Memories and Tail Beliefs *

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Abstract

We show that selective recall of events spanning six decades shapes beliefs about rare downside outcomes today. Recalled memories in a representative survey exhibit both recency *and* primacy: events close to the time of recall and early-life experiences are disproportionately likely to come to mind. The impact of memories on tail beliefs is governed by similarity and interference: memory negativity is strongly associated with perceived stock market crash risk, even controlling for objective lifetime experiences. Rather than simply shifting subjective return distributions, selective recall of influential events changes their perceived shape by disproportionately affecting downside risk. Belief updating is consistent with a memory-based model in which similarity, interference, and representativeness determine how new information is interpreted. Households adjust their portfolio allocations only in response to higher perceived tail risk, and perceived safe-haven assets depend on the type of tail event.

Keywords: memories, experiences, belief formation, household finance.

JEL classification: G11, G12, G41, G51, G53, D84, E44

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1 Introduction

Tail risk neglect can contribute to the build-up of risk such as during the U.S. housing boom prior to the financial crisis of 2008, or to insufficient crisis preparedness regarding pandemics, wars, or other tail events. Conversely, overstating risks could lead to under-investment, over-saving, or panics upon bad news. Understanding how tail beliefs are formed is therefore crucial, but empirical evidence is scarce. In particular, understanding when people over-estimate or under-estimate tail risks remains a major open puzzle. Kahnemann and Tversky's work on the availability and representativeness heuristics suggests selective recall from memory could play an important role in making belief formation context-dependent (Kahneman and Tversky 1972; Tversky and Kahneman 1973). During booms, individuals may recall more positive events and neglect risks, whereas during crashes they may suddenly recall past negative events and over-react.

We design a customized survey to test the predictions of a memory-based model of belief formation and we document new facts on the link between memories and tail beliefs. Our conceptual framework builds on Bordalo et al. (2025), in which the belief formation process can be broken down into two steps: recall and simulation. In the recall step, a decision maker retrieves past experiences according to similarity. Events that are more similar to the cue are more likely to come to mind. The cue includes not only the event being forecast, but also the current context. For example, assessing the probability of a stock market crash after a string of bad news may evoke recalling a larger share of negative past events than after a string of good news. In the simulation step, the decision maker uses repeated draws from her memory database to simulate the outcome. Recalling more negative past events therefore raises the perceived probability of similar adverse events in the future.

We use open-ended, category-cued free-recall questions to measure memories. Respondents receive broad thematic retrieval cues but no event-specific cues or response options and freely generate up to ten events from memory. Specifically, in a representative survey of German households, we ask a subset of respondents to write down up to ten "important events in the economy and financial markets over approximately the past 60 years". Another subset of respondents is asked to recall "important events in society, culture and sport over approximately the past 60 years". Respondents enter each event in an open text field and report the year they associate with it. We then ask them to report the stock market impact they remember for each event. In addition, we elicit beliefs about the likelihood and perceived impact of future tail events.

Our first main result provides evidence on the temporal similarity function governing individuals' recall of economic events. Memory research has documented two central regularities of temporal similarity. The *recency* effect predicts that distant experiences are harder to recall than recent experiences. *Primacy* is present when experiences early in life are recalled more easily than experiences at intermediate ages. Both effects are well established in the memory literature (see, e.g., Kahana, Diamond, and Aka, 2024), but only recency has played a prominent role in economics: Malmendier and Nagel (2011, 2016) document recency effects in the impact of objective lifetime experiences on beliefs and decisions, and recency is implicit in constant-gain learning models (see, e.g., Orphanides and Williams, 2005; Barberis et al., 2015; Adam et al., 2017). By contrast, the primacy effect, first documented by the 19th century experimental psychologist Hermann Ebbing-

haus (Ebbinghaus, 1885), has thus far received little attention in economics.[1] To the best of our knowledge, we are the first to use survey data that directly measure individuals' recall of economic events to test for both recency and primacy.

Following Gennaioli et al. (2024), we model temporal similarity as a linear-quadratic function of the normalized distance between an event and the time of recall. We estimate this temporal similarity function and find a pronounced U-shape. Close to the survey date, recall probabilities decline with temporal distance, consistent with recency. After bottoming out for events experienced around the middle of an individual's life, recall probabilities rise again for events experienced early in life, consistent with primacy. This finding has direct implications for economic modeling. Early-life experiences can matter for beliefs and choices today not *despite* being distant in time, but precisely *because* first experiences have unusually persistent effects on memory. Primacy can therefore generate cohort patterns in beliefs that differ from those implied by recency alone; for example, it may help explain cohort heterogeneity during episodes of high inflation expectations after long periods of stable inflation.

Our second main result concerns the *link* between memories and tail beliefs. Specifically, we test the predictions of a memory-based model of belief formation, under the assumption that, when simulating the probability of a stock market crash in the near future, past events with a *negative* stock market impact are considered more similar than past events with a *positive* recalled impact. In the model, an individual with a higher frequency of negative events in her memory database is more likely to recall a larger share of negative events in a category-cued free-recall question. Due to the higher frequency of negative events in her memory database, she will also recall a larger share of negative events when asked to assess the likelihood of a stock market crash, for which she therefore simulates a higher probability. We test this prediction by regressing respondents' perceived probability of a stock market crash on a measure of the negativity of their recalled memories, controlling for socio-demographic characteristics and objective lifetime stock market experiences.

Memory negativity is positively and significantly associated with perceived tail risk across specifications, consistent with the predictions of the memory-based model. Subjectively recalled events and their remembered stock market impact need not coincide with objective lifetime experiences, and we find the subjective memories are more strongly related to beliefs than objective experiences. Indeed, once we control for individuals' recalled economic memories, the association between objective lifetime experiences and perceived tail risk is no longer significantly different from zero. The relationship between memory negativity and perceived tail risk holds both when memories are elicited before beliefs and when memories are elicited only afterward. It is also robust across economic and cultural memory elicitation frames. Moreover, the relationship is not confined to narrowly domain-specific recall. When we split recalled events into domain-specific and non-domain-specific memories, negativity in both groups is associated with higher perceived tail risk, but the association is stronger for domain-specific memories, consistent with the principle of similarity. Personal experiences of hardship display a similar pattern: both economic and non-economic hardships are positively related to perceived tail risk, with a stronger association for economic hardships.

Our evidence from individuals' subjective return distributions shows that the relation-

[1]The only exception we are aware of is Gennaioli et al. (2024), who document primacy effects for inflation expectations based on objectively experienced inflation by age cohort. We measure individuals' subjective memories and study a financial context.

ship between memory negativity and beliefs operates through the downside tail. Using the distributional elicitation of Bloom et al. (2020), we find that more negative memories are associated with a substantially more negative 10th percentile of expected DAX returns. A one-standard-deviation increase in memory negativity is associated with a roughly five percentage point lower 10th percentile of returns. By contrast, memory negativity displays no economically or statistically meaningful association with the 90th percentile. Moreover, the effect on the 10th percentile is roughly 2.5 times stronger than the effect on the mean, implying a change in the perceived shape of the return distribution—a thicker left tail—rather than a parallel shift of the entire distribution. Our results highlight the importance of extreme downside memories for understanding not only tail beliefs, but also mean beliefs about future stock market returns. In addition to the changed shape of the distribution, the mean-shift associated with an increased share of recalled downside tail events, is larger than the mean-shift associated with a commensurate increase in memories of regular events, suggesting an influential role for memories of extreme negative events in shaping beliefs across various parts of the subjective return distribution.

Our third main result concerns belief updating in response to new information. Over time, individuals get exposed to new information which they incorporate into their memory database. Understanding how beliefs respond to this information is key, since the dynamics of beliefs could potentially facilitate boom-bust cycles in which tail risk is under-estimated during booms and over-estimated during busts. In the memory-based model, belief heterogeneity can arise through two channels. The first channel is based on heterogeneity in lifetime experiences. Given that individuals born at different points in time incorporate different events into their memory database and may recall them selectively, their beliefs are likely to differ. Second, individuals may differ in the similarity they assign to any given event. A natural source of such heterogeneity is representativeness (Kahneman and Tversky, 1972). Individuals who view the current state as a boom may regard negative events as less similar to the present and may therefore recall fewer of them; individuals who view the current state as a bust may regard negative events as more similar and therefore assign higher crash probabilities.

We test this mechanism using an information treatment embedded in our memory wave. Respondents receive a list of past stock market crashes and the size of each crash. Objectively, this information is less surprising for respondents who had already recalled a larger share of negative events over the same period, or who remembered these events as having a more negative stock market impact. We call these respondents high memory negativity individuals. Under standard learning rules, high memory negativity individuals should react *less* to the negative information, because it is less negatively surprising relative to their prior memories. Under representativeness, the opposite can occur. We derive the belief-updating rule of the memory-based model and show that, if high prior memory negativity reflects higher perceived similarity of negative events to the current context, high memory negativity respondents may update *more* strongly in response to negative information instead of less.

The evidence is consistent with this prediction. Respondents with a higher prior share of negative recalled memories respond more negatively to the treatment than respondents with a higher share of positive memories. Respondents who associate a more negative impact with recalled events also revise their beliefs more negatively. These patterns run counter to standard updating rules in which objectively less surprised agents should respond *less* to the information (see, e.g., Armona et al., 2019; Beutel and Weber, 2026). By contrast, the similarity mechanism in the memory-based model can jointly explain

more negative recall, higher prior tail probabilities, and larger belief revisions among high memory negativity individuals. Memory-based belief updating thus has the potential to micro-found models of representativeness in which individuals overreact or underreact to news depending on the state they view as representative (see also Bordalo, Coffman, Gennaioli, Schwerter, and Shleifer, 2021; Kahana, Paron, and Wachter, 2024).

Fourth, we provide novel evidence on the link between tail beliefs and financial decisions. In a motivating regression without any treatment interventions, we first show that a one standard deviation change in perceived tail risk displays a stronger correlation with individuals' assessment on whether it is a good time to buy real estate, or whether it is a good time to buy equity, than a one standard deviation change in respondents' central tendency beliefs. To quantify the causal link between perceived tail risk and (hypothetical) changes in respondents' financial portfolio allocation, we field information treatments, as well as a dedicated decision module in an additional survey wave. The decision module contains a vignette experiment that generates exogenous variation in the perceived likelihood of four specific tail events. We find that households respond asymmetrically to changes in perceived risk: they reduce risky asset holdings in response to increases in tail risk, but adjust little when perceived risk declines. This pattern is consistent with models featuring loss aversion, in which increases in downside risk have a disproportionate effect on utility (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991). Second, exploiting exogenous variation from information treatments in our news provision waves, we find that perceived safe haven assets are event-specific. For instance, negative news about the risk a new financial crisis *reduces* individuals' inclination to invest in real estate, whereas negative news about the risk of a new pandemic *increases* individuals' inclination to invest in real estate. These event-specific reactions are consistent with past experiences and the idea that memories shape which assets are perceived as safe. Our results on tail beliefs and financial decisions suggest memory-based models can help to better understand investor behavior (see also Jiang et al. 2025), and they contribute to a recent literature showing how subjective beliefs shape behavior, not only through expectations about the central tendency of macro-financial outcomes, but also through beliefs about rare events (see, e.g., Shiller 2000; Barseghyan et al. 2013; Roth and Wohlfart 2020; Beutel et al. 2021; Giglio et al. 2021; Dietrich et al. 2024; Menkhoff 2025).

Overall, our paper contributes to several strands of the literature. First, it relates to a large literature showing that personal experiences shape beliefs and behavior (see, e.g., Malmendier and Nagel, 2011, 2016; Kuchler and Zafar, 2019; D'Acunto et al., 2021; Malmendier et al., 2021). More specifically, we contribute to recent work emphasizing memory as a belief formation mechanism in different economic domains (see, e.g., Bordalo et al. 2023; D'Acunto and Weber 2023; Wachter and Kahana 2024; Gennaioli et al. 2024; Conrad et al. 2024; Enke et al. 2024; Graeber et al. 2024; Malmendier and Wachter 2024; Jiang et al. 2025; Charles 2025, 2022; Gödker et al. 2025; Voigt 2025; Kuang et al. 2026). This work builds on a long-standing literature in psychology studying selective recall of memories (see, e.g., Kahana, Diamond, and Aka 2024 for an excellent overview). Selective recall has also been suggested as a mechanism underlying Kahneman and Tversky (1972)'s representativeness heuristic (see, e.g., Gennaioli and Shleifer 2010; Bordalo et al. 2021, Kahana, Paron, and Wachter 2024). The representativeness heuristic, in turn, micro-founds diagnostic models of tail risk neglect which can generate boom-bust cycles in financial innovation, asset prices and credit (see, e.g, Gennaioli et al. 2012, 2015; Bordalo et al. 2026). A related literature in macro-finance emphasizes the importance of unlikely

but potentially catastrophic events - rare disasters - for asset pricing (see, e.g, Rietz 1988; Barro 2006; Gabaix 2012; Wachter and Zhu 2025). Our results show how selective recall can make beliefs about rare disaster risk subjective, time-varying, and heterogeneous across individuals.

Perhaps the most closely related paper to our study is Jiang et al. (2025). They study expectations and memories about stock returns in a large sample of Chinese retail investors, matched with administrative data on their actual stock market trading. They show that returns on the survey day affect recalled stock market experiences, which in turn predict expected stock market returns and subsequent trading behavior. Their paper provides important field evidence that memory shapes financial-market beliefs and actual investment decisions. Our paper is complementary, but studies a different object: beliefs about tail risk. In particular, we study how selective recall of aggregate events over several decades shapes beliefs about rare downside outcomes today.

We make four central contributions to the literature. First, we shift the focus of the memory-based belief formation literature from beliefs about central tendencies to beliefs about tails. We show that memory negativity is strongly associated with downside tail beliefs and with the left tail of subjective return distributions, but not with the right tail. Selective recall can therefore change the shape of individuals' subjective return distributions. Furthermore, we show tail experiences are particularly influential, both for the tail, and for the mean of subjective distributions, and perceived tail risk is strongly correlated with individuals' perception of whether it is a good time to invest in property and equity. Second, we measure memories using open-ended text questions and estimate the temporal similarity function governing individuals' recall. We show that both recency and primacy shape which events come to mind. This channel is distinct from contemporaneous return cues, suggesting that both temporal similarity and feature similarity matter for memory-based belief formation. Moreover, our broad elicitation shows that even non-domain-specific memories, such as political or cultural events, can affect subjective probability distributions over financial market outcomes. Third, we derive and test a memory-based updating rule, documenting heterogeneous updating consistent with representativeness and interference. Fourth, we provide causal evidence that experimentally induced changes in perceived tail risk affect market timing perceptions and (hypothetical) financial decisions in event-specific and asymmetric ways.

The remainder of our paper is organized as follows: Section 2 introduces our conceptual framework. Section 3 describes our survey design and provides descriptive evidence on recalled events. Section 4 documents recency and primacy effects in the recall of economic and cultural memories. Section 5 provides evidence on the role of memory in shaping perceived probability distributions, and section 6 analyzes individuals' response to new information. Section 7 summarizes our results on the pass-through from tail beliefs to financial decisions. Section 8 concludes.

2 Conceptual Framework

2.1 Memory-Based Model of Belief Formation

To guide our empirical analysis, we present a memory-based model of belief formation based on Bordalo et al. (2025). Consider an agent i who estimates the probability of an event H. As a running example for event H, consider for instance a stock market crash of at least 25% during the next 12 months. We assume the mental process of the agent can

be broken down into two steps. The first step is recall of experiences. When thinking about the probability of a stock market crash in the future, more and less similar past events may come to the agent's mind. The second step is called simulation. For any given set of experiences that come to the agent's mind, she maps her recalled experiences into an estimate of the probability of event H. Breaking down the belief formation process into these two components is done for conceptual reasons. In practice, the process may happen subconsciously.

We formalize the first step of the belief formation process as follows. The event being forecast and the current context act as cues for recall. For example, consider an individual estimating the probability of the same event H (e.g. stock market crash) in different contexts, such as during an economic boom, or during a recession. Even though the event is the same, the individual may be more likely to recall more negative memories during a recession, while she may recall less such memories during an economic boom. We denote the cue C as a function of the event being forecast H, and the context O, that is $C \equiv C(H, O)$. Moreover, we denote by $S(e) \equiv S(e, C)$ the similarity between experience e in the agent's memory database and the cue C. An experience e can be an aggregate event that took place in the economy, or a personal experience that was specific to the individual. The similarity function S maps a cue-experience pair into the $[0, 1]$ interval. In particular, we can think of experiences as vectors $e = (e_1, \ldots, e_J)$ encoding features such as the time of the past event, the return associated with the event, and various other characteristics. The similarity between a cue C and an experience e can be defined as the average pairwise similarity of their features:

$$S(e, C) = \sum_{e_j} \sum_{C_j} S(e_j, C_j) \frac{1}{|e|} \frac{1}{|C|} \tag{1}$$

$S(e, C)$ is symmetric and rises in feature overlap between the members of e and C.

The similarity between an experience e in the agent's memory database E and the cue C determines the probability of recall:

Assumption 1 (Cued Recall)**.** *When thinking about C, the likelihood that the agent recalls experience $e \in E$, denoted $r(e)$, is proportional to its similarity, $S(e)$:*

$$r(e) = \frac{S(e)}{\sum_{e \in E} S(e)} \tag{2}$$

The numerator of (2) implies experience e is more likely to be recalled when it is more similar to the cue C. The denominator of (2) captures interference: all experiences $e \in E$ compete for retrieval. Other experiences that are either particularly similar to the cue or frequent in the memory database may lower the likelihood of recalling e.

The second step of the belief formation process consists of simulating the probability of event H based on the recalled experiences. In line with Bordalo et al. (2025), we formalize this process by a second similarity function $\sigma(e) \in [0, 1]$ which assigns to each recalled experience e a contribution to the simulated probability of event H. A particularly simple simulation similarity function $\sigma(e)$ would be binary, classifying each event either as relevant, $\sigma(e) = 1$ or irrelevant, $\sigma(e) = 0$ (see, e.g., Bordalo et al. 2023). More generally, the simulation similarity function can be continuous, and may vary with the agent's perception of the state of the economy.

Assumption 2 (Simulation)**.** *Based on the retrieved experience $e \in E$, the agent simulates H with a probability $\sigma(e) \in [0,1]$ that increases in similarity, i.e. $\sigma(e) \geq \sigma(u)$ if and only if $S(e) \geq S(u)$. The simulated probability of H is then given by:*

$$\hat{\pi}_E = \sum_{e \in E} r(e)\sigma(e) \tag{3}$$

The simulated probability $\hat{\pi}_E$ is a weighted average of the simulation similarity of each event in the database. The weight of each σ_e is given by the probability of recalling the corresponding event $r(e) = \frac{S(e)}{\sum_{e \in E} S(e)}$. Since $r(e) \in [0,1]$ and $\sigma(e) \in [0,1]$ the probability $\hat{\pi}$ is also bounded on the $[0,1]$ interval. Belief formation by simulation (see, e.g., Kahneman and Tversky 1982) can be thought of as a process where the agent draws a large number of samples from her memory database according to the recall probability $r(e)$, and for every sample simulates whether it leads to the outcome H.

We illustrate this belief formation process with a simple example. Consider an investor assessing the probability of a stock market crash at a given point in time. For ease of exposition, suppose the events in the investor's memory database can be categorized into positive events e^+ and negative events e^-. Negative events are perceived as more similar to a stock market crash than positive events, specifically let $S(e^+) = 0.1$ and $S(e^-) = 0.2$. For the sake of this example, we assume the investor's memory database E contains 1 negative event, and 8 positive events, such that $\sum_{e \in E} S(e) = 1$ and hence similarity equals probability of recall, that is $S(e) = r(e)$ in (2). More generally, the denominator of (2) ensures that $\sum_{e \in E} r(e) = 1$ even as more experiences are added to the database, or if we re-scale similarity. Turning to the simulation step, we assume a binary simulation similarity function σ_e, in which the investor considers negative experiences as relevant, $\sigma(e^-) = 1$, and positive experiences as irrelevant for simulating a stock market crash, $\sigma(e^+) = 0$. By (3) the simulated probability is $\hat{\pi}_E = 0.2$, reflecting the dominant share of positive events in the example's memory database. While positive events are considered as irrelevant for simulating the event H, they are nevertheless recalled with non-zero probability and therefore lower the probability of recalling relevant simulation material. This effect is called interference. The simulated probability would be lowered further, if $\sigma(e^-) < 1$, that is past crashes are perceived as similar, but not perfectly similar to the current context during simulation.

The next sections discuss the testable predictions of this model with respect to similarity, simulation, and the processing of news.

2.2 Similarity and Recall

Similarity in recall is governed by the function $S(e)$ which maps events into the $[0,1]$ interval. An event is a multidimensional object whose similarity to a cue can be broken down into two broad categories which we label temporal similarity and feature similarity.

Temporal Similarity Memory research has documented two key regularities regarding temporal similarity. Recency predicts that more recent experiences are easier to recall than experiences in the more distant past. Primacy is present when experiences early in life are more easily recalled than experiences at intermediate ages. Both of these effects are well-established in the memory literature (see, e.g., Kahana, Diamond, and Aka 2024), but thus far, only the recency effect plays a prominent role in economics.

Recency effects arise naturally in the model outlined above when the temporal context of a cue today is more similar to recent events than to distant events. For instance, if a new pandemic were to break out tomorrow, an investor might consider the economic environment during the Covid pandemic of 2020 as more similar than the economic environment during the influenza pandemic of 1918 ("the Spanish Flu"). The so-called primacy effect was first observed by Hermann Ebbinghaus, a 19th century experimental psychologist (Ebbinghaus, 1885). He noticed that the first items in a list of words are recalled more easily than items in the middle of the list. This effect has been confirmed in subsequent lab experiments and neuro-imaging studies (see, e.g., Glanzer and Cunitz 1966; Kahana 1996; Polyn et al. 2005). One explanation for the primacy effect is that the first items or experiences get more attention because the learner starts fresh, and they can be rehearsed more often. By contrast, later items compete with earlier ones for mental resources, so they do not get equal rehearsal. Therefore, early items are more likely to move from short-term memory into long-term memory, generating primacy. In the context of biographic memories, another potential mechanism is that early lifetime experiences are more strongly remembered since these are formative and possibly particularly emotional. To the best of our knowledge, we are the first to use survey data measuring individuals' recall of economic events to test both primacy and recency effects.

We follow Gennaioli et al. (2024) in modeling temporal similarity as follows, while replacing objective experiences with the subjective memories elicited in our survey. We define each individual's normalized distance to a recalled event as $d = s_k/a$, where s_k is the difference between the year of the survey and the year of event k. s_k is normalized by respondents' age a such that $d \in [0, 1]$, when the temporal similarity function is restricted to events within an individual's lifetime. This implies that a recalled event $s = 25$ years ago is "early life" ($s_k/a \approx 0.8$) and hence distant for a 30-year-old, but "middle life" and hence less distant for a 60-year-old ($s_k/a \approx 0.4$). An individual's probability to recall an event k is modeled as follows:

$$P(recall)_{i,k} = \beta_0 + \beta_1 d_{i,k} + \beta_2 d_{i,k}^2 + \gamma X_{i,k} + \epsilon_{i,k} \tag{4}$$

where $P(recall)_{i,k}$ is the probability that individual i recalls an experience k (that is $r(e_k)$ in the model above), distance $d_{i,k} = s_k/a_i$, $X_{i,k}$ is a vector of control variables which may vary with individual i or experience k, and $\epsilon_{i,k}$ reflects idiosyncratic measurement noise in survey data. $X_{i,k}$ may include controls for the feature similarity of the event relative to the cue or its general salience (see section 2.3 for more details). This specification allows us to test for primacy and recency effects as follows:

Prediction 1 (Recency and Primacy)**.** *Given the temporal similarity function (4), recency and primacy predict the following:*

i) if ***neither recency nor primacy*** *are present, P(recall) is independent of distance, that is $P(recall)$ equals some constant $c \in [0, 1]$ for any distance.*

ii) if ***recency*** *is the only effect, P(recall) is* ***monotonically*** *decreasing in distance, that is $\frac{\partial P(recall)}{\partial d} < 0$ for any $d \in [0, 1]$.*

iii) if ***primacy*** *is the only effect, P(recall) is* ***monotonically increasing*** *in distance, that is $\frac{\partial P(recall)}{\partial d} > 0$ for any $d \in [0, 1]$.*

iv) if both ***recency and primacy*** *are present, P(recall) is* ***U-shaped****, that is it decreases for $0 \leq$ distance $< d^\star$ and increases for $d^\star <$ distance ≤ 1, where $d^\star = \min_{distance} P(recall)$.*

To interpret Prediction 1 we note that $\frac{\partial P(recall)}{\partial d} < 0$ if and only if $\beta_1 < -2\beta_2 d$. Recency with linearly decreasing probability of recall would for instance be given by $\beta_1 < 0$ and $\beta_2 = 0$. An example of case iii) in which both recency and primacy effects are present would be $\beta_1 < 0$ and $\beta_2 > 0$, with β_2 sufficiently large such that we get a U-shaped probability of recall on the unit interval. Figure 1 visualizes some possible shapes of the P(recall) function. The minimum of the U-shaped function (red line) is obtained for distance $d^\star = -\frac{1}{2}\frac{\beta_1}{\beta_2}$. The orange line reflects recency with diminishing marginal decay. The green line illustrates the hypothetical case where only primacy is present. As a benchmark, the blue line visualizes the case in which all experiences are recalled with a probability that is independent of their temporal distance. We will estimate the parameters determining the actual shape of the temporal similarity function using our survey data.

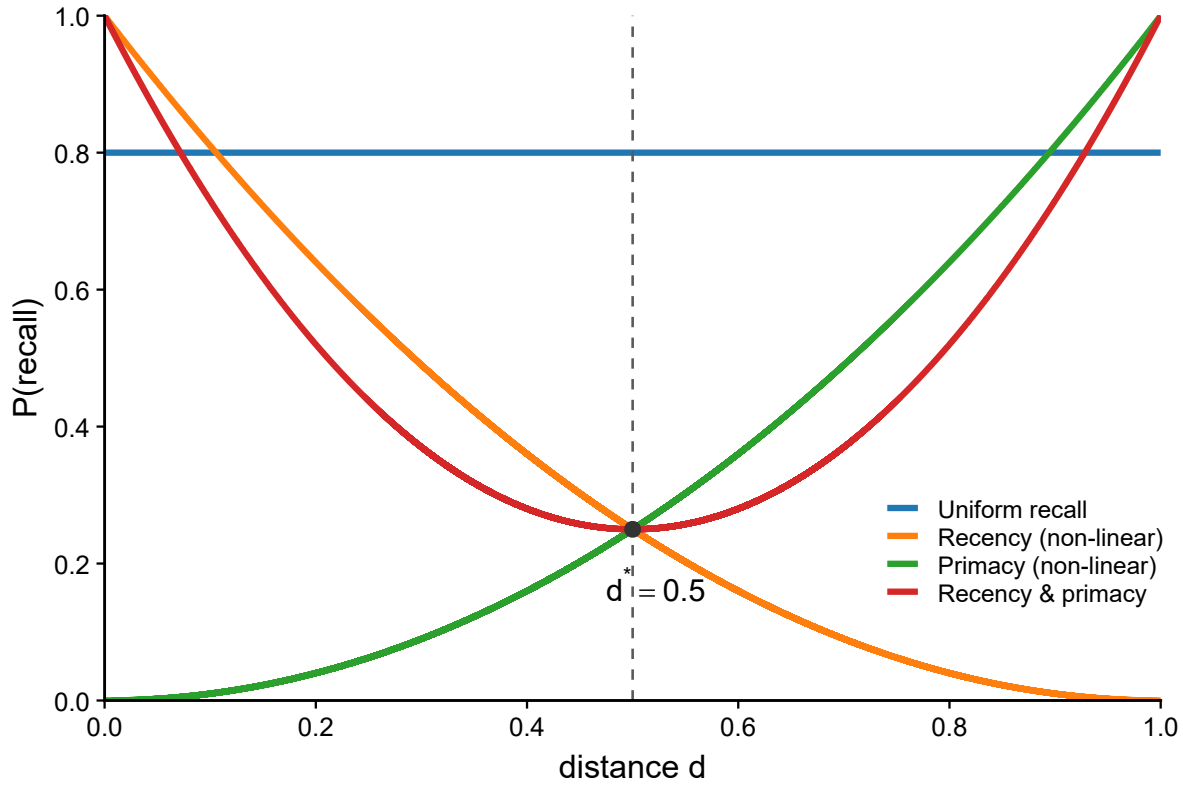


Figure 1: Recall probability as a function of distance.

Note: The figure plots $P(\text{recall}) = \beta_0 + \beta_1 d + \beta_2 d^2$ on $d \in [0, 1]$. Uniform recall with imperfect memory is obtained for $\beta_0 = 0.8$, $\beta_1 = \beta_2 = 0$. The non-linear recency specification ($\beta_0 = 1$, $\beta_1 = -2, \beta_2 = 1$) allows for diminishing marginal decay and flattens at the maximal distance. The non-linear primacy specification is increasing in d ($\beta_0 = 0$, $\beta_1 = 0, \beta_2 = 1$). The combined recency *and* primacy specification ($\beta_0 = 1$, $\beta_1 = -3, \beta_2 = 3$) generates a U-shaped pattern, with weakest recall at intermediate distances and elevated recall for both very recent and very distant events.

Feature Similarity Similarity, and hence, the probability of recalling an event according to (2), depends not only on temporal distance, but also on the similarity between other features of each event and the cue. Empirically, we measure individuals' memories in two types of questions. One random subset of respondents is asked to recall important economic events over the last 60 years. Another random subset of respondents is asked to recall important events in society, sports, and culture (see section 3 for more details on our survey design). For ease of exposition, we refer to the outcome of these questions as *economic* memories, and *cultural* memories. Since both subsets of respondents are representative of the German population, we can compare the outcomes in both groups to learn about recall patterns in the general population.

We elicit respondents' memories in a category-cued free-recall setting. While the questions provide broad domain cues, respondents receive no event-specific retrieval cues or response options and generate all recalled events in open-text fields. Given the category-cue, if similarity drives recall, as in (2), we would expect the cultural question to evoke a more diverse set of memories encompassing events in politics, sports, and culture; whereas we would expect the economic question to yield a more homogeneous set of memories with a focus on economic events. We will see this is indeed the case (see section 3.6), but we view this as a sanity check rather than a distinctive prediction of the postulated model. Instead, in the next section, we design a more specific test of the memory-based model of belief formation which tests the implications of feature similarity for the link between memories about past events and beliefs about the future.

2.3 Memory and Simulation

Consider a population of individuals who report their memories in a category-cued free-recall question. Suppose these events can be categorized into positive and negative events measured by their stock market impact. We also observe a measure of each individual's perceived probability of a stock market crash. We interpret the share of recalled negative events as a proxy for each individual's propensity to recall negative stock market events, $\sum_{e \in E^-} r(e)$, where E^- is the set of all negative stock market experiences in the database $E = E^+ \cup E^-$. Moreover, we assume that negative past events are considered more similar to a stock market crash than positive past events during both recall and simulation, that is $S(e \in E^-) > S(e \in E^+)$ and $\sigma(e \in E^-) > \sigma(e \in E^+)$. The model of memory-based belief formation then yields the following prediction, where M denotes a sample from an individual's experience database E as reported in a category-cued free-recall question:

Prediction 2 (Similarity and Tail Beliefs)**.** *Suppose the recalled events M can be separated into positive memories M^+ and negative memories M^- such that $M = M^+ \cup M^-$. Based on Assumption 1 (Cued Recall) and Assumption 2 (Simulation), an individual with a larger share of M^- memories is more likely to perceive a higher probability of a stock market crash.*

Prediction 2 follows directly from (2), and (3). For instance, an individual with a higher frequency of negative events in her memory database, is more likely to recall a larger share of negative events in a category-cued free-recall question. Due to the higher frequency of negative events in her memory database, she will also recall more negative events when asked to assess the likelihood of a stock market crash, for which she therefore simulates a higher probability (all else equal). In addition, we use the Bloom distribution question to test whether the relationship between numerically similar memories and

beliefs holds across different parts of individuals' subjective return distributions. We also investigate whether the principle of similarity holds across the qualitative dimension of domain-specific (DS) versus non-domain specific (NDS) memories and across economic versus other personally experienced hardships. In particular, feature similarity predicts a stronger link between beliefs about economic outcomes and DS memories or economic hardships, as opposed to NDS memories or other hardships.

2.4 Belief Updating in Response to News

Over time, individuals get exposed to new information which they incorporate into their memory database. Understanding how beliefs respond to this information is key, since the dynamics of beliefs could potentially lead to boom bust cycles in which tail risk is under-estimated during booms and over-estimated during busts (see, e.g., Gennaioli et al. 2015). To shed more light on the conditions under which this may happen, we derive the belief updating rules implied by the model defined in (2) and (3). While the memory-based model of belief formation does not require agents to update their probability beliefs continuously, we consider the thought experiment in which an agent receives a piece of news, and we cue her simulated probability of an event H directly before and after receiving the news. This setup resembles information provision RCTs, which we can use to test the additional predictions of the memory-based model derived in this section.[2]

Proposition 1 (Memory-Based Belief Updating Rule)**.** *Consider a database E^0 to which a new experience e' is added, such that the new database is $E^1 = E^0 \cup e'$, then*

i) The new belief $\hat{\pi}^1$ is a weighted average of similarity $\sigma(e')$ and the old belief $\hat{\pi}^0$:

$$\hat{\pi}^1 = (1 - G_E)\hat{\pi}_0 + G_E\sigma(e') \tag{5}$$

where

$$G_E \equiv \frac{S(e')}{\sum_{e \in E^1} S(e)} = r(e') \tag{6}$$

ii) This is equivalent to

$$\Delta\hat{\pi} \equiv \hat{\pi}^1 - \hat{\pi}^0 = G_E \left[\sigma(e') - \hat{\pi}^0\right] \tag{7}$$

The first part of the proposition states that the new belief $\hat{\pi}^1$ is a weighted average of the old belief $\hat{\pi}^0$ and the simulation similarity $\sigma(e')$ of the new experience or information. The weight G_E is given by the probability of recalling the new experience e'. The memory-based updating rule resembles the familiar form of standard Bayesian updating models, but there are several important differences. In the context of the memory model, the "surprise" $\sigma(e') - \hat{\pi}^0$ in equation 7 measures the (subjective) distinctiveness of the information received relative to the existing memory database of the individual. The signal $\sigma(e')$ is subjective and reflects individuals' similarity function, contrasting with standard Bayesian updating models in which the signal typically reflects objective quantities, such as the inflation rate or the return over the last period (see, e.g., Armona et al. 2019; Beutel and Weber 2026). Moreover, the "gain" G_E reflects individuals' recall probability $r(e')$ which depends on their entire memory database E^1.

[2]The proof of proposition 1 is provided in appendix section A.1.

Belief Updating and Memories The memory-based belief updating rule allows us to think about how individuals with different prior memories respond to an information treatment. Suppose individual j has recalled a larger share of negative events in the category-cued free-recall question than individual k. Let us further assume that Prediction 2 holds, such that individual j assigns a higher prior probability to a negative tail event. Which individual will respond to a negative information treatment with a higher upward revision of her tail beliefs? The answer depends critically on the source of their differences in recall.

Consider first the case, where the reason for recalling a larger share of negative events is that individual j has experienced a larger share of negative events during her lifetime than individual k, while their subjective similarity functions are the same. In this case, the key difference in the updating rule of equation 7 is that individual j has a higher prior belief $\hat{\pi}^0$ than individual k. Moreover, given her larger share of high similarity (negative) events, the gain G_E of individual j may be smaller. Both effects lead individual j to revise her belief upwards by *less* than individual k in response to the same information, that is $\Delta\hat{\pi}_j < \Delta\hat{\pi}_k$. The upward revision in the perceived tail probability of individual j will be smaller than for individual k, since the new information is less distinct from her existing memory database. This property is similar to many other learning rules such as Bayesian updating, where an individual who is less surprised by the news responds less to it (see, e.g., Armona et al. 2019; Beutel and Weber 2026).

On the other hand, suppose the reason for recalling a larger share of negative events is that individual j perceives a higher similarity of negative events to the current context than individual k. A natural reason for this could be the representativeness heuristic (Kahneman and Tversky, 1972). For instance, individual j may view the current state of the economy as bad ("bust" state) while individual k may view it as good ("boom" state).[3] Since individual j perceives negative events as more similar to the current state, she is more likely to recall negative past events, and consequently simulates a higher prior probability of a negative tail event (even when both individuals' objective lifetime experiences are identical). While the higher prior probability $\hat{\pi}^0$ tends to lower her belief revision in equation 7, the higher similarity $\sigma(e')$ pushes her belief revision in the opposite direction. The higher $S(e')$ may additionally boost G_E. Hence, if $\Delta\hat{\pi}_j > \Delta\hat{\pi}_k$, despite $\pi^0_j > \pi^0_k$, we have to conclude that $\sigma(e')_j > \sigma(e')_k$ and/or $S(e')_j > S(e')_k$. In other words, individual j's higher subjective similarity of negative experiences, can jointly explain a higher probability of recalling negative events, a higher prior tail probability, and a larger belief revision.

The predictions of these two alternative cases are summarized as follows:

Prediction 3 (Heterogeneity in Belief Updating)**.** *Consider two individuals j and k with $r(e^-)_j > r(e^-)_k$ and $\hat{\pi}^0_j > \hat{\pi}^0_k$.*

i) ***Homogeneity of Similarity Functions:*** *If $\sigma_j = \sigma_k$ and $S_j = S_k$, the belief updating rule of equation 7 implies $\Delta\hat{\pi}_j < \Delta\hat{\pi}_k$ since $\pi^0_j > \pi^0_k$.*

ii) ***Heterogeneity of Similarity Functions:*** *If $\Delta\hat{\pi}_j > \Delta\hat{\pi}_k$ despite $\pi^0_j > \pi^0_k$, this implies $S(e')_j > S(e')_k$ and/or $\sigma(e')_j > \sigma(e')_k$.*

[3]The representative state may itself be a slow-moving threshold process depending on the string of news received recently. That is, a single piece of news does not change the representative state, but a string of good or bad news may change it (see, e.g., Gennaioli et al. 2015).

We test this prediction via an information treatment embedded in our memory wave. Individuals receive a list of past stock market crashes together with the size of the associated stock market downturn. From the perspective of a learning rule with homogeneity in similarity functions, this list yields a smaller negative surprise for respondents who previously recalled a larger share of negative past events over the same time period, and/or who recalled these negative events to have a larger stock market impact. By contrast, from the perspective of a memory-based model in which the representativeness heuristic is a key force, type j respondents may subjectively perceive negative past events as more similar to the current state than type k respondents, that is $S(e_j^-) > S(e_k^-)$, and/or $\sigma(e_j^-) > \sigma(e_k^-)$. Therefore, type j respondents may over-weight the negative information relative to respondents of type k, and increase their probability by more as in Prediction 3 ii).[4] We test this prediction using the information treatment in our memory wave (see section 6).

Hence, we use our measures of individuals' recalled memories and an information provision experiment to test for representativeness against the alternative of homogeneous similarity functions across individuals. Moreover, under the plausible assumption that older individuals have a larger database of experiences and therefore face larger interference during recall (Bordalo et al., 2025), we obtain an additional testable implication on the relative size of belief revisions between older and younger cohorts of respondents:

Prediction 4 (Interference)**.** *Consider a database E^0 to which a new experience e' is added, such that the new database is $E^1 = E^0 \cup e'$. Suppose older individuals have a larger event database, that is $\sum_{e \in E^{old}} S(e) > \sum_{e \in E^{young}} S(e)$, such that $G_{old} < G_{young}$, all else equal. Then, older individuals should respond less to any new experience e', that is $|\Delta\hat{\pi}_{old}| < |\Delta\hat{\pi}_{young}|$.*

The next section outlines the design of a survey to test predictions 1 to 4 of the memory-based model of belief formation.

3 Survey Design and Stylized Facts

3.1 Overview

We embed randomized controlled trials (RCTs), and customized questions on tail beliefs, memories, and decisions, into four waves of the Bundesbank Survey of Consumer Expectations, a large representative survey of German households. The survey is a key data source for the Bundesbank on households' inflation expectations, consumption behavior, and income expectations. Each wave of the survey collects rich demographic, income, and wealth data as well as households' economic expectations. The survey is administered online by the survey company Forsa and has been running monthly since April 2020. The four customized survey waves for this project were fielded in August 2022 (news provision module), November 2022 (additional news provision module), August 2023 (memory module), and November 2023 (decision module). The key module for this paper is the memory module with roughly 4,000 respondents. In this section, we first describe the memory module, before briefly explaining the other modules.

[4]The effect of differences in similarity becomes more likely to dominate the belief revision as the level of the prior belief $\hat{\pi}^0$ goes to zero. In this sense, we may be more likely to find this effect for small probability events as opposed to beliefs about the central tendency.

3.2 Memory Elicitation

The dominant approach in the existing literature has been to relate objective experiences based on individuals' year of birth directly to their expectations (see, e.g., Malmendier and Nagel 2011, 2016), or to use objective experiences as a proxy for individuals' memories (see, e.g., Gennaioli et al. 2024). Yet, recent research shows that individuals' memories may deviate from their objective (macroeconomic) experiences (Jiang et al. 2025; Conrad et al. 2024). We therefore elicit a broad set of economic and other memories in a category-cued free-recall setting using open-ended text questions. Respondents receive broad thematic retrieval cues but no event-specific cues or response options and freely generate up to ten events from memory.

We elicit memories about economic events using the following question:

> Thinking of important events in the **economy and financial markets** over approximately the past 60 years, which ones do you think have led to major increases or decreases in the DAX (i) stock market index? In what year did these events take place?
> *Input: open text fields for up to 10 events (and 10 dates) per respondent.*

A different set of respondents receives the following question for eliciting memories of cultural events:

> Thinking of important events in **society, culture and sport** over approximately the past 60 years, which ones do you think played a major role in Germany? In what year did these events take place?
> *Input: open text fields for up to 10 events (and 10 dates) per respondent.*

For both economic and cultural events, we follow up with a question on the recalled financial market impact:

> By how much do you think the DAX stock market index increased or decreased in the wake of the events that you listed?
> (Please enter a positive value if you think there was an increase in the DAX and a negative value if you think there was a decrease in the DAX.)
> *List of events previously entered is shown with an input field for each event, asking respondents to indicate the change of the DAX index in percent.*

This gives us for each respondent a set of up to 10 memories in text form, along with the recalled year of the event, and the stock market impact recalled by the respondent. Some respondents do not report any memories, or choose not to answer other relevant questions, such that the effective sample will be slightly smaller than the initial sample. Throughout our paper, we treat item non-response on a case-by-case basis and report the effective number of observations in each regression table.

3.3 Randomization

We randomly split the sample of our memory module into four groups of approximately 1,000 respondents each. Due to randomization, each group remains broadly representative of the entire population.[5] The group *econ pre* receives the economic memories question prior to belief elicitation. By contrast, the group *econ post* receives the economic memories question *after* belief elicitation. This allows us to rule out that a potential link

[5] We document in appendix A.2 that the randomization successfully preserves the distribution of demographics across the treatment and control groups.

between memories and beliefs is an artefact of eliciting memories before beliefs. The group *cultural* receives the cultural memories question before belief elicitation. Finally the group *info* receives an information treatment consisting of a list of all past stock market crashes over the past 60 years and the stock market decline associated with each event. These are 11 events with an average 1-year stock market return of approximately -35 percent (see Figure 2 for a visualization). The ordering of questions in the *info* group is memory elicitation, information treatment, and finally belief elicitation. The groups *info* and *econ pre* differ only in whether or not an information treatment is provided, and therefore allow us to measure the causal effect of the information treatment. We choose the period starting in 1964 for the info treatment as it represents the longest available sample of returns for the German stock market index DAX. Across all groups, the period of memory elicitation ("over approximately the past 60 years") is chosen to match the time period covered by the information treatment.

3.4 Tail Belief Elicitation

Our elicitation of tail beliefs in the memory module focuses on stock market crashes, thereby allowing a close link between the elicited memories, the information treatment, and the belief outcomes. We consider beliefs about a broader set of tail events in our two news provision modules (see section 3.7).

Direct Elicitation of Tail Beliefs We elicit two dimensions of tail beliefs which we label magnitude and probability. For a given event type (here: a stock market crash) we first ask respondents about the impact associated with the event conditional on its realization:

> Imagine there would be a sharp decline in the DAX stock market index within the next 12 months. By what percentage do you think the DAX would fall in this case?
> *... percent*
> *Notes:*
>
> - *Please indicate how much lower (as a percentage) you think the DAX would be after 12 months if this event were to occur compared to if it had not occurred.*
> - *If you expect a decline, please enter a positive value.*
> - *If you do not expect a decline, please enter a value of zero.*

We label the outcome of this question as the subjective "magnitude" that individuals assign to the event.

The magnitude question is followed by a "probability" question:

> How likely do you think it is that the DAX stock market index will experience such a decline within the next 12 months?
> *... percent*
> *Notes: The aim of this question is to determine how likely you think it is that something specific will happen in the future. You can rate the likelihood on a scale from 0 to 100, with 0 meaning that an event is completely unlikely and 100 meaning that you are absolutely certain it will happen. Use values between the two extremes to moderate the strength of your opinion.*

The rationale behind eliciting these two dimensions in this order is to account for subjective interpretations of event definitions. When asked about a stock market crash (or

some other event), individuals may consider outcomes that differ in scope and magnitude. Some may perceive a decline of 15% as a stock market crash, while others might consider only declines of more than 25% as a crash. An obvious alternative would be to precisely define the event and then ask for its probability, but respondents might not fully read or understand the definition, or their answers might not reflect their real views if the framing is too academic. Therefore, we first elicit their perceived magnitude in a very simple question, and then use their answer to define the event for which we elicit their subjective probability assessment.

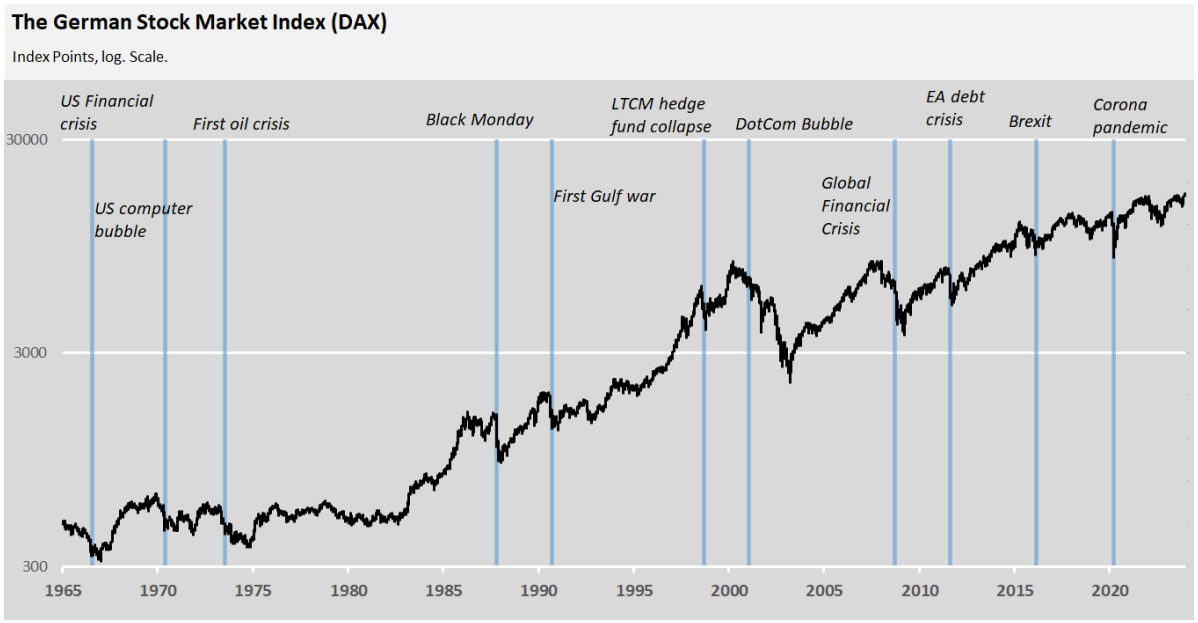


Figure 2: Evolution of the DAX Index and identification of crash episodes

Note: This figure displays the evolution of the German stock market index DAX from the end of 1964 to the end of 2023. The DAX is a return index, comprising both price changes and the reinvestment of dividends. The vertical axis is presented on a logarithmic scale to better illustrate proportional changes over time. Eleven major crisis episodes are indicated, corresponding to years in which the DAX experienced a downturn of more than 25% from the previous year's peak, identified using monthly data.

"Bloom" Distribution Elicitation As an additional outcome variable, we elicit individuals' subjective probability distribution about the return of the DAX over the next 12 months. Specifically, we include in our memory module an innovative new question format suggested by Bloom et al. (2020) and Altig et al. (2022) in which respondents first choose the bins of their subjective distribution, and then assign probabilities to their endogenously chosen bins. This question format addresses key shortcomings of standard probability density questions (Manski, 2018), such as the risk of influencing individuals' reported beliefs through anchoring or cueing effects of pre-defined bins (see, e.g. Weber et al. 2022; Gennaioli et al. 2024).

The wording of the first question of this form of belief elicitation is as follows:

We would now like you to think more specifically about various possible developments in the DAX stock market index over the next 12 months.
Question: What percentage change in the DAX stock market index would you expect in each of the following scenarios?

a In a **worst case** scenario, I would expect the DAX to change by ... *percent*

b In a **bad** scenario, I would expect the DAX to change by ... *percent*

c In a **neutral** scenario, I would expect the DAX to change by ... *percent*

d In a **good** scenario, I would expect the DAX to change by ... *percent*

e In a **best case** scenario, I would expect the DAX to change by ... *percent*

Notes:

- *Please enter a positive value if you expect an increase in the DAX and a negative value if you expect a decrease in the DAX.*
- *If you expect there to be no change, please enter a value of zero.*

This question allows respondents to choose their bins endogenously, without providing any numerical anchor or cue. The question is followed by an assignment of probability mass to the bins chosen by the individual.

Question: For each of the possible changes in the DAX stock market index that you have entered, please now indicate how likely you think it is that these will occur within the next 12 months.

a **Worst case** scenario: The likelihood of a *(answer from a)* % change is ... *percent*

b **Bad** scenario: The likelihood of a *(answer from b)* % change is ... *percent*

c **Neutral** scenario: The likelihood of a *(answer from c)* % change is ... *percent*

d **Good** scenario: The likelihood of a *(answer from d)* % change is ... *percent*

e **Best case** scenario: The likelihood of a *(answer from e)* % change is ... *percent*

Notes: *The aim of this question is to determine how likely you think it is that something specific will happen in the future. You can rate the likelihood on a scale from 0 to 100, with 0 meaning that an event is completely unlikely and 100 meaning that you are absolutely certain it will happen. Use values between the two extremes to moderate the strength of your opinion. Please note that your answers to all scenarios have to add up to 100.*

Taken together, these two Bloom-style questions provide information about each individual's subjective probability distribution over the return of the DAX over the next 12 months. As a measure of downside tail risk we compute the 10th percentile of each individual's distribution. For comparison, we also compute the mean, the standard deviation, and the 90th percentile of each individual's distribution.

3.5 Control Variables

We use a set of control variables to account for variation in tail beliefs that might not be driven by the memories themselves, but instead by other respondent characteristics. First, we observe a variety of socio-demographic characteristics. In our empirical analysis, we include controls for age, as well as indicator variables for gender, marital status, having at least one child, college education or higher, household income categories, stock ownership, and the presence of any outstanding debt.

Second, we construct measures of objective macroeconomic experiences based on each respondent's year of birth. To study the link between objective experiences and tail beliefs, we define the following individual-specific measures: experienced lifetime stock market volatility and the share of experienced stock market crashes. To compute these (objective) measures, we use daily stock market return data for the German stock market index, DAX, starting at the end of 1964. We compute annual stock market returns and stock market volatility for each calendar year (measured by the variance of daily returns). We also create a binary variable that indicates whether the stock market has been in a downturn of more than 25% in the calendar year, relative to the peak of the last year based on monthly data. This approach yields the 11 crisis episodes, which are shown in Figure 2. For each year of birth, we compute a "lifetime average" of both of these variables, using the weighting function approach described in Equation (1) of Malmendier and Nagel (2011) which overweights more recent events.[6]

Third, in our memory module, we elicit respondents' domain and non-domain specific experiences of hardship, closely following the approach in Bordalo et al. (2025). Respondents are asked to select which of the following personal hardships they have experienced during their lives: unemployment, significant financial lossess, inability to service debt, "other economic adversities", and serious health problems, flight/migration experiences, major safety/health risks at work, other great personal misfortune or adversity. The first four items describe personally experienced economic adversities, while the last four items describe personally experienced non-economic adversities. The ordering of the question items was randomized when presented to each respondent. Our measures of individual-specific experiences are defined as the total number of experiences an individual has reported in each category. Eliciting individual-specific experiences in addition to recalled aggregate events allows us to control for idiosyncratic events experienced at the level of each individual. Motivated by Bordalo et al. (2025), we also elicit as an additional control variable an estimate of individuals' tendency to overestimate small probabilities across domains in a setting without risk. While Bordalo et al. (2025) use questions about the prevalence of "red hair" or "snow" in a given population or location, the Bundesbank survey required us to ask a question in an economic context, and hence we asked respondents how many ATMs there are in Germany per 1,000 inhabitants allowing for one decimal place (true answer 0.5). The exact question texts for personally experienced hardships and ATM frequency are documented in appendix A.3.

We control for all of these variables when testing the model's predictions using our memory wave. The ATM measure forms part of our $CONTROL$ vector which also contains all socio-demographic characteristics mentioned above. Inclusion of personal hardships, and objective stock market experiences is indicated separately for each specification.[7]

3.6 Description of Recalled Events

We conclude the presentation of our memory module with descriptive evidence on the recalled events. This motivates our analysis of the drivers of recall at the respondent level in the next section. Panel A of Table 1 shows the most frequently recalled *economic*

[6]For our baseline estimates, we exogenously set the weighting parameter λ to 1, in line with estimates of this parameter in different contexts (see Malmendier and Wachter 2024).

[7]The available control variables in the news provision waves and the decision modules differ slightly from those available in our memory wave, and are therefore listed separately in the respective table notes.

events, as well as the year associated with each event. The categories have been assigned by professional coders at the survey company with the objective of minimizing the total number of categories subject to ensuring homogeneity within each category. Among the most frequently cited economic events are the the global financial crisis of 2008, the Covid pandemic of 2020, the outbreak of the war in Ukraine in 2022, and the oil crises during the 1970s. Moreover, there are many other events with a lower but non-negligible recall frequency, illustrating the diversity of the episodes that come to respondents' minds.

Panel B of Table 1 shows the recalled cultural events (society, sports, and culture). The German reunification features as the most frequently recalled cultural event, generating an overlap with the economic events. Yet, while German reunification is reported by 75% of respondents of the cultural events question, only 22% report it when asked for major economic events. The Covid pandemic, wars and uprisings, as well as economic and financial crises also overlap with the memories of economic events. However, domestic political events and sports events play a far larger role in responses to the cultural event question. Football world cups are ranked fourth in terms of the frequency of recalled events, mentioned by 40% of respondents to the cultural events question. These examples illustrate that the different cues of the economic and cultural event frame do generate variation in the recalled events, as expected based on the similarity principle.

While, on average, respondents have a relatively good assessment of the year the event took place (mode), the standard deviation of the recalled year (SD) reveals considerable cross-sectional heterogeneity within event categories. This heterogeneity may stem from respondents thinking of different events within a category (e.g. "domestic political events" may comprise events from different time periods), as well as from imperfect recall of the exact year each event took place. In our quantitative analysis, we use the exact year recalled by each respondent for each specific event they listed, along with their subjectively recalled financial market impact for each event.

Figure 3 visualizes respondents' estimates of the DAX impact in each event category. In the cultural memory elicitation frame (second panel), the cross-sectional average perceived impact of each event (mean or median) shows a clear distinction between positive events (e.g. Euro introduction, German reunification) and negative events (e.g. Covid pandemic, economic and financial crises). Cross-sectional heterogeneity in the perceived impact may be due to the exact year a respondent was thinking about (e.g. the boom or the bust phase of the dotcom bubble), as well as disagreement in the subjectively recalled impact for any given year. In the economic memory elicitation frame (first panel), cross-sectional heterogeneity (e.g. IQR) is generally larger, and the mean or median assessment of positive and negative events is less clearly split by event type (for instance the average impact of the Covid pandemic is only slightly negative in the economic memories frame). The economic memories question appears to have induced reports of more pre-dominantly negative events, whereas responses to the cultural memories question evoked positive and negative memories more evenly, which could have caused respondents to be more careful in entering positive versus negative signs in front of their perceived stock market impact. In sum, our memory questions generated a substantial amount of variation we can exploit, but we also expect noise in survey data to make it harder to detect statistically significant effects, in particular for respondents in the economic memories frame.

Table 1: Memories of important economic and cultural events over the past 60 years

	Event	Year	
	% recalled	Mode	SD
Panel A: Major Economic events			
Global Financial Crisis	42	2008	8.3
Covid-Pandemic	36	2020	2.0
War in Ukraine	34	2022	1.8
Oil crises	24	1973	5.4
General economic and financial crises	24	2008	10.4
German reunification	22	1989	2.8
9/11 Terror Attack	17	2001	2.9
DotCom Bubble	10	2000	3.6
General war and uprises	9	1990	18.8
Gulf Wars	7	1990	7.4
Cold War	7	1961	8.2
Introduction of Euro	5	2002	4.6
European debt crisis	5	2010	2.8
Refugee crisis	5	2015	6.1
Energy crisis	3	2022	23.9
Nuclear Incidents	3	1986	12.7
Electoral events	3	2021	20.0
Extreme Weather events	2	2000	17.6
General Terrorism	2	2001	15.6
Black Monday	2	1987	6.1
Brexit	1	2016	1.9
Technology Bubble	1	2000	9.0
Panel B: Major Cultural events			
German reunification	75	1989	2.7
Domestic political events	68	2015	23.4
War/rebellions	50	2022	19.7
Football world cup	40	2006	15.8
Covid pandemic	31	2020	2.2
Terrorism	28	2001	15.7
Economic and financial crises	24	2008	16.9
World political events	15	2016	18.8
Euro introduction	15	2002	2.1
Climate change/extreme weather	14	2021	21.7
Other sport events	13	1972	17.1
Technological advances	10	1969	16.1
Nuclear incidents	10	1986	11.9
Cultural events	6	1960	20.8
Energy crisis	6	2023	19.7
Football general	4	2006	19.7

Note: The categories are coded by professional coders at the survey company. *% recalled* is the share of respondents who mentioned the respective event. *Mode* shows the most commonly referred year of an event. *SD* describes the standard deviation of the respective calendar years the event was associated with. The categories are ordered by the share of respondents recalling the event. Respondents were invited to report several events, thus the recall frequencies sum to a value larger than 1.

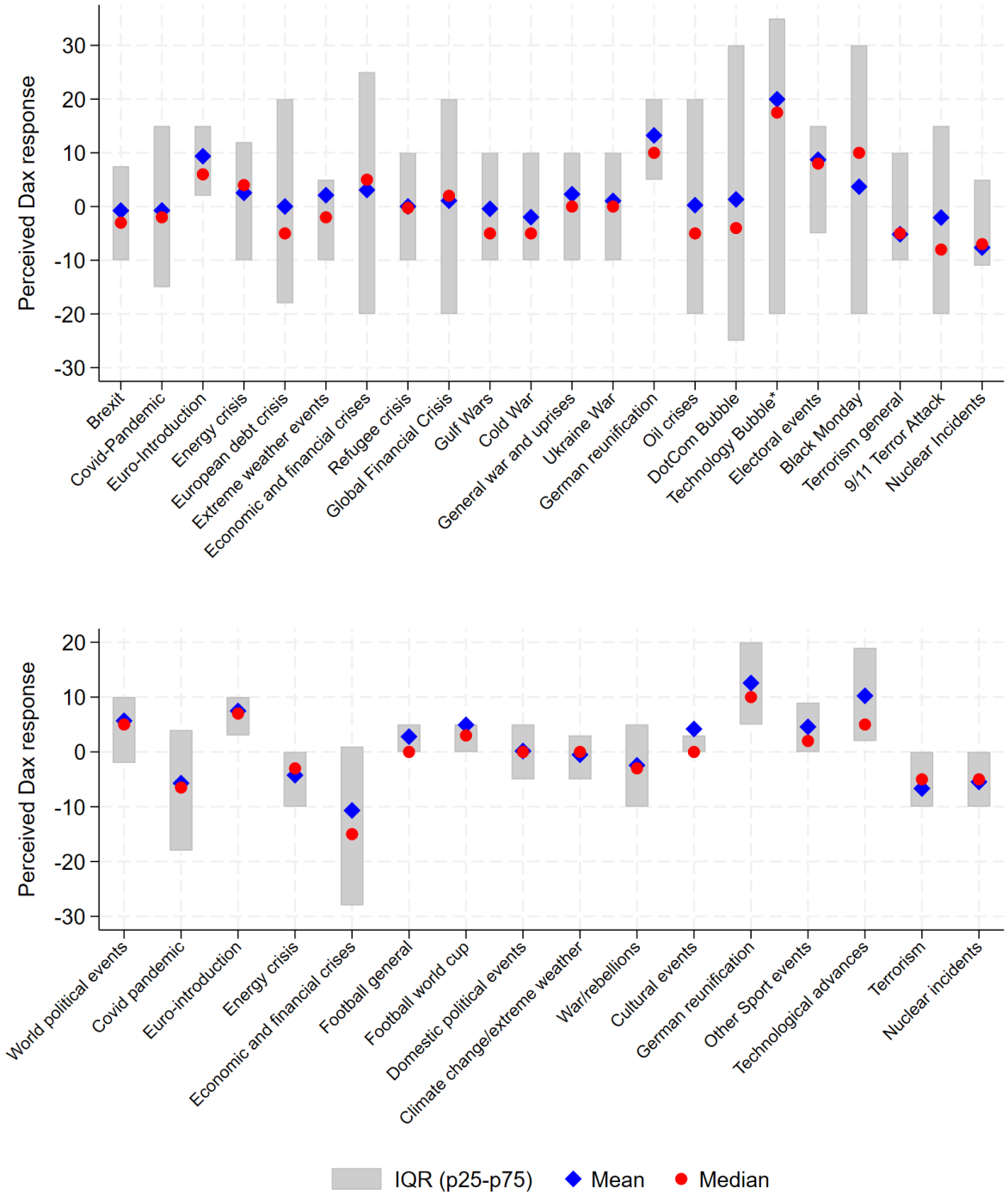


Figure 3: Recalled Impact of Events

Note: Perceived development of the DAX in the year following each recalled event. Horizontal axis lists the coded response categories. Vertical axis displays the estimated change in the DAX (in percentage points). The blue diamond indicates the cross-sectional average magnitude in each category. The red circle indicates the cross-sectional median magnitude. The shaded area indicates the interquartile range between the 25% to 75% percentiles of the distribution of responses across individuals.
* The IQR for the category *Technology Bubble* in the economic events Panel is truncated to improve readability of the mean/median values across events. The 75th percentile for the category *Technology Bubble* is 50 percentage points.

3.7 Additional Survey Modules

Throughout our paper, we first present the results from our memory module, which allow us to directly test the predictions of the model derived in section 2. In addition, our news provision module generates exogenous variation in tail beliefs via positive and negative information treatments regarding five disaster types (new financial crisis, new pandemic, China-Taiwan escalation, severe energy crisis, systemic Cyber attack). We exploit the exogenous variation in tail beliefs generated by these information treatments, to study the link between tail beliefs and respondents' assessment on whether it is a good time to invest in the stock market or the real estate market. In the decision module, we use a vignette design to investigate how shocks to individuals' tail beliefs induce respondents to update their financial portfolio allocations in hypothetical scenarios. More details on the news provision and decision modules are embedded in the corresponding section (section 7). In addition, the appendix includes the exact wording of all questions included for all four modules of our study (see appendix B).[8]

4 Recency and Primacy in Recall

To examine temporal similarity patterns in recall, we estimate equation (4) based on a respondent-year panel. For each respondent and each year within the memory horizon (1960-2023), we code a binary indicator equal to one if the respondent recalled an event in that year and zero otherwise. Given roughly 3,000 respondents who answered the economic events question (and about 1,000 who answered the cultural events question), and a 64-year span of recalled events, this yields a maximum of 192,000 (64,000) respondent-year observations. In our baseline specification, we restrict the sample to events that occurred within each respondent's lifetime ($s/a \leq 1$), thereby excluding years before birth (robustness checks provided below). To estimate equation (4), we regress the recall indicator on the temporal distance of the event from the survey date ($distance$), normalized by the respondent's age, and its square ($distance^2$). This approach allows us to model recall as a function of the event's temporal distance from the survey date, controlling for other covariates, thereby providing a test for the presence of recency and primacy effects based directly on measured memories (as opposed to proxies based on objective events during respondents' lifetimes).

Baseline Estimates Table 2 shows the likelihood of recall declines with distance (first row), consistent with recency effects, but rises again for events early in life (second row), consistent with primacy effects. The estimated coefficients are robust to including objective measures of financial market developments, and controlling for socio-demographic characteristics (columns 2 and 3). To account for the possibility that more salient or impactful years are more likely to be remembered, we augment the model with objective measures of financial market developments during the year of the recalled event: annual DAX volatility and the absolute value of annual DAX returns, split into positive and negative returns to capture potential asymmetries (column 2). Both variables are standardized, allowing the coefficients to be interpreted as the change in recall probability

[8]The Bundesbank Survey on Consumer Expectations website provides additional details about its methodology, access to its data, and the full questionnaires from all waves (in English and German). https://www.bundesbank.de/en/bundesbank/research/survey-on-consumer-expectations.

associated with a one-standard-deviation change in the respective measure. Higher stock market volatility is associated with higher recall: a one-standard-deviation increase raises the likelihood of recalling an event from that year by about 2.9 percentage points. Negative returns exhibit a similar effect, while large positive returns are linked to a lower recall probability (columns 2-3).

The left chart in Figure 4 visualizes the estimated recall probabilities for economic events from our preferred specification with all controls (Table 2, column 3). A distance close to zero corresponds to events that occurred most recently in a respondent's lifetime, while a distance close to one corresponds to events early in life. The curve is U-shaped, with recall probabilities lowest at a normalized age of roughly 0.64 ($s_t/a_t^* = -\frac{1}{2}\frac{\beta_1}{\beta_2} = -\frac{1}{2}\frac{-0.251}{0.195}$), close to the minimum of 0.685 reported by Gennaioli et al. (2024) for objective inflation experiences. This implies that primacy effects dominate for events in the first third of life, whereas recency effects dominate for the latter two-thirds. We find these primacy effects despite the fact that some of the most salient events, such as the war in Ukraine (2022), the Covid pandemic (2020), the European debt crisis (2012), or the global financial crisis (2008) are clustered towards the end of our sample and are therefore recent for respondents.

Robustness We estimate the same regression specification for respondents in the cultural memory frame. Results are shown in Table 2, column 4. We also find a U-shaped pattern for cultural events with a local minimum at around half of respondents' normalized age (Figure 4, right chart). Hence, primacy effects are even more pronounced for cultural events. A possible explanation could be that economic topics might be less salient to children and teenagers than cultural events such as soccer world cups or headline-grabbing events such as wars/rebellions. Cultural events may therefore be more likely to catch young individuals' attention and to move from their short-term memory to their long-term memory, facilitating recall during adulthood.[9]

Figure 5 shows the recall curve for splits by age cohort. Older respondents (age > 65) display markedly stronger primacy effects than younger respondents (age ≤ 65), consistent with findings in the cognitive sciences (see, e.g., Rubin and Schulkind 1997; Munawar et al. 2018). But even for relatively younger respondents, the recall of early life experiences is markedly larger than if recency were the only effect.

Some respondents recall events that occurred before their birth. Consistent with Gennaioli et al. (2024), these are not considered as primacy effects, which specifically refer to the disproportionate recall of formative early-life experiences. Including pre-birth events reduces the estimated primacy coefficient, indicating that such events are less likely to be recalled than own early-life events (see Table A.5, columns 3-4).[10] In addition, the results are robust to using different starting ages for memory formation (see Table A.5, columns 5-8). Results are also robust to excluding the event of the German Reunification from the sample (see the last two columns of Table A.5).

Interpretation Our results indicate that both primacy and recency effects shape the likelihood of recalling past events. We show these effects are present in direct measures of individuals' economic memories. Distinguishing recency and primacy effects provides an explanation for two seemingly conflicting observations. On the one hand, individuals

[9]For memories of cultural events (column 4), higher stock market volatility boosts recall, but the marginal additional effect of extreme returns on the likelihood of recalling cultural events is negative, reflecting the more diverse nature of the stated cultural events, which need not coincide with objectively large market movements, and whose recall might even be prone to interference from major economic events.

[10]For instance, the probability of recalling the two oil crises of the 1970s shows a clear increase for respondents who experienced these events during their lifetime (see Figure A.1).

are often assumed to forget distant experiences, on the other hand early life-time experiences are sometimes thought to have long-lasting effects. When recency is exclusively assumed, long-lasting effects can only arise when the initial experience was extraordinarily large (or the decay is small). The "forgetting curve" implied by recency provides one important channel through which selective recall can lead to tail risk neglect. The more distant the last crisis becomes, the less people think about it, and therefore may fail to fully appreciate the risk of similar tail events in the future. Our estimates provide direct evidence for selective recall of memories as a micro-foundation for decaying weights on experiences (see, e.g., Malmendier and Nagel 2011, 2016). Primacy may in turn lead to richer cohort patterns, which might otherwise be surprising based on recency effects alone. For instance, Gennaioli et al. (2024) show that primacy effects help to explain otherwise puzzling cohort behavior in inflation expectations during the post-Covid inflation surge. Beyond that, primacy effects have thus far not received much attention in the economics literature. However, they provide a natural foundation for long-lasting experience effects (a.k.a. "Depression Babies"): Early lifetime experiences matter not *despite* being distant in time (as in recency weighting), but because these first experiences can have a particularly long-lasting effect on individuals' memories.

Table 2: Probability of Recall as Function of Temporal Distance

	Economic events			Cultural events
	(1)	(2)	(3)	(4)
Distance	-0.209***	-0.268***	-0.251***	-0.206***
	(0.008)	(0.010)	(0.010)	(0.021)
Distance × Distance	0.139***	0.225***	0.195***	0.198***
	(0.007)	(0.009)	(0.009)	(0.020)
Annual Volatility		0.029***	0.025***	0.028***
		(0.001)	(0.001)	(0.001)
Annual Return				
negative domain		0.026***	0.030***	-0.016***
		(0.001)	(0.001)	(0.002)
positive domain		-0.008***	-0.007***	-0.026***
		(0.001)	(0.001)	(0.002)
Cons	0.103***	0.099***	0.121***	0.112***
	(0.002)	(0.003)	(0.004)	(0.012)
CONTROL	No	No	Yes	Yes
R^2	0.01	0.05	0.08	0.02
N	164645	154653	154653	51852

Note: For each respondent-year pair, a dummy variable equals one if the respondent recalled an event in that specific year, and zero otherwise. We restrict the sample to $s/a \leq 1$, i.e., to events that occurred during a respondent's lifetime. *Distance* is the temporal distance between the recalled event and the survey date (in years), normalized by the respondent's age. *Annual Volatility* denotes the annual volatility of the DAX, and *Annual Return* the absolute value of the DAX return, estimated separately for years with negative returns and years with positive returns. Both variables are standardized. *Controls* include the full set of socio-demographic characteristics described in Section 3.5. Columns 1-3 are estimated for respondents who answered the question on *economic events*, while column 4 is estimated for *cultural events*. All regressions are estimated using OLS with standard errors clustered at the individual level. * indicates significance at the 90%, ** at the 95% and *** at the 99% level.

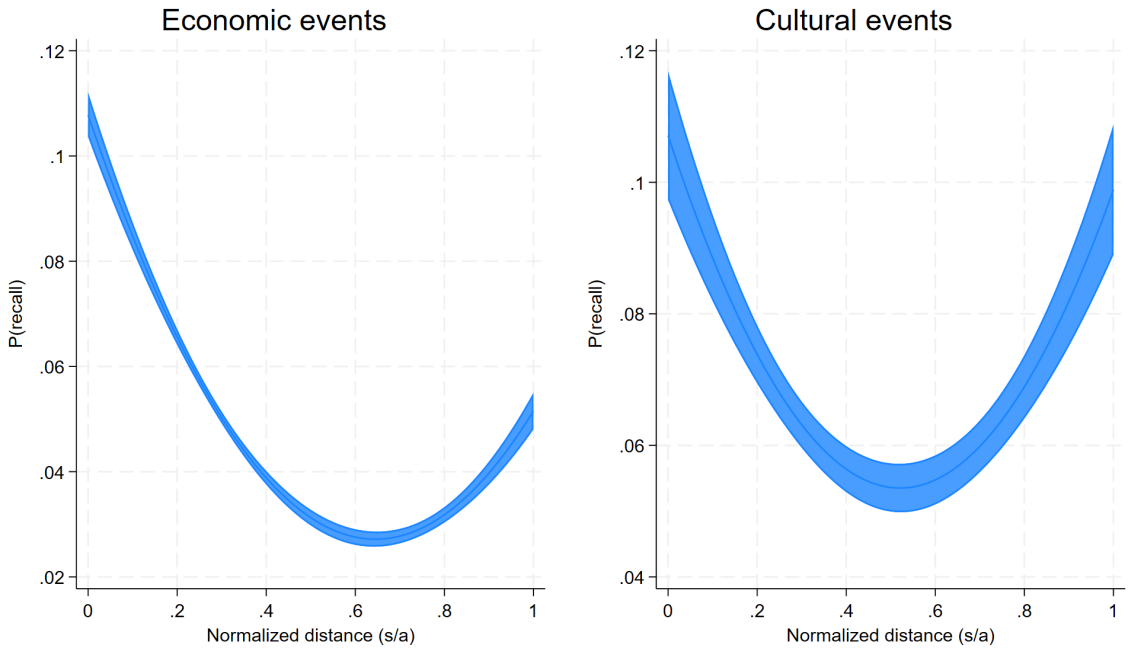


Figure 4: Marginal Effects - Primacy and Recency

Note: Marginal effects based on estimated coefficients in Table 2, for economic events (column 3, left chart) and cultural events (column 4, right chart). The x-axis corresponds to respondents' normalized age. Hence, a value close to zero refers to the most recent events in individuals' lifetime, whereas a value close to one refers to events that took place early in life. Remaining control variables, as described in the table, are kept at their means. Shaded areas show the 95% confidence intervals, reflecting the uncertainty of the estimates.

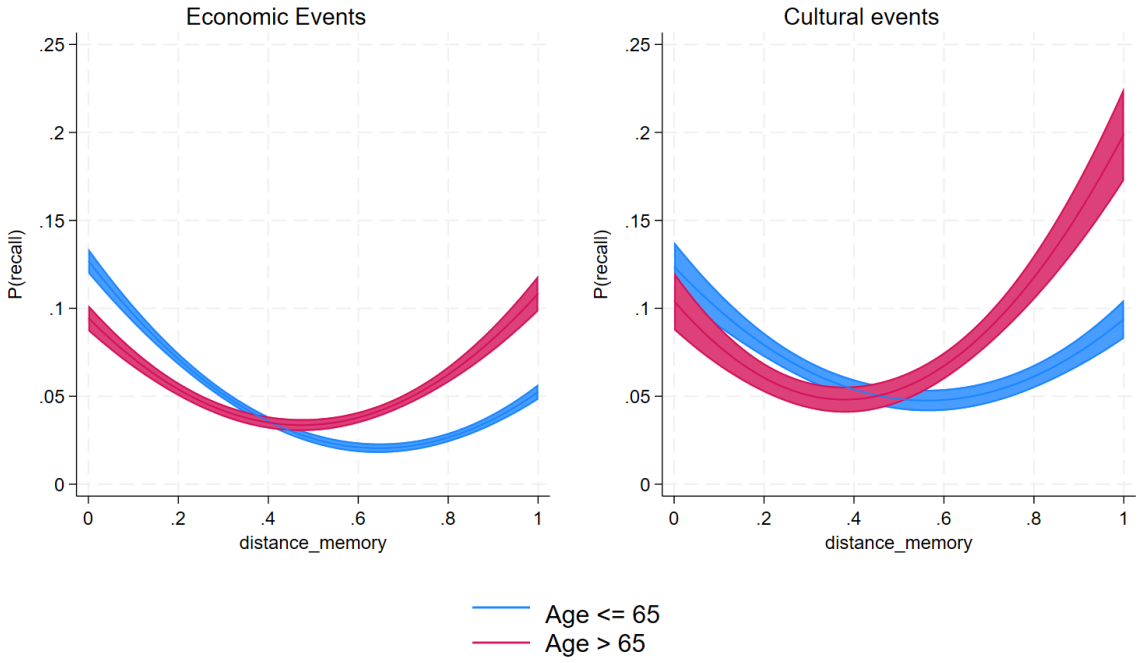


Figure 5: Primacy and Recency by Age Cohort

Note: Marginal effects based on estimated coefficients corresponding to Table 2 split by age cohort, for economic events (column 3) and cultural events (column 4). Shaded areas show the 95% confidence intervals, reflecting the uncertainty of the estimates.

5 Similarity and Simulation

In this section, we test whether recalling more similar events is associated with simulating a higher probability of a given event, consistent with prediction 2. The simulated event is a crash of the German stock market index DAX, and we therefore assume that recalled past events with a negative recalled stock market impact are more similar to the simulated event. Specifically, we test whether more negative memories are associated with higher perceived tail risk, and we report the results for both our direct measure of downside tail beliefs, and the "Bloom" distribution based measures.

Test using Direct Measure of Downside Tail Beliefs To implement the empirical test based on our direct measure, we follow Bordalo et al. (2025) in constructing a composite measure of an individual's tail belief based on the z-score of her perceived magnitude and probability of a stock market crash. Specifically, we define an individual's perceived tail risk as the average of her standardized answers to the probability and magnitude question, that is

$$tailRisk_i = \left(\frac{prob_i - \overline{prob}}{std(prob)} + \frac{mag_i - \overline{mag}}{std(mag)} \right) /2, \tag{8}$$

where $prob_i, mag_i$ are individual i's answer to the probability and magnitude questions regarding a crash of the German stock market index DAX within the next 12 months, and $\overline{prob}, \overline{mag}$, $std(prob), std(mag)$ the corresponding cross-sectional averages and standard deviations. The rationale behind this choice is the following. Consider two individuals with equal probability assessment $prob_1 = prob_2$. However, suppose the first individual has estimated this probability for a much stronger crash scenario, e.g. $mag_1 = 2mag_2$. Clearly, we want to assign a higher perceived crash risk to the first individual compared to the second, since their answers imply a larger perceived probability of a stock market crash of fixed magnitude for the first individual, $prob_1(\overline{mag}) > prob_2(\overline{mag})$.[11] To ease interpretation, we finally take the z-score of the combined measure, $tailRisk_i$.

Correspondingly, we measure the similarity of an individual's recalled memories, by a combined z-score measuring the negativity of her recalled events. Mirroring the definition of the tail belief measure, our memory negativity measure is constructed as a combined z-score of the fraction of recalled negative events and the average market impact of these events recalled by the individual, that is

$$memoryNegativity_i = \left(\frac{fracNeg_i - \overline{fracNeg}}{std(fracNeg)} + \frac{impact_i - \overline{impact}}{std(impact)} \right) /2. \tag{9}$$

To ease interpretation, we finally take the z-score of the combined measure, $memoryNegativity_i$.

We then regress our measure of perceived tail risk on our measure of memory negativity, controlling for a number of potential confounding factors captured by X_i:

$$tailRisk_i = \beta_0 + \beta_1 memoryNegativity_i + \gamma X_i + \epsilon_i \tag{10}$$

The central test of prediction 2 is whether $\beta_1 > 0$. We control for objective lifetime experiences, as they might affect individuals' beliefs through channels other than the

[11] An alternative would be to define the tail risk measure as the product of the two measures, i.e. $tailRisk_i = prob_i \times mag_i$. However, we stick with the approach of Bordalo et al. (2025) as it is more robust to measurement error in reported probabilities and magnitudes.

postulated memory channel. We also control for personal experiences of economic and other hardships, as such personal memories might affect individuals' estimated tail risk in addition to their memories about aggregate outcomes. Finally we control for our ATM measure, age, age squared, and a host of other socio-demographic variables. The error term captures idiosyncratic noise in survey data.[12]

The left panel of Table 3 (columns 1 to 3) shows the result for the sub-sample of respondents from whom we elicited their memories about economic events, while excluding the sub-sample of respondents who subsequently received an information treatment (the effect of the information treatment will be the subject of section 6). Across all specifications, we observe that the coefficient on the memory negativity index, β_1, is positive and significantly different from zero. By contrast, the association with *objective* lifetime experiences is insignificant when controlling for subjective memories of economic events. Our results suggest that measuring individuals' memories represents an important ingredient for explaining individuals' tail beliefs. Individuals' subjectively recalled events and their market impact may deviate from their objective lifetime experiences, and these subjective memories display a stronger association with individuals' beliefs. These results, including $\beta_1 > 0$, hold not only when measuring individuals' memories prior to eliciting their beliefs, but also when eliciting memories only after beliefs (as documented in appendix section A.6). We note that personal experiences of economic hardships are associated with higher perceived tail risk as well. This suggests individuals use not only memories of aggregate events to simulate tail events, but also memories of personal experiences.

The right panel of Table 3 (columns 4-6) shows that we also obtain $\beta_1 > 0$ for the subset of respondents asked to recall cultural events. In fact, the β_1 coefficient in the cultural frame is even larger than in the economic frame. We attribute the larger effect to the cleaner distinction between positive and negative memories in the cultural frame, as suggested by the descriptive evidence on their memories in section 3.6. The coefficient on objective lifetime stock market volatility is positive in all but the last specification (where age controls mediate its effect). Hence, higher experienced lifetime volatility is associated with higher tail beliefs. The coefficient on objective lifetime stock market returns is negative, so lower lifetime returns are associated with higher tail beliefs. Consistent with the coverage of events in the two memory elicitation frames (see section 3.6), memories of cultural events do not fully crowd out the effects of objective stock market experiences, whereas this is the case for memories of economic events. In sum, more negative memories are associated with higher tail beliefs in both the economic and the cultural frame consistent with prediction 2.

Spillovers across Domains The large coefficient of memory negativity in the cultural frame suggests that both domain-specific (DS) and non domain-specific (NDS) memories may influence expected tail risk. To test this point more directly, we replace the separation into economic and cultural events by a separation into DS and NDS events.[13] Table A.8 shows that negativity in both DS memories (column 2) and NDS memories (column 3) is positively associated with higher tail risk. When we include both DS and NDS memories in the same specification (column 4) both coefficients remain positive, but only DS memories are statistically significant. Hence, negativity in both DS and NDS memories is

[12] With slight abuse of notation, we denote the error terms in *all* regressions throughout the paper by ϵ, taking it as common knowledge that the ϵ will typically not be the same across different specifications.

[13] The separation into domain-specific (DS) and non-domain specific (NDS) events used for this analysis is shown in Table A.12. While such a separation is never unique, our results also hold under reasonable perturbations of the separation into more versus less domain-specific events.

positively associated with higher expected tail risk, but consistent with feature similarity, the link is stronger for DS memories. Regarding personally experienced hardships, Table A.9 shows that both economic hardships (column 1) and other hardships (column 2) display a positive association with perceived tail risk, while only the former stays significant in the joint specification (column 3 and 4). Foreshadowing the results for the Bloom distribution measure, we document in Table A.10 that the signs of the coefficients for DS and NDS memories are the same across all outcome variables, both individually (panel B and C), and in the joint specification (panel A). Similar to Table A.8, the association is stronger for DS memories than for NDS memories. Personal hardships are significantly associated with a more negative lower tail, while the coefficients of economic and other hardships are not statistically different from each other in the case of the Bloom question (see Table A.9). Overall, the results are consistent with spillovers across domains and the principle of similarity.

Test using Bloom Distribution Measures The Bloom distribution measure provides an additional test of prediction 2, and allows us to investigate how individuals' memories affect different parts of their subjective distributions. Figure 6 illustrates the relationship between the memory negativity measure defined in equation 9, and the 10th percentile, mean, and 90th percentile of the Bloom measure of each individual's subjective distribution of the return of the stock market index DAX over the next 12 months. The figure shows that larger memory negativity is associated with a more negative 10th percentile of perceived future stock market returns. The 10th percentile of returns goes from roughly 0% to -15% when the standardized measure of memory negativity goes from -1 to 2. In other words, a one standard deviation increase in memory negativity is associated with a roughly 5% more negative stock return in the lower tail of an individual's subjective distribution. As the 90th percentile (measuring upside risk) is largely orthogonal to memory negativity, more negative downside tail risk mechanically leads to a lower average expected return. These findings are confirmed in Table 4, which shows a statistically significant negative association between the memory negativity index and the 10th percentile (column 3), while the association with the 90th percentile is neither economically nor statistically significant. Memory-related higher downside tail risk is also associated with a lower (mean) expected return and a higher standard deviation of the subjective return distribution. This holds for both economic events (columns 1 to 4) and cultural events (columns 5 to 8).[14]

We can rationalize these results in light of the memory-based model of belief formation. Following Bordalo et al. (2025), assumption 2 states the simulated probability of an event H is given by:

$$\hat{\pi}_E = \sum_{e \in E} r(e)\sigma(e) \tag{11}$$

We can extend this model to probability distributions, by noting that each bin of the

[14]Figure 6 and Table 4 show the results after dropping respondents with implausible observations in the Bloom distribution question. Specifically, we drop respondents who report a worst case scenario return of positive 10% or more. This is motivated in particular by the fact that while for most respondents more negative worst case scenario returns are associated with higher magnitudes of a stock market crash in the direct question, the opposite holds for respondents reporting a worst case scenario of positive 10% or more (roughly a third of respondents), which renders their answers in the Bloom question implausible (see Figure A.2, panel magnitude). We conjecture this happens because respondents are not always careful in putting a negative sign before their negative scenarios in the Bloom question (while there is no need to sign their answer in the direct tail magnitude question). That being said, it is important to note that the results continue to hold if we do not impose this plausibility condition, and simply include all respondents (see Table A.13).

Bloom distribution measure defines an event. For instance, the worst case scenario may encode returns of -15% or more, the bad scenario may encode returns above -15% but below -5%, and so on for the neutral, good, and best scenario, with the bounds of the bins given by the individual-specific endogenously assigned returns for each scenario.[15] Hence, by applying equation 11 to each of the individual-specific bins, we obtain model predictions for the Bloom probability distribution reported by each individual. To ensure that the probability mass of the resulting distributions sums to 1, we can additionally assume that

$$\hat{\pi}_k^{final} = \hat{\pi}_k / \sum_{j=1}^{K} \pi_j \quad \text{(Assumption 3)} \tag{12}$$

where $k = 1, \ldots, K$ refers to the number of bins of the distribution. We can think of this normalization step as follows. When we ask respondents to rate the likelihood of their chosen scenarios by assigning values between 0 and 100, they first use equation 11 to determine the subjective probability of each event (bin). In a second step, they use equation 12 to normalize the sum of the probability mass across bins to 1 (or in fact 100 in the survey question), in effect proportionally increasing or decreasing the probability assigned to each bin. Individuals may perform this normalization either because they intrinsically require their resulting probability distribution to be normalized, or because the survey question requires them to normalize the sum of the probability mass assigned across bins. Conceptually, we note that the normalization step is not crucial in the sense that decisions in an expected utility framework would not depend on the normalization of the probability weights, what matters are the relative proabilitiy weights assigned to different outcomes.

We can use this conceptual framework to sharpen the interpretation of our estimates in Table 4. In particular, we observe that memory negativity lowers the 10th percentile of individuals' return distributions, as well as the mean of individuals', while it is not significantly associated with their 90th percentile. The effect on the 10th percentile is roughly 2.5 times stronger than the effect on the mean. Our estimates imply that an individual with higher memory negativity perceives a worst case scenario of given magnitude as more likely than an individual with lower memory negativity. By contrast, these individuals do not differ systematically in the likelihood of a given best case scenario. In other words, the distribution of a high memory negativity individual is more skewed to the left. The heavier lower tail in combination with an identical upper tail mechanically leads to a lower mean by a smaller amount, and a larger dispersion of the subjective return distribution, which is exactly what we find in Table 4.

Figure 7 visualizes the resulting probability distributions for respondents in the bottom 10th percentile and top 90th percentile of the memory negativity distribution. The figure clearly shows that selective recall of memories by different respondents is not just associated with a shift of their probability distribution about future stock market outcomes. Instead, respondents with more negative memories (p10) report probability distributions with a heavier lower tail, while their upper tail is largely unchanged. Our findings are distinct from a simple location shift of the entire distribution, which would affect the mean and all quantiles equally, while leaving the standard deviation of the distribution

[15] More precisely, we define bin boundaries as the midpoint of the distance between the returns assigned by individuals to each scenario. For instance, suppose the worst case scenario gets assigned a value of -15%, the bad scenario gets assigned a value of -5%, and the neutral scenario a value of 5%, then the lowest bin of the resulting probability distribution is defined as -10% or worse, whereas the bad scenario goes from -10% to 0%.

unchanged.[16]

In sum, the 10th percentile of individuals' return distribution displays a strong negative association with memory negativity, while the 90th percentile is largely orthogonal. Memories of negative events are similar (and hence likely to be recalled) when thinking about worst case scenarios, while the upside scenario is similar to a different type of events and hence largely uncorrelated with the recall of negative events.

Regular Experiences and Tail Experiences We have shown that respondents with more negative memories entertain probability distributions with a heavier lower tail (Table 4), and that this relationship holds for domain-specific and, to a smaller extent, for non-domain specific memories (Table A.10), consistent with the principle of similarity. In addition, we can investigate whether memories of tail experiences are more strongly correlated with individuals' beliefs than memories of regular experiences. To this end we compute terciles of the distribution of recalled DAX impacts of the recalled tail events across respondents. We take an individual's share of memories in the bottom tercile of this distribution as a proxy for her recall of downside tail memories, the middle tercile as a proxy for her regular memories, and the top tercile as a proxy for her upside tail memories.

Table 5 shows estimates from regressing the mean, standard deviation, 10th percentile, and 90th percentile of each respondent's Bloom distribution on the share of memories in each tercile. We find that the bottom tercile (downside tail memories) displays the largest association with both tail beliefs, R_{p10}, and mean beliefs, $E(R)$. This holds across both elicitation frames (economic and cultural memories). The absolute magnitude of the association between tail experiences (bottom tercile) and mean beliefs is stronger than that of regular experiences (middle tercile), suggesting an influential role for recalled extreme negative events in shaping individuals' beliefs across the distribution. Respondents' share of upside tail memories (top tercile) is positively associated with their mean beliefs in the economic events frame, but close to zero in the cultural events frame. Moreover, the probability distribution of respondents' with a larger share of downside tail memories has a larger dispersion (SD) than the distribution of respondents with a larger share of regular or upside tail memories. Consistent with our findings above, we observe that downside tail memories display an even stronger (negative) association with the 10th percentile of individuals' return distributions, than with their mean, implying that their subjective return distribution differs in shape. By contrast, regular memories tend to be associated with a reversal of this change of shape, increasing the 10th percentile, and in fact slightly compressing the distribution by also decreasing the 90th percentile. In sum, our results suggest extreme downside memories can help to understand not only tail beliefs, but also mean beliefs about future stock market returns.

[16] Our modeling approach is similar to Gennaioli et al. (2024), who show that eliciting probability distributions entails different cues than eliciting point estimates. In the limiting case where the cues of our probability distribution or tail probability point estimates completely determine individuals' recall, we might have found no systematic association between these measures and individuals' memories in the category-cued free-recall question preceding them. For instance, if cueing an extreme negative bin makes all respondents recall the financial crisis of 2008 and the Covid crash of 2020, then their more selective recall in the category-cued free-recall task preceding belief elicitation might become irrelevant. By contrast, we find robust evidence for a link between memory negativity in the category-cued free-recall task and tail beliefs across both elicitation frames, clarifying that while cueing can have important effects on beliefs, selective recall also remains key for explaining belief heterogeneity across respondents.

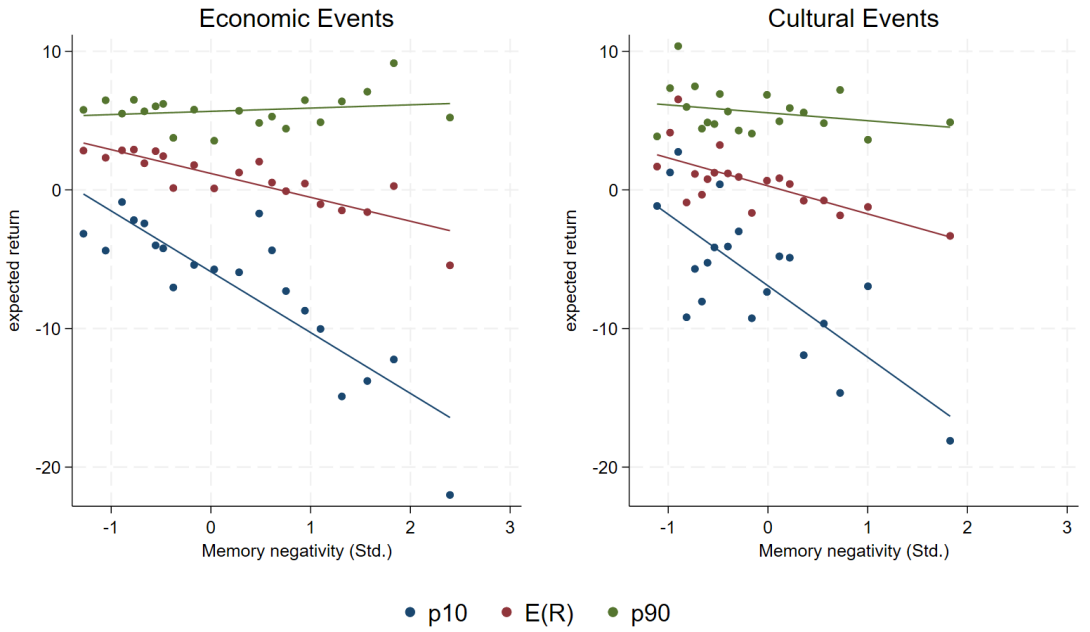


Figure 6: Return Expectations and Memory negativity

Note: Binned scatterplots showing the relationship between the memory negativity measure, defined in equation 9, and the 10th percentile, the mean, and the 90th percentile of each respondent's subjective distribution of DAX returns over the next 12 months. Includes controls for the full set of covariates, as reported in Table 4.

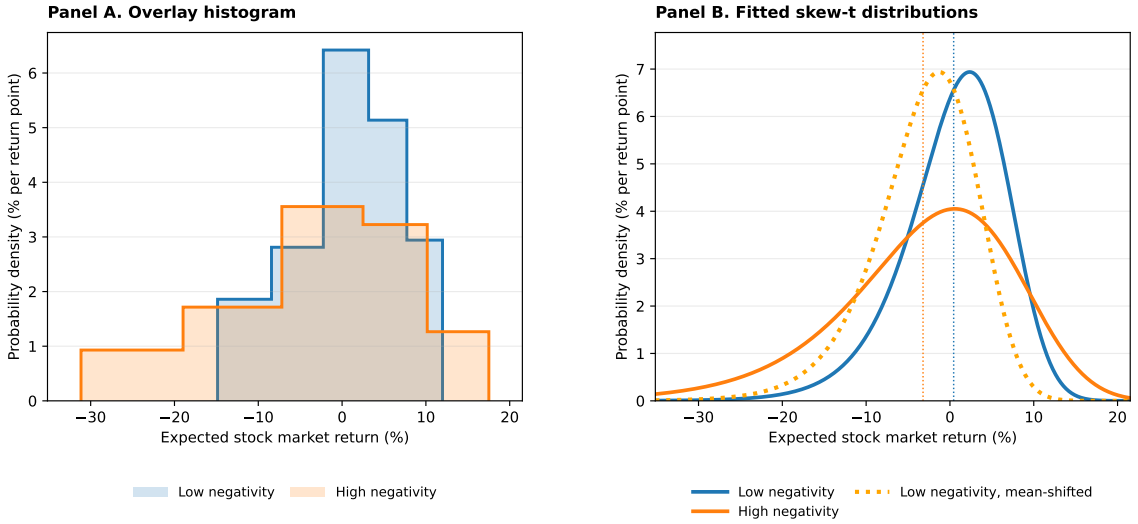


Figure 7: Return Distribution and Memory negativity

Note: Histogram (Panel A) and fitted distribution (Panel B) for high memory negativity and low memory negativity individuals. High (low) memory negativity individuals are those in the top (bottom) 10th percentile of our memory negativity measure defined in equation 9. Panel A displays histograms resulting from individuals' answers to the Bloom subjective distribution question, averaged across all individuals in the respective group (low memory negativity, high memory negativity). Panel B displays skew-t distributions fitted to the histograms in Panel A. The blue line shows the average subjective probability distribution of low memory negativity individuals. The solid orange line shows the same distribution for high memory negativity individuals. For comparison, the dotted orange line shows a counterfactual mean-shift of the low negativity distribution by the same amount of the change in the mean of the high negativity group. Hence, the comparison between the solid orange line (high negativity individuals), and the dotted orange line shows the extent to which the distribution of high memory negativity individuals changes shape relative to a hypothetical mean-shift only.

Table 3: Tail Belief (Direct Measure) as Function of Memory Negativity

	Economic events			Cultural events		
	(1)	(2)	(3)	(4)	(5)	(6)
Lifetime experiences						
Stock market volatility	0.005	-0.003	-0.184	0.151**	0.162**	-0.321*
	(0.044)	(0.044)	(0.125)	(0.071)	(0.070)	(0.186)
Stock market return	0.063	0.059	0.027	-0.142*	-0.177**	-0.161
	(0.048)	(0.048)	(0.128)	(0.076)	(0.073)	(0.186)
Recalled events						
Negativity Index	0.130***	0.130***	0.120***	0.225***	0.220**	0.244***
	(0.032)	(0.031)	(0.032)	(0.085)	(0.088)	(0.087)
Personal experiences						
Personal hardship		0.083**	0.095***		0.159***	0.158***
		(0.038)	(0.037)		(0.060)	(0.055)
Memory post	0.005	0.010	0.013			
	(0.063)	(0.063)	(0.061)			
CONTROL	No	No	Yes	No	No	Yes
R^2	0.03	0.04	0.06	0.04	0.07	0.11
N	1559	1559	1559	814	814	814

Note: Memory negativity is positively associated with the direct measure of tail beliefs. The dependent variable is the standardized tail belief summary index, constructed from respondents' perceived probability and perceived magnitude of a stock market crash (eq. 8). Columns (1)–(3) use respondents assigned to the economic-events memory elicitation, while columns (4)–(6) use respondents assigned to the cultural-events memory elicitation. The memory negativity index is defined in equation 9. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. *Personal experience* captures respondents' number of reported experiences of hardship. All explanatory variables are standardized to ease interpretation. *Memory post* is an indicator for respondents whose memories were elicited after belief elicitation. *Controls* include the full set of socio-demographic characteristics and the ATM estimate, described in Section 3.5. Regressions use survey weights. Huber–White robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Tail Belief (Bloom Measure) as Function of Memory Negativity

	Economic events				Cultural events			
	(1) E(R)	(2) SD	(3) R_{p10}	(4) R_{p90}	(5) E(R)	(6) SD	(7) R_{p10}	(8) R_{p90}
Lifetime experiences								
Stock market volatility	2.030**	0.533	2.265	1.357*	0.156	-0.660	0.258	-0.155
	(0.848)	(0.734)	(1.711)	(0.807)	(1.478)	(1.064)	(2.952)	(1.190)
Stock market return	-0.122	-0.616	-0.600	-0.115	1.526	-0.488	1.701	1.261
	(0.727)	(0.664)	(1.951)	(0.817)	(1.164)	(0.785)	(2.343)	(1.233)
Recalled events								
Negativity Index	-1.714***	1.485***	-4.400***	0.292	-2.020***	1.451***	-5.139***	-0.498
	(0.266)	(0.194)	(0.525)	(0.267)	(0.405)	(0.378)	(0.903)	(0.400)
Personal experiences								
Personal hardship	-0.118	0.225	-0.722	0.135	-0.682*	0.176	-1.022	-0.169
	(0.250)	(0.190)	(0.498)	(0.256)	(0.356)	(0.283)	(0.671)	(0.353)
Memory post	0.390	-0.650*	1.733*	-0.251				
	(0.475)	(0.344)	(0.940)	(0.472)				
CONTROL	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.13	0.20	0.20	0.04	0.13	0.13	0.17	0.07
N	1017	1017	1059	1059	572	572	598	598

Note: Memory negativity is associated with a more pessimistic downside tail of respondents' subjective return distributions. The dependent variables are moments of each respondent's subjective distribution of DAX returns over the next 12 months, elicited using the Bloom measure: the mean expected return $E(R)$, the standard deviation SD, the 10th percentile R_{p10}, and the 90th percentile R_{p90}. Columns (1)–(4) use respondents assigned to the economic-events memory elicitation, while columns (5)–(8) use respondents assigned to the cultural-events memory elicitation. The memory negativity index is defined in equation 9. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. *Personal experience* captures respondents' number of reported experiences of hardship. *Memory post* is an indicator for respondents whose memories were elicited after belief elicitation. *Controls* include the full set of socio-demographic characteristics and the ATM estimate, described in Section 3.5. Regressions use survey weights. Huber–White robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Tail Belief (Bloom Measure) as Function of Tail and Regular Experiences

	Economic events				Cultural events			
	(1) E(R)	(2) SD	(3) R_{p10}	(4) R_{p90}	(5) E(R)	(6) SD	(7) R_{p10}	(8) R_{p90}
Share Memories in								
Bottom Tercile	-0.032***	0.027***	-0.085***	0.008	-0.044***	0.031***	-0.115***	-0.012
	(0.006)	(0.005)	(0.012)	(0.006)	(0.011)	(0.009)	(0.023)	(0.010)
Middle Tercile	0.013**	-0.037***	0.077***	-0.032***	0.031***	-0.048***	0.112***	-0.015
	(0.006)	(0.004)	(0.012)	(0.006)	(0.010)	(0.008)	(0.020)	(0.010)
Top Tercile	0.027***	0.004	0.025*	0.024***	0.003	0.043***	-0.049	0.039**
	(0.007)	(0.005)	(0.014)	(0.007)	(0.017)	(0.014)	(0.038)	(0.015)
CONTROL	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lifetime experience	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Personal experiences	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Memory post	Yes	Yes	Yes	Yes	No	No	No	No

Note: Downside tail memories display stronger association with mean and tail beliefs than regular or upside tail memories. The independent variables are the share of a respondent's memories that fall within the first, second, and third tercile of the distribution of recalled DAX impacts of the recalled tail events, across all respondents. To avoid perfect multicollinearity, the table displays the coefficients for separate regressions for each memory tercile. The dependent variables are moments of each respondent's subjective distribution of DAX returns over the next 12 months, elicited using the Bloom measure: the mean expected return $E(R)$, the standard deviation SD, the 10th percentile R_{p10}, and the 90th percentile R_{p90}. Columns (1)–(4) use respondents assigned to the economic-events memory elicitation, while columns (5)–(8) use respondents assigned to the cultural-events memory elicitation. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. *Personal experience* captures respondents' number of reported experiences of hardship. *Memory post* is an indicator for respondents whose memories were elicited after belief elicitation. *Controls* include the full set of socio-demographic characteristics and the ATM estimate, described in Section 3.5. Regressions use survey weights. Huber–White robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6 Response to Information

Individuals' response to new information provides an additional dimension for testing the model of memory-based belief updating. As explained in section 2.4, individuals' belief revisions in response to information treatments allow us to test for systematic heterogeneity in similarity functions and for interference effects. We embed an RCT in our memory wave, in which we randomize respondents into different subgroups depending on the type and ordering of memory elicitation, and on whether or not they receive an information treatment. For the group *econ pre, cultural* and *info* we elicit memories prior to beliefs, whereas the ordering is reversed for *econ post*. The group *cultural* receives a different memory elicitation question than the other groups (see section 3 for details). The only group that receives an information treatment is the group *info*.

Average Treatment Effects We first assess whether there are significant differences in perceived tail risk across the different subgroups, using the following specification:

$$tailRisk_i = \delta_0 + \delta_1 econPost_i + \delta_2 cultural_i + \delta_3 info_i + \gamma X_i + \epsilon_i \tag{13}$$

where $econPost$, $cultural$, and $info$ are dummy variables indicating the respective treatment group. Thus, $econPre$ is the omitted category with belief revision δ_0. δ_1, δ_2, and δ_3 measure the difference in the belief revision of *econPost*, *cultural*, and *info* relative to *econPre*. We control for a vector of respondent characteristics, although we expect the effect of adding controls to be small, given that the group dummies *econPost*, *cultural*, and *info* are approximately orthogonal due to randomization.

Figure 8 visualizes the treatment effects estimated in equation (13). The first important insight from this RCT is that the ordering of memory elicitation has no effect on the level of reported tail risk. This result rules out many mechanical explanations for the observed link between (similar) memories and tail beliefs documented in section 5. In particular, if the act of eliciting individuals' memories would change their beliefs relative to the beliefs they would have simulated without prior memory elicitation, we would have observed differences in the beliefs reported in the group *econ post* compared to *econ pre*. We observe a small positive difference between *cultural* and *econ pre*, suggesting that the cultural frame stimulated individuals' recall somewhat more than the economic frame, consistent with our results in section 5. The second observation from this introductory specification is that information about past crises leads to markedly higher perceived tail risk. Individuals' memory database can be incomplete and hence the effect of the information treatment can be interpreted as adding a set of negative experiences to their database, leading to an upward revision of their perceived tail risk consistent with proposition 1. Given this, we can exploit individuals' response to the information treatment to test for systematic heterogeneity as motivated by the representativeness heuristic against the alternative of homogeneous similarity functions across individuals.

Heterogeneity Consider two groups of individuals who differ in the share of recalled negative experiences prior to the treatment. Suppose group j recalled a larger share of negative experiences than group k, and/or the perceived impact of the recalled events was more negative. According to prediction 3, belief updating under representativeness can lead to a larger belief revision of group j compared to group k, controlling for other dimensions of heterogeneity. This prediction represents a stark contrast to a model where similarity functions are not systematically different across respondents.

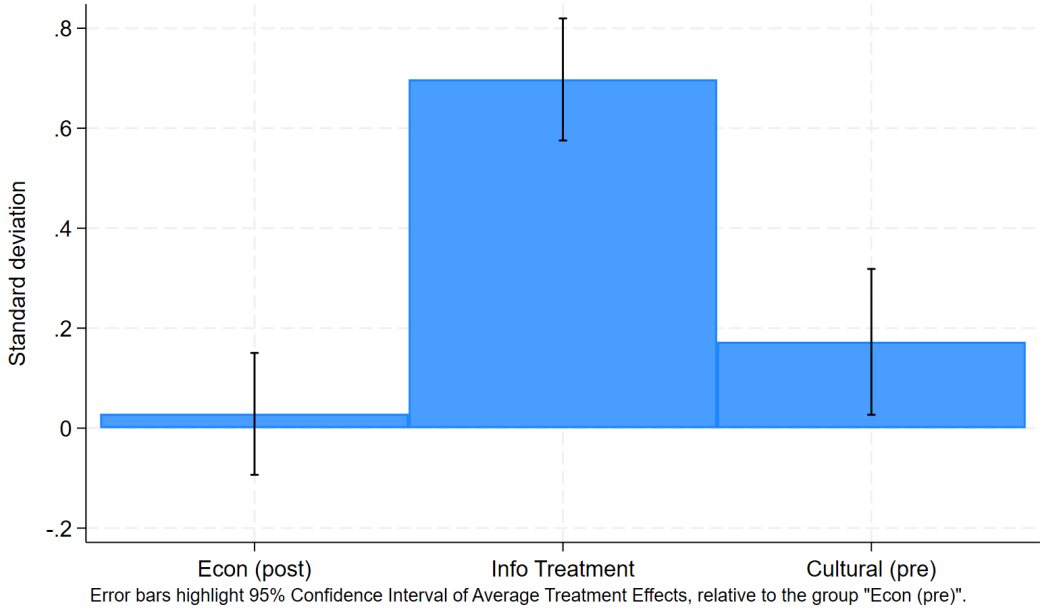


Figure 8: Treatment effects with respect to tail risk index

Note: The figure reports average treatment effects on the standardized tail risk summary index, estimated using equation 13, relative to the baseline group *Econ (pre)*, in which respondents report economic memories before belief elicitation. *Econ (post)* elicits economic memories after belief elicitation, *cultural (pre)* elicits cultural memories before belief elicitation, and *Info Treatment* elicits economic memories before providing information about past stock market crashes. Estimates control for the full set of covariates described in Section 3.5. Bars show 95% confidence intervals.

To test these competing predictions, we estimate the following specification, in which we interact the effect of the information treatment with the relevant dimensions of heterogeneity:

$$tailRisk_i = \delta_0 + \delta_1 info_i + \delta_2 het_i + \delta_3 info_i \times het_i + \gamma X_i + \epsilon_i \tag{14}$$

where the sample consists of all individuals who received the information treatment and all individuals in the *memory pre* group, who received the same set of questions but no information treatment. het_i is a binary indicator that indicates if a respondent is above (1) or below the median (0) of a given measure of heterogeneity.

Table 6 documents the resulting regression coefficients and their standard errors, with column headers indicating the dimension of heterogeneity used as interaction variable. The first line of column (1) shows the effect of the information treatment is positive, that is the treatment caused an increase in perceived tail risk relative to the reference group of untreated individuals in *memory pre*, consistent with Figure 8. The interaction term (second line) shows that respondents with high prior memory negativity reacted significantly *more* strongly to the treatment, by a magnitude of 0.22 standard deviations in perceived tail risk (or 45 percent of the treatment effect for low prior memory negativity individuals). Columns (2) and (3) show the results hold for both sub-components of the negativity index. Thus, consistent with prediction 3 (representativeness), respondents with more negative prior memories, respond to the treatment with a larger upward revision of their tail risk beliefs. These observations run counter to standard updating rules in which (objectively) more surprised agents should respond more to the information treatment.

Table 6: Heterogeneity of Treatment Effects

	Representativeness			Interference	
	(1) Negativity Index	(2) Share negative events	(3) Magnitudes	(4) Age	(5) Hardship
Treat	0.48***	0.50***	0.44***	0.70***	0.58***
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
High × Treat	0.22**	0.21**	0.25***	-0.25***	-0.01
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
CONTROL	Yes	Yes	Yes	Yes	Yes
Lifetime experiences	Yes	Yes	Yes	Yes	Yes
R^2	0.12	0.12	0.13	0.12	0.11
N	1619	1909	1619	1909	1909

Note: The table reports estimates from equation 14, where the effect of the information treatment is interacted with binary indicators for whether a respondent is above the median of the respective heterogeneity variable. Columns (1)–(3) test heterogeneity related to representativeness: the memory negativity index defined in equation 9, the share of recalled events with a negative DAX impact, and the average recalled magnitude of these events. Columns (4) and (5) test heterogeneity related to interference, using respondents' age and reported personal hardship experiences. The dependent variable is the standardized tail risk summary index, constructed from respondents' perceived probability and perceived magnitude of a stock market crash (eq. 8). *Treat* denotes the information treatment and *High* × *Treat* denotes its interaction with the above-median indicator for the respective heterogeneity variable. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. *Personal experience* captures respondents' number of reported experiences of hardship. *Controls* include the full set of socio-demographic characteristics described in Section 3.5 apart from *age*. Regressions use survey weights. Huber–White robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Overall, we find evidence for systematic heterogeneity in similarity, consistent with the predictions of the representativeness heuristic. Our evidence illustrates the potential for the representativeness heuristic to provide a memory-based micro-foundation for diagnostic models of tail risk neglect, such as Gennaioli et al. (2015) or Bordalo et al. (2026), which can generate belief-driven boom-bust cycles in asset prices and credit. The representativeness heuristic may reflect deep subconscious psychological mechanisms, or "system 1" thinking (see, e.g., Kahneman 2011). In addition, similarity assessments could potentially be affected by somewhat more deliberate considerations such as mental models (see, e.g., Andre et al. 2022, 2026; Laudenbach et al. 2024; Beutel and Weber 2026) or motivated recall (see, e.g., Bénabou and Tirole 2002; Amelio and Zimmermann 2023). While subjective models of the economy may provide an alternative explanation for differential belief updating in response to news, they do not provide predictions on the link between prior memories and belief updating. Our evidence suggests that accounting for selective recall helps to explain the joint behavior of reported memories, beliefs, and individuals' response to information. Selective recall itself can be driven by several forces, including recency, primacy, and representativeness, as well as potentially by other factors such as motivated recall.

Interference Under the plausible assumption that older individuals have a larger database of experiences, they should face larger interference during recall. Therefore, controlling for other differences, older individuals should respond less to any information than younger individuals. Table 6 shows this is indeed the case, the interaction effect of age is negative

and statistically significant. Hence, older respondents react significantly less to the information treatment than younger respondents, controlling for other socio-demographic characteristics. Thus, the evidence from our information provision experiment is consistent with interference, supporting the findings of Bordalo et al. (2025). There are no significant interference effects from personal experiences of hardships for our information treatment. Table A.14 in the appendix shows that the results do not change when we include all heterogeneity variables and their interactions with the treatment into one regression. In other words, memory negativity, age (and hardship) are largely orthogonal and matter on their own, even controlling for the other dimensions of heterogeneity and their treatment interactions.

Bloom Tail Belief Measure We report the results for the 10th percentile of the return distribution based on the Bloom design in Figure A.3 and Table A.15 in the appendix. Consistent with the treatment effects on the direct measure of perceived tail risk, the information treatment leads to a significant downward revision of the 10th percentile of roughly 8 percentage points. (The mean decreases by roughly 2 percentage points, and the standard deviation increases by roughly 4 percentage points, consistent with our correlational evidence on changes in the shape of subjective distributions in section 5.) High memory negativity individuals, those with a larger share of negative memories, or larger tail magnitudes, react more strongly to the treatment consistent with representativeness, but these interaction effects are statistically not significant. (Notice how the coefficients for the Bloom p10 measures flip sign relative to the direct tail risk measure, as expected given their definitions.) Similarly, respondents in the high age group and those with more experienced hardships respond less to the treatment consistent with interference, but the interaction effects of age and hardship are again not statistically significant in the Bloom design.[17] Overall, the treatment interaction effects on the downside tail belief measure from the Bloom design are qualitatively consistent with our results for the direct measure, while they do not share their statistical significance.

7 Pass-through from Tail Beliefs to Decisions

A key question is whether and how individuals' tail beliefs translate into decisions such as investing in the stock market or buying a home. We start by presenting motivating evidence, showing a strong correlation between tail beliefs and individuals' inclination to invest in real estate or equity. Yet, correlations between beliefs and outcomes may suffer from endogeneity or omitted variable bias. To overcome this identification challenge we design a news provision module, allowing us to investigate whether treatment-induced belief revisions affect respondents' views on whether they see it as a good time to invest in equity or housing. Moreover, we present additional evidence from a dedicated decision module, showing how individuals plan to adjust their financial portfolios in different scenarios.

Motivating Evidence We elicit individuals' post-treatment assessment of the timing of stock and housing market investments using the following question.

[17] These results are obtained after cleaning implausible responses as explained in footnote 14. Without this step, the Bloom design would yield insignificant results for both the average effect of the information treatment and the heterogeneity across respondents.

Do you think now is a good or a bad time to ... ?
(a) ... buy property (house / apartment)
(b) ... invest money into the stock market

Answers are given on a 5-point Likert scale (very bad, bad, neither good nor bad, good, very good).

Table 7 provides correlational evidence from an OLS regression of individuals property or equity market assessment ('good time to buy') on their tail beliefs and their mean beliefs, as well as on the full set of socio-demographic control variables, including income, education, and wealth. This regression is restricted to control group individuals, thus showing pure correlations, without any treatment interventions. Control group individuals are asked for their assessments of all four tail scenarios in the first news provision module. Since the answers in the question eliciting scenarios jointly tend to be strongly correlated within individuals, we aggregate the four scenarios into an average tail belief across scenarios.[18]

In line with intuition, we find that higher perceived tail risk is associated with a lower inclination to invest in real estate or property (columns 1 and 4). Conversely, a higher expected price growth for real estate, and a higher expected stock return, is associated with being more inclined to invest in real estate or property (columns 2 and 5). The strong effect of tail beliefs is robust to controlling for mean beliefs in the same regression (columns 3 and 6). All variables are standardized and hence the coefficient sizes can be compared across variables. For instance, a one-standard deviation higher tail risk perception, is associated with a 0.16 standard deviation lower inclination to invest in property, while a one standard deviation higher mean house price growth beliefs is associated with a 0.1 standard deviation higher inclination to invest in property. Overall, the results in Table 7 suggest a potentially important role for tail beliefs in affecting household decisions, even after controlling for differences in mean beliefs. A distinct role for tail beliefs is consistent with our evidence on changes in the perceived shape of distributions documented in section 5, whereas measuring tail risk would be redundant in case of mean-shifts only.

While the estimates in Table 7 control for observable demographics including income, wealth, and education, there may be unobservable respondent characteristics and endogeneity which could bias the estimated coefficients. To name just one example, suppose an unobserved character trait such as low risk aversion simultaneously makes some individuals more inclined to invest in the stock market, and less likely to search for news about tail risks. The resulting negative correlation between perceived tail risk and inclination to invest in equity could be spurious in the following sense. The causal effect of an exogenous increase in perceived tail risk (e.g. due to personally experiencing a negative tail event) could be smaller in magnitude than suggested by the correlation, as lower risk aversion reduces the effect on these individuals' investment decision. The remainder of this section therefore focuses on measuring causal effects of treatment-induced exogenous variation in tail beliefs, which could potentially differ from the correlations observed in our motivating regression.

[18]The average tail belief is computed for each individual as the average of her tail risk measure (defined in equation 8) across the four disaster scenarios. Mean real estate beliefs are measured as the mean of individuals' probability density for real estate price growth reported in the core part of the survey (before any questions on tail beliefs). Mean stock return expectations are measured as individuals' expected change of the DAX stock market index (a return index).

Table 7: Correlations between Beliefs and Good Time to Invest

	Buy property			Buy stocks		
	(1)	(2)	(3)	(4)	(5)	(6)
Tail Beliefs						
Average across scenarios	-0.16***		-0.15***	-0.23***		-0.24***
	(0.05)		(0.05)	(0.07)		(0.07)
Mean Beliefs						
Real estate		0.10**	0.10**			
		(0.05)	(0.05)			
Stock market					0.15***	0.13***
					(0.05)	(0.05)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
N (control group)	940	959	919	940	904	889
R^2	0.070	0.057	0.075	0.091	0.084	0.122

Note: This table shows estimated coefficients from an OLS regression of good time to invest in real estate (left panel) and good time to invest in equity (right panel) on tail beliefs and central tendency beliefs. The regression is restricted to control group respondents and therefore reflects pure correlations without any treatment interventions. The control vector *Demographics* comprises respondents' gender, age, household income and household size, and dummies that indicate if respondents already retired, have at least a college degree, and if they lived in East Germany prior to re-unification. Huber-White robust standard errors are in parentheses. * indicates significance at the 90%, ** at the 95% and *** at the 99% level.

Exogenous Variation in Tail Beliefs Experimentally, we can generate exogenous variation in tail beliefs using information treatments in which different subsets of respondents receive different news about tail risks. Our news provision module is designed as a classic information provision RCT. We first elicit respondents' prior beliefs about the magnitude and probability of five disaster scenarios: i) new financial crisis, ii) new pandemic, iii) China-Taiwan escalation, iv) severe energy crisis, and v) systemic Cyber attack. We then randomize respondents into 11 treatment groups. For each of the 5 disaster types we field two treatment arms, a positive news treatment and a negative news treatment. One group serves as a control condition and receives no information. (The control group provides the sample for the motivating regression above.) Each respondent gets assigned to exactly one treatment group. After the treatment stage, we re-elicit respondents' tail beliefs using a slightly different question wording, thereby obtaining a measure of their belief revision.[19] We document in Table A.16 that respondents receiving a negative piece of news revise their perceived tail risk upwards relative to respondents receiving a positive piece of news (see column 2). Thus, as expected (see proposition 1), the treatments are successful in generating exogenous variation in respondents' tail beliefs. In addition, Table A.17 shows that the treatments rarely move individuals' mean beliefs, suggesting that the bulk of any treatment effects on individuals' inclination to invest in real estate or equity (documented below) operate through respondents' tail beliefs.

[19] Additional details on this RCT, and the exact treatment texts provided to each group are documented in appendix section A.11.

Timing of Stock and Housing Market Investments We have a positive and a negative information treatment for each disaster type, and we are interested in the wedge these treatments potentially drive into individuals' market assessments. We estimate the following regression specification for each disaster type:

$$y_i = \alpha + \beta T_i^{neg} + \delta X_i + \epsilon_i, \tag{15}$$

where y_i reflects respondent i's answer to the "good time to buy" question, respectively for property or equity, measured on a scale from 1 (very bad time to purchase) to 5 (very good time to purchase). T_i^{neg} is one if respondent i is in the negative treatment arm, and zero otherwise. Hence, α is the outcome in the positive treatment arm, and β is the outcome in the negative arm expressed as the difference to the positive arm.

Table 8 reports the coefficient of interest β for each disaster type (in rows), and across three specifications (in columns). The columns differ in the set of control variables included (socio-demographics, prior tail beliefs, and posterior mean beliefs). Our preferred specification is the one including all control variables (column 3), which provides the cleanest identification of the effect we want to measure. In particular, we include post-treatment mean beliefs to account for any indirect effects mediated by central tendency beliefs. That being said, the effects of the control variables tend to be minor. The left panel reports the results for property, and the right panel for the stock market.

Interestingly, the sign of the treatment effect for property market timing depends on the disaster type. For the financial crisis and the energy crisis, bad news makes respondents think it is a comparably bad time to buy property. Given a cross sectional standard deviation of 0.95, the effect sizes account for 26% of a standard deviation for the financial crisis scenario and 15% of a standard deviation for the Energy crisis scenario. By contrast, bad news about a potential conflict between mainland China and Taiwan, or about a new pandemic makes respondents think it is a comparably good time to invest in property. Both effect sizes are economically meaningful at around 15% of a standard deviation and statistically significant at conventional levels.

These effects are intuitive, and consistent with the view that memories of similar events in the past shape beliefs and decisions. The global financial crisis of 2008 was associated with a house price bust in the U.S. and many other countries, and more generally, tighter financial conditions have tended to be associated with lower housing valuations. Hence, based on recent experiences, individuals may lower their inclination to invest in the housing market, if they perceive a higher likelihood or magnitude of a financial crisis. Similarly, an energy crisis is likely to hurt economic growth and disposable incomes, and may evoke memories of past recessions, thereby reducing individuals' inclination to buy property. By constrast, when contemplating the consequences of a China-Taiwan conflict, which might potentially entail a clash between two of the world's superpowers, individuals might plausibly think there is no safe place to hide in financial markets. Instead, they may bet on a safe haven effect for German real estate, broadly consistent with past experiences.[20] Similarly, the Covid pandemic of 2020, and the resulting jump in remote work, was associated with a substantial increase in German residential real estate prices, such that the positive response of property market assessments to negative news about the risk of a new pandemic is in line with experience, too.

The heterogeneous response to different types of disasters is a novel finding with

[20]The German word "Beton-Gold" literally translates to "concrete-gold", and captures a widespread view that German real estate is a safe and stable investment, and a safe haven in times of crisis.

Table 8: Treatment effects - Good time to invest

	Buy property			Buy stocks		
	1	2	3	4	5	6
Financial Crisis						
neg. - pos.	-0.23***	-0.27***	-0.25***	-0.04	-0.07	-0.09
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
New pandemic						
neg. - pos.	0.09	0.14**	0.15***	-0.01	-0.03	-0.01
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
China-Taiwan conflict						
neg. - pos.	0.16***	0.15***	0.14**	-0.05	-0.06	-0.09
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Energy crisis						
neg. - pos.	-0.17***	-0.16**	-0.14**	-0.11*	-0.09	-0.12*
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Cyber attack						
neg. - pos.	0.07	0.05	0.02	-0.06	-0.06	-0.07
	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Demographics	No	Yes	Yes	No	Yes	Yes
Posterior mean beliefs	No	No	Yes	No	No	Yes
Prior tail beliefs	No	Yes	Yes	No	Yes	Yes

Note: Effect of treatments on good time to invest in property, and, respectively, stocks elicited from the two news provision modules. Separate regression for each crisis type. Dependent variables are a qualitative measure ranging from 1 to 5, where 1 implies a "very bad time to purchase" and 5 a "very good time". *Demographics* comprises respondents' gender, age, household income and household size, and dummies that indicate if respondents already retired, have at least a college degree, and if they lived in East Germany prior to re-unification. Regression uses survey weights. *Posterior beliefs* is a set of beliefs about central tendency of GDP growth, stock market returns (DAX), real estate price growth, and disposable household income growth over the next 12 months, elicited after the information treatment. *Prior tail beliefs* include respondents' beliefs about the level of tail risk (probability and magnitude) prior to the treatment, to account for any potential attenuation effects. Huber-White robust standard errors are in parentheses. * indicates significance at the 90%, ** at the 95% and *** at the 99% level.

potentially important implications. It suggests tail risk is not one-dimensional but multi-dimensional. Relying exclusively on probability distribution questions could lead to ambiguous results on the link between tail beliefs and investment decisions, given that the lower tail of the resulting distributions could reflect different types of tail risks, with possibly offsetting effects on investment decisions. By contrast, the real-world disaster scenarios used in our news provision module and our decision module help to uncover this heterogeneity across disaster types.

The effect on perceived good times to buy stocks is always negative, though statistically insignificant at conventional levels except for the energy-crisis treatment. Conceptually, a key difference between households' real estate and stock market investments is that the former are typically debt-financed (while this is rarely the case for German households' stock market investments). Losses on leveraged positions are nonlinear around collateral constraints making tail risk particularly consequential: when asset values fall sufficiently, borrowers may lose access to refinancing or be forced to delever, generating amplification effects emphasized in models of collateral constraints and leverage cycles (Kiyotaki and Moore, 1997; Geanakoplos, 2010; Brunnermeier and Sannikov, 2014).[21]

[21]The literature on delinquency and foreclosure during the 2008 housing crisis documents the household-level effects of leveraged real estate investments (Foote et al., 2008; Mian and Sufi, 2011).

By contrast, households can often "sit out" stock market losses, especially when they view themselves as long-term investors. Indeed, as we document below, the most frequently cited reasons for not adjusting financial portfolios are that households expect markets to recover after a crash and/or consider themselves hedged over the long run, a reasoning consistent with recent reversal experiences such as the rapid equity-market rebound after the Covid crash of 2020.

Additional Evidence from a Dedicated Decision Module To further quantify the causal impact of tail beliefs on decisions, we field a dedicated "decision module" in our final survey wave. In this module, we present respondents with hypothetical scenarios in which they are offered to adjust their financial portfolio and consumption choices based on exogenous shocks to their beliefs about tail risks. This vignette design introduces exogenous variation into individuals' tail beliefs (see, e.g., Andre et al. 2022) allowing us to estimate the elasticity of portfolio decisions to beliefs about tail events. [22]

Since the main focus of our paper is on the role of memories for the formation of tail beliefs, we only provide a brief summary of the results from this additional survey wave. For more details, we refer the interested reader to appendix A.12. One key result of our decision module is that households respond asymmetrically to changes in perceived risk: they reduce risky asset holdings in response to increased tail risk, but show little adjustment when risks decline. This pattern is consistent with models featuring loss aversion, in which increases in downside risk have a disproportionate effect on utility (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991). Adjustments are also event-specific: increased financial crisis risk reduces equity shares, while heightened pandemic risk lowers cash holdings, again consistent with past experiences. Another interesting result is that individuals frequently cite that they expect markets to recover, or consider themselves hedged as key reasons for not adjusting their portfolios in response to a shock to their tail beliefs. Such reasoning might contribute to tail risk neglect in decisions during good times, and could potentially flip into panic during busts.

In sum, our evidence on individuals' views about the timing of equity and real estate investments, and on their portfolio choices in different scenarios contributes to a recent literature showing how subjective beliefs can shape behavior, not only through expectations about the central tendency of macro-financial outcomes, but also through beliefs about rare events (see, e.g., Roth and Wohlfart 2020, Giglio et al. 2021, Beutel et al. 2021). Overall, our results suggest that memory-based models could help to better understand investor behavior and belief formation.

[22] Our decision module is related to a growing literature which treats survey-based intentions as informative for actual behavior. Evidence from spending behavior and portfolio allocations suggests that survey responses, even when not incentivized, often closely mirror real-world behavior. For instance, both past spending and spending intentions of households measured in surveys align with actual spending behavior measured in scanner or aggregate data (see, e.g., Bachmann et al. 2015; D'Acunto et al. 2022; Coibion et al. 2022). Hackethal et al. (2023) show portfolio and other decisions under uncertainty essentially do not differ between incentivized and non-incentivized survey experiments. In line with these findings, the pass-through from beliefs to portfolios in a non-incentivized survey experiment by Beutel and Weber (2026), is broadly similar to the pass-through in administrative data observed by Giglio et al. (2021). Clearly, where available, administrative data is ideal, and indeed Jiang et al. (2025) document a memory-mediated association between beliefs and brokerage accounts of Chinese investors.

8 Conclusion

Selective recall from memory offers a micro-foundation for the formation of tail beliefs and the impact of experiences. We show in a representative survey that memories of events spanning six decades shape beliefs about rare downside outcomes. Selective recall implies that memories are not merely noisy reflections of objective lifetime experiences; rather, they are retrieved selectively, and their link to beliefs about rare events depends systematically on temporal and feature similarity.

One of our central findings is that recall is governed by both recency and primacy. Events close to the time of recall and early-life experiences are disproportionately likely to come to mind. The primacy effect implies that formative episodes can remain salient long after they occurred and continue to shape beliefs decades later. This mechanism can generate cohort patterns in beliefs that differ sharply from those implied by recency alone.

The link between memories and tail beliefs operates through the perceived downside tail. Individuals who recall more negative events perceive higher stock market crash risk, even after controlling for objective lifetime experiences. Selective recall of past negative events does not simply shift individuals' subjective return distributions, it changes their perceived shape by disproportionately affecting downside risk. The relationship between domain and non-domain specific memories and subjective distributions is governed by the principle of similarity.

Memory can also shape belief dynamics. Respondents with more negative prior memories update more negatively in response to information about past crashes, despite being less surprised by this information under a standard learning rule. Moreover, older individuals respond less to information, controlling for prior memories and other characteristics. These patterns are consistent with a memory-based updating rule in which similarity, representativeness, and interference determine how new information is interpreted. The same information can therefore produce different belief revisions depending on the memories it evokes and the context in which it is processed.

Finally, tail beliefs matter for household decisions. Experimentally induced increases in perceived tail risk reduce risky investment, while declines in perceived risk have little effect. In addition, perceived safe-haven assets are event-specific: the same asset can be viewed as safe in one tail scenario and risky in another. Our results suggest perceived tail risk is multidimensional and context-dependent: understanding household portfolios requires knowing not only whether individuals are optimistic or pessimistic, but also which rare events they consider likely and which memories those events bring to mind.

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A Appendix

A.1 Proof of Proposition 1 (Memory-based Belief Updating Rule)

Consider a database E^0 to which a new experience e' is added, such that the new database is $E^1 = E^0 \cup e'$.

According to equation 3, the belief under the new database E_1 is:

$$\hat{\pi}^1 = \sum_{e \in E^1} r(e)\sigma(e) = \sum_{e \in E^1} \frac{S(e)}{\sum_{e \in E^1} S(e)} \sigma(e) \tag{16}$$

We can split this up into the contribution of the events in the prior database E_0 and the new event e':

$$\hat{\pi}^1 = \sum_{e \in E^0} \frac{S(e)}{\sum_{e \in E^1} S(e)} \sigma(e) + \frac{S(e')}{\sum_{e \in E^1} S(e)} \sigma(e') \tag{17}$$

$$= \underbrace{\frac{\sum_{e \in E^0} S(e)}{\sum_{e \in E^1} S(e)}}_{=1-r(e')} \underbrace{\sum_{e \in E^0} \frac{S(e)}{\sum_{e \in E^0} S(e)} \sigma(e)}_{=\hat{\pi}_0} + \underbrace{\frac{S(e')}{\sum_{e \in E^1} S(e)}}_{=r(e')} \sigma(e') \tag{18}$$

where the second and third underbrace follow directly from the definitions of the model. To obtain the first underbrace we note that

$$\frac{\sum_{e \in E^0} S(e)}{\sum_{e \in E^1} S(e)} = \frac{\sum_{e \in E^1} S(e) - S(e')}{\sum_{e \in E^1} S(e)} = 1 - r(e') \tag{19}$$

In sum, we obtain

$$\hat{\pi}^1 = (1 - G_E)\pi_0 + G_E \sigma(e') \tag{20}$$

where

$$G_E = r(e') = \frac{S(e')}{\sum_{e \in E^1} S(e)}. \tag{21}$$

A.2 Balance across Observable Characteristics

To document the comparability of treatment and control groups, we present balance tables summarizing key characteristics across the different experimental conditions for each of the four waves. We present sub-sample means and their standard errors for all socio-demographic characteristics. The key insight is that the randomization successfully preserves the balance of observables across the treatment groups.

Tables A.2 - A.4 show the balance between randomized subgroups along the following demographic characteristics. *Age* reports the mean age of respondents, *Female* is the share of women in the given sample. *College educ. or higher* shows the share of respondents who have at least a college degree. *Retiree* reports the share of respondents who have already retired. *Household size* is the average reported size of the household in which the respondent currently lives. *No. of children* reports the average number of children under the age of 18, who currently still live in the household. Regarding respondents' household income, we report the share of respondents with high income, defined as income *above 5000 EUR*, and with low income, defined as *below 1500 EUR*. *Tenure* reports the share of respondents indicating that they are the owners of a property. *East Germany* reports the share of respondents who lived in the Eastern part of Germany prior to re-unification in 1990 (the question is only asked to respondents born before the re-unification date). We find that the randomization successfully preserves the balance of observables across the treatment groups. We account for any potentially remaining small imbalances, by including control variables in our regressions.

Table A.1: Balance across Demographics - Memory module Aug. 23

	Full Sample	Memory pre	Memory post	Memory pre+Treatment	Memory pre obfuscate
Age	48.63	48.43	49.37	47.72	48.97
	(0.44)	(0.86)	(0.85)	(0.93)	(0.90)
Female	0.50	0.50	0.54	0.47	0.50
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
College educ. or higher	0.29	0.27	0.30	0.30	0.28
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Retiree	0.26	0.25	0.25	0.26	0.26
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Worker	0.64	0.65	0.66	0.61	0.64
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Household size	2.28	2.22	2.22	2.33	2.36
	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)
No. of children	0.39	0.37	0.34	0.41	0.45
	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Household income					
above 5000 EUR	0.22	0.20	0.23	0.22	0.22
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
below 1500 EUR	0.09	0.10	0.08	0.09	0.10
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Housing tenure	0.59	0.59	0.60	0.62	0.57
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
East Germany	0.20	0.17	0.21	0.22	0.21
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
N	3859	985	952	968	954

Note: The table shows the average demographic characteristics separately for each randomized subgroup at the "memory" wave (Aug 2023). Means are calculated using survey weights. Huber-White robust standard errors are enclosed in parentheses.

Table A.2: Balance across Demographics - News provision module (part 1) Aug. 2022

	Full Sample	Fin. Crisis		New pandemic		China's attack on Taiwan		Energy crisis		Control
		pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	
Age	50.42	50.81	49.68	49.99	51.11	50.86	49.81	49.94	51.24	48.74
	(0.29)	(0.85)	(1.00)	(0.81)	(0.78)	(0.79)	(0.80)	(0.77)	(0.81)	(0.95)
Female	0.50	0.49	0.50	0.55	0.50	0.50	0.51	0.47	0.53	0.48
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
College educ. or higher	0.26	0.26	0.26	0.27	0.27	0.28	0.26	0.26	0.25	0.26
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Retiree	0.30	0.31	0.33	0.29	0.30	0.30	0.30	0.29	0.31	0.28
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Worker	0.60	0.58	0.56	0.61	0.63	0.60	0.60	0.62	0.58	0.61
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Household size	2.24	2.20	2.26	2.25	2.19	2.27	2.30	2.23	2.24	2.24
	(0.02)	(0.05)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
No. of children	0.34	0.34	0.39	0.34	0.33	0.32	0.33	0.34	0.34	0.36
	(0.01)	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Household income										
above 5000 EUR	0.18	0.18	0.19	0.16	0.18	0.18	0.20	0.20	0.19	0.21
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
below 1500 EUR	0.11	0.12	0.11	0.10	0.14	0.09	0.11	0.09	0.11	0.09
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Housing tenure	0.61	0.57	0.61	0.58	0.60	0.63	0.63	0.62	0.63	0.62
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
East Germany	0.19	0.21	0.20	0.19	0.17	0.16	0.21	0.22	0.18	0.21
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
N	7610	951	952	938	956	963	941	953	956	961

Note: The table shows the average demographic characteristics separately for each randomized subgroup at the "memory" wave (Aug 2023). Means are calculated using survey weights. Huber-White robust standard errors are enclosed in parentheses.

Table A.3: Balance across Demographics - News provision module (part 2) Nov. 2022

	Full Sample	Control	Cyber attack	
			pos.	neg.
Age	50.70	51.13	50.23	50.78
	(0.49)	(0.92)	(0.86)	(0.78)
Female	0.50	0.51	0.50	0.50
	(0.01)	(0.02)	(0.02)	(0.02)
College educ. or higher	0.29	0.27	0.28	0.31
	(0.01)	(0.02)	(0.02)	(0.02)
Retiree	0.30	0.31	0.30	0.29
	(0.01)	(0.02)	(0.02)	(0.02)
Worker	0.62	0.60	0.61	0.65
	(0.01)	(0.02)	(0.02)	(0.02)
Household size	2.28	2.25	2.29	2.30
	(0.03)	(0.07)	(0.05)	(0.05)
No. of children	0.36	0.35	0.37	0.36
	(0.02)	(0.05)	(0.03)	(0.03)
Household income				
above 5000 EUR	0.17	0.14	0.17	0.19
	(0.01)	(0.01)	(0.01)	(0.01)
below 1500 EUR	0.10	0.12	0.09	0.10
	(0.01)	(0.02)	(0.01)	(0.02)
Housing tenure	0.60	0.60	0.60	0.60
	(0.01)	(0.02)	(0.02)	(0.02)
East Germany	0.20	0.21	0.21	0.18
	(0.01)	(0.02)	(0.02)	(0.01)
N	5102	1697	1703	1702

Note: The table shows the average demographic characteristics separately for each randomized subgroup at the "memory" wave (Aug 2023). Means are calculated using survey weights. Huber-White robust standard errors are enclosed in parentheses.

Table A.4: Balance across Demographics - Decision module Nov. 2023

	Full Sample	Financial Crisis	New pandemic	China-Taiwan conflict	Cyber attack
Age	48.24	47.62	47.91	48.07	49.43
	(0.47)	(0.86)	(0.97)	(0.99)	(0.90)
Female	0.49	0.46	0.49	0.50	0.52
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
College educ. or higher	0.28	0.30	0.27	0.29	0.27
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Retiree	0.26	0.24	0.25	0.26	0.28
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Worker	0.64	0.67	0.65	0.62	0.63
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Household size	2.29	2.28	2.35	2.28	2.25
	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)
No. of children	0.38	0.36	0.40	0.40	0.37
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Household income					
above 5000 EUR	0.22	0.21	0.25	0.23	0.19
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
below 1500 EUR	0.08	0.07	0.07	0.09	0.10
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Housing tenure	0.62	0.63	0.63	0.61	0.62
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
East Germany	0.19	0.19	0.19	0.21	0.17
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
N	3821	965	965	946	945

Note: The table shows the average demographic characteristics separately for each randomized subgroup at the "memory" wave (Aug 2023). Means are calculated using survey weights. Huber-White robust standard errors are enclosed in parentheses.

A.3 Additional Question Texts in the Memory Wave

Personal experiences. To elicit respondents' personal experiences, we closely follow the approach in Bordalo et al. (2025) and ask the following question:

Question: Which of the following situations have you already personally experienced in your life?
(a) Unemployment
(b) Fleeing a country as an asylum seeker or moving country as a migrant
(c) Significant financial losses on investments (e.g. shares, funds, real estate, holdings in a company)
(d) Inability to service debt
(e) Job with major risks to safety or health
(f) Health problems (e.g. serious accident, life-threatening illness, etc.)
(g) Other serious economic or financial problems
(h) Other great personal misfortune or adversity
Note: Please select all answers that apply

The question items were randomized (except items (g) and (h)). Respondents indicated whether they have experienced the specific situation or not. Four items describe experiences of *economic hardship* (job loss, financial loss, debt repayment problems, and "other economic adversities") and the other four items describe experiences of *non-economic hardship*.

Tendency to overestimate small probabilities. This question is motivated by Bordalo et al. (2025) who show that the tendency to overestimate small probabilities across domains explains some of the variation in perceived Covid lethality. Similarly to their "red hair" or "snow" question, we elicit the tendency to overestimate small probabilities in a setting without risk. As the Bundesbank survey requires questions in an economic or financial context, we used the following framing:

Question: In your estimation, how many ATMs are there in Germany per 1,000 inhabitants?
... per 1,000 inhabitants *Note: Please enter a value in the input field (values may have one decimal place).*

A.4 Robustness of Temporal Recall Pattern

Table A.5: Robustness of temporal recall with respect to different age cut-offs and the reunification event

	Baseline		Allow $d > 1$		Age 12 Cutoff		Age 16 cutoff		Exclude Reunification	
	(1) Economic	(2) Cultural	(3) Economic	(4) Cultural	(5) Economic	(6) Cultural	(7) Economic	(8) Cultural	(9) Economic	(10) Cultural
Distance	-0.251***	-0.206***	-0.097***	-0.047***	-0.302***	-0.318***	-0.318***	-0.362***	-0.278***	-0.307***
	(0.010)	(0.021)	(0.003)	(0.007)	(0.011)	(0.023)	(0.012)	(0.024)	(0.010)	(0.021)
$Distance^2$	0.195***	0.198***	0.025***	0.009***	0.243***	0.306***	0.255***	0.342***	0.211***	0.256***
	(0.009)	(0.020)	(0.001)	(0.003)	(0.010)	(0.021)	(0.010)	(0.022)	(0.009)	(0.020)
Annual volatility	0.025***	0.028***	0.022***	0.025***	0.027***	0.030***	0.028***	0.029***	0.022***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Annual Return										
negative	0.030***	-0.016***	0.030***	-0.013***	0.029***	-0.018***	0.029***	-0.018***	0.035***	0.006***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)
positive	-0.007***	-0.026***	-0.007***	-0.025***	-0.007***	-0.027***	-0.007***	-0.027***	-0.003***	-0.013***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
Constant	0.123***	0.112***	0.111***	0.101***	0.149***	0.143***	0.162***	0.158***	0.132***	0.134***
	(0.006)	(0.012)	(0.005)	(0.011)	(0.007)	(0.013)	(0.007)	(0.014)	(0.006)	(0.011)
CONTROL	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.06	0.02	0.05	0.02	0.06	0.02	0.06	0.03	0.06	0.02
N	154653	51852	176320	58928	134516	45154	125208	42058	154091	51166

Note: The table reports robustness checks for the temporal recall pattern. The dependent variable is a binary indicator equal to one if respondent i recalled an event in year k, and zero otherwise. Columns (1)–(2) show the baseline results from Table 2 using the full set of controls. Columns (3)–(4) allow recalled events to occur before respondents' birth, i.e., $d > 1$. Columns (5)–(6) restrict the memory horizon to events that occurred after age 12, while columns (7)–(8) restrict it to events that occurred after age 16. Columns (9)–(10) exclude German reunification from the set of recalled events. *Distance* denotes the temporal distance between the recalled event and the survey date, normalized by respondents' age; $Distance^2$ is its square. *Annual Volatility* denotes the annual volatility of the DAX, and *Annual Return* the absolute value of the DAX return, estimated separately for years with negative and positive returns. Both variables are standardized. Controls include the full set of socio-demographic characteristics described in Section 3.5. Columns labelled *Economic* use respondents assigned to the economic-events memory elicitation, while columns labelled *Cultural* use respondents assigned to the cultural-events memory elicitation. All regressions are estimated using OLS with standard errors clustered at the individual level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

A.5 Probability of Recalling Specific Events

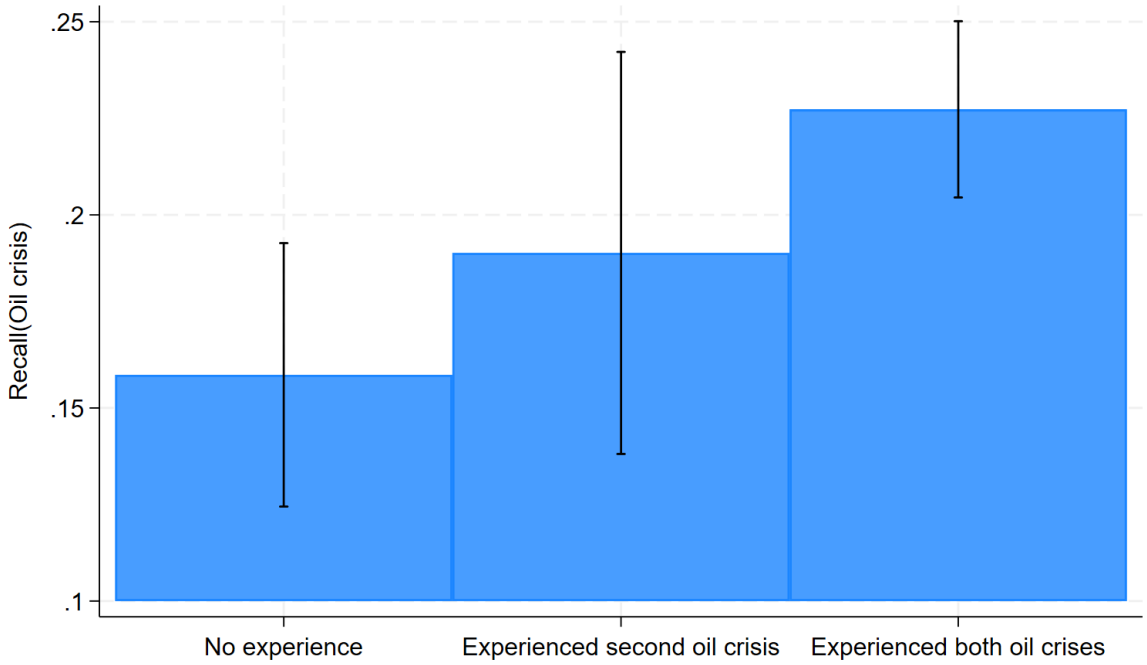


Figure A.1: Probability of mentioning oil crisis

Note: The figure shows predicted probabilities of recalling the economic event category "oil crises", estimated using a logit model. The sample is split into three age groups based on respondents' exposure to the oil crises of the 1970s. Respondents born in or before 1973 (age ≥ 50 at the time of the survey) were alive during both oil crises. Respondents born between 1974 and 1979 (age 44- 49) were exposed to the second oil crisis during early childhood. Respondents born in or after 1980 (age ≤ 43) did not experience either event. Bars indicate 95% confidence intervals around the predicted probabilities. The difference in recall between respondents who were alive during both events and those who did not experience either event is statistically significant (p-val < 0.01). The effect remains robust when adding socio-demographic controls.

A.6 Sub-sample Effects on Similarity and Simulation

Table A.6: Tail Belief as Function of Memory Negativity - Subsample: Memories of Economic Events elicited **Post** Belief Elicitation

	(1)	(2)	(3)
Lifetime experiences			
Stock market volatility	-0.027	-0.036	-0.223
	(0.066)	(0.066)	(0.186)
Stock market return	0.054	0.051	0.007
	(0.068)	(0.068)	(0.195)
Recalled events			
Negativity Index	0.187***	0.185***	0.174***
	(0.048)	(0.048)	(0.049)
Personal experiences			
Personal hardship		0.058	0.061
		(0.044)	(0.045)
CONTROL	No	No	Yes
R^2	0.04	0.05	0.07
N	745	745	745

Note: The table provides a robustness check to Table 3 by restricting the sample to respondents for whom economic memories were elicited *after* belief elicitation. The dependent variable is the standardized tail belief summary index. The memory negativity index is defined in equation 9. Lifetime experiences are measured by respondents' lifetime exposure to stock market volatility and returns. Personal experiences refer to respondents' reported personal experiences of economic hardship and other hardship. ATMs denotes respondents' estimate of the number of ATMs in Germany per 1,000 inhabitants. Controls include the full set of socio-demographic characteristics described in Section 3.5. Regressions use survey weights. Huber–White robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A.7: Tail Belief as Function of Memory Negativity - Subsample: Memories of Economic Events elicited **Pre** Belief Elicitation

	(1)	(2)	(3)
Lifetime experiences			
Stock market volatility	0.025	0.019	-0.206
	(0.058)	(0.058)	(0.172)
Stock market return	0.069	0.063	0.078
	(0.063)	(0.063)	(0.164)
Recalled events			
Negativity Index	0.080**	0.083**	0.064
	(0.040)	(0.039)	(0.042)
Personal experiences			
Personal hardship		0.106*	0.131**
		(0.056)	(0.055)
Memory post			
CONTROL	No	No	Yes
R^2	0.04	0.05	0.08
N	814	814	814

Note: The table provides a robustness check to Table 3 by restricting the sample to respondents for whom economic memories were elicited *prior to* belief elicitation. The dependent variable is the standardized tail belief summary index. The memory negativity index is defined in equation 9. Lifetime experiences are measured by respondents' lifetime exposure to stock market volatility and returns. Personal experiences refer to respondents' reported personal experiences of economic hardship and other hardship. ATMs denotes respondents' estimate of the number of ATMs in Germany per 1,000 inhabitants. Controls include the full set of socio-demographic characteristics described in Section 3.5. Regressions use survey weights. Huber–White robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

A.7 Correlation between Direct and Bloom Tail Belief Measures

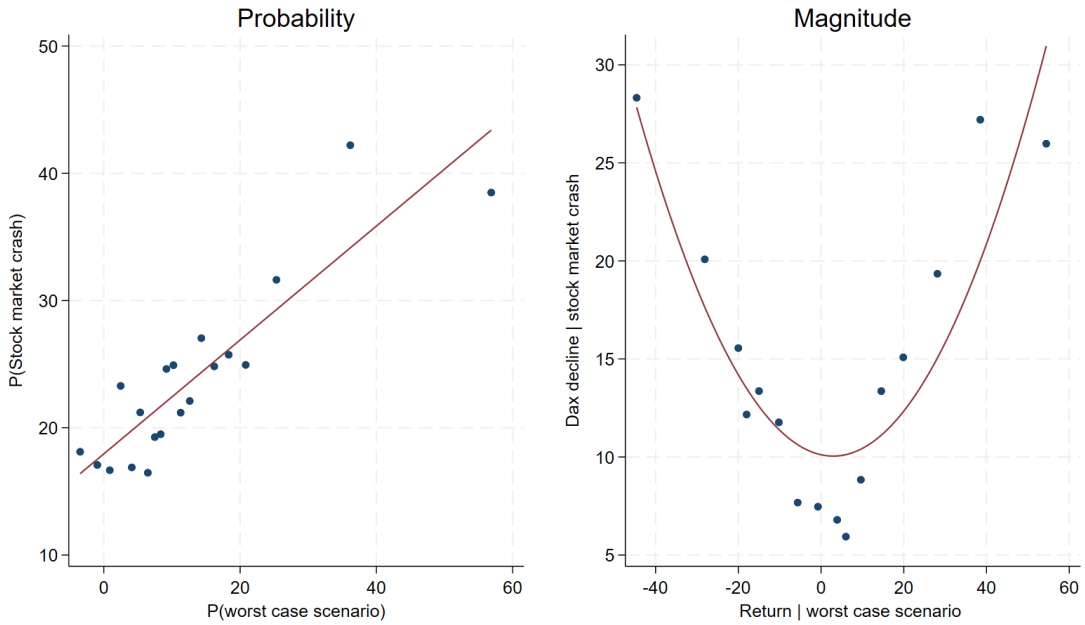


Figure A.2: Correlation between tail belief measures

Note: The figure shows binned scatterplots of the relationship between the direct tail belief measures and the corresponding moments of respondents' subjective DAX return distributions elicited using the Bloom measure. The left panel relates the perceived probability of a stock market crash from the direct elicitation to the probability mass assigned to the worst-case stock market scenario. The right panel relates the perceived magnitude of a stock market crash from the direct elicitation to the return reported for the worst-case scenario. The figures take into account survey weights and controls for the full set of socio-demographic controls.

A.8 Robustness of Similarity and Simulation Results

Table A.8: Tail Belief as Function of Negativity Index - Heterogeneity by domain-specificity in memories

	(1)	(2)	(3)	(4)
Recalled events				
Negativity Index	0.139***			
	(0.033)			
DS Negativity Index		0.104***		0.089***
		(0.029)		(0.029)
NDS Negativity Index			0.069**	0.038
			(0.035)	(0.036)
Personal experiences				
Personal hardship	0.112***	0.115***	0.115***	0.113***
	(0.030)	(0.030)	(0.030)	(0.030)
CONTROL	Yes	Yes	Yes	Yes
Lifetime experiences	Yes	Yes	Yes	Yes
Treatment-group-Dummy	Yes	Yes	Yes	Yes
R^2	0.06	0.06	0.05	0.06
N	2373	2373	2373	2373

Note: The table provides a robustness check to Table 3, by separating the Negativity index into domain-specific (DS) and non-domain specific memories (NDS) based on the open-end text response provided by the survey participants. Coded responses are allocated into DS and NDS groups according to Table A.12. The memory negativity index for DS and NDS memories is derived analogously to equation 9. The dependent variable is the standardized tail belief summary index, constructed from respondents' perceived probability and perceived magnitude of a stock market crash (eq. 8). *Personal experience* captures respondents' number of reported experiences of hardship. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. All explanatory variables are standardized to ease interpretation. *Controls* include the full set of socio-demographic characteristics and the ATM estimate, described in Section 3.5. *Treatment-group-Dummy* is an indicator for the timing and framing of the memory elicitation. Huber–White robust standard errors are reported in parentheses. * indicates significance at the 90%, ** at the 95% and *** at the 99% level.

Table A.9: Tail Belief as Function of Negativity Index - Heterogeneity by domain-specificity in experiences

	(1)	(2)	(3)	(4)
Recalled events				
Negativity Index	0.140***	0.142***	0.139***	
	(0.034)	(0.033)	(0.034)	
DS Negativity Index				0.089***
				(0.030)
NDS Negativity Index				0.038
				(0.036)
Personal experiences				
Economic hardship	0.101***		0.088***	0.087***
	(0.030)		(0.031)	(0.031)
Other hardship		0.076**	0.053*	0.055*
		(0.031)	(0.032)	(0.032)
CONTROL	Yes	Yes	Yes	Yes
Lifetime experiences	Yes	Yes	Yes	Yes
Treatment-group-Dummy	Yes	Yes	Yes	Yes
R^2	0.06	0.06	0.06	0.06
N	2373	2373	2373	2373

Note: The table provides a robustness check to Table 3, by separating the measure of personal experiences of personal hardship into a domain of *Economic hardship* and *Other hardship*. In column 4, the *Negativity index* is again split into a domain-specific (DS) and non-domain specific (NDS) *Negativity Index*. Classification is based on the open-end text response provided by the survey participants, allocation of events into DS and NDS follows Table A.12. The dependent variable is the standardized tail belief summary index, constructed from respondents' perceived probability and perceived magnitude of a stock market crash (eq. 8). *Economic hardship* and *Other hardship* capture respondents' number of reported personal experiences of hardship in each category. All explanatory variables are standardized to ease interpretation of coefficients. *Controls* include the full set of socio-demographic characteristics and the ATM estimate, described in Section 3.5. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. *Treatment-group-Dummy* is an indicator for the timing and framing of the memory elicitation. Huber–White robust standard errors are reported in parentheses. * indicates significance at the 90%, ** at the 95% and *** at the 99% level.

Table A.10: Tail Belief (Bloom Measure) as Function of Memory Negativity - Heterogeneity by domain-specificity in memories

	E(R)	SD	R_{p10}	R_{p90}
Panel A: DS and NDS memories				
Recalled events				
DS Negativity Index	-1.452***	1.278***	-3.849***	0.214
	(0.236)	(0.183)	(0.479)	(0.241)
NDS Negativity Index	-0.432**	0.297*	-1.032***	-0.079
	(0.193)	(0.167)	(0.399)	(0.203)
Personal experiences				
Personal hardship	-0.310	0.179	-0.807**	-0.001
	(0.209)	(0.165)	(0.400)	(0.212)
R^2	0.10	0.16	0.17	0.04
N	1589	1589	1657	1657
Panel B: DS memories only				
Recalled events				
DS Negativity Index	-1.601***	1.380***	-4.207***	0.186
	(0.225)	(0.176)	(0.458)	(0.232)
Personal experiences				
Personal hardship	-0.344	0.203	-0.886**	-0.007
	(0.209)	(0.163)	(0.399)	(0.210)
R^2	0.10	0.16	0.17	0.04
N	1589	1589	1657	1657
Panel C: NDS memories only				
Recalled events				
NDS Negativity Index	-0.850***	0.665***	-2.156***	-0.016
	(0.195)	(0.168)	(0.410)	(0.195)
Personal experiences				
Personal hardship	-0.371*	0.233	-0.949**	0.007
	(0.212)	(0.171)	(0.423)	(0.214)
R^2	0.06	0.11	0.11	0.03
N	1589	1589	1657	1657
CONTROL	Yes	Yes	Yes	Yes
Lifetime experiences	Yes	Yes	Yes	Yes
Treatment-group-Dummy	Yes	Yes	Yes	Yes

Note: The table provides a robustness check to Table 4 by separating the *Negativity Index* into domain-specific (DS) and non-domain specific memories (NDS) based on the open-end text response provided by the survey participants. Coded responses are allocated into DS and NDS groups according to Table A.12. The memory negativity index for DS and NDS memories is derived analogously to equation 9. The dependent variable is the standardized tail belief summary index, constructed from respondents' perceived probability and perceived magnitude of a stock market crash (eq. 8). *Personal hardship* captures respondents' number of reported personal experiences of hardship. All explanatory variables are standardized to ease interpretation. *Controls* include the full set of socio-demographic characteristics and the ATM estimate, described in Section 3.5. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. *Treatment-group-Dummy* is an indicator for the timing and framing of the memory elicitation. Huber–White robust standard errors are reported in parentheses. * indicates significance at the 90%, ** at the 95% and *** at the 99% level.

Table A.11: Tail Belief (Bloom Measure) as Function of Memory Negativity - Heterogeneity by domain-specificity in personal experiences

	E(R)	SD	R_{p10}	R_{p90}
Panel A: DS and NDS experiences				
Recalled events				
Negativity Index	-1.782***	1.495***	-4.578***	0.101
	(0.226)	(0.171)	(0.450)	(0.227)
Personal experiences				
Economic hardship	-0.282	0.195	-0.488	-0.054
	(0.211)	(0.150)	(0.388)	(0.200)
Other hardship	-0.105	0.023	-0.534	0.054
	(0.219)	(0.177)	(0.421)	(0.246)
R^2	0.11	0.17	0.18	0.03
N	1589	1589	1657	1657
Panel B: DS experiences only				
Recalled events				
Negativity Index	-1.788***	1.496***	-4.606***	0.103
	(0.225)	(0.171)	(0.449)	(0.229)
Personal experiences				
Economic hardship	-0.303	0.200	-0.600	-0.043
	(0.205)	(0.147)	(0.380)	(0.192)
R^2	0.11	0.17	0.18	0.03
N	1589	1589	1657	1657
Panel C: NDS experiences only				
Recalled events				
Negativity Index	-1.795***	1.504***	-4.599***	0.098
	(0.226)	(0.170)	(0.448)	(0.227)
Personal experiences				
Other hardship	-0.163	0.063	-0.635	0.043
	(0.212)	(0.173)	(0.411)	(0.238)
R^2	0.11	0.17	0.18	0.03
N	1589	1589	1657	1657
CONTROL	Yes	Yes	Yes	Yes
Lifetime experiences	Yes	Yes	Yes	Yes
Treatment-group-Dummy	Yes	Yes	Yes	Yes

Note: The table provides a robustness check to Table 4 by separating the measure of personal experiences of personal hardship into a domain of *Economic hardship* and *Other hardship*. Panel A includes both measures of experiences jointly, Panel B only experiences of *Economic hardship* and Panel C only the measure *Other hardship*. *Controls* include the full set of socio-demographic characteristics and the ATM estimate, described in Section 3.5. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. *Treatment-group-Dummy* is an indicator for the timing and framing of the memory elicitation. Huber–White robust standard errors are reported in parentheses. * indicates significance at the 90%, ** at the 95% and *** at the 99% level.

Table A.12: Categorization of recalled events

Panel A: Economic events frame

Domain-specific	**Non domain-specific**
Brexit	Extreme weather events
Covid pandemic	Refugee crisis
War in Ukraine	General war and uprises
Oil crises	German reunification
General economic and financial crises	Electoral events
European debt crisis	General Terrorism
Global Financial Crisis	Nuclear Incidents
Gulf wars	Other
Cold war	
DotCom Bubble	
Technology Bubble (Computer)	
Black Monday	
9/11 Terror Attack	

Panel B: Cultural events frame

Domain-specific	**Non domain-specific**
Covid pandemic	World political events
Euro introduction	Football world cup
Energy crisis	Football general
Economic and financial crises	Other sport events
Technological advances	Domestic political events
	Climate change/extreme weather
	War/rebellions
	German reunification
	Terrorism
	Nuclear incidents
	Other

Note: This table shows the categorization of recalled events in domain specific events and non domain-specific events for the two elicitation frames (economic events, Panel A; cultural events, Panel B). The open-ended text responses were labelled and categorized in the listed categories by a professional survey company.

Table A.13: Robustness without cleaning Bloom responses: Tail Belief as Function of Memory Negativity

	Economic events				Cultural events			
	(1) E(R)	(2) SD	(3) R_{p10}	(4) R_{p90}	(5) E(R)	(6) SD	(7) R_{p10}	(8) R_{p90}
Lifetime experiences								
Stock market volatility	0.051	-0.170	-0.481	-0.254	1.200	0.167	1.677	0.897
	(1.034)	(0.663)	(2.061)	(0.908)	(1.679)	(0.997)	(3.044)	(1.231)
Stock market return	0.341	0.455	1.087	-0.374	0.281	-0.464	1.887	0.663
	(0.953)	(0.655)	(2.325)	(0.813)	(1.481)	(0.894)	(3.235)	(1.277)
Recalled events								
Negativity Index	-2.286***	0.989***	-5.276***	0.023	-2.577***	0.888**	-5.998***	-0.617
	(0.290)	(0.162)	(0.608)	(0.258)	(0.609)	(0.349)	(1.273)	(0.412)
Personal experiences								
Personal hardship	0.481	0.286	0.474	0.404	0.473	0.419	0.285	0.139
	(0.309)	(0.181)	(0.612)	(0.252)	(0.507)	(0.289)	(0.959)	(0.366)
Memory post	0.929*	-0.691**	2.229**	-0.125				
	(0.551)	(0.303)	(1.101)	(0.462)				
CONTROL	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.14	0.11	0.17	0.02	0.11	0.07	0.11	0.06
N	1439	1439	1531	1531	742	742	791	791

Note: The table provides a robustness check to Table 4, which excludes respondents with implausible responses for the worst case scenario. The dependent variables are moments of each respondent's subjective distribution of DAX returns over the next 12 months: the mean expected return $E(R)$, the standard deviation SD, the 10th percentile R_{p10}, and the 90th percentile R_{p90}. Columns (1)–(4) use respondents assigned to the economic-events memory elicitation, while columns (5)–(8) use respondents assigned to the cultural-events memory elicitation. The memory negativity index is defined in equation 9. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. *Personal hardship* captures respondents' number of reported personal experiences of hardship. All explanatory variables are standardized to ease interpretation. *Memory post* is an indicator for respondents whose memories were elicited after belief elicitation. *Controls* include the full set of socio-demographic characteristics and the ATM estimate, described in Section 3.5. Regressions use survey weights. Huber–White robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

A.9 Robustness Heterogeneity of Treatment Effects

Table A.14: Heterogeneity Treatment Effects - Joint Specification

	(1)	(2)	(3)
Info Treatment	0.56***	0.54***	0.53***
	(0.09)	(0.09)	(0.09)
$T \times I^{Highage}$	-0.23**	-0.23**	-0.24**
	(0.09)	(0.09)	(0.09)
$T \times I^{Hardship}$	0.08	0.08	0.07
	(0.09)	(0.09)	(0.09)
$T \times I^{Negativity}$	0.19**		
	(0.09)		
$T \times I^{Highsharenegative}$		0.21**	
		(0.09)	
$T \times I^{Highseverity}$			0.22**
			(0.09)
$I^{Highage}$	0.33***	0.34***	0.34***
	(0.10)	(0.10)	(0.10)
$I^{Hardship}$	0.15**	0.16**	0.17***
	(0.07)	(0.07)	(0.07)
$I^{Negativity}$	-0.02		
	(0.07)		
$I^{Highsharenegative}$		-0.04	
		(0.07)	
$I^{Highseverity}$			-0.21***
			(0.07)
CONTROL	Yes	Yes	Yes
Lifetime Experiences	Yes	Yes	Yes
R^2	0.13	0.13	0.13
N	1619	1619	1619

Note: The table provides a robustness check to Table 6, estimating the heterogeneity in treatment effects jointly across the different dimensions of heterogeneity. The dependent variable is the standardized tail risk summary index. The sample includes respondents assigned to the information treatment and respondents in the *Econ pre* group. *Info Treatment* is an indicator for receiving information about past stock market crashes. The interaction terms indicate whether the treatment effect differs for respondents above the median of the respective heterogeneity variable. *Controls* include the full set of socio-demographic characteristics and the ATM estimate, described in Section 3.5. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. Regressions are estimated without survey weights and use Huber–White robust standard errors, reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

A.10 Memory RCT Effects on Bloom Belief Measures

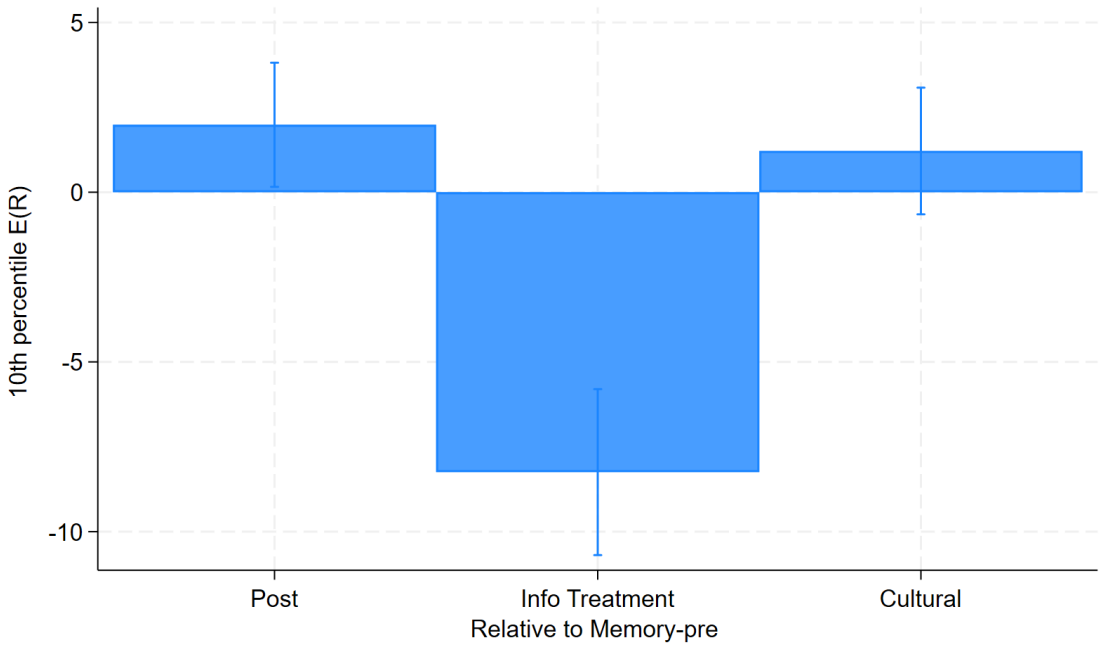


Figure A.3: Treatment Effects

Note: The figure reports average treatment effects on the 10th percentile of respondents' subjective distribution of DAX returns over the next 12 months, elicited using the Bloom measure. Estimates are shown relative to the baseline group *Memory pre*, in which respondents report economic memories before belief elicitation and receive no information treatment. *Post* refers to respondents whose economic memories are elicited after belief elicitation. *Info Treatment* refers to respondents who receive information about past stock market crashes before belief elicitation. *Cultural* refers to respondents who report cultural memories before belief elicitation. Estimates control for the full set of covariates described in Section 3.5. Bars show 95% confidence intervals.

Table A.15: Heterogeneity Treatment Effects - p10- Return

	Representativeness			Interference	
	(1) Negativity Index	(2) Share negative events	(3) Magnitudes	(4) Age	(5) Hardship
Info Treatment	-7.68***	-7.53***	-8.27***	-9.26***	-8.64***
	(1.50)	(1.56)	(1.77)	(1.33)	(1.34)
High × Treat	-1.80	-2.27	-0.86	1.93	0.63
	(2.03)	(2.05)	(2.17)	(1.94)	(1.94)
CONTROL	Yes	Yes	Yes	Yes	Yes
Lifetime experiences	Yes	Yes	Yes	Yes	Yes
R^2	0.18	0.18	0.16	0.16	0.15
N	1020	1020	1020	1156	1156

Note: The table reports heterogeneous treatment effects of the information treatment on the 10th percentile of respondents' subjective distribution of DAX returns over the next 12 months, elicited using the Bloom measure. The dependent variable is the 10th percentile of the subjective return distribution. *Info Treatment* denotes respondents who receive information about past stock market crashes before belief elicitation. *High* × *Treat* denotes the interaction between the information treatment and an indicator for whether a respondent is above the median of the respective heterogeneity variable. Columns (1) to (3) test heterogeneity related to representativeness, using the memory negativity index, the share of recalled events with a negative DAX impact, and the average recalled magnitude of these events. Columns (4) and (5) test heterogeneity related to interference, using respondents' age and reported personal hardship experiences. *Controls* include the full set of socio-demographic characteristics and the ATM estimate, described in Section 3.5. Objective *lifetime experiences* are measured by respondents' lifetime exposure to stock market volatility and stock market returns. Huber-White robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

A.11 News Provision RCT: Detailed Description

We designed our first two survey waves to characterize tail beliefs and their response to news in the form of short excerpts from typical media articles. The August 2022 wave was administered to roughly 9,000 respondents, while the November 2022 wave was administered to roughly 6,000 respondents. The August wave includes 8 treatment groups and 1 control group, resulting in roughly 1,000 respondents per group. The November wave includes 2 treatment groups and 1 control group, resulting in roughly 2,000 respondents per group. We field a set of 9 customized questions in each of these two survey waves.

Structure The structure of each of the two waves is i) pre-treatment beliefs, ii) information treatments, and iii) post-treatment beliefs and decisions. We elicit individuals' subjective tail probability and magnitude for each disaster type pre-treatment. The disaster types in the first news provision wave are i) financial crisis, ii) new pandemic, iii) China-Taiwan escalation, iv) energy crisis (info boxes are used to further characterize these events, more details in the following). In the second core wave, the disaster type is described as an event in which v) the power supply in Germany were to suffer outages lasting multiple days as a result of a cyber attack. The second news provision wave doubles the number of respondents per treatment group in order to increase the power of our tests. Individuals are then randomly assigned into one of the treatment or control groups. Each group, except the control group, receives a treatment containing, respectively, positive or negative information on each of the five disaster types. After the treatments, respondents are asked about various outcome variables relating to beliefs and decisions.

Due to the random assignment of respondents, between-treatment group differences in outcome variables reflect the reaction of otherwise identical groups of participants to the information treatments. In other words, these differences reflect causal treatment effects.

After the treatments, we elicit whether it is a good time to buy property, or, respectively, equity. Respondents are then asked to provide a detailed breakdown of their planned financial portfolio allocation into different asset classes. In addition, we elicit their consumption plans for the next 12 months. After that, we re-elicit their tail magnitudes and probabilities, but we change the time horizon over which they are asked to provide their assessments from 3-years to 2-years in order to avoid asking the same question twice (Weber et al., 2022). Finally, we elicit individuals' post-treatment central tendency beliefs about the evolution of various macroeconomic variables over the next 12 months, namely GDP, the stock market index, house prices, and household-specific disposable income. We include these in our set of control variables in order to cleanly separate tail beliefs and central tendency beliefs. The exact wording of these questions is provided below.

Information Treatments For each disaster type, we field a positive and a negative treatment. The precise wording of each treatment is shown in the following box. The treatments have been carefully constructed using the following criteria. The information treatments should consist of pieces of news that arise truthfully and naturally in the news. Each treatment should be potentially relevant for assessing the risk of the corresponding event. Yet, the treatments should *not* provide a *quantitative* estimate for either the probability or magnitude. This mitigates potential anchoring or experimenter demand effects and is more representative of typical news disseminated by the media. We did not provide respondents with the media source of the news as this could be a confounding factor for their response. Instead, respondents are aware the survey is conducted on behalf of Deutsche Bundesbank, which is one of the most trusted institutions in Germany, insuring that differences across treatments are not driven by the source of the news. Finally, each treatment should be of roughly equal length, especially in a pair-wise comparison between positive and negative treatment arms.

T1: (Control Group Wave 1) *No information shown.*

T2: (Financial crisis, positive) Banks have become significantly more resilient since the 2008 global financial crisis. Capital buffers, which are crucial for the resilience of banks, have since risen by around 50%. This makes it easier for banks to get through economically challenging times without being forced to constrain their lending to firms and households.

T3: (Financial crisis, negative) Overvalued assets, such as real estate, constitute a vulnerability for the German financial system. The German stock index (DAX) has lost around 20% of its value since the beginning of the year. According to Bundesbank estimates, property prices in Germany are overvalued by approximately 20-35%. If property prices suddenly fall and many households are no longer able to service their loans, banks will face heavy losses.

T4: (New pandemic, positive) In order to effectively prevent or mitigate future pandemics, a number of measures are being worked on at full speed. By utilising mRNA technology, it should be possible for effective vaccines to be rolled out quickly, effective drugs to be developed rapidly and pandemic surveillance to be improved. In future, these and other measures can help contain the spread of pathogens at an early stage.

T5: (New pandemic, negative) Experts are warning that a new pandemic could occur at any time. For example, the keeping of certain animal species in China is linked to the SARS outbreak of 2002, and in the Middle East to the MERS outbreak of 2012. In Europe, intensive livestock farming is a potential source of new pathogens. Given a lack of preparedness, the consequences could be just as great or even more far-reaching than those of the COVID-19 pandemic.

T6: (China-Taiwan conflict, positive) Experts assume that China would **not** be prepared to invade Taiwan at present. If the situation were to escalate in future, efforts made by the United States and Europe to become less dependent on imports from Taiwan and China would limit the economic fallout. To this end, production facilities in Europe and the United States are to receive around Euro 40-50 billion in funding, respectively.

T7: (China-Taiwan conflict, negative) High-ranking US military officials warn that there is a danger that China will invade Taiwan within the next five years. As Taiwan produces two-thirds of the world's semiconductors, this could have severe economic effects on motor vehicle production, for instance, in Germany and worldwide. China's role as a production base and sales market could amplify the economic impact in the event of tensions between China and the United States as well as possible sanctions against China.

T8: (Energy crisis, positive) Germany's leading economic research institutions do **not** expect there to be a gas supply gap until the end of 2023 in the event that Russian gas deliveries are stopped immediately, meaning that German industrial enterprises would not then have to limit their gas consumption. The provision of gas to households and social facilities would not be jeopardised in any case.

T9: (Energy crisis, negative) The Federal Minister for Economic Affairs and Energy announced that the Emergency Plan for Gas would move to its second stage. The reason cited for this was the reduction in Russian gas deliveries since mid-June and the high prices on the gas market. According to the minister, a threefold increase in gas prices for households and firms is considered possible, as well as restrictions on the supply of gas to industrial enterprises.

T10: (Control Group Wave 2) *No information shown.*

T11: (Cyber attack, positive) Germany's energy supply is regarded as quite secure by international standards: four different power grid zones make it more difficult for local-level disruption to spread throughout Germany. The increasingly decentralised generation of electricity using renewable energy sources also helps to contain any disruptions at the local level. In addition, a recent survey reveals that a large majority (88%) of operators of critical infrastructure, such as the energy supply, consider themselves to be "well" or "very well" protected against modern cyber-attacks.

T12: (Cyber attack, negative) In Germany, the threat posed by cyber-attacks has intensified further over the past few years. The number of cyber-attacks on critical infrastructure, including the energy supply, has risen sharply in recent years. According to experts, a failure in the power supply would have particularly far-reaching consequences. Not only production in industrial enterprises, but all economic sectors would be affected by the failure of computer systems, communication channels and transport routes.

Tail Magnitudes To elicit tail magnitudes, we ask respondents what growth rate of GDP and which stock return they would expect conditional on a given (tail) event occurring.

> Imagine that **one of the following events** were to occur within the next three years. As a percentage, how much lower would you expect Germany's economic output to be in each case?
> (a) Financial crisis ... percent
> (b) Pandemic involving a new pathogen ... percent
> (c) Chinese attack on Taiwan ... percent
> (d) Energy crisis ... percent
> *Note: Please indicate the percentage by which Germany's economic output would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than zero. If you do not expect a decline, please enter a value of zero.*

A similar question was asked regarding the percentage decrease in the DAX return index conditional on each of these events. Respondents could click on info boxes that further characterize each disaster event, as well as an info box defining "economic output" in terms of GDP. The exact text of these info boxes can be found in section B.2 (see P3206).

Tail Probabilities After obtaining individuals' expected loss conditional on an event materializing, we elicit their conditional probability of the occurrence of each event within the next three years. We elicit these probabilities using the following question:[23]

> In your opinion, how likely is it that each of the events will occur within the next three years?
> (a) Financial crisis ... percent
> (b) Pandemic involving a new pathogen ... percent
> (c) Chinese attack on Taiwan ... percent
> (d) Energy crisis ... percent
> *Note: Please enter a value between 0 and 100 in each case. 100 means that you are absolutely certain that the event will occur; 0 means that you believe the event is completely impossible.*

Treatment Effects on Tail Beliefs In this section, we test whether positive and negative news drive a wedge between tail beliefs in the respective treatment arms (see also proposition 1). Our identification is based on the pairwise difference between the negative and the positive treatment arm for each disaster type (j). Due to randomization, each treatment group is a representative sub-sample of the population, and any systematic

[23]Each tail event is characterized by a triplet consisting of i) the scenario in the question text (e.g. "Chinese attack on Taiwan"), ii) the info boxes further characterizing the event, and iii) the perceived tail magnitude (conditional GDP loss, and conditional DAX decline associated with the event) which we elicit before the probability. Conceptually, what should be key for decisions at date t are not unconditional probabilities or historical frequencies (e.g. how often an event occurs in 100 years), but conditional probabilities at the time of the survey (the likelihood assigned to the event occurring within the next h years). Therefore, we elicit individuals' conditional probability of the occurrence of each thus defined event within the next three years pre-treatment and within the next two years post-treatment (striking a balance between longer horizons and the horizon a representative household may plausibly be able to express expectations about).

post-treatment difference between the groups can be attributed to the information treatments.[24] Specifically, we estimate the following regression specification for each disaster type separately:

$$\Delta y_i^j = \alpha^j + \beta^j T_i^{neg,j} + \delta^j X_i + \epsilon_i^j, \tag{22}$$

where Δy_i^j denotes the revision from pre- to post-treatment in the tail belief of respondent i for crisis scenario j. Hence, depending on the specification, Δy_i^j denotes either the revision in the tail probability, the revision in the tail magnitude, or the revision of our tail risk measure defined in equation 8. α^j is the average revision in the positive treatment arm, and β^j the difference between the average belief revision in the negative arm and the revision in the positive arm. We have negative and positive treatments for j disaster types, $\{T^{neg}, T^{pos}\}_{j=1}^{J}$. X_i is a vector of control variables, including socio-demographic characteristics and post-treatment beliefs about the central tendency of several macroeconomic variables (GDP growth, stock returns, real estate price growth, and disposable household income growth). The error term ϵ_i^j captures remaining idiosyncratic noise (e.g. measurement error) in the observed belief revisions.

Table A.16 presents estimates of β_j for each disaster type and different sets of control variables. Our preferred specifications are in the second column (tail risk), fourth column (probability) and the sixth column (magnitude), in which we control for socio-demographics and posterior central tendency ("mean") beliefs. Hence, the treatment effects on tail beliefs are net of any indirect effects mediated through central tendency beliefs. In columns 1, 3 and 5, we do not control for the effects of central tendency beliefs and find that the estimated coefficients remain qualitatively and quantitatively comparable.

For tail probabilities, we find that four out of five treatments drive a statistically significant positive wedge between the revisions in the negative minus the positive treatment arm. For example, in the *China-Taiwan conflict* treatment group, respondents who receive a negative information treatment increase the perceived likelihood of the event by 5.0 percentage points more (p-val. < 0.01) than respondents who receive the positive information treatment. This corresponds to 21% of a standard deviation in respondents' prior tail probability for the *China-Taiwan conflict* scenario. Only the wedge induced in the financial crisis treatment group is insignificant, although it remains positive. For tail magnitudes, we find positive and significant wedges for the financial crisis, the China-Taiwan conflict, and the Cyber attack treatments. The remaining two disaster types display positive but insignificant wedges. The treatment effects on the tail risk measure combining probability and magnitude assessments as defined in equation 8 is positive and significant for all five disaster types (column 2).

Taken together, the negative information treatments clearly increase perceived tail risk relative to the positive treatment arm, by increasing either individuals' probability or magnitude (or both), for each disaster type. We explore in section 7 of the main text, whether these increases in perceived tail risks are associated with individuals' assessment of whether it is a good time to invest in real estate or equity.

[24] The control group allows us to obtain estimates of all post-treatment outcomes for a representative subset of individuals who have not been exposed to any information treatments. We provide balance tables with respect to observable demographic characteristics in appendix section A.2.

Table A.16: Treatment effects on tail beliefs

	$\Delta TailRisk$		$\Delta Probability$		$\Delta Magnitude$	
	1	2	3	4	5	6
Financial Crisis						
negative	0.110	0.122*	0.053	0.056	0.097	0.114*
	(0.075)	(0.068)	(0.070)	(0.070)	(0.076)	(0.069)
New pandemic						
negative	0.139**	0.147**	0.118*	0.135**	0.078	0.084
	(0.069)	(0.069)	(0.066)	(0.068)	(0.069)	(0.069)
Cina-Taiwan conflict						
negative	0.359***	0.378***	0.302***	0.294***	0.241***	0.259***
	(0.073)	(0.069)	(0.069)	(0.069)	(0.074)	(0.069)
Energy crisis						
negative	0.171**	0.208***	0.139**	0.179***	0.094	0.102
	(0.067)	(0.066)	(0.065)	(0.062)	(0.064)	(0.066)
Cyber attack						
negative	0.338***	0.349***	0.305***	0.314***	0.171***	0.178***
	(0.076)	(0.066)	(0.074)	(0.070)	(0.066)	(0.061)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Posterior Mean Beliefs	No	Yes	No	Yes	No	Yes

Note: This table shows the estimated effects of the differential information treatments on the revisions of individuals' tail outcome index (columns 1-2) and seperately for the tail probability (columns 3-4) and magnitude (columns 5-6) from pre- to post-treatment. Following equation (22), the regression is estimated separately for each of the five disaster types, and for different sets of control variables. *Demographics* comprises respondents' gender, age, household income and household size, and dummies that indicate if respondents already retired, have at least a college degree, and if they lived in East Germany prior to re-unification. *Posterior beliefs* is a set of beliefs about central tendency of GDP growth, stock market returns (DAX), real estate price growth, and disposable household income growth over the next 12 months, elicited *after* the information treatment. Regression uses survey weights. Huber-White robust standard errors are in parentheses. * indicates significance at the 90%, ** at the 95% and *** at the 99% level.

A.11.1 Treatment Effects on Mean Beliefs

Table A.17 presents estimates of the effect of the treatments on central tendency beliefs (in short: mean beliefs). While the effect of the information treatments on tail risk, documented in Table A.16 above, are always significant, the effect of the treatments on mean beliefs is only occasionally statistically significant. This is reassuring as the treatments have been constructed to convey information about tail risks in particular. The small and mostly insignificant effects on mean beliefs suggest that the bulk of the treatment effects on individuals' inclination to invest in real estate or equity operate through their effects on respondents' tail beliefs.

Table A.17: Treatment effects on Macro Expectations

	GDP		Stock return		Real estate		Disposable Income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Financial Crisis								
negative	-0.048	-0.052	-0.094	-0.099	-0.137***	-0.143***	-0.113	-0.119*
	(0.069)	(0.070)	(0.073)	(0.073)	(0.052)	(0.052)	(0.070)	(0.071)
New pandemic								
negative	-0.036	-0.036	-0.053	-0.055	0.079	0.074	0.030	0.027
	(0.073)	(0.073)	(0.064)	(0.063)	(0.056)	(0.057)	(0.070)	(0.070)
China-Taiwan conflict								
negative	-0.088	-0.085	-0.134**	-0.118*	-0.045	-0.059	-0.182**	-0.156**
	(0.068)	(0.069)	(0.061)	(0.061)	(0.051)	(0.052)	(0.071)	(0.071)
Energy crisis								
negative	0.044	0.046	0.011	0.019	0.085	0.061	0.096	0.095
	(0.075)	(0.074)	(0.067)	(0.067)	(0.057)	(0.059)	(0.071)	(0.070)
Cyber attack								
negative	0.070	0.060	0.085	0.071	0.047	0.007	0.240***	0.218***
	(0.059)	(0.056)	(0.057)	(0.054)	(0.047)	(0.045)	(0.066)	(0.062)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Posterior Tail beliefs	No	Yes	No	Yes	No	Yes	No	Yes
Prior mean beliefs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the estimated effects of the differential information treatments on individuals' expectations about the change in GDP (column 1-2), stock market returns based on the German stock market index DAX (columns 3-4), real estate prices in the area (columns 5-6) and their disposable household income (columns 7-8) over the next 12 months. These measures are elicited *after* treatment. The regression is estimated separately for each of the five disaster types as the difference in revision between the negative and positive treatment arm, and repeated for different sets of control variables. *Demographics* comprises respondents' gender, age, household income and household size, and dummies that indicate if respondents already retired, have at least a college degree, and if they lived in East Germany prior to re-unification. *Prior mean beliefs* is a set of beliefs about macroeconomic expectations elicited prior to the experiment (inflation expectations, real estate price growth and qualitative beliefs about GDP growth and stock market returns (DAX). *Posterior tail beliefs* includes controls for the $TailRisk$ index (c.f. equation (8)) elicited *after* the treatment stage. Regression uses survey weights. Huber-White robust standard errors are in parentheses. * indicates significance at the 90%, ** at the 95% and *** at the 99% level.

A.12 Tail Beliefs and Portfolios: Evidence from a Hypothetical Vignettes Design

With this wave, we deepen the investigation of the effect of tail beliefs on decisions. We use a vignette design to introduce exogenous variation into individuals' tail beliefs (see, e.g., Andre et al. 2022), and open-ended text questions to get at the narratives behind individuals' decisions. We first elicit respondents' prior tail beliefs (probability and magnitude) and their actual prior financial portfolio allocation. Specifically, we elicit the nominal amounts allocated to the following six categories: "cash", "bank account", "fixed income", "equity","precious metals" and "other". Tail beliefs are elicited in the context of one of four crisis types, to which respondents are randomly assigned (financial crisis, new pandemic, China-Taiwan conflict, and systemic Cyber attack). Within each crisis type, respondents are randomly assigned to one of two hypothetical scenarios. In one scenario, which, for the purpose of this text, we label the "low risk" scenario, they are asked to assume the probability of the crisis event is 5 percent. In the second scenario, which we label the "high risk" scenario, they are asked to assume the probability of the crisis event is 40 percent.

This vignette design is different from the information treatments used in the two news provision waves. While the information treatments can lead to small belief revisions for some disaster types (which is natural when receiving a single piece of news), the vignette design allows us to directly control the assumed probabilities thereby inducing larger belief revisions. Having a high risk and a low risk scenario typically leads to both positive and negative surprises for the same *type* of respondent.[25] The information treatments mimic the arrival of news over time, whereas the vignette design essentially asks a "what if" question. It thereby "forces" respondents to think about which portfolio adjustment they would make (if any), conditional on an exogenously given change in their beliefs.

In the final part of the vignette experiment, respondents are asked if they would like to make adjustments to their portfolio allocation. Those who choose to adjust are able to modify the (Euro) amounts in their reported actual portfolios towards a new allocation they would choose in the scenario with either a high or a low risk of the given disaster type (depending on the vignette group they are in). For both adjusters and non-adjusters, we follow up with a question asking respondents to state up to five reasons for making adjustments or for not making adjustments.

A.12.1 Financial Portfolio Allocation

We investigate respondents' portfolio adjustments in response to a (hypothetical) shock to perceived tail-risks, by estimating the following regression model for each crisis type j and asset class k:[26]

$$\Delta y_k^j = \alpha_k^j + \beta_k^j shock^j + \gamma_k^j y_{k,pre}^j + \delta_k^j P(tail)_{pre}^j + \Theta_k^j \mathbf{X} + \epsilon^j, \tag{23}$$

[25] For instance, consider a specific type of respondents, say wealthy, female respondents. Due to randomization, each individual in this group of respondents gets assigned to either the "low risk" or the "high risk" scenario with equal probability. Assuming the prior belief of this group is between 5 and 40 percent (in line with typical estimates in the first core wave), the "high risk" scenario amounts to a positive (hypothetical) belief revision, whereas the "low risk" scenario amounts to a negative (hypothetical) revision.

[26] To ease notation, we drop the subscript i for this equation.

where Δy_k^j defines the changes in k different portfolio shares. $shock^j$ is defined as the difference between the scenario $P(tail)_{5,40}^j - P(tail)_{pre}^j$. To account for non-linearities, we include respondents' prior portfolio share $y_{k,pre}^j$, and their prior tail belief $P(tail)_{pre}^j$ as control variables. The control vector $\mathbf{X}$ contains macroeconomic expectations elicited prior to the experiment, and socio-demographic characteristics.

Table A.18 focuses on the share of equity as our main outcome variable of interest, while the effects on other dimensions of the financial portfolio are discussed subsequently. Panel A presents the total effect, which is essentially the product of the extensive and the intensive margin of adjustment. Let us first consider the financial crisis scenario. A 1 percentage point increase in the probability of a financial crisis induces a decrease in the chosen equity share of 0.09 percentage points. The sensitivity is statistically significant though economically limited. For instance, a 10 percentage point increase in the probability of a financial crisis would lead to an equity share reduction of roughly 1 percentage point, that is, for instance, from 50% to 49% equity share.[27,28]

The effect sizes are quantitatively much smaller for the other crisis types and only statistically significant for the Cyber attack scenario. Moreover, households who perceive a high probability of a financial crisis ex-ante intend to further diminish their equity share when given the opportunity to re-assess their portfolio allocation. This could point to an important friction in the transmission of beliefs to portfolio choices - infrequent updating of portfolio positions (see, e.g., Abel et al., 2007; Adam et al., 2015). Under this view, the initial portfolio allocation may not yet fully incorporate respondents' prior beliefs about tail risks. Indeed, Panel B shows that respondents with a high prior perceived tail risk are more likely to adjust their portfolios (extensive margin) when given the opportunity. The small (and for some crisis scenarios insignificant) pass-through from beliefs about tail risks to portfolio decisions could either stem from a large share of non-updaters (extensive margin) or from small adjustment sizes conditional on updating (intensive margin). We will explore both mechanisms in turn.

Extensive Margin To see whether changes in beliefs about tail risk cause respondents to adjust their portfolio at the extensive margin, we slightly modify regression equation 23. Specifically, our dependent variable becomes an indicator that equals 1 if and only if respondents adjust at least one item of their portfolio in response to the individual-specific shock implied by the scenario to which they have been assigned. Since the probability of adjusting should depend on the size of *shock*, we take the absolute value. To account for the direction of the *shock*, we interact the size with the direction of the shock.

Panel B of Table A.18 shows the results using OLS regression.[29] We find a strong, positive relationship between the probability of adjusting the portfolio and the size of the shock when the shock is positive, i.e. when the probability of the tail scenario *increases*. A 1 percentage point higher probability of tail scenario k increases the probability of ad-

[27]The limited size of the sensitivity is reminiscent of Giglio et al. (2021), who find only a limited pass-through from beliefs about the likelihood of a stock market crash to changes in the equity share of investors.

[28]The levels of prior tail beliefs are as follows. Similarly to the two news provision waves, the probabilities range from roughly 20-30%. The expected 1-year DAX decline is between 10-20%. In the fourth wave, we additionally elicit 5-year DAX declines conditional on each crisis type, which range from roughly 5-10%, hence respondents perceive tail events to be persistent but also expect some mean reversion following the event.

[29]Logit regressions lead to qualitatively similar results (available upon request), but the interpretation of coefficient sizes is slightly more complicated.

Table A.18: Sensitivity of equity share to changes in beliefs about tail risk

	(1) Financial Crisis	(2) New pandemic	(3) China-Taiwan	(4) Cyber attack
Panel A:Total Effect				
Shock	-0.0904***	-0.0060	-0.0184	-0.0191**
	(0.0250)	(0.0087)	(0.0164)	(0.0080)
$P(Tail)^{pre}$	-0.0778***	0.0019	-0.0196	-0.0072
	(0.0252)	(0.0109)	(0.0153)	(0.0075)
Controls	Yes	Yes	Yes	Yes
R^2	0.18	0.08	0.12	0.07
N	800	824	795	789
Panel B: Extensive Margin				
$Abs(Shock)$				
× negative domain	-0.34*	0.06	0.10	-0.11
	(0.18)	(0.13)	(0.19)	(0.19)
× positive domain	0.61***	0.16	0.45***	0.57***
	(0.19)	(0.12)	(0.14)	(0.13)
$P(Tail)^{pre}$	0.32**	-0.02	0.23	0.19
	(0.15)	(0.10)	(0.16)	(0.14)
Controls	Yes	Yes	Yes	Yes
R^2	0.09	0.04	0.11	0.08
N	814	830	800	796
Panel C: Intensive Margin				
Shock	-0.1723**	0.0617	0.0625	0.0349
	(0.0690)	(0.0893)	(0.0749)	(0.0510)
$P(Tail)^{pre}$	-0.1854**	0.0477	0.1025	0.0449
	(0.0755)	(0.1093)	(0.1065)	(0.0624)
Controls	Yes	Yes	Yes	Yes
R^2	0.55	0.47	0.59	0.33
N	254	106	140	167

Note: Estimates are based on ordinary least squares (OLS) regressions, run separately for each crisis type. The dependent variable in Panel A is the change in the equity share of respondents' portfolios. In Panel B, the dependent variable is an indicator equal to 1 if respondents adjust at least one portfolio item in response to the shock. In Panel C, the dependent variable is the change in the equity share, conditional on portfolio adjustment taking place. The key independent variable is the *shock* to the perceived probability of the tail-event materializing. $P(Tail)^{pre}$ indicates respondents' prior assessment of the likelihood of the specific tail scenario they received. Respondents are randomly allocated into one of the four tail scenarios which are reflected in the four column heads. *Controls* include a range of control variables concerning respondents' prior equity share, prior beliefs (beliefs about stock market returns, expected impact of tail event on stock market returns, beliefs about the likelihood of policy interventions (fiscal and monetary policy), inflation expectations, house price expectations, socio-demographic characteristics (age, gender) and socio-economic information (financial wealth (log), financial literacy and stockownership. Regression uses survey weights. Huber-White robust standard errors are in parentheses. * indicate significance at a 90%, ** at a 95% and *** at a 99% level of confidence.

justing the portfolio by around 0.5 to 0.6 percentage points (depending on the scenario). The effect is statistically significant for three of the four scenarios and economically sizable. In contrast, the coefficient is small (and in some cases even negative) for households receiving a negative news shock, i.e., who reduce the likelihood of their tail scenario.

Figure A.4 visualizes these results, using a logit instead of an OLS regression, in order to keep all predicted probabilities bounded below 100%. For the financial crisis scenario (top left), the likelihood of adjusting portfolios under the "positive shock" (higher tail risk) increases from 30% to 60% as the shock size increases from 0 to 50 percentage points. In contrast, under the "negative shock" (lower tail risk), the likelihood decreases slightly for a larger shock size. In other words, there is a base level of roughly 30% of respondents who adjust their portfolios irrespective of shock direction and size, and only the higher tail risk scenario increases the propensity to adjust, while lower tail risk does not increase the probability of adjusting, and can even reduce it. The same qualitative pattern holds for the other crisis scenarios, albeit at varying base levels. This one-sided stickiness in the pass-through from tail beliefs to portfolio decisions is generally consistent with households displaying "loss aversion" (Kahneman and Tversky, 1979; Tversky and Kahneman, 1991). An increased likelihood of a tail event is more likely to trigger a reaction to avoid substantial losses. In contrast, when the probability of a tail event decreases, the perceived reduction in risk may not induce individuals to change their portfolio allocation.[30]

In sum, our results on the extensive margin show that changes in beliefs about tail risks can serve as a trigger to induce households to reallocate their portfolio shares. However, the results also show that there might be important frictions in place given that i) households' decisions to adjust the portfolio are only sensitive towards higher, not lower tail risk; and ii) shocks to beliefs need to be large in order to substantially increase the probability of updating. In section A.12.2 we will further investigate the motives and reasons behind respondents' decisions to adjust or to not adjust their portfolios.

Intensive Margin To shed light on the intensive margin, we estimate the shock sensitivity for respondents who do update their portfolio. We re-estimate equation 23, again focusing on the equity share as our main dependent variable, but condition our analysis on respondents who have adjusted the amounts invested in at least one portfolio category. The results are shown in Table A.18, Panel C.

Conditional on updating their portfolio, a 1 percentage point increase in the perceived probability of a financial crisis causes a decrease in the preferred equity share of 0.17 percentage points. The sensitivity is statistically significant at the 5% level. Compared to the overall effect (Panel A), the effect size almost doubles. The effect sizes are quantitatively much smaller for the other crisis types and statistically insignificant. An interpretation of these results is that individuals may perceive a direct link between the risk of a financial crisis and their stock market investment, whereas they find it harder to assess the implications of the other crisis types for their optimal equity share. In the following paragraph, we explore adjustments in other dimensions of individuals' portfo-

[30] In some heterogeneous agents asset pricing models, prices are influenced by beliefs that are weighted according to investors' wealth (see, e.g., Aron-Dine et al. 2024). To explore if wealthier households have a higher sensitivity to tail risk at the extensive margin, we apply wealth-weights and replicate the margin plots above (available upon request). We generally observe very similar patterns with the exception of the *China-Taiwan* vignette. In this scenario, the reaction of wealthier respondents is more sensitive to a positive shock (higher risk) compared to the reaction of all respondents.

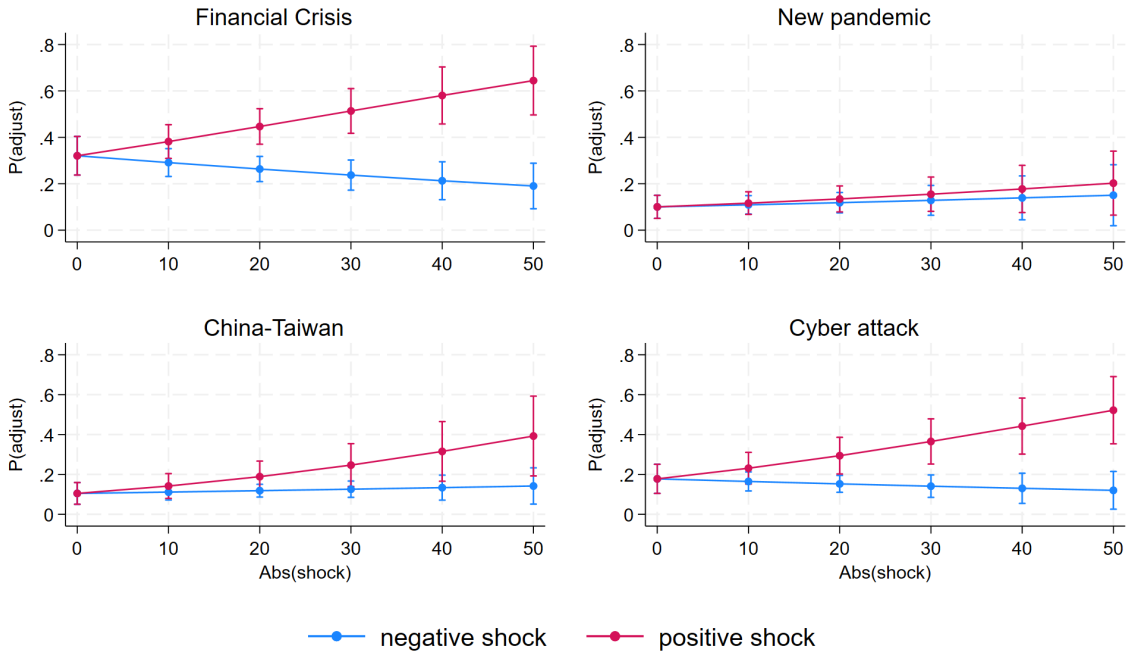


Figure A.4: Predicted probability of respondents to adjust their portfolio holding

Note: Marginal predicted probabilities are derived from a logit regression where the dependent variable is a binary indicator equal to 1 if respondents adjust at least one item in their portfolio. The key independent variable is the individual-specific shock, measured as the absolute difference between the scenario probability and the respondent's prior belief. We include the same array of control variables as in Table A.18. Regressions are weighted using survey weights and estimated separately for each crisis type. Error bars represent 95% confidence intervals.

lios (beyond equity), and we explore respondents' reasons for adjusting or not adjusting in section A.12.2.

Multi-asset Allocation Thus far, we have focused our analysis on the sensitivity of the equity share. However, beliefs about tail risks may induce households to adjust other asset classes in their financial portfolio as well. Based on our findings from the news provision waves, we hypothesize that households' responses may be specific to the crisis scenario. In the next step, we therefore estimate the sensitivities of all portfolio components elicited in the survey, conditional on updating the portfolio (intensive margins). Table A.19 summarizes the estimated coefficients β_k^j of equation 23 for every crisis j (rows) and asset class k (columns).

A 1 percentage point increase in the probability of a financial crisis leads respondents to decrease their equity share by 0.17 percentage points, while increasing their cash and precious metal holdings (though the latter effects are not significant individually). In other words, respondents pull out of risky equity, but likely do not consider banks as safe in a financial crisis, and hence move into cash and precious metals. By contrast, a higher risk of a pandemic leads to a significant decrease in the cash share. In turn, respondents increase the share of bank and bond holdings. A likely reason could be that cash is considered less useful during a pandemic, while bank accounts can be used for online shopping or cashless in-store payments. A higher probability of a conflict between mainland China and Taiwan causes respondents to increase their metal/gold share (while reducing their cash share) consistent with a flight-to-safety motive into tangible assets.

Table A.19: Sensitivity of portfolio adjustment to shock

	(1) Cash	(2) Bank	(3) Bonds	(4) Equity	(5) Prec. metals	(6) Other
Financial Crisis	0.160	-0.043	-0.022	-0.172**	0.099	0.006
	(0.114)	(0.134)	(0.067)	(0.069)	(0.078)	(0.035)
R^2	0.19	0.34	0.21	0.55	0.15	0.07
N	254	254	254	254	254	254
New pandemic	-0.331**	0.239	0.111	0.062	-0.000	0.030
	(0.168)	(0.242)	(0.095)	(0.089)	(0.113)	(0.023)
R^2	0.33	0.39	0.19	0.47	0.23	0.16
N	106	106	106	106	106	106
China-Taiwan	-0.149	0.098	0.049	0.063	0.229*	-0.103
	(0.173)	(0.195)	(0.071)	(0.075)	(0.117)	(0.090)
R^2	0.32	0.48	0.11	0.59	0.31	0.11
N	140	140	140	140	140	140
Cyber attack	0.005	0.000	-0.109**	0.035	0.133	-0.014
	(0.173)	(0.167)	(0.054)	(0.051)	(0.083)	(0.035)
R^2	0.17	0.19	0.12	0.33	0.07	0.30
N	167	167	167	167	167	167

Note: Table shows how responsive household portfolio allocations are towards a *shock* to the likelihood of a tail event of 1 percentage point. Analysis restricted to households who adjust their portfolio at least in one category (intensive margin). Dependent variable is the percentage share of financial wealth invested in an asset class (represented by each column head). We include the same array of control variables as in Table A.18. Regression run separately for each crisis type and asset class. Regression uses survey weights. Huber-White robust standard errors are in parentheses. * indicates significance at the 90%, ** at the 95% and *** at the 99% level.

Households respond to an increased threat of a Cyber attack with a reduction of their bond share which tends to be shifted towards precious metals. Overall, these results reconfirm that households' responses to tail risk are event-specific. In the next section, we will further explore the motives behind respondents' portfolio decisions.

A.12.2 Reasons for Portfolio Adjustment

We use open-ended text questions to understand the narratives behind the observed portfolio adjustments. Specifically, both adjusters and non-adjusters were asked to provide up to five reasons underlying their choices. We report the frequency of these reasons, which have been categorized into seven groups by professional coders at the survey company, in Table A.20.[31] The top panel shows reasons for re-balancing, and the bottom panel shows reasons for *not* re-balancing. Across all crisis types (column 1), the most frequent category of reasons for adjusting portfolios, cited by roughly 40% of adjusters, is "Diversification/Stability" which encompasses arguments such as "reduce risk", "diversify risk", or "stability of investments". The second most frequent category evolves around

[31]To ease the readability of the results, we combine two categories for reasons of rebalancing, as they capture similar economic concepts evolving around the security of an investment, and we omit the category "Other".

the "Return" motive, in particular fears about losses from stocks and other assets are mentioned there. The third most frequent category is 'Liquidity", with 24% of respondents citing perceived liquidity or safety benefits of cash. 16% of respondents cite "lack of trust in institutions" as a reason for adjusting portfolios. The cited institutions include the ECB, the government, but also banks and the stock market more generally.

Columns 2-9 of table A.20 (Panel A) show how reasons to rebalance vary by crisis type and direction of shock. Respondents who receive the financial crisis vignette mention a need for liquidity significantly more often when they receive a positive shock, implying higher risk (25%, column 3) versus a negative shock, implying lower risk (12%, column 2). Similarly, respondents in the China-Taiwan vignette mention concerns about security and high uncertainty as a reason significantly more often when they receive a positive shock (47%, column 7) than those who receive a negative shock (16%, column 6).

Panel B of Table A.20 shows the main reasons why households chose to *not* re-balance are they perceive themselves hedged against the crisis, they expect markets to recover, or they have little to no assets. Each of these reasons is cited by roughly 20-30% of respondents. "Lack of knowledge" is mentioned by 9% of respondents. "Expected market recovery" is cited much less frequently for a China-Taiwan escalation, which might plausibly be associated with persistent effects on the world economy and financial markets. "Long-term hedging" and "having little or no assets" have similar importance across all crisis types.

The cited reasons to not rebalance highlight the importance of investment frictions limiting the pass-through from beliefs to portfolio decisions. Several of the mentioned reasons ("Too much effort", "no knowledge", "too few assets") are consistent with households not updating their portfolios because transaction costs (e.g., with respect to time, effort, or financial costs) outweigh gains in utility.[32] A second line of argument relates to households' long-term investment horizons. If a crisis is perceived as a temporary perturbation, investors may (ex-ante) plan to look through it and refrain from adjusting their portfolios.

[32]Citing the reason "too few or no assets" is strongly related to respondents' reported financial wealth. While around 60% of non-adjusters in the lowest wealth quartile cite this reason, its frequency drops to 6% in the highest wealth quartile.

Table A.20: Reasons to adjust and to not adjust the portfolio

	All	Financial Crisis		New pandemic		China-Taiwan		Cyber attack	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		-	+	-	+	-	+	-	+
Panel A: Reasons for adjusting									
Liquidity	0.24	**0.12**	**0.25**	0.24	0.30	0.12	0.11	0.43	0.37
Return	0.29	0.38	0.39	0.35	0.29	0.29	0.32	0.08	0.16
Security/Uncertainty	0.21	0.16	0.15	0.25	0.29	**0.16**	**0.47**	0.15	0.26
Trust in Institutions	0.16	0.22	0.18	0.12	0.06	0.14	0.21	0.18	0.09
Diversification/Stability	0.39	0.37	0.37	0.35	0.37	0.52	0.41	0.45	0.36
N	566	100	111	37	47	60	56	58	97
Panel B: Reasons for non-adjusting									
Wait and see	0.04	0.02	0.01	0.04	0.08	0.03	0.02	0.03	0.07
Too much effort	0.03	0.01	0.03	0.03	0.04	0.04	0.03	0.02	0.05
Expect market recovery	0.24	**0.18**	**0.27**	0.28	0.26	**0.26**	**0.13**	0.22	0.27
no knowledge/expertise	0.09	0.10	0.08	0.08	0.07	0.09	0.09	0.09	0.11
Long-term hedging	0.29	0.35	0.30	0.27	0.28	0.29	0.40	0.22	0.24
Shock too low	0.05	**0.06**	**0.02**	0.03	0.02	0.07	0.05	0.05	0.06
Too few or no assets	0.29	0.30	0.32	0.30	0.25	0.27	0.31	0.32	0.27
N	2273	333	171	325	326	366	207	261	284

Note: Table shows the fraction of respondents who provided the respective reason why they choose to rebalance their portfolios (Panel A) or why they choose not to rebalance (Panel B). Respondents are invited to provide multiple reasons, thus fractions do not sum to 1. Column 1 summarizes the information provided for the entire sample, columns 2-9 differentiate by the randomly assigned type of tail scenario (column heads), further differentiated by the direction of the *shock*, where a positive news shock (indicated with a +) means that respondents assume a higher probability of a tail event, and vice versa for a negative shock (indicated with a −). Bold-faced numbers in columns 2-9 highlight significant differences (p-val < 0.05) across pairwise tests within a tail scenario.

B Online Appendix

This online appendix contains the survey questions that we included in the Bundesbank Survey of Consumer Expectations during four waves, in August and November 2022 and in August and November 2023, respectively. The survey is administered in German. We attach the English translations of the survey questions. The complete questionnaire for each wave can be accessed online (in English and German) via the following link: https://www.bundesbank.de/en/bundesbank/research/survey-on-consumer-expectations-bop-hh/questionnaires-850746. The questionnaires shown below include coding instructions which are not shown to survey participants, but are useful for fully understanding randomization and other features. We start our presentation of the questionnaires with the memory module, which is the key wave for our paper.

B.1 Memory module (August 2023)

P4417 | **2022_14** | **Tendency to overestimate small probabilities | small_probab**

Respondent group: all

Input filter: drandom4 = 2-5

Range of valid values: 0.0 to 1,000.0

We will now ask you some general questions.

Question: In your estimation, how many ATMs are there in Germany per 1,000 inhabitants?

Note: Please enter a value in the input field (values may have one decimal place).

Input field per 1,000 inhabitants

P4418 | **2022_14** | **Personal experiences | experiences_[a-h]**

Respondent group: all

Input filter: drandom4 = 2-5

Randomise items except g and h

Question: Which of the following situations have you already personally experienced in your life?

Note: Please select all answers that apply.

1 Item selected
2 Item not selected

a Unemployment
B Fleeing a country as an asylum seeker or moving country as a migrant

c Significant financial losses on investments (e.g. shares, funds, real estate, holdings in a company)
d Inability to service debt
e Job with major risks to safety or health
f Health problems (e.g. serious accident, life-threatening illness, etc.)
g Other serious economic or financial problems
h Other great personal misfortune or adversity

P4419A | 2022_14 | Memory of past events | year_[a-j], event_[a-j]

Respondent group: all

Input filter: drandom4 = 2 | 4

Range of valid values: year_[a-j]: 1960 to 2023; text input field: max. 50 characters

Error messages:
- If respondents wish to proceed without answering: “You can enter up to ten events. Even entering fewer than ten events will be of great help to us.”
- If respondents enter an incorrect year: “Please enter an event that took place between 1960 and 2023.”

Info box after the term “DAX”: “The DAX (Deutscher Aktienindex) is a stock market index that tracks the performance of the most important corporate shares in Germany. It is a total return index, taking both changes in share prices and dividend payments (profit distributions) into account. Changes in the DAX thus represent changes in the return that would be realised by an investor.”

Question: Thinking of important events in the economy and the financial markets over approximately the past 60 years, which ones do you think have led to major increases or decreases in the DAX (i) stock market index? In around what year did these events take place?

Notes:
- There are no right or wrong answers here. We are only interested in your estimates.
- Please enter as many events as you can. You can enter up to ten events in the period from 1960 to 2023.
- Please describe the event in a few words, preferably in one or two terms.
- If the event lasted for several years, please enter the year in which it started.
- If you are using your smartphone to answer this question, please hold it in landscape mode.

Event	Year
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field

P4419B | 2022_14 | Memory of past events | year_[a-j], event_[a-j]

Respondent group: all

Input filter: drandom4 = 5

Range of valid values: year_[a-j]: 1960 to 2023; text input field: max. 50 characters

Error messages:

- If respondents wish to proceed without answering: “You can enter up to ten events. Even entering fewer than ten events will be of great help to us.”
- If respondent enters an incorrect year: “Please enter an event that took place between 1960 and 2023.”

Question: Thinking of important events in society, culture and sport over approximately the past 60 years, which ones do you think played a major role in Germany? In around what year did these events take place?

Notes:

- There are no right or wrong answers here. We are only interested in your estimates.
- Please enter as many events as you can. You can enter up to ten events.
- Please describe the event in a few words, preferably in one or two terms.
- If the event lasted for several years, please enter the year in which it started.
- If you are using your smartphone to answer this question, please hold it in landscape mode.

Event	Year
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field

P4420A | 2022_14 | Memory of past crises_magnitude | past_magnitude_[a-j]

Respondent group: all

Input filter: drandom4 = 2 | 4

Show answers from year_[a-j], event_[a-j]

Range of valid values: -100.0 to +100.0

Info box after the term “DAX”: “The DAX (Deutscher Aktienindex) is a stock market index that tracks the performance of the most important corporate shares in Germany. It is a total return index, taking both changes in share prices and dividend payments (profit distributions) into account. Changes in the DAX thus represent changes in the return that would be realised by an investor.”

Question: By how much do you think the DAX (i) stock market index increased or decreased in the wake of the events that you listed?

Notes:

- There are no right or wrong answers here. We are only interested in your estimates.

- Please enter a positive value if you think there was an increase in the DAX and a negative value if you think there was a decrease in the DAX.
- If you are using your smartphone to answer this question, please hold it in landscape mode.

Event	Year	DAX change in percent
event_a	year_a	Input field percent
event_b	year_b	Input field percent
event_c	year_c	Input field percent
event_d	year_d	Input field percent
event_e	year_e	Input field percent
event_f	year_f	Input field percent
event_g	year_g	Input field percent
event_h	year_h	Input field percent
event_i	year_i	Input field percent
event_j	year_j	Input field percent

P4420A | 2022_14 | Memory of past crises_magnitude | past_magnitude_[a-j]

Respondent group: all

Input filter: drandom4 = 5

Show answers from year_[a-j], event_[a-j]

Range of valid values: -100.0 to +100.0

Info box after the term “DAX”: “The DAX (Deutscher Aktienindex) is a stock market index that tracks the performance of the most important corporate shares in Germany. It is a total return index, taking both changes in share prices and dividend payments (profit distributions) into account. Changes in the DAX thus represent changes in the return that would be realised by an investor.”

Question: By how much do you think the DAX (i) stock market index increased or decreased in the wake of the events that you listed?

Notes:

- There are no right or wrong answers here. We are only interested in your estimates.
- Please enter a positive value if you think there was an increase in the DAX and a negative value if you think there was a decrease in the DAX.
- If you are using your smartphone to answer this question, please hold it in landscape mode.

Event	Year	DAX change in percent
event_a	year_a	Input field percent
event_b	year_b	Input field percent
event_c	year_c	Input field percent
event_d	year_d	Input field percent
event_e	year_e	Input field percent
event_f	year_f	Input field percent
event_g	year_g	Input field percent
event_h	year_h	Input field percent
event_i	year_i	Input field percent
event_j	year_j	Input field percent

2022_14 | Treatment text

Respondent group: all

Input filter: drandom4 = 4

Response time for this page is needed.

Info box after the term “DAX”: “The DAX (Deutscher Aktienindex) is a stock market index that tracks the performance of the most important corporate shares in Germany. It is a total return index, taking both changes in share prices and dividend payments (profit distributions) into account. Changes in the DAX thus represent changes in the return that would be realised by an investor.”

Info box after the term “Decline in the DAX”: “Greatest loss in the DAX per event, based on the decline from the highest to the lowest level of the DAX within 12 months.”

The DAX (i) stock market index has recorded a total of **eleven significant declines over the past 60 years**. The table provides an overview of the individual events.

Event	Year	Decline in the DAX (i)
Financial crisis in the United States	1966	-29%
Tech-stock crash in the United States	1970	-33%
First oil crisis	1973	-34%
Black Monday: Correction following boom and panic	1987	-41%
Outbreak of the Gulf War	1990	-33%
Near collapse of the Long-Term Capital Management (LTCM) hedge fund	1998	-37%
Dotcom crash	2000	-60%
Global financial crisis	2008	-49%
European sovereign debt crisis	2011	-33%
Brexit	2016	-29%
Outbreak of the coronavirus pandemic	2020	-39%

Source: Bundesbank calculations

P4421 | 2022_14 | Magnitude of stock market crash | magnitude_crash

Respondent group: all

Input filter: drandom4 = 2-5

Range of valid values: 0.0 to +100.0

Info box after the term “DAX”: “The DAX (Deutscher Aktienindex) is a stock market index that tracks the performance of the most important corporate shares in Germany. It is a total return index, taking both changes in share prices and dividend payments (profit distributions) into account. Changes in the DAX thus represent changes in the return that would be realised by an investor.”

Info box after the term “Decline in the DAX”: “Greatest loss in the DAX per event, based on the decline from the highest to the lowest level of the DAX within 12 months.”

Question: Imagine that there would be a sharp decline in the DAX (i) stock market index within the next 12 months. By what percentage do you think the DAX (i) would fall in this case?

Notes:

- Please indicate how much lower (as a percentage) you think the DAX would be after 12 months if this event were to occur compared to if it had not occurred.
- If you expect a decline, please enter a positive value.
- If you do not expect a decline, please enter a value of zero.

Decline in the DAX (i) of Input field percent

P4422 | 2022_14 | Probability of stock market crash | probability_crash

Respondent group: all

Input filter: drandom4 = 2-5

Range of valid values: 0 to 100

Info box after the term "DAX": "The DAX (Deutscher Aktienindex) is a stock market index that tracks the performance of the most important corporate shares in Germany. It is a total return index, taking both changes in share prices and dividend payments (profit distributions) into account. Changes in the DAX thus represent changes in the return that would be realised by an investor."

Question: How likely do you think it is that the DAX (i) stock market index will experience such a decline within the next 12 months?

Note: The aim of this question is to determine how likely you think it is that something specific will happen in the future. You can rate the likelihood on a scale from 0 to 100, with 0 meaning that an event is completely unlikely and 100 meaning that you are absolutely certain it will happen. Use values between the two extremes to moderate the strength of your opinion.

Input field percent

P4423 | 2022_14 | Scenarios stock market crash | scenarios_dax_[a-e]

Respondent group: all

Input filter: drandom4 = 2-5

Range of valid values: -100.0 to +100.0

Info box after the term "DAX": "The DAX (Deutscher Aktienindex) is a stock market index that tracks the performance of the most important corporate shares in Germany. It is a total return index, taking both changes in share prices and dividend payments (profit distributions) into account. Changes in the DAX thus represent changes in the return that would be realised by an investor."

We would now like you to think more specifically about various possible developments in the DAX stock market index over the next 12 months.

Question: What percentage change in the DAX (i) stock market index would you expect in each of the following scenarios?

Notes:

- Please enter a positive value if you expect an increase in the DAX and a negative value if you expect a decrease in the DAX.
- If you expect there to be no change, please enter a value of zero.

a In a **worst case** scenario, I would expect the DAX to change by Input field percent.
b In a **bad** scenario, I would expect the DAX to change by Input field percent.
c In a **neutral** scenario, I would expect the DAX to change by Input field percent.
d In a **good** scenario, I would expect the DAX to change by Input field percent.
e In a **best case** scenario, I would expect the DAX to change by Input field percent.

P4424 | 2022_14 | Probability of scenarios stock market crash | prob_scenarios_dax_[a-e]

Respondent group: all

Input filter: drandom4 = 2-5 & if at least two of scenarios_dax_[a-e] =! -9997 | -9998

Only those fields should be active for which a value has been provided in scenarios_dax_[a-e]. If only one value has been provided, this question should not be shown.

Range of valid values: 0 to 100

The programming of the question requires the sum of the variables to be 100. The current sum of all entered points is shown to the respondent when answering the question. If the sum does not equal 100, respondents are asked to correct their responses with the following error message: “Please note that your answers to all scenarios have to add up to 100.”

Info box after the term “DAX”: “The DAX (Deutscher Aktienindex) is a stock market index that tracks the performance of the most important corporate shares in Germany. It is a total return index, taking both changes in share prices and dividend payments (profit distributions) into account. Changes in the DAX thus represent changes in the return that would be realised by an investor.”

Question: For each of the possible changes in the DAX (i) stock market index that you have entered, please now indicate how likely you think it is that these will occur within the next 12 months.

Note: The aim of this question is to determine how likely you think it is that something specific will happen in the future. You can rate the likelihood on a scale from 0 to 100, with 0 meaning that an event is completely unlikely and 100 meaning that you are absolutely certain it will happen. Use values between the two extremes to moderate the strength of your opinion. Please note that your answers to all scenarios have to add up to 100.

a **Worst case** scenario: The likelihood of a [scenarios_dax_a]% change is Input field percent.
b **Bad** scenario: The likelihood of a [scenarios_dax_b]% change is Input field percent.
c **Neutral** scenario: The likelihood of a [scenarios_dax_c] change is Input field percent.
d **Good** scenario: The likelihood of a [scenarios_dax_d]% change is Input field percent.
e **Best case** scenario: The likelihood of a [scenarios_dax_e]% change is Input field percent.

P4419A | 2022_14 | Memory of past events | year_[a-j], event_[a-j]

Respondent group: all

Input filter: drandom4 = 3

Range of valid values: year_[a-j]: 1960 to 2023; text input field: max. 50 characters

Error messages:

- if respondents wish to proceed with answering: “You can enter up to ten events. Even entering fewer than ten events will be of great help to us.”
- If respondents enter an invalid year: “Please enter an event that took place between 1960 and 2023.”

Info box after the term “DAX”: “The DAX (Deutscher Aktienindex) is a stock market index that tracks the performance of the most important corporate shares in Germany. It is a total return index, taking both changes in share prices and dividend payments (profit distributions) into account. Changes in the DAX thus represent changes in the return that would be realised by an investor.”

Question: Thinking of important events in the economy and the financial markets over approximately the past 60 years, which ones do you think have led to major increases or decreases in the DAX (i) stock market index? In around what year did these events take place?

Notes:

- There are no right or wrong answers here. We are only interested in your estimates.
- Please enter as many events as you can. You can list up to ten events in the period from 1960 to 2023.
- Please describe the event in a few words, preferably in one or two terms.
- If the event lasted for several years, please enter the year in which it started.
- If you are using your smartphone to answer this question, please hold it in landscape mode.

Event	Year
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field
Input field	Input field

P4420A | 2022_14 | Memory of past crises_magnitude | past_magnitude_[a-j]

Respondent group: all

Input filter: drandom4 = 3

Show answers from year_[a-j], event_[a-j]

Range of valid values: change DAX: -100.0 - +100.0

Info box after the term “DAX”: “The DAX (Deutscher Aktienindex) is a stock market index that tracks the performance of the most important corporate shares in Germany. It is a total return index, taking both changes in share prices and dividend payments (profit distributions) into account. Changes in the DAX thus represent changes in the return that would be realised by an investor.”

Question: By how much do you think the DAX (i) stock market index increased or decreased in the wake of the events that you listed?

Notes:

- There are no right or wrong answers here. We are only interested in your estimates.
- Please enter a positive value if you think there was an increase in the DAX and a negative value if you think there was a decrease in the DAX.

Event	Year	DAX change in percent
event_a	year_a	Input field percent
event_b	year_b	Input field percent
event_c	year_c	Input field percent
event_d	year_d	Input field percent
event_e	year_e	Input field percent
event_f	year_f	Input field percent
event_g	year_g	Input field percent
event_h	year_h	Input field percent
event_i	year_i	Input field percent
event_j	year_j	Input field percent

--- | --- | **END SPLIT SAMPLE 4**

B.2 First News Provision Wave (August 2022)

P3206 | 2022_14 | Magnitude of tail event | mag_tail_pre [a-d]

Respondent group: all

Info boxes

a A financial crisis is a serious disruption to the financial system. In a financial crisis, the financial system is no longer able to fully carry out its key tasks. Lending is restricted and individual banks or investment funds may have to be resolved.

b A pandemic is the global spread of an infectious disease, such as COVID-19. Voluntary or government-mandated measures to reduce contact can lead to disruptions in economic activity. Please note: This refers to future pandemics involving other – potentially as yet unknown – infectious diseases.

c China regards Taiwan as a renegade province and aims to merge it with China, while Taiwan sees itself as a sovereign state. Due to potential US military support for Taiwan and the importance of China and Taiwan for the global economy, any conflict between them might well have global economic repercussions.

d Severe bottlenecks in the supply of energy to enterprises and/or households in Germany. A substantial part of German industry might not be adequately supplied with gas, and intermittent power outages could occur.

e Economic output is usually measured by gross domestic product (GDP). GDP is the total value of all goods and services produced within Germany during a year.

Range of valid values for every item: 0 to 100, values may have one decimal place.

The order of items a-d is randomised. The randomisation needs to be stored and used for questions P3207, P3211E, P3212E, P3213E.

Question: Imagine that **one of the following events** were to occur within the next three years. As a percentage, how much lower would you expect Germany's economic output (ie) to be in each case?

Note: Please indicate the percentage by which Germany's economic output would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

a	Financial crisis (ia)	*[Input field]* percent
b	Pandemic involving a new pathogen (ib)	*[Input field]* percent
c	Chinese attack on Taiwan (ic)	*[Input field]* percent
d	Energy crisis (id)	*[Input field]* percent

P3207 | 2022_14 | Perceived probabilities of tail events| prob_tail_pre_[a-d]

Respondent group: all

Info boxes from the previous question

Range of valid values for every item: 0 to 100. No decimal places possible.

The order of items a-d is as in the stored randomisation for P3206.

Question: In your opinion, how likely is it that each of the events will occur within the next three years?

Note: Please enter a value between 0 and 100 in each case. 100 means that you are *absolutely certain* that the event will occur; 0 means that you believe the event is completely impossible.

a Financial crisis (ia) *[Input field]* percent
b Pandemic involving a new pathogen (ib) *[Input field]* percent
c Chinese attack on Taiwan (ic) *[Input field]* percent
d Energy crisis (id) *[Input field]* percent

--- | --- | START SPLIT SAMPLE 2

--- | Split sample 2| RANDOMISATION

Respondent group: all

The sample is split randomly into **nine** groups. Randomisation dummy (drandom2) is used for several questions between P3208-P3214.

One factor variable: drandom2

1 group A2 – one-ninth of the total sample
2 group B2 – one-ninth of the total sample
3 group C2 – one-ninth of the total sample
4 group D2 – one-ninth of the total sample
5 group E2 – one-ninth 9 of the total sample
6 group F2 – one-ninth of the total sample
7 group G2 – one-ninth of the total sample
8 group H2 – one-ninth of the total sample
9 group I2 – one-ninth of the total sample

We will now show you some current information. Please take some time to read this information carefully.

[drandom2==1]
Banks have become significantly more resilient since the 2008 global financial crisis. Capital buffers, which are crucial for the resilience of banks, have since risen by around 50%. This makes it easier for banks to get through economically challenging times without being forced to constrain their lending to firms and households.

[drandom2==2]
Overvalued assets, such as real estate, constitute a vulnerability for the German financial system. The German stock index (DAX) has lost around 20% of its value since the beginning of the year. According to Bundesbank estimates, property prices in Germany are overvalued by approximately 20-35%. If property prices suddenly fall and many households are no longer able to service their loans, banks will face heavy losses.

[drandom2==3]
In order to effectively prevent or mitigate future pandemics, a number of measures are being worked on at full speed. By utilising mRNA technology, it should be possible for effective vaccines to be rolled out quickly, effective drugs to be developed rapidly and pandemic surveillance to be improved. In future, these and other measures can help contain the spread of pathogens at an early stage.

[drandom2==4]
Experts are warning that a new pandemic could occur at any time. For example, the keeping of certain animal species in China is linked to the SARS outbreak of 2002, and in the Middle East to the MERS outbreak of 2012. In Europe, intensive livestock farming is a potential source of new pathogens. Given a lack of preparedness, the consequences could be just as great or even more far-reaching than those of the COVID-19 pandemic.

[drandom2==5]
Experts assume that China would **not** be prepared to invade Taiwan at present. If the situation were to escalate in future, efforts made by the United States and Europe to become less dependent on imports from Taiwan and China would limit the economic fallout. To this end, production facilities in Europe and the United States are to receive around €40-50 billion in funding, respectively.

[drandom2==6]
High-ranking US military officials warn that there is a danger that China will invade Taiwan within the next five years. As Taiwan produces two-thirds of the world's semiconductors, this could have severe economic effects on motor vehicle production, for instance, in Germany and worldwide. China's role as a production base and sales market could amplify the economic impact in the event of tensions between China and the United States as well as possible sanctions against China.

[drandom2==7]
Germany's leading economic research institutions do **not** expect there to be a gas supply gap until the end of 2023 in the event that Russian gas deliveries are stopped immediately, meaning that German industrial enterprises would not then have to limit their gas consumption. The provision of gas to households and social facilities would not be jeopardised in any case.

[drandom2==8]
The Federal Minister for Economic Affairs and Energy announced that the Emergency Plan for Gas would move to its second stage. The reason cited for this was the reduction in Russian gas deliveries since mid-June and the high prices on the gas market. According to the minister, a threefold increase in gas prices for households and firms is considered possible, as well as restrictions on the supply of gas to industrial enterprises.

[drandom2==9]
No information

P3208 | 2022_14 | Investment environment | good_time_[a-b]

Respondent group: all

Question: Do you think now is a good or a bad time to …

1 Very bad
2 Bad
3 Neither good nor bad
4 Good
5 Very good

a … buy property (house/apartment).
b … invest money in the stock market.

P3209 | 2022_14 | Financial asset allocation | hyp_pf_share_[a-e]

Respondent group: all

The programming of the question requires each variable to be a non-negative number and the sum of the variables to be 100. The current sum of all entered points is shown to the respondent when answering the question. Respondents are asked to correct their responses if the sum does not equal 100.

Range of valid values for every item: 0 to 100 No decimal places possible.

Assume you have saved a third of your annual earnings and wish to invest this money starting today.

Question: What percentage of the investment amount would you invest in each asset class?

Note: Please enter a value in the input field. Your answers have to add up to 100.

a	Cash and bank account	*[Input field]* percent
b	Shares (including funds and ETFs)	*[input field]* percent
c	Fixed-income securities (including funds and ETFs)	*[input field]* percent
d	Gold/precious metals (including ETFs)	*[Input field]* percent
e	Other investment opportunities	*[input field]* percent

P3210 | 2022_14 | Future expenditure| spend_future_[a-d]

Respondent group: all

Info box (I): Other expenditure includes the following items in particular: essential goods (e.g. food and beverages, non-food items such as cleaning products or similar), clothing and footwear, entertainment/recreation (e.g. restaurant visits, cultural events, gym), mobility (e.g. fuel, car loans and running costs, bus and train tickets), services (e.g. hairdresser, childcare, medical costs) as well as expenditure on travel and holidays.

Range of valid values for every item: 0 to 100,000

You will now again be shown some everyday items that you can or need to buy.

Question: How much do you plan to spend in euro **on average per month** on each of the following items over the next twelve months?

Note: Please enter an amount in every field (with no decimal places). If you are not quite sure, please give a rough estimate.

a	Major purchases (e.g. car, furniture, electrical appliances, etc.)	*[Input field]*
b	Housing costs (e.g. rent, mortgage, ancillary costs)	*[Input field]*
c	Other expenditure (e.g. shopping, mobility, services, travel) (i)	*[Input field]*
d	Savings (e.g. savings account, shares, bonds)	*[Input field]*

P3211A | 2022_14 | Magnitude of tail event | mag_tail_post_a

Respondent group: all

Input filter drandom2=1 or 2

Info boxes

a A financial crisis is a serious disruption to the financial system. In a financial crisis, the financial system is no longer able to fully carry out its key tasks. Lending is restricted and individual banks or investment funds may have to be resolved.

e Economic output is usually measured by gross domestic product (GDP). GDP is the total value of all goods and services produced within Germany during a year.

Range of valid values: 0 to 100, values may have one decimal place.

We would now like to learn a little more about your assessment of the impact and likelihood of potential crises. There is no right or wrong answer; we are interested in your personal opinion.

Question: Imagine that a **financial crisis (ia)** were to occur within the next two years. As a percentage, how much lower would you expect Germany's economic output (ie) to be in this case?

Note: Please indicate the percentage by which Germany's economic output would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3211B | 2022_14 | Magnitude of tail event | mag_tail_post_b

Respondent group: all

Input filter drandom2=3 or 4

Info boxes:

b A pandemic is the global spread of an infectious disease, such as COVID-19. Voluntary or government-mandated measures to reduce contact can lead to disruptions in economic activity. Please note: This refers to future pandemics involving other – potentially as yet unknown – infectious diseases.

e Economic output is usually measured by gross domestic product (GDP). GDP is the total value of all goods and services produced within Germany during a year.

Range of valid values: 0 to 100, values may have one decimal place.

We would now like to learn a little more about your assessment of the impact and likelihood of potential crises. There is no right or wrong answer; we are interested in your personal opinion.

Question: Imagine a **pandemic involving a new pathogen (ib)** were to occur within the next two years. As a percentage, how much lower would you expect Germany's economic output (ie) to be in this case?

Note: Please indicate the percentage by which Germany's economic output would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3211C | 2022_14 | Magnitude of tail event | mag_tail_post_c

Respondent group: all

Input filter drandom2=5 or 6

Info boxes:

c China regards Taiwan as a renegade province and aims to merge it with China, while Taiwan sees itself as a sovereign state. Due to potential US military support for Taiwan and the importance of China and Taiwan for the global economy, any conflict between them might well have global economic repercussions.

e Economic output is usually measured by gross domestic product (GDP). GDP is the total value of all goods and services produced within Germany during a year.

Range of valid values: 0 to 100, values may have one decimal place.

We would now like to learn a little more about your assessment of the impact and likelihood of potential crises. There is no right or wrong answer; we are interested in your personal opinion.

Question: Imagine that a **Chinese attack on Taiwan (ic)** were to occur within the next two years. As a percentage, how much lower would you expect Germany's economic output (ie) to be in this case?

Note: Please indicate the percentage by which Germany's economic output would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3211D | 2022_14 | Magnitude of tail event | mag_tail_post_d

Respondent group: all

Input filter drandom2=7 or 8

Info boxes:

d Severe bottlenecks in the supply of energy to enterprises and/or households in Germany. A substantial part of German industry might not be adequately supplied with gas, and intermittent power outages could occur.

e Economic output is usually measured by gross domestic product (GDP). GDP is the total value of all goods and services produced within Germany during a year.

Range of valid values: 0 to 100, values may have one decimal place.

We would now like to learn a little more about your assessment of the impact and likelihood of potential crises. There is no right or wrong answer; we are interested in your personal opinion.

Question: Imagine that an **energy crisis** (id) were to occur within the next two years. As a percentage, how much lower would you expect Germany's economic output (ie) to be in this case?

Note: Please indicate the percentage by which Germany's economic output would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3211E | 2022_14 | Magnitude of tail event | mag_tail_post_[a-d]

Respondent group: all

Input filter drandom2=9

Info boxes

a A financial crisis is a serious disruption to the financial system. In a financial crisis, the financial system is no longer able to fully carry out its key tasks. Lending is restricted and individual banks or investment funds may have to be resolved.

b A pandemic is the global spread of an infectious disease, such as COVID-19. Voluntary or government-mandated measures to reduce contact can lead to disruptions in economic activity. Please note: This refers to future pandemics involving other – potentially as yet unknown – infectious diseases.

c China regards Taiwan as a renegade province and aims to merge it with China, while Taiwan sees itself as a sovereign state. Due to potential US military support for Taiwan and the importance of China and Taiwan for the global economy, any conflict between them might well have global economic repercussions.

d Severe bottlenecks in the supply of energy to enterprises and/or households in Germany. A substantial part of German industry might not be adequately supplied with gas, and intermittent power outages could occur.

e Economic output is usually measured by gross domestic product (GDP). GDP is the total value of all goods and services produced within Germany during a year.

Range of valid values for every item: 0 to 100, values may have one decimal place.

The order of the items a-d is as in the stored randomisation for P3206.

We would now like to learn a little more about your assessment of the impact and likelihood of potential crises. There is no right or wrong answer; we are interested in your personal opinion.

Question: Imagine that **one of the following events** were to occur within the next two years**.** As a percentage, how much lower would you expect Germany's economic output (ie) to be in each case?

Note: Please indicate the percentage by which Germany's economic output would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

a Financial crisis (ia) *[Input field]* percent
b Pandemic involving a new pathogen (ib) *[Input field]* percent
c Chinese attack on Taiwan (ic) *[Input field]* percent
d Energy crisis (id) *[Input field]* percent

P3212A | 2022_14 | Magnitude of tail event | mag_tail_financial_a

Respondent group: all

Input filter drandom2=1 or 2

Info box:

a A financial crisis is a serious disruption to the financial system. In a financial crisis, the financial system is no longer able to fully carry out its key tasks. Lending is restricted and individual banks or investment funds may have to be resolved.

f The DAX is the most well-known German stock index. It measures the performance of the 40 largest and most liquid companies in the German stock market.

Range of valid values: 0 to 100, values may have one decimal place.

Question: And by what percentage do you think the German stock index (DAX) (if) would fall in this case, i.e. if **a financial crisis (ia)** were to occur within the next two years?

Note: Please indicate the percentage by which the DAX would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3212B | 2022_14 | Magnitude of tail event | mag_tail_financial_b

Respondent group: all

Input filter drandom2=3 or 4

Info box:

b A pandemic is the global spread of an infectious disease, such as COVID-19. Voluntary or government-mandated measures to reduce contact can lead to disruptions in economic activity. Please note: This refers to future pandemics involving other – potentially as yet unknown – infectious diseases.

f The DAX is the most well-known German stock index. It measures the performance of the 40 largest and most liquid companies in the German stock market.

Range of valid values: 0 to 100, values may have one decimal place.

Question: And by what percentage do you think the German stock index (DAX) (if) would fall in this case, i.e. if a **pandemic involving a new pathogen** (ib) were to occur within the next two years?

Note: Please indicate the percentage by which the DAX would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3212C | 2022_14 | Magnitude of tail event | mag_tail_financial_c

Respondent group: all

Input filter drandom2=5 or 6

Info box:

c China regards Taiwan as a renegade province and aims to merge it with China, while Taiwan sees itself as a sovereign state. Due to potential US military support for Taiwan and the importance of China and Taiwan for the global economy, any conflict between them might well have global economic repercussions.

f The DAX is the most well-known German stock index. It measures the performance of the 40 largest and most liquid companies in the German stock market.

Range of valid values: 0 to 100, values may have one decimal place.

Question: And by what percentage do you think the German stock index (DAX) (if) would fall in this case, i.e. if **China were to attack Taiwan (ic)** within the next two years?

Note: Please indicate the percentage by which the DAX would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3212D | 2022_14 | Magnitude of tail event | mag_tail_financial_d

Respondent group: all

Input filter drandom2=7 or 8

Info box:

d Severe bottlenecks in the supply of energy to enterprises and/or households in Germany. A substantial part of German industry might not be adequately supplied with gas, and intermittent power outages could occur.

f The DAX is the most well-known German stock index. It measures the performance of the 40 largest and most liquid companies in the German stock market.

Range of valid values: 0 to 100, values may have one decimal place.

Question: And by what percentage do you think the German stock index (DAX) (if) would fall in this case, i.e. if **an energy crisis (id)** were to occur within the next two years?

Note: Please indicate the percentage by which the DAX would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3212E | 2022_14 | Magnitude of tail event | mag_tail_financial_[a-d]

Respondent group: all

Input filter drandom2=9

Info boxes

a A financial crisis is a serious disruption to the financial system. In a financial crisis, the financial system is no longer able to fully carry out its key tasks. Lending is restricted and individual banks or investment funds may have to be resolved.

b A pandemic is the global spread of an infectious disease, such as COVID-19. Voluntary or government-mandated measures to reduce contact can lead to disruptions in economic activity. Please note: This refers to future pandemics involving other – potentially as yet unknown – infectious diseases.

c China regards Taiwan as a renegade province and aims to merge it with China, while Taiwan sees itself as a sovereign state. Due to potential US military support for Taiwan and the importance of China and Taiwan for the global economy, any conflict between them might well have global economic repercussions.

d Severe bottlenecks in the supply of energy to enterprises and/or households in Germany. A substantial part of German industry might not be adequately supplied with gas, and intermittent power outages could occur.

f The DAX is the most well-known German stock index. It measures the performance of the 40 largest and most liquid companies in the German stock market.

Range of valid values for every item: 0 to 100, values may have one decimal place.

The order of the items a-d is as in the stored randomisation for P3206.

Question: And by what percentage do you think the German stock index (DAX) (if) would fall if one of the following events were to occur within the next two years?

Note: Please indicate the percentage by which the DAX would be lower one year after the event than it would be if the event did not occur. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

a Financial crisis (ia) *[Input field]* percent

b Pandemic involving a new pathogen (ib) *[Input field]* percent

c Chinese attack on Taiwan (ic) *[Input field]* percent

d Energy crisis (id) *[Input field]* percent

P3213A | 2022_14 | Perceived probability of tail events| prob_tail_post_a

Respondent group: all

Input filter drandom2=1 or 2

Info box:

a A financial crisis is a serious disruption to the financial system. In a financial crisis, the financial system is no longer able to fully carry out its key tasks. Lending is restricted and individual banks or investment funds may have to be resolved.

Range of valid values: 0 to 100

Question: In your opinion, how likely is it that a **financial crisis** (ia) will occur within the next two years?

Note: Please enter a value between 0 and 100. 100 means that you are *absolutely certain* that the event will occur; 0 means that you believe the event is completely impossible.

[Input field] percent.

P3213B| 2022_14 | Perceived probability of tail events| prob_tail_post_b

Respondent group: all

Input filter drandom2=3 or 4

Info box:

b A pandemic is the global spread of an infectious disease, such as COVID-19. Voluntary or government-mandated measures to reduce contact can lead to disruptions in economic activity. Please note: This refers to future pandemics involving other – potentially as yet unknown – infectious diseases.

Range of valid values: 0 to 100

Question: In your opinion, how likely is it that a **pandemic involving a new pathogen** (ib) will occur within the next two years?

Note: Please enter a value between 0 and 100. 100 means that you are *absolutely certain* that the event will occur; 0 means that you believe the event is completely impossible.

[Input field] percent.

P3213C| 2022_14 | Perceived probability of tail events| prob_tail_post_c

Respondent group: all

Input filter drandom2=5 or 6

Info box:

c China regards Taiwan as a renegade province and aims to merge it with China, while Taiwan sees itself as a sovereign state. Due to potential US military support for Taiwan and the importance of China and Taiwan for the global economy, any conflict between them might well have global economic repercussions.

Range of valid values: 0 to 100

Question: In your opinion, how likely is it that **China will attack Taiwan (ic)** within the next two years?

Note: Please enter a value between 0 and 100. 100 means that you are *absolutely certain* that the event will occur; 0 means that you believe the event is completely impossible.

[Input field] percent.

P3213D| 2022_14 | Perceived probability of tail events| prob_tail_post_d

Respondent group: all

Input filter drandom2=7 or 8

Info box:

d Severe bottlenecks in the supply of energy to enterprises and/or households in Germany. A substantial part of German industry might not be adequately supplied with gas, and intermittent power outages could occur.

Range of valid values: 0 to 100

Question: In your opinion, how likely is it that an **energy crisis** (id) will occur within the next two years?

Note: Please enter a value between 0 and 100. 100 means that you are *absolutely certain* that the event will occur; 0 means that you believe the event is completely impossible.

[Input field] percent.

P3213E| 2022_14 | Perceived probability of tail events| prob_tail_post_[a-d]

Respondent group: all

Input filter drandom2=9

Info boxes:

a A financial crisis is a serious disruption to the financial system. In a financial crisis, the financial system is no longer able to fully carry out its key tasks. Lending is restricted and individual banks or investment funds may have to be resolved.

b A pandemic is the global spread of an infectious disease, such as COVID-19. Voluntary or government-mandated measures to reduce contact can lead to disruptions in economic activity. Please note: This refers to future pandemics involving other – potentially as yet unknown – infectious diseases.

c China regards Taiwan as a renegade province and aims to merge it with China, while Taiwan sees itself as a sovereign state. Due to potential US military support for Taiwan and the importance of China and Taiwan for the global economy, any conflict between them might well have global economic repercussions.

d Severe bottlenecks in the supply of energy to enterprises and/or households in Germany. A substantial part of German industry might not be adequately supplied with gas, and intermittent power outages could occur.

Range of valid values: 0 to 100

The order of the items a-d is as in the stored randomisation for P3206

Question: In your opinion, how likely is it that each of the following events will occur within the next two years?

Note: Please enter a value between 0 and 100. 100 means that you are *absolutely certain* that the event will occur; 0 means that you believe the event is completely impossible.

a Financial crisis (ia) *[Input field]* percent

b Pandemic involving a new pathogen (ib) *[Input field]* percent

c Chinese attack on Taiwan (ic) *[Input field]* percent

d Energy crisis (id) *[Input field]* percent

P3214 | 2022_14 | Macro expectations quantitative | expectations_quant_[a-d]

Respondent group: all

Info boxes:

e Economic output is usually measured by gross domestic product (GDP). GDP is the total value of all goods and services produced within Germany during a year.

f The DAX is the most well-known German stock index. It measures the performance of the 40 largest and most liquid companies in the German stock market.

g Disposable income (i): Disposable income includes, in particular, wages and salaries, income from self-employment, income from pensions, earnings from rents and income received through public aid (such as housing allowance or child benefits), less taxes and social security contributions.

Range of valid values: -100 to 100. Values may have one decimal place.

Let us now return to your expectations concerning the **most likely** development of key economic metrics from the beginning of the questionnaire. Please give us your assessment of the developments you expect over the next twelve months.

Question: What developments do you believe are the **most likely** to occur in the following metrics over the next twelve months?

Note: Please enter a percentage value in the input field (values may have one decimal place). Use negative numbers if you think that the metric in question would be lower in twelve months than it is today and positive numbers if you think that it would be higher than today.

a	Germany's economic output (ie):	[Input field] percent
b	The German stock index (DAX) (if)	[Input field] percent
c	Real estate prices in your area	[Input field] percent
d	Your household's disposable income (ig)	[Input field] percent

--- | --- | **END SPLIT SAMPLE 2**

B.3 Second News Provision Wave (November 2022)

P3504 | 2022_14 | Magnitude of tail event | mag_tail_pre_e

Respondent group: all

Info boxes

a "A cyberattack is an external, targeted digital attack on larger computer networks that are important for a specific IT infrastructure, designed to sabotage, gather information or blackmail."

b "Economic output is usually measured by gross domestic product (GDP). GDP is the total value of all goods and services produced within Germany during a given year."

Range of valid values: 0 to 100 One decimal place allowed.

Question: Imagine that, within the next three years, the **power supply in Germany** were to suffer **outages lasting multiple days** as a result of a **cyberattack** (ia). As a percentage, how much lower would you expect Germany's economic output (ib) to be in this case?

Note: Please indicate the percentage by which Germany's economic output would be lower one year after the event than it would have been if the event had not occurred. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3505 | 2022_14 | Perceived probabilities of tail events| prob_tail_pre_e

Respondent group: all

Info box ia from P3504

Range of valid values: 0 to 100 No decimal places possible.

Question: In your opinion, how likely is it that the **power supply in Germany** will suffer **outages lasting multiple days as a result of a cyberattack** (ia) within the next three years?

Note: Please enter a value between 0 and 100. 100 means that you are *absolutely certain* that the event will occur; 0 means that you believe the event is completely impossible.

[Input field] percent

--- | --- | START SPLIT SAMPLE 2

--- | Split sample 2 | RANDOMISATION 2

Respondent group: all

The sample is split randomly into **three** groups. Randomisation dummy (drandom2) is used only for information treatment.

One factor variable: drandom2

1 group A2 – one-third of the total sample

2 group B2 – one-third of the total sample

3 group C2 – one-third of the total sample

--- | 2022_14 | Information treatments

Info box ia from P3504

We will now show you some current information. Please take some time to read this information carefully.

[drandom2 = 1]
Germany's energy supply is regarded as quite secure by international standards: four different power grid zones make it more difficult for local-level disruption to spread throughout Germany. The increasingly decentralised generation of electricity using renewable energy sources also helps to contain any disruptions at the local level. In addition, a recent survey reveals that a large majority (88%) of operators of critical infrastructure, such as the energy supply, consider themselves to be "well" or "very well" protected against modern cyberattacks (ia).

[drandom2 = 2]
In Germany, the threat posed by cyberattacks (ia) has intensified further over the past few years. The number of cyberattacks on critical infrastructure, including the energy supply, has risen sharply in recent years. According to experts, a failure in the power supply would have particularly far-reaching consequences. Not only production in industrial enterprises, but all economic sectors would be affected by the failure of computer systems, communication channels and transport routes.

[drandom2 = 3]
No information

P3506 | 2022_14 | Investment environment | good_time_[a,b]

Respondent group: all

Question: Do you think now is a good or a bad time to …

1 Very bad
2 Bad
3 Neither good nor bad
4 Good
5 Very good

a … buy property (house/apartment).
b … invest money in the stock market.

P3507 | 2022_14 | Financial asset allocation | hyp_pf_share_[a-e]

Respondent group: all

The programming of the question requires each variable to be a non-negative number and the sum of the variables to be 100. The current sum of all entered points is shown to the respondent when answering the question. Respondents are asked to correct their responses if the sum does not equal 100.

Range of valid values for every item: 0 to 100. No decimal places possible.

Assume you have saved a third of your annual earnings and wish to invest this money starting today.

Question: What percentage of the investment amount would you invest in each asset class?

Note: Please enter a value in the input field. Your answers have to add up to 100.

a	Cash and bank account	*[Input field]* percent
b	Shares (including funds and ETFs)	*[Input field]* percent
c	Fixed-income securities (including funds and ETFs)	*[Input field]* percent
d	Gold/precious metals (including ETFs)	*[Input field]* percent
e	Other investment opportunities	*[Input field]* percent

P3508 | 2022_14 | Future expenditure | spend_future_[a-d]

Respondent group: all

Info box (i): “Other expenditure includes the following items in particular: essential goods (e.g. food and beverages, non-food items such as cleaning products or similar), clothing and footwear, entertainment/recreation (e.g. restaurant visits, cultural events, gym), mobility (e.g. fuel, car loans and running costs, bus and train tickets), services (e.g. hairdresser, childcare, medical costs) as well as expenditure on travel and holidays.”

Range of valid values for every item: 0 to 100,000

You will now again be shown some everyday items that you can or need to buy.

Question: How much do you plan to spend in euro **on average per month** on each of the following items over the next twelve months?

Note: Please enter an amount in every field (with no decimal places). If you are not quite sure, please give a rough estimate.

a	Major purchases (e.g. car, furniture, electrical appliances, etc.)	*[Input field]*
b	Housing costs (e.g. rent, mortgage, ancillary costs)	*[Input field]*
c	Other expenditure (e.g. shopping, mobility, services, travel) (i)	*[Input field]*
d	Savings (e.g. savings account, shares, bonds)	*[Input field]*

P3509 | 2022_14 | Magnitude of tail event | mag_tail_post_e

Respondent group: all

Info boxes: Cyberattacks and economic output, see P3504

Range of valid values: 0 to 100, values may have one decimal place.

We would now like to learn a little more about your assessment of the impact and likelihood of potential crises. There is no right or wrong answer; we are interested in your personal opinion.

Question: Imagine that, within the next two years, the **power supply in Germany** were to suffer **outages lasting multiple days** as a result of a **cyberattack** (ia). As a percentage, how much lower would you expect Germany's economic output (ib) to be in this case?

Note: Please indicate the percentage by which Germany's economic output would be lower one year after the event than it would have been if the event had not occurred. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3510 | 2022_14 | Magnitude of tail event | mag_tail_financial_e

Respondent group: all

Info box:

a See P3504

c "The DAX is the most well-known German stock index. It measures the performance of the 40 largest and most liquid companies in the German stock market."

Range of valid values: 0 to 100, values may have one decimal place.

Question: And by what percentage do you think the German stock index (DAX) (ic) would fall if, within the next two years, the **power supply in Germany** were to suffer **outages lasting multiple days** as a result of a **cyberattack** (ia).

Note: Please indicate the percentage by which the DAX would be lower one year after the event than it would have been if the event had not occurred. If you expect a decline, please enter a value greater than 0. If you do **not** expect a decline, please enter a value of zero.

[Input field] percent

P3511 | 2022_14 | Perceived probabilities of tail events | prob_tail_post_e

Respondent group: all

Info box See P3504

Range of valid values: 0 to 100 No decimal places possible.

Question: In your opinion, how likely is it that the **power supply in Germany** will suffer **outages lasting multiple days as a result of a cyberattack** (ia) within the next two years?

Note: Please enter a value between 0 and 100. 100 means that you are *absolutely certain* that the event will occur; 0 means that you believe the event is completely impossible.

[Input field] percent

P3512 | 2022_14 | Macro expectations quantitative | expectations_quant_[a-d]

Respondent group: all

Info boxes:

b Economic output is usually measured by gross domestic product (GDP). GDP is the total value of all goods and services produced within Germany during a year.

c The DAX is the most well-known German stock index. It measures the performance of the 40 largest and most liquid companies in the German stock market.

d Disposable income includes, in particular, wages and salaries, income from self-employment, income from pensions, earnings from rents and income received through public aid (such as housing allowance or child benefits), less taxes and social security contributions.

Range of valid values: -100 to 100. Values may have one decimal place.

Let us now return to your expectations concerning the **most likely** development of key economic metrics from the beginning of the questionnaire. Please give us your assessment of the developments you expect over the next twelve months.

Question: What developments do you believe are the **most likely** to occur in the following metrics over the next twelve months?

Note: Please enter a percentage value in the input field (values may have one decimal place). Use negative numbers if you think that the metric in question would be lower in twelve months than it is today and positive numbers if you think that it would be higher than today.

a	Germany's economic output (ib):	[Input field] percent
b	The German stock index (DAX) (ic)	[Input field] percent
c	Real estate prices in your area	[Input field] percent
d	Your household's disposable income (id)	[Input field] percent

B.4 Decision module (November 2023)

P4708 | 2023_15 | Financial wealth | savings_pf1_[a-f]

Respondent group: all

Range of valid values: 0 to 1,000,000

Show SUM of savings_pf1_[a-f] to respondents

After the term “cash”, an info box with the following text is shown: “This refers to the amount in euro that you store at home or in a safe deposit box.”

Question: How much, in euro, of your financial assets do you hold in each of the following categories?

Note: Please enter an amount in every field (with no decimal places). If you are not quite sure, please give a rough estimate.

a Cash (i): [Input field] euro
b Bank balances (e.g. current accounts, savings accounts): [Input field] euro
c Fixed-income securities (e.g. government bonds, corporate bonds, bond funds): [Input field] euro
d Shares (e.g. individual shares, equity funds, ETFs): [Input field] euro
e Precious metals (e.g. gold): [Input field] euro
f Other: [Input field] euro

--- | Split sample 5 | RANDOMISATION 5

Respondent group: all

The sample is split randomly into four groups. Randomisation dummy (drandom5) is used for questions P4709-P4712, P4715

One factor variable: drandom5
group A5 – one-quarter of the sample
group B5 – one-quarter of the sample
group C5 – one-quarter of the sample
group D5 – one-quarter of the sample

P4709 | 2023_15 | Policy intervention | intervention_[a,b]

Respondent group: all

After the term “pathogen”, an info box with the following text is shown: “A pandemic is the significant global spread of an infectious disease with high numbers of cases and, generally speaking, serious disease progression, such as COVID-19. Please note: Here, this refers to future pandemics involving other – potentially as yet unknown – infectious diseases.”

After the term “Taiwan”, an info box with the following text is shown: “The People’s Republic of China regards Taiwan as a breakaway province and aims to reunify it with China, while Taiwan considers itself a sovereign state.”

After the term “cyberattack”, an info box with the following text is shown: “A cyberattack is a targeted, external digital attack on larger computer networks that are critical for a specific IT infrastructure. Cyberattacks are intended to sabotage, extract information, or blackmail.”

We would now like to learn a little about your assessment of the impact of a potential crisis. There is no right or wrong answer; we are interested in your personal opinion.

If drandom5 = 1

Imagine that you woke up tomorrow and learned that a **financial crisis** had broken out. The financial system would be severely disrupted. During a financial crisis, lending would be restricted and individual banks or investment funds may become insolvent.

If drandom5 = 2

Imagine that you woke up tomorrow and learned that a **pandemic with a novel pathogen** (i) had broken out.

If drandom5 = 3

Imagine that you woke up tomorrow and learned that **China had attacked Taiwan** (i). Due to potential US military support for Taiwan and the importance of both China and Taiwan for the global economy, any conflict between them could have global economic repercussions.

If drandom5 = 4

Imagine that you woke up tomorrow and learned that a **cyberattack** (i) had caused power outages in Germany that would last for several days.

Question: How strongly do you think the **German Federal Government** and the **European Central Bank (ECB)** would respond to mitigate the potential economic impact on households and enterprises in such a scenario?

1 – Not at all strongly
2 -> 9 [no label]
10 – Very strongly

a German Federal Government
b European Central Bank

P4710A | 2023_15 | Hypothetical expectations| mag_tail_financial1_[a-d]

Respondent group: all

Infobox (i) after the term "DAX": "The DAX is the most well-known German stock market index. It measures the performance of the 40 largest companies in the German stock market."

Now we would like to ask you about how you would expect the **German stock market index (DAX)** (i) to develop over the next twelve months and next five years if {if drandom5 = 1: a financial crisis broke out tomorrow} {if drandom5 = 2: a pandemic with a novel pathogen broke out tomorrow} {if drandom5 = 3: China launched an attack on Taiwan tomorrow} {if drandom5 = 4: Germany were to suffer a cyberattack tomorrow that resulted in power outages lasting several days}. Please compare this with the developments that you would expect under normal circumstances.

If {if drandom5 = 1: **a financial crisis broke out tomorrow**} {if drandom5 = 2: **a pandemic with a novel pathogen broke out tomorrow**} {if drandom5 = 3: **China launched an attack on Taiwan tomorrow**} {if drandom5 = 4: **Germany were to suffer a cyberattack tomorrow that resulted in power outages lasting several days**}, I would expect that …

a. … over the next twelve months, the DAX would:

1 decrease
2 increase

b. … over the next five years, the DAX would:

1 decrease
2 increase

Under **normal circumstances** – i.e. if this event did not occur – I would expect that …

c. … over the next twelve months, the DAX would:

1 decrease
2 increase

d. … over the next five years, the DAX would:

1 decrease
2 increase

P4710B | 2023_15 | Hypothetical expectations| mag_tail_financial1_[e-h]

Respondent group: all

Infobox (i) after the term "DAX": "The DAX is the most well-known German stock market index. It measures the performance of the 40 largest companies in the German stock market."

Input filter: mag_tail_financial_[a-d] != -9997 | -9998

Range of valid values: 0 to 100

Thank you for your assessments of developments in the **German stock market index (DAX)** (i). We would now like you to provide more detailed assessments as best you can.

Note: Please enter a value between 0 and 100 in each case.

If {if drandom5 = 1: **a financial crisis broke out tomorrow**} {if drandom5 = 2: **a pandemic with a novel pathogen broke out tomorrow**} {if drandom5 = 3: **China launched an attack on Taiwan tomorrow**} {if drandom5 = 4: **Germany were to suffer a cyberattack tomorrow that resulted in power outages lasting several days**}, I would expect that …

e. … over the next twelve months, the DAX would [P4711A a] by [input field] percent.
f. … over the next five years, the DAX would [P4711A b] by [input field] percent.

Under **normal circumstances** – i.e. if this event did not occur – I would expect that …

g. … over the next twelve months, the DAX would [P4711A c] by [input field] percent.
h. … over the next five years, the DAX would [P4711A d] by [input field] percent.

P4711 | 2023_15 | Perceived probability of tail events | prob_tail_post

Respondent group: all

Range of valid values: 0 to 100

Question: In your opinion, how **likely** is it that {if drandom5 = 1: a financial crisis will break out} {if drandom5 = 2: a pandemic with a novel pathogen will break out} {if drandom5 = 3: China will launch an attack on Taiwan} {if drandom5 = 4: Germany will suffer a cyberattack resulting in power outages lasting several days} over the next twelve months?

Note: Please enter a value between 0 and 100. 100 means that you are absolutely certain that the event will occur; 0 means that you believe the event is completely impossible.

[Input field] percent

--- | Split sample 6 | RANDOMISATION 6

Respondent group: all

The sample is split randomly into two groups. Randomisation dummy (drandom6) is used for the questions P4712-P4713, P4715

One factor variable: drandom6
group A6 – one-half of the sample
group B6 – one-half of the sample

P4712 | 2023_15 | Portfolio adjustment | pf_adjust

Respondent group: all

Input filter: (savings_pf1_a | savings_pf1_b | savings_pf1_c | savings_pf1_d | savings_pf1_e | savings_pf1_f >0) & (prob_tail_post != -9997 | -9998)

You indicated that you estimate the likelihood of {if drandom5 = 1: a financial crisis breaking out} {if drandom 5 = 2: a pandemic with a novel pathogen breaking out} {if drandom5 = 3: China launching an attack on Taiwan} {if drandom5 = 4: Germany suffering a cyberattack resulting in power outages lasting several days} over the next twelve months to be [prob_tail_post] percent.

{if drandom6 = 1 & prob_tail_post != 5} | {if drandom6 = 2 & prob_tail_post != 40}
Now please assume that the **actual likelihood of** {if drandom5 = 1: **a financial crisis breaking out**} {if drandom5 = 2: **a pandemic with a novel pathogen breaking out**} {if drandom5 = 3: **China launching an attack on Taiwan**} {if drandom5 = 4: **Germany suffering a cyberattack resulting in power outages lasting several days**} over the next twelve months is {if drandom6 = 1: **5 percent**} {if drandom6 = 2: **40 percent**}.

(if drandom6 = 1 & prob_tail_post = 5) | (drandom6 = 2 & prob_tail_post = 40)
Now please assume that the **actual likelihood of** {if drandom5 = 1: **a financial crisis breaking out**} {if drandom5 = 2: **a pandemic with a novel pathogen breaking out**} {if drandom5 = 3: **China launching an attack on Taiwan**} {if drandom5 = 4: **Germany suffering a cyberattack resulting in power outages lasting several days**} over the next twelve months is exactly the value you provided of {if drandom6 = 1: **5 percent**} {if drandom6 = 2: **40 percent**}.

Question: Would you make adjustments to the allocation of your financial assets in this scenario, i.e. would you reduce the amounts of money that you held in certain asset classes and increase the amounts in others?

1 Yes
2 No

P4713 | 2023_15 | Portfolio adjustment 2 | rebalance_[a-f]

Respondent group: all

Input filter: if pf_adjust = 1

Info box (I) after "Scenario":
{if drandom5 = 1: "This refers to a scenario in which the actual likelihood of a financial crisis breaking out over the next twelve months is {if drandom6 = 1: 5 percent} {if drandom6 = 2: 40 percent}."}
{if drandom5 = 2: "This refers to a scenario in which the actual likelihood of a pandemic with a novel pathogen breaking out over the next twelve months is {if drandom6 = 1: 5 percent} {if drandom6 = 2: 40 percent}."}
{if drandom5 = 3: "This refers to a scenario in which the actual likelihood of China launching an attack on Taiwan over the next twelve months is {if drandom6 = 1: 5 percent} {if drandom6 = 2: 40 percent}."}
{if drandom5 = 4: "This refers to a scenario in which the actual likelihood of Germany suffering a cyberattack resulting in power outages lasting several days over the next twelve months is {if drandom6 = 1: 5 percent} {if drandom6 = 2: 40 percent}."}

Range of valid values: 0 to 1,000,000

Pre-fill fields with euro amounts from savings_pf1_[a-f]

Plausibility check: Show the old and new totals at the bottom. The new total must equal the old total.

Question: And to what extent would you increase or decrease the investments you hold in each category of your financial assets in this scenario (i)?

Notes:

- Please assume that your total financial assets would remain the same.
- The figures for the current allocation of your financial assets have been pre-filled here from the previous question.

Asset class	Current allocation	New allocation
Cash:	savings_pf1_a euro	[Input field] euro
Bank balances (e.g. current accounts, savings accounts):	savings_pf1_b euro	[Input field] euro
Fixed-income securities (e.g. government bonds, corporate bonds, bond funds):	savings_pf1_c euro	[Input field] euro
Shares (e.g. individual shares, equity funds, ETFs):	savings_pf1_d euro	[Input field] euro
Precious metals (e.g. gold):	savings_pf1_e euro	[Input field] euro
Other:	savings_pf1_f euro	[Input field] euro
	sum_savings_pf1_[a-f]	sum_rebalance_[a-f]

P4714A | 2023_15 | Portfolio adjustment 2 – reasons | rebalance_reasons

Respondent group: all

Input filter: if pf_adjust = 1 & (rebalance_[a-f] != -9997 | -9998 | (savings_pf1_[a-f] != rebalance_[a-f]))

Open data has been coded and is stored into data set as rebalance_reasons_[a-g]

Question: In your opinion, what are the most important reasons for wanting to make **adjustments** to your financial assets?

Note: Please provide up to five reasons why you would want to make adjustments.

[Input text field]

P4714B | 2023_15 | Reasons for no rebalancing | rebalance_no_reasons

Respondent group: all

Input filter: if pf_adjust = 2 | (savings_pf1_[a-f] = rebalance_[a-f])

Open data has been coded and is stored into data set as rebalance_no_reasons_[a-h]

Question: In your opinion, what are the most important reasons for **not** wanting to make **adjustments** to your financial assets?

Note: Please provide up to five reasons why you would not want to make adjustments.

[Input text field]

P4715 | 2023_15 | Future expenditure | spend_future1_[a-e]

Respondent group: all

Input filter: prob_tail_post != -9997 | -9998

Info box (i): “Other expenditure includes the following items, in particular: essential goods (e.g. food and beverages, non-food items such as cleaning products or similar), clothing and footwear, mobility (e.g. fuel, car loans and running costs, bus and train tickets) and expenditure for services (e.g. hairdresser, childcare, medical costs).”

{if drandom6 = 1 & prob_tail_post != 5} | {if drandom6 = 2 & prob_tail_post != 40}
Please continue to assume that the **actual likelihood of** {if drandom5 = 1: **a financial crisis breaking out**} {if drandom5 = 2: **a pandemic with a novel pathogen breaking out**} {if drandom5 = 3: **China launching an attack on Taiwan**} {if drandom5 = 4: **Germany suffering a cyberattack resulting in power outages lasting several days**} over the next twelve months is {if drandom6 = 1: **5 percent**} {if drandom6 = 2: **40 percent**}.

(if drandom6 = 1 & prob_tail_post = 5) | (drandom6 = 2 & prob_tail_post = 40)
Please continue to assume that the **actual likelihood of** {if drandom5 = 1: **a financial crisis breaking out**} {if drandom5 = 2: **a pandemic with a novel pathogen breaking out**} {if drandom5 = 3: **China launching an attack on Taiwan**} {if drandom5 = 4: **Germany suffering a cyberattack resulting in power outages lasting several days**} over the next twelve months is exactly the value you provided of {if drandom6 = 1: **5 percent**} {if drandom6 = 2: **40 percent**}.

Question: In this scenario, would you adjust your **expenditure** in the following categories over the next twelve months? Please compare this with your currently planned expenditure.

Note: Please select one answer for each row.

1 Plan to spend considerably less
2 Plan to spend slightly less
3 Plan to spend roughly the same
4 Plan to spend slightly more
5 Plan to spend considerably more

a Major purchases (e.g. car, furniture, electrical appliances, etc.)
b Housing costs (e.g. rent, mortgage, ancillary costs)
c Entertainment and travel (e.g. holiday, restaurant visits, cultural events, gym)
d Other expenditure (e.g. shopping, mobility, services) (i)
e Savings (e.g. savings account, shares, bonds)

--- | --- | END SPLIT SAMPLE 5

--- | --- | END SPLIT SAMPLE 6