wealth and the squared preceding-one-day CDAX return, which are two well-known variables from household finance literature that have been shown to have a meaningful impact on individual investor trading. For instance, a one-standard-deviation increase in *dVVSTOXX* leads to an increase of 0.0052 (= 0.0013 × 3.987) in the probability to log in.[11] This compares to the standardized effect of the squared preceding-one-day CDAX return, a proxy for attention, for which the effect is even slightly smaller at a value of 0.0045 (= 24.79 × 0.00018).[12] We

[10] *FEARS* was originally proposed by Da, Engelberg, and Gao (2015) and it is the aggregate of daily Google search volume innovations of negative and economic-related terms such as “financial crisis,” “bankruptcy,” or “recession.” Da, Engelberg, and Gao (2015) constructed this index for the U.S. However, since we are exploring the trading behavior of German individual investors and want to control for German sentiment, we use the German *FEARS* index, which was constructed by Kostopoulos, Meyer, and Uhr (2020). This is available to us for the period from 2010 through 2015. Kostopoulos, Meyer, and Uhr (2020) show that their German *FEARS* index is indeed the German equivalent, as its effect on the German stock market is highly consistent with what Da, Engelberg, and Gao (2015) find. Additionally, they find that *FEARS* has a significant impact on individual investor trading

[11] The standard deviation of *dVVSTOXX* is 3.987 (see Table I).

[12] The coefficient estimate for the squared preceding-one-day CDAX return is 24.79 (see Table A.I. in the Appendix) and the standard deviation is 0.00018.

conclude that the ambiguity effect we find is of the same order of magnitude as another important effect (attention) discussed in the literature.

Turning to the columns titled "*Trades*" (columns (4) to (6)), we see a similar pattern: Innovations in aggregate ambiguity are associated with an increased probability to trade. This point estimate is statistically significant at the 1% level; and the economic magnitude of this effect is comparable to the effect of wealth and the squared preceding-one-day CDAX return.

We conclude that when the aggregate ambiguity is high, the probability of an individual investor to trade and to log in is significantly higher. These results are not only statistically significant but also economically relevant. We interpret these results as follows: When the aggregate ambiguity in the market is high, investors have a hard time assessing investment opportunities and future security outcomes. Accordingly, they seem to feel less certain about their investments and seem to hence require updates on their portfolios more often. Therefore, they log in more frequently in these periods. Moreover, when the aggregate ambiguity in the market is high, individual investors not only focus more on their portfolios, but they also seem to adjust their portfolios, as they then trade more. Our empirical findings contradict the no-trade hypothesis and support the hypothesis that ambiguity shocks lead to higher activity in financial markets.

3.2 The effect of ambiguity on risk-taking

The previous section has shown that when the aggregate ambiguity is high, the propensity of individual investors to log in and trade is higher, which shows that they then adjust their portfolios. It is interesting to ask what these portfolio adjustments look like. In particular, we investigate how the risk-taking behavior of our investors is affected by shocks in ambiguity.

To better understand how increased ambiguity changes the risk-taking of our investors, we construct a trading variable measuring the purchase activity of risky assets. When this variable is high, investors increase their exposure to the risky asset market, but when it is low, they decrease their exposure to the risky asset market. Specifically, we use excess buy-sell imbalances, which are standard in the literature and defined as follows:

$$ExBSI^{\#} = \frac{Buy^{\#}_{i,t}}{Buy^{\#}_{i,t} + Sell^{\#}_{i,t}} - \frac{Buy^{\#}_{i,y(t)}}{Buy^{\#}_{i,y(t)} + Sell^{\#}_{i,y(t)}}, \quad (2)$$

$$ExBSI^{EUR} = \frac{Buy^{EUR}_{i,t}}{Buy^{EUR}_{i,t} + Sell^{EUR}_{i,t}} - \frac{Buy^{EUR}_{i,y(t)}}{Buy^{EUR}_{i,y(t)} + Sell^{EUR}_{i,y(t)}}. \quad (3)$$

The excess buy-sell imbalance of investor i on day t is computed as the buy-sell imbalance of this investor on that day minus the average buy-sell imbalance of the same investor over the preceding year, which we denote as $y(t)$.[13] That is, we measure the purchase activity of an investor relative to its typical purchase activity. Another frequently used way to demean buy-sell imbalances is to subtract the average buy-sell imbalance of the corresponding calendar year. Our results are robust to this alternative demeaning methodology. For robustness, we compute two risk-taking measures. The one is based on the number of trades ($ExBSI^{\#}$) and the other one is based on the euro-values of trades ($ExBSI^{EUR}$). To formally test the relation between the time-varying aggregate ambiguity and the risk-taking, we employ the following panel regressions with investor fixed effects:

$$ExBSI_{i,t} = \alpha + \beta\ dVVSTOXX_t + \gamma\ C_{i,t} + \varepsilon_{i,t}\,. \quad (4)$$

ExBSI is either $ExBSI^{\#}$ or $ExBSI^{EUR}$. Table VI presents the point estimates β of different specifications from model (4). In columns (1) to (3), we use $ExBSI^{\#}$ and in columns (4) to (6), we use $ExBSI^{EUR}$ as the dependent variable.

[Insert Table VI about here]

Column (1) shows that increases in ambiguity are associated with lower buy-sell imbalances. Put it differently, when aggregate ambiguity in the market is high, investors reduce risk in their portfolios. In columns (2) and (3), we include *dVSTOXX* and *FEARS* to model (4). Controlling for risk and sentiment does not change the coefficient estimate qualitatively. For example, when *dVVSTOXX* increases by one unit, $ExBSI^{\#}$ decreases by 0.000551. In terms of economic significance, a one-standard-deviation increase in *dVVSTOXX* leads to a decrease of 0.0022 (= 0.000551 x 3.987) in $ExBSI^{\#}$. If we compare the magnitude of this effect with the ones of wealth (0.0569 = 0.0203 x 2.8044) and the squared preceding-one-day CDAX return (0.0018 = 5.03 x

[13] The buy-sell imbalance is defined as the purchases relative to all trades (purchases and sells).

0.00036), we obtain similar patterns as in the previous section:[14] The effect of ambiguity is smaller than the effect of wealth but larger than the effect of the squared preceding-one-day CDAX return. Again, the ambiguity effect remains economically meaningful.

Another interesting aspect is the comparison of the effect of ambiguity with the effect of risk. When we benchmark these two effects—this is what we essentially do, because in our models we always include both uncertainty measures—we find the interesting results that risk-taking of individual investors is significantly driven by innovations in ambiguity and not in risk. Although surprising at first glance, this result is consistent with what Anderson, Ghysels, and Juergens (2009) report. They find that the ambiguity-return trade-off is stronger than the risk-return trade-off.

From the columns titled "EUR," we see that replacing $ExBSI^{\#}$ by $ExBSI^{EUR}$ leads to similar results. The signs, magnitudes of the coefficients as well as the statistical and economic significances are highly comparable. We conclude that our results are neither driven by a few large nor by many small transactions.

Our results suggest that ambiguity shocks lead to negative buy-sell imbalance which implies that stock market investments decrease. We re-run the previous regression but additionally include 10 lags for the subsequent 10 days to find out whether increases in ambiguity and subsequent negative buy-sell imbalances reverse over the following days. If the reaction of individual investors towards innovations in ambiguity were transitory, we would expect to find a reversal pattern over the following 10 days. Table VII shows that the contemporaneous and first lag of *dVVSTOXX* exert the strongest effect. We find no reversal of the initial negative effect of *dVVSTOXX* and *dVVSTOXX (lag 1)* up to lag 10. Yet, lag 8 and 9 show small reversal patterns which are much smaller than the ones we observe for days 1 and 2.

[Insert Table VII about here]

Our results are along the line of what Mele and Sangiorgi (2015) find, namely, that ambiguity is related to the risk-taking behavior of investors. More precisely, they show that an ambiguity shock can cause investors to exit the risky asset market. Our results are also in line with Garlappi, Uppal, and Wang (2006) and Peijnenburg (2018), who find that higher perceived

[14] The coefficient estimate for preceding-one-day CDAX return is 5.03 (see Table A.II. in the Appendix) and the standard deviation is 0.00036. The coefficient estimate for wealth is -0.0203 (see Table A.II. in the Appendix) and the standard deviation is 2.8044.

ambiguity leads investors to reduce the risky asset share of their portfolios. All these results are broadly consistent with other theoretical papers, postulating a link between ambiguity and asset prices or participation in the risky asset market (Cao, Wang, and Zhang (2005), Dow and Werlang (1992), Easley and O'Hara (2009), Epstein and Schneider (2010), Bloom (2009)).

3.3 Ambiguity and sentiment

It is well documented that investors are subject to sentiment.[15] A broadly accepted definition of investor sentiment is formulated in Baker and Wurgler (2007): "Investor sentiment, defined broadly, is a belief about future cash flows and investment risks [...]." This definition stems from experimental evidence that people in good moods are more optimistic than people in bad moods (Johnson and Tversky (1983), Wright and Bower (1992)). A long strand of literature finds that investor sentiment drives stock market outcomes as well as individual investor trading decisions (e.g., Baker and Wurgler (2006), Garcia (2013), Schmittmann et al. (2015)).

Hirshleifer (2001) suggests that sentiment should be more pronounced when ambiguity is high. An investor sentiment index particularly capturing the fear of households concerning the economy is the *FEARS* index by Da, Engelberg, and Gao (2015), which we introduced above. Kostopoulos, Meyer, and Uhr (2020) explore the impact of *FEARS* on risky choices and find that when *FEARS* is high—that is, when sentiment is low—individual investors are on the sell-side of the market. Specifically, they explore the effect of *FEARS* on buy-sell imbalances, which we also use in this paper to analyze risky choices.

In this section, we test the theoretical prediction that sentiment increases, when ambiguity is high. We call this conjecture "Hirshleifer's hypothesis." If this hypothesis is true, we should find that the sentiment effect documented in Kostopoulos, Meyer, and Uhr (2020) is stronger, when the level of ambiguity is high.[16] To directly test Hirshleifer's hypothesis, we employ the following model, which is inspired by Garcia (2013):

[15] An excellent summary can be found in Hirshleifer (2001).
[16] The results of Kostopoulos, Meyer, and Uhr (2020) are in line with other sentiment studies investigating individual investor trading (Schmittmann et al. (2015), Kaustia and Rantapuska (2016), Kostopoulos and Meyer (2018)).

$$ExBSI_{i,t} = \alpha + \beta_1\, FEARS_t \times HighVVSTOXX_t + \beta_2\, FEARS_t \times LowVVSTOXX_t + \gamma\, C_{i,t} + \varepsilon_{i,t}\,. \tag{6}$$

The regression equation (6) represents panel regressions with investor fixed effects. *HighVVSTOXX* is a dummy variable taking on the value one if $VVSTOXX$ is above its mean and zero otherwise. *LowVVSTOXX* is defined as 1 - *HighVVSTOXX*. As in all our models, in addition to the vector of control variables, C, we include *dVSTOXX* to account for any effects related to risk. In essence, model (6) splits the overall effect of *FEARS* into two mutually exclusive but collectively exhaustive parts: periods of high aggregate ambiguity and periods of low aggregate ambiguity. We are interested in the point estimates β_1 and β_2 and how they differ.

Before we discuss the results of model (6), we recall the overall effect of *FEARS* on *ExBSI*, which is presented in Table VI. When *FEARS* increases by one unit, $ExBSI^{\#}$ and $ExBSI^{EUR}$ decrease by 0.00734 and 0.00784, respectively. Both estimates are statistically significant at conventional levels. This means that lower sentiment is linked with the tendency to sell securities. This result is fully in line with Kostopoulos, Meyer, and Uhr (2020) and all other household finance papers investigating the effect of sentiment on individual investor trading we are aware of.

Table VIII, Panel A presents the point estimates β_1 and β_2 form model (6). From column (1), we see that on days, on which the aggregate ambiguity is high, a one-unit increase in *FEARS* leads to a decrease of 0.0105 in $ExBSI^{\#}$. This estimate is statistically significant at the 1% level. The magnitude of this coefficient is 43% larger than the overall effect we report in Table VI. On the other hand, on days, when the aggregate ambiguity is low, a one-unit increase in *FEARS* leads to a decrease of only 0.0036 in $ExBSI^{\#}$. Nevertheless, this estimate is statistically significant at the 5% level. The magnitude of this coefficient is 50% smaller than the overall effect we report in Table V. Hence, we argue that these differences are economically meaningful. In column (2) we use $ExBSI^{EUR}$ as the dependent variable and observe very similar patterns: In both cases (high and low aggregate ambiguity), the impact of *FEARS* on the purchase activity of our investors is negative; on days, when ambiguity is high, this effect is stronger than the overall effect and statistically significant at the 1% level; and on days, when ambiguity is low, this effect is weaker than the overall effect and statistically significant at the 5% level. Panel B of Table VIII presents the results of the analysis where we test whether the difference $\beta_1 - \beta_2$ is significantly different from zero. For both specifications, we find that the differences are not only economically but also statistically significant at the 1% level.[17]

[Insert Table VIII about here]

We conclude that sentiment appears in both high and low ambiguity periods. However, in high ambiguity periods individual investors seem to be more prone to sentiment, as the effects we find are more pronounced during these periods. The differences in sentiment between high and low ambiguity periods are statistically significant and economically large. We interpret these results as strong evidence for Hirshleifer's hypothesis.

4 Time-varying ambiguity and ambiguity preferences of investors

This paper so far tests if and how time-varying aggregate ambiguity affects investor trading. The perceived ambiguity might not only depend on the level of aggregate ambiguity in the market but also the individual ambiguity preferences of investors. Similar to Dimmock et al. (2016), we argue that more ambiguity averse investors might subjectively perceive a certain ambiguity shock more intense than investors that are less ambiguity averse. If this is true, the main effect we present in the previous section—increased ambiguity leading to less risk-taking—should be more pronounced for those investors who are more ambiguity averse.

To test this conjecture, we conduct a survey and identify whether an investor is ambiguity averse, ambiguity neutral, or ambiguity seeking. The survey was conducted in the first two weeks of January 2018. The bank randomly selected 10,000 clients from our sample. People were invited via email on January 6, 2018. On January 12, 2018 the bank sent out a reminder. The total number of investors in our sample who took part in this survey is 644. The non-response bias seems small as results for people who completed the questionnaire before January 9, 2018 and those who replied later show no meaningful differences. The average age of the surveyed investor is 55 and the proportion of males is 89%. These figures are similar to the original sample. We incentivized the clients using the following lottery: For every 500 participants, we drew one 200-Euro check, two 100-Euro checks and three 50-Euro checks. To elicit ambiguity aversion, we follow Dimmock et al. (2016) who use an Ellsberg-type urn setting. Participants are shown two urns (A and B), as presented in Figure 4. Both urns include 100 balls. Urn A contains 50 white and 50 black balls—that is, the distribution of urn A is

[17] We control for time-fixed effects (year and moth fixed effects), which rules out that our results are driven by other economic sources or structural breaks of ambiguity.

known. Urn B also contains white and black balls, but there is no information about the distribution. The respondent is asked to choose one urn from which one ball will be randomly drawn or to state that she is indifferent. If the drawn ball is white, the respondent wins 100 Euros and otherwise nothing. This is a fictitious game. We did not pay out prizes other than the checks from the lottery we describe above. If a respondent chooses urn A, she is ambiguity averse; if she chooses urn B she is ambiguity seeking; and if she is indifferent between the two urns, she is ambiguity neutral. Moreover, to test the relationship between ambiguity aversion and risk aversion, we measure the risk aversion of each survey participant. To measure risk aversion, we used the scaled from the Survey of Consumer Finances (SCF) on risk tolerance question widely used in the literature. The scale asks which level of risk the respondent is willing to take when saving or making investments: substantial risk expecting to earn substantial returns, above-average risk to earn above-average returns, average risk expecting to earn average returns, and not willing to take any financial risks.

In our survey, 58.7% of our investors are ambiguity averse; 12% are ambiguity neutral; 29.3% are ambiguity seeking. These results are comparable with Dimmock et al. (2016). Our results are also in line with Ellsberg (1961), who finds that people tend to be ambiguity averse. Concerning risk aversion, we find that 45% of our clients report being willing to take above average financial risks. We do not find differences in risk aversion when sorting by ambiguity aversion. The correlation between risk aversion and ambiguity aversion is as low as 2%. Thus, and in line with e.g., Brenner and Izhakian (2018), we find ambiguity aversion being distinct from risk aversion.

Next, we test whether ambiguity averse investors are more prone to ambiguity shocks. To this end, we run three regressions, which are presented in Table IX. The dependent variable is always $ExBSI^{EUR}$. Using $ExBSI^{\#}$ yields qualitatively similar results. The regression of the first column includes all investors minus 378 investors surveyed and identified as ambiguity averse. Given that our main regressions are based on approximately 61,000 investors and the number of excluded investors is only 378, this sample is very similar to the original one in column (6) of Table VI. As expected, because we exclude a set of investors which is ambiguity averse, the effect is slightly smaller (-0.000576 versus -0.000585). The regression of the second column includes only the 378 investors who were surveyed and identified as ambiguity averse, which represents 0.6% of the original sample. For this subsample, we obtain a much higher coefficient estimate. Precisely, this coefficient is about 4.5 times the estimate of column (1). We note that although the power of this test is fairly low, this point estimate is still statistically significant at the 5% level. Our results suggest that ambiguity averse investors show a stronger reaction to ambiguity fluctuations than the average investor. To formally test the significance of this difference, in column (3) we use the full sample and include the interaction term *dVVSTOXX x Ambiguity*, where *Ambiguity* is a dummy variable, which takes on the value one if an investor was surveyed and identified as ambiguity averse. The coefficient on this interaction term picks up the difference between the ambiguity averse and the average investor. Again, our results suggest that ambiguity averse investors react stronger to increases (innovations) in aggregate ambiguity and that this difference is economically meaningful and statistically significant at the 10% level.

[Insert Table IX about here]

It is important to note that our identification is imperfect and that this imperfection acts against our results. While the identification of the one subsample—ambiguity averse investors—is clear, the other subsample represents the average investor. This means, it includes ambiguity averse, ambiguity neutral and ambiguity seeking individuals. The only way to improve the identification is to use the surveyed investors who were identified as ambiguity seeking and estimate the difference in the effect between ambiguity averse and seeking investors. However, the subsample of ambiguity seeking investors only includes 189 investors (= 644 × 0.293). When we run a regression only including the ambiguity seeking investors, we get a point estimate of 0.000611. Because these investors are ambiguity seeking and not averse, the sign flips. This yields further evidence that our time-varying ambiguity measure, indeed, measures ambiguity. However, this specification suffers so much from statistical power that the estimate is not statistically significant. Similarly, when we estimate the difference in the coefficients between the ambiguity averse and seeking investors, we get a difference that is approximately 50% larger than the one we report in Table IX. This estimate is (due to power issues) not statistically significant (p-value = 0.16).

Although this section has some limitations due to small sample sizes, we find several interesting results: First, we show that the sample of our investors is representative for their attitudes towards ambiguity, as the ambiguity preferences we document are consistent with Dimmock et al. (2016). Second, given an ambiguity shock, ambiguity averse investors reduce risks but ambiguity seeking investors increase risks in their portfolios. We interpret this result as strong evidence that changes in V-VSTOXX, as argued in section 2.1, represent innovations in ambiguity. Third and perhaps most importantly, we can show that ambiguity averse investors tend to be more prone to ambiguity shocks than the average investor. In other words, we document an interaction between time-varying ambiguity and ambiguity preferences of individuals.

5 Robustness test: Alternative ambiguity measures

In this paper, we use the V-VSTOXX as ambiguity measure. However, there is no clear consensus in the literature on the ambiguity measure that should be chosen. To show the robustness of our results towards other measures of ambiguity, we rerun our main specifications containing controls for three alternative measures of ambiguity. First, we calculate a survey-based measure of ambiguity that build on the dispersion of forecasts of professional forecasters following a strand of literature (e.g., Anderson, Ghysels, and Juergens (2009), Drechsler (2013), Andrei and Hasler (2015), Ulrich (2013), David and Veronesi (2013), Branger, Schlag, and Thimme (2019)). Second, we compute the market-based ambiguity measure recently introduced by Brenner and Izhakian (2018) for the EuroStoxx. Third, we use a newspaper-based measure and control for the economic policy uncertainty (EPU) following Baker, Bloom, and Davis (2016).

To compute these measures, we downloaded the Survey of Professional Forecasters (SPF) data provided by the European Central Bank. We use the forecasts of real gross domestic product growth for the next calendar years that forecasters are asked to provide as a point estimate as well as a probability distribution of forecasted outcomes. We calculate the standard deviation using the probability distribution for each forecaster and each quarter separately and derive the ambiguity measure by the standard deviation of the standard deviation of all individual forecasters in each quarter.

For an alternative market-based ambiguity measure we follow the methodology introduced by Brenner and Izhakian (2018) and calculate ambiguity from market data by the time-series values of the monthly degree of ambiguity. Therefore, we take the intraday data of the EuroStoxx in five-minute intervals during the trading hours at the Euronext stock exchange between January 2010 and December 2015. We exactly follow Brenner and Izhakian (2018) and also divide the range of daily returns (from -6% to 6%) into 60 bins and also include returns below -6% and above 6% in bin 61 and 62. We use this measure because the vol-of-vol measure might be stake dependent as it is a function of return.

Finally, we downloaded the index of economic policy uncertainty (EPU) for Europe[18] calculated by Baker, Bloom, and Davis to proxy for newspaper-based uncertainty.

We rerun table VI and control for the three alternative ambiguity measures. Columns (1) and (2) show specifications with the survey-based measure whereas columns (3) and (4) show specifications with the market-based measure by Brenner and Izhakian (2018). Columns (5) and (6) show specifications containing the EPU for Europe as a control variable. Controlling for the alternative measures yields qualitatively unaltered results and our coefficients on the *VVSTOXX* remain in the same ballpark. These findings provide evidence that our results are robust to alternative measures of ambiguity and policy uncertainty and that investors do react to changes in the *V-VSTOXX*. Of course, it is still possible that other forms or measures of ambiguity also play a role. But to the extent that we included them, we do not find them to explain our findings.

[Insert Table X about here]

6 Conclusion

In this paper, we relate ambiguity to individual investor trading. We use a unique data set on the trading records of individual investors from a large German online brokerage for the period from March 2010 through December 2015. We match these data with a measure for time-varying aggregate ambiguity—innovations in the V-VSTOXX.

We present four primary findings. First, increases in ambiguity are associated with increased investor activity, as measured by logins and trades. Second, an increase in ambiguity is associated with less risk-taking that does not reverse within the following days. Third, Hirshleifer's hypothesis that the effect of sentiment increases when ambiguity is high is also well-supported by the data. Finally, we use a survey to measure the ambiguity aversion of investors and document that more ambiguity averse investors are reacting stronger to increases in ambiguity and therefore reduce their stock market exposure. Our results are qualitatively unaltered when controlling for alternative survey-based, newspaper-based and market-based measures of ambiguity.

[18] All country-level data can be downloaded here: https://www.policyuncertainty.com/.

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Figures

Figure 1 The time series of V-VSTOXX and VSTOXX.

This graph plots the daily time series of the V-VSTOXX and VSTOXX for the period from March 2010 through June 2017. The data come from Stoxx Limited.

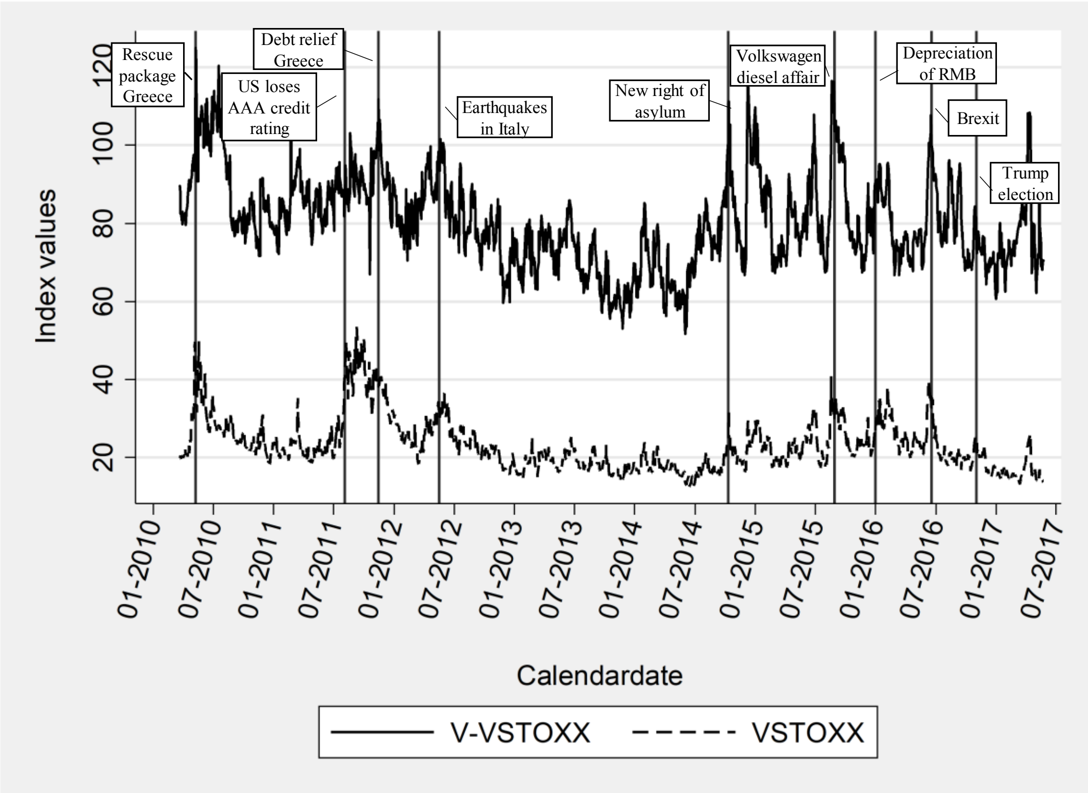


Figure 2 The time series of VSTOXX, VIX, and VDAX.

This graph plots the daily time series of the VSTOXX, the VIX, and the VDAX for the period from March 2006 through June 2017. VSTOXX comes from Stoxx Limited, VIX and VDAX come from Datastream.

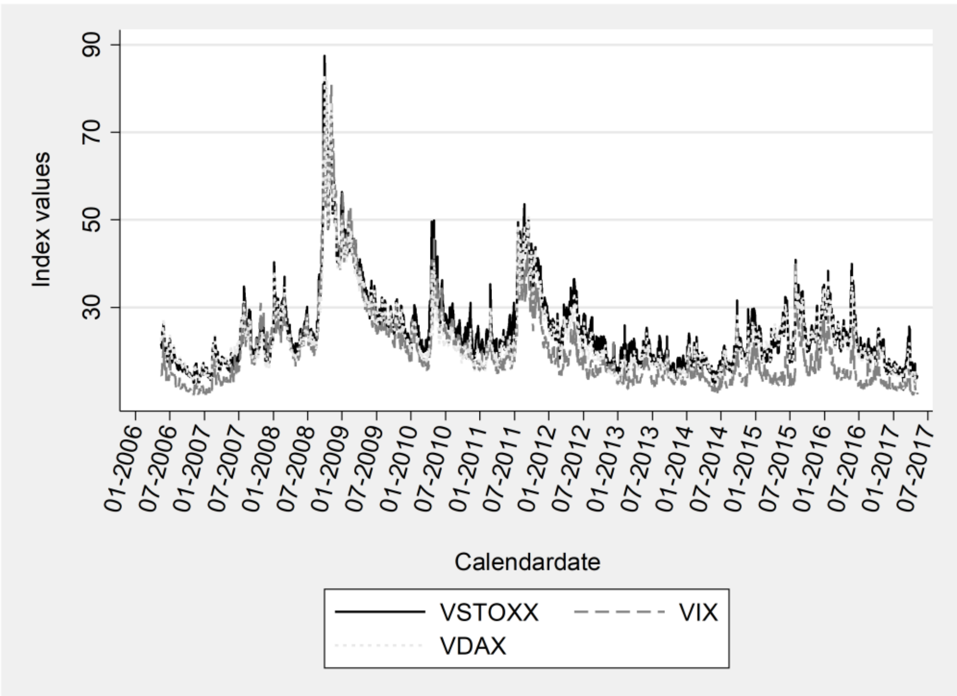


Figure 3 The time series of V-VSTOXX and V-VIX.
This graph plots the daily time series of the V-VSTOXX and the V-VIX for the period from March 2006 through June 2017. V-VSTOXX comes from Stoxx Limited, and V-VIXX comes from Datastream.

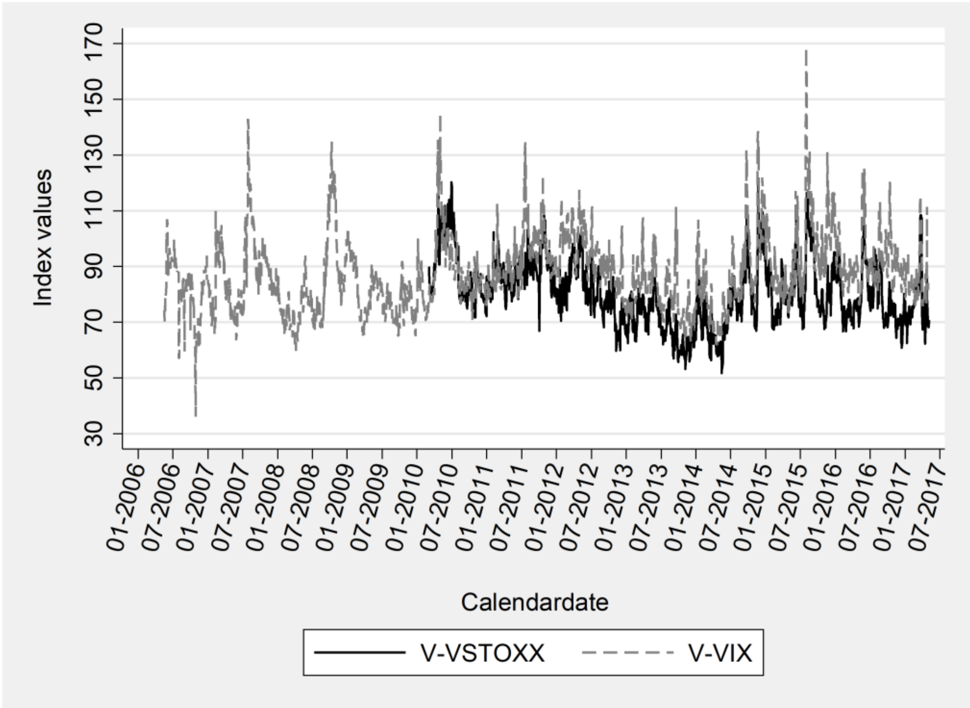
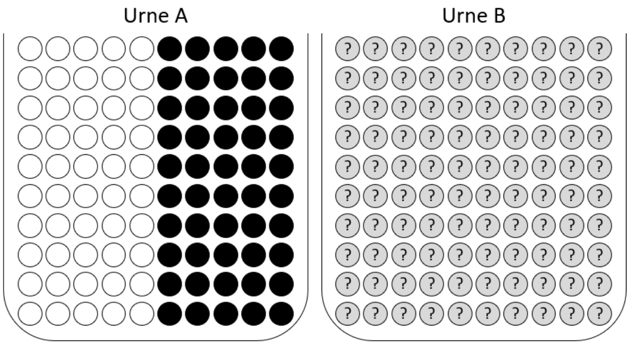


Figure 4 Urns for measuring the ambiguity aversion of investors.
This shows a screenshot of the two urns that have been shown to the respondents who took part in the survey.



Tables

Table I. Sample statistics for uncertainty measures and return data

This table presents summary statistics for the uncertainty measures and the return data. The sample period is from March 2010 through December 2015. VSTOX and V-VSTOXX are from Stoxx Limited. All other market data are from Datastream.

	N	Mean	Median	SD	Min	Max
dVVSTOXX	1,469	-0.0117	-0.3238	3.9870	-22.649	31.294
dVSTOXX	1,508	0.0007	-0.0300	1.7278	-10.940	12.790
dVDAX	1,508	0.0022	-0.0100	1.4401	-6.520	10.700
VVSTOXX	1,470	80.962	79.922	12.266	51.765	124.870
VSTOXX	1,508	23.591	22.080	6.9201	12.710	53.550
VDAX	1,508	21.722	20.185	6.5108	12.170	50.740
STOXX	1,508	0.0002	0.0001	0.0137	-0.0629	0.0985
DAX	1,508	0.0004	0.0006	0.0129	-0.0600	0.0521

Table II. Correlations matrix for uncertainty measures and return data

This table presents correlations between the uncertainty measures and the return data. The sample period is from March 2010 through December 2015. VSTOX and V-VSTOXX are from Stoxx Limited. All other market data are from Datastream. ***, **, 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)
dVVSTOXX	(1)	1.00							
dVSTOXX	(2)	0.36***	1.00						
dVDAX	(3)	0.37***	0.95***	1.00					
VVSTOXX	(4)	0.16***	0.04	0.04	1.00				
VSTOXX	(5)	0.06**	0.12***	0.13***	0.72***	1.00			
VDAX	(6)	0.06**	0.09***	0.11***	0.63***	0.96***	1.00		
STOXX	(7)	-0.33***	-0.82***	-0.79***	-0.08***	-0.13***	-0.11***	1.00	
DAX	(8)	-0.35***	-0.79***	-0.80***	-0.09***	-0.14***	-0.12***	0.95***	1.00

Table III. Sample statistics for investor data

This table presents summary statistics for our investor transaction data. The data is obtained from one of the largest German online brokerages. We exclude investors who obtain financial advice. Further, we exclude transfers among personal accounts and transactions from saving plans.

Panel A: Individual investors and transactions	
Number of individual investors	103,113
Total number of trades	23.4 million
Total number of buys	12.6 million (53.85%)
Total number of sales	10.8 million (46.15%)
Total transaction value	154.1 billion €
Total value of buys	83.2 billion € (53.99%)
Total value of sales	70.9 billion € (46.01%)
Panel B: Individual investor characteristics	
Share of male investors	84.32%
Average age (in years)	53.17
Age (1. quartile)	45.00
Age (median)	52.00
Age (3. quartile)	61.00
Portfolio value (in Euro)	56,475.17 €
Portfolio value (1. quartile)	14,519.55 €
Portfolio value (median)	32,499.22 €
Portfolio value (3. quartile)	64,701.55 €
Length relationship between bank and client (in years)	15.10
Length relationship (1. quartile)	14.00
Length relationship (median)	14.00
Length relationship (3. quartile)	14.00
Herfindahl-Hirschman Index (HHI)	35.56%
HHI (1. quartile)	5.55%
HHI (median)	22.28%
HHI (3. quartile)	53.03%
Risk class (1 to 5; 1 = lowest risk and 5 = highest risk)	3.63798
Risk class (1. quartile)	3
Risk class (median)	4
Risk class (3. quartile)	5
Share of married investors	59.51%
Share of investors with PhD	6.80%
Share of employed investors	47.92%
Share of self-employed investors	19.28%
Share of retired investors	12.92%

Table IV. List of control variables

This table lists the control variables used in all our specifications and gives a short description. Panel A lists the calendar variables; Panel B lists the market-specific variables; Panel C lists the 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 trading days before school vacations.
First trading day after school vacation	Dummy variable, indicating trading days after school vacations.
Public holidays	Dummy variable, indicating public holidays.
First trading day after public holidays	Dummy variable, indicating trading days after public holidays.
Last trading day before public holidays	Dummy variable, indicating trading days before public holidays.
First trading days of month	Dummy variable, indicating first trading days of the month.
Last trading days of month	Dummy variable, indicating last trading days of the month.
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.
Monday	Dummy variable, indicating Mondays.
Friday	Dummy variable, indicating Fridays.
Year Fixed Effects	5 Dummy variables, for every year in our sample omitting 2015.
Month Fixed Effects	11 Dummy variables, for each month of the year omitting December.
Panel B: Market-Related Variables	
CDAX 1-day-return	Preceding-one-day log realized return of CDAX.
$CDAX^2$ 1-day-return	Squared preceding-one-day log realized return of CDAX.
CDAX 3-months-return	Preceding-three-months 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 V. The effect of ambiguity on trading and login activity

The table presents panel regressions using investor-fixed effects on excess buy-sell imbalances. The columns titled "#" use $ExBSI^{\#}$ and the columns titled "EUR" use $ExBSI^{EUR}$ as the dependent variable. The key variables of interest are aggregate ambiguity aversion (*dVVSTOXX*), expected volatility (*dVSTOXX*) and sentiment (*FEARS*). The columns titled "Logins" use a dummy variable equal to one if customers log in on a given day and the columns titled "Trades" use a dummy variable that is equal to one if an investor trades on a given day as the dependent variable. All specifications include the control variables listed in Table IV. Coefficient estimates for the control variables are not displayed, but tables with the full set of variables are available in the Appendix. All regressions incorporate year and 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Logins			Trades		
dVVSTOXX	0.000492***	0.00132***	0.00130***	0.000201***	0.000189***	0.000186***
	(1.03e-05)	(1.26e-05)	(1.25e-05)	(4.87e-06)	(5.39e-06)	(5.39e-06)
dVSTOXX		-0.00400***	-0.00396***		5.82e-05***	6.33e-05***
		(3.83e-05)	(3.82e-05)		(1.56e-05)	(1.56e-05)
FEARS			0.00840***			0.00113***
			(0.000172)			(7.70e-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

Table VI. The effect of ambiguity on risk-taking

The table presents panel regressions using investor-fixed effects on excess buy-sell imbalances. The columns titled "#" use $ExBSI^{\#}$ and the columns titled "EUR" use $ExBSI^{EUR}$ as the dependent variable. The key variables of interest are aggregate ambiguity aversion (*dVVSTOXX*), expected volatility (*dVSTOXX*) and sentiment (*FEARS*). All specifications include the control variables listed in Table IV. Coefficient estimates for the control variables are not displayed, but tables with the full set of variables are available in the Appendix. All regressions incorporate year and 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	#			EUR		
dVVSTOXX	-0.000542***	-0.000562***	-0.000551***	-0.000589***	-0.000596***	-0.000585***
	(8.73e-05)	(7.52e-05)	(7.53e-05)	(8.99e-05)	(7.75e-05)	(7.76e-05)
dVSTOXX		0.000168	0.000203		6.44e-05	0.000101
		(0.000257)	(0.000257)		(0.000263)	(0.000264)
FEARS			-0.00734***			-0.00784***
			(0.00124)			(0.00127)
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

Table VII. The effect of ambiguity on risk-taking

The table presents panel regressions using investor-fixed effects on excess buy-sell imbalances. The columns titled "#" use *ExBSI*$^{\#}$ and the columns titled "EUR" use *ExBSI*^{EUR} as the dependent variable. The key variables of interest are aggregate ambiguity aversion (*dVVSTOXX*) and ten lags of this variable. All specifications include the control variables listed in Table IV. Coefficient estimates for the control variables are not displayed, but tables with the full set of variables are available in the Appendix. All regressions incorporate year and 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.

	(1)	(2)
	#	EUR
dVVSTOXX	-0.000583***	-0.000620***
	(8.22e-05)	(8.48e-05)
dVVSTOXX (lag 1)	-0.000438***	-0.000449***
	(7.65e-05)	(7.86e-05)
dVVSTOXX (lag 2)	0.000124*	0.000102
	(7.53e-05)	(7.71e-05)
dVVSTOXX (lag 3)	8.76e-05	2.73e-05
	(7.39e-05)	(7.58e-05)
dVVSTOXX (lag 4)	-0.000592***	-0.000617***
	(7.16e-05)	(7.35e-05)
dVVSTOXX (lag 5)	1.30e-05	-1.56e-05
	(7.29e-05)	(7.46e-05)
dVVSTOXX (lag 6)	-0.000162**	-0.000186**
	(7.19e-05)	(7.39e-05)
dVVSTOXX (lag 7)	-0.000256***	-0.000293***
	(7.14e-05)	(7.31e-05)
dVVSTOXX (lag 8)	0.000256***	0.000227***
	(6.85e-05)	(7.02e-05)
dVVSTOXX (lag 9)	0.000188***	0.000192***
	(6.97e-05)	(7.14e-05)
dVVSTOXX (lag 10)	-9.16e-05	-9.73e-05
	(6.92e-05)	(7.10e-05)
dVSTOXX	-0.000221	-0.000305
	(0.000255)	(0.000262)
Year Fixed Effects	YES	YES
Month fixed effects	YES	YES

Table VIII. Ambiguity and sentiment

The table presents panel regressions using investor-fixed effects on excess buy-sell imbalances. The column titled "#" uses $ExBSI^{\#}$ and the column titled "EUR" uses $ExBSI^{EUR}$ as the dependent variable. Panel A presents the coefficient estimates for the interaction of *FEARS* and a dummy variable which is equal to one if the *VVSTOXX* is high (low). We also control for *dVSTOXX*. All specifications include the control variables listed in Table IV. Coefficient estimates for the control variables are not displayed, but tables with the full set of variables are available in the Appendix. All regressions incorporate year and 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. Panel B presents the differences between the two interaction terms and tests whether this difference is significantly different from zero. ***, **, and * indicate that the estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Panel A: Regressions		
	#	EUR
FEARS x HighVVSTOXX	-0.0105***	-0.0114***
	(0.00170)	(0.00174)
FEARS x LowVVSTOXX	-0.00360**	-0.00361**
	(0.00171)	(0.00175)
dVSTOXX	-8.23e-05	-0.000188
	(0.000268)	(0.000275)
Control Variables	YES	YES
Year Fixed Effects	YES	YES
Month Fixed Effects	YES	YES
Panel B: Tests ($\beta_1 = \beta_2$)		
Difference	-0.0069	-0.00779
F-value	8.48	10.17
p-value	0.004	0.001

Table IX. The effect of ambiguity conditional on ambiguity preferences of investors

The table presents panel regressions using investor-fixed effects on the value of the excess buy-sell imbalance ($ExBSI^{EUR}$). Columns (1) and (2) present the coefficient estimates for *dVVSTOXX*. Column (1) is based on the original sample excluding all investors who were surveyed and identified as ambiguity averse. Column (2) is based on the investors who were surveyed and identified as ambiguity averse. Column (3) presents the results from including the interaction term *dVVSTOXX x Ambiguity*. *Ambiguity* is a dummy variable, which takes on the value one if and only if an investor was surveyed and identified as ambiguity averse. All specifications include the control variables listed in Table IV. Coefficient estimates for the control variables are not displayed, but tables with the full set of variables are available in the Appendix. All regressions incorporate year and 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.

	(1)	(2)	(3)
	All without ambiguity averse	Ambiguity averse	Interaction
dVVSTOXX	-0.000576***	-0.00255**	-0.000575***
	(7.77e-05)	(0.00120)	(7.78e-05)
dVVSTOXX x Ambiguity aversion			-0.00220*
			(0.00131)
dVSTOXX	0.000107	-0.00131	0.000101
	(0.000265)	(0.00301)	(0.000264)
Control Variables	YES	YES	YES
Year Fixed Effects	YES	YES	YES
Month Fixed Effects	YES	YES	YES

Table X. The effect of ambiguity on risk-taking (robustness)

The table presents panel regressions using investor-fixed effects on excess buy-sell imbalances. The columns titled "#" use $ExBSI^{\#}$ and the columns titled "EUR" use $ExBSI^{EUR}$ as the dependent variable. The key variables of interest are aggregate ambiguity aversion (using the volatility of volatility of GDP forecasts, the ambiguity measure by Brenner and Izhakian (2018), or the economic policy uncertainty index for Germany instead of *dVVSTOXX*), expected volatility (*dVSTOXX*) and sentiment (*FEARS*). Columns (1) and (2) contain the ambiguity measure build from the Survey of professional forecasters as outlined in section 5 as a control variable. Columns (3) and (4) contain omegas as introduced by Brenner and Izhakian (2018) as a control variable. Columns (5) and (6) contain the economic policy uncertainty index for Europe as a control variable. All specifications include the control variables listed in Table IV. Coefficient estimates for the control variables are not displayed, but tables with the full set of variables are available in the Appendix. All regressions incorporate year and 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Forecaster		Omega		EPU	
	#	EUR	#	EUR	#	EUR
dVVSTOXX	-0.000555***	-0.000587***	-0.000552***	-0.000584***	-0.000559***	-0.000591***
	(7.53e-05)	(7.76e-05)	(7.53e-05)	(7.76e-05)	(7.53e-05)	(7.76e-05)
dVSTOXX	0.000201	0.000109	0.000187	9.82e-05	-2.98e-05	-0.000111
	(0.000257)	(0.000264)	(0.000256)	(0.000263)	(0.000257)	(0.000263)
FEARS	-0.00741***	-0.00780***	-0.00745***	-0.00784***	-0.00750***	-0.00788***
	(0.00124)	(0.00127)	(0.00124)	(0.00127)	(0.00124)	(0.00127)
Ambiguity (alternative)	-0.0495***	-0.0485***	-0.00135	-0.000656	0.000121***	0.000115***
	(0.0155)	(0.0164)	(0.00157)	(0.00161)	(5.10e-06)	(5.21e-06)
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

Appendix

Table A.I. The effect of ambiguity on trading and login activity (including the full set of control variables)

The table presents panel regressions using investor-fixed effects on excess buy-sell imbalances. The columns titled "#" use $ExBSI^{\#}$ and the columns titled "EUR" use $ExBSI^{EUR}$ as the dependent variable. The key variables of interest are aggregate ambiguity aversion (*dVVSTOXX*), expected volatility (*dVSTOXX*) and sentiment (*FEARS*). The columns titled "Logins" use a dummy variable equal to one if customers log in on a given day and the columns titled "Trades" use a dummy variable that is equal to one if an investor trades on a given day as the dependent variable. All specifications include the control variables listed in Table IV. All regressions incorporate year and 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	Logins			Trades		
dVVSTOXX	0.000492***	0.00132***	0.00130***	0.000201***	0.000189***	0.000186***
	(1.03e-05)	(1.26e-05)	(1.25e-05)	(4.87e-06)	(5.39e-06)	(5.39e-06)
dVSTOXX		-0.00400***	-0.00396***		5.82e-05***	6.33e-05***
		(3.83e-05)	(3.82e-05)		(1.56e-05)	(1.56e-05)
FEARS			0.00840***			0.00113***
			(0.000172)			(7.70e-05)
Log wealth	0.0193***	0.0193***	0.0193***	0.00257***	0.00257***	0.00257***
	(0.00481)	(0.00481)	(0.00481)	(0.000744)	(0.000744)	(0.000744)
CDAX 1-day-return	0.102***	0.148***	0.150***	-0.0347***	-0.0354***	-0.0351***
	(0.00376)	(0.00389)	(0.00389)	(0.00172)	(0.00176)	(0.00176)
$CDAX^2$ 1-day-return	24.15***	24.16***	24.79***	4.819***	4.819***	4.903***
	(0.227)	(0.227)	(0.229)	(0.103)	(0.103)	(0.103)
CDAX 3-months-return	0.00978***	0.0106***	0.0106***	0.00110***	0.00109***	0.00108***
	(0.000278)	(0.000279)	(0.000279)	(0.000121)	(0.000122)	(0.000122)
School vacation	-0.00318***	-0.00313***	-0.00324***	0.000109	0.000108	9.26e-05
	(0.000186)	(0.000186)	(0.000186)	(7.06e-05)	(7.06e-05)	(7.06e-05)
Public holidays	-0.0435***	-0.0441***	-0.0433***	-0.00752***	-0.00751***	-0.00741***
	(0.000334)	(0.000335)	(0.000333)	(0.000124)	(0.000124)	(0.000123)
First trading day before school vacation	0.00467***	0.00405***	0.00378***	0.000306**	0.000315**	0.000278**
	(0.000308)	(0.000308)	(0.000308)	(0.000127)	(0.000127)	(0.000127)
First trading day after school vacation	0.0146***	0.0142***	0.0144***	0.000315**	0.000321**	0.000349**
	(0.000333)	(0.000333)	(0.000333)	(0.000138)	(0.000138)	(0.000138)
SAD	0.00505***	0.00455***	0.00453***	0.000423***	0.000430***	0.000428***
	(0.000146)	(0.000146)	(0.000146)	(6.42e-05)	(6.42e-05)	(6.42e-05)
First trading day after public holidays	-0.0332***	-0.0337***	-0.0350***	-0.00708***	-0.00707***	-0.00725***
	(0.000412)	(0.000412)	(0.000416)	(0.000175)	(0.000175)	(0.000176)
Last trading day before public holidays	-0.0177***	-0.0156***	-0.0158***	-0.00703***	-0.00706***	-0.00708***
	(0.000565)	(0.000564)	(0.000564)	(0.000248)	(0.000248)	(0.000248)
First trading days of month	0.00356***	0.00361***	0.00351***	-0.000606***	-0.000607***	-0.000619***
	(0.000139)	(0.000139)	(0.000139)	(5.56e-05)	(5.56e-05)	(5.56e-05)
Last trading days of month	-0.000528***	0.000997***	0.000895***	-0.000426***	-0.000448***	-0.000461***
	(0.000129)	(0.000130)	(0.000130)	(5.34e-05)	(5.36e-05)	(5.36e-05)
Monday	0.00406***	0.00466***	0.00332***	0.000273***	0.000264***	8.52e-05
	(0.000106)	(0.000107)	(0.000108)	(5.06e-05)	(5.07e-05)	(5.22e-05)
Friday	-0.0369***	-0.0373***	-0.0364***	-0.00416***	-0.00416***	-0.00404***
	(0.000217)	(0.000218)	(0.000215)	(6.53e-05)	(6.53e-05)	(6.50e-05)
Day light saving time change (forward)	0.0382***	0.0383***	0.0386***	-2.63e-05	-2.77e-05	1.58e-05
	(0.000742)	(0.000742)	(0.000742)	(0.000312)	(0.000312)	(0.000312)
Day light saving time change (backward)	-0.0144***	-0.0113***	0	-0.00617***	-0.00621***	0
	(0.000523)	(0.000522)	-0.0113***	(0.000219)	(0.000219)	-0.00622***
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES

Table A.II. The effect of ambiguity on risk-taking (including the full set of control variables)

The table presents panel regressions using investor-fixed effects on excess buy-sell imbalances. The columns titled "#" use *ExBSI*$^{\#}$ and the columns titled "EUR" use *ExBSI*^{EUR} as the dependent variable. The key variables of interest are aggregate ambiguity aversion (*dVVSTOXX*), expected volatility (*dVSTOXX*) and sentiment (*FEARS*). All specifications include the control variables listed in Table IV. All regressions incorporate year and 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	#			EUR		
dVVSTOXX	-0.000542***	-0.000562***	-0.000551***	-0.000589***	-0.000596***	-0.000585***
	(8.73e-05)	(7.52e-05)	(7.53e-05)	(8.99e-05)	(7.75e-05)	(7.76e-05)
dVSTOXX		0.000168	0.000203		6.44e-05	0.000101
		(0.000257)	(0.000257)		(0.000263)	(0.000264)
FEARS			-0.00734***			-0.00784***
			(0.00124)			(0.00127)
Log wealth	-0.0203***	-0.0203***	-0.0203***	-0.0208***	-0.0208***	-0.0208***
	(0.000400)	(0.000400)	(0.000400)	(0.000418)	(0.000418)	(0.000418)
CDAX 1-day-return	-0.305***	-0.304***	-0.306***	-0.285***	-0.285***	-0.288***
	(0.0334)	(0.0328)	(0.0328)	(0.0340)	(0.0334)	(0.0334)
CDAX^{2} *1-day-return*	5.018***	5.029***	5.030***	5.520***	5.524***	5.525***
	(0.799)	(0.798)	(0.798)	(0.819)	(0.818)	(0.818)
CDAX 3-months-return	-0.0210***	-0.0211***	-0.0210***	-0.0201***	-0.0201***	-0.0200***
	(0.00107)	(0.00105)	(0.00105)	(0.00111)	(0.00109)	(0.00109)
School vacation	-0.00411***	-0.00413***	-0.00400***	-0.00408***	-0.00408***	-0.00395***
	(0.000721)	(0.000720)	(0.000720)	(0.000774)	(0.000774)	(0.000774)
Public holidays	0.0298***	0.0297***	0.0297***	0.0302***	0.0302***	0.0302***
	(0.00224)	(0.00224)	(0.00224)	(0.00229)	(0.00229)	(0.00229)
First trading day before school vacation	0.00659***	0.00666***	0.00671***	0.00555**	0.00558**	0.00563**
	(0.00232)	(0.00232)	(0.00232)	(0.00238)	(0.00238)	(0.00238)
First trading day after school vacation	0.00283	0.00284	0.00254	0.00211	0.00211	0.00179
	(0.00213)	(0.00213)	(0.00213)	(0.00219)	(0.00219)	(0.00219)
SAD	0.00250***	0.00251***	0.00252***	0.00235***	0.00235***	0.00236***
	(0.000853)	(0.000851)	(0.000851)	(0.000875)	(0.000873)	(0.000873)
First trading day after public holidays	-0.00397	-0.00397	-0.00295	-0.00380	-0.00380	-0.00272
	(0.00287)	(0.00287)	(0.00287)	(0.00292)	(0.00292)	(0.00293)
Last trading day before public holidays	-0.0162***	-0.0163***	-0.0159***	-0.0144***	-0.0144***	-0.0139***
	(0.00366)	(0.00366)	(0.00366)	(0.00373)	(0.00373)	(0.00373)
First trading days of month	-0.0136***	-0.0136***	-0.0137***	-0.0141***	-0.0141***	-0.0142***
	(0.000912)	(0.000910)	(0.000911)	(0.000932)	(0.000931)	(0.000931)
Last trading days of month	0.00622***	0.00620***	0.00627***	0.00641***	0.00640***	0.00648***
	(0.000884)	(0.000885)	(0.000885)	(0.000904)	(0.000905)	(0.000905)
Monday	0.00665***	0.00660***	0.00737***	0.00719***	0.00717***	0.00800***
	(0.000770)	(0.000782)	(0.000792)	(0.000787)	(0.000799)	(0.000809)
Friday	-0.0143***	-0.0143***	-0.0149***	-0.0141***	-0.0141***	-0.0147***
	(0.000718)	(0.000718)	(0.000724)	(0.000732)	(0.000731)	(0.000737)
Day light saving time change (forward)	0.0168***	0.0169***	0.0162***	0.0187***	0.0187***	0.0179***
	(0.00497)	(0.00496)	(0.00496)	(0.00510)	(0.00508)	(0.00508)
Day light saving time change (backward)	0.00817*	0.00792	0.00807*	0.00503	0.00493	0.00510
	(0.00488)	(0.00486)	(0.00486)	(0.00502)	(0.00500)	(0.00500)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES

Table A.III. The effect of ambiguity on risk-taking (including the full set of control variables)

The table presents panel regressions using investor-fixed effects on excess buy-sell imbalances. The columns titled "#" use $ExBSI^{\#}$ and the columns titled "EUR" use $ExBSI^{EUR}$ as the dependent variable. The key variables of interest are aggregate ambiguity aversion (*dVVSTOXX*) and the lags of this variable. All specifications include the control variables listed in Table IV. All regressions incorporate year and 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.

	(1)	(2)
	#	EUR
dVVSTOXX	-0.000583***	-0.000620***
	(8.22e-05)	(8.48e-05)
dVVSTOXX (lag 1)	-0.000438***	-0.000449***
	(7.65e-05)	(7.86e-05)
dVVSTOXX (lag 2)	0.000124*	0.000102
	(7.53e-05)	(7.71e-05)
dVVSTOXX (lag 3)	8.76e-05	2.73e-05
	(7.39e-05)	(7.58e-05)
dVVSTOXX (lag 4)	-0.000592***	-0.000617***
	(7.16e-05)	(7.35e-05)
dVVSTOXX (lag 5)	1.30e-05	-1.56e-05
	(7.29e-05)	(7.46e-05)
dVVSTOXX (lag 6)	-0.000162**	-0.000186**
	(7.19e-05)	(7.39e-05)
dVVSTOXX (lag 7)	-0.000256***	-0.000293***
	(7.14e-05)	(7.31e-05)
dVVSTOXX (lag 8)	0.000256***	0.000227***
	(6.85e-05)	(7.02e-05)
dVVSTOXX (lag 9)	0.000188***	0.000192***
	(6.97e-05)	(7.14e-05)
dVVSTOXX (lag 10)	-9.16e-05	-9.73e-05
	(6.92e-05)	(7.10e-05)
dVSTOXX	-0.000221	-0.000305
	(0.000255)	(0.000262)
Log wealth	-0.0200***	-0.0205***
	(0.000396)	(0.000414)
CDAX 1-day-return	-0.300***	-0.282***
	(0.0323)	(0.0329)
$CDAX^2$ 1-day-return	4.872***	5.290***
	(0.817)	(0.838)
CDAX 3-months-return	-0.0214***	-0.0205***
	(0.00107)	(0.00111)
School vacation	-0.00338***	-0.00329***
	(0.000762)	(0.000815)
Public holidays	0.0303***	0.0307***
	(0.00248)	(0.00253)
First trading day before school vacation	0.00675***	0.00592**
	(0.00240)	(0.00246)
First trading day after school vacation	0.00472*	0.00428*
	(0.00248)	(0.00256)
SAD	0.000277	0.000155
	(0.000887)	(0.000910)
First trading days of month	-0.0117***	-0.0123***
	(0.000961)	(0.000983)
Last trading days of month	0.00861***	0.00881***
	(0.000935)	(0.000955)
Monday	0.00584***	0.00649***
	(0.000839)	(0.000857)
Friday	-0.0151***	-0.0150***
	(0.000781)	(0.000796)
Day light saving time change (forward)	0.0274***	0.0301***
	(0.00607)	(0.00621)
Day light saving time change (backward)	0.00454	0.00111
	(0.00516)	(0.00529)
Year Fixed Effects	YES	YES
Month fixed effects	YES	YES

Table A.IV. Ambiguity and sentiment (including the full set of control variables)

The table presents panel regressions using investor-fixed effects on excess buy-sell imbalances. The column titled "#" uses *ExBSI*$^{\#}$ and the column titled "EUR" uses *ExBSI*^{EUR} as the dependent variable. Panel A presents the coefficient estimates for the interaction of *FEARS* and a dummy variable which is equal to one if the *VVSTOXX* is high (low). We also control for *dVSTOXX*. All specifications include the control variables listed in Table IV. All regressions incorporate year and 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 estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	#	EUR
FEARS x HighVVSTOXX	-0.0105***	-0.0114***
	(0.00170)	(0.00174)
FEARS x LowVVSTOXX	-0.00360**	-0.00361**
	(0.00171)	(0.00175)
dVSTOXX	-8.23e-05	-0.000188
	(0.000268)	(0.000275)
Log wealth	-0.0205***	-0.0211***
	(0.000401)	(0.000419)
CDAX 1-day-return	-0.311***	-0.293***
	(0.0329)	(0.0335)
CDAX^{2} *1-day-return*	4.412***	4.893***
	(0.795)	(0.816)
CDAX 3-months-return	-0.0213***	-0.0203***
	(0.00105)	(0.00109)
School vacation	-0.00390***	-0.00383***
	(0.000712)	(0.000765)
Public holidays	0.0298***	0.0304***
	(0.00224)	(0.00230)
First trading day before school vacation	0.00665***	0.00558**
	(0.00232)	(0.00238)
First trading day after school vacation	0.00177	0.00103
	(0.00213)	(0.00218)
SAD	0.00270***	0.00256***
	(0.000851)	(0.000873)
First trading day after public holidays	0.0110***	0.0114***
	(0.00254)	(0.00260)
Last trading day before public holidays	-0.0167***	-0.0153***
	(0.00291)	(0.00297)
First trading days of month	-0.0118***	-0.0123***
	(0.000890)	(0.000911)
Last trading days of month	0.00616***	0.00635***
	(0.000880)	(0.000900)
Monday	0.00656***	0.00708***
	(0.000770)	(0.000787)
Friday	-0.0146***	-0.0144***
	(0.000720)	(0.000733)
Day light saving time change (forward)	0.0174***	0.0194***
	(0.00496)	(0.00508)
Day light saving time change (backward)	0.00937*	0.00653
	(0.00486)	(0.00500)
Year Fixed Effects	YES	YES
Month fixed effects	YES	YES

Table A.V. The effect of ambiguity conditional on ambiguity preferences of investors (including the full set of control variables)

The table presents panel regressions using investor-fixed effects on the value of the excess buy-sell imbalance (*ExBSI*^{EUR}). Columns (1) and (2) present the coefficient estimates for *dVVSTOXX*. Column (1) is based on the original sample excluding all investors who were surveyed and identified as ambiguity averse. Column (2) is based on the investors who were surveyed and identified as ambiguity averse. Column (3) presents the results from including the interaction term *dVVSTOXX x Ambiguity*. *Ambiguity* is a dummy variable, which takes on the value one if and only if an investor was surveyed and identified as ambiguity averse. All specifications include the control variables listed in Table IV. All regressions incorporate year and 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.

	(1)	(2)	(3)
	All without ambiguity averse	Ambiguity averse	Interaction
dVVSTOXX	-0.000576***	-0.00255**	-0.000575***
	(7.77e-05)	(0.00120)	(7.78e-05)
dVVSTOXX x Ambiguity			-0.00220*
			(0.00131)
dVSTOXX	0.000107	-0.00131	0.000101
	(0.000265)	(0.00301)	(0.000264)
FEARS	-0.00786***	-0.00700	-0.00784***
	(0.00127)	(0.0200)	(0.00127)
Log wealth	-0.0208***	-0.0593***	-0.0208***
	(0.000417)	(0.00991)	(0.000418)
CDAX 1-day-return	-0.291***	0.361	-0.288***
	(0.0335)	(0.418)	(0.0334)
CDAX^2 1-day-return	5.534***	3.069	5.523***
	(0.819)	(13.40)	(0.818)
CDAX 3-months-return	-0.0199***	-0.0372**	-0.0200***
	(0.00109)	(0.0171)	(0.00109)
School vacation	-0.00395***	-0.00547	-0.00395***
	(0.000776)	(0.0122)	(0.000774)
Public holidays	0.0302***	0.0200	0.0302***
	(0.00230)	(0.0330)	(0.00229)
First trading day before school vacation	0.00545**	0.0454	0.00563**
	(0.00239)	(0.0356)	(0.00238)
First trading day after school vacation	0.00186	-0.00935	0.00179
	(0.00219)	(0.0309)	(0.00219)
SAD	0.00241***	-0.00974	0.00236***
	(0.000875)	(0.0132)	(0.000873)
First trading day after public holidays	-0.00237	-0.0747*	-0.00271
	(0.00294)	(0.0419)	(0.00293)
Last trading day before public holidays	-0.0137***	-0.0554	-0.0139***
	(0.00374)	(0.0661)	(0.00373)
First trading days of month	-0.0142***	-0.0104	-0.0142***
	(0.000933)	(0.0144)	(0.000931)
Last trading days of month	0.00643***	0.0133	0.00648***
	(0.000907)	(0.0152)	(0.000905)
Monday	0.00793***	0.0213	0.00800***
	(0.000811)	(0.0130)	(0.000809)
Friday	-0.0147***	-0.0251**	-0.0147***
	(0.000739)	(0.0108)	(0.000737)
Day light saving time change (forward)	0.0179***	0.0350	0.0179***
	(0.00510)	(0.0762)	(0.00508)
Day light saving time change (backward)	0.00526	-0.0327	0.00510
	(0.00501)	(0.0774)	(0.00500)
Year Fixed Effects	YES	YES	YES
Month fixed effects	YES	YES	YES

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