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Ambiguity and private investors' behavior after forced fund liquidations

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ABSTRACT

We investigate individual investors' decisions under time-varying ambiguity (VVIX) using plausibly exogenous forced mutual fund liquidations at a German brokerage. Investors reinvest 87% of forced liquidations when the refund occurs on a day of low ambiguity and 0% when it occurs on a day of high ambiguity. Instead of reinvesting, investors become inert and keep the refund in their cash holdings. The effect reverses approximately six months after the liquidation. If investors reinvest, they decrease their risk-taking under ambiguity. Our results are not driven by risk, rebalancing decisions, experiencing losses, or attention and are robust to alternative measures of ambiguity.

1. Introduction

Risk refers to situations when probabilities of future outcomes are known, and it plays a key role in investment decisions. Yet, much less is known about the role of ambiguity, which refers to situations in which the probabilities of future outcomes are unknown (Knight, 1921). Ambiguity may arise from either model uncertainty (the agent is worried the reference model may be incorrect) or parameter uncertainty (the agent is worried the estimated parameters may be wrong). A Bayesian with standard expected utility preferences would treat model uncertainty and uncertainty about events both as risk (Illut and Schneider, 2022). In contrast to a Bayesian, the decisions of ambiguity-averse investors will change if the model or parameter uncertainty increases even if the expected average risk does not change. In a thought experiment, Ellsberg (1961) argues that individuals tend to be averse to ambiguity; i.e., they prefer a choice with known probabilities. Using experimental methods, the literature shows that individuals indeed tend to be ambiguity averse, and ambiguity affects their financial decisions (e.g., Dimmock, Kouwenberg, Mitchell, and Peijnenburg, 2016; Kostopoulos, Meyer, and Uhr, 2022). The relation between ambiguity and individuals' portfolio choices has been modeled in theoretical papers. These theoretical papers suggest that ambiguity and/or ambiguity aversion can cause non-participation or a reduction in risky investments (e.g., Dow and Werlang, 1992; Garlappi, Uppal, and Wang, 2007; Peijnenburg, 2018).

In addition, there are papers using dynamic equilibrium models to

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analyze the effect of temporary shocks in ambiguity on ambiguity-averse investors.[1] These models allow researchers to account for risk and ambiguity in individuals' decision-making processes. These (and related) models, including Epstein and Wang (1994), Maenhout (2004), Cao, Wang, and Zhang (2005), and Leippold, Trojani, and Vanini (2008), have shown that ambiguity (aversion) may help to explain the equity premium puzzle. Other papers demonstrate that higher ambiguity or ambiguity aversion is associated with portfolio inertia in both risk-free assets and risky portfolios (Epstein and Wang, 1994; Illeditsch, 2011). However, sudden shocks to firms, such as cash flow or dividend fluctuations, can end this inertia, leading to excess volatility and amplification effects (Routledge and Zin, 2009; Guidolin and Rinaldi, 2010; Illeditsch, 2011; Mele and Sangiorgi, 2015). Ozsoylev and Werner (2011) show that ambiguity can negatively affect liquidity. Epstein and Schneider (2008), Epstein, Noor, and Sandroni (2010), and Illeditsch (2011) find that ambiguity aversion can lead to asymmetric reactions to good and bad news. Furthermore, evidence suggests that ambiguity aversion may cause otherwise informed investors not to reveal information, potentially negatively affecting price discovery (Condie and Ganguli, 2017). Finally, several papers indicate that ambiguity-aversion increases home bias (Uppal and Wang, 2003; Huang, 2007; Cao, Han, Hirshleifer, and Zhang, 2011).

This study relates to these theoretical models by empirically identifying the link between the investment decisions of private investors and ambiguity. For our empirical approach, we follow Meyer and Pagel (2022) and use mutual fund liquidations to identify the causal effect of ambiguity on investment decisions. Fund management companies must publicly announce fund liquidations six months (four weeks) before closure for funds domiciled in Germany (Luxemburg). Most liquidations are announced in annual reports, but investors do not get personal notifications from the fund management company or the bank we are working with. Therefore, the refund from the liquidation hits most investors unexpectedly. Investors subject to a fund liquidation receive the current market value, which is the net asset value (NAV) of their investment when the fund is finally liquidated. The refund is likely salient to investors, as it is approximately 10% of the average investor's portfolio value. Investigating fund liquidations provides the advantage that the refund does not change the net wealth of investors and is independent of the consumption choices of clients because clients have not planned for them or initiated the sale.[2]

Information on fund closures in Germany is combined with a unique dataset of 113,000 brokerage clients that contains information on individuals' time-stamped security transactions and holdings, balances, and transactions in checking, savings, and settlement accounts from 1999 to 2016. Thus, the combination of data allows the investigation of the (re)investment decisions of investors after a plausibly exogenous forced liquidation.[3] The final sample consists of 18,836 investors who trade in funds that are ultimately subject to forced liquidation. Of these investors, 1,958 are directly affected by a fund liquidation event.

We combine this dataset with a measure of ambiguity about volatility. Therefore, we follow the stream of literature that uses the volatility of volatility of the stock market (e.g., VVIX or V-VSTOXX) as an ambiguity measure (e.g., Bali and Zhou, 2016; Baltussen, van Bekkum, and van der Grient, 2018; Bollerslev, Tauchen, and Zhou, 2009; Epstein and Ji, 2013).[4] Using an index option linked measure, like the VVIX, goes back to Drechsler (2013) who uses a representative agent endowment economy to investigate the effects of ambiguity, specifically model uncertainty, on index options for investors who want their consumption and portfolio choice decisions to be robust to potential model uncertainty. In this setting, investors are assumed to be averse to model uncertainty which is one form of ambiguity. He shows that model uncertainty generates level and time-variation in index options. We use the VVIX as a proxy for ambiguity about volatility. The VVIX is the 30-day implied volatility of the VIX that represents the volatility of volatility of the S&P 500.[5] Intuitively, one can think of an individual investor who seeks to determine the volatility of the market, then a higher VVIX would signal more disagreement about the correct estimate.

Taken together, this creates a sample of investors who are closed out of their fund investment and receive the refund on days with high or low ambiguity. Almost all investors hold the fund until the actual refund takes place, and as the fund management company is obliged to announce the closure at least four weeks before, the ambiguity on the day of closure is unanticipated by the investor and the fund management and hence exogenous. As a result, funds closed on days with high or low ambiguity are very similar. It is almost certain to assume that affected investors would not have sold the fund had it not been closed. Assuming investors hold a portfolio close to their desired one, they should reinvest the proceeds of the refund in a similar security.

We start by investigating the net reinvestment after the forced liquidation and find that this is not the case. Investors shy away from reinvesting the refund from fund liquidations when ambiguity is high on the day of the closure. If ambiguity is low, investors reinvest 87% of the refund. In contrast, if ambiguity is high, their reinvestment is close to 0% of the refund. This finding suggests that investors become inert and do not reinvest when ambiguity is high. This observation holds for 5 and 30 days after the liquidation, although periods of high ambiguity do not last long and decrease to low levels within approximately 8 days for the average closure event (median 3 days). When investigating a more long-term perspective of 3 months, investors closed out at high ambiguity reinvest 52%, compared to investors closed out at low ambiguity reinvesting 89%. The negative effect of ambiguity is almost offset after 6

[1] Other theory papers have also modeled ambiguity using different approaches, which led to qualitatively comparable results suggesting ambiguity (aversion) should affect equity market participation. One group of studies uses the multiple prior approach (also known as maximin) in which agents evaluate policies by optimizing for the worst-case belief (e.g., Gilboa and Schmeidler, 1989; Chen and Epstein, 2002; Epstein and Wang, 1994). The second group of papers uses a smooth preferences approach which allows separating ambiguity from aversion to it (e.g., Klibanoff, Marinacci, and Mukerji, 2005, 2009; Chen, Ju, and Miao, 2014). A third group of papers uses the robust control approach, where agents start with a reference model and then take alternative models into account. The optimal strategy then takes deviations in terms of model uncertainty into account and penalizes models and solutions that are farther away from the reference model (e.g., Anderson, Hansen, and Sargent, 2003; Maenhout, 2004, 2006).

[2] Also note that more than 75% of investors affected by forced liquidations have bought the fund liquidated more than a year before the closure. The median investor bought the fund 687 days before its closure.

[3] We refer to Meyer and Pagel (2022) for a detailed discussion of the methodology.

[4] The literature distinguishes between ambiguity about volatility and ambiguity about drift (see Kostopoulos, Meyer, and Uhr, 2022 for a review of the literature). This study focuses on ambiguity about volatility following the call for research on the empirical investigation of ambiguity about volatility (Epstein and Ji, 2013). For the sake of brevity, we label ambiguity about volatility simply as "ambiguity" throughout this study.

[5] The VVIX is a market-based, model-free, and forward-looking measure that is computed based on liquid securities with daily availability. As such, it is the most suitable measure of ambiguity for our research question. Kostopoulos, Meyer, and Uhr (2022) use the V-VSTOXX because it is the regionally closest measure to German brokerage data. While this argument also holds true for our setting, the V-VSTOXX is only available from March 2010 onward. Applying the V-VSTOXX to fund liquidations would dramatically reduce the number of observations in our setting. Thus, we chose the VVIX instead of the V-VSTOXX because it is available for the full observation period of our investor data. The correlation between the VVIX and V-VSTOXX is high (see the correlation matrix in Table A.1 in the Internet Appendix and Kostopoulos, Meyer, and Uhr (2022)).

months when the difference between being closed out at high or low ambiguity becomes statistically insignificant. As a next step, we delve deeper into trading decisions. We show that investors choose less risky securities when reinvesting after a forced liquidation on days of high ambiguity and securities of comparable risk when ambiguity is low compared to their initial and liquidated investment.

The drastically decreased reinvestment when being closed out at high levels of ambiguity is unlikely to be driven by rebalancing decisions because controlling for the portfolio's 3 or 12 months return before the fund closure does not change the results. To address the potential concern that investors might not be aware of the liquidation, we also run our analysis restricted to investors who are active within 30 days after their fund's liquidation. Our results replicate. We run additional analyses to investigate what investors are doing in the short run if they are not reinvesting the money. In line with the theory of portfolio inertia, we find that they leave the remaining refund proceeds in their cash accounts and do not transfer them out of the bank or withdraw them.

The literature has not yet reached a consensus on which empirical measure of ambiguity about volatility to use. While we choose the VVIX as it is a bias-free, market-based, and most importantly a daily available measure that best fits our data and research question, we acknowledge alternative ways of measuring ambiguity. In the robustness section, we replace the VVIX with three alternative measures of ambiguity. First, we use the market-based omega measure by Brenner and Izhakian (2018) that builds on high-frequency data and faces the risk that the volatility of volatility—that is a function of return—might be stake-dependent. Second, we construct a survey-based measure of ambiguity as the dispersion of opinion of professional forecasters using the Survey of Professional Forecasters (SPF) by the European Central Bank as suggested by Illut and Schneider (2014). Using these alternative measures leads to qualitatively unchanged results. Finally, we also replace the VVIX with the V-VSTOXX and the results go in the same direction.[6] To disentangle the effect of risk and ambiguity and to rule out the possibility that our ambiguity measure captures similar effects as risk, we also include the level of expected volatility (VIX index) on the day of the closure in our specification. The interaction with high VIX and the liquidation event is statistically insignificant, suggesting that our results are unlikely to be driven by a latent relation between the estimates of expected volatility and expected ambiguity. Finally, controlling for investor characteristics does also not change our conclusions.

Our empirical findings are related to the propositions of theoretical models in several dimensions. In line with Illeditsch (2011), a significant proportion of our investors exhibit inertia rather than reinvesting in high ambiguity scenarios. This inertia persists for over 90 days, surpassing the time required for the VVIX to recover from high levels. Our findings also suggest that this lack of reinvestment is related to lower trading volumes among investors who are closed out of funds on days with high ambiguity, which seems to lend partial support to Ozsoylev and Werner (2011). Moreover, the findings are in line with theory suggesting a negative relation between ambiguity aversion and the fraction of financial assets allocated to risky assets (e.g., Garlappi, Uppal, and Wang, 2007; Peijnenburg, 2018). However, our results suggest that effects from ambiguity shocks are temporary. When thinking of participation as the change in stock market exposure of investors, where not reinvesting the refund corresponds to a reduction in stock market participation, our findings on inertia in response to high ambiguity and temporarily decreasing risk-taking can also be related to Dow and Werlang (1992).

Our study also contributes to the existing empirical literature investigating the link between ambiguity and investors' behavior. The study by Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016) elicits ambiguity preferences of US households in a survey using the Ellsberg urn experiment. They show that ambiguity aversion negatively affects stock market participation and stock holdings. Specifically, they show that ambiguity-averse households allocate a lower fraction of financial assets to stocks, prefer stocks they are more familiar with (own company stocks and fewer foreign stocks), and were more likely to sell stocks during the financial crisis, a period of high ambiguity. The study by Bianchi and Tallon (2019) combines administrative panel data and survey data. It shows that ambiguity-averse investors are more likely to keep their risk exposure constant over time, rebalance their portfolio more actively, and are subject to a higher home bias. Kostopoulos, Meyer, and Uhr (2022) investigate time-varying ambiguity and its effect on the trading behavior of investors by combining brokerage data with a daily market-based measure of ambiguity (V-VSTOXX) and a more long-term but less frequent ambiguity measure based on the dispersion of professional forecasters (SPF). They find that daily changes in ambiguity are linked to investors' attention and a reduction in risk-taking.

This paper goes beyond the existing empirical literature by using a panel of trading data and investigating exogenous and time-varying ambiguity rather than the ambiguity preferences of the individuals. The setting with exogenous ambiguity levels at the time of fund liquidations is new and allows for identifying the effects of ambiguity on portfolio choice and trading over a few days (5 and 30 days) and longer periods (up to 180 days). It adds the findings that investors become inert and reinvest almost nothing when ambiguity is high. This leads to a non-linear effect on portfolio choice, as investors reduce risk-taking when ambiguity is high but do not increase it above previous levels when ambiguity is low.[7] Furthermore, the effects persist over up to 90 days and dissipate after approximately 180 days, although periods of high ambiguity are transitory and decrease to lower levels within 8.6 days after the fund's closure on average. Finally, we add that money not reinvested when ambiguity is high is not consumed or withdrawn and instead kept in cash accounts.

The setting of actual investor transactions under ambiguity contributes to the literature as it contains real-world situations. However, this setting also bears limitations. The sample investors may have multiple stock trading accounts, so their holdings with the sample bank do not necessarily represent their overall portfolio. Still, the sample is representative of the average brokerage client (e.g., Barber and Odean, 2001); however, the sample is not representative of the average German citizen. Finally, we lack data on the investors' level of ambiguity aversion and, therefore, implicitly assume that most investors are ambiguity averse. Previous studies such as Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016) and Kostopoulos, Meyer, and Uhr (2022) show that most investors are ambiguity averse. By looking at all investors without disentangling their ambiguity preferences, we likely underestimate the effect of ambiguity on ambiguity-averse investors.

Reinvestment decisions have recently received attention in the literature. Imas (2016) and Meyer and Pagel (2022) show that people consider realized gains and losses when deciding the level of risk for their reinvestment. We contribute to these studies by showing that, beyond the effect of gains and losses, the ambiguity level also significantly affects private investors' investment and risk-taking.

The paper proceeds as follows. Chapter 2 explains the data sources and Chapter 3 outlines the identification strategy. In Chapter 4, we describe the empirical approach and the results. Chapter 5 contains robustness tests and further analyses, and Chapter 6 concludes.

[6] Note that the coefficients in the analyses using the V-VSTOXX are not statistically significant in all specifications due to power issues. These power issues arise because the V-VSTOXX is only available from March 2010 onward.

[7] This effect might be a result of a budget constraint as investors may not have the funds to invest more money than they are getting refunded under low ambiguity. However, note that these budget constraints are not binding for the risk-taking decision when reinvesting the refund. They could easily choose riskier funds and securities under low ambiguity. We do not find such an effect.

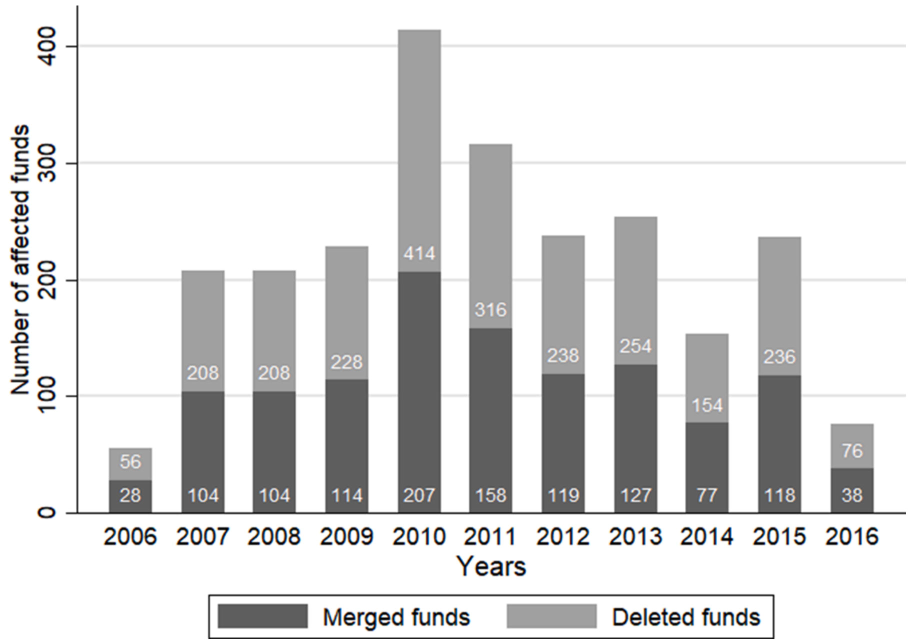

Fig. 1. Number of merged and closed mutual funds in Germany
This bar chart illustrates the number of funds affected by closures or mergers. The x-axis presents the year, and the y-axis shows the total number of affected funds. The dark grey bars represent the number of funds that are merged into another fund without being liquidated. The light grey bars show the number of deleted funds that are liquidated and reimbursed to investors. Note that the figure contains all deleted funds in Germany. Not all of them are held by at least one of the investors in our sample.

2. Data

In this paper, we combine three sources of data. We use data on forced fund closures containing information on the date of closure and the ISIN, a measure of market-based ambiguity (VVIX), and a sample of brokerage clients with information on their security transactions from 1999 to 2016. We describe the three sources of data in more detail below.

2.1. Fund closure data

According to the Bundesverband für Investmentfonds (BVI, the German equivalent of the ICI), between 8,596 and 11,922 investment funds were available for private investors at each year-end in the time

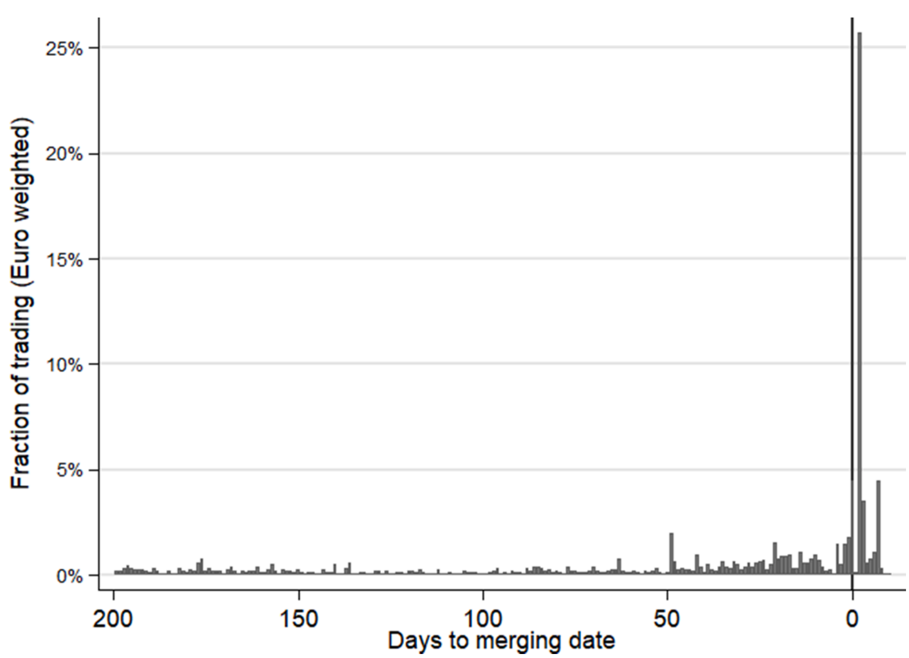

Fig. 2. Trading behavior before and after fund closure
This figure illustrates the fraction of trading in funds that are terminated at t = 0. The x-axis illustrates the days before and after closure. The days left of zero are the days before closure, and the days right of zero are the days after closure. The y-axis contains the fraction of trading on a specific day relative to the total trading 200 days before and 10 days after closure. The weighting is in euros. Note that it depends on the settlement arrangements when a refund of a mutual fund investment appears on the clients' account.

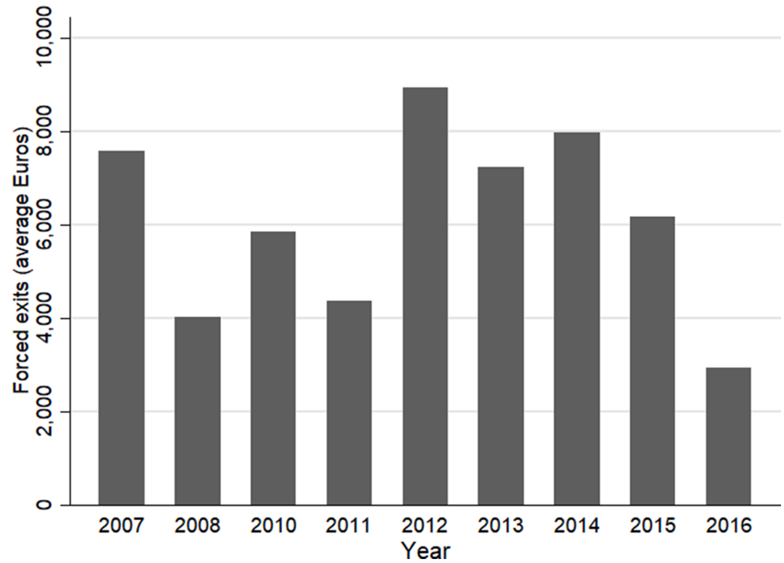

Fig. 3. Forced fund liquidations in euro by year of liquidation
This figure illustrates the average reimbursement of forced fund liquidation (in euros) per year. The x-axis illustrates the years, and the y-axis illustrates the average euro value of forced fund liquidations.

period from 2006-2014 (BVI, 2015, page 76). Every year, new funds are established, and existing funds cease to exist. These mutual fund terminations are decisions made by fund management companies. Reasons for termination may be too little investor demand, too small funds, or a performance that would make attracting additional assets unrealistic. When a fund is terminated, the mutual fund company has two options. Option one is to merge the fund with another existing fund. The assets under management are then transferred to the merged entity. Option two is to terminate the fund and refund clients their investment at the fund's net asset value on the day of its closure. After termination, investors' money is available for reinvestment once the settlement is done (usually around two days). Mutual fund terminations and mergers must be announced publicly. This announcement is not made via personal mail or email by the fund management company or the bank to the investor. Instead, it is announced only in the fund's half or full-year report or in a general press release. Both the mergers and terminations are announced half a year before termination in Germany and four weeks before termination for funds domiciled in Luxemburg.

The BVI provided a list of all mutual fund terminations and mergers in Germany between 2006 and 2016. The data includes the ISIN of the fund, its name, the date of termination, and whether the money was reimbursed to the investors or transferred to another (existing) fund. It also includes information on whether the fund was a target date fund. Fig. 1 provides information on the number of affected funds split into merged or fully terminated funds. Fig. 1 already excludes all target-date funds. The data on fund closures is discussed in greater detail, particularly concerning the reasons for closures, in Meyer and Pagel (2022). Not all closed funds are held by the investors in our sample. The final sample consists of 180 fully closed funds that reimbursed money to 1,958 distinct clients. In total, we observe 2,222 closure events for clients in our sample. Thus, only very few clients are hit by two or more fund termination events.

Fig. 2 shows a bar chart of days before and after fund liquidation and investors' trading behavior in our sample. It starts 200 days before the liquidation of the fund. The graph points out that very little trading occurs around the termination announcement (6 months for funds domiciled in Germany and one month for funds domiciled in Luxemburg), suggesting that the liquidation and refunding come as a surprise for most of our investors. Instead, the trading takes place once the settlement is complete and clients see the money in their accounts. Fig. 3 shows that our private investors are usually refunded between 4,000 and 8,000 Euros on a fund closure, about 10% of the average client's portfolio value.

2.2. Measure of ambiguity

To measure time-varying ambiguity about volatility we use the volatility of volatility (vol-of-vol) as a market-based measure frequently used in previous literature (e.g., Baltussen, van Bekkum, and van der Grient, 2018; Hollstein and Prokopczuk, 2018; Huang, Schlag, Shaliastovich, and Thimme, 2019; Bali and Zhou, 2016; Bollerslev, Tauchen, and Zhou, 2009; Epstein and Ji, 2013).[8] We use the VVIX as our measure of ambiguity. The VVIX is the 30-day forward price (implied volatility) of the VIX based on the S&P 500 index. Thus, the VVIX is the vol-of-vol of the S&P 500. While the VIX measures the expected volatility over the following 30 days, the VVIX represents second-order beliefs and measures the expected ambiguity about future volatility over the next 30 days. The use of an index option linked measure, like the VVIX, goes back to theoretical work of Drechsler (2013). The VVIX is very close to what Epstein and Ji (2013) label ambiguity about volatility. The VVIX has several appealing features for our research question. It is not only market-based and, thereby, a natural measure for the investigation of stock market investment decisions, but also model-free, forward-looking, and is available daily. We obtain data on the VVIX from Refinitiv Datastream. Intuitively, one can think of an individual investor who seeks to determine the volatility of the market, then a higher VVIX would signal more disagreement about the correct estimate.

Since the VVIX is available daily and hence best fits our data structure we based our main analyses on this proxy. However, this choice is unrelated to a belief that VVIX is in fact the best measure of ambiguity. There is no consensus in the literature which empirical measure should be used to proxy for ambiguity. Hence, in the robustness section, we also use three alternative measures of ambiguity frequently used in the literature. (1) Among the first to propose a measure of ambiguity were Illut and Schneider (2014). They propose and use the dispersion in survey forecasts of professional forecasters as a proxy for ambiguity. The intuition in their measure is that when households seek to set expectations, they would likely seek the opinions of experts to make the best-informed decisions. The higher the disagreement among the

[8] See, e.g., Kostopoulos, Meyer, and Uhr (2022) for a review of the literature.

Table 1
Summary statistics.

	Mean	25th Percentile	Median	75th Percentile	Standard deviation
Panel A. Socio-demographics					
Age (in years)	52.53	45.00	51.00	59.00	11.79
Client risk aversion (high = 1 and low = 5)	3.36	3.00	4.00	5.00	1.44
Gender (1 = male)	0.84				
Length of relationship between bank and client (in years)	12.78	11.00	11.00	13.00	3.34
Ph.D. (1 = investor holds doctoral degree)	0.10				
Panel B. Portfolio & fund trading					
Average Herfindahl-Hirschman index (HHI)	0.10	0.02	0.06	0.14	0.11
Average number of funds	6.06	2.68	4.79	7.84	5.23
Average number of securities	13.93	6.75	10.72	17.00	12.58
Number of fund purchases (p.a.)	9.22	1.14	2.89	6.67	38.18
Number of fund sales (p.a.)	7.86	1.60	2.86	5.67	35.29
Roundtrip duration per fund (in days)	868.61	361.00	686.76	1,323.50	618.99
Portfolio value (in euros)	59,363.23	19,682.34	36,723.89	63,448.38	118,275.00
Liquidation (liquidation value of forced fund closures, in euros)	7,137.07	1,451.92	4,020.00	8,602.61	9,838.46
Loss (funds closed at a loss)	0.23				
Number of observations	2,222				

This table reports summary statistics for all individuals who were forced to sell at least one fund during the sample period. The sample ranges from January 1999 to May 2016. Panel A contains the investors' socio-demographic information, and Panel B illustrates the investors' portfolio characteristics and trading behavior in funds. It refers to the overall trading behavior of individuals subject to a forced fund liquidation.

experts, the lower the confidence in probability assessments of a situation an ambiguity-averse person would be concerned about. In the absence of an aversion against this form of disagreement or ambiguity there would be no reaction to (changes) in the dispersion of forecasts as long as the average point estimate remains unchanged. We follow Illut and Schneider (2014) and construct an alternative measure of ambiguity based on the dispersion of opinion derived from the Survey of Professional Forecasters by the European Central Bank (ECB). (2) Izhakian (2017) has theoretically developed the omega measure which he suggests to be unrelated to ambiguity aversion. He empirically implements it by using fluctuations in high frequency market (index) data (Brenner and Izhakian, 2018). We directly follow this approach and construct omega based on high-frequency data from TAQ. (3) The V-VSTOXX is the European equivalent of the VVIX downloaded from Eurex. Note that the correlation between the VVIX and V-VSTOXX is high, but the time series of the VVIX is much longer.[9]

2.3. Investor data

The sample consists of 113,000 private investors who own a portfolio at a large German online brokerage between January 1999 and May 2016.[10] Since the fund closure data are available from 2006 onward, the sample period for the analyses is from January 2006 to May 2016.[11] The data contains detailed information on all security transactions of these investors. We observe the trading in financial securities such as stocks, mutual funds, bonds, and structured financial products. Additionally, the bank collected socio-demographic information as part of the know-your-customer process. The data also allow for identifying investors who make use of financial advice. In this study, we exclude all investors who use financial advice because we are interested in the investor's decision-making and not in the recommendations of financial advisors. We also exclude automated trades (e.g., savings plan transactions), which are likely not representing self-directed trades of clients.

The 113,000 investors in our initial sample traded about 65,000 different mutual funds from 1999 to 2016. Directly affected by mutual fund closures are 1,958 investors. A few of them are affected by more than one forced liquidation, so the final sample consists of 2,222 forced liquidations. The investors (Table 1) subject to forced liquidations (double counting those who are affected more than once) are, on average, 53 years old, male (84%), are holding their portfolio with the bank for 13 years, have a risk aversion of 3.4 measured on a scale from 1 (high risk aversion) to 5 (low risk aversion), and have a portfolio value of 59,363 euros (median 36,724 euros). They hold, on average, 14 distinct securities, of which six are mutual funds. On average, they purchase nine and sell eight funds annually with a roundtrip duration per fund of 869 days. Due to the broad diversification of mutual funds, the average mutual fund holder is reasonably well diversified, with an average Herfindahl-Hirschman index (HHI)[12] of 10%. The investor characteristics are comparable to those presented in previous studies using brokerage data (e.g., Barber and Odean, 2001), and the average portfolio value is even slightly higher than the average portfolio value reported for the average German stock market investor by the European Central Bank (2017), suggesting that the sample is unlikely to consist of play money accounts.[13] The study by Kostopoulos, Meyer, and Uhr (2022) uses data from the same German brokerage but investigates the trading decisions of all investors.[14] Our sample of investors and fund closure events is identical to the one used in Meyer and Pagel (2022).

[9] A correlation matrix for all ambiguity measures used in this study, VDAX, VIX, and VSTOXX, as well as return data of the DAX, STOXX, and S&P500, is presented in Table A.1 in the Internet Appendix.

[10] This is a randomly chosen sample drawn by the bank that is representative of the bank's average client.

[11] In the robustness section, we use the V-VSTOXX as an alternative measure of ambiguity. The V-VSTOXX is only available from March 2010 onward and, thus, the observation period starts in March 2010 for this analysis.

[12] The HHI is used as a measure of diversification and portfolio efficiency and is calculated as the sum of the squared portfolio weights of each asset in a portfolio at each month-end. We follow Dorn, Huberman, and Sengmueller (2008) and count mutual funds as 100 different securities. The lower the value of this measure, the higher the degree of diversification.

[13] Note that gambling would rather go against our results because gamblers perceive trading as entertainment (Dorn and Sengmueller, 2009) and might trade irrespective of the economic environment or even more in economic downturns (Kumar, 2009).

[14] From the sample of 113,000 individual investors, Kostopoulos, Meyer, and Uhr (2022) exclude investors who are receiving financial advice and all automated trades (e.g., savings plans) to investigate self-driven trades only. In this study, we use the same restrictions but additionally restrict to investors who are subject to a forced fund liquidation.

Table 2
Characteristics of funds closed at high and low ambiguity.

	Funds closed out on a day with low ambiguity (N = 506)				Funds closed out on a day with high ambiguity (N = 154)				
	Mean	25th Percentile	Median	75th Percentile	Mean	25th Percentile	Median	75th Percentile	p-value
Panel A. Fund characteristics									
Retaining fund (dummy, yes = 1)	0.65	0	1	1	0.69	0	1	1	0.3296
Domicile Luxemburg (dummy, yes = 1)	0.54	0	1	1	0.53	0	1	1	0.7688
Domicile Germany (dummy, yes = 1)	0.35	0	0	1	0.36	0	0	1	0.7983
Target date fund (dummy, yes = 1)	0.11	0	0	0	0.14	0	0	0	0.2793
Currency euros (dummy, yes = 1)	0.84	1	1	1	0.84	1	1	1	0.9933
Fund age (in years)	14.07	9.63	11.93	16.74	13.58	9.75	12.97	16.77	0.3380
Initial charge (in %)	3.27%	2.50%	4.00%	5.00%	2.75%	0.00%	3.00%	5.00%	0.0139
Annual charge (in %)	1.08%	0.70%	1.08%	1.50%	1.05%	0.53%	1.00%	1.50%	0.5565
Panel B. Investment focus									
Alternative fund (dummy, yes = 1)	0.03	0	0	0	0.01	0	0	0	0.0306
Bonds fund (dummy, yes = 1)	0.16	0	0	0	0.16	0	0	0	0.8997
Commodity fund (dummy, yes = 1)	0.02	0	0	0	0.03	0	0	0	0.4959
Equity fund (dummy, yes = 1)	0.41	0	0	1	0.39	0	0	1	0.6346
Balanced fund (dummy, yes = 1)	0.23	0	0	0	0.18	0	0	0	0.2321
Money market fund (dummy, yes = 1)	0.03	0	0	0	0.05	0	0	0	0.4567
Fund with other investment focus (dummy, yes = 1)	0.12	0	0	0	0.19	0	0	0	0.0601
Panel C. Total net assets									
1 month before closure (in mio euros)	60.70	1.90	7.90	29.30	38.70	1.41	4.54	15.90	0.2984
6 months before closure (in mio euros)	78.10	2.92	9.77	37.30	51.80	2.13	6.80	27.40	0.3006
12 months before closure (in mio euros)	89.30	4.00	12.10	46.60	54.00	3.95	11.00	33.50	0.1472
24 months before closure (in mio euros)	106.00	5.75	15.60	64.00	65.10	7.38	17.60	45.10	0.1477
48 months before closure (in mio euros)	108.00	7.27	21.50	71.50	62.90	7.73	19.30	61.30	0.0896
Panel D. Returns									
6 months before closure (in %)	-2.34%	-10.65%	0.28%	10.97%	-4.13%	-10.35%	0.67%	6.26%	0.5405
12 months before closure (in %)	-3.87%	-10.64%	0.04%	7.11%	0.04%	-4.27%	1.26%	6.99%	0.0313
24 months before closure (in %)	-2.77%	-9.68%	-0.01%	5.38%	-0.16%	-3.19%	1.05%	5.22%	0.0203

This table reports summary statistics for all funds liquidated between January 1999 and May 2016. Panel A contains fund characteristics, Panel B illustrates the investment focus of the closed fund, Panel C shows the size of the fund before closure, and Panel D summarizes the fund's past returns before closure.

3. Identification strategy

The data section has already indicated that the fund termination events, although announced publicly, hit private investors by surprise. Therefore, fund closures are plausibly exogenous events to clients. In addition, fund closures neither affect the wealth nor the gains and losses investors have. The money in the fund is transferred at the net asset value of the fund to the client's bank account at zero direct cost. Any endogeneity from liquidity needs, treatments, or windfalls that affect total wealth, e.g., lottery gains, does not exist. Yet, the refund is a salient event to clients and prompts a reinvestment decision. It is also important to note that the fund liquidations are so sizeable (about 10% of portfolio value) that investors cannot overlook them. Combining these plausibly exogenous fund closures with a measure of ambiguity that clients also do not influence is another randomization factor. Importantly, fund management companies, when deciding to close a fund, announce this decision from four weeks (funds domiciled in Luxemburg) to six months (funds domiciled in Germany) before the liquidation. Thus, the ambiguity at the fund closure cannot be managed or foreseen by the fund management companies. In Table 2, we provide descriptive statistics of funds closed on days with low ambiguity versus funds closed on days with high ambiguity. In line with the intuition that the ambiguity on the day of the closure is exogenous, the two groups of funds are highly similar.

All in all, our setting allows identifying the effects of ambiguity on investment decisions and risk-taking over time periods of 5 up to 180 days. The setting of actual investor transactions under ambiguity contributes to the literature as it contains real-world situations. However, we lack data on the investors' level of ambiguity aversion and, therefore, implicitly assume that most investors are ambiguity averse. Previous studies such as Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016) and Kostopoulos, Meyer, and Uhr (2022) show that most investors are ambiguity averse (50% to 60%). Still, a substantial fraction of investors can be ambiguity seeking (up to 40%) or ambiguity neutral (around 10%). According to theory, ambiguity-neutral investors are not affected by shocks in ambiguity, while ambiguity-seeking investors may even increase their risky exposure in response to ambiguity (e.g., Dow and Werlang, 1992; Illeditsch, 2011). In the results section (Fig. 4), we will show that about 20% of investors increase their investment in response to high ambiguity. It is reasonable to believe that most of them are ambiguity seeking. By looking at all investors without disentangling their ambiguity preferences, we likely underestimate the effect of ambiguity on ambiguity-averse investors.

We run three different regression specifications. First, we measure reinvestment as the net flow into the portfolio within 5 or 30 days after the fund closure, and, for the more long-term perspective, we use 90 and 180 days. Second, we investigate whether money not reinvested is kept in investors' cash accounts or taken out of the bank for, e.g., spending. Third, we test whether the level of ambiguity affects the risk-taking or propensity to invest in mutual funds when reinvesting. To make interpretation easier, we use dummy variables on high and not high ambiguity about volatility. We split the level of the daily time series of the VVIX at its 75^{th} percentile to classify each day in the sample as a day of high or low ambiguity. There is no guiding theory in selecting a threshold. We choose the 75^{th} percentile but show in the Internet Appendix that using the median as an alternative threshold does not qualitatively alter the results (Table A.2 in the Internet Appendix). The direction and significance levels of the main variables of interest remain qualitatively unchanged, but some coefficients are smaller in magnitude. We choose to use dichotomous variables for expositional purposes.

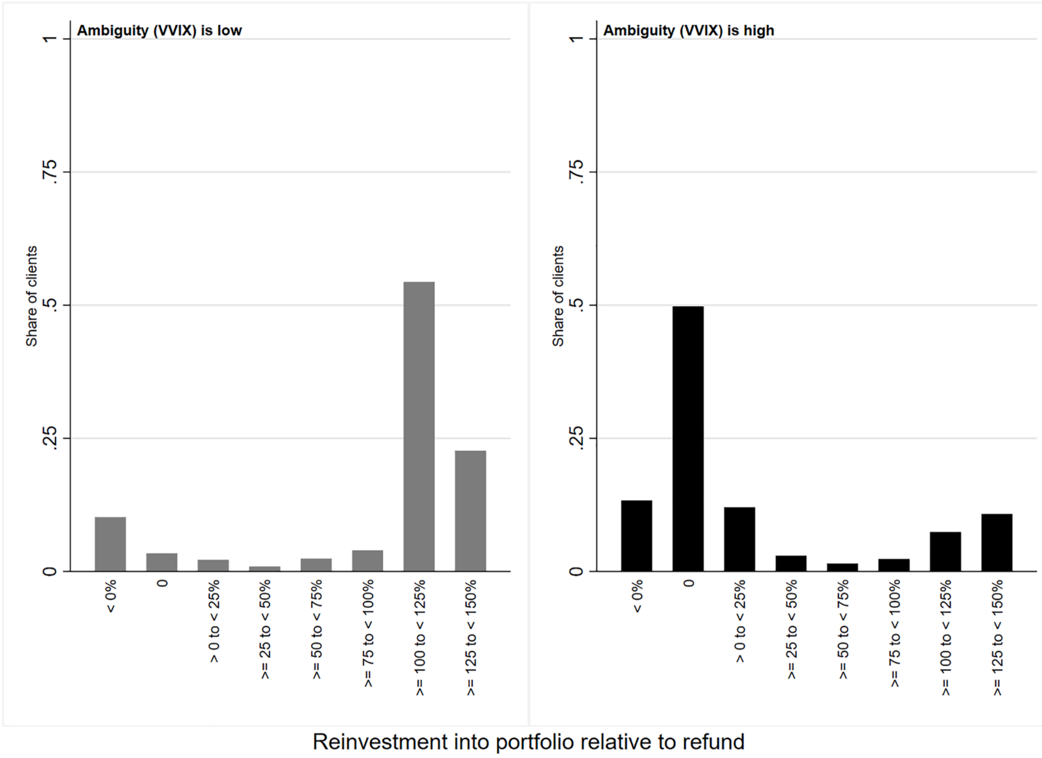

Fig. 4. Fraction of reinvestments into the portfolio relative to the refund
This figure illustrates the fraction of reinvestments into the portfolio relative to refunds from forced fund liquidation. The x-axis illustrates the share reinvested relative to the refund in percent in bins, and the y-axis illustrates the percentage of clients. The left graph contains investors closed out on days with low ambiguity, whereas the right graph contains investors closed out on days with high ambiguity. Ambiguity is high if the daily level of the VVIX on the day of the fund's closure is above the 75-percentile and low otherwise.

High ambiguity regimes do not persist. For the average fund closure on a day of high ambiguity, the level of ambiguity decreases to low levels within 8.6 days (median 3 days). Hence, all investors closed out on a day of high ambiguity experience low levels of ambiguity within the extended investigation period of 30 and up to 180 days. The extended investigation period, therefore, allows us to investigate if potential effects of high ambiguity persist or reverse once ambiguity is back to normal. The exact regression specifications we run are discussed in the relevant chapters.

We define the dummy variable utilizing the level of VVIX. This approach deviates from Kostopoulos, Meyer, and Uhr (2022), who are using daily changes in VVIX to investigate the effect of ambiguity on daily trading decisions of the average brokerage investor. When investigating daily trading decisions, incremental changes in ambiguity may be more important than the level of ambiguity as the changes reflect new information. In contrast, this study investigates the behavior after exogenously forced liquidations of mutual funds, which may be less affected by changes in ambiguity from the day before the liquidation to the day of the liquidation. The mean holding period of mutual funds is long (on average, 869 days), and the fund liquidations come as a surprise that the investor does not initiate or anticipate. Hence, when considering fund investments, we argue that investors are less likely to monitor ambiguity about volatility constantly before the fund closure. Therefore, we assume that it is more likely the level of VVIX than its change that plays the most important role. Nevertheless, in the Internet Appendix (Table A.3), we present our main analyses using changes as an alternative approach. The direction and significance levels of the main variables of interest remain qualitatively unchanged, but some coefficients are smaller in magnitude.

To disentangle the effect of risk and ambiguity and to rule out the possibility that our ambiguity measure captures similar effects as risk, we also include the level of expected volatility (VIX index) on the day of the closure in one of our specifications. Another concern in our identification strategy could be that investors may not reinvest because of rebalancing considerations or depending on past performance and market situations. In our main specification, we already include month-by-year fixed effects. Nevertheless, in a robustness test, we also control the portfolio performance 3 or 12 months before the closure to capture rebalancing needs. High past performance would lead to high rebalancing needs. Controlling for past performance does not change our results. Thus, rebalancing needs do not seem to drive our results. It might also be a concern that investors are not aware of the fund liquidation and did not realize the refund in their settlement account. In another robustness test, we show that our results replicate when restricting the sample to active investors, i.e., investors who conduct at least one trade within the days after the liquidation event.

4. Time-varying ambiguity, trading decisions, and risk-taking

4.1. Reinvestment decisions under ambiguity after fund closures

Our first analyses investigate the reinvestment decisions after a forced fund liquidation on a day with different levels of ambiguity. As discussed before, the refund of the fund's net asset value on the day of its termination is likely surprising to most investors. The investor did not decide to sell the fund; thus, we would expect that investors fully reinvest the refunded money in a similar fund. Meyer and Pagel (2022) have already shown that the reinvestment is below 100% and highly depends on whether the fund is closed at a gain or a loss.[15] In our investigation, we are interested in the effect of ambiguity on the day of the closure.

[15] Our results are independent of the gain or loss of a fund liquidation (see Table 4).

As a first step, we plot the fraction of money reinvested from the liquidation amount under high versus low ambiguity. Fig. 4 shows the results. The x-axis illustrates the fraction of money reinvested from the liquidation amount in bins within 30 days after the liquidation, and the y-axis displays the share of clients. A reinvestment of 0% means that investors do not reinvest the refund, whereas a reinvestment of 100% reflects a full reinvestment of the refund. Reinvestments above 100% occur when investors reinvest more than the refunded amount by increasing their portfolio value; reinvestments below 0% occur when investors do not reinvest and decrease their portfolio holdings by selling additional securities. The graph on the left contains all investors closed out on a day of low ambiguity, and the right diagram contains all investors closed out on a day of high ambiguity. Ambiguity is high if the level of the VVIX on the day of the fund's closure is above the 75-percentile and it is defined as low otherwise. Fig. 4 shows that approximately 65% of the investors reinvest 100% or more of the refund on days with low ambiguity. In contrast, on days with high ambiguity, 80% of investors reinvest less than 25% of the refund. Specifically, under high ambiguity, approximately 51% of the investors do not reinvest (reinvestment = 0%), while roughly 10% do not reinvest and even decrease their portfolio values further, and another 20% reinvest up to 25% of the refund. Approximately 20% of the investors reinvest 100% and even increase their portfolio values further. Investors who increase their risk exposure on days with high ambiguity act as if they were ambiguity-seekers.

To investigate these remarkable differences in reinvestment decisions under high and low ambiguity more formally, we run the following basic regression specification

$$\Delta Inv_{j,\ t,\ t+\tau}^{i,\ EUR} = \propto\ +\ \beta_1 Liq_{j,\ t}^{i,\ EUR} +\ \beta_2 MFE_t + \beta_3 ISIN_j +\ \varepsilon_{j,\ t}^{i}, \tag{1}$$

where $\Delta Inv_{j,\ t,\ t+\tau}^{i,\ EUR}$ is the net reinvestment in euros in the portfolio for investor i summed up between day t to $t+\tau$ after the forced liquidation of fund j. We define the bandwidth τ as 5 calendar days.[16] $Liq_{j,\ t}^{i,\ EUR}$ is the amount (in euros) of the forced sale of fund j for investor i at date t. MFE_t indicates month-by-year fixed effects[17], and $ISIN_j$ indicates ISIN (fund) fixed effects. We adjust standard errors for heteroskedasticity using the robust White (1980) method. Alternatively, we cluster standard errors at the month-by-year level.

Additionally, we extend specification (1) by splitting up $Liq_{j,\ t}^{i,\ EUR}$ into its effect under high and low ambiguity as follows[18]

Table 3
Net reinvestments under ambiguity 5 days after forced fund liquidations.

	Net reinvestment in portfolio 5 days after fund closure			
Panel A.	(1)	(2)	(3)	(4)
Liquidation	0.7220***	0.7425***	0.8088***	0.8088***
	(0.0665)	(0.0604)	(0.0202)	(0.1053)
Month-by-year fixed effects		YES	YES	YES
ISIN fixed effects			YES	YES
Month-by-year clustering				YES
Observations	2,222	2,222	2,222	2,137
R-squared	0.3298	0.4540	0.5446	0.5075
Panel B.	**(5)**	**(6)**	**(7)**	**(8)**
Liquidation	0.8283***	0.8316***	0.8656***	0.8656***
	(0.0542)	(0.0518)	(0.0203)	(0.0609)
Liquidation *High ambiguity	-0.8597***	-0.7845***	-0.8742***	-0.8742***
	(0.0622)	(0.0632)	(0.0797)	(0.0611)
Month-by-year fixed effects		YES	YES	YES
ISIN fixed effects			YES	YES
Month-by-year clustering				YES
Observations	2,222	2,222	2,222	2,137
R-squared	0.3966	0.4937	0.5700	0.5349

This table represents the coefficients of running the regressions as specified in Equations (1) and (2). The sample consists of all forced sales. The dependent variable *net reinvestment in the portfolio 5 days after fund closure* is an investor's net reinvestment in euros within 5 days after the fund closure. In Panel A, we regress this variable on *liquidation,* which is the amount of a forced liquidation in euros. In Panel B, we regress the net reinvestment on *liquidation* and an interaction term of high ambiguity and liquidation (*liquidation*high ambiguity*). *High ambiguity* is a dummy variable that takes the value of one if the daily level of the VVIX is above the 75-percentile on the day of the fund's closure. Columns (2) and (6) contain month-by-year fixed effects, and columns (3), (4), (7), and (8) have month-by-year and ISIN fixed effects. Standard errors are displayed in parentheses and are computed using the robust White (1980) method or, in columns (4) and (8), are clustered at the month-by-year level. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

$$\Delta Inv_{j,\ t,\ t+\tau}^{i,\ EUR} = \propto\ + \beta_1 Liq_{j,\ t}^{i,\ EUR} +\ \beta_2 Liq_{j,\ t}^{i,\ EUR} x Ambi\ high_{j,\ t} + \beta_3 MFE_t + \beta_4 ISIN_j +\ \varepsilon_{j,\ t}^{i}, \tag{2}$$

where the term x indicates an interaction with the indicator for high ambiguity and liquidation. $Ambi\ high_{j,\ t}$ is a dummy variable that takes the value of one if the daily level of the VVIX on the day of the fund's closure is above the 75-percentile and zero otherwise. Using the median as a threshold does not affect the results of this paper (Table A.2 in the Internet Appendix).

Table 3 shows the results for running these specifications for a τ of 5 days. Panel A corresponds to specification (1), and Panel B shows the results of running specification (2). Panel A shows that, in general, investors reinvest 81% within the 5 days after a forced fund closure in a specification containing month-by-year and ISIN fixed effects and heteroskedacity robust standard errors using the White (1980) method (column (3)) or a clustering on a month-by-year level (column (4)). This result is in line with what Meyer and Pagel (2022) find. Panel B shows that reinvestment decisions highly depend on the level of market-based ambiguity. Investors reinvest 87% of the refund when ambiguity is low (column (8)). If, in contrast, ambiguity is high on the day of the forced closure, investors reinvest 87% less (column (8)), i.e., they do not reinvest at all. This finding is in line with the theory of portfolio inertia in high ambiguity scenarios (e.g., Illeditsch, 2011). When thinking of participation as the change in stock market exposure of investors, where not reinvesting the refund corresponds to a reduction in stock market participation, our findings on inertia in response to high ambiguity can also be related to Dow and Werlang (1992), although we later show that

[16] Using a bandwidth of 30 days does not change the results qualitatively. For the sake of brevity, we report the analysis for a bandwidth of 5 days only.

[17] Additionally, including day-of-the-week fixed effects does not change our results qualitatively.

[18] Regressing the liquidation amount on the net reinvestment replicates a marginal propensity to consume and is a common approach in the empirical literature on consumption choices (e.g., Shapiro and Slemrod, 2003; Johnson, Parker, and Souleles, 2006; Shapiro and Slemrod, 2009; Sahm, Shapiro, and Slemrod, 2012; Parker, Souleles, Johnson, and McCelland, 2013; Sahm, Shapiro, and Slemrod, 2015; Parker and Souleles, 2019; Baker, Farrokhnia, Meyer, Pagel, and Yannelis, 2023). This approach is also used in Meyer and Pagel (2022). Based on insights from experimental literature, regressing the high ambiguity dummy on a net reinvestment proportion, $\frac{Inv_{j,\ t,\ t+\tau}^{i,\ EUR}}{Liq_{j,\ t}^{i,\ EUR}}$, could be an alternative approach to reduce the complexity of the specification. It is important to mention that such a net reinvestment proportion in our setting, in contrast to experiments or surveys, may produce outliers (e.g., because small refunds generate unbounded values). In Table A.7 in the Internet Appendix, we run the alternative specification with alternative approaches to mitigate the effect of outliers in the net reinvestment proportion. Our results are qualitatively unchanged when using this alternative approach. Investors reinvest approximately 70% to 80% less out of the refund within 5 days after the closure when being closed out at a day of high ambiguity.

Table 4
Net reinvestments under ambiguity 5 days after forced fund liquidations.

	Net reinvestment in portfolio 5 days after fund closure			
Panel A.	(1)	(2)	(3)	(4)
Liquidation	0.8795***	0.8606***	0.8971***	0.8971***
	(0.0534)	(0.0529)	(0.0213)	(0.0173)
Liquidation *High ambiguity	-0.9753***	-0.3966	-0.5311*	-0.5311***
	(0.2165)	(0.3310)	(0.2901)	(0.1162)
Liquidation *Loss	-0.3669**	-0.1966	-0.2435***	-0.2435
	(0.1459)	(0.1398)	(0.0527)	(0.2468)
Liquidation *High ambiguity *Loss	-0.9083***	-0.8338***	-0.9026***	-0.9026***
	(0.0620)	(0.0597)	(0.0796)	(0.0190)
Month-by-year fixed effects		YES	YES	YES
ISIN fixed effects			YES	YES
Month-by-year clustering				YES
Observations	2,222	2,222	2,222	2,137
R-squared	0.4117	0.4983	0.5748	0.5401
Panel B.	(5)	(6)	(7)	(8)
Liquidation	0.8324***	0.8360***	0.8649***	0.8649***
	(0.0532)	(0.0522)	(0.0205)	(0.0624)
Liquidation *High ambiguity	-0.8086***	-0.7445***	-0.8843***	-0.8843***
	(0.1018)	(0.0746)	(0.0892)	(0.0502)
Liquidation *High volatility (VIX)	-0.1842	-0.1341	0.0247	0.0247
	(0.2533)	(0.1150)	(0.0975)	(0.0552)
Month-by-year fixed effects		YES	YES	YES
ISIN fixed effects			YES	YES
Month-by-year clustering				YES
Observations	2,222	2,222	2,222	2,137
R-squared	0.3982	0.4943	0.5700	0.5349
Panel C.	(9)	(10)	(11)	(12)
Liquidation	0.8358***	0.8401***	0.8643***	0.8643***
	(0.0529)	(0.0527)	(0.0206)	(0.0636)
Liquidation *High ambiguity	-0.8634***	-0.7959***	-0.8667***	-0.8667***
	(0.0686)	(0.0571)	(0.1050)	(0.0636)
Liquidation *High volatility (VIX)	-0.3370	-0.2714	0.0497	0.0497
	(0.4629)	(0.2639)	(0.1252)	(0.0922)
Liquidation *High ambiguity *High volatility (VIX)	-0.8801***	-0.7934***	-0.8806***	-0.8806***
	(0.0773)	(0.0985)	(0.1181)	(0.0643)
Month-by-year fixed effects		YES	YES	YES
ISIN fixed effects			YES	YES
Month-by-year clustering				YES
Observations	2,222	2,222	2,222	2,137
R-squared	0.3993	0.4949	0.5700	0.5350

This table represents the coefficients of running the regressions as specified in Equations (3) to (5). The sample consists of all forced sales. The dependent variable *net reinvestment in the portfolio 5 days after fund closure* is an investor's net reinvestment in euros within 5 days after the fund closure. *Liquidation* is the amount of a forced liquidation in euros and *high ambiguity* is a dummy variable that takes the value of one if the daily level of the VVIX is above the 75-percentile on the day of the fund's closure. *Loss* is a dummy variable that takes the value of one if an investor in the fund is closed at a loss and zero if it is closed at a gain. *High volatility* is a dummy variable that takes the value of one if the daily level of the VIX is above the 75-percentile on the day of the fund's closure. The specifications contain month-by-year fixed effects and ISIN fixed effects as specified in the table. Standard errors are displayed in parentheses and are computed using the robust White (1980) method or, in columns (4), (8), and (12), are clustered at the month-by-year level. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

the effect reverses after approximately 180 days.

Meyer and Pagel (2022) find that investors are reinvesting a higher proportion of the reimbursed money if the fund closed at a gain than at a loss. To investigate whether the effect is robust to the inclusion of realized gains and losses and whether the effect of high ambiguity is exacerbated when being closed out at a loss rather than a gain, we directly follow Meyer and Pagel (2022) and additionally include an interaction term between high ambiguity, loss, and the liquidation. The specification is as follows.

$$\Delta Inv^{i,\ EUR}_{j,\ t,\ t+\tau} = \propto + \beta_1 Liq^{i,\ EUR}_{j,\ t} + \beta_2 Liq^{i,\ EUR}_{j,\ t} xAmbi\ high_{j,\ t} + \beta_3 Liq^{i,\ EUR}_{j,\ t} xLoss^{i}_{j,\ t} + \beta_4 Liq^{i,\ EUR}_{j,\ t} xAmbi\ high_{j,\ t} xLoss^{i}_{j,\ t} + \beta_5 MFE_t + \beta_6 ISIN_j + \varepsilon^{i}_{j,\ t}, \tag{3}$$

where $Loss^{i}_{j,\ t}$ is a dummy variable that takes the value of one if fund *j* is closed at a loss for investor *i*.

Panel A in Table 4 presents the results and shows that the effect of ambiguity on reinvestment occurs irrespective of whether the fund closes at a gain or a loss. In detail, if ambiguity on the day of the closure is low and the fund closes at a gain, investors reinvest about 90%, whereas investors reinvest less if the fund closes at a loss (column (4)). Thus, at low ambiguity, the findings mirror the results of Meyer and Pagel (2022). When we additionally distinguish between closures on days with high and low ambiguity, we find that there is reduced reinvestment on days with high ambiguity, irrespective of whether the investor is closed at a gain or loss. Moreover, there is some evidence that reinvestment on days with high ambiguity is negatively impacted if investors are also closed out at a loss. This finding suggests that the negative experience of being closed out at a loss adds to the reduced willingness to reinvest when ambiguity is high.

In Table 4, we additionally include specifications with interaction terms with expected volatility to disentangle the effect of risk and ambiguity. The expected volatility can be seen as expected risk and, as shown in previous literature, is distinct from ambiguity (e.g., Chen and Epstein, 2002). We include the expected volatility in our specification to rule out the possibility that our ambiguity measure captures similar effects as the expected volatility. As measure of expected volatility, we use the forward-looking volatility based on the implied volatility of options on the S&P 500 index, the VIX. In fact, the correlation between VVIX and VIX is positive at 0.36, so our results could be purely driven by risk if the VIX and VVIX are high on the same days. We extend specification (2) by including the VIX as a dummy variable interacted with *liquidation*.

$$\Delta Inv^{i,\ EUR}_{j,\ t,\ t+\tau} = \propto + \beta_1 Liq^{i,\ EUR}_{j,\ t} + \beta_2 Liq^{i,\ EUR}_{j,\ t} xAmbi\ high_{j,\ t} + \beta_3 Liq^{i,\ EUR}_{j,\ t} xVIX\ high_{j,\ t} + \beta_4 MFE_t + \beta_5 ISIN_j + \varepsilon^{i}_{j,\ t} \tag{4}$$

VIX is a dummy variable equaling one if the daily level of the VIX is above the 75-percentile on the day of the fund's closure.[19] Thus, the coefficient of this interaction term can be interpreted as the additional reinvestment in percent after a forced fund liquidation on a day of high volatility. We present the results of running Equation (4) in Panel B in Table 4 for a bandwidth of net-reinvestment of 5 days. Including the interaction term does not change the significance levels, direction, or magnitude of the findings. On days with low ambiguity, investors reinvest 87% of the refunds from fund liquidations, which is fully offset at days with high ambiguity (column (8)). The interaction between liquidation and VIX is not statistically significant and small in magnitude. Hence, when capturing ambiguity, high VIX does not affect investors' propensity to reinvest. This result alleviates the potential concern that our results could be driven by a latent relation between the estimates of volatility and ambiguity.

[19] Using the median of the VIX does not change the magnitude and significance of the results.

Table 5
Net reinvestments under ambiguity 30, 90, and 180 days after forced fund liquidations.

	Net reinvestment in portfolio 30 days after fund closure			
Panel A.	(1)	(2)	(3)	(4)
Liquidation	0.7969***	0.8182***	0.8624***	0.8624***
	(0.0601)	(0.0571)	(0.0310)	(0.0485)
Liquidation *High ambiguity	-0.7590***	-0.7693***	-0.8305***	-0.8305***
	(0.1356)	(0.1439)	(0.1216)	(0.2621)
Month-by-year fixed effects		YES	YES	YES
ISIN fixed effects			YES	YES
Month-by-year clustering				YES
Observations	2,222	2,222	2,222	2,137
R-squared	0.2155	0.3200	0.4079	0.3635

	Net reinvestment in portfolio 90 days after fund closure			
Panel B.	(5)	(6)	(7)	(8)
Liquidation	0.8839***	0.9080***	0.8945***	0.8945***
	(0.0883)	(0.0873)	(0.0390)	(0.0510)
Liquidation *High ambiguity	-0.6643**	-0.6903**	-0.3738**	-0.3738
	(0.2735)	(0.3061)	(0.1531)	(0.3225)
Month-by-year fixed effects		YES	YES	YES
ISIN fixed effects			YES	YES
Month-by-year clustering				YES
Observations	2,222	2,222	2,222	2,137
R-squared	0.1942	0.2385	0.3097	0.2792

	Net reinvestment in portfolio 180 days after fund closure			
Panel C.	(9)	(10)	(11)	(12)
Liquidation	0.9646***	1.0049***	0.9938***	0.9938***
	(0.1090)	(0.1064)	(0.0652)	(0.0770)
Liquidation *High ambiguity	-0.2917	-0.5042	0.1531	0.1531
	(0.4101)	(0.3732)	(0.2558)	(0.2495)
Month-by-year fixed effects		YES	YES	YES
ISIN fixed effects			YES	YES
Month-by-year clustering				YES
Observations	2,222	2,222	2,222	2,137
R-squared	0.1012	0.1472	0.1892	0.1671

This table represents the coefficients of running the regressions as specified in Equation (2). The sample consists of all forced sales. The dependent variable *net reinvestment in portfolio after fund closure* is an investor's net reinvestment in euros within 30 days (Panel A), 90 days (Panel B), or 180 days (Panel C) after the fund closure. We regress the net reinvestment on *liquidation*, which is the amount of a forced liquidation in euros, and an interaction term of high ambiguity and liquidation (*liquidation*high ambiguity*). *High ambiguity* is a dummy variable that takes the value of one if the daily level of the VVIX is above the 75-percentile on the day of the fund's closure. The specifications contain month-by-year and ISIN fixed effects as specified in the table. Standard errors are displayed in parentheses and are computed using the robust White (1980) method or, in columns (4), (8), and (12), are clustered at the month-by-year level. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

In Panel C in Table 4, we investigate whether investors are more/less likely to reinvest refunds on days with high ambiguity and low risk as opposed to refunds on days with high ambiguity and high risk. Therefore, we include a triple interaction term between liquidation, high VVIX, and high VIX as follows.

Table 6
Changes in account balances after forced fund liquidations under ambiguity.

	5 days		30 days	
	Cash account (1)	Total outflows out of the bank (2)	Cash account (3)	Total outflows out of the bank (4)
Liquidation	0.1304***	-0.0015	0.1429**	-0.0158
	(0.0498)	(0.0091)	(0.0586)	(0.0279)
Liquidation *High ambiguity	0.6981***	0.0790*	0.7790***	-0.0542
	(0.1107)	(0.0467)	(0.1981)	(0.1504)
Month-by-year fixed effects	YES	YES	YES	YES
ISIN fixed effects	YES	YES	YES	YES
Observations	2,222	2,222	2,222	2,222
R-squared	0.3226	0.5091	0.2751	0.3124

This table represents the coefficients of running the regressions as specified in Equation (6). The sample consists of all forced sales. The dependent variable *Cash account* is the sum of the changes in an investor's current account and savings account in euros within 5 days (column (1)) or 30 days (column (3)) after the fund closure. The dependent variable *Total outflows out of the bank* are the total flows leaving the bank in euros within 5 days (column (2)) or 30 days (column (4)) after the refund. We regress the net reinvestment on *liquidation*, which is the amount of a forced liquidation in euros, and an interaction term of high ambiguity and liquidation (*liquidation*high ambiguity*). *High ambiguity* is a dummy variable that takes the value of one if the daily level of the VVIX is above the 75-percentile on the day of the fund's closure. All columns contain month-by-year and ISIN fixed effects. Standard errors are displayed in parentheses and are computed using the robust White (1980) method. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

$$\Delta Inv^{i,\ EUR}_{j,\ t,\ t+\tau} = \propto + \beta_1 Liq^{i,\ EUR}_{j,\ t} + \beta_2 Liq^{i,\ EUR}_{j,\ t} x\ Ambi\ high_{j,\ t} + \beta_3 Liq^{i,\ EUR}_{j,\ t} x\ \ VIX\ high_{j,\ t} + \beta_4 Liq^{i,\ EUR}_{j,\ t} x\ Ambi\ high_{j,\ t}\ x\ VIX\ high_{j,\ t} + \beta_5 MFE_t + \beta_6 ISIN_j + \varepsilon^i_{j,\ t} \tag{5}$$

The coefficient of the triple interaction term can be interpreted as the additional reinvestment in percent after a forced fund liquidation on a day of high/low ambiguity with high/low risk (VIX). The results are robust to including triple interaction terms. The direction and significance levels remain unchanged, and the magnitude is in a similar ballpark. On days with low ambiguity, investors reinvest 86% out of forced fund liquidations (column (12)). If the ambiguity on the day of the closure is high (but VIX is low), investors reinvest 87% less. If the day of the closure is a day with high ambiguity and high VIX instead, investors reinvest 88% less.

Periods of high ambiguity do not last long and decrease to low levels within approximately 8 days for the average closure event (median 3 days). To investigate whether the effect is a short-term phenomenon that reverses within a few days (such as sentiment), we run Equation (2) for a τ of 30 days (Panel A), 90 days (Panel B), and 180 days (Panel C). The results are shown in Table 5. Allowing for an extended reinvestment period of 30 days does not change the direction, significance, or magnitude of the coefficients. If closed out on a day with low ambiguity, investors reinvest 86% of the refund (column (3)). If they are closed out on a day with high ambiguity, they reinvest 83% less. Thus, the reinvestment on a day with high ambiguity is approximately 3%.[20]

When investigating a period of three months after the liquidation,

[20] We also present the results of running Equations (3) to (5) for a τ of 30 days in the Internet Appendix (Table A.4). Also here, our results remain qualitatively unchanged.

the results replicate, and investors closed out on a day with high ambiguity still reinvest less. However, the magnitude of the effect decreases. When being closed out on a day with high ambiguity, investors reinvest 52% (column (7), 89% - 37%)). This result is statistically significant on the 5% level but loses its statistical significance when clustering standard errors by month-by-year (column (8)). Finally, when allowing for a reinvestment period of six months, investors reinvest 99% when being closed out on a day with low ambiguity, and the difference on days with high ambiguity is statistically not significant (columns (11) and (12)).

We interpret these findings as evidence that high ambiguity on the day of the closure negatively affects reinvestment decisions in the medium term but reverses over the long term of six months. Thus, the effect of ambiguity negatively affects average risky shares and also lasts significantly longer than the effect of sentiment, for example (around 5 days, see Tetlock, 2007; Da, Engelberg, and Gao, 2015; Kostopoulos, Meyer, and Uhr, 2020).

In the next step, we investigate what happens with the remaining proceeds that are not reinvested. After the forced fund liquidation, the refund appears in the investor's settlement account. If investors did not (fully) reinvest the refund, they could then keep the refund as cash holdings[21] or transfer the money out of the bank for, e.g., consumption. To follow the refund, we investigate the changes in investors' cash holdings and track flows that leave the bank after the forced liquidation. The results are shown in Table 6.

Specifically, we run specification (2) but change the dependent variable to two alternative measures of changes in investor i's accounts.

$$\Delta Flow^{i,\ EUR}_{j,\ t,\ t+\tau} = \propto + \beta_1 Liq^{i,\ EUR}_{j,\ t} + \beta_2 Liq^{i,\ EUR}_{j,\ t} x Ambi\ high_{j,\ t} + \beta_3 MFE_t + \beta_4 ISIN_j + \varepsilon^i_{j,\ t} \quad (6)$$

where $\Delta Flow^{i,\ EUR}_{j,\ t,\ t+\tau}$ is either the change in euros in the current account and savings account (columns (1) and (3)) or the total flow out of the bank (columns (2) and (4)) for investor i summed up between day t to $t+\tau$ after the forced liquidation of fund j. We define the bandwidth τ as 5 calendar days or 30 calendar days. $Liq^{i,\ EUR}_{j,\ t}$ is the amount (in euros) of the forced sale of fund j for investor i at date t. $Ambi\ high_{j,\ t}$ is a dummy variable that takes the value of one if the daily level of the VVIX on the day of the fund's closure is above the 75-percentile and zero otherwise. The term x indicates an interaction with the indicator for high ambiguity and liquidation. MFE_t indicates month-by-year fixed effects, and $ISIN_j$ indicates ISIN (fund) fixed effects. We adjust standard errors for heteroskedasticity using the robust White (1980) method.

Table 6 shows that most of the refund goes into cash accounts when ambiguity is high and is not taken out of the bank. When ambiguity on the day of the closure is low, investors keep approximately 13% of the refund in cash (column (1)). In contrast, if ambiguity is high on the day of the closure, investors keep approximately 83% of the refund in cash (13% + 70%, column (1)). These results replicate when investigating 30 days after the fund closure event (column (3)). In addition, column (2) shows some weak evidence that investors take a minor portion of the refund out of the bank when ambiguity on the day of the closure is high. However, over a period of 30 days, this effect becomes insignificant and marginally positive (column (4)).

4.2. Risk-taking and asset selection under ambiguity after fund closures

In our next set of analyses, we look at the risk-taking and security choices under ambiguity. Therefore, we consider two distinct variables as dependent variables. (1) The net reinvestments in euros to the portfolio times each risk class[22] of the reinvestment within 30 days after the fund closure and (2) a dummy variable indicating whether the investor reinvests into a mutual fund as opposed to any other security class within 30 days after the fund closure. Specifically, to investigate risk-taking, we run the following specification.

$$\Delta Inv\ risk\ class^{i,\ EUR}_{j,\ t,\ t+\tau} = \propto + \beta_1 Liq^{i,\ EUR}_{j,\ t} * risk\ class_j + \beta_2 \left(Liq^{i,\ EUR}_{j,\ t} * \ risk\ class_j\right) x\ Ambi\ high_{j,\ t} + \beta_3 MFE_t + \beta_4 ISIN_j + \varepsilon^i_{j,t}, \quad (7)$$

where $risk\ class_j$ is the risk class of the closed fund j and the dependent variable $Inv\ risk\ class^{i,\ EUR}_{j,\ t,\ t+\tau}$ is formally described as

$$\Delta Inv\ risk\ class^{\ i,EUR}_{j,t,\ t+\tau} = \sum_{s=1}^{n} \left(Inv^{i,s,EUR}_{j,\ t,\ t+\tau} * \ risk\ class^s\right) \quad (8)$$

where $Inv^{i,\ s,EUR}_{j,\ t,\ t+\tau}$ is the reinvestment in euros in security s for investor i between day t to $t+\tau$ after the forced liquidation of fund j and $risk\ class^s$ is the risk class of security s. Hence, the dependent variable is the sum of all reinvestments in euros times the risk class of the respective security for all purchased securities between day t to $t+\tau$ after the forced liquidation of fund j for investor i. If the investors reinvest 100% of the refund in funds of the same risk class, β_1 is equal to one. If the coefficient

Table 7
Risk-taking and fund investments under ambiguity after forced fund liquidations.

	Net reinvestment risk class (1)	Reinvestment into funds (2)
Liquidation multiplied by risk class	0.7413***	
	(0.0557)	
Liquidation multiplied by risk class *High ambiguity	-0.6679***	
	(0.1681)	
Liquidation		0.5582***
		(0.0237)
Liquidation *High ambiguity		0.5000
		(0.3690)
Month-by-year fixed effects	YES	YES
ISIN fixed effects	YES	YES
Observations	2,222	2,222
R-squared	0.3406	0.2011

This table represents the regression coefficients as specified in Equations (7) and (9). The sample consists of all forced sales. The dependent variable *net reinvestment risk class* in column (1) is the value-weighted risk class of the net reinvestment (in euros) within 30 days after the fund closure. The risk class is an officially established classification of each security going from 1 (lowest risk, e.g., savings accounts or German government bonds) to 5 (highest risk, e.g., options and futures). The dependent variable *reinvestment into funds* in column (2) is a dummy variable that takes the value of one if the investor reinvests into a fund within 30 days after the fund closure. We regress the net reinvestment on *liquidation*, which is the amount of a forced liquidation in euros, and an interaction term of high ambiguity and liquidation (*liquidation*high ambiguity*). In column (1), *liquidation* is multiplied by the risk class of the closed fund. *High ambiguity* is a dummy variable that takes the value of one if the daily level of the VVIX is above the 75-percentile on the day of the fund's closure. All specifications contain month-by-year and ISIN fixed effects. Standard errors are displayed in parentheses and are computed using the robust White (1980) method. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

[21] Cash holdings comprise all accounts that contain easily available liquidity, i.e., settlement accounts and savings accounts. Savings accounts are potentially bearing low-interest rates and are like moving money into a money market fund in the US.

[22] The risk class is an officially established classification of each security going from 1 (lowest risk, e.g., savings accounts or German government bonds) to 5 (highest risk, e.g., options and futures).

is above 1, the euro-weighted risk class increases. If it is below one, the euro-weighted risk class decreases. β_2 tests whether the euro-weighted risk class is smaller or larger on days of high ambiguity. To investigate whether investors are more or less likely to reinvest in mutual funds as opposed to any other security class after the fund closure, we run the following specification.

$$Fund^i_{j,\ t,\ t+\tau} = \propto + \beta_1 Liq^{i,\ EUR}_{j,\ t} + \beta_2 Liq^{i,\ EUR}_{j,\ t} x Ambi\ high_{j,\ t} + \beta_3 MFE_t + \beta_4 ISIN_j + \varepsilon^i_{j,\ t}, \tag{9}$$

where $Fund^i_{j,\ t,\ t+\tau}$ is a dummy variable that takes the value of one if investor i reinvests into a fund between day t to $t+\tau$ after the forced liquidation of fund j.

In both specifications, $Liq^{i,\ EUR}_{j,\ t}$ is the amount (in euros) of the forced sale of fund j for investor i at date t. $Ambi\ high_{j,\ t}$ is a dummy variable that takes the value of one if the daily level of the VVIX on the day of the fund's closure is above the 75-percentile and zero otherwise. The term x indicates an interaction with the indicator for high ambiguity and liquidation. MFE_t indicates month-by-year fixed effects, and $ISIN_j$ indicates ISIN (fund) fixed effects. We adjust standard errors for heteroskedasticity using the robust White (1980) method.

Table 7 presents the results of running Equations (7) and (9). The coefficient of 0.74 in column (1) shows that investors, after a fund closure, reinvest in a slightly lower euro-weighted risk class overall. The interaction term shows that they decrease the risk class significantly when ambiguity is high on the day of the closure. Hence, when closed out on a day with high ambiguity, investors who decide to reinvest choose a risk class that is lower than the risk class of the initial and liquidated fund. Measuring the security risk by beta instead of the risk class leads to qualitatively unaltered conclusions.[23] Both effects are statistically significant at the 1%-level. This finding shows that high ambiguity does not only affect the portion of reinvestment. Investors also tend to decrease the risk class of securities if they decide to reinvest when ambiguity is high, which speaks to the theoretical models on risk-taking under ambiguity (e.g., Garlappi, Uppal, and Wang, 2007; Peijnenburg, 2018). Given a low ambiguity on the day of the forced liquidation, the probability of an investor reinvesting into a mutual fund is 56% (column (2)). However, high ambiguity on the day of the closure does not exacerbate the propensity to reinvest into funds. This result is not surprising because the level of ambiguity on the day of the closure is unrelated to the fund investment itself and does not bear a negative experience with fund investments such as, e.g., a loss experience would represent.

5. Further analyses and robustness tests

This chapter discusses if potentially unaccounted factors can explain our results. We show the robustness of our results to the exclusion of potential outliers and consider the effect of rebalancing needs, attention, and investor characteristics. We also rerun our analyses using alternative measures of ambiguity.

5.1. Treatment of outliers

The main analysis, Equation (2), may be affected by extreme values in the variables net reinvestment in portfolio after fund closure, $Inv^{i,\ EUR}_{j,\ t,\ t+\tau}$, and liquidation, $Liq^{i,\ EUR}_{j,\ t}$. The extended descriptive statistics for those variables in Table A.5 in the Internet Appendix show that there are indeed a few extreme values in both tails of the distributions, documented by kurtosis statistics above the value of 20. To address potential outlier issues related to those kurtosis values, we re-run Equation (2) for 5 and 30 days using two alternative approaches: (1) We drop the largest (smallest) one percent of the values and (2) we winsorize the largest (smallest) one percent of the values. The kurtosis of the trimmed or winsorized variables is more than halved as shown in Table A.5.

In Table A.6, we present the results of running Equation (2) for 5 and 30 days using the trimmed variables (Panel A) and winsorized variables (Panel B). Our results remain qualitatively unaltered. On days with high ambiguity, people reinvest significantly less. When dropping or winsorizing the largest (smallest) one percent of values, the absolute reinvestment on low ambiguity days is smaller than before. It drops from a reinvestment of over 80 cents on the Euro refunded to around 75 cents on the Euro refunded. Yet, the effect of high ambiguity on the reinvestment is still sizeable, and for the winsorizing approach, the relative magnitudes are almost unchanged.[24]

5.2. Endogenous closures under ambiguity

To provide a complete picture of trading choices under ambiguity, we also include self-directed sales of fund positions. Self-directed fund sales may often be driven by liquidity needs or other trading motives of private investors. Hence, the effects should differ from those of forced fund liquidations. Using different dependent variables as specified before, we run the following regressions

$$\begin{aligned}\Delta Inv^{i,\ EUR}_{j,\ t,\ t+\tau} = \ & \propto + \beta_1 Liq^{i,\ EUR}_{j,\ t} x\ Forc^i_{j,\ t} + \beta_2 Liq^{i,\ EUR}_{j,\ t} x\ Reg^i_{j,\ t} \\ & + \beta_3 Liq^{i,\ EUR}_{j,\ t} x\ Forc^i_{j,\ t} x\ Ambi\ high_{j,\ t} \\ & + \beta_4 Liq^{i,\ EUR}_{j,\ t} x\ Reg^i_{j,\ t} x\ Ambi\ high_{j,\ t} + \beta_5 MFE_t + \beta_6 ISIN_j \\ & + \varepsilon^i_{j,\ t}\end{aligned} \tag{10}$$

$$\begin{aligned}\Delta Inv\ risk\ class^{i,\ EUR}_{j,\ t,\ t+\tau} = \ & \propto + \beta_1 \left(Liq^{i,\ EUR}_{j,\ t} * risk\ class_j\right) x\ Forc^i_{j,\ t} \\ & + \beta_2 \left(Liq^{i,\ EUR}_{j,\ t} * risk\ class_j\right) x\ Reg^i_{j,\ t} \\ & + \beta_3 \left(Liq^{i,\ EUR}_{j,\ t} * risk\ class_j\right) x\ Forc^i_{j,\ t} x\ Ambi\ high_{j,\ t} \\ & + \beta_4 \left(Liq^{i,\ EUR}_{j,\ t} * risk\ class_j\right) x\ Reg^i_{j,\ t} x\ Ambi\ high_{j,\ t} \\ & + \beta_5 MFE_t + \beta_6 ISIN_j + \varepsilon^i_{j,\ t}\end{aligned} \tag{11}$$

$$\begin{aligned}Fund^i_{j,\ t,\ t+\tau} = \ & \propto + \beta_1 Liq^{i,\ EUR}_{j,\ t} x\ Forc^i_{j,\ t} + \beta_2 Liq^{i,\ EUR}_{j,\ t} x\ Reg^i_{j,\ t} \\ & + \beta_3 Liq^{i,\ EUR}_{j,\ t} x\ Forc^i_{j,\ t} x\ Ambi\ high_{j,\ t} \\ & + \beta_4 Liq^{i,\ EUR}_{j,\ t} x\ Reg^i_{j,\ t} x\ Ambi\ high_{j,\ t} + \beta_5 MFE_t + \beta_6 ISIN_j \\ & + \varepsilon^i_{j,\ t}\end{aligned} \tag{12}$$

where $Liq^{i,\ EUR}_{j,\ t}$ is the amount (in euros) of any sale of a fund j by investor i at time t. $Ambi\ high_{j,\ t}$ is a dummy variable that takes the value of one if the daily level of the VVIX on the day of the fund's closure is above the 75-percentile and zero otherwise. $Forc^i_{j,\ t}$ is a dummy variable equaling one if the sale was a forced liquidation, whereas $Reg^i_{j,\ t}$ is a dummy variable equaling one if the sale was a deliberate sale initiated by the client. Note that the observations for these specifications increase by also including all self-directed mutual fund sales by investors subject to a fund liquidation restricting to 200 days before the liquidation event. The term x indicates an interaction with the indicators for liquidation, high ambiguity, and type of sale. MFE_t indicates month-by-year fixed effects,

[23] For the sake of brevity, we do not include these analyses in the paper.

[24] In unreported analyses, we also re-run the regression on net reinvestment within 90 or 180 days after the fund closure. The results remain qualitatively unchanged, still suggesting that the effect of high ambiguity is offset in the long run. Moreover, to allow for comparison with Meyer and Pagel (2022), we also test the winsorizing and trimming approach for running Equation (3). The results are also qualitatively unchanged.

Table 8
Net-reinvestment, risk-taking, and fund investments under ambiguity after forced fund liquidations.

	Net reinvestment (5 days) (1)	Net reinvestment (30 days) (2)	Net reinvestment risk class (5 days) (3)	Net reinvestment risk class (30 days) (4)	Reinvestment into fund (5 days) (5)	Reinvestment into fund (30 days) (6)
Forced liquidation	0.8463***	0.8519***	0.4489***	0.7979***	0.3115***	0.6926***
	(0.0576)	(0.0631)	(0.0448)	(0.0599)	(0.0320)	(0.0306)
Self-directed liquidation	-1.0634***	-0.8896***	-0.0023	-0.1393	0.1842***	0.0580***
	(0.1682)	(0.1738)	(0.0694)	(0.0925)	(0.0196)	(0.0199)
Forced liquidation at high ambiguity	-0.9655***	-1.3025***	-0.8919***	-1.3769***	-0.0080	-0.1669**
	(0.0875)	(0.3079)	(0.2499)	(0.3250)	(0.0617)	(0.0709)
Self-directed liquidation at high ambiguity	0.0978	0.3199*	-0.0023	-0.1393	0.0277**	0.0101
	(0.1606)	(0.1871)	(0.0694)	(0.0925)	(0.0117)	(0.0105)
Month-by-year fixed effects	YES	YES	YES	YES	YES	YES
ISIN fixed effects	YES	YES	YES	YES	YES	YES
Observations	25,982	25,982	25,980	25,980	25,982	25,982
R-squared	0.0395	0.0671	0.1643	0.2401	0.2034	0.1411

This table represents the regression coefficients as specified in Equations (10) to (12). The sample consists of all forced and self-directed sales in affected funds, i.e., liquidated funds, held by an investor at some point within the sample period. The dependent variable *net reinvestment* is an investor's net reinvestment in euros within 5 days (column (1)) or 30 days (column (2)) after the fund closure. The dependent variable *net reinvestment risk class* is the value-weighted risk class of the net reinvestment (in euros) within 5 days (column (3)) or 30 days (column (4)) after the fund closure. The risk class is an officially established classification of each security going from 1 (lowest risk, e.g., savings accounts or German government bonds) to 5 (highest risk, e.g., options and futures). The dependent variable *reinvestment into funds* is a dummy variable that takes the value of one if the investor reinvests into a fund within 5 days (column (5)) or 30 days (column (6)) after the fund closure. We regress these variables on forced or self-directed liquidations at high or low ambiguity. *Forced liquidation* is the amount of liquidation due to a forced fund closure in euros, whereas *Self-directed liquidation* is the amount of deliberate liquidations in euros. *High ambiguity* is a dummy variable that takes the value of one if the daily level of the VVIX is above the 75-percentile on the day of the fund's closure. All specifications contain month-by-year and ISIN fixed effects. Standard errors are displayed in parentheses and are computed using the robust White (1980) method. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Table 9
Net reinvestments under ambiguity after forced fund liquidations including previous portfolio performance controls.

	Net reinvestment after fund closure			
	5 days		30 days	
	(1)	(2)	(3)	(4)
Liquidation	0.8662***	0.8662***	0.8628***	0.8630***
	(0.0506)	(0.0506)	(0.0572)	(0.0572)
Liquidation *High ambiguity	-0.8731***	-0.8749***	-0.8321***	-0.8313***
	(0.0585)	(0.0582)	(0.2232)	(0.2225)
Portfolio Performance (last 3 months)	-21,731.0308		15,629.8889	
	(24,802.0563)		(31,312.4456)	
Portfolio Performance (last 12 months)		2,742.7561		7,221.4485
		(2,499.7016)		(6,844.5835)
Month-by-year fixed effects	YES	YES	YES	YES
ISIN fixed effects	YES	YES	YES	YES
Observations	2,220	2,220	2,220	2,220
R-squared	0.5703	0.5703	0.4080	0.4081

This table presents the regression coefficients specified in Equation (2) and includes two additional control variables. The sample consists of all forced sales. The dependent variable is *net reinvestment in the portfolio after fund closure* in euros within 5 days (columns (1) and (2)) or 30 days (columns (3) and (4)). We regress the net reinvestment on *liquidation*, which is the amount of a forced liquidation in euros, and an interaction term of high ambiguity and liquidation (*liquidation*high ambiguity*). *High ambiguity* is a dummy variable that takes the value of one if the daily level of the VVIX is above the 75-percentile on the day of the fund's closure. The variable *Portfolio Performance (last three months) (Portfolio Performance (last 12 months))* is the total portfolio performance of a client 3 months (12 months) before the forced fund closure. All columns contain month-by-year and ISIN fixed effects. Standard errors are displayed in parentheses and are computed using the robust White (1980) method. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

and $ISIN_j$ indicates ISIN (fund) fixed effects. We adjust standard errors for heteroskedasticity using the robust White (1980) method.

Table 8 shows the results of running Equations (10) to (12). Column (1) contains the same left-hand side variable *net reinvestment* as Tables 3 and 4 but also includes interactions on self-directed liquidations under high or low ambiguity. This alternative specification provides qualitatively the same results as before. Still, coefficients change as the sample also changes. If investors are subject to a forced fund liquidation at high ambiguity, they reinvest significantly less than if they were closed out under low ambiguity. The reinvestment with self-directed liquidations is substantially lower and even negative. That means when investors liquidate a fund, they additionally liquidate additional securities in the following days. However, this effect is not mediated by ambiguity. It is likely driven by endogenous trading motives, like liquidity needs or consumption plans. Including self-directed security trading decisions underscores the importance of the exogenous nature of fund closure to assess the impact of ambiguity.

In columns (3) and (4), we again find a reduction in risk-taking when investors are forced out of a fund and decide to reinvest on days of high ambiguity. For self-directed liquidations, we do not find any effects in risk-taking.

Table 10
Net reinvestments under ambiguity after forced fund liquidations conditional on trading or controlling for socio-demographic variables.

	Net reinvestment in portfolio after fund closure			
	5 days		30 days	
	(1)	(2)	(3)	(4)
Liquidation	0.8925***	0.8909***	0.8869***	0.8689***
	(0.0206)	(0.0477)	(0.0311)	(0.0584)
Liquidation *High ambiguity	-0.9302***	-0.7865***	-0.7181***	-0.8569***
	(0.1223)	(0.0923)	(0.1844)	(0.2583)
Month-by-year fixed effects	YES	YES	YES	YES
ISIN fixed effects	YES	YES	YES	YES
Socio-demographics	NO	YES	NO	YES
Observations	1,927	2,222	1,927	2,222
R-squared	0.6141	0.5783	0.4871	0.4128

This table represents the coefficients of running the regressions as specified in Equation (2) including additional socio-demographic control variables of investors in columns (2) and (4). The sample consists of all forced sales in columns (2) and (4) but excludes all refunds after which an investor does not trade within 30 days in columns (1) and (3). The dependent variable is *net reinvestment in the portfolio after fund closure* in euros within 5 days (columns (1) and (2)) or 30 days (columns (3) and (4)). We regress the net reinvestment on *liquidation*, which is the amount of a forced liquidation in euros, and an interaction term of high ambiguity and liquidation (*liquidation*high ambiguity*). *High ambiguity* is a dummy variable that takes the value of one if the daily level of the VVIX is above the 75-percentile on the day of the fund's closure. The specifications contain month-by-year and ISIN fixed effects. As control variables, we include the age of the investor in years, a dummy variable for gender, a dummy variable for whether the investor holds an academic title (Ph.D., Dr., Prof.), the length of the relationship with the bank in years, the average portfolio value of the investor over the full time-span of the sample, the number of trades, the average portfolio diversification measured by the Herfindahl-Hirschman index (HHI), and the average risk class traded measured on a scale from 1 (lowest risk) to 5 (highest risk). Standard errors are displayed in parentheses and are computed using the robust White (1980) method. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

5.3. Rebalancing needs as an alternative explanation

It might be a concern that investors perceive the forced fund liquidation as a costless opportunity to rebalance their portfolio. Investors with positive portfolio returns may have already sensed the need for rebalancing. Knowing that a fund would be terminated, they wait for this to happen. By not reinvesting, they use the opportunity to rebalance their portfolios. If this conjecture was true, we should only observe effects for investors with positive previous portfolio returns. To check whether this conjecture is true, we run a robustness test for Equation (2) for a τ of 5 and 30 days, including the portfolios 3 or 12 months return before the fund closure.

Table 9 shows that including the portfolio performance does not change the significance or direction of the results. Thus, the effects are unlikely to be driven by rebalancing considerations or market movements affecting the portfolio of a sub-group of investors.

5.4. Reinvestment decisions conditional on trading or with socio-demographic control variables

It might be a concern that the results are driven by investors not being aware of the liquidation event and refund in their settlement account. To mitigate this concern, we rerun Equation (2) but restrict the sample to investors with at least one trade within 30 days after the liquidation event. If investors trade within 30 days after the liquidation event, they will likely realize that the balance of their settlement account increased, and a fund position got liquidated. Running Equation (2) conditional on investors trading within the 30 days after the liquidation does not change our results qualitatively. The results are shown in columns (1) and (3) in Table 10.

Moreover, although the level of ambiguity on the day of closure is exogenous and people have not selected themselves to hold a closing fund,[25] it might still be possible and interesting to see if a particular group of investors drives the effects we document. Therefore, in columns (2) and (4) of Table 10, we include socio-demographic characteristics of the investors as additional control variables. We include the age of the investor in years, a dummy variable for gender, a dummy variable for whether the investor holds an academic title (Ph.D., Dr., Prof.), the length of the relationship with the bank in years, the average portfolio value of the investor over the whole period of the sample, the number of trades, the average portfolio diversification measured by the Herfindahl-Hirschman index (HHI), and the average risk class traded measured on a scale from 1 (lowest risk) to 5 (highest risk). Including these control variables also does not change the direction, significance levels, or magnitude of our findings.

5.5. Alternative measures of ambiguity

The literature has not yet agreed on the empirical measure to choose when investigating ambiguity about volatility. In our study, we use the VVIX because it is a market-based measure available daily and it spans the entire sample period. However, we are aware of and acknowledge different literature streams and approaches to measure ambiguity empirically. In this robustness chapter, we will replace our ambiguity measure with three alternative measures of ambiguity. (1) For an alternative market-based measure, we calculate the omega measure proposed by Brenner and Izhakian (2018). This ambiguity measure addresses the criticism that the volatility of volatility might be stake-dependent. We take intraday data of the EuroStoxx index in five-minute intervals during the trading hours at the Euronext stock exchange. Strictly following their methodology, we divide the daily returns range into 60 bins. (2) For a survey-based measure, we download the Survey of Professional Forecasters (SPF) the European Central Bank provides. The survey is conducted quarterly and asks forecasters to provide forecasts of different variables as a point estimate and a probability distribution. The ambiguity measure is based on forecasts of real gross domestic product growth for the next calendar years. We calculate the standard deviation using the probability distribution for each forecaster and each quarter separately. We then derive the ambiguity measure using the interquartile range of the standard deviations of each forecaster in each quarter.[26] (3) Finally, we replace the VVIX with the V-VSTOXX. We do so because the V-VSTOXX might be closer to German investors than the VVIX. We need to drastically shrink the sample for this analysis because the V-VSTOXX is only available from March 2010 onward.

We rerun Equation (2) with month-by-year fixed effects, ISIN fixed effects, and robust standard errors for 5 and 30 days after fund closure and replace our measure of ambiguity (VVIX) with one of the three alternatives.

The results are shown in Table 11. For all alternative ambiguity

[25] Note that more than 75% of investors that are closed out of their funds have bought the funds more than a year before closure. The median investor bought the fund 687 days before closure.

[26] As such, this construction uses the interval forecasts of each forecaster to elicit the standard deviation embedded in each forecast directly following the suggestion by Engelberg, Manski, and Williams (2009). They state that it remains unclear whether forecasters report means, medians, modes, or anything else when reporting point forecasts. They also state that even if forecasters report point predictions in the same way, the point predictions still do not provide information about the uncertainty that forecasters might feel. In their study, they recommend using interval forecasts to derive a consistent measure of ambiguity.

Table 11
Net reinvestments under ambiguity after forced fund liquidations (alternative measures of ambiguity).

	Net reinvestment in portfolio after fund closure					
	Omega		Forecasters		V-VSTOXX	
	5 days (1)	30 days (2)	5 days (3)	30 days (4)	5 days (5)	30 days (6)
Liquidation	0.8532*** (0.0541)	0.8488*** (0.0644)	0.9180*** (0.0493)	0.9076*** (0.0572)	0.2229 (0.1894)	0.3791 (0.2378)
Liquidation *High ambiguity	-0.6585** (0.2658)	-0.5987** (0.2923)	-0.7400*** (0.1448)	-0.6722*** (0.1968)	-0.2330 (0.1894)	-0.7467*** (0.2490)
Month-by-year fixed effects	YES	YES	YES	YES	YES	YES
ISIN fixed effects	YES	YES	YES	YES	YES	YES
Observations	2,222	2,222	2,222	2,222	543	543
R-squared	0.5595	0.4016	0.5822	0.4127	0.3588	0.4378

This table presents the coefficients of running the regressions as specified in Equation (2). The sample consists of all forced sales. The dependent variable is *net reinvestment in the portfolio after fund closure* in euros within 5 days (uneven columns) or 30 days (even columns). We regress the net reinvestment on *liquidation*, which is the amount of a forced liquidation in euros, and an interaction term of high ambiguity and liquidation (*liquidation*high ambiguity*). High ambiguity and low ambiguity are calculated based on the daily level of three different ambiguity measures. For columns (1) and (2), the ambiguity measure is based on Omega; for columns (3) and (4), the ambiguity measure is based on professional forecasters; and for columns (5) and (6), the ambiguity measure is based on the V-VSTOXX. *High ambiguity* is a dummy variable that takes the value of one if the level of the respective ambiguity measure is above the 75-percentile on the day of the fund's closure. All columns contain month-by-year fixed effects and ISIN fixed effects. Standard errors are displayed in parentheses and are computed using the robust White (1980) method. ***, **, and * indicate that the coefficient estimates are significantly different from zero at the 1%, 5%, and 10% levels, respectively.

measures, the results are going in the same direction, i.e., if ambiguity is high at the closure, investors reinvest less. Note that all alternative measures are positively correlated with the VVIX except for Omega. Using Omega, the coefficients are almost in the same ballpark as for using the VVIX (columns (1) and (2)). All coefficients are statistically significant at the 1%-level or 5%-level. Thus, using an alternative market-based measure leads to qualitatively unaltered results. Using a survey-based measure of ambiguity also leads to qualitatively similar results that are statistically significant at the 1%-level (columns (3) and (4)). In columns (5) and (6), we replace the VVIX with the V-VSTOXX. Unfortunately, the V-VSTOXX is not available for the entire observation period; thus, the number of observations is drastically reduced. But still, using the V-VSTOXX yields comparable results.

6. Conclusion

This paper relates time-varying ambiguity about volatility to investment and risk-taking decisions. We use a unique combination of data consisting of trading records of investors from a large German online brokerage, a comprehensive list of fund closures in Germany, and different empirical measures of ambiguity derived from previous literature. Investigating reinvestment decisions after forced fund liquidations under high or low ambiguity allows for a plausibly exogenous setting of investment and risk-taking decisions under ambiguity.

Theoretical models on ambiguity suggest that high ambiguity causes portfolio inertia and decreases individuals' risk-taking. Our findings provide supporting evidence for these models. We show that investors reinvest significantly less if forced out of a fund on a day of high ambiguity, i.e., investors are inert in high ambiguity scenarios. This finding occurs not only for the 5 days after the fund's liquidation but also when investigating 30 days after the fund's liquidation, even though the level of ambiguity reaches conventional levels within 8.6 days on average. In line with the idea of portfolio inertia, investors do not withdraw the proceeds and keep them in their cash accounts instead. Even after 90 days, the reinvestment of investors closed out on days with high ambiguity is significantly lower. The negative effect of high ambiguity on investors reverses and is almost offset after 6 months. Hence, our results suggest a negative effect of ambiguity on investors' reinvestment decisions that persists in the short- to medium-term but reverses in the long-run. In line with theoretical models, if investors reinvest after a forced liquidation at high ambiguity, they tend to choose less risky securities.

CRediT authorship contribution statement

Steffen Meyer: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Charline Uhr:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Pseudo data for Meyer/Uhr (Original data) (Mendeley Data)

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Supplementary materials

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