The Psychology of Macroeconomic Expectations

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Abstract

Building on Bordalo et al. (2025), we present a memory-based theory of "animal spirits", in which uninformative context and emotions shape the ability to retrieve and imagine future aggregate states, shaping macroeconomic expectations. We causally assess this mechanism by priming households in the Dutch National Bank Household Survey to recall personal financial or health adversities before eliciting their inflation and home price growth expectations. Consistent with the model's predictions, the treatment creates systematic and quantitatively sizable heterogeneity and instability in beliefs and reasoning based on the measured database of experiences and similarity. We argue that memory offers a disciplined psychological foundation for several documented features of expectations, such as the role of narratives, and produces a "confidence multiplier": spending by some agents cues aggregate optimism for other agents, supporting further spending.

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1. Introduction

In his *Treatise on Probability* (1921) Keynes argued that under conditions of uncertainty people form beliefs through partial and unstable weighting of evidence, not through the strict rules of probability calculus. *The General Theory* (1936) further stressed that investment and consumption decisions are based on spontaneous emotions and confidence, also called "animal spirits". The role of "sentiment" or "confidence" has been documented in macroeconomics (e.g., Ludvigson 2004, Barsky and Sims 2012, Blanchard, L'Huillier, and Lorenzoni 2013, Shapiro, Sudhof, and Wilson 2022) and finance (e.g., Lee, Shleifer, and Thaler 1991, Baker and Wurgler 2006). Keynes's intuitions also relate to the concept of "narratives", defined by Shiller (2018) as "mixtures of fact and emotion and human interest and other extraneous detail". Yet the notion of confidence remains "amorphous" (Mankiw 2009). Indeed, existing models of beliefs, rational or behavioural, rely on a stable – albeit potentially distorted – statistical calculus. Do emotions and mental states shape beliefs? How can we address this question?

We show that progress can be made by marshalling the cognitive forces of salience and memory. Using this approach, purely psychological shifters of macroeconomic optimism can be modelled, measured, and causally assessed. We find that these forces deliver quantitatively sizable *instability* and *heterogeneity* of beliefs, shed light on a range of disparate findings on measured macroeconomic expectations, and deliver new economic predictions.

We build on a model of mnemonic expectations where, following Bordalo et al. (2023, 2025), a salient cue affects retrieval of experiences, which are then used to simulate the future. The cue includes the task itself, which in our case is forecasting inflation or home price growth, but also the agent's emotions or mood or other top-of-mind experiences. These experiences may be Domain Specific (DS), such as past inflation, or Non-Domain Specific (NDS), such as personal

financial distress. Retrieved experiences in turn support different types of simulation, shaping forecasts. DS experiences of high inflation are directly projected into high future inflation. NDS experiences are instead used analogically: the feeling of personal financial distress helps imagine high future inflation. Irrelevant context and emotions therefore matter by aiding the imagination of specific future states, and beliefs do not merely reflect "statistical counting". Critically, memory offers a set of cross equation restrictions based on: i) the DS and NDS experiences lived by a person, ii) their perceived similarity to specific target outcomes, and iii) the reasoning used to make forecasts. These inputs are measurable, disciplining memory effects on beliefs.

We test the model by leveraging a novel survey design on over 4000 households from the DNB Households Survey (DHS). Preliminary analysis of the DHS reveals that households in a worse current financial or health situation expect higher aggregate inflation and home price growth. This finding is consistent with the effect of NDS experiences on macro beliefs documented by Cenzon (2025) and Taubinsky et al. (2024). These experiences are not informative about macroeconomic states, pointing to non-statistical drivers of beliefs, as in Keynes.

We take the next step and causally test the memory mechanism. To this end, before eliciting inflation and home price growth expectations we prime some subjects to recall a personal financial or health adversity. We then elicit, from treated and control subjects: i) other NDS experiences they have lived, ii) the perceived similarity of these experiences to high inflation and home price growth, iii) inflation and home price back-casts, and iv) their reasons for the reported forecasts.

Three aspects of the design are crucial. First, priming recall of personal experiences is irrelevant in any model where prior information is always recalled. Second, priming recall of NDS experiences changes the forecasting context but conveys no information about the target variable. These features allow us to identify how changing mental states affect beliefs through memory,

ruling out confounds from unobserved public or private news. Third, measuring experiences, similarity, and reasons allows us to describe the precise recall and simulation mechanism.

The data support four key model predictions. First, we see similarity-based experience effects: households who lived NDS experiences perceived to be more similar to high inflation or home price growth expect higher inflation or home price growth in the future compared to households who lived less similar experiences. Second, we see similarity-based instability: households who are primed to recall financial or health adversities expect higher inflation or home prices than control households who lived these experiences but are not primed. Third, priming financial adversities leads to higher beliefs than priming health ones, consistent with the higher similarity of financial adversities to high inflation and home price growth. Fourth, priming changes beliefs by generating: i) higher inflation or home price growth back-casts, consistent with greater use of cue-congruent DS adversities, and ii) personal and negative affective reasoning about forecasts, consistent with greater use of cue-congruent NDS adversities.

Quantitatively, the effects are large: priming is associated with significant instability in beliefs, shifting inflation (home price growth) expectations by up to 1.01 (0.87) percentage points, relative to a mean of 5.46% (6.51%). We also see substantial heterogeneity: the interquartile range of NDS databases is associated with an 0.74 (0.91) percentage point increase in expectations at the baseline. This is comparable to well-documented disagreement along socio-demographics such as top vs. bottom income quintile or gender (Weber et al. 2022).

We offer a measurable psychological foundation for "animal spirits", "sentiment", or "narratives" -- subjective mental states that shape macroeconomic expectations through recall and simulation based on salient cues, separately from public or private news. Our analysis reconciles disparate findings on macroeconomic expectations including i) the role of NDS experiences for

macroeconomic forecasts documented by Cenzon (2025) and Taubinsky et al. (2024), which we identify causally, ii) the insensitivity of beliefs to statistical information (Sims 2003), iii) the average bias in inflation expectations (Weber et al. 2022), and iv) their overreaction to sharp inflation changes (Bonaglia et al. 2025, Gennaioli et al. 2025, Link et al. 2023). The model also explains why beliefs, mental models (Andre et al. 2022), and narratives (Andre et al. 2024) are highly heterogeneous across people with similar information, such as reading the same inflation news or seeing the same gas or home prices. Differences in past experiences or current emotions affect what different people retrieve and hence their ability to imagine different future outcomes.

In Sections 6 and 7 we argue that this mechanism can have important implications. Because experiences are not randomly assigned, memory implies that heterogeneity of expectations can have non-trivial allocative consequences. In addition, because the choice of a person is a cue for another, a form of belief externality arises. Higher consumption by some people cues an economic expansion for other people, inducing them to be more optimistic and to themselves consume more, producing a "confidence multiplier."

Current approaches to macroeconomic expectations, rational or behavioural, rely on stable information processing or preferences. Theories of under and over reaction assume stable mis-specified models of the DGP (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). Belief heterogeneity is then explained by differences in the models people use or in information. Malmendier and Nagel (2011, 2016) model beliefs based on Bayesian learning from personal experiences rather than from common information. Another body of work stresses motives: distortions in information processing are 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 is needed to account for the data.

Section 2 presents motivating evidence on the link between NDS experiences and macroeconomic beliefs in the DHS. Section 3 introduces our memory model. Section 4 describes our survey experiment and how we test the model's predictions. Section 5 presents the tests. Section 6 argues that discusses disparate finding on macroeconomic beliefs in light of our model and its new implications, including the confidence multiplier. Section 7 concludes.

2. Motivating Evidence

2.1 The DNB Household Survey

The DNB Household Survey (DHS) is conducted annually since 1993 by CentERdata at Tilburg University. Each wave surveys personal circumstances 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). Survey expectations cover retirement age, household income, mortgage rates, and our macro variables of interest: inflation and home price growth. We focus on the 2012-2022 surveys.

We elicit a household's modal inflation expectations using the DNBHS 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 various personal circumstances. Some reflect demographics such as age, gender, relationship status, occupation type (employed, self-employed, student, retired),

household income (brackets), accommodation (tenant, subtenant, owner), and degree of urbanization, which are known to predict macro beliefs (e.g., Das, Kuhnen, and Nagel 2020). These proxies do not point to a specific mechanism, so we use them as controls. We also control for a measure of numeracy derived from standard probability questions.

Other proxies measure personal experiences and attitudes, mostly in five domains: health status, happiness, financial status, risk taking, and experience with financial management. We focus on a person's health and financial status, which are directly linked to personal experiences, offering clear guidance for our experimental manipulation. 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 adversity indices, a higher value implies a worse state.[1]

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 inflation (column 1) and home price growth expectations (column 3). Results are robust to

[1] The full list of questions used to construct the Financial Adversity Index is in Appendix B, and includes recent and 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?"*. Some questions (such as this last example) may be related to expectations about aggregate outcomes, and the results of Table 1 are robust to removing them.

demographic controls for inflation (column 2), while financial adversity loses significance for home price growth (column 4).[2] Coefficients are higher for financial than health adversity, consistent with a stronger role of financial experiences for inflation and home price growth.

Table 1: Adversity and Macroeconomic Beliefs in the DHS

	Inflation		Housing	
	(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 and a 0.02 (0.03) std increase in home price growth forecasts. These are large magnitudes, corresponding to a 0.51 p.p. increase in expected inflation relative to a 3.05% baseline, and a 0.11 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

[2] Higher education, student status, higher income, and homeownership are negatively correlated with expected inflation. Age, rural residence, and homeownership are negatively correlated with expected house price growth. The DHS asks respondents whether they think the value of their house has changed over the past two years. Respondents who answer positively provide an estimate of the price change. The patterns in column (4) are robust to controlling for perceived house price increase (which comes out positive and significant in the regression).

[3] Our DHS sample covers the years 2012-2022. The sample mean (SD) of the inflation expectations is 3.05% (2.13); the equivalent statics for home price growth expectations are 1.84% (4.90). In Table 1, a one standard deviation increase in financial (health) adversity entails a 0.24 (0.06) std increase in inflation, which is equivalent to 0.51 p.p. (= 0.2413 x 2.13 p.p.) increase. For home price growth, we obtain 0.11 p.p. (= 0.0223 x 4.90 p.p.).

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. Individual level variation in adversities is uninformative about future inflation and home price growth, rejecting information channels as Cenzon (2025) and Taubinsky et al. (2024) also show.[4] The anchoring of beliefs to uninformative states is also at odds with canonical rational or behavioural models, in which beliefs depend on statistical data. One may argue that personal circumstances correlate with access or attention to news. This may explain a lower accuracy in expectations of adversity-prone people, but not their systematic pessimism.

The evidence seems more consistent with Keynes' perspective that macro beliefs and confidence embed personal psychological states, not just a statistical calculus. One such mechanism could be motivated beliefs: being more exposed to high inflation or home price growth, people with higher adversities prepare for their worst-case scenario (Hansen and Sargent 2010, Bhandari, Borovicka, and Ho 2025). An alternative explanation is memory: when thinking about macroeconomic conditions, people retrieve past experiences, including irrelevant personal adversities, which help them imagine bad outcomes, such as higher inflation or home price growth. Bordalo et al. (2025) detect this mechanism in non-economic domains in which people have no direct experience: COVID lethality and cyberattack risk.

Here we experimentally test the role of memory and irrelevant personal experiences for expectations in macro, a domain in which people have many direct experiences and news. Relative to recent work on NDS experiences and macroeconomic beliefs (Cenzon 2025, Taubinsky et al.

[4] Appendix B shows that individual adversities predict neither next-year inflation nor home prices growth. The results are robust to constructing the Financial Adversities index without including proxies that may be related to aggregate states, such as whether expenditures are expected to outpace income.

2024), we causally identify the role of memory by priming recall of different experiences, by studying the role of similarity, of the broader memory database, and the effect of experiences on reasoning. Compared to motivated beliefs, which depend on un-measured tastes, the structure of memory can be measured and linked to clear predictions, that distinguish it from other theories.

3. Selective Memory and Belief Formation

We rely on the psychology of selective retrieval (Kahana 2012) and of memory-based simulation of the future (Hassabis et al. 2007). We now formalize these ingredients and then study their implications for inflation and housing expectations.

3.1 The Setup

The database is a frequency distribution $\boldsymbol{n} = \{n_e\}_{e \in E}$ over categories of experiences in memory space E, where n_e is the number of lived experiences in category $e \in E$. A category e is a vector $e = (x, v, c)$ containing that category's: signal/realization $x \in \mathbb{R}$, its subjective emotional valence $v \in \mathbb{R}$, and its context $c \in C$, where C is a metric space. x is an objective marker of the experience, for instance realized inflation or its forecast in the news. v is the emotion associated with it, which is known to play a key role in memory encoding and retrieval (Kensinger 2009).

Context C partitions experiences semantically, $C = C_{\text{M}} \cup C_p$ where $c \in C_{\text{M}}$ and $c \in C_p$ capture macro and personal contexts, respectively. In macro, context further separates inflation experiences, $c \in C_{\Pi}$, from home price growth ones, $c \in C_{\Gamma}$ (so $C_{\Pi} \cup C_{\Gamma} \subseteq C_{\text{M}}$). Within personal, context further separates financial experiences, $c \in C_f$, from health ones, $c \in C_h$ (so $C_f \cup C_h \subseteq$

C_p). We denote macro context using Greek capitals and personal context using Latin lowercases. As we show later, context separates DS from NDS experiences.[5]

Retrieval from E 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 similarity to q, frequency, and interference from other experiences. Specifically, given a similarity function $S(e, q)$, the probability of recalling e based on q and database $\boldsymbol{n}$ is:

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

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 well-established forces have been used to study the role of memory for expectations (Bordalo et al. 2023, 2025, Taubinsky et al. 2024, Cenzon 2025, Bonaglia et al. 2025), consumer choice (Bordalo et al. 2020), and advertising (Bordalo et al. 2025).

Simulation maps retrieved experiences into a forecast. Consider a person who forms a point estimate of inflation $\mathbb{E}(\pi)$ or home price growth $\mathbb{E}(\gamma)$. Mathematically, the forecasting task is also a cue: $t_\Pi = (\mathbb{R}, 0, c_\Pi)$ for inflation and $t_\Gamma = (\mathbb{R}, 0, c_\Gamma)$ 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.

A simulation function projects, for a given task t_X, 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:

[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.

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

Simulation distinguishes between DS and NDS experiences. In task t_{X}, the DS experiences are vectors $e = (x, v, c) \in E$ having the same context as the forecasting task, $c = c_{\mathrm{X}}$: namely experiences of past inflation in t_{Π} and of home price growth in t_{Γ} (possibly broadened to prices of specific goods or homes). The context of NDS experiences is instead incongruent with the task, $c \neq c_{\mathrm{X}}$: a past illness is NDS for inflation or home prices (but DS for own health).

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 embeds the task t_{X} but also another experience $\tilde{e} \in E$ the agent may be thinking about, for instance an illness or a recent op-ed on inflation she read. Our experimental manipulations will precisely rely on manipulating the cue in this way. The features of the top of mind experience $\tilde{e}$ then pollute t_{X}, generating the cue:

$$q_{\tilde{e},\mathrm{X}} = (\mathbb{R}, \{v_{\tilde{e}}\} \cup \{0\}, C_{\mathrm{X}} \cup \{c_{\tilde{e}}\}). \tag{3}$$

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

$$r_e(\boldsymbol{\omega}_X, \boldsymbol{n}) = \sum\nolimits_{\tilde{e} \in E} r_e\big(q_{\tilde{e},\mathrm{X}}, \boldsymbol{n}\big) \cdot \omega_{\tilde{e},\mathrm{X}}, \tag{4}$$

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

$$\mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n}) = \sum\nolimits_{e \in E} r_e(\boldsymbol{\omega}_X, \boldsymbol{n}) \cdot \sigma_{\mathrm{X}}(e), \tag{5}$$

which is expected simulation across selectively retrieved experiences. Due to spontaneous retrieval and simulation, Equation (5) offers a theory of macroeconomic beliefs and confidence where, as in Keynes' animal spirits, beliefs can depend on irrelevant emotions and context. This is not so with rational expectations, which optimally combine statistical priors and signals. Standard

behavioural approaches similarly rely on statistical reasoning: beliefs may under- or overreact, but are still formed based on a (mis-specified) statistical model.

Mnemonic beliefs are more general: they are driven by similarity to past experiences and their frequency, which may or may not be informative. These forces cause systematic errors (Bordalo et al. 2024), even with full information (Bordalo et al. 2025). Some errors are due to spurious features of DS experiences: a numerical inflation realization prompt statistical reasoning, rational or distorted as in diagnostic expectations (Bordalo et al. 2018, Bonaglia et al. 2025, Gennaioli et al. 2025). But the cognitive role of emotions and context also produces non-statistical sources of optimism and pessimism, capturing such mechanisms as animal spirits or narratives.

Existing work on "mental states" formalizes narratives as partial models, and emotions as mechanical boosters of optimism or pessimism (Loewenstein 2000) but does not offer a foundation for these forces. Memory traces them to retrieval of experiences and to simulation based on similarity, offering a clear measurable structure with distinctive predictions. To highlight the role of memory context effects in the most extreme way, we exogenously manipulate recall of wholly informative NDS experiences. More generally, memory implies that even DS experiences can act through context: recalling a specific economic depression makes it easier to imagine, through valence and context, how many people can be unemployed, promoting pessimistic beliefs.

3.2 Beliefs, Experiences and Priming Effects

We show that under mild assumptions on similarity and simulation our model offers several testable predictions for the working of experience effects and for our causal priming experiment.

Assumptions on $S(e,q)$ and $\sigma_X(e)$. Following Nosofsky (1986), we assume that similarity declines with dissonant features, a property that we later validate empirically.

Assumption 1 (*Similarity*). *There are numbers* $\overline{S}, \underline{S} \in (0,1)$ *with* $\overline{S} > \underline{S}$ *such that similarity between* $e = (x, v, c)$ *and* $q = (x_q, v_q, c_q)$ *satisfies:*

$$S(e,q) = \begin{cases} 1 & if \quad v \cdot v_q > 0 \text{ and } c \in c_q \\ \overline{S} & if \quad either\ v \cdot v_q \leq 0 \ \text{ or } \ c \notin c_q \\ \underline{S} & if \quad v \cdot v_q \leq 0 \text{ and } c \notin c_q \end{cases}.$$

Similarity is maximal, equal to 1, if the valence and context of e are congruent with those of q (i.e. $c \in c_q$ and they are both adversities $v, v_q < 0$ or good times $v, v_q > 0$). It then drops to $\overline{S} < 1$ if one feature is incongruent, and to $\underline{S}$ if both features are incongruent. Similarity could be smoother and act also along the objective realization x. We use this functional form for simplicity, what matters is that valence and semantic context create an associative hierarchy. A person cued with a personal financial adversity (i.e. $v_q < 0$ from personal financial context c_f) most easily recalls other personal 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).

The simulation function projecting a retrieved experience e into a point estimate for task t_{X} satisfies the following properties, that we also later assess empirically.

Assumption 2. *Fix an experience* $e = (x, v, c)$. *Its simulation in task* $t_{\mathrm{X}} = (\mathbb{R}, 0, c_{\mathrm{X}})$ *is a function* $\sigma_{\mathrm{X}}(e)$ *of the signal* $x \in \mathbb{R}$ *and valence* $v \in \mathbb{R}$ *of* e. *Simulation is less sensitive to these values if the target context* c_{X} *is more discrepant from that of the experience* c*:*

$$\frac{\partial}{\partial d(c, c_{\mathrm{X}})} \left| \frac{\partial \sigma_{\mathrm{X}}(e)}{\partial y} \right| \leq 0, \qquad y = x, v.$$

If e *is a valence neutral NDS experience,* $v = 0$ *and* $c \neq c_{\mathrm{X}}$*, it simulates agnostic default* $\delta_{\mathrm{X}} \in \mathbb{R}$.

Simulation uses the signal x or valence v of the experience to imagine the target outcome. Upon recalling a DS inflation episode, the DM may extrapolate its numerical realization, say s =10%, into the future, simulating $\sigma_{\Pi}(e)$ =10%, or use the episode's negative valence $v < 0$ to imagine unpleasant high inflation states, or a combination of the two. Upon recalling her past NDS financial troubles, the DM may extrapolate the objective income shortfall s or its negative valence v to imagine a high inflation state. In this way, these recalled DS and NDS fuel pessimism.

Assumption 2 entails a realistic hierarchy of the two: the DS experience has a ceteris paribus stronger effect on beliefs than the less similar NDS one. This yield also the similarity hierarchy "experience effects" documented in Bordalo et al. (2025). Simulation is accordingly inhibited if the experience has incongruent context and no valence ($v = 0$): thinking about our usual breakfast, walking to the office, etc., do not help imagination. They thus cause the forecast to rely on an agnostic default δ_{X} such as the midpoint or a salient element in the response scale.[6] Random context does not generally affect beliefs: congruence along some features is necessary.

Crucially, we do not need to specify how exactly simulation depends on x, v or other features. We can recover the structure of $\sigma_{\mathrm{X}}(e)$ from the: i) elicited similarity judgments between the primed adversities and the target macro states, and from the ii) "experience effects" of these same adversities in our control condition. This is sufficient for mnemonic beliefs to imposes a rich set of within and cross domain restrictions on experience and priming effects, as we now show.

Experience effects capture a change in the database $\boldsymbol{n}$. By Equation (5), having lived a higher frequency n_e of experiences in category e shapes beliefs as follows:

[6] An example of function in domain Y is $\sigma_Y(x, v) = \mu_1 \cdot x + \mu_2 \cdot \rho \cdot v + (1 - \mu_1 - \mu_2) \cdot \delta_Y$, where $\rho < 0$ implies that adversities $v < 0$ are projected into higher inflation or house price growth (at least for people who consider them adverse events), and $\mu_1 + \mu_2$ drops in context distance, with $\mu_1 = 1$ and $\mu_2 = 0$ for DS (or quasi DS) experiences.

$$\frac{\partial \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n})}{\partial n_e} = \frac{r_e(\boldsymbol{\omega}_X, \boldsymbol{n})}{n_e} \cdot [\sigma_{\mathrm{X}}(e) - \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n})]. \quad (6)$$

Higher n_e boosts recall of e and dampens recall of other experiences $e' \neq e$ across all cues. Expectations are then higher if and only if e prompts stronger simulation of high inflation or home price growth than other experiences in E, namely the term in square brackets is positive. This can occur because e is a DS high inflation experience (Malmendier and Nagel 2016), but also because e is an uninformative NDS that helps imagine a good or bad state (Cenzon 2025; Taubinsky et al. 2024). Retrieval is key: if e is not spontaneously retrieved when thinking about the task, $r_e(\boldsymbol{\omega}_X, \boldsymbol{n}) = 0$, the mere experience does not affect beliefs, even if it helps simulation. In our analysis, we explore the role of similarity in experience effects and connect it to priming effects.

Priming effects capture a change in the cue $\boldsymbol{\omega}_X$. Specifically, priming $\tilde{e}$ in task t_{X} sets the probability of cue $q_{\tilde{e},\mathrm{X}}$ to one, $\omega_{\tilde{e},\mathrm{X}} = 1$, changing beliefs according to:

$$\mathbb{E}(x|\mathbf{1}_{\tilde{e}}, \boldsymbol{n}) - \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n}) = \sum\nolimits_{e \in E} r_e\big(q_{\tilde{e},\mathrm{X}}, \boldsymbol{n}\big) \cdot [\sigma_{\mathrm{X}}(e) - \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n})], \quad (7)$$

where $\mathbf{1}_{\tilde{e}}$ is degenerate on $q_{\tilde{e},\mathrm{X}}$. The forecast increases if the prime boosts recall of above average simulation experiences e, having $[\sigma_{\mathrm{X}}(e) - \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n})] > 0$. Equation (7) links experience and priming effects. Priming $\tilde{e}$ increases its recall, which raises beliefs *in and of itself* if $\tilde{e}$ fosters simulation, $[\sigma_{\mathrm{X}}(\tilde{e}) - \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n})] > 0$. Critically, though, priming $\tilde{e}$ can also boost beliefs by creating recall spillovers on other experiences e', as we characterize next.

Proposition 1. *Suppose that, for each $c \in C$, the frequency of valence-neutral experiences from incongruent contexts is high enough in both the database and the cue, $\sum_{e\prime:v\prime=0,c\prime\neq c} n_{e\prime} > \overline{n}$ and $\sum_{e\prime:v\prime=0,c\prime\neq c} \omega_{e\prime,\mathrm{X}} > \overline{\omega}$. Then priming a non-neutral experience $\tilde{e}$ with a positive (negative) experience effects causes beliefs in t_X to change in the same direction. Formally:*

$$\mathbb{E}(x|\mathbf{1}_{\tilde{e}}, \boldsymbol{n}) - \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n}) \gtrless 0 \Rightarrow \frac{\partial \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n})}{\partial n_{\tilde{e}}} \gtrless 0. \quad (8)$$

If the experience effect of $\tilde{e}$ is positive (negative), then priming $\tilde{e}$ should have a positive (negative) effect on beliefs, *strengthening* the experience effect of $\tilde{e}$. This occurs because $\tilde{e}$ prompts recall of experiences similar to it, triggering simulation based on their similar valence or context.[7] This first "cross equation" restriction disciplines memory across observed priming and experience effects.

If instead there is no experience effect, either because $\tilde{e}$ is not spontaneously recalled, $r_e(\boldsymbol{\omega}_X, \boldsymbol{n}) \approx 0$, or it is not a source of simulation, $[\sigma_{\mathrm{X}}(e) - \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n})] \approx 0$, priming can still affect beliefs by encouraging recall of $\tilde{e}$ or of other simulating experiences. In this case, the model predicts that priming $\tilde{e}$ should affect beliefs more than priming e' if the former experience is more similar to a target state. This is second "cross equation" restriction disciplines memory, with respect to the observed experience effects and measured similarity.

Critically, a third "cross-equation" restriction also disciplined memory: priming should change the mode of thinking, favouring simulation based on otherwise forgotten DS or NDS experiences. As a result, the narratives or emotions used when reasoning about the macroeconomic future will more likely employ features related to those of the primed experience $\tilde{e}$ itself.

These cross-equation restrictions discipline memory foundations of non-statistical context effects, and hence for the "animal spirits" or "narratives" used to imagine future macro states. Two important advantages relative to existing theories follow. First, memory ties beliefs to externally measured parameters such as experiences, similarity, features, rather than to unobserved tastes or

[7] As in Bordalo et al. (2025), the condition that simulation-prone experiences capture a small portion of a person's database guarantees that priming one such experience $\tilde{e}$ fosters recall of experiences more similar to the cue $q_{\tilde{e},\mathrm{X}}$.

information. Second, it allows to explain why beliefs, and the models they are based upon, vary systematically across people and exhibit instability with changing cues and experiences.

4. The Survey: Design and Basic Facts

Section 4.1 describes the survey experiment and link it to the model. Section 4.2 documents basic facts that allow us to derive our model's predictions.

4.1 The Survey Experiment

We fielded our survey in June 2024 on the DHS households, with a second wave in October 2024.[8] Here we describe its basic structure, see Appendix B for details. The survey's key innovation is to measure not just beliefs but also memory factors and to manipulate the latter.

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 housing 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.

[8] 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, we used the enlarge 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.

Cues: Priming NDS experiences. We randomly assigned participants to one of three groups: financial ($N = 1267$), health ($N = 1262$), denoted $p\text{T} = f\text{T}, h\text{T}$, respectively and control ($N = 1284$), denoted by $\emptyset$. In fT, prior to the forecasting task t_{X} respondents are primed to recall whether they or a loved one ever faced personal or family struggles with financial hardship. In hT they are instead primed to recall a serious or chronic illness, or a serious accident involving them or a loved one. In both treatments, respondents describe the event, including the time, the associated difficulties, and their emotions. Priming is the only difference from Control, where no recall was prompted.

Primed recall changes the respondent's mental context during forecasting t_{X} by increasing the salience of the financial or health context c_p, its objective adversity s_p, and its subjective valence v_p, $p = f, h$. In the model, priming sets the cue at $q_{p,\text{X}}$, $p = f, h$. In Control $\emptyset$ the cue is instead drawn from the (unobserved) distribution $\boldsymbol{\omega}_{\text{X}}$. Critically, fT and hT change context without conveying news. Indeed, people recall experiences they have lived through, and hence already *know* about. In addition, such experiences are pure NDSs, which have no informative content with respect to inflation and home price growth. Thus fT and hT should play no role in any model, rational or behavioural, in which memory is perfect and beliefs only depend on news or stable tastes. This is not so with memory, where priming shapes what people think about during t_{X}.

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 $\sigma_{\mathrm{X}}(e)$. 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 cued experience e_f in fT and e_h in hT. 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.[9] The second wave fills a 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

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 house price expectations as a point forecast for the expected 12-month percentage change in national

[9] 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.

house 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 the beliefs in the DHS.[10]

Our experiment tests whether memory can account for significant baseline disagreement due to experiences and to belief instability from changing context. Before considering our priming intervention, we study the correlation between macro beliefs and the financial and health adversities in our control sample, in the spirit of the DHS analysis in Table 1. We describe other measured experiences in the next Section. Using data from Control, we estimate:

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

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

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 0.68 pp increases in forecasts, against baseline averages of 5.46% and 6.51% respectively (Table 2, wave 1).[11] Health adversity is instead not associated with

[10] 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 in the case of 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.

[11] 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.

pessimism, its coefficient is insignificant (and directionally negative effect 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	Housing
	(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 housing 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 weaker role of health adversities in Table 3 either due to: i) the failure of spontaneously retrieving them when thinking about inflation or housing (namely $r_{e_h}(\boldsymbol{\omega}_{\mathrm{X}}, n) \approx 0$ in Equation (6)) or to ii) their limited simulation potential (namely $[\sigma_{\mathrm{X}}(e_h) - \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n})] \approx 0$). The positive coefficient on health adversities in Table 1 supports simulation from e_h and hence hypothesis i). This account is consistent with the fact that the DHS measures *current* health adversities, which are naturally top of mind and hence spontaneously retrieved by the respondent.

In the end, however, these hypotheses and more broadly the role of cues and experiences in shaping beliefs is a mater that can be systematically studied and tested based on the cross equation restrictions of our memory model. Specifically, we prime recall of personal financial or health experiences and jointly study priming and experience effects. In so doing, our measurement of memory parameters is key, and we describe it next.

4.3 Measured Memory Parameters

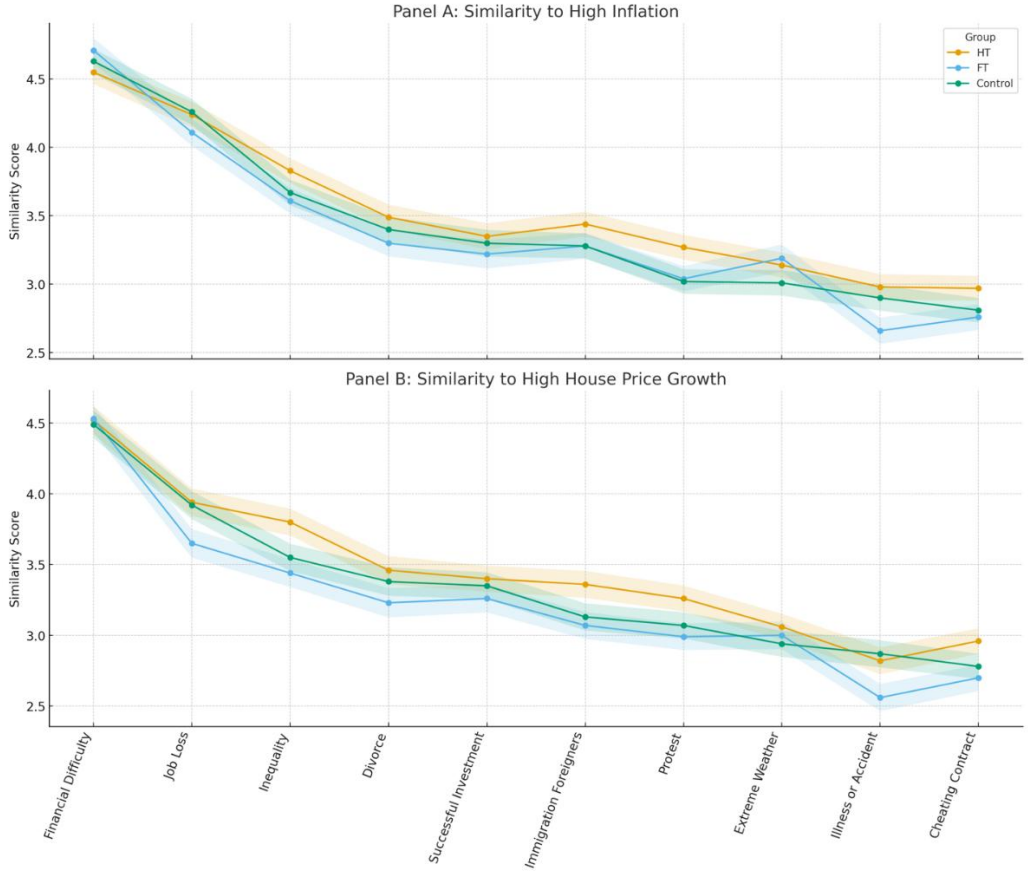
Experiences. The NDS experiences we prime are frequent, with some financial or health adversity being reported by 39% and 45% of participants in fT and hT, respectively. Frequent experiences in Control are also divorce (47%), job loss (37%), being cheated on a contract (37%). These frequencies are similar across treatment and control groups (Appendix C). There is considerable variation in experiences across people, which leads to belief disagreement. Experiences occur in clusters: financial and health troubles, unemployment and divorce are naturally linked via interactions and personal traits (Appendix B). Priming creates exogenous variation to detect memory effects and measuring the database controls for experiences.[12]

Similarity. Figure 1 plots the mean and 95% confidence interval of respondents' similarity scores of each NDS experience to high inflation (Panel A) and high home price growth (Panel B). 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 the inflation and housing domains, so there is some contextual similarity, but also the adverse nature of high inflation and home price growth for many people, creating

[12] 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).

similarity in valence. Financial adversity is more similar to inflation than to home price growth (4.9 vs 4.7, p<0.001), predicting a stronger priming effect for inflation than for housing.

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



Notes: This figure shows subjects' perceived similarity between each elicited non-domain-specific (NDS) experience and the scenarios of high inflation (Panel A) and high national house-price growth (Panel B). Results are shown separately by treatment group: Health Treatment (hT), Finance Treatment (fT), and Control. Similarity is measured on a 1–7 scale, where 1 indicates "not similar at all" and 7 indicates "extremely similar." Points show experience-level means; the shaded areas denote 95 percent confidence intervals. Data are pooled across both survey waves.

Illness or Accident and *being cheated on a contract* are the least similar NDS experiences, with average scores around 2.7-3 for inflation and housing. The semantic context of these NDS experiences is very different from macro outcomes. Similarity however is non-zero: suffering an illness or being cheated are adversities, like high inflation and home price growth for many people. Thus, consistent with Assumption 1, context and valence shape similarity. Similarity rankings are stable across treatments, suggesting that fT and hT mainly affect cues, not similarity or simulation.

There is significant individual variation: the standard deviation of similarity ranges from 1.6 to 1.8 across experiences (see Appendix C). This is not only noise: a person's similarity rating has a 0.3 correlation across Waves 1 and 2.[13] Estimating for each target t_X 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 for inflation and home price growth similarity, respectively. In psychology, variation in similarity is tied to differential attention to features (Nosofsky 1986, Bordalo et al. 2025). For instance, people more focused on emotions than on context perceive higher similarity between personal and macroeconomic bad states. We use this variation to test for similarity-driven 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 hT (N=1,262; left panel) and fT (N=1,267; right panel). Word size reflects frequency after removing common function words (175 stopwords). Total corpus: 41,776 words in hT and 31,760 words in fT.

[13] In particular, 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 memory as a source of "animal spirits", namely expectations that depend on uninformative mental states and emotions, and to quantify its explanatory power for heterogeneity and instability of macro expectations. Our interventions provide no information, so priming effects on beliefs rule out standard models relying on a correct or distorted reaction to statistical news, including fixed mis-specified models or Bayesian learning from experiences (Malmendier and Nagel 2011, 2016). Priming effects also rule out motivated beliefs, either due to a desire for robustness (Hansen and Sargent 2010) or wishful thinking (Brunnermeier and Parker 2005). Tastes are by definition unaffected by uninformative recall interventions. Critically, we do not merely use priming effects in reference to existing models. We systematically exploit the significant measured variation in NDS databases $\boldsymbol{n}$, similarity of experiences to the task $S(e, t_{\mathrm{X}})$ (and hence simulation $\sigma_{\mathrm{X}}(e)$), and in cues $q_{\tilde{e},X}$ to test the cross-equation restrictions of memory and to quantify its explanatory power.

Section 5.1 studies priming-induced instability and compares it to the baseline effect of having lived an experience. Section 5.2 compares the effects of primed and non-primed NDS experiences and of their similarity. Section 5.3 builds on our memory model to link beliefs to the model people use. To this end, we analyse the text of inflation and housing reasoning.

5.1 Instability: The causal effect of primed recall on beliefs

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

Prediction 1 *In task t_X, the regression pooling the control and the p*T *treatment samples:*

$$z_{i,\mathrm{X}} = \alpha_{\mathrm{X}} + \sum\nolimits_{p=f,h} \epsilon_{e_p,X} \cdot \mathbb{I}_{i,e_p} + \sum\nolimits_{p=f,h} \beta_{p\mathrm{T},\mathrm{X}} \cdot \mathbb{I}_{i,p\mathrm{T}} + \tau_{\mathrm{X}} \cdot X_i + u_{i,X}. \qquad (11)$$

has the following properties:

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

ii) *The sum of experience and priming effects* $\epsilon_{e_p,\mathrm{X}} + \beta_{p\mathrm{T},\mathrm{X}}$ *is higher for experiences* p *and tasks* X *where the experience is more similar to high target outcomes.*

Relative to Equation (9), Equation (11) adds the second sum, which captures the effect of being randomly assigned to a treatment in which adversity e_p is primed. Coefficient $\epsilon_{e_p,\mathrm{X}}$ is the pure experience effect $\partial \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n})/\partial n_{e_p}$ in Equation (6), coefficient $\beta_{p\mathrm{T},\mathrm{X}}$ is the priming effect $\mathbb{E}\left(x|\mathbf{1}_{\boldsymbol{e_p}}, \boldsymbol{n}\right) - \mathbb{E}(x|\boldsymbol{\omega}_X, \boldsymbol{n})$ in Equation (7). By Proposition 1, we immediately obtain prediction 1.i): priming a source of positive experience effects should raise beliefs further by prompting associative recall of similar simulation events. Based on Table 3, then, priming financial adversities should be associated with higher inflation and home price growth expectations.

Prediction 1.ii) imposes additional restrictions on which combinations of experiences and forecasting tasks allow for stronger memory effects (including for cases of zero experience effect, $\epsilon_{e_p,\mathrm{X}} \approx 0$). Fixing task t_{X}, people who have both lived *and* top of mind an experience more similar to high target outcomes should hold higher beliefs than people who have both lived and top of mind a less similar experience.[14] Based on Table 3 and on the similarity gradient in Figure 1, the sum of experience and priming effects should then be larger for financial than for health adversities for both inflation and home price growth.

[14] 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.

Second, the effect of having lived and having top of mind a given experience e_p should be stronger in a domain where e_p is more similar to a high target outcome. Based on Figure 1, the sum of experience and priming effects of financial adversities should be larger for inflation than for housing because e_f is more similar to high inflation than to high home price growth.

Table 4 tests these predictions. Columns (1) and (3) consider an Intent to Treat (ITT) sample, so the "treatment" dummy $\mathbb{I}_{i,p\mathrm{T}}$ is one also for subjects assigned to the treatment who did not have the primed experience (who then do not recall anything). Columns (2) and (4) instead implement a Treatment on Treated (TOT) test, by restricting $\mathbb{I}_{i,p\mathrm{T}} = 1$ 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)
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 fT and hT 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. Consider 1.i): priming a financial adversity boosts pessimism about inflation and housing in the ITT and TOT tests, consistent with the positive experience effect in Table 3 but also in Table 4. Beliefs of finance-primed TOT respondents are 0.14 standard deviations higher for inflation and 0.17 for housing 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 a 1.01 pp increase in inflation forecasts (against a baseline average of 5.46%) and 0.87 pp increase in home price growth forecasts (average of 6.51%).

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 deviations for Inflation and 0.25 versus 0.13 for Housing. The financial adversity is more similar to high inflation than housing and, consistent with memory, its combined effect is larger in the former domain (0.3 vs. 0.25). These similarity hierarchy of these results in turn ties the hierarchy of experience effects in Table 3.

In sum, exogenous recall of uninformative events affects macroeconomic expectations, rejecting statistical models of expectations as well as models in which beliefs are tainted by tastes. Memory produces such “animal spirits” because after recalling a personal financial or health adversity, the low valence mental state helps imagine adversities due to inflation or more expensive housing, increasing the assessed likelihood of such outcomes. Memory imposes a range of restrictions on this process, which rely on similarity: i) beliefs are most unstable when a sufficiently

similar NDS becomes salient, and ii) there is more disagreement among who are differentially exposed to experiences that are highly similar to the target outcome. We next assess the role of these forces more fully as well as quantitatively, exploiting the full NDS database and similarity.[15]

5.2 Heterogeneity: the NDS Experiences Database and Similarity

In our model, some people are more pessimistic than others because they have lived and are reminded of adverse personal experiences that help them imagine adverse aggregate scenarios. Alternatively, some people can be more pessimistic than others because they focus more on adversity relative to context, perceiving higher similarity between personal and macroeconomic adversity and hence exhibiting stronger NDS effects. In this way, memory can cause heterogeneity in macroeconomic expectations, in the baseline and in reaction to cues. We now document the importance of these effects using our measured and primed NDS experiences and their similarity.

To capture the "pessimism-potential" in a subject's NDS database we compute, following Bordalo et al. (2025), the average similarity of the NDS experiences the subject reports:

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

where E is the set of NDS we elicit, $\mathbb{I}_{i,e}$ is a dummy for whether the respondent had experience e, and $S_i(e, X)$ is the respondent's stated similarity of e to high inflation (X= Π) or home price growth (X= Γ). We set $\mathrm{S}_{\mathrm{X},i}(\boldsymbol{n}_i) = 0$ for respondents who have not had any of the elicited experiences. A respondent with a higher index $\mathrm{S}_{\mathrm{X},i}(\boldsymbol{n}_i)$ has lived NDS experiences more similar to high target outcomes, so should exhibit higher beliefs.

[15] Taste based explanations are also rejected when separately looking at owners and renters. In our Control sample, owners have lower housing beliefs than renters, and respond less to health adversities (Appendix D). However, priming effects on Housing beliefs are robustly similar across the two groups. This suggests that priming a past adversity helps retrieve negative associations with home price growth also for owners, for example by retrieving bad past experience when still a renter, or a bad contingency such as the forced need to move to an expensive city.

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

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

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

Prediction 2 *Given task t_X, regression*

$$z_{i,\mathrm{X}} = \alpha_{\mathrm{X}} + \epsilon_{E,\mathrm{X}} \cdot \mathrm{S}_{\mathrm{X},i}(n_i) + \beta_{p\mathrm{T},X} \cdot \mathrm{S}_{\mathrm{X},i}(e_p) + \tau_{\mathrm{X}} \cdot X_i + u_{i,X}, \qquad (12)$$

detects a positive similarity gradient of NDS experiences $\epsilon_{E,\mathrm{X}} > 0$ and their priming $\beta_{p\mathrm{T},X} > 0$.

Table 5 reports the estimates. To interpret magnitudes, we scale each index by its standard deviation within each wave. Consistent with our model, coefficients are positive: experience and priming effects increase in perceived similarity. Thus, more similar experiences are more likely to be spontaneously retrieved and used in simulation, but also the effect of priming them is stronger.[16]

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 (Housing) beliefs by 0.10 (0.07) std. A one–standard deviation increase in the similarity of the primed experience increases Inflation (Housing) beliefs by 0.06 (0.06) std. Adding our two proxies increases the regression R^2 from 0.114 (0.055) to 0.128 (0.066) compared to only having controls.

[16] 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.

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 potential concern in these regressions is that individual similarity may be spuriously anchored to beliefs (e.g. people reporting higher expectations 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 constructing our indices using average rather than individual similarity ratings, which rules out anchoring to stable belief differences. Appendix D reports several other robustness checks.[17]

[17] 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), 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. Results are consistent across the finance and health treatments.

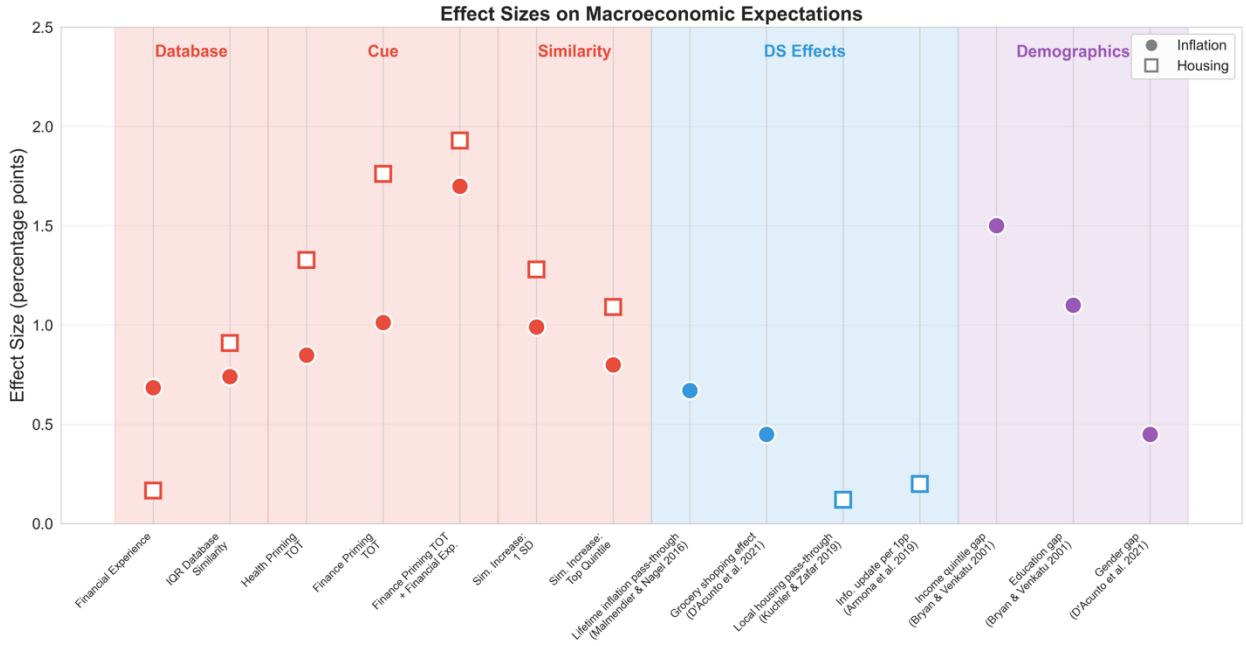
Quantification of Effects. Table 4 detects belief heterogeneity due to having lived financial or health adversities and to their differential current salience (priming). Table 5 additionally detects belief heterogeneity due to the broader NDS database and similarity judgments. Figure 3 collects these quantitative effects and compares them to standard demographics and experience effects.

To see the role of the NDS database, consider the distribution of $S_{X,i}(\boldsymbol{n}_i)$ computed at average similarity. We first estimate the impact of a given NDS experience, say a job loss, on beliefs by adding that experience to every database and computing the entailed change in the average (across participants) $S_X(\boldsymbol{n})$. Using Table 5, adding a job loss experience leads to an increase in Inflation (Housing) forecasts of 0.18 p.p. and 0.10 p.p. respectively (Appendix D). This is interesting because the incidence of such job loss experience changes across macro states, creating endogenous context effects. Second, we consider the interquartile range of the distribution of $S_{X,i}(\boldsymbol{n}_i)$ at average similarity. By construction, this variation only depends on different lived NDS experiences. Its interquartile range corresponds to a 0.74 p.p. increase in inflation expectations and a 0.91 p.p. increase in home price growth expectations. Importantly, these results are not driven only, or even mainly, by finance experiences: other NDSs have a comparable similarity-weighted impact on beliefs (Appendix D).

Consider similarity next. At the representative agent database $S_X(\boldsymbol{n})$, increasing the average similarity of experiences by a one standard deviation of similarity increases Inflation (Housing) forecasts by 0.99 pp (1.28 pp). Individual level variation is also important. At the average database, increasing similarity from the average to the top quintile for each experience increases Inflation (Housing) forecasts by 0.80 p.p. (1.09 p.p.). Appendix D shows that even in a regression setting individual similarity predict beliefs after controlling for average similarity.

These quantifications are summarized in Figure 3, distinguishing: heterogeneity arising from differences in the database, in similarity, and instability from changing cues. Memory effects are large compared to standard experience effects and demographics. Priming a finance adversity quantitatively matches the disagreement observed when moving from the top to the bottom income quintile (Bryan and Venkatu 2001, Weber et al. 2022). Demographic effects may in part reflect systematic differences in economic experiences and in the extent to which they are top of mind when making macro forecasts. The same mechanism extends to DS: the low valence of higher gas prices may be more attended to by a low-income household, causing a stronger effect of the same experience.

Figure 3: Quantification of memory effects.



Note: This figure compares effect sizes reported in this paper with benchmark effects from the literature. Effects are expressed in percentage points (pp) of expected inflation (filled circles) or home price growth (open squares). 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 macro states. We next show how this mechanism for "animal spirits" can offer a foundation for models of beliefs tainted by momentary emotions (Loewenstein 2000) or partial models/narratives (Shiller 2018).

5.3. How Priming Changes Reasoning About Forecasts

Mnemonic reasoning relies on analogies based on the features of personal experiences. For instance, Taubinsky et al. (2024) argue that negative emotions from personal adversities cue recall of past high inflation, a DS experience, causing high expected inflation. This is not the only possible mechanism in our model. Based on the cue, the agent can alternatively retrieve an NDS adversity and use it to form a partial model (e.g. "things can go bad") that invites pessimism. This second mechanism ties to Andre et al. (2022), who show that recall of personal experiences, including NDS ones, promotes different macro "models" and forecasts based on the same shock.

We can test these mechanisms in our experiment. In our model, beliefs are formed using DS and NDS experiences whose features are similar to the cue $q_{\tilde{e},\mathrm{X}}$. We can then study memory by tracing treatment effects to the features (s, v, c) of reasoning and their link to beliefs.[18]

Priming effects on (x, v, c). We proxy the objective signal x of recalled DS experiences for Inflation and Housing using our elicitation of the 12-month Inflation and Housing backcasts, respectively (we do not observe s for retrieved NDS experiences). We extract retrieved valence v

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

and context c from self-reported forecasts' reasons, as follows. Using chatGPT, fine-tuned with detailed instructions and manual validation, we categorized each text along two dimensions: first, proxying for c, we measure 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 use of NDS experiences, category ii) use of DS ones. Second, proxying for v, we classify texts based on whether they reflect negative or positive valence, are factual, or unclassified.[19]

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 low valence, personal experiences (less, money, meet ends, buy). Appendix E lists exemplar reasons of all classifications.

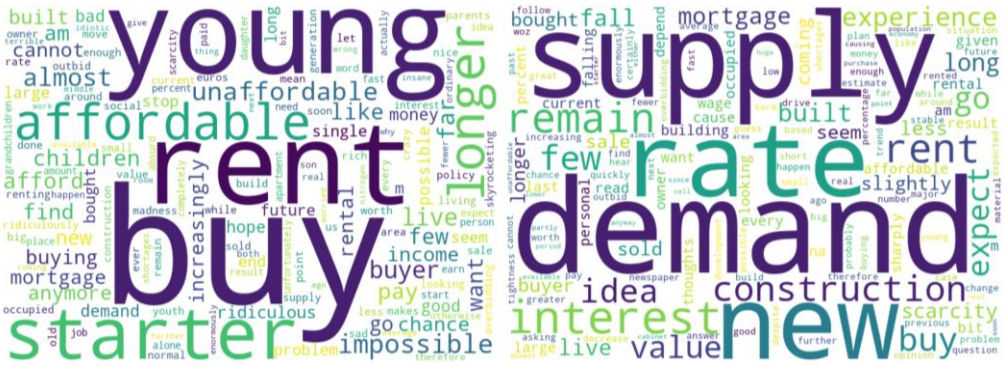
Figure 4: Word clouds for negative (left) or neutral valence (right).

Panel A: Inflation



Panel B: Housing

[19] 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).



Notes: Word clouds of open-ended macroeconomic reasoning, comparing texts classified as expressing negative affect (left) versus neutral or news-based reasoning (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.

Based on these proxies, our model makes the following prediction:

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

i) recall of high Inflation and Housing back casts (DS effect).

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

Effect i) immediately follows from mood congruent recall (Bower 1981) applied to DS experiences: priming an adverse NDS favours retrieval of high compared to low inflation and home price growth states due to similar low valence. Taubinsky et al. (2024) use this mechanism to explain the link between adverse NDSs and high inflation forecasts. Effect ii) is an additional memory effect: priming an adverse NDS experience prompts recall of other adverse NDSs, increasing simulation and hence reasoning based on personal context and low valence.

Columns (1) and (2) of Table 6 report the TOT effects on back casts. Both fT and hT cue recall of higher past inflation and home price growth, consistent with Prediction 3. This test provides causal evidence of the link between experiences and back casts, consistent with

Taubinsky et al. (2024). The effect is stronger for finance than for health, consistent with higher similarity of the financial adversity context to DS Inflation and Housing experiences.

Table 6: Back casts, Context and Valence

	Back casts (%), TOT		**Personal or Negative, TOT**	
	Inflation (1)	Housing (2)	Inflation (3)	Housing (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 featuring either personal context or negative valence relative to Control, for both Inflation and Housing forecast. Appendix E further shows that priming NDS adversities predicts an increase in reasoning based directly on low-valence and personal experiences, and a switch away from news-based reasoning.[20]

Recalled features and forecasts. We conclude by circling back to forecasts. Our model predicts that higher back casts should be associated with higher forecasts. It also predicts that

[20] 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.

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 2019, Andre et al. 2022) based on vividly imagining bad future macro states.[21] To test this link we use an instrumental variables (IV) approach. In the first stage, we use fT and hT to obtain exogenous variation in reasons as in Table 6. In the second stage, we regress the macroeconomic beliefs on the first stage predicted back casts, negative valence or personal logic from the first stage.

Table 7: Beliefs and Predicted Backcasts, 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 backcasts 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 backcasts (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 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The results in Table 7 show that the priming-driven shift to more inflated backcasts, or towards personal logic or negative valence, substantially raises inflation and housing forecasts. The first stage F-statistic is strong for reasoning, less so for back casts, which is intuitive and

[21] The mechanism helps explain systematic instability as well as heterogeneity in terms of what is top of mind 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, Zimmermann 2024) and in part because they provide better simulation material.

informative: the back cast task is more strongly anchored to actual experienced inflation than to the treatment cue. The recall of low valence or personal experiences is instead more strongly based on the NDS cue that our treatments induce, yielding a stronger first stage effect.

Consistent with memory, our tests show that 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

In our theory, uncertainty is represented "in context" based on semantic or emotional cues that shape retrieval of experiences and the ability to imagine good vs. bad aggregate states. We isolated this mechanism by priming uninformative NDS events. Similar forces are at play with DS experiences, which in addition carry objective information. We next argue that the context effects of NDS and DS experiences can have significant implications for macroeconomics.

Consider an agent forecasting an adversity, such as inflation, based on two types of experiences: a share n_Π of DS experiences of constant inflation $\overline{\pi}$, and a share $n_p = 1 - n_\Pi$ of NDS adversities.[22] DS experiences feature valence $v(\overline{\pi}) < 0$, where $v(.)$ is decreasing: higher inflation is associated with more emotional distress. NDS experiences have constant valence $v_p = v(\overline{\pi} + \gamma)$ where we assume $\gamma > 0$: realistically personal adversities are more distressing for the agent than experienced inflation. The agent simulates future inflation based on the valence of the retrieved experience. If she retrieves a DS experience, she simulates the inflation corresponding to

[22] For simplicity we abstract from good NDS, which is akin to setting their similarity in Assumption 1 to $\underline{S} = 0$.

their valence $v(\overline{\pi})$, which is $\overline{\pi}$ itself. If she retrieves an NDS, she extracts the inflation level corresponding to their valence $\overline{\pi} + \gamma = v^{-1}(v_p)$ but her simulation is weaker due to discrepant context, as in Assumption 2. Formally, based on an NDS the agent simulates inflation $\varphi_p(\overline{\pi} + \gamma)$, where $\varphi_p \in (0,1)$ captures the extent of NDS simulation. This highly stylized setup delivers the model's intuitions in a clean way, but the same effects arise in a richer setting with heterogeneous DS and NDS experiences and with a stochastic inflation-valence mapping.

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

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

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

Insensitivity and bias. 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.[23] Interference also causes expectations *above* experienced inflation $\overline{\pi}$ if the NDS experiences are distressing enough, $\gamma > \left(\frac{1-\varphi_p}{\varphi_p}\right) \overline{\pi}$. Household expectations of inflation are indeed too high (Mankiw, Reis, and Wolfers 2003, Coibion,

[23] For fixed valence v_p of NDS, higher $\overline{\pi}$ commensurately reduces γ, leaving the second term unaffected.

Gorodnichenko, and Weber 2022), consistent with our model but not with rational inattention (Sims 2003), which entails insensitivity but no systematic bias.

DS context and overreaction. Our experiment causes belief instability by cuing NDS adversities, which de-anchors beliefs from DS experiences. The same effect works for DS events: consider an increase in *current* inflation from $\overline{\pi}$ to $\pi' = \overline{\pi} + \partial\pi,\ 0 < \partial\pi < \gamma$. This change increases the similarity S_p of the inflation environment to personal distress and reduces its similarity S_Π to regular inflation $\overline{\pi}$.[24] From Equation (13), this change entails:

$$\frac{\partial \mathbb{E}(\pi|q,\boldsymbol{n})}{\partial \pi} \propto \left[\gamma - \left(\frac{1-\varphi}{\varphi}\right)\overline{\pi}\right] \cdot \frac{\partial}{\partial \pi}\left(\frac{S_p}{S_\Pi}\right). \tag{14}$$

which is positive if NDS adversities create a positive inflation bias (positive term in brackets). This happens even if inflation is entirely transitory. Crucially, the agent does not have a general tendency to overreact to news (which captures neither insensitivity to historical inflation $\overline{\pi}$ nor the bias γ caused by NDS events). Context provides a cue bottom up, so higher similarity to distressing NDS relative to DS events increases pessimism, leading to a strong reaction especially if the change $\partial\pi$ is large, even if transient.[25]

Narratives and Partial Models. The concept of narratives has been invoked as a powerful driver of aggregate consumption and investment decisions, on the basis of compelling examples and psychological intuition (Shiller 2018). Our framework offers a foundation for narratives in terms of context-based beliefs, and integrates these ideas into a testable and tractable macroeconomic framework.

[24] Formally, at $\pi' = \overline{\pi} + \partial\pi$, the current context has valence $v(\overline{\pi} + \partial\pi)$ so the cue is $(v(\overline{\pi} + \partial\pi), c_\Pi)$. Compared to the baseline $(v(\overline{\pi}), c_\Pi)$, this cue has lower valence discrepancy with the NDS, $|v(\overline{\pi} + \gamma) - v(\overline{\pi} + \partial\pi)| < |v(\overline{\pi} + \gamma) - v(\overline{\pi})|$ while it has higher valence discrepancy with the DS, $|v(\overline{\pi}) - v(\overline{\pi} + \partial\pi)| > |v(\overline{\pi}) - v(\overline{\pi})| = 0$.

[25] 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.

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

The same mechanism may be at play in narratives that leverage everyday experiences, such as "restaurants are full, the economy is doing well."[26] 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. Crucially, which "partial model" obtains is predicted by a person's experiences, similarity judgments, and context. This leads to predictable and 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, it is hard to reconcile contagion with models of stable distortions of beliefs. Our model explains how context can drive instability of beliefs, by changing which experiences underlie them. Crucially, however, the memory mechanism makes clear predictions about how evolving context can shape

[26] 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

the narrative, but also puts limits on contagion, including as a function of experiences. (Concepts like "inoculation" against a narrative may turn out to be appropriate). This opens the door to the study of dynamics of beliefs, to which we now turn.

Confidence and Business Cycles. A large body of work shows that consumer and investor confidence are powerful predictors of aggregate expansions and contractions (Ludvigson 2004). In standard accounts, confidence arises from truly informative signals about aggregate TFP (Lorenzoni 2009, and Blanchard, L'Houllier, and Lorenzoni 2013, Beaudry and Portier 2006). In Angeletos and Lian (2018), closer to Phelps (1970) and Lucas (1972), confidence is the belief of agents that they will experience an increase in the relative price of the good they supply, which increases their permanent income, demand, and boosts output due to sticky prices. A similar mechanism is at play in Angeletos and La'O (2013), in which lack of common knowledge allows beliefs to depend on arbitrary, yet unmodelled, optimism shifters.

Our theory is complementary to these approaches: shifting aggregate context can produce effects similar to non-fundamental noise shocks, as in Lorenzoni (2009), while cross-sectional variation in NDS and context can create idiosyncratic heterogeneity of expectations as in Angeletos and Lian (2018), including departures from common knowledge. However, the key implication of memory is that confidence depends not only on the information environment – captured by exogenous statistical signals – but also on current context, including the endogenous actions of agents. This creates new belief externalities: the decision of a loan officer to deny credit to a firm increase its macroeconomic pessimism even absent information, which reduces the firm's investment over and above the amount of credit that was denied.

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). The expectation $\mathbb{E}(x_1|x_0, \boldsymbol{n})$ depends on the current equilibrium outcome x_0, even conditional on the objective information it conveys about x_1. The reason is that higher current consumption x_0 cues recall of economic expansions, 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 $\varphi = 1$ and $S(e, q) = \exp\left[-\delta\left|x_q - x_e\right|\right]$, we obtain an equilibrium condition for x_0:

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

The last term 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 sustain 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.

Neoclassical models create multiplicity by assuming technological complementarities, in investment or other actions (e.g. sequential servicing constraint in bank runs), and rational expectations adjust to sustain the good or bad equilibrium. Memory creates multiplicity through expectations themselves. "Positive" choices cue "positive" memories, sustaining similar choices in others. This occurs despite the fact that, unlike in herding models, these choices convey no information. Thus, a suitable aggregate transfer or investment policy can produce spontaneous optimism and sustain an economic expansion, consistent with Bellifemine et al. (2025).

7. Conclusions

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 2024) 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 our ability to vividly 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.

These features can matter for macroeconomics. Consider heterogeneity of beliefs stemming from different NDS experiences. Because these experiences are not randomly assigned, memory driven disagreement can have non-trivial allocative consequences. Consistent with Das, Kuhnen, and Nagel (2020), people with worse personal financial experiences are ceteris paribus more pessimistic about the future, limiting their willingness to consume, invest, or search for a job. These 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.

Instability on the other hand implies that a common shock can change the ability to imagine good versus bad outcomes for many people over and beyond its information value. Blanchard (1993) argues that the U.S. recession of 1990-91 could have been due to the Iraq War, which triggered a non-fundamental drop in consumer confidence. Similarly, macro 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 shrinking. In this way, changes in aggregate context can affect business fluctuations as in Keynes' original intuition. These forces may help understand the effects of economic policy and communication. We leave these topics to future work.

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