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THE PSYCHOLOGY OF MACROECONOMIC EXPECTATIONS

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ABSTRACT

We present a model of "animal spirits" in which context and emotions affect macroeconomic beliefs by shaping which experiences people recall to simulate similar future aggregate states. We test this mechanism by priming Dutch National Bank Survey respondents to recall personal financial or health adversities before eliciting inflation and home price expectations. The treatment causes instability in beliefs and reasoning tied to the measured similarity of the primed experiences to different macro states. This similarity structure also accounts for heterogeneity in beliefs and reasoning based on a range of other personal experiences we measure. The model micro founds several features of macroeconomic beliefs, including narratives, and yields a "confidence multiplier": spending by some agents cues optimistic context for others, raising their spending.

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1. Introduction

In the *Treatise on Probability* (1921), Keynes argued that beliefs over an uncertain future reflect unstable weighting of evidence, not a strict probabilistic calculus. In *The General Theory* (1936), he further stressed that economic decisions depend on confidence and emotions, also called "animal spirits". Many papers in macroeconomics and finance document the role of sentiment or confidence (e.g. Lee et al. 1991; Ludvigson 2004; Baker and Wurgler 2006; Barsky and Sims 2012; Blanchard et al. 2013; Shapiro et al. 2022) and relate them to narratives (Shiller 2018). Yet existing rational and behavioural models view beliefs as a stable function of news, leaving concepts like sentiment or confidence "amorphous" (Mankiw 2009). How can purely psychological states shift beliefs in the absence of news and, if so, through what mechanism?

We propose and test a model of mnemonic expectations in which, following Bordalo et al (2023, 2025a), a salient cue causes retrieval of similar experiences from memory, which are then used to simulate the future, shaping beliefs. The cue includes the forecasting task, such as inflation, but also emotions and experiences currently top-of-mind. The forecasting task then cues recall of similar Domain-Specific (DS) experiences such as past inflation, which directly help simulate similar future inflation states. Current negative emotion cues the recall of similar Non-Domain-Specific (NDS) experiences, such as personal financial distress. These NDS experiences affect beliefs analogically, helping simulate similarly bad future inflation states. In a nutshell, mental states influence beliefs by altering the set of recalled experiences used for imagining the future.

The model yields sharp, testable predictions that link the heterogeneity of beliefs across people (due to different experiences and similarity perceptions) to the instability of beliefs from changing cues. We test these predictions using a novel survey experiment on more than 4,000 households in the Dutch National Bank Household Survey (DHS). Motivating evidence shows that households experiencing worse financial or health conditions report higher expected inflation and home price growth, consistent with the role of NDS experiences documented by Cenzon (2025) and Taubinsky et al. (2026). Because such experiences are uninformative about aggregate conditions, this evidence points to non-statistical drivers of beliefs.

We take the next step and causally test the role of memory. Before eliciting inflation and home price growth expectations, we randomly prime respondents to recall a personal financial or health adversity. We then measure a respondent's (i) additional NDS experiences, (ii) their perceived similarity to high inflation and home price growth, (iii) back casts, and (iv) reasons for the forecasts. The design isolates memory from information: priming an NDS experience is irrelevant with full recall and does not convey news about the target aggregate variable. Any effect must reflect a change in mental context. Associative memory further implies that priming one experience cascades into recall of other similar ones, allowing us to trace how cues reshape recall and hence the reasoning behind the forecasts, not only the forecasts' numerical values.

The evidence supports four main predictions. The first is similarity-based experience effects: people with NDS experiences perceived as more similar to high inflation or home price growth report higher expectations, exhibiting more pessimism than people who have not lived such experiences. The second is similarity-based instability: people who are primed to recall a lived NDS adversity are more pessimistic than comparable individuals who are not primed. Third, priming financial adversities affects beliefs more strongly than priming health ones, consistent with the higher similarity of the former to bad macro states. Fourth, and crucially, priming changes both recall and reasoning: it raises back casts (consistent with greater retrieval of similarly adverse DS experiences) and encourages reasoning focused on personal affordability concerns and negative emotions (consistent with greater retrieval of adverse NDS experiences).

The effects are large. Priming shifts inflation (home price growth) beliefs up by 1.01 (1.08) percentage points relative to a 5.46% (6.51%) average. Disagreement is also large: moving across the interquartile range of NDS experiences raises these beliefs by 0.74 (0.91) percentage points, comparable to observed disagreement among key socio-demographic groups (Weber et al. 2022).

We provide a micro-founded and testable account of "animal spirits," sentiment, and narratives as drivers of macroeconomic beliefs that are independent of news or stable tastes. This mechanism unifies several observations, including: i) the role of NDS experiences (Cenzon 2025; Taubinsky et al. 2026), which we identify causally, ii) insensitivity to statistical information (Sims 2003), iii) average bias in inflation forecasts (Weber et al. 2022), iv) overreaction to salient inflation changes (Bonaglia et al. 2025; Gennaioli et al. 2025; Link et al. 2023), and v) strong distaste of inflation due to its mental association with personal financial distress. Idiosyncratic mental states also explain belief disagreement by agents exposed to similar inflation news or gas prices (Schwartzstein and Sunderam 2021; Andre et al. 2022; Shiller 2018; Andre et al. 2024).

The implications of memory go beyond our causal experiment. It is well known that expectations matter for economic choices (Dominitz and Manski 2007; Armona, Fuster, and Zafar 2019; Bailey et al. 2019; Giglio et al. 2021; Coibion et al. 2023; Jiang et al. 2025) including due to NDS experiences (Cenzon 2025; Taubinsky et al. 2025). Our mechanism implies that persistent interpersonal differences in behavior can arise from belief disagreement due to different experiences and personal contexts. In line with Das, Kuhnen, and Nagel (2020), memory predicts more pessimism by people with worse socioeconomic status, who likely experience both more adversities and more negative context – with non-trivial allocative consequences.

Memory also generates amplification: a bad shock carries not only bad news but also negative context, triggering recall of related adverse macroeconomic or personal experiences. Due to these recall spillovers, beliefs overreact to the shock. Memory also implies a "confidence multiplier": because one agent's actions serve as cues for others, higher consumption by one person cues optimism for others, encouraging their spending in line with Bellifemine et al. (2025). Memory offers a new mechanism for demand fluctuations due to self-sustaining changes in confidence (Akerlof and Shiller 2009, Lorenzoni 2009, Angeletos and La'O 2013).

Existing models of expectations rely on stable news processing or tastes. Theories of under and over reaction assume stable mis-specified models (e.g., Barberis et al. 1998, Mankiw and Reis 2002, Sims 2003, Woodford 2003, Fuster, Laibson, and Mendel 2010, Gabaix 2014, Angeletos, Huo, and Sastry 2021). Models of disagreement trace it to different models or priors. Malmendier and Nagel (2011, 2016) model Bayesian learning from personal DS experiences. Another body of work stresses motives: distortions in news processing due to a stable preference for robustness (Hansen and Sargent 2010) or wishful thinking (Brunnermeier and Parker 2005). These approaches cannot explain why priming a personal adversity changes beliefs and reasoning without providing any information and via spurious similarity. A memory model in which beliefs reflect what is top of mind is needed to account for the data.

Section 2 presents motivating evidence. Section 3 develops the model. Section 4 describes the experiment. Section 5 tests the model. Section 6 discusses implications. Section 7 concludes.

2. Motivating Evidence

2.1 The DNB Household Survey

The DHS is conducted annually since 1993 by CentERdata at Tilburg University. Each wave surveys personal events and perceptions of more than 2,000 Dutch households, along with their financial and demographic information (51% of households participate for 3 years or more).

Expectations cover retirement age, income, mortgage rates, and two macro variables: inflation and home price growth. We focus on the 2012-2022 surveys to avoid the financial crisis period.

We elicit a household's modal inflation expectations using the DHS question: "*What do you think is the most likely (consumer) price increase over the next twelve months?*" Subjects choose a value between 0% and 10%. For the growth of home prices, the survey asks: "*What do you expect the prices of homes in the next two years will do? Will the prices rise, fall or stay about the same? By how many percent per year on average will prices [rise / fall]?".*

The DHS measures demographics such as age, gender, relationship status, occupation, income, accommodation (tenant, subtenant, owner), and urbanization, which are known to predict macro beliefs (e.g., Das, Kuhnen, and Nagel 2020). These proxies do not identify a mechanism, so we use them as controls. We also control for numeracy using standard probability questions.

Other questions measure experiences and attitudes in five domains: health, happiness, financial status, risk taking, and financial management. We focus on health and financial status, which are directly linked to experiences, guiding our experiment. We construct a *Health Adversity Index* by averaging a respondent's z-standardized answers to: *"How is your health in general?" (1: excellent; 5: poor)*, and *"How many times did you contact your general practitioner about your own health in the previous year?"*. We construct a *Financial Adversity Index* by averaging z-standardized answers to questions such as: *"How well can you manage on the total income of your household?" (1: very easy; 5: very hard)*, or *"Have you, in the previous year, consulted with your bank or financial institution, because you had or expected payment problems with the repayment of a loan or mortgage?"* For both indices, a higher value implies a worse state.[1]

[1] Appendix B reports the questions in the Financial Adversity Index. Some include near future outcomes, such as *"Do you think the expenditures of your household, in the next 12 months, will be higher, about the same, or lower than the income of your household?"*. Table 1 is robust to removing such questions (which may depend on macro beliefs).

2.2 Personal Adversities and Macroeconomic Beliefs

Table 1 reports non-causal regressions of inflation and housing beliefs on the adversity indices, controlling for time dummies in columns (1) and (3), and additionally for demographics (unreported) in columns (2) and (4). Health and financial adversities are correlated with sharply higher expectations of inflation (column 1) and home price growth (column 3). Results are robust to demographic controls for inflation (column 2), but financial adversity loses significance for home price growth (column 4). Coefficient magnitudes indicate that, in line with intuition, financial experiences matter more for inflation and home price growth than health ones.[2]

Table 1: Adversity and Macroeconomic Beliefs in the DHS

	Inflation		Home Price Growth	
	(1)	(2)	(3)	(4)
Health Adversity	0.0803***	0.0583***	0.0393***	0.0302**
	(0.0189)	(0.0187)	(0.0128)	(0.0138)
Financial Adversity	0.3043***	0.2413***	0.0614***	0.0223
	(0.0238)	(0.0259)	(0.0222)	(0.0244)
Observations	22081	19852	17928	16504
Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R Sq.	0.0311	0.0476	0.0016	0.0203

Notes: We report OLS regressions of standardized inflation and house price beliefs on two individual-level adversity measures: health adversity and financial adversity (higher values indicate worse health or financial conditions). Dependent variables are standardized within survey year; adversity indices are standardized across the pooled sample. Columns (1)–(2) focus on inflation; columns (3)–(4) on housing. We include survey-year fixed effects and control for age, gender, education, occupation, degree of urbanization, household income brackets, accommodation type, relationship status, numeracy, and province fixed effects (not shown). Standard errors are clustered at the individual level. Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

In columns 2 and 4, a one standard deviation increase in financial (health) adversity entails a 0.24 (0.06) std increase in inflation forecasts and a 0.02 (0.03) std increase in home price growth forecasts. These are large magnitudes: financial adversity is associated with a 0.51 p.p. increase in

[2] Higher education, student status, income, and homeownership are negatively correlated with expected inflation. Age, rural residence, and homeownership are negatively correlated with expected home price growth. Column (4) is robust to controlling for perceived house price increase (positive and significant coefficient), which is available in the DHS.

expected inflation relative to a 3.05% baseline, health adversity with a 0.15 p.p. increase in expected home price growth relative to a 1.84% baseline.[3] It would be hard to get comparable disagreement from domain-specific experiences such as historical inflation, which varies only across cohorts, or from food or gas prices (Kuchler and Zafar 2019, Coibion, Gorodnichenko, and Weber 2022), which are largely common across people.

This explanatory power does not come from aggregate economic conditions, which are controlled for with time dummies. Furthermore, Cenzon (2025) and Taubinsky et al. (2026) show that individual level variation in adversities is uninformative about future inflation and home price growth, rejecting information channels.[4] The evidence is also at odds with canonical rational or behavioural models, in which beliefs depend on statistical data. Personal events may correlate with access to news, but this may explain higher noise in beliefs, not systematic pessimism.

The evidence is consistent with Keynes' idea that macroeconomic beliefs and confidence embed psychological states, not just a statistical calculus. One explanation is motivated beliefs: people prepare for their worst-case scenario (Hansen and Sargent 2010, Bhandari, Borovicka, and Ho 2025) depending on their exposure to inflation or home price risk. Another explanation is memory: when thinking about inflation or home prices, people retrieve personal experiences and their emotions, which help people imagine specific macro outcomes depending on their similarity.

We causally test memory by priming recall of personal adversities without giving any news. This intervention should have no effect in models relying on a correct or distorted statistical calculus, including Bayesian learning from experiences (Malmendier and Nagel 2011, 2016). It

[3] The sample mean (SD) of inflation expectations is 3.05% (2.13), that for home price growth ones is 1.84% (4.90). Thus, a one standard deviation increase in financial adversity entails a 0.24 std increase in inflation, equivalent to 0.51 p.p. (= 0.2413 x 2.13 p.p.). For home price growth, health adversity yields a 0.15 p.p. effect (= 0.0302 x 4.90 p.p.)

[4] Also in the DHS personal adversities do not predict macro states (see Appendix B). Results are robust to excluding from Financial Adversities proxies related to macro states, e.g. whether expenditures are expected to outpace income.

should also have no effect in motivated belief models, including based on robustness (Hansen and Sargent 2010) or wishful thinking (Brunnermeier and Parker 2005) because stable tastes are unaffected by uninformative recall interventions. Our goal here is not to reject these models but to test a rich set of memory predictions based on measured experiences, similarity and reasoning. Bordalo et al. (2025a) study these predictions in novel domains (e.g. large scale cyberattacks). Here we focus on macroeconomic domains in which people have many direct experiences and information. Relative to Cenzon (2025) and Taubinsky et al. (2026), we causally identify memory by priming recall of experiences, and by studying the roles of similarity, of the broader memory database, as well as of reasoning. Compared to motivated beliefs, which depend on unobserved tastes, the structure of memory can be measured and linked to new predictions.

3. Selective Memory and Belief Formation

We rely on the psychology of selective retrieval (Kahana 2012) and of mnemonic simulation of the future (Hassabis et al. 2007). We formalize these ingredients and then study their implications for inflation and home price growth expectations.

3.1 The Setup

The database is a frequency distribution $\boldsymbol{n} = \{n_e\}_{e \in E}$ over categories of experiences $e \in E$, where n_e is the number of lived experiences in category e and E is the memory space. e is a vector $e = (x, v, c)$ where $x \in \mathbb{R}$ is a realization, namely an objective marker of the experience (e.g. realized inflation or its forecast in the news), $v \in \mathbb{R}$ is the emotion associated with it, known to play a key role in memory encoding and retrieval (Kensinger 2009), and c is context.

Context belongs to a metric space C and partitions experiences semantically, $C = C_{\mathrm{M}} \cup C_p$ where $c \in C_{\mathrm{M}}$ and $c \in C_p$ capture macroeconomic and personal contexts, respectively. Macro context separates inflation experiences, $c \in C_\Pi$, from home price growth ones, $c \in C_\Gamma$ (so $C_\Pi \cup C_\Gamma \subseteq C_{\mathrm{M}}$). Personal context separates financial experiences, $c \in C_f$, from health ones, $c \in C_h$ (so $C_f \cup C_h \subseteq C_p$). As we show later, context allows us to separate DS from NDS experiences.[5]

Retrieval is triggered by a cue q, which is a subset (x_q, v_q, c_q) of E. Retrieval of $e \in E$ depends on its similarity to q, its frequency, and interference from other experiences. Given a similarity function $S(e,q)$, the probability of recalling e based on q and database $\boldsymbol{n}$ is:

$$r_e(q, \boldsymbol{n}) = \frac{S(e,q) \cdot n_e}{\sum_{e' \in E} S(e',q) \cdot n_{e'}}. \tag{1}$$

The numerator captures associativity and frequency: experiences more similar to the cue and more frequently lived are more likely to be recalled. The denominator captures interference: even if e is similar to q and frequent, its recall can be blocked by an experience $e' \neq e$ that is even more similar to q or more frequent. These forces have been used to study the role of memory for expectations (Bordalo et al. 2023, 2025a, Taubinsky et al. 2026, Cenzon 2025, Bonaglia et al. 2025), consumer choice (Bordalo et al. 2020), and advertising (Bordalo et al. 2025b).

Simulation maps retrieved experiences into a forecast. Consider a person who forms a point estimate of inflation $\mathbb{E}(\pi)$ or home price growth $\mathbb{E}(\gamma)$. The forecasting task is also a cue, denoted by $t_{\mathrm{T}} = (\mathbb{R}, 0, c_{\mathrm{T}})$ with $\mathrm{T} = \Pi$ for inflation and $\mathrm{T} = \Gamma$ for home price growth. The first entry in the task is any possible inflation or home price growth rate in $\mathbb{R}$. The second entry, valence, is neutral, $v = 0$. The third entry is the task's domain, inflation c_Π or housing c_Γ.

The task's context distinguishes between DS and NDS experiences. In task t_{T}, the DS experiences are vectors $e = (\tau, v, c_{\mathrm{T}}) \in E$ having the forecasting context c_{T} and its realizations

[5] Categories arise because people store similar events together (e.g., they do not distinguish in memory between 2.9% and 2.8% inflation). Categories can be highly specific if the context defining them is granular, for instance inflation in 1971 may be a separate category from that in 1972. Not fully granular categories simplify our formal analysis.

$\tau = \pi$ for inflation and $\tau = \gamma$ for home price growth (possibly broadened to prices of specific goods or homes). The context of NDS experiences is instead incongruent with the task, $c \neq c_{\mathrm{T}}$: a past illness is NDS for inflation or home price growth (but DS for own health).

A simulation function projects, for a given task t_{T}, the features of a generic experience e onto a point estimate, formally $\sigma: \{t_{\Pi}, t_{\Gamma}\} \times E \to \mathbb{R}$, where we use the shorthand:

$$\sigma_{\mathrm{T}}(e) \equiv \sigma(t_{\mathrm{T}}, e), \qquad \mathrm{T} = \Pi, \Gamma. \tag{2}$$

Beliefs are then formed by retrieving experiences from E based on the cue q (Equation 1) and by using them to simulate the future (Equation 2). The cue is influenced by an experience $\tilde{e} \in E$ the agent is thinking about, for instance an illness or a recent op-ed on inflation she has read; $\tilde{e}$ pollutes the valence and context of the task t_{T}, while leaving the inflation or home price space of realizations $\mathbb{R}$ unaffected. Formally, the cue is given by:[6]

$$q_{\tilde{e},\mathrm{T}} = (\mathbb{R}, v_{\tilde{e}}, c_{\tilde{e}}). \tag{3}$$

A probability distribution of thoughts, denoted by $\boldsymbol{\omega}_T = \{\omega_{\tilde{e},\mathrm{T}}\}_{\tilde{e} \in E}$, induces a distribution of cues when solving t_{T}, where $\omega_{\tilde{e},\mathrm{T}}$ is the probability of cue $q_{\tilde{e},\mathrm{T}}$. Integrated across cues, the probability of recalling $e \in E$ in task t_{T} (and of using it for simulation) is then given by:

$$r_e(\boldsymbol{\omega}_T, \boldsymbol{n}) = \sum_{\tilde{e} \in E} r_e(q_{\tilde{e},\mathrm{T}}, \boldsymbol{n}) \cdot \omega_{\tilde{e},\mathrm{T}}, \tag{4}$$

where $r_e(q_{\tilde{e},\mathrm{T}}, \boldsymbol{n})$ follows Equation (1). The average belief in task t_{T} is given by:

$$\mathbb{E}(\tau | \boldsymbol{\omega}_T, \boldsymbol{n}) = \sum_{e \in E} r_e(\boldsymbol{\omega}_T, \boldsymbol{n}) \cdot \sigma_{\mathrm{T}}(e), \tag{5}$$

which is expected simulation across retrieved experiences. Due to spontaneous retrieval and simulation, Equation (5) offers a theory in which, as in Keynes' animal spirits, beliefs and

[6] An alternative assumption is that the cue's context retains also the context of the task, $c_{\tilde{e},\mathrm{T}} = c_{\mathrm{T}} \cup c_{\tilde{e},}$. Our results also hold under this assumption, but the current formalization simplifies the algebra in the proofs.

confidence can depend on irrelevant emotions and context. This is not so with standard models of expectations, which combine statistical priors and signals in either an optimal or a distorted but context independent way. Mnemonic beliefs are more general: they are driven by similarity to past experiences and their frequency, which may be informative DS experiences (Bordalo et al. 2018, Bonaglia and Gennaioli 2025, Bonaglia et al. 2025, Gennaioli et al. 2025) or uninformative NDS ones, which methodologically allow to identify mechanisms such as animal spirits and narratives.

To test this mechanism, we prime recall of a personal experience e_p which triggers the cue $q_{e_p,\mathrm{T}}$, changing the DM's mental state. Memory makes prediction very different from standard reminder effects which exclusively bring to mind previously forgotten information (Karlan et al 2016, Calzolaro and Nardotto 2017). In our case, reminding a person about an uninformative personal experience causes a similarity-based cascade that brings to mind many other experiences that shape beliefs directly via simulation and indirectly by crowding out other information.

Existing work on "mental states" views emotions as boosters of optimism or pessimism (Schwarz and Clore 1983, Loewenstein 2000, Damasio 1994, Sharot et al 2007). Memory explains why this can occur via experiences and through simulation based on similarity, offering new measurement and tests. To highlight context effects most sharply, we prime uninformative NDS experiences. More generally, even DS experiences can act through context, yielding new implications that we discuss in Section 6.

3.2 Beliefs, Experiences and Priming Effects

Assumptions on Similarity $S(e,q)$, Simulation $\sigma_\mathrm{T}(e)$, and the database. Following Nosofsky (1986), similarity declines with dissonant contextual and valence features. Following Hassabis et al. (2007) and Bordalo et al. (2025a), simulation projects the features of the experience into a point estimate, more strongly so if the context of e is closer to the context of the task t_T. These broad properties, which we later validate, drive our predictions. To obtain an intuitive characterization we make more specific assumptions (but prove general results in Appendix A).

Assumption 1 (*Similarity*). *There is a* $K \in (0,1/2)$ *such that similarity between* $e = (x, v, c)$ *and* $q = (x_q, v_q, c_q)$ *satisfies:*

$$S(e,q) = \begin{cases} 1 & if \quad v \cdot v_q > 0 \; and \; c \in c_q \\ 1-K & if \quad either \; v \cdot v_q \leq 0 \;\; or \;\; c \notin c_q \, , but \; not \; both. \\ 1-2K & if \quad v \cdot v_q \leq 0 \; and \; c \notin c_q \end{cases}$$

Similarity is maximal, equal to 1, if the context of e is congruent with that of q and if their valence is also congruent (i.e. e and q are both adversities or good times). It drops by K if one feature is incongruent, by $2K$ if both features are incongruent. Similarity could be smoother and also act along the objective realization τ. What matters is that valence and context create an associative hierarchy. A person cued with a personal adversity $v_q < 0$ in financial context c_f most easily recalls other financial adversities (two congruent features), she next recalls non-financial adversities or good personal financial states (one congruent feature), and she lastly recalls favourable non-financial events (zero congruent features).

Assumption 2. *Simulation in task* $t_{\mathrm{T}} = (\mathbb{R}, 0, c_{\mathrm{T}})$ *based on experience* $e = (x, v, c)$ *satisfies:*

$$\sigma_{\mathrm{T}}(e) = \delta_{\mathrm{T}} + \sigma_{\mathrm{T}}(c) \cdot v,$$

where δ_{T} *is a zero-valence default state. The sensitivity of simulation to valence satisfies* $\sigma_{\mathrm{T}}(c) \leq 0$ *if a higher target realization* τ *has lower valence and* $\sigma_{\mathrm{T}}(c) \geq 0$ *otherwise. Simulation is less sensitive to valence if the discrepancy* $d(c, c_{\mathrm{T}})$ *between the target context* c_{T} *and the experience's context* c *is larger,* $\frac{\partial |\sigma_{\mathrm{T}}(c)|}{\partial d(c, c_{\mathrm{T}})} < 0$. *Congruent context entails full simulation,* $|\sigma_{\mathrm{T}}(c_{\mathrm{T}})| = 1$.

Because high inflation has low valence, its simulation coefficient is negative, $\sigma_{\Pi}(c) \leq 0$. Thus, if the DM recalls a high inflation episode, a DS adversity, she uses its low valence $v < 0$ to simulate a bad high inflation state. Crucially, even if the DM recalls past personal financial troubles, an NDS adversity, she can use its negative valence to imagine high inflation.

Unlike in motivated beliefs models, the valence of a future macro state does not mechanically link to the person's utility from such a state. Concretely, high inflation and home price growth may benefit current homeowners holding fixed-rate mortgages. However, these people may still view these macro states as bad, either due to their past experiences as wage-earning renters or due to social conventions about the valence of these outcomes (e.g. the concerns of many people about the affordability of goods and housing when their prices increase rapidly). In Section 4 we measure the perceived similarity of adverse experiences, including personal financial distress, to high inflation and home price growth, which disciplines $\sigma_{\mathrm{T}}(c)$.

The sensitivity to valence is full for a DS experience $\sigma_{\Pi}(c_{\Pi}) = -1$, attenuated for NDS financial experiences, and even more attenuated for less similar health experiences, namely $0 > \sigma_{\Pi}(c_f) > \sigma_{\Pi}(c_h) > -1$. The same holds for home price growth, $0 > \sigma_{\Gamma}(c_f) > \sigma_{\Gamma}(c_h) > \sigma_{\Gamma}(c_{\Gamma}) = -1$. Highly dissimilar experiences with sharply incongruent context or valence inhibit simulation. In these cases, $\sigma_{\mathrm{T}}(c) = 0$ or $v = 0$, and the forecast anchors to a neutral default such as a "normal" state or a random element in the response scale.

Assumption 2 then implies that DS and NDS experiences shape pessimism according to the similarity hierarchy in Bordalo et al. (2025a).[7] The structure of this hierarchy, captured by the magnitude and sign of $\sigma_{\mathrm{T}}(e)$ is then empirically recovered from: i) perceived similarity between

[7] For NDS experiences, simulation relies on valence, not on the realization x (which is incompatible with the target τ). For DS experiences simulation can instead also use x (i.e. the DM projects past 10% inflation into future 10% inflation). Assumption 2 entails no loss of generality if there is a one to one mapping between the two, $v(\tau) = -\tau$.

the primed adversities and the target macro states, and ii) "experience effects" of these adversities in our control condition. In turn, this hierarchy disciplines experience and priming effects.

Consider finally the database. Let $C_\emptyset$ be the set of valence-neutral contexts, $n_\emptyset$ their numerosity, and $C_{-\emptyset} \subseteq C$ the set of valence-charged contexts. Neutral contexts capture routine events such as having our usual breakfast, walking to the office, etc. Being highly dissimilar from macro states, they do not foster simulation. We then consider the following database structure.

Assumption 3 *Within each $\tilde{c} \in C_{-\emptyset}$ the distribution of valence is symmetric around $v = 0$, $n_{(v,\tilde{c})} = n_{(-v,\tilde{c})}$ and the distribution of cues is also symmetric, $\omega_{(v,\tilde{c}),\mathrm{T}} = \omega_{(-v,\tilde{c}),\mathrm{T}}$.*

We then characterize the effect on beliefs caused by adding an experience e_p to an otherwise valence-neutral "representative" database $\boldsymbol{n}$, and the effect of priming recall of e_p compared to a valence-neutral distribution of cues $\boldsymbol{\omega}_\mathrm{T}$.

3.3 Characterizing Experience and Priming Effects

Consider our model's predictions for experience and priming effects. We focus on the relevant case for us: higher target realizations τ have lower valence, $\sigma_\mathrm{T}(c) \leq 0$, and the lived and primed event e_p is an adversity, $v_p < 0$. The logic intuitively extends to the other cases.

The Experience effect of adding adversity e_p to the baseline database $\boldsymbol{n}$, resulting in an enriched database $\boldsymbol{n}_p$, causes a change in beliefs given by:

$$\mathbb{E}(\tau|\boldsymbol{\omega}_T, \boldsymbol{n}_p) - \mathbb{E}(\tau|\boldsymbol{\omega}_T, \boldsymbol{n}) = r_{e_p}(\boldsymbol{\omega}_T, \boldsymbol{n}_p) \cdot \left[\sigma_\mathrm{T}(e_p) - \overline{\sigma_\mathrm{T}(e)}_{-p}\right], \tag{6}$$

where $\overline{\sigma_\mathrm{T}(e)}_{-p}$ is a weighted average of simulation from previous experiences $e \neq e_p$. Living e_p causes its recall and simulation based on it, and dampens recall of other experiences $e \neq e_p$ and simulation based on them. This occurs across all cues in the distribution $\boldsymbol{\omega}_T$. The DM is then more pessimistic if and only if e_p promotes simulation of high inflation or home price growth compared to the average (the term in square brackets is positive). This occurs if e_p is a DS high inflation experience (Malmendier and Nagel 2016) or if e_p is an NDS whose low valence helps imagine a bad state (Cenzon 2025; Taubinsky et al. 2026). Recall is key: if e_p is not spontaneously recalled, $r_e(\boldsymbol{\omega}_T, \boldsymbol{n}_p) \approx 0$, its mere experience does not affect beliefs, even if it helps simulation.

Priming e_p for someone who has lived this experience shifts the cue from the baseline $\boldsymbol{\omega}_T$ to $q_{e_p,\mathrm{T}}$, thereby setting $\omega_{e_p,\mathrm{T}} = 1$. Beliefs then change according to:

$$\mathbb{E}\left(\tau|\mathbf{1}_{e_p}, \boldsymbol{n}_p\right) - \mathbb{E}\left(\tau|\boldsymbol{\omega}_T, \boldsymbol{n}_p\right) = \sum_{e\in E} r_e\left(q_{e_p,\mathrm{T}}, \boldsymbol{n}\right) \cdot [\sigma_{\mathrm{T}}(e) - \mathbb{E}(\tau|\boldsymbol{\omega}_T, \boldsymbol{n})], \tag{7}$$

where $\mathbf{1}_{e_p}$ is degenerate on $q_{e_p,\mathrm{T}}$. Priming e_p boosts its recall, raising beliefs if $\left[\sigma_{\mathrm{T}}\left(e_p\right) - \mathbb{E}(\tau|\boldsymbol{\omega}_T, \boldsymbol{n})\right] > 0$. Again, this condition is met if simulation based on e_p is stronger than average simulation across $e \neq e_p$. Thus, the direct priming effect of e_p is analogous to its experience effect.

Critically, the other addenda in Equation (7) show that priming e_p also creates recall and simulation spillovers to other experiences $e \neq e_p$. Spillovers can produce a positive priming effect even if the direct priming effect of e_p and its experience effect are zero or negative.

Proposition 1. *If the frequency of neutral experiences is high enough,* $n_\emptyset > \overline{n}$, *priming adversity* e_p *with a positive experience effect causes beliefs in* t_T *to change in the same direction. Formally:*

$$\mathbb{E}\left(\tau|\boldsymbol{\omega}_T, \boldsymbol{n}_p\right) - \mathbb{E}(\tau|\boldsymbol{\omega}_T, \boldsymbol{n}) > 0 \Rightarrow \mathbb{E}\left(\tau|\mathbf{1}_{e_p}, \boldsymbol{n}_p\right) - \mathbb{E}\left(\tau|\boldsymbol{\omega}_T, \boldsymbol{n}_p\right) > 0. \tag{8}$$

If having lived e_p predicts pessimism, then priming e_p should boost pessimism, *strengthening* the experience effect. A positive experience effect is thus sufficient but not necessary for a positive priming effect. Even if the experience effect of e_p is not positive, priming can boost beliefs in two cases. First, when e_p fosters simulation but it is not spontaneously recalled, $r_{e_p}(\boldsymbol{\omega}_T, \boldsymbol{n}_p) \approx 0$. Here the experience effect of e_p is zero but priming nevertheless increases beliefs by causing recall of e_p. Second, e_p may not be a source of positive simulation, $\left[\sigma_{\mathrm{T}}(e_p) - \overline{\sigma_{\mathrm{T}}(e)}_{-p}\right] \leq 0$. Here the direct priming effect of e_p is non-positive but priming can nevertheless increase beliefs via recall spillovers on other, highly simulating, DS and NDS experiences.

Overall, memory puts structure in otherwise amorphous forces such as "animal spirits" or "narratives" based on three cross-equation restrictions. The first links experience and priming effects (Equation (8)). Second, similarity matters: the experience and priming effects of adversity e_p should be stronger than those of adversity $e_{p'}$ if the former is more similar to high inflation or home price growth. Third, priming affects reasoning: it changes the DS or NDS experiences that are used to form beliefs, changing how people think about the future. We next test this structure.[8]

4. The Survey: Design and Basic Facts

Section 4.1 describes the survey experiment and links it to the model. Section 4.2 documents basic facts that allow us to derive our model's predictions, which we test in Section 5.

4.1 The Survey Experiment

We fielded our survey in June 2024 on the DHS households, with a second wave in October 2024. The survey's key innovation is to measure not just beliefs but also memory factors and to manipulate those. Appendix B describes the survey in detail. [9]

[8] Our measurement focuses on NDS adversities but the model symmetrically produces optimism for positive NDS experiences. Appendix B shows that in the DHS positive health changes or financial experiences predict lower inflation and home price growth expectations, similar to Taubinsky et al's (2026) findings.

[9] In our first wave, we contacted 6,514 households in the DHS panel and obtained complete responses from 4,348 (67%) of them. In the second survey we surveyed 4,301 households, with a 89% response rate. For this experiment,

The outcomes: macroeconomic beliefs. Following the DHS, we elicited beliefs about 12-month ahead consumer price inflation: the modal forecast and the probability of a "7% or larger" tail. We also elicited beliefs about the 12-month ahead percentage change in national home prices: the modal forecast and the probability of a 10% or greater increase. These measures correspond to the inflation and home price growth tasks, t_Π and t_Γ, in the model. As with the DHS data, we construct inflation and home price growth z-scores.

Reasons. Right after reporting beliefs, respondents write 3 to 4 sentences about thoughts or experiences that came to mind when answering the inflation and home prices growth questions. This text lets us see how primed mental states change the mental models people use.

Cues: Priming NDS experiences. We randomly assign participants to one of three groups: financial ($N = 1267$), health ($N = 1262$), denoted $p\mathrm{R} = f\mathrm{R}, h\mathrm{R}$ respectively, and control ($N = 1284$), denoted by $\emptyset$. In fR, prior to the forecasting task t_T people are primed to *recall* (hence the "R" index in fR) whether they or a loved one ever faced personal or family struggles with financial hardship. In hR they are instead primed to recall a serious or chronic illness, or a serious accident involving them or a loved one. In both treatments, people describe the event, including the time, difficulties, and emotions. Priming is the only difference from Control.

Primed recall changes the respondent's mental context during forecasting t_T by increasing the salience of the financial or health context c_p, its objective realization x_p, and its subjective valence v_p, $p = f, h$, setting the cue at $q_{p,\mathrm{T}}$, $p = f, h$. In Control $\emptyset$ the cue is instead drawn from the unobserved distribution $\boldsymbol{\omega}_\mathrm{T}$. Critically, fR and hR do not convey news. People recall events they have lived through, and hence already *know* about. In addition, such NDS events contain no

we used the enlarged DHS panel, combining panel members from both the Centerpanel and the LISS (Longitudinal Internet Studies for the Social Sciences) panel, both of which are administered by CentERdata.

information about inflation and home price growth. Thus fR and hR should play no role in any model, rational or behavioural, in which memory is perfect and beliefs only depend on news or tastes. This is not so with memory, where priming shapes what people think about during t_{T}.

Other NDS experiences and similarity. After beliefs and reasons, respondents reported whether they or a loved one lived each of a list of ten NDS experiences: health adversities, financial struggles, extreme weather, inequality, social conflict, contract breaches, successful investments, immigration, unemployment, and divorce. These experiences proxy for the database $\boldsymbol{n}$. We then asked respondents to report, on a 1-7 scale, the similarity of each NDS experience with high inflation and home price growth. These subjective ratings are informative about the similarity and simulation function $\sigma_{\mathrm{T}}(e)$. These measures allow us to test memory's cross-equation restrictions: i) across experience and priming effects, ii) across different primes, and iii) across domains.

At the end of the survey, we elicited a range of demographics and a numeracy score (asking the share of Dutch people 90 years or older) so as to replicate individual level controls in Table 1. In our June survey, the provider failed to elicit the similarity of the primed experience: e_f in fR and e_h in hR. We collected this measure in a second wave in October 2024. To minimize painful memories we did not ask respondents to again recall the adversity e_p. They i) could revise their earlier description of adversity if they wished, and ii) were asked to report inflation and home price growth beliefs, experiences, as well as perceived similarity between experiences and macro outcomes.[10] The second wave fills the data gap but also allows us to test the stability of beliefs, experiences, and similarity. We focus on the first wave but also discuss second wave results.

4.2 Forecasts and Experiences in the Control Sample

[10] In the finance (health) treatment, 11% (15%) of participants added text to their earlier answers from the first wave. Among those who added text, 11% (26%) had not reported a health/financial adversity in the first wave.

Table 2 reports descriptive statistics for beliefs about inflation and home price growth across the two survey waves, in the treatment and control samples.

Table 2: Summary Statistics for Macroeconomic Beliefs

	Wave 1			**Wave 2**		
	Mean	**Median**	**SD**	**Mean**	**Median**	**SD**
Inflation (Point Forecast)	5.46	3	8.40	5.27	3.5	6.72
Inflation (Threshold)	4.42	4	2.48	4.65	5	2.45
Housing (Point Forecast)	6.51	5	7.55	7.06	5	6.96
Housing (Threshold)	4.80	5	2.42	5.20	5	2.37

Notes: We elicited inflation expectations as point forecasts for the expected 12-month change in consumer prices, together with subjective probabilities that inflation will exceed a 7% threshold (measured on a 0–10 scale). We similarly elicited home price growth expectations as a point forecast for the expected 12-month percentage change in national home prices and the subjective probability of a 10% or greater increase. The table reports the mean, median, and standard deviation of each belief measure by survey wave.

Inflation and home price growth point forecasts exhibit strong disagreement (8.4 and 7.55 std, respectively) and are highly right skewed (means are about 0.29 and 0.20 std higher than medians, respectively). Beliefs about tail events are also heterogeneous but less skewed. These statistics are stable across waves and are comparable to beliefs in the DHS.[11]

Following the DHS analysis in Table 1, consider the correlation between beliefs and the financial and health adversities. Using data from Control, we estimate:

$$z_{i,\mathrm{T}} = \alpha_{\mathrm{T}} + \epsilon_{f,\mathrm{T}} \cdot \mathbb{I}_{i,f} + \epsilon_{h,\mathrm{T}} \cdot \mathbb{I}_{i,h} + \eta_T \cdot X_i + u_{i,T}, \tag{9}$$

where $z_{i,\mathrm{T}}$ is the belief z-score (higher $z_{i,\mathrm{T}}$ means higher inflation for $\mathrm{T} = \Pi$ or home price growth for $\mathrm{T} = \Gamma$), $\mathbb{I}_{i,e}$ is a dummy for whether respondent i reports having had financial ($e = f$) or health ($e = h$) adversities. X_i includes our socio-demographic controls and the measure of numeracy.

[11] In 2024, the mean (median) inflation and home price growth point forecasts in the DHS were 4.09% (3%) and 3.93% (3%), respectively, which are comparable to Table 2 for inflation but lower for home price growth. DHS home price growth forecasts are elicited from a smaller sample (typically 1600, compared to 2500 for DHS inflation forecasts, and 3800 for our sample) and are more volatile across surveys.

Consistent with Table 1, Table 3 shows that experienced financial adversity is associated with substantially higher inflation and home price growth expectations. The effect is quantitatively large, leading to a 1.27 pp and 0.67 pp increases in forecasts, against baseline averages of 5.46% and 6.51% respectively (Table 2, wave 1).[12] Health adversity is instead not associated with pessimism, its coefficient is insignificant (and directionally negative for inflation), differently from Table 1. Appendix C reports estimated coefficients for all covariates.

Table 3: Experience Effects and Macroeconomic Beliefs

	Control Group – Wave 1	
	Inflation	Home Price Growth
	(1)	(2)
Finance Experience	0.1815***	0.1048**
	(0.0552)	(0.0515)
Health Experience	-0.0177	0.0523
	(0.0559)	(0.0513)
Controls	Yes	Yes
R Sq.	0.1280	0.0595
Adj. R Sq.	0.1170	0.0476
Observations	1284	1284

Notes: We report OLS regressions of standardized inflation beliefs in Column 1 and home price growth beliefs in Column 2 for the control group in Wave 1, on binary indicators for having experienced a financial ("Finance Experience") or health ("Health Experience") adversity. Dependent variables are composite indices that average the standardized point forecast (winsorized at the 2nd and 98th percentiles) and threshold measure, then standardized within wave. Regressions control for Age, Education, Occupation Type, Degree of Urbanization, Household Income, Accommodation Type, Gender, Relationship Status, and Beliefs about Elderly (not shown). Standard errors are heteroskedasticity-robust. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Our model explains the effect of financial adversities as reflecting their spontaneous retrieval and use for simulating high inflation or home price growth scenarios. It can explain the

[12] To obtain effect sizes in p.p., we multiply the z-score coefficient by the loading of the standardized point forecasts on the composite (0.83 for inflation, 0.85 for housing) and by the standard deviation of point forecasts in p.p. (8.40 pp for inflation, 7.55 pp for housing). We perform a comprehensive quantification in Section 5.

weaker role of health adversities in Table 3 due to either: i) the failure of spontaneously recalling them when thinking about inflation or housing ($r_{e_h}(\boldsymbol{\omega}_{\mathrm{T}}, n) \approx 0$ in Equation (6)), or to ii) their small simulation potential ($\left[\sigma_{\mathrm{T}}(e_h) - \overline{\sigma_{\mathrm{T}}(e_h)}_{-h}\right] \approx 0$). Because the DHS measures current events, which are naturally recalled, the positive coefficient on health adversities in Table 1 supports simulation from e_h and hence hypothesis i). These hypotheses, however, and the broader role of cues and experiences can be directly studied using the measured memory parameters.

4.3 Measured Memory Parameters

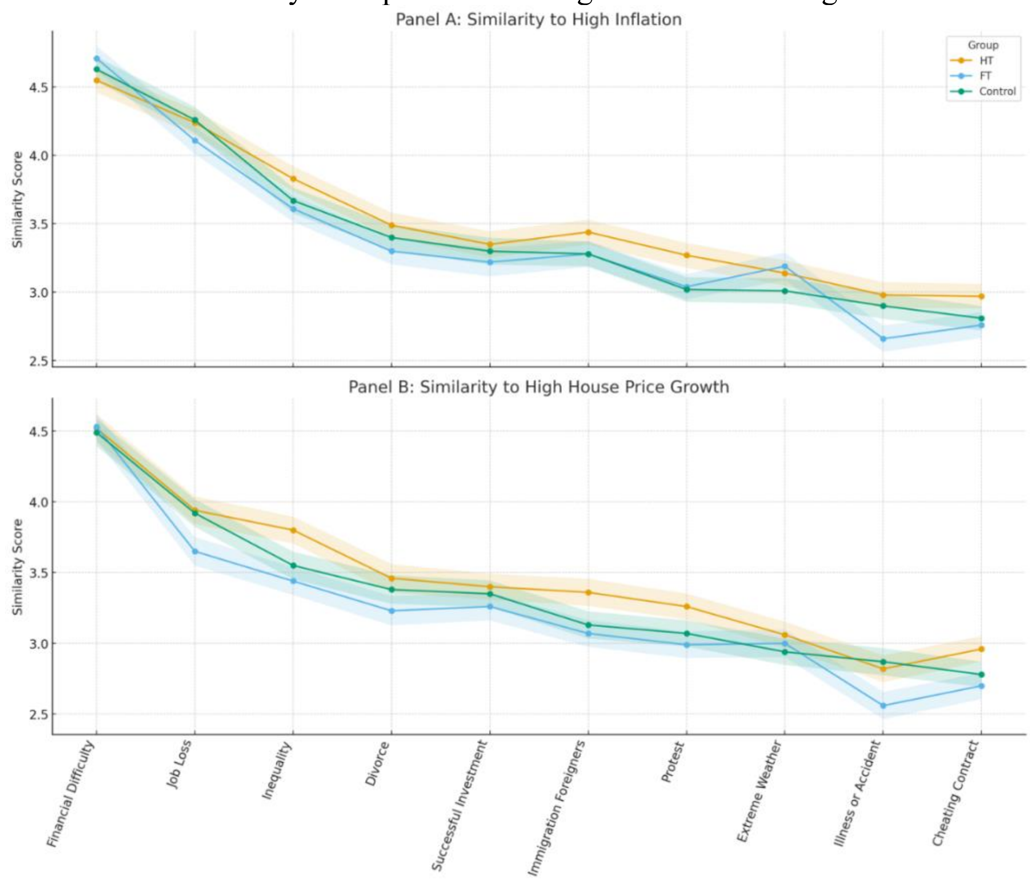
Experiences. The primed NDS experiences are frequent, with financial or health adversity being reported by 39% and 45% of participants in fR and hR, respectively. Frequent experiences in Control are also divorce (47%), job loss (37%), and being cheated on a contract (37%). These frequencies are similar across treatment and control groups (Appendix C). There is large variation in experiences across people, which may lead to belief disagreement. Experiences also cluster: financial and health troubles, unemployment, and divorce are linked via interactions and personal traits (Appendix B). Priming causally tests for memory effects by exogenously varying the extent to which these experiences are salient in context, controlling for their presence in the database.[13]

Similarity. Figure 1 plots the mean similarity scores of each NDS experience to high inflation (Panel A) and high home price growth (Panel B), with 95% confidence intervals. A score of 1 means "not similar at all" a score of 7 means "extremely similar". The data comes from Wave 1 when available and Wave 2 otherwise. Intuitively, *financial difficulty* is most similar to both high inflation and home price growth, with average scores around 4.5. This reflects the financial nature of inflation and housing, so there is some contextual similarity, but also the adverse nature

[13] In our model priming is further amplified by correlated experiences: a person primed with a health adversity may also recall associated financial or family adversities, fostering spillovers in Equation (8).

of high inflation and home price growth for many people, creating similarity in valence. Financial adversity is about equally similar to inflation and home price growth (4.93 vs 4.85, p=0.09) and likewise for health (2.95 vs 2.92, p=0.67, see Appendix C).

Figure 1: Perceived Similarity of Experiences to High Inflation and High Home Price Growth



Notes: We report subjects' mean similarity between each non-domain-specific (NDS) experience and the scenarios of high inflation (Panel A) and high national home price growth (Panel B), pooled across waves. We report separately the Health Treatment (hT), Finance Treatment (fT), and Control. Ratings are on a 1–7 scale, where 1 indicates "not similar at all" and 7 indicates "extremely similar." The shaded areas denote 95 percent confidence intervals.

Illness or Accident is among the least similar NDS adversities in our list, with average scores around 2.7-3 for inflation and home price growth. These NDS experiences are semantically different from macroeconomic states. However, similarity is non-zero: an illness is an adversity, like high inflation and home price growth for many people. As in Assumption 1, context and valence shape similarity. The fact that financial and health adversities are perceived as similar to high inflation and high home price growth is consistent with $\sigma_{\mathrm{T}}(e) \leq 0$ in Assumption 2.

Similarity is stable across income brackets, home ownership status, and our measures of lived experiences, confirming that simulation does not reflect individual tastes. Similarity is also stable across treatments, suggesting that fR and hR mainly affect cues, not simulation (see Appendix C). There is significant variation in similarity across people, with standard deviation ranging from 1.6 to 1.8 for different experiences. This is not only noise: a person's similarity rating has a 0.3 correlation across Waves 1 and 2.[14] In psychology, variation in perceived similarity is tied to differential attention to features (Nosofsky 1986, Bordalo et al. 2026). For instance, people more focused on emotions than on context perceive higher similarity between personal and macroeconomic adversities.[15] We use this variation to test for heterogeneity in treatment effects.

Cues. Priming affects beliefs by increasing the salience of adverse financial or health experiences. To validate this assumption, we report word clouds of subjects' descriptions of primed experiences which prominently feature the primed adversity and its low valence.

Figure 2: Word clouds for Priming treatments, health (left) and finance (right).

Notes: Word clouds of open-ended experience descriptions in hR (N=1,262; left panel) and fR (N=1,267; right panel). Word size reflects frequency after removing common function words (175 stopwords). Total corpus: 41,776 words in hR and 31,760 words in fR.

[14] Estimating for each t_{T} a pooled regression of wave 1 on wave 2 similarity scores and demographics predicts an interpersonal variation of 0.59 and 0.62 standard deviations of similarity in Π and Γ, respectively.

[15] Having had an experience tends to increase its perceived similarity to inflation (Appendix C), which may reflect the increased ability to simulate negative affect events based on such experiences.

5. Context, Memory, and Macroeconomic Expectations

We use our survey to test and quantify memory as a source of "animal spirits": beliefs that depend on uninformative mental states and emotions. Section 5.1 studies priming effects and compares them to experience effects. Section 5.2 explores the roles of non-primed NDS experiences and of similarity. Section 5.3 asks how priming changes the way in which people reason about inflation and home price growth.

5.1 Instability: The causal effect of primed recall on beliefs

We test for priming effects building on Equation (9). Let dummy $\mathbb{I}_{i,e_p,\mathrm{R}}$ take the value of one if respondent i was in treatment pR. The cue in task t_T is $q_{e_p,\mathrm{T}}$, which is concentrated on experience e_p compared to the baseline distribution of cues $\boldsymbol{\omega}_\mathrm{T}$. We then have:

Prediction 1 *In task t_T, the regression pooling the control and the treatment samples:*

$$z_{i,\mathrm{T}} = \alpha_\mathrm{T} + \sum\nolimits_{p=f,h} \epsilon_{e_p} \cdot \mathbb{I}_{i,e_p} + \sum\nolimits_{p=f,h} \beta_{e_p,\mathrm{R}} \cdot \mathbb{I}_{i,e_p,\mathrm{R}} + \eta_T \cdot X_i + u_{i,T}. \tag{11}$$

has the following properties:

i) *If an experience effect is positive, $\epsilon_{e_p} > 0$, then the corresponding priming effect is also positive, $\beta_{e_p,\mathrm{R}} > 0$.*

ii) *The sum of experience and priming effects $\epsilon_{e_p} + \beta_{e_p,\mathrm{R}}$ is higher for an experience e_p that is more similar to high target outcomes.*

Relative to Equation (9), Equation (11) adds the second sum, namely the effect of being randomly assigned to a treatment in which adversity e_p is primed. Coefficient ϵ_{e_p} is the pure experience effect $\mathbb{E}(\tau|\boldsymbol{\omega}_T, \boldsymbol{n}_p) - \mathbb{E}(\tau|\boldsymbol{\omega}_T, \boldsymbol{n})$ in Equation (6), coefficient $\beta_{e_p,\mathrm{R}}$ is the priming effect $\mathbb{E}(\tau|\mathbf{1}_p, \boldsymbol{n}_p) - \mathbb{E}(\tau|\boldsymbol{\omega}_T, \boldsymbol{n}_p)$ in Equation (7).[16] By Proposition 1, we obtain prediction 1.i): priming financial adversities, which in Table 3 exhibit positive experience effects, should raise inflation and home price growth beliefs by causing recall of events with similar simulation.

Prediction 1.ii) highlights the role of similarity: people who are primed a lived experience more similar to high inflation or home price growth should be more pessimistic in the respective domain than people who have top of mind an experience that is less similar.[17] Based on Table 3 and on the similarity gradient in Figure 1, the sum of experience and priming effects should then be higher for financial than for health adversities for both inflation and home price growth.

Table 4 tests these predictions. Columns (1) and (2) consider an Intent to Treat (ITT) sample, so dummy $\mathbb{I}_{i,p}$ is equal to one also for subjects assigned to the treatment who report not having had the primed experience (and who do not answer recall questions). Columns (3) and (4) implement a Treatment on Treated (TOT) test, by setting $\mathbb{I}_{i,e_p,\mathrm{R}} = 1$ only for subjects who had the primed experience and hence are effectively treated. The TOT tests implement the decomposition of Equation (10) and are the relevant treatment for assessing prediction ii). In the ITT sample coefficient magnitudes also reflect the frequency of experiences, not only their similarity.

Table 4: Effects of Cued Financial and Health Adversity on Macroeconomic Beliefs

	ITT		TOT	
	Inflation (1)	Housing (2)	Inflation (3)	Housing (4)
Finance Prime	0.0640*	0.0707*	0.1388**	0.1690***
	(0.0376)	(0.0375)	(0.0653)	(0.0633)
Health Prime	0.0418	0.0966**	0.1440***	0.1347**
	(0.0368)	(0.0381)	(0.0524)	(0.0554)

[16] These coefficients depend on the task T, but we omit the subscript for simplicity of notation.
[17] The model does *not* predict that the priming effect alone should be stronger for the more similar experience, because the latter may be spontaneously remembered with high probability, possibly leading to small priming effects.

Finance Experience	0.1850***	0.1275***	0.1565***	0.0795*
	(0.0338)	(0.0347)	(0.0464)	(0.0454)
Health Experience	-0.0132	0.0339	-0.0704	-0.0019
	(0.0315)	(0.0335)	(0.0479)	(0.0468)
N	3813	3813	2367	2367
Controls	Yes	Yes	Yes	Yes
R^2	0.1153	0.0595	0.1254	0.0641

Notes: We report OLS regressions of the impact of fR and hR on the z-scores on Inflation and Housing beliefs. Columns (1) and (2) present ITT estimates, columns (3) and (4) TOT ones. "Finance Experience" and "Health Experience" indicate if a respondent lived a financial or a health adversity. Dependent variables are composite indices that average the standardized point forecast (winsorized at the 2nd and 98th percentiles) and threshold measure and then standardized within wave. All regressions use Wave 1 data; the TOT sample is restricted to respondents who complied with treatment. We control for Age, Education, Occupation Type, Degree of Urbanization, Household Income, Accommodation Type, Gender, Relationship Status, Beliefs about Elderly (not shown). Robust standard errors are in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10.

Prediction 1 is confirmed. Begin with 1.i): priming a financial adversity boosts pessimism about inflation and home price growth in both the ITT and TOT tests, consistent with the positive experience effect in Tables 3 and Table 4. Beliefs of finance-primed TOT respondents are 0.14 standard deviations higher for inflation and 0.17 for home price growth compared to people who have lived but are not primed to recall the experience. Priming health is also associated with more pessimism, especially in the TOT sample, equal to 0.14 standard deviations for inflation and 0.13 for home price growth. These effects are large, corresponding to increases in inflation forecasts of 0.97 pp (1.01pp), against a baseline average of 5.46%, and an increase in home price growth forecasts of 1.08 pp (0.86 pp respectively), against an average of 6.51%.[18]

Prediction 1.ii) is also confirmed. The financial adversity is more similar than the health adversity to higher target outcomes and, consistent with memory, it exhibits a larger combined experience and priming effects in both domains, corresponding to 0.30 versus 0.07 standard

[18] Consistent with the model, the treatment effects are concentrated in TOT (and hence weaker in ITT). For participants who did not have the experience, the treatment is milder: after being asked if they had the experience, they are not asked to recall it. Appendix D then shows that such treatment has no effect on beliefs. Also consistent with the model, the priming dummy does not absorb the experience effect (and vice versa).

deviations for inflation and 0.25 versus 0.13 for housing. The similarity hierarchy of these results in turn ties the hierarchy of experience effects in Table 3.[19]

Exogenous recall of uninformative events affects macroeconomic beliefs, rejecting statistical models.[20] The evidence is also inconsistent with motivated beliefs: people imagine aggregate states that are similar to what is top of mind, not what is fundamentally good or bad for them. For instance, priming financial adversities increases expected home price growth for both home-owners and renters, consistent with the similarity judgments of both groups (Appendix D).

5.2 Heterogeneity: the NDS Database and Similarity

Memory creates systematic heterogeneity. Some people are more pessimistic than others because: i) they have lived and are reminded of adverse personal experiences that help them imagine adverse macro states, or because ii) they perceive stronger similarity between adverse NDS and bad macro states (due to higher attention to valence compared to context). Such disagreement can manifest itself both in the baseline and in reaction to cues.

To test for these predictions, we capture the "pessimism-potential" in a subject's NDS database and similarity perceptions, by computing, following Bordalo et al. (2025a), the average similarity of the NDS experiences the subject reports:

$$\mathrm{S}_{\mathrm{T},i}(\boldsymbol{n}_i) = \frac{\sum_{e \in E} \mathbb{I}_{i,e} \cdot S_i(e, \mathrm{T})}{\sum_{e \in E} \mathbb{I}_{i,e}},$$

where E is the set of NDS we elicit, $\mathbb{I}_{i,e}$ is as before a dummy for whether the respondent had experience e, and $S_i(e, \mathrm{T})$ is the respondent's stated similarity of e to high inflation ($\mathrm{T} = \Pi$) or home price growth ($\mathrm{T} = \Gamma$). We set $\mathrm{S}_{\mathrm{T},i}(\boldsymbol{n}_i) = 0$ for respondents who have not had any of the

[19] As noted in Section 4, both financial and health adversities approximately equally similar to high inflation and housing, and their combined effects are not statistically different across domains, in line with the model.

[20] In line with recall being shaped by the current cue, priming in wave 1 has low persistence to wave 2 (Appendix D).

elicited experiences. A respondent with a higher index $\mathrm{S}_{\mathrm{T},i}(\boldsymbol{n}_i)$ has lived NDS experiences more similar to high target outcomes, and so should exhibit higher beliefs.

To capture similarity in driving heterogeneous priming effects we construct the proxy:

$$\mathrm{S}_{\mathrm{T},i}(e_p) = \mathbb{I}_{i,e_p} \cdot \mathbb{I}_{i,e_p,\mathrm{R}} \cdot S_i(e_p, \mathrm{T}),$$

which is non-zero for TOT subjects, who have $\mathbb{I}_{i,e_p} \cdot \mathbb{I}_{i,e_p,\mathrm{R}} = 1$, and increases in the similarity of the primed experiences with high inflation or home price growth. Higher $\mathrm{S}_{\mathrm{T,i}}(e_p)$ means that, when primed to recall e_p, the person better simulates adverse scenarios, leading to a stronger increase in inflation and home price growth beliefs. From Equation (11), Prediction 1, we then obtain:

Prediction 2 *Given task* t_{T}*, the regression*

$$z_{i,\mathrm{T}} = \alpha_{\mathrm{T}} + \epsilon_{\mathrm{S,T}} \cdot \mathrm{S}_{\mathrm{T},i}(n_i) + \beta_{e_p,\mathrm{S,T}} \cdot \mathrm{S}_{\mathrm{T},i}(e_p) + \eta_{\mathrm{T}} \cdot X_i + u_{i,\mathrm{T}}, \tag{12}$$

detects a positive similarity gradient of NDS experiences $\epsilon_{\mathrm{S,T}} > 0$ *and their priming* $\beta_{e_p,\mathrm{S,T}} > 0$.

Table 5 reports the estimates. To interpret magnitudes, we scale each index by its standard deviation within each wave. Consistent with the model, coefficients are positive: experience and priming effects increase in perceived similarity. More similar experiences are more likely to be spontaneously retrieved and used in simulation, and the effect of priming them is also stronger.[21]

Coefficient magnitudes can be read directly as the effect of a one–standard deviation increase in similarity on standardized beliefs. The effects are sizable: a one–standard deviation increase in average similarity of lived experiences raises inflation (home price growth) beliefs by 0.10 (0.07) std. A one–standard deviation increase in the similarity of the primed experience

[21] To study memory interference, we decompose the average similarity index into its numerator and denominator: the numerator captures the total summed similarity across lived NDSs, the denominator is the total number of NDSs. Appendix D shows that the numerator enters positively and the denominator negatively: holding total similarity constant, many lived NDSs interfere, reducing the effect of similar experiences on beliefs.

increases inflation (home price growth) beliefs by 0.06 (0.06) std. Adding our two proxies increases the regressions' R^2 from 0.114 to 0.128 for inflation, and from 0.055 to 0.066 for home price growth, compared to having only controls.

Table 5: Effect of Experience Similarity on Inflation and Home Price Growth Beliefs

	TOT	
	Inflation	Housing
	(1)	(2)
Avg. Similarity Lived Experiences	0.0956***	0.0689***
	(0.0255)	(0.0234)
Similarity Primed Experience	0.0560***	0.0600***
	(0.0173)	(0.0184)
N	2367	2367
Controls	Yes	Yes
R^2	0.1278	0.0664

Notes: We report TOT estimates of OLS regressions of z-score of inflation (column 1) and home price growth (column 2) beliefs in Wave 1 on "Avg. Similarity Lived Experiences" (the average similarity rating across all experiences lived by the respondent, rescaled by the unconditional standard deviation pooled across all experiences) and "Similarity Primed Experience" (the similarity rating for the primed experience, rescaled by the same unconditional SD. Respondents in the control group are assigned a value of zero). Dependent variables are composite indices that average the standardized point forecast (winsorized at the 2nd and 98th percentiles) and threshold measure, and then standardized within wave. We control for Age, Education, Occupation Type, Degree of Urbanization, Household Income, Accommodation Type, Gender, Relationship Status, and Beliefs about Elderly (not shown). Standard errors are heteroskedasticity-robust. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10.

One concern is that individual similarity may be spuriously anchored to beliefs (e.g. people reporting higher beliefs may anchor to higher numbers when subsequently reporting similarity). We rule out this possibility by showing that our results are robust to instrumenting individual similarity or beliefs across waves, which rules out anchoring to noise. Our results are also robust to using average rather than individual similarity ratings, which rules out anchoring of similarity to stable belief differences. Appendix D reports several other robustness checks.[22]

[22] Table 5 is also robust to using the ITT sample, which includes all subjects in our treatments, as well as if we exclude demographic controls (see Appendix D), suggesting that the effect of memory parameters is largely independent of

Quantification of Effects. We saw that having lived financial or health adversities and their current salience affects beliefs (Table 4), and that additional belief heterogeneity arises from the broader NDS database and similarity judgments (Table 5). Figure 3 collects these quantitative effects and compares them to standard demographics and experience effects.

To quantify the role of the NDS database, consider the distribution of $S_{T,i}(\boldsymbol{n}_i)$ computed at average similarity. We first estimate the impact of a given NDS experience on beliefs by adding it to every database and computing the entailed change in the average (across participants). Using Table 5, adding a job loss experience increases inflation (home price growth) forecasts by 0.18 p.p. and 0.10 p.p. respectively (Appendix D). The real-world intensity of job loss (experienced directly or by acquaintances) varies across macro states, creating aggregate context effects. We next consider the interquartile range of the distribution of $S_{T,i}(\boldsymbol{n}_i)$ at average similarity. By construction, variation arises only from different NDS experiences. Such interquartile range corresponds to a 0.74 p.p. and 0.91 p.p. increase in inflation and home price growth beliefs, respectively. Importantly, these results are not driven only, or even mainly, by finance experiences: other NDS experiences have comparable similarity-weighted impacts on beliefs (Appendix D).

Consider similarity next. Increasing the average similarity of experiences by a one standard deviation of similarity increases inflation (home price growth) forecasts by 0.99 pp (1.28 pp).[23] Individual level similarity is also important: increasing it from the average to the top quintile for each experience increases inflation (home price growth) forecasts by 0.80 p.p. (1.09 p.p.). Even in a regression setting, individual similarity matters controlling for average similarity (Appendix D).

demographics. Allowing our similarity proxies to also enter quadratically – i.e. giving higher weight to experiences deemed more similar – yields comparable coefficients. Results are consistent across the finance and health treatments.

[23] The quantification regresses z-scored beliefs on the z-standardized /by cross-person SD) average similarity of lived experiences. A one-standard-deviation increase in similarity refers to the pooled SD of raw similarity ratings across experiences and respondents. The pooled SD is about twice the SD of the person-level similarity across experiences, so the implied effects are larger than a naive multiplication of Table 5 coefficients by the footnote 12 factor.

These quantifications are summarized in Figure 3, which distinguishes: heterogeneity due to different database, similarity, and instability from cues. Effects are large compared to standard DS experience effects and demographics. Priming a finance adversity quantitatively matches the disagreement observed when moving from the top to the bottom income quintile (Weber et al. 2022). Demographics may partly capture systematic differences in experiences and the extent to which they are top of mind when making macroeconomic forecasts. The same mechanism extends to DS experiences: the low valence of higher gas prices may be more attended to by a low-income household, causing via similarity a stronger experience effect.

Figure 3: Quantification of memory effects.

Note: This figure compares our estimated effect sizes with benchmark effects from the literature. Effects are expressed in percentage points (pp) of expected inflation (filled circles) or home price growth (open squares), converted from the composite z-score index using factor loading × standard deviation (inflation: 0.83 × 8.40; housing: 0.85 × 7.55). This paper's estimates (red) include: (i) Database effects, which are the coefficient on having a financial experience and the effect of moving from the 25th to 75th percentile of the NDS similarity distribution (IQR); (ii) Cue effects, which are treatment-on-the-treated (TOT) effects of health and finance priming, and the combined effect of finance priming plus financial experience; (iii) Similarity effects, which are the impact of a one standard deviation increase in similarity ratings and the effect of moving to the top quintile of similarity. All estimates are from OLS regressions on the TOT sample (N=2,367) in Wave 1, controlling for demographics. Literature benchmarks (blue) include lifetime inflation pass-through (Malmendier and Nagel 2016), local house price pass-through (Kuchler and Zafar 2019), grocery shopping effects (D'Acunto et al. 2021), and information updating (Armona et al. 2019). Demographic gaps (purple) show differences by income quintile, education, and gender from Bryan and Venkatu (2001), Weber et al. (2022), and D'Acunto et al. (2021). Effects are grouped into categories indicated by shaded background.

In sum, memory offers a cognitively founded mechanism for generating sizable and realistic heterogeneity and instability of macroeconomic expectations based on non-informative experiences that influence the ability to imagine different macroeconomic states.

5.3. Priming Changes Reasoning About Forecasts

Mnemonic reasoning uses the features of personal experiences analogically. First, negative emotions from personal adversities cue recall of high past inflation, a DS experience, causing high expected inflation, as in Taubinsky et al. (2026). In addition, a person can retrieve an NDS adversity and form a partial model (e.g. “things can go bad”) that invites pessimism. Consistent with this mechanism, Andre et al. (2022) show that recall of personal experiences, including NDS ones, creates heterogeneous “macro models” and disagreement based on the same shock. In our model, primed recall of e_p causes these different reasonings by fostering recall of DS and NDS experiences that are similar to the cue $q_{e_p,\mathrm{T}}$. We should thus observe treatment effects in inflation and home price growth reasoning that reflect the features (x, v, c) of experiences retrieved based on the prime, in turn causing pessimistic beliefs.[24]

Priming effects on retrieved $(\boldsymbol{x}, \boldsymbol{v}, \boldsymbol{c})$. We proxy for the realization τ of recalled DS inflation and home price growth experiences using our elicited 12-month inflation and housing back casts, respectively. Schacter et al. (2012) show that selective recall mechanism shapes the reconstruction of the past and imagination of the future. In our model, when a recalled inflation or

[24] We also study the similarity between reasoning and recall, as a proxy for simulation. Consistent with the model, fR (resp. hR) increases the similarity of reasons to recalled financial (resp. health) experiences (see Appendix E).

home price growth DS episode is top of mind, it influences the forecast and is used to impute a backcast.[25]

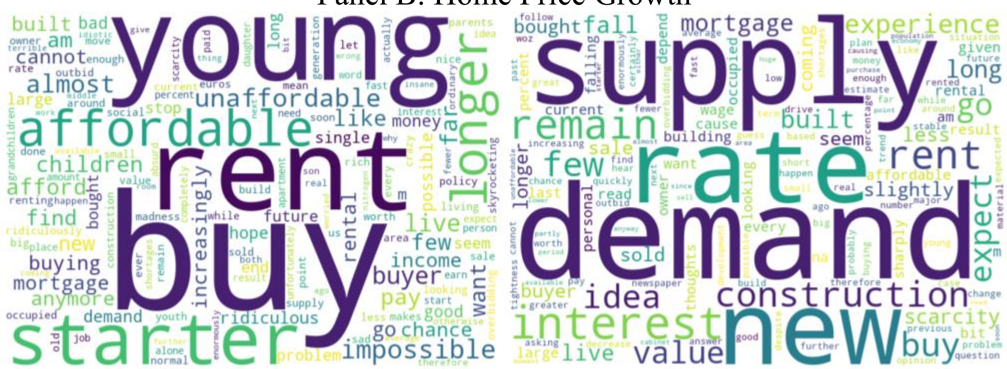
We then extract the key drivers of simulation, valence v and context c, from self-reported forecasts' reasons. We use chatGPT, fine-tuned with detailed instructions and manual validation, to categorize each text as follows. First, proxying for c, we categorize whether reasoning primarily relies on i) personal experiences (e.g. household hardship, personal finances, or family events), on ii) news or expert sources (e.g. media reports, government policy, central bank actions), or is iii) unclassified. Category i) captures the personal context of NDS experiences, category ii) the domain specific context of DS ones. Second, proxying for v, we classify texts based on whether they reflect negative or positive valence, are factual, or unclassified. Negative valence reflects the DS and NDS adversities shaping pessimistic forecasts.[26]

Figure 4 shows word clouds for reasoning classified as negative versus neutral valence, showing that the latter emphasizes aggregate quantities (interest rates, supply and demand) while the former emphasizes negative valence, often in the context of personal experiences (less, money, meet ends, buy). Similarly, Figure 5 shows word clouds for reasoning classified as personal versus news based. Appendix E lists exemplar reasons of all classifications.

Figure 4: Word clouds for negative (left) or neutral (right) valence.
Panel A: Inflation

[25] For NDS we only observe x for primed experiences (i.e. the financial trouble or disease in e_p). In our model this feature is not used for imagining future inflation or home price growth, so we do not use this data it in our analysis.
[26] We validate the GPT classifications against human-coded subsets, confirming high agreement rates (78% for inflation and 70% for housing, for personal logic; 85% for inflation and 92% for housing, for valence).

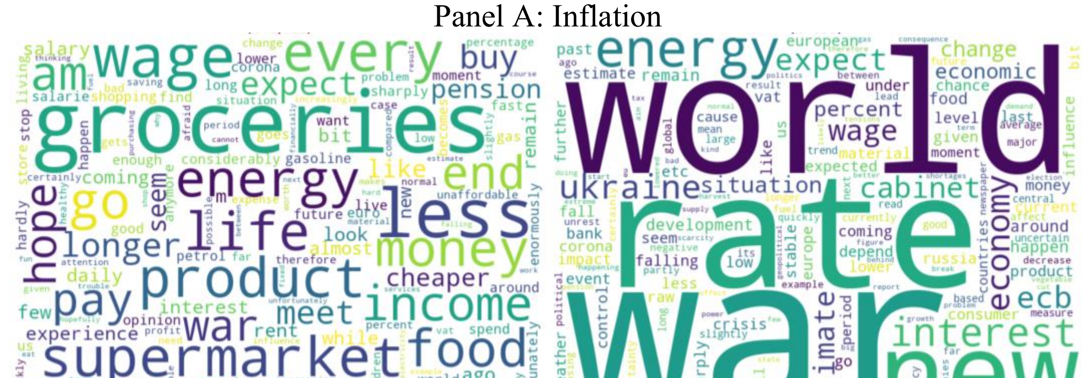
Panel B: Home Price Growth



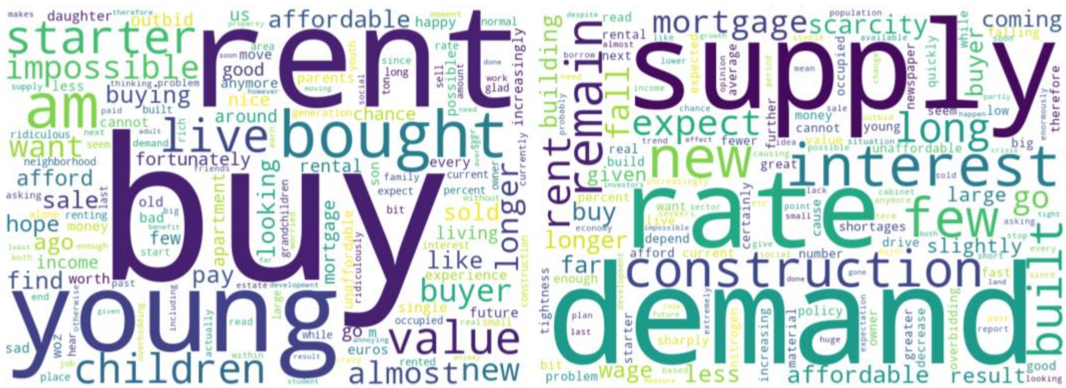
Notes: Word clouds of open-ended macroeconomic reasoning, comparing texts classified as expressing negative affect (left) versus neutral affect (right). The top panel shows inflation reasoning; the bottom panel shows housing reasoning. Emotional valence is classified using GPT-4 analysis of the English translations. Sample sizes: inflation reasoning includes 1,167 negative affect and 2,459 neutral texts; housing reasoning includes 1,029 negative affect and 2,644 neutral texts. Word size reflects frequency after removing common function words and shared topic words (e.g., "price," "inflation," "house") to highlight differences between categories.

Figure 5: Word clouds for personal (left) or news-based (right) reasoning.

Panel A: Inflation



Panel B: Home Price Growth



Notes: Word clouds of open-ended macroeconomic reasoning, comparing texts classified as expressing personal reasoning (left) versus news-based reasoning (right). The top panel shows inflation reasoning; the bottom panel shows housing reasoning. Personal vs news-based reasoning is classified using GPT-4 analysis of the English translations. Word size reflects frequency after removing common function words and shared topic words (e.g., "price," "inflation," "house") to highlight differences between categories.

Our model makes the following prediction about these proxies:

Prediction 3 *Priming an adverse NDS experience should increase the relative recall of adverse DS experiences compared to favourable DS experiences, as well as the recall of NDS experiences compared to DS ones, all compared to Control. As a consequence, priming should increase:*

i) high Inflation and Home Price Growth back casts (DS effect).

ii) the incidence of personal logic (NDS effect) and low valence in reasons (DS and NDS effect).

Effect i) follows from mood congruent recall (Bower 1981) of DS experiences: priming an NDS adversity favours retrieval of high compared to low inflation and home price growth states due to similar low valence, as in Taubinsky et al. (2026). Effect ii) is an additional memory effect: priming an adverse NDS experience prompts recall of other adverse NDS experiences, increasing simulation and reasoning based on personal context and low valence.

Columns (1) and (2) of Table 6 report the TOT effects on back casts. Both fR and hR are associated with higher past inflation and home price growth, consistent with Prediction 3. This test provides causal evidence of the mechanism in Taubinsky et al. (2026). The effect is stronger for finance than for health, consistent with higher similarity of the financial adversity to inflation and home price growth experiences. Magnitudes are large: the finance prime increases inflation (home price growth) back casts by 1.8pp (1.2pp), against a baseline of 10% (9%).

Table 6: Back casts, Context and Valence

	Backcasts (%), TOT		**Personal or Negative, TOT**	
	Inflation	Housing	Inflation	Housing
	(1)	(2)	(3)	(4)
Health Prime	0.9422*	0.3574	0.0598**	0.0797***
	(0.4814)	(0.3921)	(0.0241)	(0.0236)
Finance Prime	1.8253***	1.2384**	0.0971***	0.1195***
	(0.5811)	(0.5304)	(0.0269)	(0.0269)
N	2367	2367	2367	2367
Controls	Yes	Yes	Yes	Yes
R^2	0.0512	0.0410	0.0365	0.0341

Notes: We report treatment-on-treated (TOT) regressions for Wave 1. Columns (1) and (2) estimate how treatments affect respondents' back casts of inflation and house price growth. Back casts are expressed in percentage terms. Columns (3) and (4) estimate whether treatments increase the likelihood that respondents invoke personal experiences or express negative affect in their macroeconomic reasoning. These indicators are classified using GPT-4 analysis of open-text responses, where "Personal or Negative" equals one if the respondent's reasoning is classified as using personal logic or expressing negative affect. All specifications include demographic controls: age, gender, education, occupation, degree of urbanization, household income, accommodation type, relationship status, and beliefs about the elderly. Standard errors are heteroskedasticity-robust. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Columns (3) and (4) show the results for context and valence. Consistent with Prediction 3, priming an adversity increases the likelihood of reasons including either personal context or negative valence relative to Control, for both inflation and home price growth forecast. The effects are large: finance priming raises the likelihood of personal/negative valence reasoning in inflation by 9.7 pp (inflation) and 12.0 pp (housing). The corresponding figures for health are 6.0pp and

8.0 pp. Appendix E shows that priming NDS adversities raises the share of reasoning based directly on low-valence and personal experiences, and a switch away from news-based reasoning.[27]

Recalled features and forecasts. We next circle back to forecasts. Our model predicts that higher back casts should be associated with higher forecasts. It also predicts that personal logic and low valence reasoning based on NDS experiences should also increase the forecasts, consistent with a greater reliance on pessimistic memory-based narratives (Shiller 2018, Andre et al. 2022) that help imagine future bad states.[28] To test this link we use an instrumental variables (IV) approach. In the first stage, we use fR and hR to obtain exogenous variation in reasons as in Table 6. In the second stage, we regress macroeconomic beliefs on the first stage predicted back casts, negative valence or personal logic from the first stage.

Table 7: Beliefs and Predicted Back casts, Context and Valence

	Inflation	Housing		Inflation	Housing
Back cast (predicted)	0.1257***	0.1805***	Personal or Negative (predicted)	2.1061***	1.7089***
	(0.0299)	(0.0440)		(0.5007)	(0.3766)
Observations	2,367	2,367	Observations	2,367	2,367
R^2	0.0083	0.0082	R^2	0.0081	0.0092
F-stat (1st stg)	5.86	3.08	F-stat (1st stg)	9.39	15.65

Notes: This table reports second-stage instrumental variable (IV) regressions examining whether back casts and reasoning features help explain contemporaneous belief formation. The dependent variables are standardized belief z-scores constructed from respondents' point and threshold forecasts. Columns (1) and (2) use predicted back casts (respondents' retrospective assessments of past inflation or house price growth) as the endogenous regressor. Columns (3) and (4) use predicted "Personal or Negative" (a binary indicator equal to one if the respondent's macroeconomic reasoning invokes personal experiences or expresses negative affect, as classified by GPT-4 analysis of open-text responses). The first-stage regressions are reported in Table 6, where each mechanism is regressed on the randomized treatment assignments (Health Prime and Finance Prime), which serve as excluded instruments. F-stat (1st stg) reports

[27] Table 6 measures the disjunction "personal logic or negative valence" to allow for news-based forecasts that also feature low valence, in line with the retrieval of bad inflation or housing experiences from the adverse NDS.

[28] The mechanism helps explain instability and heterogeneity in recall and beliefs. For example, Blanchard (1993) offers evidence consistent with the U.S. recession of 1990-91 being triggered by a drop in consumer confidence due to the Iraq War. Salient events such as a war can affect beliefs by helping people imagine good or bad states, in turn affecting consumption and investment. Link et al. (2023) show that people who think more about inflation tend to be more pessimistic about it. In our model, attention to inflation shapes the cue, which then leads to selective retrieval of high inflation outcomes. Memory also explains why beliefs tend to respond more to specific stories than to statistics (Kahneman Tversky 1972, 1982), in part because stories are more memorable than experiences (as shown experimentally in Graeber, Roth, and Zimmermann 2024) and in part because they provide better simulation material.

the first-stage F-statistic as a diagnostic for instrument strength. Each outcome is estimated separately. All regressions use robust standard errors (in parentheses). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7 shows that the causal increase in back casts or in the reliance on personal logic or negative valence substantially raise inflation and home price growth forecasts. The first stage F-statistic is strong for reasoning, less so for back casts. This is intuitive: the recall of low valence or personal experiences is more strongly based on the NDS cue that our treatments induce, yielding a stronger first stage effect. Put together, the effects of priming on reasoning and beliefs are large: higher predicted personal/negative reasoning raises inflation expectations by 1.5 pp and home price growth expectations by 1.3 pp with the finance prime.[29] For health, these numbers are 0.93pp and 0.88pp. These are substantial magnitudes relative to Figure 3.

Consistent with memory, experiences and cues drive forecasts by endogenously shaping the *content* of reasoning: experiences similar to the task, or cued by the environment, affect not only the selective retrieval of DS data but also the simulation of scenarios based on non-statistical features of irrelevant NDS experiences, such as their negative valence. We next outline some implications of this mechanism for macroeconomic expectations and outcomes.

6. Macroeconomic Implications

We showed that uncertainty is represented "in context" based on semantic or emotional cues that shape the ability to imagine good vs. bad states. We detect these context effect causally, in a clean way. Beyond the specific events that we prime, our findings have broader relevance for macro because they identify the belief formation *mechanism*. They unify well-documented features of beliefs (Section 6.1) and yield new implications for confidence cycles (Section 6.2).

[29] The pp conversion for Tables 6-7 uses the factor loading and standard deviation computed on the TOT Wave 1 subsample (0.84×8.73 for inflation; 0.86×7.52 for housing), which differ slightly from the values in footnote 11.

6.1 Unifying features of macro expectations

Consider an agent forecasting an adversity, such as inflation. To see the intuition most starkly, consider a stylized database with a share n_Π of DS experiences of constant inflation $\overline{\pi}$, and a share $n_p = 1 - n_\Pi$ of NDS adversities.[30] As in Assumption 2, the agent simulates future inflation based on the valence of the retrieved experiences. DS experiences have valence $v(\overline{\pi}) = -\overline{\pi} < 0$, while NDS experiences have valence $v_p = v(\overline{\pi} + \gamma) = -(\overline{\pi} + \gamma)$. Here $\gamma > 0$ realistically captures the fact that personal adversities are more distressing for the agent than experienced inflation (the analysis generalizes to a richer setting with heterogeneous DS and NDS events). As in Assumption 2, NDS-based simulation is weaker due to discrepant context: the agent simulates inflation $|\sigma_p| \cdot (\overline{\pi} + \gamma)$, where $-\sigma_p \in (0,1)$ is the sensitivity of simulation to the valence of NDS.

A cue q is identified by its valence v_q and context c_q. Given similarities between q and DS and NDS experiences, $\mathrm{S}_\Pi \equiv S(q, e_\Pi)$ and $\mathrm{S}_p \equiv S(q, e_p)$ respectively, expected inflation is:

$$\mathbb{E}(\pi|q, \boldsymbol{n}) = \left[\frac{n_\Pi \cdot \mathrm{S}_\Pi}{n_\Pi \cdot \mathrm{S}_\Pi + n_p \cdot \mathrm{S}_p}\right] \cdot \overline{\pi} + \left[\frac{|\sigma_p| \cdot n_p \cdot \mathrm{S}_p}{n_\Pi \cdot \mathrm{S}_\Pi + n_p \cdot \mathrm{S}_p}\right] \cdot (\overline{\pi} + \gamma). \qquad (13)$$

The first term is a DS effect: more DS experiences, higher n_Π, promote retrieval of inflation $\overline{\pi}$, thus anchoring the forecast to it. The second term is an NDS effect: personal financial troubles, higher n_p, prompts the retrieval of distress and simulation of a high inflation state $(\overline{\pi} + \gamma)$.

i) Insensitivity. In Equation (13), personal events interfere "bottom up" with the retrieval of DS experiences: when forecasting inflation, a person may recall her financial troubles or the prices she saw, neglecting aggregate DS data. Interference from NDS experiences thus causes insensitivity to DS ones: increasing experienced inflation $\overline{\pi}$ by one unit while leaving v_p constant increases expectations by less than one unit.

[30] For simplicity we abstract from good NDS, akin to setting their similarity in Assumption 1 to zero, $K = 1/2$.

ii) Bias. Interference can also cause expectations to be *above* experienced inflation $\overline{\pi}$. This occurs if NDS experiences are distressing enough, $\gamma > \left(\frac{1-|\sigma_p|}{|\sigma_p|}\right)\overline{\pi}$. Households' expected inflation is indeed too high (Mankiw, Reis, and Wolfers 2003, Coibion, Gorodnichenko, and Weber 2022).

Insensitivity in i) may seem consistent with rational inattention (Sims 2003), but bias in ii) is not. Bias reflects perceived similarity between inflation and NDS experiences. Importantly, this explains why households strongly dislike inflation: via similarity, high inflation reminds people of personal financial troubles, affordability, and negative valence experiences.

iii) DS context and overreaction. Our experiment causes instability of beliefs by cuing NDS adversities. Similar effect however arise for DS events: an increase in *current* inflation from $\overline{\pi}$ to $\pi' = \overline{\pi} + \partial\pi$, $0 < \partial\pi < \gamma$ increases the similarity S_p of the inflation environment to personal distress and reduces its similarity S_Π to regular inflation $\overline{\pi}$. Forecasts then increase if and only if NDS adversities cause a positive inflation bias.[31] This happens even if the inflation shock is transitory. Memory does not cause a general tendency to overreact to news: the agent is insensitive to historical inflation $\overline{\pi}$ and exhibits a constant NDS-driven bias γ. Yet, she overreacts after seeing a salient inflation surge, which cues her bottom up to retrieve distressing NDS financial troubles and interferes with historically more moderate DS events, increasing pessimism and causing overreaction especially if the change $\partial\pi$ is large, even if transient.[32]

iv) Narratives and Partial Models. Narratives have been invoked as a powerful driver of aggregate consumption and investment decisions using compelling examples and psychological

[31] The increase in current inflation reduces the valence distance in S_p from γ to $\gamma - \partial\pi$, and increases the valence, and numerical, distance in S_Π from 0 to $\partial\pi$. Equation (13) then implies $\frac{\partial \mathbb{E}(\pi|q,\boldsymbol{n})}{\partial\pi} \propto \left[\gamma - \left(\frac{1-|\sigma_p|}{|\sigma_p|}\right)\overline{\pi}\right] \cdot \frac{\partial}{\partial\pi}\left(\frac{S_p}{S_\Pi}\right)$.

[32] As described earlier, this mechanism can produce overreaction even in a database with only DS experiences, as documented in Bonaglia et al. (2025) and Gennaioli et al. (2025). Our model is more general and nests this effect if we allow for realized inflation π to vary across DS traces in the database. We leave a characterization of when interference by NDS generates over or underreaction to future work.

intuition (Shiller 2018). Our framework offers a foundation in terms of context-based beliefs and integrates these ideas into a testable and tractable macroeconomic framework.

For example, an increase in the salience with which a feature is discussed in the media can – by changing the cue q – shift which experiences come to mind and beliefs. Shiller (2018) shows that stories about the "Great Depression" were more viral during the 2007-8 than the 1981-2 recession, even though unemployment was higher in 1981-2. The salience of the "financial crisis" feature increased contextual similarity between 2008 and 1929 even though the Great Depression was objectively not very informative. Superficial similarity drives incorrect DS analogies.

The same mechanism may be at play in narratives that leverage everyday experiences, such as "restaurants are full, the economy is doing well."[33] These narratives focus attention on familiar experiences, and crowd out potentially more relevant information due to interference. The resulting beliefs are based on a subset of the person's DS or NDS experiences, which highlight specific features or channels, i.e. they are partial models. The "partial model" used by a person is then predicted by her experiences, similarity judgments, and context. This leads to systematic heterogeneity: consumers tend to adopt narratives that emphasize experiences familiar to them (Andre et al. 2022, Coibion, Gorodnichenko, and Weber 2022).

Lastly, narratives are unstable. At the heart of the literature on narratives is the idea of contagion (Shiller 2018, Flynn and Sastry 2025), an abrupt change in beliefs driven not by fundamentals but by exposure to the narrative, which is a form of context. By its nature, such contagion is hard to square with models of stable belief distortions. We explain how context can drive instability: by changing which experiences underlie beliefs. In particular, memory disciplines

[33] This example is based on a famous quote by former Italian prime minister Silvio Berlusconi, see https://www.abc.net.au/news/2011-11-14/berlusconi-gaffes-quips-and-pranks/3663534

how context shapes narratives, also putting limits to contagion, for instance based on heterogeneity of experiences. This opens the door to the study of belief dynamics, to which we turn next.

6.2 Macroeconomic Implications: Heterogeneity, Confidence and Business Cycles

Cross-Sectional Heterogeneity. Variation in NDS experiences create belief heterogeneity. This variation does not wash out in the aggregate because NDS experiences (and contexts) are not randomly assigned. Specifically, and consistent with Das, Kuhnen, and Nagel (2020), people with worse personal financial experiences are ceteris paribus more pessimistic about the future. This dampens their willingness to consume, invest, or search for a job. Critically, these very people may have the highest "rational" MPC and job search incentives, so their pessimism can stunt an important driver of economic recovery during a recession. Through these nonlinearities, memory driven belief heterogeneity can affect aggregate outcomes.

Aggregate Confidence. A second and direct link between mnemonic context effects and the business cycles arises through endogenous business confidence. A large body of work suggests that consumer and investor confidence are powerful predictors of aggregate expansions and contractions (Ludvigson 2004), and typically traces them to changes in beliefs triggered by aggregate statistical signals. Memory driven confidence does not rely on statistical signals; it can also arise from current context, including the endogenous actions of other agents. This creates new belief externalities. For instance, the decision by a loan officer to deny credit to a firm increases its macroeconomic pessimism even absent information, which reduces the firm's investment over and above the amount of credit that was denied.

The same mechanism can also work in a positive direction: the decision by a government to purchase more goods from firms cues economic expansion, increasing these firms' optimism, consistent with Bellifemine et al. (2025). To see this mechanism at play, suppose that the current optimal action x_0 increases in the expectation about the future value x_1 of the action itself:

$$x_0 = \mathbb{E}(x_1|x_0, \boldsymbol{n}). \tag{15}$$

For instance, current consumption x_0 should increase in the expectation of future consumption, as in the permanent income hypothesis (Hall 1978), and current investment should increase in the expectation of future marginal return, as in q-theory (Hayashi 1982).

Due to memory, the expectation $\mathbb{E}(x_1|x_0, \boldsymbol{n})$ depends on the current equilibrium outcome x_0, over and above its objective information (if any) about x_1. The reason is that higher current consumption x_0 cues recall of economic expansions or reduces recall of past adversities, increasing expected future consumption. This crucially implies that Equation (15) entails feedback that further increases current consumption x_0. The result is a "confidence multiplier": an increase in confidence creates a current expansion that cues a favourable context, which in turn supports confidence and an additional expansion.

To see this formally, we apply Equations (13) to positive events (i.e. context and valence are now positively related). Combining it with Equation (15), setting for simplicity $\sigma_p = 1$ and $S(e,q) = \exp\left[-\delta\left|x_q - x_e\right|\right]$, we obtain an equilibrium condition for x_0:

$$x_0 = \bar{x} + \frac{n_p \cdot e^{-\delta[|x_0 - \bar{x} - \gamma| - |x_0 - \bar{x}|]}}{n_\mathrm{T} + n_p \cdot e^{-\delta[|x_0 - \bar{x} - \gamma| - |x_0 - \bar{x}|]}} \cdot \gamma. \tag{16}$$

The last term captures the distortion due to NDS-based simulation. It has a sigmoidal shape so that, under some parameter values, Equation (16) admits two stable equilibria, x_L^* and x_H^*, at low and high consumption respectively. The presence of confidence multipliers creates self-fulfilling booms, associated with the high equilibrium x_H^*, in which the consumption of atomistic agents creates a "boom context" that fuels each other's optimism and sustains high consumption, and a low equilibrium x_L^* in which agents restrain consumption, creating a "depression context" that fuels each other's pessimism and sustains low consumption. With an elastic aggregate supply, confidence driven cycles can arise.

This mechanism is complementary to current statistical accounts. In some models, confidence arises from informative signals about aggregate TFP (Lorenzoni 2009, and Blanchard, L'Huillier, and Lorenzoni 2013, Beaudry and Portier 2006). In Angeletos and Lian (2018), closer to Phelps (1970) and Lucas (1972), confidence reflects optimism about the price of the good an agent supplies, which increases her permanent income, demand, and boosts output under sticky prices. Similarly, in Angeletos and La'O (2013) lack of common knowledge allows beliefs to depend on arbitrary, yet unmodelled, optimism shifters. Shifting aggregate context can produce effects similar to non-fundamental noise shocks, as in Lorenzoni (2009), while cross-sectional variation in NDS experiences and context can create idiosyncratic heterogeneity of expectations as in Angeletos and Lian (2018), including departures from common knowledge.

Memory offers a new testable structure based on similarity and experiences. It also creates multiplicity through expectations themselves, without assuming technological complementarities (e.g. sequential service constraints in bank runs). "Positive" choices cue "positive" memories, sustaining similar choices in others. This occurs even when, unlike in herding models, these choices convey no information. A suitable aggregate transfer or investment policy may then produce spontaneous optimism and sustain an economic expansion. These forces may shed light on the effects of economic policy and communication. We leave these topics to future work.

7. Conclusion

About a century ago, Keynes proposed that changes in animal spirits, defined as spontaneous non-statistical forms of business confidence, are a key driver of consumption, investment, and business cycles. By now, abundant evidence shows "excess volatility" in asset prices (Shiller 1981, Bordalo, Gennaioli, LaPorta and Shleifer 2024, 2025) and in macroeconomic aggregates tied to non-rational earnings expectations (Bordalo, Gennaioli, LaPorta, O'Brien, and Shleifer 2024b) or to indices of consumer and business "confidence" that are hard to trace to fundamental news (Blanchard 1993, Barsky and Sims 2012, Beaudry and Portier 2006).

We present a foundation that ties animal spirits to a major force in cognitive science: the role of context in driving memory and attention. Personal or public events shape our semantic and emotional states, shaping how we imagine the future. This approach does not preclude the dependence of beliefs on historical frequencies, which are embedded in the memory database, but stresses that "imagining" a future state comes before "counting" the odds of its occurrence. Mnemonic beliefs can be systematically studied using measurable and controllable memory parameters: experiences, similarity, and cues. The resulting animal spirits exhibit two key features: large heterogeneity based on different personal experiences, especially non-informative ones (NDS), and strong common instability when changes in aggregate context cue similar thoughts.

Instability implies that a common shock can change the ability to imagine good versus bad outcomes for many people above and beyond its information value. Macroeconomic events or policies in one domain can create spillovers into other domains. For instance, periods of rapidly increasing inflation can cue many people with anxiety and distress, prompting them to simulate high future unemployment even if current unemployment is low or even falling. In this way, changes in aggregate context can affect business fluctuations, as in Keynes' original intuition.

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Appendix

Appendix A: Proofs

Appendix B: The Survey Instruments

Appendix C: Further results on measuring Experiences and Similarity

Appendix D: Further results on Experience and Priming Effects

Appendix E: Further results on Reasoning

Appendix A. Proofs

Proof of Proposition 1. We first characterize expectations, experience and priming effects generally. We then we connect them and prove the result using Assumptions 1, 2 and 3.

Characterization of Experience and Priming effects. Expectation $\mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n})$ obeys:

$$\mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}) = \sum_{\tilde{e}\in E} \mathbb{E}\big(\tau|q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\big)\cdot\omega_{\tilde{e},\mathrm{T}}, \tag{A.1}$$

$$\mathbb{E}\big(\tau|q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\big) = \sum_{e\in E} r_e\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\big)\cdot\sigma_{\mathrm{T}}(e) \quad \text{for all } q_{\tilde{e},\mathrm{T}}. \tag{A.2}$$

The experience effect of e_p is the change in belief caused by increasing the frequency of e_p from $n_{e_p}=0$ in the baseline to $n_{e_p}=1$, where p is f or h, not both. Let $\boldsymbol{n}_p$ be the database containing e_p. Recall of different experiences changes by:

$$r_{e_p}\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n_p}\big) - r_{e_p}\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\big) = r_{e_p}\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n_p}\big) = \frac{S\big(e_p,q_{\tilde{e},\mathrm{T}}\big)}{S\big(e_p,q_{\tilde{e},\mathrm{T}}\big)+\sum_{e\neq e_p}S\big(e,q_{\tilde{e},\mathrm{T}}\big)\cdot n_e}$$

$$r_e\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n_p}\big) - r_e\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\big) = -r_{e_p}\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n_p}\big)\cdot r_e\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\big).$$

The experience effect of e_p is then equal to:

$$\begin{aligned}
\mathbb{E}\big(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\big) - \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}) &= r_{e_p}\big(\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n_p}\big)\cdot\sigma_{\mathrm{T}}\big(e_p\big) \\
&\quad + \sum_{e\neq e_p}\sum_{\tilde{e}\in E}\big[r_e\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n_p}\big) - r_e\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\big)\big]\cdot\omega_{\tilde{e},\mathrm{T}}\cdot\sigma_{\mathrm{T}}(e), \\
&= r_{e_p}\big(\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n_p}\big)\cdot\sigma_{\mathrm{T}}\big(e_p\big) - \sum_{e\neq e_p}\sum_{\tilde{e}\in E} r_{e_p}\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n_p}\big)\cdot r_e\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\big)\cdot\omega_{\tilde{e},\mathrm{T}}\cdot\sigma_{\mathrm{T}}(e), \\
&= r_{e_p}\big(\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n_p}\big)\big[\sigma_{\mathrm{T}}\big(e_p\big) - \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n})\big] \\
&\quad - \sum_{\tilde{e}\in E}\Big[r_{e_p}\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n_p}\big) - r_{e_p}\big(\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n_p}\big)\Big]\cdot\mathbb{E}\big(\tau|q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\big)\cdot\omega_{\tilde{e},\mathrm{T}}.
\end{aligned} \tag{A,3}$$

The first key term, $r_{e_p}\big(\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n_p}\big)\big[\sigma_{\mathrm{T}}\big(e_p\big) - \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n})\big]$, shows that the experience effect increases in the difference between simulation based on e_p and the baseline belief. The second term, which we show to be less important than the first, drops in the covariance between recall of e_p and the baseline belief across cues $q_{\tilde{e},\mathrm{T}}$.

Another way to write (A.3), which we exploit in the text, is:

$$\begin{aligned}
&\mathbb{E}\big(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\big) - \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}) = \\
&= r_{e_p}\big(\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n_p}\big)\cdot\sigma_{\mathrm{T}}\big(e_p\big) - \sum_{e\neq e_p} r_{e_p}\big(q_{\tilde{e},\mathrm{T}},\boldsymbol{n_p}\big)\cdot\omega_{\tilde{e},\mathrm{T}}\cdot\mathbb{E}\big(\tau|q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\big),
\end{aligned}$$

$$= r_{e_p}(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n_p}) \left[\sigma_{\mathrm{T}}(e_p) - \sum\nolimits_{e \neq e_p} \frac{r_{e_p}(q_{\tilde{e},\mathrm{T}}, \boldsymbol{n_p}) \cdot \omega_{\tilde{e},\mathrm{T}}}{r_{e_p}(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n_p})} \cdot \mathbb{E}(\tau | q_{\tilde{e},\mathrm{T}}, \boldsymbol{n})\right],$$

where the second term in square brackets is precisely $\overline{\sigma_T(e)}_{-p}$.

Consider next the effect of priming e_p. It is equal to:

$$\mathbb{E}(\tau | \mathbf{1}_p, \boldsymbol{n}_p) - \mathbb{E}(\tau | \boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}_p) = \sum_e \left[r_e\left(q_{e_p,\mathrm{T}}, \boldsymbol{n}_p\right) - r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}_p)\right] \cdot \sigma_T(e), \qquad (A.4)$$

so the database is always $\boldsymbol{n}_p$, only the cue changes.

Linking Experience and Priming effects. To link $(A.3)$ to $(A.4)$, we approximate the effect of changing the cue as a change in similarity around a neutral cue $\boldsymbol{q}$ that is representative of the distribution $\boldsymbol{\omega}_{\mathrm{T}}$, so $c_{\boldsymbol{q}} = c_{\emptyset}$ and $v_{\boldsymbol{q}} = 0$ due to the large number of neutral experiences in the database.[34] Changing the similarity of each experience $e \in E$ from $S(e, \boldsymbol{q})$ to $S(e, q_{\tilde{e},\mathrm{T}})$ affects recall of e according to:

$$\begin{aligned} r_e(q_{\tilde{e},\mathrm{T}}, \boldsymbol{n}) - r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) &\approx \frac{\partial S(e,.)n_e}{\sum_e S(e', \boldsymbol{q})\, n_{e'}} - \frac{S(e, \boldsymbol{q}) n_e [\sum_e \partial S(e',.) n_{e'}]}{[\sum_e S(e', \boldsymbol{q})\, n_{e'}]^2} \\ &= \frac{\partial S(e,.)}{S(e, \boldsymbol{q})} r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) - r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) \sum\nolimits_{e'} \frac{\partial S(e',.)}{S(e', \boldsymbol{q})} r_{e'}(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) \\ &= r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) \left[\frac{\partial S(e,.)}{S(e, \boldsymbol{q})} (1 - r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n})) - \sum\nolimits_{e' \neq e} \frac{\partial S(e',.)}{S(e', \boldsymbol{q})} r_{e'}(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n})\right] \end{aligned}$$

where $\partial S(e,.)$ is the change in similarity and we approximate $r_e(\boldsymbol{q}, \boldsymbol{n})$ with $r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n})$.

Using this expression in $(A.4)$ we obtain the priming effect:

$$\begin{aligned} &\mathbb{E}(\tau | \mathbf{1}_p, \boldsymbol{n}_p) - \mathbb{E}(\tau | \boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}_p) \\ &\quad \approx \sum_e r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}_p) \left[\frac{\partial S(e, \boldsymbol{q})}{S(e, \boldsymbol{q})} \left(1 - r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}_p)\right) \cdot \sigma_T(e) \right. \\ &\quad \left. - \sum\nolimits_{e' \neq e} \frac{\partial S(e', \boldsymbol{q})}{S(e', \boldsymbol{q})} r_{e'}(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}_p) \cdot \sigma_T(e)\right] \\ &\quad = \sum\nolimits_{e \in E} \frac{\partial S(e, \boldsymbol{q})}{S(e, \boldsymbol{q})} r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) [\sigma_{\mathrm{T}}(e) - \mathbb{E}(\tau | \boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n})], \end{aligned} \qquad (A.5)$$

[34] Formally, we can set the cue to minimize the average discrepancy between recall under $\boldsymbol{q}$ and the baseline distribution $\boldsymbol{\omega}_{\mathrm{T}}$, $\min_{\boldsymbol{q} \in \boldsymbol{E}} \sum_e |r_e(\boldsymbol{q}, \boldsymbol{n}) - r_e(\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n})| n_e$, or between beliefs under $\boldsymbol{q}$ and the baseline belief δ_{T}. If neutral experiences are sufficiently numerous, the cue $\boldsymbol{q}$ is then neutral.

where the second step follows from swapping the order of summation. The priming effect is a sum of "experience effect" terms $[\sigma_{\mathrm{T}}(e) - \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n})]$ for all experiences whose similarity and hence recall increases with the cue $\partial S(e, \boldsymbol{q}) > 0$. This includes the primed experience: cueing e_p increases the belief if $\sigma_{\mathrm{T}}(e_p) - \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) > 0$. Priming e_p however also spills over to other experiences $e \neq e_p$, boosting simulation and beliefs provided $\sigma_{\mathrm{T}}(e) - \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) > 0$. This explains why a positive experience effect implies a positive priming effect: because if the experience effect is positive, $\sigma_{\mathrm{T}}(e_p) - \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) > 0$, then cueing e_p boosts beliefs both directly and through spillovers to similar, and hence also simulating, experiences.

Analytical solution using Assumptions 1,2 and 3. First, some notation. We denote a generic non-neutral experience by its context $\tilde{c}$ and denote the adverse variety of the context by $\tilde{c}_-$ and the positive variety by $\tilde{c}_+$. The number of experiences with this context is $n_{\tilde{c}}$ and it is shared equally, by symmetry, into $n_{\tilde{c}}/2$ positive and $n_{\tilde{c}}/2$ negative experiences. We denote by $v_+ > 0$ the average valence of positive experiences and by v_- the one of negative ones, where symmetry again implies $v_- = -v_+$. We denote by $q_{\tilde{c}_+,\mathrm{T}}$ and $q_{\tilde{c}_-,\mathrm{T}}$ a positive and negative valence cue in the same context, whose probabilities, by symmetry, obey $\omega_{\tilde{c}_+,\mathrm{T}} = \omega_{\tilde{c}_-,\mathrm{T}}$. We denote by $\emptyset$ the set of neutral experiences, V_+ and V_- the sets of positive and negative valence ones, where $E = \emptyset \cup V_+ \cup V_-$. N is the total number of experiences.

As a first step, we compute the average belief for specific cues $q_{\tilde{e},\mathrm{T}}$. For neutral cues, we have:

$$\mathbb{E}(\tau|q_{\tilde{e},\mathrm{T}}, \boldsymbol{n}) = \delta_{\mathrm{T}} + \sum\nolimits_{e\in E} r_e(q_{\tilde{e},\mathrm{T}}, \boldsymbol{n}) \cdot \sigma_{\mathrm{T}}(c_e) \cdot v_{\tilde{e}}$$
$$= \delta_{\mathrm{T}} + \sum\nolimits_{c\in V_+\cup V_-} \frac{n_c}{2N} \cdot \sigma_{\mathrm{T}}(c) \cdot \bar{v} = \delta_{\mathrm{T}} \quad \text{for } q_{\tilde{e},\mathrm{T}} \in \emptyset. \qquad (A.6)$$

The first step follows from the simulation function, the second step from all experiences being equally similar to a neutral cue, so recall is frequentist, and the last from the database, from the independence assumption between context and valence and from valence symmetry, $\bar{v} = 0$.

Consider now a non-neutral positive valence cue, $\tilde{e} \in V_+$. Let $n_{-\emptyset}$ be the number of non-neutral experiences and $n_{-\tilde{c}}$ that of those with context different from $\tilde{e}$. Then:

$$\mathbb{E}(\tau|q_{\tilde{e},\mathrm{T}}, \boldsymbol{n}) = \delta_{\mathrm{T}} + \sum\nolimits_{e\in E} r_e(q_{\tilde{e},\mathrm{T}}, \boldsymbol{n}) \cdot \sigma_{\mathrm{T}}(c_e) \cdot v_e =$$
$$= \delta_{\mathrm{T}} + \frac{K}{2} \cdot \frac{n_{-\emptyset} \cdot \overline{\sigma_{\mathrm{T}}(c_{-\emptyset})}}{n_{\tilde{c}} \cdot (1 - K/2) + n_{-\tilde{c}} \cdot (1 - 3K/2) + (1 - 2K) n_{\emptyset}} v_+, \qquad q_{\tilde{e},\mathrm{T}} \in V_+. \qquad (A.7)$$

where $\overline{\sigma_{\mathrm{T}}(c_{-\emptyset})}$ is the average (frequency weighted) simulation sensitivity of experiences with non-neutral context, including the cued one $\tilde{c}$. For a negative cue $q_{\tilde{e},\mathrm{T}} \in V_{-}$, an analogous expression holds, with the opposite sign in the second term. Averaged across cues, we obtain:

$$\mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) = \delta_{\mathrm{T}} + v_{+} \cdot \frac{K}{2} \cdot (\omega_{+\mathrm{T}} \cdot B_{+} - \omega_{-\mathrm{T}} \cdot B_{-}), \tag{A.8}$$

where $\omega_{+\mathrm{T}}$ is the aggregate probability of positive cues, B_{+} is proportional to the average simulation coefficient across them, $\omega_{-\mathrm{T}}$ and B_{-} are the corresponding quantities for negative cues. Symmetry of cues implies $\mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) = \delta_{\mathrm{T}}$. The average belief is at the neutral default.

Experience Effect. Adding adversity e_p (and its negative valence $-v_{+}$) to the database $\boldsymbol{n}$ affects beliefs in (A.6) and (A.7) as a function of its similarity with cues $\tilde{e}$. For a neutral cue:

$$\mathbb{E}(\tau|q_{\tilde{e},\mathrm{T}}, \boldsymbol{n}_p) = \delta_{\mathrm{T}} - \frac{\sigma_{\mathrm{T}}(c_p)}{N+1} v_{+} \quad \text{for } q_{\tilde{e},\mathrm{T}} \in \emptyset. \tag{A.9}$$

Adding adversity e_p breaks the symmetry of the database, moving the average belief due to the e_p's negative valence. The average effect is positive if the target outcome is also an adversity, $\sigma_{\mathrm{T}}(c_p) < 0$, and negative otherwise. For a neutral cue, retrieval is frequentist and so the average effect is scaled by the new number of experiences $N+1$. For a non-neutral cue:

$$\mathbb{E}(\tau|q_{\tilde{e},\mathrm{T}}, \boldsymbol{n}_p) = \delta_{\mathrm{T}} + \tag{A.10}$$

$$\begin{cases} -\dfrac{\sigma_{\mathrm{T}}(c_p) + n_{-\emptyset} \cdot (K/2) \cdot \overline{\sigma_{\mathrm{T}}(c_{-\emptyset})}}{1 + (1-3K/2) \cdot n_{-\emptyset} + (1-2K) \cdot n_{\emptyset}} \cdot v_{+} & \text{for} \quad \tilde{e} = e_{p-} \\ \dfrac{-(1-K) \cdot \sigma_{\mathrm{T}}(c_p) + n_{-\emptyset} \cdot (K/2) \cdot \overline{\sigma_{\mathrm{T}}(c_{-\emptyset})}}{(1-K) + (1-3K/2) \cdot n_{-\emptyset} + (1-2K) \cdot n_{\emptyset}} \cdot v_{+} & \text{for} \quad \tilde{e} = e_{p+} \\ -\dfrac{(1-K) \cdot \sigma_{\mathrm{T}}(c_p) + n_{-\emptyset} \cdot (K/2) \cdot \overline{\sigma_{\mathrm{T}}(c_{-\emptyset})}}{(1-K) + (1-K/2) \cdot n_{\tilde{c}} + (1-3K/2)(n_{-\tilde{c}} - 1) + (1-2K) n_{\emptyset}} \cdot v_{+} & \text{for} \quad \tilde{e} \in V_{-} \backslash e_{p-} \\ \dfrac{-(1-2K) \sigma_{\mathrm{T}}(e_p) + n_{-\emptyset} \cdot (K/2) \cdot \overline{\sigma_{\mathrm{T}}(c_{-\emptyset})}}{(1-2K) + (1-K/2) \cdot n_{\tilde{c}} + (1-3K/2)(n_{-\tilde{c}} - 1) + (1-2K) n_{\emptyset}} \cdot v_{+} & \text{for} \quad \tilde{e} \in V_{+} \backslash e_{p+} \end{cases}.$$

When adversity e_p is added to the database, similarity to any cue moves in the same direction, determined by the sign of $\sigma_{\mathrm{T}}(c_p)$. Averaging over cues, beliefs are:

$$\mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}_p) = \delta_{\mathrm{T}} - Z_{e_p} \cdot \sigma_{\mathrm{T}}\left(c_{e_p}\right) \cdot v_{+} + W_{-\emptyset} \cdot \overline{\sigma_{\mathrm{T}}(c_{-\emptyset})} \cdot v_{+} \tag{A.11}$$

where both Z_{e_p} and $W_{-\emptyset}$ are positive, the latter because adding e_{p-} to the database creates recall interference on other non-neutral experiences. Such interference is stronger for negative valence ones. Formally, the denominator on the first and third row is larger than that on the second and fourth rows, respectively. Given that positive and negative cues have the same probability, the effect across cues of non-neutral experiences different from e_p is skewed toward positive valence which, starting from a zero baseline, implies $W_{-\emptyset} > 0$.

Consider now experience effects. Because our target outcomes T, inflation and home prices, are adversities, we have $\sigma_{\mathrm{T}}(c) \leq 0$ for all contexts, including $\sigma_{\mathrm{T}}(c_p) \leq 0$. A positive experience effect occurs if $\mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}_p) - \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}) > 0$, namely (A.10) should be larger than (A.6), which corresponds to:

$$\sigma_{\mathrm{T}}(c_p) < \frac{W_{-\emptyset} \cdot \overline{\sigma_{\mathrm{T}}(c_{-\emptyset})}}{Z_{e_p}}. \tag{A.12}$$

The right hand side of (A.12) is strictly negative because $c_{-\emptyset}$ contains DS experiences with strong simulation potential. Thus, a positive experience effect reveals $\sigma_{\mathrm{T}}\left(c_{e_p}\right) \ll 0$. Adversity e_p must be close enough in context to the target T that it comes to mind spontaneously and boosts simulation to an extent that offsets the interference it creates for other adversities.

Priming effects. A positive priming effects occurs when

$$\mathbb{E}\left(\tau|q_{e_{p-},\mathrm{T}}, \boldsymbol{n}_p\right) > \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}, \boldsymbol{n}_p)$$

which using (A.10) and (A.11) is equivalent to:

$$\frac{\sigma_{\mathrm{T}}(c_p)}{1 + (1 - 3K/2) \cdot n_{-c_p} + (1 - 2K) \cdot n_{\emptyset}} + \frac{n_{-\emptyset} \cdot (K/2) \cdot \overline{\sigma_{\mathrm{T}}(c_{-\emptyset})}}{1 + (1 - 3K/2) \cdot n_{-c_p} + (1 - 2K) \cdot n_{\emptyset}}$$
$$< Z_{e_p} \cdot \sigma_{\mathrm{T}}(c_p) \cdot v_+ - W_{-\emptyset} \cdot \overline{\sigma_{\mathrm{T}}(c_{-\emptyset})}$$

which reads:

$$\left[\frac{1}{1 + (1 - 3K/2) \cdot n_{-\emptyset} + (1 - 2K) \cdot n_{\emptyset}} - Z_{e_p}\right] \cdot \sigma_{\mathrm{T}}(c_p)$$
$$+ \left[\frac{n_{-\emptyset} \cdot (K/2)}{1 + (1 - 3K/2) \cdot n_{-\emptyset} + (1 - 2K) \cdot n_{\emptyset}} + W_{-\emptyset}\right] \cdot \overline{\sigma_{\mathrm{T}}(c_{-\emptyset})} < 0.$$

Given that the second term is negative (the term in brackets is positive due to $W_{-\emptyset} > 0$), the condition is surely met if the first term in square brackets is also positive, because the positive priming effect implies $\sigma_{\mathrm{T}}(c_p) < 0$.

The first term in square brackets is positive if and only if the probability of recalling e_{p-} is larger when e_{p-} is cued, compared to its average recall probability across all cues Z_{e_p}. This is guaranteed provided the probability of recalling an experience monotonically increases in its similarity with the cue. The property holds if the number of neutral experiences $n_{\emptyset}$ is sufficiently high, which is proven by Bordalo et al. (2025b) in Proposition 1.

Prediction 1. We can decompose the effect of change in the database from $\boldsymbol{n}$ to $\boldsymbol{n}_p$ and of the cue from $\boldsymbol{\omega}_{\mathrm{T}}$ to $\mathbf{1}_p$ as the sum of an experience and priming effect:

$$\mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}}+\boldsymbol{\Delta\omega},\boldsymbol{n}+\boldsymbol{\Delta n}) \approx \mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}) + \sum\nolimits_{p=h,f}\left[\mathbb{E}\left(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right)-\mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n})\right]\cdot \mathbb{I}_{e_p} +$$

$$+\sum\nolimits_{p=h,f}\left[\mathbb{E}\left(\tau|\mathbf{1}_p,\boldsymbol{n}_p\right)-\mathbb{E}\left(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right)\right]\cdot \mathbb{I}_{e_p}\cdot \mathbb{I}_{e_p,\mathrm{R}}$$

where $\mathbb{I}_{e_p}$ is an indicator equal to 1 if the person has had experience e_p and zero otherwise, and $\mathbb{I}_{e_p,\mathrm{R}}$ is an indicator equal to 1 if the person had the priming intervention concentrating the cue in experience e_p. The intervention is said to occur (treatment on treated) if the subject is in the treatment group, $\mathbb{I}_{e_p,\mathrm{R}} = 1$, and if she had the primed experience, $\mathbb{I}_{e_p} = 1$.

We characterized experience and priming effects in Proposition 1, which yields property i) namely $\epsilon_{e_p} > 0 \Rightarrow \beta_{e_p,\mathrm{R}} > 0$. For property ii), note that the sum of experience and priming effect is equal to $\mathbb{E}\left(\tau|\mathbf{1}_p,\boldsymbol{n}_p\right)$. Under our assumptions, higher similarity between e_p and the target outcome T affect this belief only through a higher simulation function $\sigma_{\mathrm{T}}\left(e_p\right)$, giving:

$$\frac{\partial\mathbb{E}\left(\tau|q_{e_p,\mathrm{T}},\boldsymbol{n}_p\right)}{\partial\sigma_{\mathrm{T}}\left(e_p\right)} = r_{e_p}\left(q_{e_p,\mathrm{T}},\boldsymbol{n}_p\right) > 0.$$

Prediction 2. We again consider beliefs $\mathbb{E}(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}) = \sum_{\tilde{e}\in E}\mathbb{E}\left(\tau|q_{\tilde{e},\mathrm{T}},\boldsymbol{n}\right)\cdot\omega_{\tilde{e},\mathrm{T}}$ by linearizing them as a function of the contextual similarity between each experience e and the target outcome T. Under our assumptions, a higher value of such similarity – denoted by $S(e,\mathrm{T})$ – affects beliefs through simulation, in particular:

$$\partial\mathbb{E}\left(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right) = r_e\left(\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right)\cdot\frac{\partial\sigma_{\mathrm{T}}(c_e)}{\partial S(e,\mathrm{T})}\cdot\partial S(e,\mathrm{T}) < 0,$$

thereby increasing the sensitivity to the valence of e, (producing more pessimism, namely higher beliefs, for negative valence experiences). This implies that we can approximate beliefs as a function of similarities as follows:

$$\mathbb{E}\left(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right) \approx \mathbb{E}_0\left(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right) - A\cdot\sum_e r_e\left(\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right)\cdot v_e\cdot\partial S(e,\mathrm{T})$$

where $\mathbb{E}_0\left(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right)$ is the belief when all experiences have minimum similarity (i.e. the cue is neutral) and $A = -\left.\frac{\partial\sigma_{\mathrm{T}}(c_e)}{\partial S(e,\mathrm{T})}\right|_{S(e,\mathrm{T})=S_0} > 0$ is the magnitude of the slope of simulation at such minimum similarity point. The belief is thus an average similarity of experiences weighted by their valence. Focusing on the adversities we measure, and assuming for simplicity that these adversities all have valence equal to $-v_+$ we have:

$$\mathbb{E}\left(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right) \approx \mathbb{E}_0\left(\tau|\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right) - A\cdot P + Av_+\sum_e r_e\left(\boldsymbol{\omega}_{\mathrm{T}},\boldsymbol{n}_p\right)\cdot\partial S(e,\mathrm{T}),$$

where $-A\cdot P < 0$ is the effect of unobserved positive experiences. In our regression the average similarity of our measured adversities proxies for the right-most term. The same logic gives the similarity based approximation for the priming effect.

Appendix B. The Survey Instruments

B.1 The DNBHS: Index Construction and results

1. *Health Adversity*

We construct the health index from the following questions:

- How is your health in general?
- How many times did you contact your general practitioner about your own health in the past year?

2. *Financial Adversity*

This index measures present perceived strain in household finances. It builds on the following questions:

- Would you, at present, like to spend more money than you have (e.g. through income)? In other words, would you like to have more money now, that you would have to pay back later?
- How well can you manage on the total income of your household?
- Is this income unusually high or low compared to the income you would expect in a 'regular' year, or is it regular?
- How is the financial situation of your household at the moment?
- Over the past 12 months, would you say the expenditures of your household were higher than the income of the household, about equal to the income of the household, or lower than the income of the household?
- Do you think the expenditures of your household, in the next 12 months, will be higher, about the same, or lower than the income of your household?
- The following statements concern your own situation compared to that of others.
    - I think my household has more assets than others in my environment.
    - If I compare myself with my friends, I think in general I am financially better off.
    - Most people in my environment are saving money.
    - I can spend more on durable consumer goods than others in my environment.
    - If necessary, I can reduce the expenditures of my household by 5% without a problem.
- Have you, in 2020, consulted with your bank or financial institution, because you had or expected payment problems with the repayment of a loan or mortgage?
- In the past 2 years, has a request you (or your partner) made for credit been turned down, or were you not given as much credit as you applied for?
- How do you think the economic situation of your household will be in five years' time in comparison to the current situation?
- Do you find it easy or difficult to control your expenditures?
- What is the chance that you will leave an inheritance (including possessions and valuable items)?

3. *Childhood Financial Education*

This index captures respondents' financial knowledge and their experiences with financial education growing up.

- How knowledgeable do you consider yourself with respect to financial matters?
- When you were between 8 and 12 years of age, did you receive an allowance from your parents then?
- When you were between 8 and 12 years of age, did you do little household chores (like washing the car) for which you received some money from your parents?
- When you were between 8 and 12 years of age, could you spend your money as you pleased?
- Did you have a job on the side (like a newspaper round, a job on Saturday etcetera) when you were between 12 and 16 years of age?
- Did your (grand)parents try to teach you how to budget when you were between 12 and 16 years of age?
- Did your (grand)parents stimulate you to save money between the age of 12 and 16?

4. *Happiness / Psychological Well-Being*

We construct this index from the following questions:

- All in all, to what extent do you consider yourself a happy person?
- I have frequent mood swings.
- I get stressed out easily.
- The following questions are about how you felt over the past month. For every question, please choose the answer that best describes how you felt during this past month. This past month…
    - I felt very anxious.
    - I felt so down that nothing could cheer me up.
    - I felt calm and peaceful.
    - I felt depressed and gloomy.
    - I felt happy.

5. *Attitudes Toward Risk*

This index relies on the following survey questions:

- The following statements concern saving and taking risks. Please indicate for each statement to what extent you agree or disagree.
    - I do not invest in shares, because I find this too risky.
    - I want to be certain that my investments are safe.
- Are you generally a person who is willing to take risks or do you try to avoid taking risks?

The following questions were initially also considered to be included in the construction of the index but were not considered due to very low or negative correlation with the included measures above.

- The following statements concern saving and taking risks. Please indicate for each statement to what extent you agree or disagree.
    - I think it is more important to have safe investments and guaranteed returns, than to take a risk to have a chance to get the highest possible returns.
    - If I think an investment will be profitable, I am prepared to borrow money to make this investment.
    - If I want to improve my financial position, I should take financial risks.
    - I am prepared to take the risk to lose money, when there is also a chance to gain money.
- How would you describe the risks that you have taken with investments over the past few years?

6. Other Attitudes: Fatalism vs. Effort

Here we use the following questions:

- Do you agree with the following statements?
    - Whether or not I get to become wealthy depends mostly on my ability.
    - In the long run, people who take very good care of their finances stay wealthy.
    - When I get what I want, it's usually because I worked hard for it.
    - My life is determined by my own actions.

We do not incorporate the following questions:

- Do you agree with the following statements?
    - It is chiefly a matter of fate whether I become rich or poor.
    - Only those who inherit or win money can possibly become rich.

7. Other Attitudes: Optimism

The optimism index is constructed from the following two questions:

- How likely is it that you will attain at least the age of x?
- On the whole, I expect more good things to happen to me than bad things.

All variables are coded in a way that higher values indicate worse outcomes. Leading up to Table 1 in the text, we first report the correlation between the indices above.

Table B.1. *Correlation Structure of Indices in the DHS*

	Health Adversity	Financial Adversity	Happiness	Risk Attitudes	Effort	Optimism	Financial Education
Health Adversity	1.0000						
Financial Adversity	0.2637	1.0000					
Happiness	0.3281	0.2366	1.0000				
Risk Attitudes	0.0324	0.0349	-0.0136	1.0000			
Effort	0.1076	0.2436	0.0870	0.0112	1.0000		
Optimism	0.3543	0.2325	0.2651	0.0594	0.1684	1.0000	
Financial Education	-0.1205	-0.2217	-0.0546	-0.1163	-0.1462	-0.2344	1.0000

Notes: Table reports pairwise correlations between the seven DHS indices used in Table 2. N = 21,614 individual-year observations from the DNB Household Survey (2012–2022). All indices are standardized composites constructed as the within-year average of the standardized underlying items. For all indices except Financial Education, higher values indicate worse outcomes (worse health, worse financial situation, lower happiness, greater risk aversion, lower effort/agency, and lower optimism). Higher Financial Education indicates greater childhood financial exposure. See Section 3.1 for construction details.

We next present regressions of macroeconomic beliefs on the Table 1 controls and the full set of indices., showing that the finance and health indices are the experiences that best predict inflation and housing beliefs.

Table B.2. *Adversity Indices and Macroeconomic Beliefs in the DHS*

	Inflation Beliefs (Z-Score)			**House Price Beliefs (Z-Score)**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Health Index		0.0548***	0.0356*		0.0477***	0.0418***	0.0398***
		(0.0192)	(0.0195)		(0.0128)	(0.0136)	(0.0135)
Financial Well-Being		0.2756***	0.2338***		0.0661***	0.0245	0.0300
		(0.0260)	(0.0280)		(0.0222)	(0.0247)	(0.0247)
Happiness		0.0065	0.0243		-0.0050	-0.0296*	-0.0271*
		(0.0163)	(0.0179)		(0.0154)	(0.0157)	(0.0155)
Risk Attitudes		0.0408***	0.0342**		-0.0138	-0.0105	-0.0063
		(0.0136)	(0.0136)		(0.0122)	(0.0122)	(0.0121)
Effort/Agency		-0.0128	-0.0181		-0.0159	-0.0053	-0.0037
		(0.0143)	(0.0148)		(0.0133)	(0.0128)	(0.0127)
Optimism		0.0667***	0.0457***		-0.0303**	-0.0231*	-0.0207
		(0.0135)	(0.0148)		(0.0123)	(0.0134)	(0.0134)
Childhood Financial Education		-0.0349	-0.0024		-0.0316*	-0.0449**	-0.0482***
		(0.0220)	(0.0243)		(0.0175)	(0.0188)	(0.0187)
Belief Price Increase Own House (Past 2Y)							0.0139***
							(0.0016)
Constant	0.3191***	-0.0596**	0.1092	0.4140***	-0.0108	0.4002***	0.4360***
	(0.0956)	(0.0258)	(0.0988)	(0.1170)	(0.0267)	(0.1043)	(0.1040)
Observations	19,852	21,566	19,501	16,504	17,547	16,228	16,228
Controls	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

R Sq.	0.0323	0.0360	0.0495	0.0202	0.0032	0.0221	0.0378

Notes: Table reports OLS regressions of macroeconomic belief z-scores on DHS adversity indices. Standard errors clustered at the individual level in parentheses. The dependent variable in columns 1–3 is the z-score of the respondent's most likely 1-year inflation rate, standardized within survey year. The dependent variable in columns 4–7 is the z-score of expected 2-year house price growth, standardized within survey year. All indices are standardized composites; higher values indicate worse outcomes except for Financial Education. Controls include age, education fixed effects, occupation fixed effects, urbanization, household income, housing status, numeracy, gender, and partner status. Column 7 additionally controls for the respondent's belief about own house price change in the past two years. Data from the DNB Household Survey, 2012–2022. * p<0.10, ** p<0.05, *** p<0.01.

Next, we present Table 1 with all covariates.

Table B.3. *Finance and Health Indices and Macroeconomic Beliefs in the DHS*

	Inflation (1)	**Inflation (2)**	**Housing (3)**	**Housing (4)**
Health Adversity Index	0.0803***	0.0561***	0.0393***	0.0288**
	(0.0189)	(0.0190)	(0.0128)	(0.0138)
Financial Adversity Index	0.3043***	0.2443***	0.0614***	0.0234
	(0.0238)	(0.0261)	(0.0222)	(0.0246)
Age		-0.0009		-0.0020**
		(0.0010)		(0.0010)
Education: Vocational		-0.0806***		-0.0135
		(0.0262)		(0.0221)
Education: University		-0.1944***		-0.0464
		(0.0309)		(0.0302)
Occupation: Employed		0.0518		-0.0050
		(0.0333)		(0.0313)
Occupation: Self-Employed		0.0344		0.0214
		(0.0517)		(0.0444)
Occupation: Student		-0.1895***		0.0947
		(0.0724)		(0.0867)
Occupation: Retired		0.1388***		0.0096
		(0.0363)		(0.0320)
Urbanization		0.0095		0.0516***
		(0.0093)		(0.0081)
Income Cat: € 10,000 - € 14,000		0.0862		0.0465
		(0.0674)		(0.0882)
Income Cat: € 14,000 and € 22,000		0.0578		0.0459
		(0.0665)		(0.0814)
Income Cat: € 22,000 and € 40,000		0.0498		0.0659
		(0.0656)		(0.0782)
Income Cat: € 40,000 and € 75,000		0.0159		0.0648
		(0.0665)		(0.0784)
Income Cat: € 75,000+		0.0290		0.1482*

		(0.0749)		(0.0873)
Housing: Subtenant		0.0434		-0.0407
		(0.1406)		(0.1561)
Housing: Owner		-0.0920***		-0.2348***
		(0.0317)		(0.0285)
Housing: Other		-0.2177**		-0.6203***
		(0.1093)		(0.0978)
Numeracy		-0.0564***		-0.0102
		(0.0105)		(0.0094)
Male		0.0025		0.0243
		(0.0238)		(0.0203)
Has Partner		0.0319		0.0205
		(0.0270)		(0.0242)
Year FE	Yes	Yes	Yes	Yes
N	22,081	19,852	17,928	16,504
R^2	0.0316	0.0470	0.0023	0.0209

Notes: This table replicates Table 1 showing all control variable coefficients. The dependent variables are inflation expectations (columns 1-2) and house price expectations (columns 3-4), both z-scored within survey year. The Health Adversity Index is the average of z-scored general health (reversed) and number of doctor visits, where higher values indicate worse health. The Financial Adversity Index is the average of 16 z-scored financial wellbeing indicators (reversed), where higher values indicate worse financial conditions. Education base category is primary/secondary education. Occupation base category is not employed. Income base category is the lowest household income bracket. Housing tenure base category is renter. Standard errors clustered at the individual level in parentheses. All specifications include year fixed effects. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Finally, we present three robustness exercises for Table 1. First, beliefs about housing and the role of experiences in it may depend systematically on whether participants are owners or renters (in particular, a rise in home prices benefits owners but can hurt renters). Table B.4 presents the same specification restricted to either owners (Panel A) or renters (Panel B). Second, the construction of the financial trouble index raises two possible objections: i) the expectations of income expenditures component may be mechanically correlated with expected inflation, and ii) the "relative position" component may be correlated with views about the aggregate state of the economy. To address these concerns, Panel C reports the main specification for the index constructed without these questions. Third, expectations of aggregate home price growth may depend on beliefs about recent experienced growth in local home prices, which may be correlated with adversities. We thus add to Panel C a specification where we control for believed home price appreciation over the previous 2 years.

Table B.4 Robustness: Housing Status and Adversity Index

Panel A: Owners

	Inflation (1)	Inflation (2)	Housing (3)	Housing (4)
Health Adversity Index	0.1023***	0.0784***	0.0142	0.0155
	(0.0192)	(0.0192)	(0.0144)	(0.0155)
Financial Adversity Index	0.2963***	0.2397***	-0.0267	-0.0077
	(0.0270)	(0.0278)	(0.0237)	(0.0269)
Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
N	15,728	14,218	13,459	12,398
R^2	0.0302	0.0416	0.0010	0.0069

Panel B: Renters

	Inflation (1)	Inflation (2)	Housing (3)	Housing (4)
Health Adversity Index	0.0508	0.0400	0.0383	0.0486*
	(0.0326)	(0.0358)	(0.0240)	(0.0277)
Financial Adversity Index	0.2822***	0.2868***	0.0437	0.0894
	(0.0477)	(0.0562)	(0.0517)	(0.0564)
Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
N	6,069	5,397	4,378	4,028
R^2	0.0229	0.0471	0.0063	0.0180

Panel C: Alternative Index of Financial Adversity

	Inflation (1)	Inflation (2)	Housing (3)	Housing (4)	Housing (5)
Health Adversity Index	0.0995***	0.0638***	0.0405***	0.0286**	0.0287**
	(0.0195)	(0.0194)	(0.0130)	(0.0140)	(0.0139)
Financial Adversity Index (Alt.)	0.1952***	0.1593***	0.0627***	0.0287	0.0300
	(0.0202)	(0.0217)	(0.0178)	(0.0188)	(0.0189)
Controls	No	Yes	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	22,047	19,840	17,900	16,493	16,493
R^2	0.0216	0.0424	0.0026	0.0212	0.0369

Notes: Panels A and B replicates Table 1 separately for homeowners and renters, respectively. The dependent variables are inflation expectations (columns 1-2) and house price expectations (columns 3-4), both z-scored within survey year.

The Health Adversity Index is the average of z-scored general health (reversed) and number of doctor visits. The Financial Adversity Index is the average of 16 z-scored financial wellbeing indicators (reversed). Controls include age, education, occupation, urbanization, household income, numeracy, gender, and partner status. Housing tenure is excluded from controls since the sample is already split by tenure. Standard errors clustered at the individual level in parentheses. Panel C replicates Table 1 using an alternative, more conservative Financial Adversity Index constructed from 7 components instead of the 16-component index used in the main specification. The alternative index excludes 9 items related to relative position assessments and income-expenditure expectations. The dependent variables are inflation expectations (columns 1-2) and house price expectations (columns 3-4), both z-scored within survey year. Controls include age, education, occupation, urbanization, household income, housing tenure, numeracy, gender, and partner status. Standard errors clustered at the individual level in parentheses. All specifications include year fixed effects. * p<0.10, ** p<0.05, *** p<0.01.

Panels A and B show that experience effects on housing expectations are driven mostly by renters. This is consistent with the idea that, for owners, forecasts of home price appreciation are not spontaneously (absent priming) perceived as adversities but instead load more on their experienced price growth of housing. Panel C shows that results are robust to using an alternative, more conservative index for financial adversity. Moreover, while beliefs about experienced local price growth shapes forecasts (and significantly increases explanatory power), the predictive power of adversities is unchanged.

Finally, we show that the finance and health indices are uncorrelated with subsequent realizations of inflation or home price growth.

Table B.5: Adversity Indices do not Predict Inflation or Housing

	Inflation				Housing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Health Adversity	-0.0398	-0.0154	-0.0009	0.0004	0.5006***	0.4862***	-0.0071	-0.0067
	(0.0260)	(0.0286)	(0.0031)	(0.0032)	(0.1026)	(0.0998)	(0.0255)	(0.0273)
Financial Adversity	0.3450***	0.4747***	-0.0045	0.0009	-1.5998***	-1.7596***	0.0376	-0.0017
	(0.0446)	(0.0549)	(0.0050)	(0.0060)	(0.1761)	(0.2038)	(0.0402)	(0.0479)
Observations	22,057	19,836	22,057	19,836	19,781	18,019	19,781	18,019
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Province FE	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.003	0.031	0.987	0.988	0.024	0.074	0.945	0.945

Notes: The table tests whether individual-level adversity indices predict actual future macroeconomic outcomes. The dependent variable in columns (1)–(4) is realized CPI inflation 12 months ahead. The dependent variable in columns

(5)–(8) is realized house price growth over a 24-month window ahead. The Health Adversity index is a standardized composite of individual health status variables; the Financial Adversity index is a standardized composite of 16 financial wellbeing measures. Both are measured at the individual level in the DNB Household Survey (DHS). Controls include age, gender, education, occupation, urbanization, income category, housing status, partner status, and numeracy. Standard errors are clustered at the individual level. Province fixed effects are included in all housing specifications (columns 5–8) to account for local house price variation; inflation is a national measure and does not vary by province. Stars denote: * p<0.10, ** p<0.05, *** p<0.01.

We conclude by showing that positive health or finance NDS experiences predict lower inflation and home price growth expectations. We construct a health index based on the average of z-score of (i) health improvement vs. last year (GEZ4, reversed), (ii) felt calm and peaceful past month (MHI003), (iii) felt happy past month (MHI005), and (iv) overall happiness (GELUK, reversed). Higher values consistently indicate more positive states. This has no mechanical correlation with the adversity index. For the financial index, we use (i) OPZIJ (saved money, binary), (ii) DNB201 (job satisfaction, reversed), (iii) has dividend income (received dividend/investment income, binary from IO48A), and (iv) received inheritance (IN25, binary). Since DNB201 is only asked of employed respondents, we also construct a version without it (positive_finance_clean_nojob) for larger sample sizes.

Table B.6: Positive Indices Negatively Predict Inflation or Housing

	(1) Inflation	(2) Inflation	(3) Housing	(4) Housing
Positive Health (Clean)	-0.0189	-0.0499**	0.0015	0.0231
	(0.0217)	(0.0210)	(0.0207)	(0.0212)
Positive Finance (Clean)	-0.1656***	-0.0906***	-0.0316**	-0.0092
	(0.0146)	(0.0149)	(0.0138)	(0.0138)
N	22,081	19,852	17,928	16,504
Controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes

*Standard errors clustered at the individual level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

The clean positive finance index is strongly significant for inflation expectations: a one standard deviation increase in positive financial experiences is associated with a 0.091 SD decrease in inflation expectations ($p < 0.01$). The positive health index becomes significant with controls

(−0.050, $p < 0.05$). Housing results are weaker, mirroring the pattern in the main paper where financial adversity dominates due to similarity. These results are robust to controlling for Health and Finance adversities, as well as for general measures of optimism and happiness.

We complement this analysis by looking at specific discrete positive shocks.

Table B.7: Positive Personal Experiences and Forecasts

	(1) Inflation	**(2) Inflation**	**(3) Inflation**	**(4) Home**	**(5) Home**	**(6) Home**
Received inheritance	-0.0769**			-0.0537*		
	(0.0331)			(0.0299)		
Dividend income		-0.1276***			0.0006	
		(0.0269)			(0.0283)	
New grandchild			-0.0165			-0.0791
			(0.0626)			(0.0572)
N	19,852	19,665	11,689	16,504	16,348	9,844
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample			Age≥45			Age≥45

*Standard errors clustered at the individual level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

Inheritance receipt and dividend income are the strongest individual predictors. Receiving an inheritance is associated with 0.077 SD lower inflation expectations ($p < 0.05$) and 0.054 SD lower housing expectations ($p < 0.10$). Having dividend income predicts 0.128 SD lower inflation expectations ($p < 0.01$). These are discrete positive financial events. The grandchild effect goes in the predicted direction but lacks statistical power (only 248 events).

B.3 Our Survey Instrument

<u>Introductory Text</u>

The goal of this survey is to explore how people form beliefs about inflation and changes in house prices, based on economic events and personal experiences. To do that, the survey includes questions about personal events you may have experienced and on your views about inflation and changes in house prices.

Q1) We want to start with a question on estimating quantities. Out of 1000 random people in The Netherlands, how many do you think are older than 90 years?

<u>Experience Prompts</u>

Programming Instructions: Use a random generator to divide respondents into three subgroups A, B and C. Group A starts with questions Q1a and Q2a and group B starts with questions Q1b and Q2b. Group C is the control group and starts the survey with question Q5.

[Health]

Q1a) In this part of the survey, we will ask you about an experience you may have had. We appreciate you taking the time to provide answers to these personal and possibly sensitive questions.

Have you or a loved one ever faced the challenges of a serious or chronic illness, or the consequences of a serious accident?

[ ] Yes	[→ *Proceed with question Q2a*]
[ ] No	[→ *Jump to question Q5*]

Q2a) Thinking back on this experience, please respond to the questions below.

1) Briefly describe what the illness or accident was, who suffered from it, and in what year/years it happened.
2) What losses, difficulties, or sacrifices do you remember from that time?
3) What emotions do you associate with thinking back on that experience?

[Finance]

Q1b) In this part of the survey, we will ask you about an experience you may have had. We appreciate you taking the time to provide answers to these personal and possibly sensitive questions.

Have you or a loved one ever struggled with financial difficulties?

[ ] Yes	[→ *Proceed with question Q2b*]
[ ] No	[→ *Jump to question Q5*]

Q2b) Thinking back on this experience, please respond to the questions below.

1) Briefly describe what was the main cause of that financial struggle, who suffered from it, and in what year/years it happened.

2) What losses, difficulties, or sacrifices do you remember from that time?
3) What emotions do you associate with thinking back on that experience?

[For Subgroups A and B who answered yes to Q1a/Q1b]
Q3) Can you tell us more about this personal experience in 3-4 sentences? Feel free to write whatever comes to mind as you think about this experience.

[For all respondents]

<u>Belief Elicitation - Inflation</u>
Programming instruction Q5: Group A and Group B respondents will be shown an additional text screen before Q5 with the following text: At this point, you will be asked about economic expectations. We understand that this is a completely different topic than the previous questions, but in the interest of the research study, we would like to ask you to answer them.

Q5) We are interested in your views on inflation in the Netherlands in the future. Inflation is the change in consumer prices in general over a period of twelve months. What do you expect inflation in the Netherlands to be in the next twelve months, i.e. what will the percentage change in consumer prices be over the next twelve months?

If you think prices will go up, please enter a positive percentage. If you think prices will fall, please enter a negative percentage (put a minus sign (-) in front of your answer). If you think prices will not change, please enter 0 (zero). You can also use decimal places if you want.
Q6) How likely do you think inflation is to be 7% or higher a year from now?

You can answer on a scale of 0 to 10, where 0 indicates that there is ‘no chance at all’ that inflation will be 7% or higher, and 10 indicates that inflation will ‘absolutely, for sure’ be 7% or higher.

0 (no chance at all)	1	2	3	4	5	6	7	8	9	10 (absolutely, for sure)
[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

Q8) Please write down 3-4 sentences about any thoughts or personal experiences that came to mind when you were answering the previous questions on inflation?

<u>Belief Elicitation - House Prices</u>

Q9) We are interested in your views on house prices in the Netherlands in the future. What do you expect to be the percentage change in house prices in the Netherlands in the next twelve months?

If you think house prices will rise, please enter a positive percentage. If you think house prices will fall, please enter a negative percentage (put a minus sign (-) in front of your answer). If you think house prices will not change, please enter 0 (zero). You can also use decimal places if you want.

Q10) How likely do you think it is that house prices will rise by 10% or more over the next twelve months?

You can answer on a scale of 0 to 10, where 0 indicates that there is 'no chance at all' that house prices will rise by 10% or more and 10 indicates that house prices will 'absolutely, for sure' rise by 10% or more.

0 (no chance at all)	1	2	3	4	5	6	7	8	9	10 (absolutely, for sure)
[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

Q12) Please write down 3-4 sentences about any thoughts or personal experiences that came to mind when you were answering the previous questions on house prices?

Programming instructions Q16: Please randomize the order of the first two response options. The last two response options should always be placed at the end.

Q16) Do you consider a rise in house prices by 10% or more to be a good or a bad thing?

[ ] A good thing
[ ] A bad thing
[ ] Neither
[ ] I do not know

Experiences

Programming instructions Q13: Respondents from group A (Health Experience Prompt) are asked the second question. Respondents from Group B (Finance Experience Prompt) are asked the first question. Respondents from group C (Control group) are asked both questions. The other questions are asked to everyone. The order of all questions should be randomized, keeping in mind that the first two questions (if offered to the respondent) should always come first.

Q13) For each of the experiences below, please indicate if you or a loved one had this past experience.

Experiences:	Yes	No
[Group B and C:] Have you or a loved one ever faced the challenges of a serious or chronic illness, or the consequences of a serious accident?		
[Group A and C:] Have you or a loved one ever struggled with financial difficulties?		

Have you or a loved one experienced a recent extreme weather event in your area, such as a very heavy storm, flood, or extreme heat?	
Have you or a loved one had an experience, for instance in your job, where an event increased inequality or was perceived as unfair?	
Have you or a loved one ever experienced protests, confrontations, or other forms of intense tension between social groups?	
Have you or a loved one ever experienced someone cheating, stealing, or breaking a contract?	
Have you or a loved one ever made a long-term investment in a business or in the stock market that has been successful in the long run?	
Have you or a loved one ever faced challenges related to immigration of foreigners?	
Have you or a loved one ever lost a job unexpectedly and experienced unemployment?	
Have you or a loved one ever experienced a divorce or separation from a long-term partner?	

<u>Inflation Similarity</u>
Programming instructions Q14: Please for every respondent use the same order of questions as shown in Q13.

Q14) Now we will ask you to rate the similarity between some personal experiences and inflation. At first sight, these events may seem dissimilar because they concern different domains. However, even experiences in different domains may share some aspects, such as personal stress, a sense of insecurity or uncertainty, impact on social life, economic consequences, etc. Therefore, when you assess similarity, we would like you to think of an overall measure of similarity between experiences, taking into account a wide range of aspects.

Keeping this in mind, please indicate for each of the experiences below **how similar you think that experience is compared to future inflation being 7% or higher?**

You can answer on a scale of 1 to 7, where 1 indicates 'not similar at all', and 7 indicates 'extremely similar'.

Experiences:	1 2 3 4 5 6 7
- A serious or chronic illness, or a serious accident	

- Struggling with financial difficulties	
- A recent extreme weather event, such as a very heavy storm, flood, or extreme heat	
- An event increasing inequality or perceived as unfair	
- Protests, confrontations, or other forms of intense tensions between social groups	
- Cheating, stealing, or breaking a contract/promise	
- A long-term investment in a business or in the stock market that has been successful in the long-run	
- Challenges related to the immigration of foreigners	
- Unexpected job loss and unemployment	
- Divorce or separation from a long-term partner	

<u>*House Prices Similarity*</u>

Programming instructions Q15: Please for every respondent use the same order of questions as shown in Q13 and Q14.

Q15) Now we will ask you to rate the similarity between some personal experiences and house prices increases. At first sight, these events may seem dissimilar because they concern different domains. However, even experiences in different domains may share some aspects, such as personal stress, a sense of insecurity or uncertainty, impact on social life, economic consequences, etc. Therefore, when you assess similarity, we would like you to think of an overall measure of similarity between experiences, taking into account a wide range of aspects.

Keeping this in mind, please indicate for each of the experiences below **how similar you think that experience is compared to future house prices increasing by 10% or more**.

You can answer on a scale of 1 to 7, where 1 indicates ‘not similar at all’, and 7 indicates ‘extremely similar’.

Experiences:	1	2	3	4	5	6	7
- A serious or chronic illness, or a serious accident							
- Struggling with financial difficulties							
- A recent extreme weather event, such as a very heavy storm, flood, or extreme heat							
- An event increasing inequality or perceived as unfair							
- Protests, confrontations, or other forms of intense tensions between social groups							

- Cheating, stealing, or breaking a contract/promise	
- A long-term investment in a business or in the stock market that has been successful in the long-run	
- Challenges related to the immigration of foreigners	
- Unexpected job loss and unemployment	
- Divorce or separation from a long-term partner	

Time Use, Family, and Backcast

Q17) One dimension we would like to ask you about has to do with the time you spend on physical activity. In a typical week, how many hours would you say you spend on average on physical activity? This can include sports, but also other activities such cycling or walking.

Q18) Another dimension we would like to ask you about has to do with time spent on house chores. In a typical week, how many hours would you say you spend performing household chores in your household? This can include cleaning and cooking, but also repairs.

Q19) Consider now your monthly expenditure. Relative to a year ago, has the price of items that you buy regularly changed, and if so by what percentage?

If you think the price of the items you buy regularly has risen, please enter a positive percentage. If you think price of the items that you buy regularly has fallen, please enter a negative percentage (put a minus sign (-) in front of your answer). If you think the price of the items that you buy regularly has not changed, please enter 0 (zero). You can also use decimal places if you want.

Q20) Finally, consider house prices in the city where you live. Relative to a year ago, has the price of houses in the city where you live changed, and if so by what percentage?

If you think the price of houses in your city has risen, please enter a positive percentage. If you think the price of the houses in your city has fallen, please enter a negative percentage (put a minus sign (-) in front of your answer). If you think that the price of the houses in the city where you live has not changed, please enter 0 (zero). You can also use decimal places if you want.

Appendix C. Further results on Experiences and Similarity

We provide further evidence on the measured components of memory (Section 3), namely on the properties of participants' databases and their perceived similarity between NDS experiences and high inflation or home price growth.

Table C.1 reports the frequency of NDS experiences in different subsamples.

Table C.1: Share of Respondents Reporting Each Experience

	Control	Health (All)	Health (TOT)	Finance (All)	Finance (TOT)
Treatment Experiences					
Health	0.416	0.502***	1.000***	0.422	0.511***
		(0.000)	(0.000)	(0.730)	(0.000)
Finance	0.411	0.395	0.485***	0.353***	1.000***
		(0.370)	(0.001)	(0.001)	(0.000)
Other Experiences					
Extreme Weather	0.117	0.110	0.151**	0.111	0.156**
		(0.495)	(0.020)	(0.598)	(0.016)
Inequality	0.279	0.301	0.375***	0.250*	0.359***
		(0.170)	(0.000)	(0.056)	(0.000)
Protest	0.104	0.106	0.128*	0.098	0.149***
		(0.882)	(0.078)	(0.537)	(0.004)
Cheating Contract	0.369	0.386	0.462***	0.368	0.557***
		(0.315)	(0.000)	(0.985)	(0.000)
Successful Investment	0.120	0.120	0.150**	0.113	0.123
		(0.965)	(0.039)	(0.527)	(0.840)
Immigration / Foreigners	0.110	0.097	0.113	0.070***	0.112
		(0.214)	(0.802)	(0.000)	(0.868)
Job Loss	0.375	0.389	0.456***	0.373	0.559***
		(0.410)	(0.000)	(0.928)	(0.000)
Divorce	0.470	0.481	0.560***	0.491	0.649***
		(0.546)	(0.000)	(0.233)	(0.000)

Notes: This table compares the Health and Finance treatment groups to the full control group. Reported values are the proportions of respondents who report each experience. P-values and significance stars derive from two-sample tests of differences in proportions relative to the unrestricted control group. Health (All): All respondents assigned to the Health treatment. Health (TOT): Health-treated respondents who did report the health adversity experience. Finance (All): All respondents assigned to the Finance treatment. Finance (TOT): Finance-treated respondents who did report the finance adversity experience. Significance Levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Stars refer to tests of differences relative to the unrestricted control group.

The first column covers the control sample, followed by the health treatment (all respondents, denoted All, and respondents who experienced a financial adversity, denoted TOT for treatment on treated), and similarly for the finance treatment. The shares in Health All and

Finance All are very similar to and mostly statistically indistinguishable from those in Control, with the main exception that Finance and Health NDS are slightly more prevalent in the health and finance treatment, respectively. One plausible reason is attention: these NDS were elicited at the outset of the survey, so people arguably exerted more effort to recall them compared to Control. The Table also shows significant differences between the databases of people in Control and the "Treatment on Treated" groups (Finance TOT and Health TOT). This may be due to the endogeneity of experiences: financial, health, and other adversities such as unemployment or divorce are naturally intertwined via interaction effects and personal characteristics.[35] Table C.2 confirms this mechanism, showing a higher than average correlation between finance and unemployment and divorce.

Table C.2: Share of Respondents Reporting Each Experience

	Health	**Finance**	**Weather**	**Ineq.**	**Protest**	**Contract**	**Invest.**	**Immig.**	**Job Loss**	**Divorce**
Health	1.00									
Finance	0.22	1.00								
Weather	0.15	0.15	1.00							
Inequality	0.23	0.29	0.20	1.00						
Protest	0.14	0.22	0.21	0.28	1.00					
Contract	0.21	0.34	0.18	0.30	0.22	1.00				
Investment	0.11	0.09	0.14	0.15	0.17	0.16	1.00			
Immigration	0.11	0.20	0.22	0.22	0.31	0.21	0.14	1.00		
Job Loss	0.18	0.31	0.15	0.34	0.19	0.26	0.12	0.19	1.00	
Divorce	0.21	0.28	0.14	0.19	0.12	0.43	0.11	0.13	0.22	1.00

Notes: This table reports pairwise correlations between the ten experience indicators elicited in the experiment. N = 3,813 respondents (Wave 1). All correlations are statistically significant at the 1% level. The ten experiences are: Health problems, Financial difficulty, Extreme weather, Inequality, Protest, Cheating on a contract, Successful investment, Immigration/foreigners, Job loss, and Divorce.

We next turn to assessments of similarity of NDS experiences to high inflation or home price growth, pooled across all treatments.

[35] An alternative possibility is that priming recall of experiences at the outset influences recall of other experiences later in the survey. This channel can be tested by comparing people who lived the primed experience in the treatment arm with people who lived the same experience in the Control sample. The comparison reveals that these subsets of the treated and control samples do not systematically differ.

Table C.3: Statistics of Individual-Level Variation in Similarity

Panel A: pooled sample

Experience	**Inflation** Mean	**Inflation** SD	**Home Price Growth** Mean	**Home Price Growth** SD
Financial Difficulty	4.64	1.59	4.53	1.74
Job Loss	4.22	1.74	3.86	1.80
Inequality	3.72	1.67	3.61	1.77
Divorce	3.30	1.81	3.36	1.84
Successful Investment	3.41	1.69	3.35	1.73
Immigration / Foreigners	3.13	1.65	3.20	1.74
Protest	3.35	1.67	3.12	1.68
Extreme Weather	3.13	1.72	3.00	1.71
Illness or Accident	2.85	1.71	2.75	1.73
Cheating a Contract	2.86	1.67	2.83	1.66
Average SD		1.70		1.73
Min SD		1.59 [Financial]		1.66 [Cheating]
Max SD		1.81 [Divorce]		1.84 [Divorce]
Levene (W50)		F(9,38120) =38.76 p<0.001		F(9,38120) =12.52 p<0.001

Panel B: Owners versus Renters

Experience	**Inflation** Owners	**Inflation** Renters	**Home Price Growth** Owners	**Home Price Growth** Renters
Financial Difficulty	4.85	5.00	4.68	4.89
Job Loss	4.45	4.40	3.97	4.05
Inequality	3.99	4.21	3.85	4.14
Successful Investment	3.74	3.84	3.65	3.66
Immigration/Foreigners	3.74	3.60	3.99	3.66
Protest	3.62	3.58	3.36	3.66
Divorce	3.32	3.57	3.41	3.38
Extreme Weather	3.15	3.54	3.05	3.57
Cheating a Contract	2.94	3.15	2.86	3.02
Illness or Accident	2.85	3.05	2.70	2.99

Notes: This table reports mean similarity scores (1–7 scale) for each personal experience, separately for inflation and house-price expectations. Higher values indicate that respondents perceive their own experience as more similar to evaluating high inflation or strong house-price growth. "Average SD" reports the mean standard deviation across the ten experiences; "Min SD" and "Max SD" identify the experiences with the lowest and highest dispersion. Levene's robust test (W50) assesses equality of variances across experiences; the test strongly rejects homoskedasticity for both inflation and house-price similarity measures ($p < 0.001$).

Table C.4. finds that having had an experience, or being primed with it, increases perceived similarity.

Table C.4: Experience database, priming, and similarity judgments

Experience	Inflation N (Yes)	Diff	p-value		Housing N (Yes)	Diff	p-value	
Financial Difficulty	1719	0.49	0.000	***	1719	0.43	0.000	***
Inequality	1413	0.54	0.000	***	1413	0.53	0.000	***
Immigration/Foreigners	492	0.63	0.000	***	492	0.75	0.000	***
Protest	532	0.42	0.000	***	532	0.43	0.000	***

Job Loss	1747	0.39	0.000	***	1747	0.26	0.000	***
Successful Investment	618	0.36	0.000	***	618	0.37	0.000	***
Cheating Contract	1736	0.27	0.000	***	1736	0.15	0.005	***
Divorce	2204	0.21	0.000	***	2204	0.24	0.000	***
Extreme Weather	555	0.19	0.019	**	555	0.19	0.016	**
Illness or Accident	2036	0.13	0.024	**	2036	0.08	0.134	

Notes: Table reports mean differences in similarity ratings between respondents who reported having lived through each experience and those who did not. N (Yes) is the number of respondents who reported having the experience. "Diff" is the difference in mean similarity rating (had experience minus did not have experience) on a 1–7 scale, and the p-value is from a two-sample t-test. Similarity to inflation (housing) is the respondent's rating of how similar each experience is to high inflation (high house price growth). The sample includes all respondents in Wave 1 (N = 3,813). * p<0.10, ** p<0.05, *** p<0.01.

Finally, Table C.5 assesses the relative similarity of the cued adversities to Inflation and Housing, in the control sample.

Table C.5 Paired t-tests, Control Sample (N = 1,284)

	Sim. to Inflation	Sim. to Housing	Difference
Finance Experience	4.630 (1.61)	4.499 (1.76)	0.131, p = 0.001
Health Experience	2.904 (1.70)	2.869 (1.74)	0.035, p = 0.352
Diff (Finance – Health)	1.726, p < 0.001	1.630, p < 0.001	

Notes: This table reports mean similarity ratings for finance and health experiences in the control group (N = 1,284). Standard deviations in parentheses. Similarity to inflation is the respondent's rating of how similar their financial (health) experience is to inflation, on a 1–7 scale. Similarity to housing is defined analogously. "Difference" reports the within-person paired t-test of similarity to inflation minus similarity to housing. "Diff (Finance – Health)" reports the paired t-test of the finance experience similarity minus the health experience similarity within the same domain. The control group received no priming treatment, so these differences reflect respondents' baseline perceptions of relevance.

Appendix D. Further results on Experience and Priming Effects

We start by presenting all covariates of Table 3 (experience effects), Table 4 (priming effects), and Table 5 (similarity hierarchy of experience and priming effects).

Table D.1: Covariates of Tables 3, 4, and 5

	Table 3		Table 4				Table 5	
	Control Group – Wave 1		ITT		TOT			
	Inflation	Housing	Inflation	Housing	Inflation	Housing	Inflation	Housing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beliefs about Elderly (z)	0.1744***	0.1139***	0.1399***	0.0784***	0.1625***	0.0991***	0.1579***	0.0955***
	(0.0402)	(0.0313)	(0.0231)	(0.0201)	(0.0296)	(0.0246)	(0.0296)	(0.0247)
Age	-0.0092***	-0.0067***	-0.0089***	-0.0090***	-0.0099***	-0.0096***	-0.0107***	-0.0098***
	(0.0026)	(0.0023)	(0.0016)	(0.0016)	(0.0021)	(0.0020)	(0.0020)	(0.0020)
Male	-0.1572***	-0.0621	-0.1747***	-0.0633*	-0.1743***	-0.0671	-0.1594***	-0.0602
	(0.0552)	(0.0520)	(0.0327)	(0.0342)	(0.0421)	(0.0423)	(0.0420)	(0.0421)
Urbanization	-0.0086	0.0090	0.0036	0.0176	-0.0019	0.0117	0.0020	0.0126
	(0.0215)	(0.0200)	(0.0120)	(0.0122)	(0.0162)	(0.0158)	(0.0162)	(0.0158)
Net Income	-0.0001***	-0.0000	-0.0001***	-0.0000	-0.0001***	-0.0000	-0.0001***	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Has Partner	0.0852	0.0789	0.0149	0.0387	0.0443	0.0516	0.0498	0.0526
	(0.0613)	(0.0577)	(0.0364)	(0.0370)	(0.0468)	(0.0466)	(0.0465)	(0.0465)
Educ: Vocational	-0.1134*	0.0435	-0.0657*	-0.0282	-0.0631	0.0124	-0.0788	0.0050
	(0.0653)	(0.0605)	(0.0394)	(0.0402)	(0.0514)	(0.0511)	(0.0515)	(0.0508)
Educ: University	-0.1720*	-0.0051	-0.2572***	-0.1852***	-0.1769***	-0.1020	-0.1847***	-0.0974
	(0.0896)	(0.0826)	(0.0496)	(0.0521)	(0.0657)	(0.0664)	(0.0652)	(0.0660)
Occ: Employed	0.0159	-0.0163	0.0097	-0.0982*	-0.0084	-0.0806	-0.0072	-0.0836
	(0.0896)	(0.0821)	(0.0557)	(0.0557)	(0.0682)	(0.0645)	(0.0682)	(0.0642)
Occ: Self-Employed	0.0466	0.0119	-0.0180	-0.0360	-0.0119	0.0441	-0.0163	0.0413
	(0.1407)	(0.1288)	(0.0840)	(0.0894)	(0.1058)	(0.1134)	(0.1061)	(0.1128)
Occ: Student	-0.4157*	-0.0838	-0.3984***	-0.3455***	-0.3946**	-0.3459**	-0.4367***	-0.3610**
	(0.2293)	(0.1833)	(0.1227)	(0.1211)	(0.1563)	(0.1433)	(0.1578)	(0.1445)
Occ: Retired	-0.0442	0.0011	-0.0404	-0.1192**	-0.0334	-0.0458	-0.0245	-0.0493
	(0.0877)	(0.0849)	(0.0542)	(0.0566)	(0.0685)	(0.0670)	(0.0682)	(0.0670)

Housing: Owner	-0.1917***	-0.1805***	-0.2481***	-0.1963***	-0.2303***	-0.2137***	-0.2365***	-0.2167***
	(0.0691)	(0.0656)	(0.0408)	(0.0417)	(0.0529)	(0.0533)	(0.0523)	(0.0530)
Constant	0.7761***	0.3787**	0.8934***	0.7504***	0.9579***	0.7462***	0.8870***	0.6889***
	(0.1956)	(0.1772)	(0.1163)	(0.1155)	(0.1533)	(0.1458)	(0.1545)	(0.1454)
R Sq.	0.1280	0.0595						
Adj. R Sq.	0.1170	0.0476	0.1153	0.0595	0.1254	0.0641	0.1278	0.0664
Observations	1284	1284	3813	3813	2367	2367	2367	2367

Notes: This table reports the full set of covariate estimates for the main specifications in Tables 3, 4, and 5. Columns 1–2 correspond to Table 3 (control group, Wave 1, N = 1,284). Columns 3–6 correspond to Table 4 (columns 3–4: ITT sample, N = 3,813; columns 5–6: TOT sample, N = 2,367). Columns 7–8 correspond to Table 5 (TOT sample, N = 2,367). The dependent variables are the inflation (odd columns) and housing (even columns) belief composite z-scores. Robust standard errors in parentheses. Base categories: No vocational/university education, Unemployed, Tenant. * p<0.10, ** p<0.05, *** p<0.01

We next assess the robustness of experience and priming effects across owners and renters.

Table D.2: Experience and Priming Effects for Owners vs Renters

Panel A: Experience Effects

Control Group – Wave 1

	Inflation		Housing	
	Owners	Renters	Owners	Renters
	(1)	(2)	(3)	(4)
Finance Experience	0.1197**	0.2705**	0.0447	0.2416**
	(0.0610)	(0.1205)	(0.0576)	(0.1122)
Health Experience	-0.0476	0.0456	0.0579	0.0060
	(0.0623)	(0.1148)	(0.0578)	(0.1072)
Controls	Yes	Yes	Yes	Yes
R Sq.	0.1215	0.1328	0.0348	0.0845
Observations	913	363	913	363

Panel B: Priming Effects

	ITT				TOT			
	Inflation		Housing		Inflation		Housing	
	Owners (1)	Renters (2)	Owners (3)	Renters (4)	Owners (5)	Renters (6)	Owners (7)	Renters (8)
Finance Prime	0.0307	0.1703**	0.0490	0.1490*	0.1249*	0.1955	0.1663**	0.2125*
	(0.0416)	(0.0789)	(0.0423)	(0.0776)	(0.0748)	(0.1238)	(0.0747)	(0.1177)

Health Prime	0.0205	0.1087	0.0661	0.1819**	0.1380**	0.1764	0.1030*	0.2505**
	(0.0406)	(0.0789)	(0.0423)	(0.0811)	(0.0579)	(0.1144)	(0.0624)	(0.1172)
Finance Experience	0.1481***	0.2298***	0.0590	0.2521***	0.1134**	0.2018**	0.0077	0.2280**
	(0.0383)	(0.0683)	(0.0390)	(0.0709)	(0.0508)	(0.0999)	(0.0499)	(0.0965)
Health Experience	-0.0121	-0.0145	0.0668*	-0.0399	-0.0929*	-0.0292	0.0235	-0.0911
	(0.0348)	(0.0680)	(0.0376)	(0.0709)	(0.0527)	(0.1001)	(0.0528)	(0.0963)
N	2663	1118	2663	1118	1631	721	1631	721
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0921	0.0870	0.0376	0.0611	0.1096	0.1089	0.0426	0.0775

Notes: Standard errors in parentheses. Controls included: beliefs about elderly, age, male, education, occupation, urbanization, income, partner. * p<0.10, ** p<0.05, *** p<0.01

Finally, we assess the persistence of priming effects. To do so, we pool data from both waves and add dummies for wave 2 and their interaction with primes. We focus on participants who were TOT in wave 1 (i.e. we exclude those that did not report an adversity or did so only in wave 2). All interaction terms are negative and mostly significant, confirming treatment effects decay from Wave 1 to Wave 2. Finance priming decay is especially strong.

Table D.3: Persistence of Priming Effects

	TOT	
	Inflation (3)	**Housing (4)**
Finance Prime	0.1345**	0.1370**
	(0.0633)	(0.0615)
Health Prime	0.1184**	0.1347**
	(0.0503)	(0.0531)
Finance Prime × Wave 2	-0.1036*	-0.1711***
	(0.0534)	(0.0615)
Health Prime × Wave 2	-0.0585	-0.1162**
	(0.0502)	(0.0584)
Health Experience	-0.0271	0.0012
	(0.0373)	(0.0368)

Finance Experience	0.1534***	0.1342***
	(0.0380)	(0.0369)
N	4800	4800
Controls	Yes	Yes
R^2	0.1107	0.0584
Clustering	Individual	Individual

Notes: We report OLS regressions pooling Wave 1 and Wave 2 data. The dependent variables are composite z-scores on Inflation and Housing beliefs. Columns (1) and (2) present ITT estimates, columns (3) and (4) TOT ones. Treatment coefficients capture Wave 1 effects; interaction terms capture the change from Wave 1 to Wave 2 (negative = decay). "Finance Experience" and "Health Experience" indicate if a respondent lived a financial or health adversity. Controls include Age, Education, Occupation, Degree of Urbanization, Household Income, Accommodation Type, Gender, Relationship Status, Beliefs about Elderly (not shown). Standard errors clustered at the individual level are in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

D.1. Reliability of Similarity Measures

We next assess whether individual similarity ratings are reliable in the context of the analysis of Table 5. Several concerns arise: first, individual ratings may be noisy, in the sense of reflecting idiosyncratic judgments that are unstable across waves. Second, individual similarity ratings may be endogenous: respondents with higher inflation expectations may retrospectively judge their experiences as more similar to high inflation.

To assess the role of noise, we perform an IV exercise in which we instrument similarity in one wave with similarity reported in the other wave, which allows us to use only the stable component of similarity variation. Note that this can only be done for non-primed experiences because we measure the similarity of e_f and e_h only in the second wave, where the correlation is on average 0.3. Results are reported in Table 8, columns 1 and 2. To address the second concern, we replace individual-level similarity ratings for experiences with the corresponding sample-average similarity ratings. This removes any direct feedback from a person's own beliefs to their similarity assessments, while still preserving variation across experiences in perceived similarity at the population level.

Table D.4 Robustness: Effects of Experience Similarity on Inflation and Housing

	TOT			
	IV Similarity		Sample Similarity	
	Inflation	Housing	Inflation	Housing
Avg. Similarity of Lived Experiences	0.0477**	0.0746***	0.0479*	0.0700***
	(0.0223)	(0.0224)	(0.0265)	(0.0219)
Similarity of Primed Experience	0.0720***	0.0640***	0.0769***	0.0641***
	(0.0202)	(0.0194)	(0.0214)	(0.0194)
Constant	1.0728***	0.7946***	1.1341***	0.8096***
	(0.1496)	(0.1395)	(0.1490)	(0.1397)
N	2367	2367	2367	2367
Controls	Yes	Yes	Yes	Yes
R^2	0.1237	0.0686	0.1221	0.0672

Notes: This table reports robustness checks for the treatment-on-the-treated (TOT) specifications in Wave 1. The dependent variables are standardized belief measures (z-scores) based on respondents' point and threshold forecasts for inflation and house price growth. The three robustness approaches modify how similarity measures or beliefs are constructed. *IV Similarity*: Similarity scores are instrumented using predicted similarity values. For each experience category, the respondent's Wave 1 similarity rating is regressed on their Wave 2 rating, and the fitted value is used as an instrumented similarity score. These instrumented values are then aggregated into (i) average similarity across all lived experiences, and (ii) similarity of the primed experience (set to zero for the control group). *Sample Similarity*: Similarity scores are defined relative to the sample-average similarity rating for each experience category. Respondents who did not report an experience receive a value of zero. The same aggregation as in the baseline (average similarity and primed similarity) is applied. All regressions include the full set of demographic controls (age, education, occupation type, degree of urbanization, household income, accommodation type, gender, relationship status, numeracy) and beliefs about elderly. Standard errors are heteroskedasticity-robust. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Across specifications, the estimated coefficients on average similarity of experiences are smaller than in Table 5 but remain sizable and significant. This attenuation is consistent with our approaches purging both measurement error *and* transitory variation, but the results confirm that our findings are not driven by noise in individual ratings. For primed similarity, the robustness checks reveal some differences across specifications. In the baseline, coefficients are around 0.07–0.08 standard deviations and highly significant. Both the IV and sample similarity specifications produce similar coefficients, pointing to the reliability of our similarity measures.

The results underscore the role of memory in experience effects, which rely on similarity, and point to systematic heterogeneity of experience and priming effects. Having a given experience can be a source of strong pessimism about, say, inflation for a person who perceives the two to be very similar, but generates less or no pessimism for a person for whom they feel dissimilar. In fact, having or being primed with a dissimilar experience interferes with recall of similar experiences from the database, and reduces pessimism. To investigate interference, we decompose the average similarity index into its numerator and denominator: the numerator captures the total summed similarity across recalled experiences; the denominator is the total number of experiences recalled. Table D.4, columns (1) and (2), shows that the numerator enters positively, while the denominator enters negatively. This shows that holding total similarity constant, recalling more experiences reduces the overall effect on beliefs. When many experiences can be recalled, they interfere with each other, affecting beliefs. To further assess robustness, in columns (3) and (4) we control for inflation and housing backcasts, respectively.

Table D.5 Robustness: Experience Similarity, Interference, and Backcasts

	TOT		TOT	
	Inflation	Housing	Inflation	Housing
	(1)	(2)	(3)	(4)
Total Similarity	0.0296***	0.0186***	0.0257***	0.0117*
	(0.0074)	(0.0070)	(0.0068)	(0.0065)
Number of Experiences	-0.0480***	-0.0088	-0.0523***	-0.0085
	(0.0178)	(0.0163)	(0.0170)	(0.0148)
Similarity Primed Exp.	0.0576***	0.0538***	0.0458***	0.0456***
	(0.0174)	(0.0183)	(0.0164)	(0.0165)
Backcast			0.0309***	0.0489***
			(0.0028)	(0.0031)
N	2367	2367	2367	2367
Controls	Yes	Yes	Yes	Yes
R^2	0.1304	0.0710	0.2168	0.2497

Notes: Standard errors in parentheses. The table decomposes the average similarity measure from Table 5 into its numerator (Total Similarity: the sum of similarity ratings across all lived experiences) and denominator (Number of Experiences: the count of experiences the respondent reported). Similarity Primed Exp. is the similarity rating for the specific experience assigned as the priming treatment. Columns 3–4 add the respondent's backcast — their belief about past inflation or house price changes over the preceding two years. All similarity variables are divided by their unconditional standard deviation. The sample is the TOT group in Wave 1 (N = 2,367). Controls: beliefs about elderly, age, male, education, occupation, urbanization, income, housing, partner. * p<0.10, ** p<0.05, *** p<0.01.

Finally, we examine the role of similarity separately for each primed experience.

Table D.6 Robustness: Similarity on Different Primed Experiences

	Inflation		Housing	
	Health	Finance	Health	Finance
	(3)	(4)	(5)	(6)
Avg. Similarity	0.0783***	0.0995***	0.0629***	0.0659***
	(0.0266)	(0.0283)	(0.0242)	(0.0253)
Similarity Primed	0.0609**	0.0579***	0.0667**	0.0636***
	(0.0257)	(0.0201)	(0.0297)	(0.0206)
N	1912	1739	1912	1739
Controls	Yes	Yes	Yes	Yes
R^2	0.1262	0.1304	0.0616	0.0683

*Notes: Standard errors in parentheses. Sample similarity uses population-average similarity scores. Controls: beliefs about elderly, age, male, education, occupation, urbanization, income, housing, partner. * p<0.10, ** p<0.05, *** p<0.01*

Table 5 is also robust to using the ITT sample, which includes all subjects in our treatments as well as if we exclude demographic controls, which reassuringly says that the effect of memory parameters is largely independent of our demographics. Allowing our similarity proxies to enter also quadratically – i.e. giving higher weight to experiences that are deemed more similar – yields comparable coefficients.

Table D.7 Robustness: Other Checks

Panel A. ITT Sample

	Inflation	**Housing**
	(1)	**(2)**
Avg. Similarity Lived Exp.	0.0932***	
	(0.0253)	
Avg. Similarity Lived Exp.		0.0727***
		(0.0233)
Similarity Primed Exp.	0.0517***	
	(0.0170)	
Similarity Primed Exp.		0.0570***

		(0.0181)
Observations	2433	2433
Controls	Yes	Yes
Sample	ITT	ITT
R Sq.	0.1257	0.0653
Adj. R Sq.	0.1199	0.0591

Notes: This table reports the Table 5 specification estimated on the ITT sample (all treatment-assigned respondents, Wave 1, N = 2,433). The dependent variables are the inflation (column 1) and housing (column 2) belief composite z-scores. Average Similarity Lived Exp. is the mean similarity rating across all experiences the respondent reported having. Similarity Primed Exp. is the similarity rating for the experience assigned as the priming treatment. All similarity variables are divided by their unconditional standard deviation. Controls: beliefs about elderly, age, male, education, occupation, urbanization, income, housing, partner. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Panel B: No Controls

	Inflation (1)	Housing (2)
Avg. Similarity Lived Exp.	0.1273***	
	(0.0262)	
Avg. Similarity Lived Exp.		0.0885***
		(0.0237)
Similarity Primed Exp.	0.0614***	
	(0.0180)	
Similarity Primed Exp.		0.0663***
		(0.0187)
Observations	2367	2367
Controls	No	No
Sample	TOT	TOT
R Sq.	0.0219	0.0163
Adj. R Sq.	0.0211	0.0155

Notes: This table reports the Table 5 specification without demographic controls. The sample is the TOT group in Wave 1 (N = 2,367). The dependent variables are the inflation (column 1) and housing (column 2) belief composite z-scores. All similarity variables are divided by their unconditional standard deviation. No demographic controls are included. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Panel C: Quadratic Similarity

	Inflation (1)	Housing (2)
Avg. Similarity Squared (z)	0.0944***	
	(0.0254)	
Avg. Similarity Squared (z)		0.0663***
		(0.0230)
Similarity Primed Squared (z)	0.0592***	
	(0.0206)	
Similarity Primed Squared (z)		0.0548***
		(0.0206)
Observations	2367	2367
Controls	Yes	Yes
R Sq.	0.1283	0.0654
Adj. R Sq.	0.1224	0.0590

Notes: This table reports a nonlinear variant of the Table 5 specification using squared similarity ratings. Individual similarity ratings (1–7 scale) are squared before averaging across the respondent's lived experiences, and the resulting averages are then standardized (z-scored). This captures whether higher similarity ratings have disproportionately larger effects on beliefs. The sample is the TOT group in Wave 1 (N = 2,367). Controls: beliefs about elderly, age, male, education, occupation, urbanization, income, housing, partner. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Panel D: Sample Similarity

	Inflation (1)	Housing (2)
Avg. Similarity (Sample Mean)	0.0999**	

	(0.0479)	
Avg. Similarity (Sample Mean)		0.1590***
		(0.0497)
Similarity Primed (Sample Mean)	0.0713***	
	(0.0209)	
Similarity Primed (Sample Mean)		0.0705***
		(0.0214)
Observations	2367	2367
Controls	Yes	Yes
R Sq.	0.1226	0.0672
Adj. R Sq.	0.1166	0.0609

Notes: This table reports the Table 5 specification using population-average similarity scores instead of individual ratings. For each experience, the population mean similarity rating is computed across all respondents in Wave 1. Each respondent's similarity measure is then the average of these population means across their lived experiences. This addresses the concern that individual similarity ratings may be endogenous to beliefs. The sample is the TOT group in Wave 1 (N = 2,367). Controls: beliefs about elderly, age, male, education, occupation, urbanization, income, housing, partner. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Panel E: IV Similarity

	Inflation (1)	Housing (2)
Avg. Similarity (IV)	0.0758**	
	(0.0355)	
Avg. Similarity (IV)		0.0728**
		(0.0335)
Similarity Primed (IV)	0.0710***	
	(0.0193)	
Similarity Primed (IV)		0.0735***
		(0.0198)
Observations	2367	2367
Controls	Yes	Yes
R Sq.	0.1238	0.0653
Adj. R Sq.	0.1179	0.0589

Notes: This table reports the Table 5 specification using instrumented similarity scores. For each experience, the respondent's Wave 1 similarity rating is regressed on their Wave 2 similarity rating, and the fitted values are used as instruments. This addresses potential measurement error in similarity ratings by exploiting the within-person stability of similarity judgments across waves. The sample is the TOT group in Wave 1 (N = 2,367). Controls: beliefs about elderly, age, male, education, occupation, urbanization, income, housing, partner. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Finally, we restrict the analysis to the ITT-TOT sample, namely the participants in the treatment groups who did not have the experience they were treated with, together with control.

Table D.8 Treatment without Primed Experience

	Inflation (1)	Housing (2)	Inflation (3)	Housing (4)
Finance Prime	-0.0370	-0.0208	0.0260	0.0209
	(0.0404)	(0.0416)	(0.0432)	(0.0451)
Health Prime	-0.0395	0.0529	-0.0604	0.0675
	(0.0447)	(0.0473)	(0.0484)	(0.0504)
Finance Experience			0.1756***	0.1054**
			(0.0461)	(0.0459)
Health Experience			-0.0994**	0.0073
			(0.0402)	(0.0420)
N	2,730	2,730	2,730	2,730
Controls	Yes	Yes	Yes	Yes

Experience Controls	No	No	Yes	Yes
R^2	0.106	0.051	0.112	0.053

The results show that the effect of treatment on people without the experience (which consisted in asking whether they had the experience, but without the subsequent retrieval task) has zero effect on their beliefs.

D.2 Quantification

Dependent Variable Construction. The dependent variable in Tables 3, 4, and 5 is a composite z-score of macroeconomic beliefs. For inflation, it is the average of the z-scored point forecast (expected 1-year inflation rate, in percentage points) and the z-scored threshold belief (probability of inflation exceeding 7%, on a 0–10 scale), re-standardized within wave. The housing composite is constructed analogously from the z-scored expected 2-year house price growth rate and the z-scored probability of house price increases.

General Conversion Formula. To convert a composite z-score coefficient to underlying units:

$$\text{Effect} = \beta\_\text{composite} \times \text{loading} \times \text{SD\_outcome}$$

where *loading* is the regression coefficient of the standardized underlying measure on the composite z-score, and *SD_outcome* is the standard deviation of the underlying measure in its natural units (percentage points or 0–10 scale). Because the composite is the re-standardized average of two equally weighted z-scores, the loading is the same for both underlying measures within each domain.

Conversion Parameters (computed on Wave 1, all respondents):

Outcome	Loading	SD (PP/scale)	Product
Inflation Point	0.8307	8.4017 pp	6.9793
Inflation Threshold (0–10)	0.8307	2.4812	2.0611
Housing Point	0.8535	7.5485 pp	6.4424
Housing Threshold (0–10)	0.8535	2.4230	2.0680

Example: Tables 3 and 4. The Finance Experience coefficient in Table 3 (TOT, inflation) is β = 0.1815. Converting to point forecast pp: 0.1815 × 0.8307 × 8.4017 = 1.27 pp. The Finance Prime coefficient in Table 4 (TOT, inflation) is β = 0.1388. Converting: 0.1388 × 6.9793 = 0.97 pp.

Table 5. The similarity variables in Table 5 are divided by their unconditional SD (pooled across all persons and 10 experiences). The same conversion formula applies: multiply the composite z-score coefficient by the loading and SD_outcome to obtain pp effects. For the quantification in Section 4.3, the population-mean similarity shift is expressed in units of the person-level average similarity SD, which requires an additional rescaling factor (pooled SD / SD of person average).

Appendix E. Further results on Reasoning

E.1 Protocol for Extraction of Valence and Context

Table E.1 GPT Classification Confusion Table

Panel A: Inflation Reasoning

	GPT: Personal	GPT: News	GPT: Unclear	Total
Human: Personal	95 (75.4%)	6 (4.8%)	25 (19.8%)	126
Human: News	23 (12.4%)	133 (71.9%)	29 (15.7%)	185
Human: Unclear	32 (23.0%)	11 (7.9%)	96 (69.1%)	139
Total	150	150	150	450

Overall agreement: 324/450 (72.0%). Cohen's κ = 0.580. Per-category accuracy: Personal 95/126 (75.4%); News 133/185 (71.9%); Unclear 96/139 (69.1%).

Panel B: Housing Reasoning

	GPT: Personal	GPT: News	GPT: Unclear	Total
Human: Personal	96 (85.0%)	8 (7.1%)	9 (8.0%)	113
Human: News	4 (3.8%)	86 (82.7%)	14 (13.5%)	104
Human: Unclear	49 (21.2%)	55 (23.8%)	127 (55.0%)	231
Total	149	149	150	448

Overall agreement: 309/448 (69.0%). Cohen's κ = 0.534. Per-category accuracy: Personal 96/113 (85.0%); News 86/104 (82.7%); Unclear 127/231 (55.0%).

Panel C: Inflation Valence

	GPT: Negative Affect	GPT: Neutral/Factual	GPT: Positive/Calm Affect	GPT: Uninformative	Total
Human: Negative Affect	53 (82.8%)	10 (15.6%)	1 (1.6%)	0 (0.0%)	64
Human: Neutral/Factual	4 (11.8%)	30 (88.2%)	0 (0.0%)	0 (0.0%)	34
Human: Positive/Calm Affect	1 (1.4%)	11 (15.5%)	59 (83.1%)	0 (0.0%)	71
Human: Uninformative	2 (2.8%)	9 (12.7%)	0 (0.0%)	60 (84.5%)	71
Total	60	60	60	60	240

Panel D: Housing Valence

	GPT: Negative Affect	GPT: Neutral/Factual	GPT: Positive/Calm Affect	GPT: Uninformative	Total

Human: Negative Affect	58 (89.2%)	7 (10.8%)	0 (0.0%)	0 (0.0%)	65
Human: Neutral/Factual	1 (2.2%)	44 (95.7%)	1 (2.2%)	0 (0.0%)	46
Human: Positive/Calm Affect	0 (0.0%)	8 (11.9%)	59 (88.1%)	0 (0.0%)	67
Human: Uninformative	1 (1.6%)	1 (1.6%)	0 (0.0%)	60 (96.8%)	62
Total	60	60	60	60	240

Inflation Logic – Prompt:

Task:

You are a text classification model. Given a piece of text, classify it into one of the following categories:

- **Personal Logic**: The response uses personal experiences, financial situations, or individual observations to form an inflation expectation.
- **News-Based Logic**: The response references media, government policies, central banks, economic reports, or broader economic events.
- **Unclear/Other**: The response does not clearly fit into the above categories.

Examples:

- Text: "I think inflation will go up because my rent increased."
    - Category: Personal Logic
- Text: "The prices of living continue to rise. If you have an outing, you will spend much more. In general, life has become much more expensive."
    - Category: Personal Logic
- Text: "Inflation is expected to decrease since the central bank is cutting rates."
    - Category: News-Based Logic

- Text: "State of the economy. Future uncertain due to wars and new cabinet."
    - Category: News-Based Logic
- Text: "I don't know, I don't follow the economy."
    - Category: Unclear/Other
- Text: "I don't really know anything about it, so any answer would be a shot in the dark."
    - Category: Unclear/Other

Housing Logic – Prompt:

Task:

You are a text classification model. Given a short free-text response, classify it into one of the following categories:

1. **Personal Logic** — The respondent references their own experience or someone close to them (e.g., buying/selling a house, children struggling to buy, local prices, personal emotions).
2. **News-Based Logic** — The respondent references media reports, economic trends, interest rates, forecasts, policies, or government decisions.
3. **Unclear/Other** — The response lacks clear reasoning or is vague, generic, or irrelevant.

Examples:

- Text: "My daughter can't find an affordable house."
    - Category: Personal Logic
- Text: "Interest rates are rising, so prices will go down."
    - Category: News-Based Logic
- Text: "I don't know."

    - Category: Unclear/Other
- Text: "Everyone says houses are getting more expensive."
    - Category: News-Based Logic
- Text: "I live in a big house and feel guilty."
    - Category: Personal Logic

Emotional Valence: Prompt

Task:

You are an expert text classifier. Your task is to classify the **emotional tone** of a respondent's answer about economic expectations. Important: Focus on *how the person feels*, not on what they predict will happen. A respondent may expect high inflation but feel calm, or expect stable prices but feel anxious. The classification should reflect emotional tone only.

Categories:

- **Negative Affect** — Negative emotions dominate, such as worry, anxiety, frustration, anger, fear, hopelessness, stress, feeling overwhelmed, bitterness, or complaint. This includes resigned negativity (e.g., "nothing we can do about it" expressed with defeat).
- **Positive/Calm Affect** — Positive emotions or genuine equanimity dominate, such as optimism, relief, hope, confidence, reassurance, or calm acceptance without distress.
- **Unclear / No Emotional Signal** — The response is purely factual, too brief to interpret, or contains no discernible emotional content. Use this category only when emotional tone cannot reasonably be inferred.

If emotions are mixed, classify according to the **dominant** tone.

Response Format:

Respond with **only one** of the following:

- "Negative Affect"
- "Positive/Calm Affect"
- "Unclear / No Emotional Signal"

Examples:

- Text: "I just can't keep up anymore. It's exhausting."
    - Category: Negative Affect
- Text: "Prices went up 4% last year."
    - Category: Unclear / No Emotional Signal
- Text: "Things are stabilizing and I'm feeling better about it."
    - Category: Positive/Calm Affect
- Text: "It's scary. I don't know how we'll manage."
    - Category: Negative Affect
- Text: "Inflation is a normal part of the economy."
    - Category: Unclear / No Emotional Signal
- Text: "I'm not too worried, these things balance out."
    - Category: Positive/Calm Affect
- Text: "The government has completely mismanaged this."
    - Category: Negative Affect
- Text: "I don't know."
    - Category: Unclear / No Emotional Signal
- Text: "We'll manage somehow, we always do."
    - Category: Positive/Calm Affect

- Text: "What can you do, that's just how it goes."
    - Category: Unclear / No Emotional Signal

The next Table shows examples of reasons that were classified as personal/news and positive/neutral/fact valence, for both inflation and housing.

Table E.2 Example Responses by Logic × Valence

Panel A Inflation

Logic	Valence	N	Example
Personal	Negative	802	"My first thought was: Should I invest my savings differently? But how? Then I decided not to put any more energy into it" "That it will all be even more expensive and people will get into even more trouble" "Too bad everything has to be more expensive again. I hope that wages will also increase enormously, just like benefits."
Personal	Positive/Calm	106	"Thinking back, I see the inflation of a few years ago, which was completely derailing. At that moment I thought for a moment that it would not be okay. I now see that it is normalizing again" "I hope that the rates do not increase as a result of the Ukraine/Russia war. I think of my children who are still studying, hopefully they will also get great opportunities" "I have the feeling that it stabilizes. As a result, I entered a lower number"
Personal	Neutral/Factual	679	"Lower inflation means lower interest rates, which is good for the price of my shares." "Prices are currently rising enormously on all fronts" "that everything is getting more expensive"
Personal	Uninformative	3	"Expensive groceries" "Increased wages" "Grocery prices"
News-Based	Negative	111	"Everything is getting more expensive war Ukraine high prices nothing is going down" "THE economy, energy problem, billions that are gone due to the influx of refugees, war threat with Russia." "In recent years you can no longer think of stable inflation..."
News-Based	Positive/Calm	33	"The news is not so gloomy about rising inflation. Price increases are levelling off and the economy is developing positively." "I think they have the prices under control again so I don't expect too much of an increase." "I'm not so afraid of high inflation, the main reason could probably be energy prices, but I don't see that escalating..."
News-Based	Neutral/Factual	588	"Inflation is very likely, but less robust than in recent years. At least, that's what is predicted and I have read here and there in the media." "I read about a lack of housing, which will cause house prices to rise." "The temporary increase in energy and the subsequent increase in wages is behind us. Inflation is returning to fairly normal, around 2%."
News-Based	Uninformative	1	"War, cabinet"
Unclear/Other	Negative	254	"Life becomes difficult" "just keep it low. but I think it's not going well. taxes, energy, climate etc." "It remains a difficult matter."

Unclear/Other	Positive/Calm	84	"well honestly I don't concern myself with that at all" "they have it under control" "I think it won't be too bad"
Unclear/Other	Neutral/Factual	789	"boring, has been high lately, but I think we are in a downward trend" "The last question was not credible" "News items on this topic. Own experiences. Experiences of friends and family."
Unclear/Other	Uninformative	394	"shop" "-" "War."

Panel B. Housing

Logic	Valence	N	Example
Personal	Negative	506	"Houses are far too expensive. Will not be built for the middle class." "I especially hope that house prices will fall. It's too crazy for words how much you pay for an owner-occupied house these days." "I hope not. It is a disaster for our youth who have nowhere to live."
Personal	Positive/Calm	106	"I thought there will not be a strong higher price immediately and I also don't want to buy another house in the near future. So it doesn't really matter to me." "Fortunately, I was able to buy a house well and for the time being it doesn't matter to us." "Good for us, we own a house"
Personal	Neutral/Factual	308	"My house has become much more valuable in a short time" "The rent is becoming more and more" "The value of our house has almost doubled 6 years after purchase..."
News-Based	Negative	298	"It is almost impossible for first-time buyers to buy a house." "House prices have been driven up for decades by speculators and other commercial parties." "The limits of affordability are in sight."
News-Based	Positive/Calm	24	"The increase in prices can't rise much more, can it? Hopefully, the demand for houses will decrease." "Increases are over. Now more stability" "The current government seems to want to prevent this."
News-Based	Neutral/Factual	1215	"Despite everything, house prices continue to rise, it was also just in the newspaper" "Housing market is overvalued due to housing shortage" "Rents rise along with owner-occupied houses"
News-Based	Uninformative	5	"Higher." "Only higher" "Newspaper reports."
Unclear/Other	Negative	224	"Genuine? Is this necessary? Difficult." "the price of a house is irresponsible, people want to earn it has become an obsession" "No one can justify that in this day and age"
Unclear/Other	Positive/Calm	46	"I am not concerned with house prices at all" "I don't know but hope that it is now well done with those price increases" "Hopefully there will be a new angle for houses for the elderly"
Unclear/Other	Neutral/Factual	639	"Also difficult to answer." "felt that it will not rise yet but not much more" "I don't know what the housing market will do."
Unclear/Other	Uninformative	471	"No" "No experience" "."

Notes: Table shows example responses for each combination of reasoning logic (Personal, News-Based, Unclear/Other) and valence (Negative, Positive/Calm, Neutral/Factual, Uninformative). N is the number of responses in each category (full sample, N = 3,813).

E.2 Robustness on Backcasts and Reasoning

We start by presenting Table 6 with all covariates.

Table E.3 Covariates of Table 6

	Inflation	**Housing**	**Inflation**	**Housing**
	Backcasts (%)	*Backcasts (%)*	*Pers. or Neg.*	*Pers. or Neg.*
	(1)	*(2)*	*(3)*	*(4)*
Health Prime	0.9422*	0.3574	0.0598**	0.0797***
	(0.4814)	(0.3921)	(0.0241)	(0.0236)
Finance Prime	1.8253***	1.2384**	0.0971***	0.1195***
	(0.5811)	(0.5304)	(0.0269)	(0.0269)
Beliefs about Elderly (z)	0.8714***	1.1304***	0.0034	-0.0118
	(0.2792)	(0.2919)	(0.0101)	(0.0096)
Age	-0.0928***	-0.0809***	-0.0011	-0.0003
	(0.0208)	(0.0189)	(0.0010)	(0.0010)
Male	-0.7699*	-0.6271	-0.1166***	-0.0970***
	(0.4214)	(0.3826)	(0.0215)	(0.0206)
Urbanization	0.2566	0.1018	0.0007	-0.0071
	(0.1650)	(0.1450)	(0.0081)	(0.0079)
Net Income	-0.0003**	-0.0001	-0.0000	0.0000***
	(0.0002)	(0.0001)	(0.0000)	(0.0000)
Has Partner	-0.1701	0.2078	-0.0089	-0.0339
	(0.4609)	(0.4202)	(0.0231)	(0.0227)
Educ: Vocational	0.0163	0.4263	0.0241	0.0566**
	(0.5115)	(0.4519)	(0.0244)	(0.0237)
Educ: University	-0.6181	-0.4571	-0.0871**	0.0188
	(0.6512)	(0.5948)	(0.0354)	(0.0339)
Occ: Employed	-2.3539***	-0.7884	-0.0256	-0.0516*
	(0.7459)	(0.6368)	(0.0311)	(0.0312)
Occ: Self-Employed	-0.4029	0.0979	-0.0143	-0.1005**
	(1.0975)	(0.9804)	(0.0505)	(0.0492)
Occ: Student	-7.0349***	-3.8223***	0.0834	0.0584
	(1.4312)	(1.3810)	(0.0806)	(0.0878)
Occ: Retired	-1.7684**	0.1236	-0.0525	-0.0618*
	(0.7180)	(0.5623)	(0.0344)	(0.0336)
Housing: Owner	0.2211	-0.4197	-0.0235	-0.0032
	(0.5258)	(0.4886)	(0.0249)	(0.0244)
Constant	18.2628***	14.4057***	0.6698***	0.3656***
	(1.5669)	(1.4110)	(0.0661)	(0.0659)

N	2367	2367	2367	2367
R Sq.	0.0512	0.0410	0.0365	0.0341

Notes: OLS regressions. Sample: TOT (treatment compliers), Wave 1. Columns (1)-(2): dependent variable is backcast of inflation/housing prices (% change, winsorized at 2nd and 98th percentiles). Columns (3)-(4): dependent variable is an indicator equal to 1 if the respondent's reasoning is classified as using personal logic OR negative affect. Standard errors in parentheses, robust to heteroskedasticity. Base categories: no vocational/university education, unemployed, tenant. * p<0.10, ** p<0.05, *** p<0.01.

Table E.4 shows that, in line with Prediction 3, priming moves people towards personal logic *and* negative valence (jointly, a stronger result than that in Table 6, columns 1 and 2), away from news based logic (columns 3 and 4), and that among news-based reasoning, priming increases the prevalence of negative valence (columns 5 and 6).

Table E.4 Priming and Reasoning

	Personal AND Negative		**News-Based Logic**		**Negative in News-Based**	
	Inflation (1)	Housing (2)	Inflation (3)	Housing (4)	Inflation (5)	Housing (6)
Health Prime	0.0462**	0.0856***	-0.0443**	-0.0137	0.1109***	0.0855***
	(0.0207)	(0.0176)	(0.0195)	(0.0235)	(0.0418)	(0.0306)
Finance Prime	0.0786***	0.0842***	-0.0379*	-0.1122***	0.0841*	0.1496***
	(0.0243)	(0.0202)	(0.0218)	(0.0248)	(0.0471)	(0.0433)
N	2367	2367	2353	2359	517	880
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R Sq.	0.0301	0.0431	0.0544	0.0537	0.0786	0.0438

Notes: OLS regressions. Sample: TOT (treatment completers), Wave 1. Controls: beliefs about elderly, age, male, education, occupation, urbanization, income, housing tenure, partner. Standard errors in parentheses, robust to heteroskedasticity. * p<0.10, ** p<0.05, *** p<0.01. Columns 1 and 2: Dependent variable is an indicator equal to 1 if the respondent's reasoning is classified as both personal logic and negative affect (24% for inflation, 14% for housing). This contrasts with the main table (Table 7), where the dependent variable uses an OR condition. Columns 3 and 4: Dependent variable is an indicator equal to 1 if the respondent's reasoning is classified as purely news-based logic (excluding mixed categories). Negative coefficients indicate that priming moves respondents away from news-based reasoning. Columns 5 and 6: Sample restricted to TOT respondents (Wave 1) whose reasoning is classified as purely news-based logic (N=517 for inflation, N=880 for housing). Dependent variable is an indicator equal to 1 if the respondent's reasoning exhibits negative affect. Positive coefficients indicate that even among those using news-based reasoning, priming increases the prevalence of negative valence.

Quantification of Tables 6 and 7. **In Table 6, backcasts are already in percentage points. For Personal or Negative reasoning, the pp change in probability is given by the coefficient × 100. For example, finance priming increases probability of personal/negative reasoning by 9.7 pp (inflation) and 12.0 pp (housing).**

For Table 7, we use the conversion Methodology: *Effect_pp = beta_z × loading × SD_point*, and the conversion parameters (computed from TOT Wave 1):

	Loading	SD (pp)	Conversion Factor
Inflation	0.8435	8.73	7.362 pp per 1 SD
Housing	0.8550	7.52	6.431 pp per 1 SD

Notes: Loading = corr(point_beliefs_z, composite_z). SD = standard deviation of raw point forecast. Conversion = loading × SD. Mean forecasts: Inflation 5.71 pp, Housing 6.60 pp.

Thus, a 1 pp increase in predicted backcast raises inflation forecasts by 0.93 pp (= 0.1257 × 0.84 × 8.73) and housing by 1.16 pp (= 0.1805 × 0.86 × 7.52). Going from 0 to 1 on predicted personal/negative reasoning raises inflation by 15.51 pp and housing by 10.99 pp. Hansen J p-values: backcast 0.96/0.22, pers/neg 0.56/0.71 (overidentification not rejected).

E.3 Similarity between Reasons and Primed Recall

The simulation function $\sigma_X(e)$ translates the features (e, v, c) of the recalled experience into a forecast. Intuitively, then, reasoning about the forecast should incorporate features that are similar to those of the simulator e. To test this mechanism, we measure the text-based similarity between Inflation or Housing reasoning to text descriptions of primed NDS adversities. According to Prediction 3, the similarity of reasoning about t_X to the description of e_p should be greater in pT than in Control.

To ensure that our results are not mechanically due to the similarity of a person's writing style across her recall and forecasting tasks, we compare a given participant's reasoning in pT to the description of e_p by *other respondents* in the same pT treatment. To compute reasoning similarity, we use sentence embeddings generated by a pre-trained Sentence-BERT model, which generates 384-dimensional vector representations of open text that is optimized for semantic comparison. Cosine similarity is then computed between two texts and ranges from -1 (opposite meaning) to +1 (identical meaning).

Table E.4 panel A shows the results. The Inflation and Housing reasoning of subjects in fT (Finance TOT, left) is more similar to descriptions of financial adversity compared to Control subjects. The effect is weaker for Housing, consistent with a smaller role of fT in this domain. The same is true for participants treated with recall of health adversities (Health TOT, right). Panel B documents a similar role of spontaneous recall: people who have lived e_p exhibit reasoning more similar to the description of e_p compared to people who have not lived the same experience. This holds for finance but not for health, consistent with the finding of Tables 3 and 4 that health adversity does not exhibit a significant experience effect. This suggests that the reasoning of people with experience.

In Panel C, we further compare the reasoning of people who have lived e_p with and without priming of p, and find no statistical difference. These results further suggest that experience and priming effects arise from the same memory mechanism, shaping beliefs through retrieval and reasoning.

Table E.5: Similarity of Reasoning Mode and NDS Recall

Panel A: Participants in treatment p

	Inflation (TOT)		House Price Growth (TOT)	
	Finance – Control Diff (p-val)	Health – Control Diff (p-val)	Finance – Control Diff (p-val)	Health – Control Diff (p-val)
Similarity to Finance	+0.016 (0.004)***		+0.004 (0.227)	

Similarity to Health	+0.007 (0.020)**	+0.005 (0.050)*

Panel B: Participants in control group with experience p

	Inflation		House Price Growth	
	Finance – Control Diff (p-val)	Health – Control Diff (p-val)	Finance – Control Diff (p-val)	Health – Control Difference (p-val)
Similarity to Finance	+0.013 (0.026)**		+0.017 (0.004)***	
Similarity to Health		-0.002 (0.76)		+0.010 (0.11)

Panel C: Treatment p (TOT) vs. Participants in control group with experience p

	Inflation		House Price Growth	
	Finance TOT − Control+Fin Exp Diff (p-val)	Health TOT − Control+Health Exp Diff (p-val)	Finance TOT − Control+Fin Exp Diff (p-val)	Health TOT − Control+Health Exp Diff (p-val)
Similarity to Finance	+0.007 (0.218)		+0.007 (0.343)	
Similarity to Health		+0.007 (0.341)		−0.003 (0.620)

Notes: We report cosine similarity, computed using a BERT model, between a subject's macroeconomic reasoning and pooled "leave out" descriptions of primed experiences. In Panel A, we compare similarity across fT and Control (first row), and hT and Control (second row). Panel B repeats the analysis for participants in the control group who reported having had either a finance or a health adversity. The table reports mean differences and standard deviation of similarity scores. Differences correspond to independent-sample TOT comparisons between treatment and control groups. Panel C compares TOT participants (who were primed with adversity p and had the experience) to control participants who reported having had experience p but received no prime. This tests whether experimental priming adds to reasoning similarity beyond what personal experience alone provides. Cosine similarity is computed using a Sentence-BERT model (all-MiniLM-L6-v2) between each respondent's macroeconomic reasoning and the pooled "leave out" corpus of adversity descriptions from the treatment group. Leave-one-out is applied for TOT participants; control participants are compared to the full corpus. Sample sizes: Finance TOT N=454, Control with Finance Experience N=470; Health TOT N=627, Control with Health Experience N=90. Differences correspond to independent-sample t-tests. None of the differences are statistically significant, suggesting that priming does not significantly increase reasoning similarity beyond what personal experience alone provides. Statistical significance is assessed using two-sided t-tests, and effect sizes are expressed as differences in mean cosine similarity scores. * p < 0.10, ** p < 0.05, *** p < 0.01.

E.5 Reasoning and Beliefs

Table E.6: Covariates of Table 8

	Backcast (predicted)		Personal or Negative (predicted)	
	Inflation	Housing	Inflation	Housing
Predicted variable	0.1222***	0.1760***	2.1982***	1.7798***
	(0.0377)	(0.0677)	(0.6995)	(0.5239)
Beliefs about Elderly	0.0553	-0.1012	0.1543***	0.1193***
	(0.0477)	(0.0918)	(0.0354)	(0.0318)
Age	0.0007	0.0044	-0.0082***	-0.0094***
	(0.0045)	(0.0065)	(0.0027)	(0.0025)
Male	-0.0887	0.0320	0.0745	0.0991
	(0.0648)	(0.0760)	(0.1000)	(0.0740)
Has Partner	0.0617	0.0131	0.0595	0.1083*
	(0.0602)	(0.0682)	(0.0641)	(0.0617)
Urbanization	-0.0302	-0.0043	-0.0005	0.0261
	(0.0223)	(0.0236)	(0.0212)	(0.0203)
Net Income	-0.0000*	0.0000	-0.0001***	-0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Educ: Vocational	-0.0738	-0.0651	-0.1247*	-0.0495
	(0.0657)	(0.0824)	(0.0700)	(0.0571)
Educ: University	-0.1090	-0.0196	0.0064	0.0413
	(0.0830)	(0.0966)	(0.1089)	(0.0814)
Occ: Employed	0.2740**	0.0506	0.0427	-0.0355
	(0.1277)	(0.1155)	(0.0880)	(0.0760)
Occ: Self-Employed	0.0392	0.0272	0.0207	0.0887
	(0.1488)	(0.1749)	(0.1381)	(0.1292)
Occ: Student	0.4393	0.3121	-0.6029***	-0.4765**
	(0.3101)	(0.3358)	(0.2154)	(0.1892)
Occ: Retired	0.1840*	-0.0663	0.0823	-0.0187
	(0.1088)	(0.0895)	(0.1006)	(0.0816)
Housing: Owner	-0.2722***	-0.1466*	-0.2030***	-0.1812***
	(0.0663)	(0.0847)	(0.0608)	(0.0599)
Constant	-1.1614	-1.7042*	-0.4032	0.1654
	(0.7373)	(1.0248)	(0.5191)	(0.2664)
Observations	2367	2367	2367	2367
R Sq.	-0.5432	-0.9599	-0.6248	-0.5469
KP F-stat	5.64	2.76	7.59	12.44

Notes: Two-stage least squares (2SLS) regressions. Sample: TOT (treatment completers), Wave 1. Dependent variable: composite belief z-score (average of z-scored point forecast and z-scored threshold belief, re-standardized within wave). In columns 1 and 2, the predicted (instrumented) variable is the backcast — the respondent's recalled past inflation or house price change. In columns 3 and 4, the predicted variable is an indicator equal to 1 if the respondent's reasoning is classified as personal logic OR exhibits negative affect. In both cases, the instruments are the randomly assigned treatment dummies (health prime and finance prime). Controls: beliefs about elderly (z-scored), age, male, urbanization, net income, has partner, education fixed effects (base: no vocational/university education), occupation fixed effects (base: unemployed), and housing tenure fixed effects (base: tenant). Standard errors in parentheses, robust to heteroskedasticity. The Kleibergen-Paap F-statistic tests instrument relevance. * p<0.10, ** p<0.05, *** p<0.01.

Table E.6: Robustness, treatment level

	Health Treatment				Finance Treatment			
	Inflation	Housing	Inflation	Housing	Inflation	Housing	Inflation	Housing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Backcast (predicted)	0.1222*	0.4403			0.1261***	0.1835***		
	(0.0734)	(0.5257)			(0.0381)	(0.0658)		
Personal or Negative (predicted)			1.6438*	1.4982**			2.2449***	1.7903***
			(0.8850)	(0.6804)			(0.7022)	(0.5345)
Observations	1912	1912	1912	1912	1739	1739	1739	1739
R Sq.	-0.6541	-11.5274	-0.3377	-0.4445	-0.6392	-1.4695	-0.7422	-0.6498
KP F-stat	3.20	0.57	7.04	13.51	10.79	6.15	16.52	25.58

Notes: Two-stage least squares (2SLS) regressions, with each treatment arm estimated separately against the control group. Sample: TOT (treatment completers), Wave 1. Dependent variable: composite belief z-score. Columns 1–4 restrict the sample to health prime and control participants (N=1,912); columns 5–8 restrict to finance prime and control participants (N=1,739). In columns 1–2 and 5–6, the instrumented variable is the backcast (recalled past inflation or house price change). In columns 3–4 and 7–8, the instrumented variable is an indicator for personal logic or negative affect. The instrument is the relevant treatment dummy (health prime in columns 1–4, finance prime in columns 5–8). Controls: beliefs about elderly (z-scored), age, male, education, occupation, urbanization, net income, housing tenure, partner. Standard errors in parentheses, robust to heteroskedasticity. The Kleibergen-Paap F-statistic tests instrument relevance. * p<0.10, ** p<0.05, *** p<0.01.

Quantification of Reasoning Analysis. To quantify the effects of treatments on reasoning (Table 6) and subsequently on beliefs (Table 7), we apply the conversion methodology:

$$Effect\_pp = beta\_z \times loading \times SD\_point$$

The conversion parameters are computed from TOT Wave 1 data:

	Loading	SD (pp)	Conversion Factor
Inflation	0.8435	8.73	7.362 pp per 1 SD
Housing	0.8550	7.52	6.431 pp per 1 SD

Notes: Loading = corr(point_beliefs_z, composite_z). SD = standard deviation of raw point forecast. Conversion = loading × SD. Mean forecasts: Inflation 5.71 pp, Housing 6.60 pp.

Table 6. Backcasts are already in percentage points. Finance priming raises inflation backcasts by 1.83 pp and housing by 1.24 pp. For Personal or Negative: coefficients × 100 = pp change in probability. Finance priming increases probability of personal/negative reasoning by 9.7 pp (inflation) and 12.0 pp (housing).

Table 7. Using Effect_pp = $\beta \times$ loading $\times$ SD: A 1 pp increase in predicted backcast raises inflation forecasts by 0.93 pp (= $0.1257 \times 0.84 \times 8.73$) and housing by 1.16 pp (= $0.1805 \times 0.86 \times 7.52$). Going from 0 to 1 on predicted personal/negative reasoning raises inflation by 15.51 pp and housing by 10.99 pp. Hansen J p-values: backcast 0.96/0.22, pers/neg 0.56/0.71 (overidentification not rejected).