Recall Fluency, Beliefs and Behavior

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Abstract

The US Health and Retirement Study measures participants' recall fluency (RF), their ability to recall words from a list, a standard measure of memory in psychology. Controlling for multiple demographics and IQ, people with a higher RF are more optimistic about stock returns, the price of their homes, and their life expectancy. Consistent with the predictions of a standard memory model, we find that the beliefs of higher RF people about each domain are more sensitive: i) to cues, ii) to experiences in that domain, but also iii) to irrelevant experiences in other domains similar to the target one. These effects, in turn, carry to investment and retirement choices. Our findings buttress the importance of memory for economic behavior, with RF emerging as a relevant personal trait.

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1 Introduction

For over a century, psychologists have studied memory by measuring people's ability to recall words from a list, known as recall fluency or RF (Ebbinghaus, 1885). The US Health and Retirement Study (HRS) has collected this measure over multiple waves for tens of thousands of participants. In the data, RF declines with age but exhibits stable variation across people orthogonal to other cognitive traits such as IQ (Krueger and Salthouse, 2011; Unsworth and Engle, 2007). This variation is economically relevant: RF is associated with more optimism about U.S. stock returns, own home price growth, and own life expectancy. Do these patterns reflect the effect of a person's memory on her beliefs? If so, does memory influence – through beliefs – investment and retirement choices, which are also measured in the HRS?

To address these issues, we take a standard mnemonic beliefs model and test its predictions about RF. Following Bordalo et al. (2025, 2026a), a salient stimulus cues frequent and similar experiences, subject to interference from other experiences. Recalled experiences are then used to imagine future states, shaping beliefs. In this setup, higher RF captures lower interference: during the memory task, people with high RF are more focused on target words, so that fewer extra-list thoughts come to mind and block targets. The link between RF and interference is consistent with much memory research (Kahana, 2012), which also shows that stronger attention to target features fosters their recall (Hartzmark et al., 2021). By capturing a general purpose "interference parameter", RF could then affect beliefs in the field: people with high RF better retrieve experiences that help them imagine the future. Thus, their beliefs are more anchored to experiences than those of low RF ones, systematically so across domains.

Indeed, in any target domain X higher RF entails four specific predictions:

1. Beliefs about X should be more sensitive to the *stock* of a person's past experiences in the same domain X. For instance, living higher (lower) average stock returns should cause more stock market optimism (pessimism) for high compared to low RF people.

2. Beliefs about X should be more sensitive to the *current* cue. A current stock return similar to the high (low) end of a person's experienced returns should cause more optimism

(pessimism) for high compared to low RF people.

3. Beliefs about X should be more sensitive to irrelevant experiences from a domain $X' \neq X$, especially if X' is similar to X, so that it helps imagine it. Having lived financial wellbeing (troubles) in childhood should cause more stock market optimism (pessimism) for high compared to low RF people.

4. Fourth, high RF people should be more confident in their beliefs about X and give fewer "I do not know" answers, due to a more vivid imagination of future outcomes.

Crucially, because RF captures a general memory "technology", these predictions hold across our domains: stock returns, home price growth, and life expectancy. We also test them for beliefs about inflation and an economic depression, for which we have shorter time series.

Following Bordalo et al. (2025) and Gennaioli et al. (2025) we proxy for the three key memory objects. First, we construct in each period a participant's memory database of past US stock returns, local home price growth, and health conditions up to that period. These experiences are domain specific (DS) for beliefs about stock prices, own home prices, and life expectancy respectively. We add to the database also indices of Childhood Health and Socio Economic Status (SES), which are measured in the RHS and capture non-domain specific (NDS) experiences for stock and home prices (we instead use past stock and home returns as NDS experiences for life expectancy). Second, we construct in each period and domain the current cue: current stock return for stocks, current home return for homes, and current health for life expectancy. Third, following Gennaioli et al. (2025) we construct a time varying index of similarity between the cue and above average DS experiences in each domain. For NDS experiences we measure similarity to each belief domain in a separate survey.

Using these proxies we test the memory model and find support for its predictions about RF in all three domains. First, the beliefs of high RF people are more sensitive to lived past DS experiences than those of low RF ones, consistent with a greater ability to recall and use them to imagine the future. Quantitatively, this effect explains why higher RF people are more optimistic than low RF ones: during the survey period stock and housing markets have done well on average, and people have had a good health status on average (they are alive).

Second, the beliefs of higher RF people are more sensitive to cues, consistent with a stronger selective recall of DS experiences that are similar to the current state. This implies the beliefs of high RF people look more extrapolative than those of low RF ones. In the stock market, for instance, high RF people show a stronger increase in optimism in the 2000's, up to the 2008 crisis, and a larger bust afterwards. Thus, high RF does not necessarily mean "better" beliefs; It can cause stronger trend chasing, consistent with a memory model.

Third, and related, the beliefs of higher RF people are more sensitive to NDS experiences, despite the fact that these experiences are uninformative for the target event. For the stock market and housing, they are less optimistic if they had lower childhood health and SES. For life expectancy, they are more optimistic if they lived through higher stock or housing returns. The similarity measurement supports a memory mechanism: health and financial troubles are deemed more similar to bad stock returns and lower own home price growth. As a result, retrieval of these childhood NDS experiences promotes pessimism, especially so by high RF people. Again, high RF people do not necessarily have better beliefs.

Fourth, and also consistent with memory, high RF people are less likely to answer "I do not know" or report low confidence, consistent with more vivid imagination of the future.

The effect of RF is quantitatively large: moving from zero to average RF increases the average experience effect roughly sevenfold for stock market beliefs, by about 70% for home price beliefs, and by about 50% for life expectancy. These magnitudes rival those of standard demographics: Moving from zero to average RF moves beliefs by about as much as an interquartile increase in education (roughly 3 years) for stock-market beliefs, 1.5 times as much for home-price beliefs, and about half as much for life-expectancy. In every domain it outweighs an interquartile increase in income (roughly $49,000 USD) by a factor of 1.4-5.5.

The HRS also reports respondents' discretionary stock and housing investment, and their retirement choices. We can thus ask: does RF affect choices through beliefs? The answer is yes: more RF-driven optimism about stocks, home prices and life expectancy predicts more stock and housing investments and more forward-looking retirement decisions. A one-standard-deviation increase in the RF-driven component of beliefs raises the probability of a new stock investment by 1.7 percentage points (17% of baseline mean investment) and of buying a new home by 0.7 percentage points (16.3% of the mean), and it increases the expected chance of working past age 70 by 1.4 percentage points (5.4% of the mean).

Growing work shows that regularities in human memory unify well-documented features of measured beliefs, such as distorted reaction to current events (which reflects the role of cues), the influence of distant personal experiences (which reflect the database and interference), across abstract probability judgments, familiar economic domains, or assessment of novel risks (Bordalo et al., 2020, 2026a,b; Conlon, 2024; Enke et al., 2024; Jiang et al., 2025; Malmendier and Nagel, 2011, 2016; Sial et al., 2023; Taubinsky et al., 2026). Hartzmark et al. (2021) show that ownership of an asset fosters attention to news about it, recall of its past performance, and belief extrapolation about it.

These papers detect memory effects using variation in cues or experiences. We instead study how cues and experiences are mediated by variation in an explicit, general purpose, memory parameter: the degree of interference, captured by RF in entirely abstract tasks. Our tests offer a sharper validation of mnemonic beliefs and of their relevance for actual investment decisions. The systematic effect of cues and experiences is in fact much stronger for people with a more powerful recall technology. A weak recall technology instead produces faint imagination, random and unconfident beliefs, reducing the impact of cues and experiences on decisions. Critically, then, our analysis also offers new insights on the nature and severity of belief biases across people. Because RF declines with age and varies systematically within a cohort, it emerges as an important source of belief and choice heterogeneity, complementing canonical heterogeneity in risk aversion, patience, and so on.

The rest of the paper is organized as follows. Section 2 describes the HRS survey, introduces recall fluency, and documents its link to beliefs. Section 3 presents the model, and Section 4 tests its predictions. Section 5 studies choice implications of RF.

2 Motivating Facts

2.1 The HRS survey

The Sample. The University of Michigan Health and Retirement Study (HRS) is a representative biennial panel of U.S. adults over age 50. It adds a new cohort roughly every six years and follows respondents until death, with some attrition. We consider ten waves, starting in 2002 when our main belief variables begin to be collected. We have 34,677 unique respondents and 189,097 person-wave observations. Appendix Table B.1 and Table B.4 describe the survey and our sample. Respondents are 53% retired, 63% married, 59% female, and average 67.7 years of age (with 11.4 s.d.), 12.5 of education (3.2 s.d.), and \$57,574 of income (\$105,371 s.d.).[1] We use age, gender, marital status, retirement status, income, and education as regression controls.

Outcomes: Beliefs and Choices. The HRS elicits beliefs about social and personal events. We focus on the stock market, the price of one's home, and life expectancy. Beliefs about these domains play a key role in economic models, are available in many waves, and are traceable to experiences.[2] The stock market question asks people to assess the percent chance that mutual fund shares invested in blue chip stocks will be worth more a year from now. The housing question asks homeowners to assess the percent chance that their own home will be worth more a year from now. The life expectancy question asks respondents to assess the percent chance that they will live to a target age, equal to 85 for respondents under 65, to 80 for those aged 65–69, to 85 for those aged 70–74, to 90 for those aged 75–79, etc.[3]

The HRS measures several choices related to these beliefs. For the stock market, we consider whether the respondent has made a new stock investment in the past 2 years (regardless of amount), and the percentage of the respondent's IRA (if positive) invested in stocks or mutual

[1] We combine salaried income, self-employment income, bonuses, social security benefits, workers compensation, and pensions. The combination of different incomes creates a high variance.

[2] The HRS also elicits expectations about US inflation and economic performance, but only in a few waves (2002-2008). We later show that our key results extend to these measures. Other beliefs are hard to trace to measured experiences (e.g. beliefs about inheritance), so we neglect them.

[3] This is the schedule used from 2006 onward; in the 2002–2004 waves the youngest respondents (aged 69 or below) were assigned a target of 80, with no separate under-65 category, and the remaining bands were unchanged. The horizon can exceed ten years for younger respondents but for brevity we refer to this belief as the chance of living ten or more years. The exact wording of each belief question, and the full target-age schedule by wave, is reproduced in Appendix Table B.1.

funds. For housing, whether the respondent has bought a new home in the past 2 years. For health, whether she expects to work past the age of 70 (if currently working), is currently retired, and the percentage of a respondent's income invested in their pension (if they have a defined contribution plan).

Memory ties beliefs to three drivers: the database, cues, and similarity. We describe how we construct proxies for the first two. In each period, a respondent's database reflects her accumulated experiences up to that period, which we construct using three sets of experiences.

Health experiences. In this domain we construct measures of: i) childhood health and ii) current health. Childhood health is the first principal component of: missed time in school for health reasons (1,0), disabled as a child (1,0), number of childhood health conditions, number of severe childhood health conditions, and number of psychological childhood health conditions. Current health is the first principal component of: days spent in bed last month, number of health conditions, self-rated health (1-5), depressed (binary), recent heart attack (binary), new/worsening severe health condition (binary), sleep quality, number of daily tasks the respondents has difficulty doing on their own, whether the respondent has a functional helper (binary), and number of tasks a functional helper helps with on a daily basis. We initialize a respondent's health database with her childhood health and then progressively add changes in current health across surveys.[4] Health experiences are Domain Specific (DS) for life expectancy beliefs, and Non Domain specific (NDS) for stock and housing market beliefs.

Stock and housing market experiences. We create a respondent's database of real stock returns over their lifetime, using the Shiller S&P500 dataset (`https://shillerdata.com/`); each entry is the trailing twelve-month log real return, computed at every month from the respondent's birth through the survey month. We measure housing real returns from the Federal Housing and Finance Agency's (FHFA) home price index (`https://www.fhfa.gov/data/hpi/datasets?tab=quarterly-data`), based on sale and appraisal data.[5]. Stock and

[4]See Appendix Table B.2, Panels 3 and 4, for construction of the current- and childhood-health indices, and Appendix Table B.3, Panel C, for construction of the health experience database.

[5]The census partitions the country into nine regions, each encompassing several states. The FHFA regional index is only available from 1975 onward; for earlier years, we used Robert Shiller's national real home price index (Case–Shiller) (`https://shillerdata.com/`) to capture the full respondent history, using variation across

housing market experiences are DS for these markets and NDS for own life expectancy.

Economic experiences. We also construct childhood socioeconomic status, defined as the first principal component of the following variables: father's years of education, mother's years of education, and whether –when the respondent was a child – the father was unemployed (1,0), the mother worked (0,1), the family moved due to financial difficulty (1,0), received financial aid (1,0), lived in a rural area (1,0), and spoke English at home (1,0).[6] This proxy reflects NDS experiences for stock and housing markets, and remote DS ones for life expectancy.

2.2 Recall Fluency and IQ

The HRS measures a range of cognitive faculties. We focus on memory but also consider mathematical ability. Memory is measured using three tasks. The first two are based on word lists, following vast work (Kahana, 2012) unveiling the robust recall regularities that underlie our model in Section 3. Respondents study a 10 word list and are asked to recall the words: i) right after the study period (Immediate Memory task), and ii) after a five minutes questionnaire on mental health (Delayed Memory task). Memory performance is the number of successful recollections. In the third task, available in waves 2010-2020, respondents must name as many animals as possible in 60 seconds. Performance is the number of recalled animals. We construct an index of *Recall Fluency* (RF) by standardizing memory scores across waves and by averaging, in each wave, a respondent's available components.[7] These tasks capture recall in an almost idealized context. They abstract from differences in education and world knowledge (the words are common), and do not entail symbol manipulation, rules, or reasoning.

Mathematical ability is also measured in the HRS using three tasks. In the first, counting backwards, respondents must perform subtractions starting from a given number. In the second, number series, they must guess a rule by filling the last item of a series. In the third, numeracy, they must convert percentages into absolute frequencies. Higher performance indi-

birth cohorts rather than only the cross-sectional variation in home prices across census regions. Appendix Table B.3, Panels A and B, details the construction of the stock-market and home price experience databases.

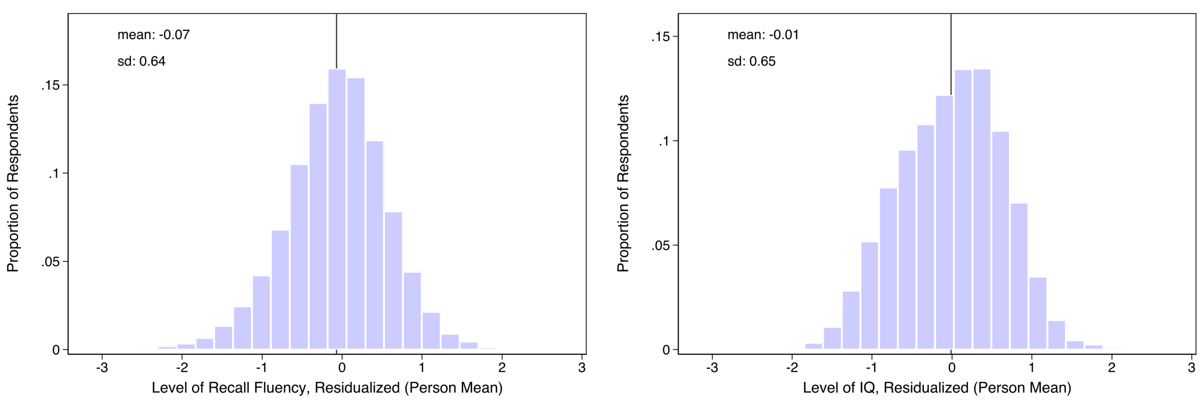
[6]See Appendix Table B.2, Panel 7, for construction of the childhood socioeconomic status index, which we use as a non-domain-specific experience.

[7]Appendix Table B.2 lists the components and aggregation of the recall-fluency and IQ indices, along with every other index used in the paper.

cates higher math ability. Counting backward is available in all years, number series is elicited in the 2010, 2012, 2016 and 2020 waves, numeracy is only asked to first-time respondents. Math ability affects the use of statistical information, a key driver of beliefs in standard models. Controlling for it allows us to isolate the effects of memory.[8] We capture math ability by index IQ, constructed by standardizing math performance in each task across waves and by averaging, in each wave, a respondent's available components.

Figure 1: Distribution of Recall Fluency and IQ.

Panel A: Recall Fluency (Residualized) *Panel B: IQ (Residualized)*



Notes: Each panel plots the distribution across respondents of a person-level average, where for each respondent the relevant index is averaged over all survey waves in which they appear (one observation per respondent). Panel A shows person-level average Recall Fluency (RF) after residualizing on IQ, age, income, education, gender, marital status, and retirement status; Panel B shows person-level average IQ after residualizing on RF and the same demographics. Both indices are constructed as the standardized mean of their components and are expressed in standard deviation units. Sample: HRS respondents, waves 2002–2020. The raw (un-residualized) person-level distributions are reported in Appendix Figure C.3, and the corresponding pooled (person-wave) distributions in Appendix Figure C.4 (residualized) and Figure C.5 (raw).

Figure 1 plots the distributions of person-level average RF (Panel A) and IQ (Panel

[8]The HRS also elicits: 1) General Knowledge, consisting in factual recall (e.g., identifying the current President or today's date), 2) word meaning, requiring definition of vocabulary items (e.g., "repair," "fabric," "plagiarize"), and 3) verbal analogies such as filling "Mother is to Daughter as Father is to [blank]". The first two measures align with the crystallized intelligence psychometric, verbal analogies are less clear. We do not incorporate these measures in our IQ index to keep the sample large: verbal analogies are available in only three survey waves (2012, 2014, and 2018), general knowledge is administered to only half of respondents in each wave, and word meanings is administered only to first-time respondents.

B) after residualizing RF (IQ) by IQ (RF) and demographics. Memory tasks do not require math ability but some math tasks (e.g. counting backwards) benefit from memory. Consistent with this notion and with the well documented association of cognitive faculties (Spearman, 1904; Unsworth et al., 2024), the correlation between RF and IQ is positive, equal to 0.4 (see Table C.1). Further statistics are in Appendix Figure C.5.

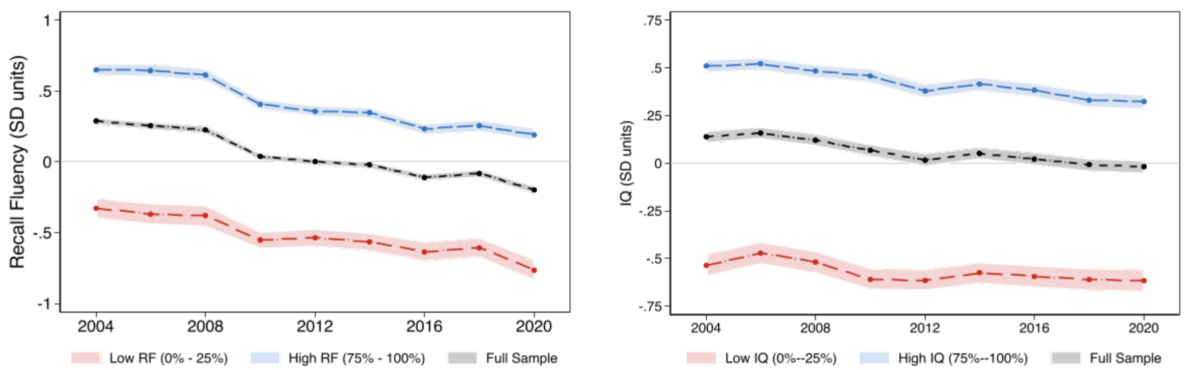
There is however large independent variation: Regressing Memory (IQ) on demographics yields an R^2 of only 0.24 (0.21). Adding IQ (Memory) to this regression raises the R^2 to 0.3 (0.28). When averaging a person's scores across waves, (Appendix Figure C.4) the standard deviation of RF shrinks by only 0.17 and that of IQ by only 0.15 after residualizing. We can thus study RF controlling for IQ. Does Figure 1 reflect stable interpersonal differences or cognitive aging/diseases?. What is their relative importance? Figure 2 reports, for the 3,643 respondents present in all waves, the average of the index over time (black line), the average among respondents in the top 25% of the index in 2002 (blue line) and that among those in the bottom 25% in 2002 (red line). RF is in Panel A, IQ in Panel B. For IQ we plot counting-backwards, which is available throughout 2002–2020. Appendix Figure C.2 shows the full IQ index alongside this sub-index.

Interpersonal differences in RF are stable, large and dominate the average over time memory decay. The interquartile range in RF is 1.68 standard deviations in 2004, and 1.4 in 2020 (in comparison, the average RF declines by 0.68 standard deviations between 2002 and 2020).[9] Stable differences emerge at the level of individual measures: Appendix Figure C.1 plots the Spearman rank correlation between each pair of memory sub-components at lags of zero to five survey waves, corresponding to a horizon of up to ten years. Correlations remain high across all lags, showing stable performance rankings. Similar patterns appear, but are less pronounced, for IQ: there is a slight average decay from 0.18 in 2002 to -0.02 standard deviations in 2020, but cross-sectional gaps are stable.

[9] We cannot compare quartiles in 2002 because we are conditioning on variation in RF which is partly driven by random shocks that revert in 2004. The "within" standard deviation due to age is 0.59, the "between" standard deviation due to average differences is 0.68, implying that the latter accounts for 54% of the total variance in RF, see Table C.2. If we residualize respondents' average RF by average IQ, the standard deviation drops by 0.13. again, there is a significant orthogonal variation in the two measures.

Figure 2: Recall Fluency and IQ Over Time, by Quartile

Panel A: Recall Fluency *Panel B: IQ*



Notes: The figure plots the average level of Recall Fluency (Panel A) and IQ (Panel B) in each survey wave from 2004 to 2020. Panel A uses the full memory index. For IQ (Panel B) we plot only the counting-backwards sub-index, the single IQ component administered in every wave, because the number series and numeracy components enter only from 2010; the full IQ index is shown alongside the always-available sub-indices in Appendix Figure C.2. Blue lines show respondents in the top 25% of the respective index in 2002; red lines show the bottom 25%; black lines show the full sample. Shaded bands are 95% confidence intervals. The sample is restricted to respondents present in all ten survey waves (2002–2020). 2002 is omitted as it is the base year for group assignment. Memory and IQ are expressed in standard deviation units.

In sum, Recall Fluency, measured following a longstanding tradition in psychology, is a stable personal trait. We next show that this trait sharply correlates with beliefs about aggregate and personal events.

2.3 Recall Fluency and Beliefs

Panel A of Figure 3 reports the raw average estimate for the "percent chance stocks are worth more in 1 year" across survey waves, for the top (blue) and bottom (red) RF quartiles.

There is a large difference between high and low RF participants, in the level and time variation of beliefs. High RF people on average estimate a stock market increase to be 8 percentage points more likely than low RF people (who estimate an average 42% probability). While on average more accurate, the high RF group is still too pessimistic relative to the frequency of stock market increases in the sample, which is 80%.

Differences in time variation are also large: the two groups respond differently to the 2008 financial crisis (dashed vertical line). High RF individuals exhibit sharper adjustments, particularly during and after the crisis, with beliefs falling by 3.4 percentage points from the 2004 peak, and recovering by 2.5 percentage points from the 2008 trough; over the same periods, low RF beliefs fall by 0.7 p.p. and recover by 0.8 p.p.

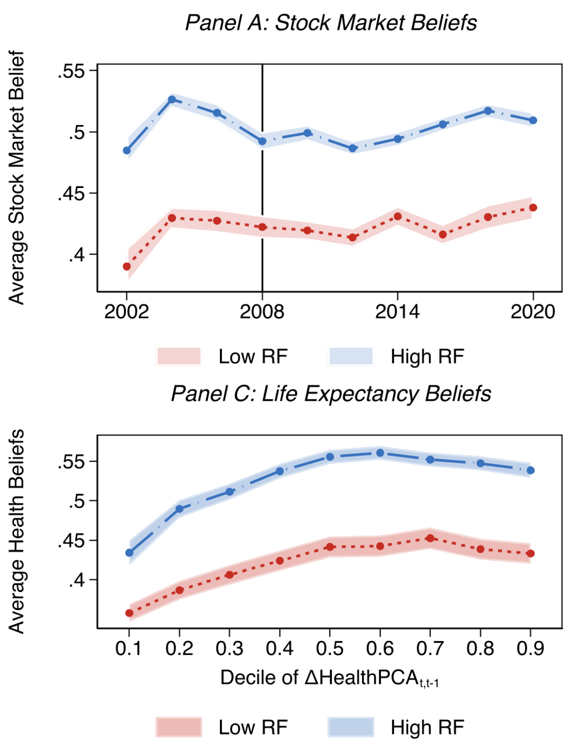
Panel B of Figure 3 reports the average estimated percent chance that the respondent's own home will be worth more in one year, again for the two RF groups. The question is asked to homeowners— who fully own or are paying off their mortgage—corresponding to 44% of the sample, and is available only from 2010 onwards, so after the financial crisis.[10] The beliefs of high RF people again exhibit sharper time variation. Right after the crisis high RF people are a bit more pessimistic about their home prices than low RF ones (their belief drops by 6.2 percentage points more than those of low RF individuals during 2010–2012). As house prices increase, though, their beliefs swiftly recover (rising by 21.5 percentage points from 2012 to 2016, versus 7.9 for low RF) and become more optimistic than the latter group. Both groups underestimate the chance of price increases relative to their frequency:[11] by 37.8 percentage points for high RF and 41.5 percentage points for low RF individuals.

Finally, Panel C of Figure 3 reports beliefs about own life expectancy as a function of "health fundamentals": the average estimated probability of surviving at least ten more years as a function of the respondent's current change in health status. High RF people are much more optimistic about their life expectancy than low RF people at every level of current measured health. Again we see higher sensitivity to changing conditions: their optimism rises more steeply as health improves. The cumulative increase in beliefs across the full health range amounts to 10.5 p.p. for the high RF group compared to 7.5 p.p. for the low RF group.

[10] The home-price question uses two framings: some homeowners report the probability that their home will be worth *more* in a year, others the probability it will be worth *less*. To use all homeowners we pool the two —reverse-coding negative-frame responses onto the probability-of-increase scale and adding a constant equal to the difference in mean belief between the two framings, so that the reverse-coded negative-frame group is level-matched to the positive-frame group. This adjustment affects levels, not the sensitivity of beliefs to experiences and cues. Appendix Figure C.8 shows the belief series separately by question framing.

[11] Because we observe regional home prices we cannot estimate each respondent's forecast accuracy.

Figure 3: Average Beliefs Over Time by Recall Fluency.



Notes: Each panel plots the average raw (un-residualized) belief for the top (blue) and bottom (red) quartile of Recall Fluency; the residualized counterpart is Appendix Figure C.7. Panel A: stock market beliefs ("chance stocks will be worth more in one year") by survey wave. Panel B: home-price beliefs ("chance home will be worth more in one year") by survey wave from 2010 onward, pooling both question framings. Panel C: life-expectancy beliefs ("chance live 10+ years") by decile of health change ($\Delta\text{HealthPCA}_{t,t-1}$). Shaded bands are 95% confidence intervals. Sample: HRS respondents, waves 2002–2020 (home prices 2010–2020). The raw belief distributions are shown in Appendix Figure C.9.

In sum, we see a strong and surprising regularity: individual performance in abstract word recall tasks is associated with sharp differences in beliefs about macroeconomic and personal events. RF shapes mean beliefs but also their reaction to changing conditions. Why is this the case? One possible answer is omitted variables: high RF people may have different tastes or information from low RF ones. This is not fully plausible because word recall tasks do not rely on information or preferences. Moreover, the pattern is quantitatively unchanged when we residualize beliefs on demographics and IQ (see Figure C.7 in the Appendix). We will systematically control for these covariates in our tests.

A different possibility is that the - analogously to economic production functions - RF genuinely captures a parameter of a person's "recall technology", which affects her performance in laboratory recall tasks but also her recall of data in the field and then her beliefs, giving rise to the patterns observed above. To assess this mechanism, we introduce a model of mnemonic beliefs. The model disciplines the role of RF, giving distinctive predictions of the memory mechanism in our setting.

3 The Model

We interpret RF through a model of mnemonic expectations (Bordalo et al., 2025, 2026a, Bonaglia and Gennaioli, 2025), which is built on the recall regularities established using word lists (Baddeley and Hitch, 1974; Kahana, 2012). We first describe the recall part of the model and link RF to one of its parameters. We then derive the model's implications for expectations and their link to RF.

3.1 The Recall Technology

Memory hinges on: i) a database of experiences, ii) the cue, and iii) a retrieval function mapping the cue to retrieval from the database. Recall follows three regularities: frequency, similarity, and interference (Kahana, 2012). We later describe how each manifests in word list tasks.

The database. A category of experiences is a trace e in a mnemonic (metric) space E. The database is a frequency distribution over E, denoted $\mathbf{f} = \{f_e\} \in \Delta(E)$. The generic vector $e \in E$ reports the objective realization/signal $s \subset \mathbb{R}$ of the experience, its emotional valence $v \subset \mathbb{R}$, and its semantic context $c \subset C$, where C is a context space, so that $e = (s, v, c)$. A category of positive stock market experiences reports a numerical return range, say $s = (2\%, 3\%)$, a marker for positive emotional valence, $v > 0$, and context features such as the semantic "stock market" context, the year, location, etc.

Similarity and cues. The mnemonic space is endowed with a function $d : E \times E \rightarrow \mathbb{R}$ that measures the discrepancy between any two experiences $e, e' \in E$, where $d(e, e')$ increases in the difference among their features. Similarity between two experiences is bounded and decreases in $d(e, e')$. If e' is a personal illness, it differs from a stock market experience along the objective, subjective, and context features, entailing a high $d(e, e')$ and hence low similarity. As in Bordalo et al. (2025, 2026a) we later measure perceived similarity.[12] A cue is a subset $q \subseteq E$ shaping retrieval from database $\mathbf{f}$ as follows:

$$r_e(q, \mathbf{f}) = \frac{S(e,q) \cdot f_e}{\sum_{e' \in E} S(e', q) \cdot f_{e'}} \tag{1}$$

The numerator captures similarity 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 even more similar to q or frequent experience $e' \neq e$. Interference is the key force RF proxies for, as we describe next.

3.2 RF in The Recall Technology

To link RF to a model parameter, we heuristically map Equation 1 to word list tasks (a precise mapping can be done using contextual drift models).

Study phase. The study of a list affects the database. A word in serial position $j = 1, \ldots, n$ has an objective signal/phonetic w_j and a context c_j capturing semantic and temporal features (we abstract from valence). Let $L \subset E$ be the set of list traces $e_j = (w_j, c_j)$. Encoding and rehearsal during study attaches positive frequency f_j to each e_j.

Recall phase. In Equation 1, the initial cue q_0 is the word list $(w_j)_j$ and the initial context is c_0. The initial cue shapes the first recalled word, which in turn affects the cue, the second recalled word, etc.

There are four key regularities (Kahana, 2024): primacy (words studied earlier in the list are more likely to be recalled), recency (words appearing later on the list are more likely to be recalled than words in the middle), contiguity (recalling a word in position 5 fosters recall

[12] A discrepancy function is usually defined in terms of the overlap of features of singleton events. It can be extended to sets of events, such as the experiences $e \in E$, by an equal-weighted average of discrepancies between singleton experiences. Rather than the distribution over a metric space, distributed memory models formalize the database as a sum of vectors (Murdock, 1982). These approaches have similar implications for our analysis.

of words in position 4 or 6), and semantic proximity (recalling "car" fosters recall of "brake").

Primacy reflects frequency: the first word studied w_1 tends to be rehearsed more often than others, increasing its encoded frequency f_1 and thus its recall in Equation 1.

The other three regularities reflect similarity. Consider recency: the last word studied w_n has a temporal context c_n similar to the retrieval context c_0, increasing its recall in Equation 1. Consider contiguity and semantic effects: as words are recalled, the cue – often formalized using the AR(1) process $q_{t+1} = \rho q_t + (1-\rho)e_j$, $(1-\rho) \in (0,1)$ – is influenced by the last recalled word. That word pollutes q_{t+1} with a context c_j that favors recall of words studied at similar times (contiguity), or that have related meanings (semantic).

Interference in the denominator of Equation 1 explains forgetting of words on the list, and hence low RF. First, recall of a frequently rehearsed, recent, contiguous, or semantically similar word e_j on the list inhibits retrieval of other words e_k that do not have these properties. Second, a randomly intruding thought from an outside-the-list experience $e \notin L$ can block recall from the list, the so called extra-list intrusions (Zaromb et al., 2006).

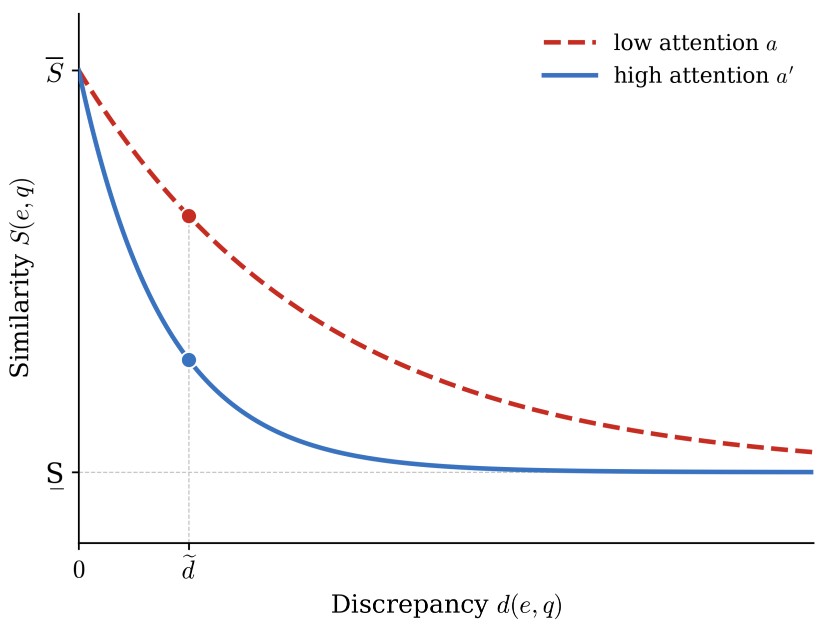
Recall Fluency. In most experiments, the time delay between study and recall is short, so forgetting – and hence low RF – is not due to depreciation of stored traces but to interference: the inability of the subject to focus on words on the list compared to distracting items. Subjects with a greater ability to focus on words on the list will exhibit higher RF. This interpretation points to RF as a parameter linked to a subject's attention: people more focused on the features of the list are less likely to recall distracting items. The role of attention in word tasks has been studied since Murdock (1965) and in fact is viewed as a main driver for the primacy effect, the tendency to better remember the first word on the list (when attention is presumably higher). Consistent with this, higher attention at encoding, as measured by pupil dilation, is associated with stronger recall (Miller and Unsworth, 2021). Related, Hartzmark et al. (2021) show that higher attention to news, caused by asset ownership, fosters recall accuracy.[13] Widely used memorization techniques rely on attending to contextual associations

[13] Also consistent with a role of attention, instructing participants to classify words along a feature, such as pleasantness or size, increases subsequent retrieval of words associated with that feature (Polyn et al., 2009),

between recall targets. Strongly encoded associations then favor sequential retrieval, reducing interference from non-targets, and increasing overall retrieval (Sederberg et al., 2008). Finally, and related to stable differences in RF, persistent variation in attention across people is also well documented (Hirmas et al., 2024; Rosenberg et al., 2016; Unsworth et al., 2024).[14]

In the model, and consistent with psychology, attention is linked to perceived similarity (Nosofsky, 1986): if two objects differ in a feature, greater attention to that feature reduces their perceived similarity. This mechanism directly maps to the similarity function in Equation 1. To see this, take the function $S(e,q) = \mathcal{S}\left[a \cdot d(e,q)\right]$ where $\mathcal{S}$ is decreasing and $a \in (0,1)$ is a measure of attention to all features. Figure 4 plots the similarity function of a person with higher a, the blue curve, and of a person with lower a, the red one.

Figure 4: Similarity as a Function of Discrepancy, at High Versus Low Attention.



Notes: We plot a similarity function $S(e,q) = \mathcal{S}[a \cdot d(e,q)]$ with $\mathcal{S}$ decreasing and bounded between $\underline{S}$ and $\overline{S}$. The blue curve reflects higher attention ($a' > a$) than the red curve. The functional form is $\mathcal{S}(x) = \underline{S} + (\overline{S} - \underline{S})\exp(-x)$.

For experiences identical to the cue, $d(e,q) = 0$, similarity is maximal and equal to $\overline{S}$,

and clustering words in noticeable categories also fosters recall.

[14] A wide range of tasks are used to measure such individual differences, including sustained attention and interference-control in Stroop-type tasks, which reveal substantial individual variation closely related to working memory and other cognitive abilities.

regardless of a. Attention matters when there are discrepancies between the cue and experiences, because the subject with higher attention a exhibits a "sharper" similarity function: an experience $\widetilde{e}$ with discrepancy $\widetilde{d}$ is perceived to be quite similar to q under low attention (red), as dissimilar under high attention (blue).[15]

The link between attention and RF follows: when cued with the list, the high attention person is less likely to recall experiences that are dissimilar from it, exhibiting better recall of targets and hence higher RF. To see this formally, consider the probability of recalling any given studied word from list L in period t (with cue q_t):

$$\Pr\left(e_j \in L | q_t\right) = \frac{\sum_{e_j \in L} \mathcal{S}\left[a \cdot d\left(e_j, q_t\right)\right] \cdot f_{e_j}}{\sum_{e' \in E} \mathcal{S}\left[a \cdot d\left(e', q_t\right)\right] \cdot f_{e'}} \tag{2}$$

By differentiating Equation 2 around $a_0 = 0$ we obtain:

$$\frac{\partial \Pr\left(e_j \in L | q_t\right)}{\partial a} > 0 \quad \iff \quad \frac{\sum_{e_j \in L} d\left(e_j, q_t\right) \cdot f_{e_j}}{\sum_{e_j \in L} f_{e_j}} < \frac{\sum_{e \notin L} d\left(e, q_t\right) \cdot f_e}{\sum_{e \notin L} f_e}. \tag{3}$$

Higher a increases the probability of recalling any target e_j if words on the list have on average more features in common with the cue q_t than do other experiences. This condition is satisfied because items in the list share many features, the time and place when they are studied, the task context, etc, compared to most experiences in the memory database. Higher attention a then increases the total number of retrieved words, increasing RF.

In sum, in a mnemonic expectations model variation in RF ties to variation in attention-driven interference. Being a domain general feature of the recall technology, RF can then influence a person's beliefs and choices in the field. We next derive comparative statics of beliefs with respect to RF, which gives rise to our predictions. From now on, we proxy for a person's attention a_i with the measured RF_i.[16]

[15] Figure 4 assumes bounded similarity, so that attention matters little for highly discrepant experiences, i.e. large $d(e, q)$. This property can be relaxed.

[16] By Equation 1, variation in RF may also arise due to differences in the encoded frequency f_j of words on the list L. This occurs if some people encode recent events more weakly (their f_j is lower) or have more numerous extralist experiences (their $\sum_{e \notin L} f_e$ is higher). This effect can contribute to the decline of RF with age: older people encode recent events less and have more irrelevant experiences than young ones (Craik and Salthouse,

3.3 Selective Recall and Beliefs

The DM forms beliefs about event $T_X \subset \mathbb{R}$, in domain $X = SP, HP, LE$, where SP and HP are stock and own home prices, LE is life expectancy. Following Bordalo et al. (2025), beliefs are formed by: i) recalling experiences $e = (s, v, c) \in E$, characterized by their realization, valence, and context, and by ii) using these experiences to imagine T_X (Hassabis et al., 2007; Schacter et al., 2007). The cue for person i at time t specifies: the current realization $s_{X,it}$ (recent stock return, home price growth or changes in personal health), the respondent's affective state v_{it} (higher values stand for better mood), and the semantic context $c = X$ (we abstract from temporal context). Formally $q_{X,it} = (s_{X,it}, v_{it}, X)$. These features ignite retrieval from E.

Upon retrieving $e \in E$, the DM uses it to imagine an outcome in the target space $\mathbb{R}$ based on a simulation function $\sigma_X : E \to \mathbb{R}$ that satisfies the following properties.

Assumption 1 *When forecasting X, simulation based on $e = (s, v, c)$ satisfies:*

$$\sigma_X(e) = \begin{cases} h(s) & if \quad c = X \\ h_X(v) & if \quad c \neq X \end{cases} \tag{4}$$

where h: $\mathbb{R} \to \mathbb{R}$ is increasing. Function h_X: $\mathbb{R} \to \mathbb{R}$ is increasing if and only if higher values in X have higher valence for the DM. h_X takes a default value δ_X for "neutral" events $(v = 0)$.

When the DM retrieves a Domain-Specific (DS) experience e in $c = X$, she imagines the future using an increasing function h of the recalled realization s. A DM is more optimistic about stock returns if she recalls a return of 10% rather than 1%. Recalling higher stock returns, home price growth, or better health prompt higher forecasts in the same domain.

When the DM retrieves a Non-Domain-Specific (NDS) experience, $c \neq X$, she simulates based on valence, imagining a rosier future if the retrieved experience has higher v. Recalling pleasurable personal financial experiences (i.e. earning a bonus) helps imagine high stock returns or growth in the price of one's own home, and conversely if bad experiences are recalled.

eds, 2008; Healey et al., 2008). This mechanism, however, is less relevant in our context where – to form beliefs – HRS respondents must also rely on changing current cues and on experiences from the remote past.

This prediction rests on higher realizations to be perceived as good by the DM, and hence similar to positive NDS, an assumption we later test. If instead the recollection is neutral, $v = 0$, simulation is inhibited: the DM picks an agnostic default δ_X such as "I do not know" or an arbitrary element in the response scale. Thinking about routine events such as walking to the same office do not aid simulation.

In sum, simulation is more powerful when the recalled experience is more similar to the target. It is sharper for DS experiences, but carries over to NDS ones that are congruent with the current affective state. Simulation is instead insensitive to experiences that differ both semantically and affectively from the cue.[17]

Based on recall and simulation, the average future state $\mathbb{E}_{it}(s_X)$ in X imagined across many memory samples by a respondent i facing a cue $q_{X,it}$ and database $\mathbf{f}_i$ obeys:

$$\mathbb{E}_{it}(s_X) = \sum_{e \in E} r_e(q_{X,it}, \mathbf{f}_i) \cdot \sigma_X(e) \tag{5}$$

The expectation is higher when the DM selectively recalls experiences leading to higher simulation. We use this equation as the source of our predictions. The probability of the events T_X elicited in the HRS in fact increases in the average expected value in domain X, so comparative statics for 5 carry to T_X.[18] To obtain predictions we linearize $S(e,q) = \mathcal{S}[a \cdot d(e,q)]$ at the constant similarity benchmark $a = 0$, and proxy attention a_i with measured RF_i.

Proposition 1 *Let $|\mathbf{f}_{it}|$ be the total number of experiences in the database of agent i at time t, and $d(q_{X,it})$ the average discrepancy of experiences in the database from the cue $q_{X,it}$. The average simulation of the future realization in domain X then satisfies:*

$$\mathbb{E}(s_X | q_{X,it}, \mathbf{f}_{it}) \approx \sum_e \frac{f_{e,it}}{|\mathbf{f}_{it}|} \cdot \sigma_X(e) + \mathrm{RF}_i \cdot \sum_e \frac{f_{e,it}}{|\mathbf{f}_{it}|} \cdot [d(q_{X,it}) - d(e, q_{X,it})] \cdot \sigma_X(e) \tag{6}$$

[17] We can generalize and allow for h_X to flatten with context distance, as in Bordalo et al. (2026a). Our predictions are strengthened if we allow for this property.

[18] Results would change little if the assessed probability of the target event is modelled as the probability of recalling experiences that allow to simulate it, $\sum_{e:\sigma_X(e) \in T_X} r_e(q_{X,it}, \mathbf{f}_i)$.

The first term on the right-hand side says that the belief is anchored to the database, summarized by frequency weighted experiences. Thus, a person is more optimistic about X (e.g. stock returns) if she had more positive DS experiences (high stock returns) or more NDS experiences that prompt stock market optimism (e.g. positive personal financial experiences). The second term captures our key mechanism: higher RF renders simulation more dependent on experiences that are above average similar to the cue. When thinking about the stock market, high RF reduces interference from a myriad of events incongruent with the cue in terms of valence, context or realization.

To separate DS and NDS experiences we postulate a tractable discrepancy function:

$$d\left(e, q_{X,it}\right) = \begin{cases} \left(s_{it} - s\right)^2 & if \quad c = X \\ K & if \quad c \neq X, \ v \subseteq v_{it} \\ K + V & otherwise \end{cases} \tag{7}$$

In Equation 7, the discrepancy of a DS experience e from the cue $q_{Xi,it}$ increases in the quadratic distance between their numerical realizations s and s_{it}. When thinking about the stock market in a year where returns were 10%, a 3% stock return experience is less similar than a 9% one.

Discrepancy then jumps to K for an NDS event with congruent valence (where K is sufficiently high that $(s_{it} - s)^2 < K$ for realistic s). When thinking about the stock market in a year where returns were 10%, a positive NDS such as an income windfall is less similar than a stock market experience, but still somewhat similar to the 10% stock return, due to shared positive valence. Discrepancy then further jumps to $V > K$ if the NDS experience is also valence-incongruent with the cue. When thinking about the stock market in a year with 10% return, a past financial trouble or a disease are least similar due to low valence.

This ranking means that the DS experience is ceteris paribus most likely to be recalled, the valence incongruent NDS least likely to be recalled, and the valence congruent NDS is in the middle. Three predictions linking RF to beliefs then follow.

Prediction 1 (DS, RF, *and beliefs*) *Let $\overline{s}_{it}$ be the average DS signal in the database. With a* *linear approximation of* $h(s)$*, there are positive constants* $\eta_0, \eta_1, \eta_2, \eta_3$ *such that beliefs satisfy:*

$$\mathbb{E}\left(s_X | q_{X,it}, \mathbf{f}_{it}\right) \approx \eta_0 + \eta_1 \cdot \overline{s}_{it} + \eta_2 \cdot \mathrm{RF}_i \cdot \overline{s}_{it} - \eta_3 \cdot \mathrm{RF}_i \cdot cov\left[s, (s - s_{it})^2\right]. \tag{8}$$

The DM imagines a higher future state if she experienced a higher average state $\overline{s}_{it}$ in her DS experiences, $\eta_1 > 0$. This "experience effect" is driven by having merely lived the event, as in Malmendier and Nagel (2011, 2016), which we capture via frequency based retrieval.

Critically, similarity entails two additional effects. First, $\eta_2 > 0$ says that the marginal impact of $\overline{s}_{it}$ is stronger for a person with higher RF: when cued to think about, say, the stock market, this person recalls many more stock market experiences, becoming more sensitive to their average value $\overline{s}_{it}$ in her database. Living an experience does not guarantee a strong effect: the experience must be recalled, which is that high RF guarantees.

Second, among DS experiences, a high RF person more strongly recalls past signals s that are close to the current cue s_{it}. That is, upon seeing a 10% stock return a high RF person recalls many past returns close to 10%. This force causes an additional belief boost if 10% returns are above the person's average experienced return (while it deflates beliefs if the same 10% are below it). Intuitively, $cov[s, (s - s_{it})^2]$ proxies for the dissimilarity between the current return and the respondent's above average experiences. A respondent's belief then over-sample her above average past return, and hence is more optimistic, if these returns are less dissimilar from the current return, namely the covariance term is lower.

Evidence for this effect of cues has been found by Gennaioli et al. (2025) who show that the inflation expectations of US households can rapidly increase if current inflation is similar to the high inflation experienced by these people in the past, as captured by a negative covariance coefficient. We make a key new prediction testable in the HRS: the effect should be stronger for people with higher RF, who better recall the similar past.

Note that these comparative statics indicate that high RF people do not necessarily have "better" beliefs: they may in fact extrapolate more from their own experiences as well as from time varying cues into the future. Thus, their beliefs may be excessively volatile with changing current conditions. This is consistent with Hartzmark et al. (2021), who find that greater attention to recent stock returns, in their case driven by ownership, leads to greater extrapolation in beliefs about future returns.

A second role of RF is its differential impact on the retrieval of NDS experiences. This is a second key way in which higher RF may not entail more accurate beliefs.

Prediction 2 *Suppose that neutral NDS experiences are frequent enough relative to others. There is an* $\eta_4 > 0$ *such that having lived a* v*-congruent NDS affects beliefs as follows:*

$$\left.\frac{\partial \mathbb{E}\left(s_X | q_{X,it}, \mathbf{f}_{it}\right)}{\partial f_{e,it}}\right|_{v \subseteq v_{it}} \approx \frac{1}{|\mathbf{f}_i|} \cdot \left[h_X(v) - \delta_X\right] + \eta_4 \cdot \mathrm{RF}_i \cdot \left[h_X(v) - \delta_X\right] \tag{9}$$

where by assumption $h_X(v) > \delta_X$ iff $v > 0$. Recall of a valence-congruent NDS experience is is "belief-boosting" if its valence is positive ¿ 0 and belief-decreasing otherwise. This role of NDS experiences has been already documented (Bordalo et al., 2025, 2026a; Cenzon, 2026; Taubinsky et al., 2026). The key new prediction here, which can also be tested in the HRS, is that if NDS experiences are numerous compared to DS ones, their effect increases with RF. The intuition is that interference hinders recall of all experiences that share some feature with the cue q_X. By reducing such interference, higher RF increases the effect of valence congruent NDS experiences. At zero RF the NDS effect may be small or zero: an individual NDS experience would face strong interference, especially in large databases. At high RF, by contrast, the NDS is selectively recalled and used in simulation.

Because many NDS are statistically uninformative about the target event (e.g. a past personal illness is uninformative about the future aggregate stock market) this prediction shows that the beliefs of high RF people may be too anchored to spurious simulation material compared to those of low RF ones. Overall, then, memory implies that higher RF is not just a proxy of less attenuation in the response to signal. It is a proxy for stronger sensitivity to cues, which may entail overreaction via excess sensitivity to DS information and simulation based on uninformative NDS experiences.

A final prediction follows from the previous two. Because a high RF person retrieves more material that helps her imagine the future, she is more likely to have a grounded opinion and less likely to exhibit the agnostic belief δ_X.

Prediction 3 (RF *and agnosticism*) *Let* $f_{n,it}$ *be the frequency of neutral events* ($v = 0$)*. The probability of an agnostic default is* $\frac{f_{n,it}}{|\mathbf{f}_{it}|} \{1 + \mathrm{RF}_i \cdot [d(q_{X,it}) - K - V]\}$*, which falls in* RF_i*.*

By anchoring beliefs to related experiences, higher RF reduces recall of irrelevant experiences and hence the use of the agnostic default. High RF causes beliefs to move more with task-related experiences and cues, even if NDS, and less with random factors.

In sum, a model of mnemonic beliefs predicts a systematic role of RF in mediating the relationship between beliefs, cues and experiences. These predictions sharply distinguish memory from standard models in which beliefs merely rely on information (in a rational or distorted way), or on tastes. Indeed, if high RF was to proxy for more extensive acquisition and processing of information, it would not be associated to a heightened role of uninformative NDS experiences (nor of personal DS experiences, which are arguably less used by an informed person compared to objective data). Preference based explanations, according to which high RF proxies for motivated beliefs, cannot explain the symmetric role of RF in amplifying the reaction to positive and negative news that we indeed saw in Section 2 (high RF people exhibit more volatile beliefs across good and bad events). We now bring these predictions to the data.

4 Testing the mechanism

We first test Prediction 1 on DS experiences, we then move to Prediction 2 on NDS ones, and conclude with Prediction 3 on agnostic responses.

4.1 Domain Specific Experiences

We estimate Equation 8 for stock prices, own home prices, and own life expectancy. DS experiences vary across these outcomes but the memory structure in Equation 8 is the same.

The estimated probability $p_{X,it}$ in domain $X = SP, HP, LE$ by respondent i at time t obeys:

$$p_{X,it} \approx \gamma_0 + \gamma_1 \cdot \overline{s}_{it} + \gamma_2 \cdot \mathrm{RF}_i \cdot \overline{s}_{it} - \gamma_3 \cdot \mathrm{RF}_i \cdot cov\left[s, (s - s_{it})^2\right], \tag{10}$$

where all coefficients are positive. We compute proxies for experiences using the database described in subsection 2.1 and Table B.3. In the stock market, $\overline{s}_{it}$ is the average yearly stock return experienced by the respondent, while the cue s_{it} is the recent stock return, which triggers retrieval of similar past returns s encoded in the respondent's stock market memories.

For home prices, $\overline{s}_{it}$ is the average home price growth experienced by the respondent, the cue s_{it} is the recent home price growth, which triggers the retrieval of similar past home price growth experiences s encoded in the respondent's housing market memories. For life expectancy $\overline{s}_{it}$ is the average change in health lived by the respondent, the cue s_{it} is the respondent's current change in health, which triggers selective retrieval of similar past changes in health s encoded in the respondent's health memories.[19] We also include childhood health as a DS regressor.

Table 1 reports, for each domain, the estimates of Equation 10 in columns 1,3, and 5. In columns 2, 4 and 6 we add RF non-interacted to control for the possibility that it may affect the level of beliefs. The results support the memory mechanisms. In each domain, beliefs increase in "positive past DS", but especially so for high RF people. Cues also matter, as indicated by the negative coefficient on the covariance term: a piece of news similar to an agent's above average experiences causes stronger optimism for high RF people. Thus, similarity works through RF, consistent with this proxy capturing a general purpose memory technology shaping retrieval in abstract tasks and the field. The the results are very robust: Table D.2 adds survey-year fixed effects, ruling out common aggregate shocks as the driver, Figure D.4 perform separate estimation in different RF quartiles, excluding a the role of functional form assumptions.

Important, the results show that RF is very distinct from IQ. The latter affects beliefs in different and independent ways from memory. Higher IQ prompts optimism about stocks

[19]The results are if anything stronger if we use the level (rather than change) in health to measure experiences.

and home prices, perhaps reflecting better information, but unlike RF it prompts pessimism about life expectancy. This confirms that higher RF may not entail normatively better beliefs: it may lead to excess extrapolation, including from personal good health. We scrutinize the role of IQ by interacting it with current news s_{it}, capturing a possible stronger reaction of intelligent people to information. Results (see Table D.1) are robust: the recall-fluency covariance term $-\gamma_3$ remains negative and significant in all domains.

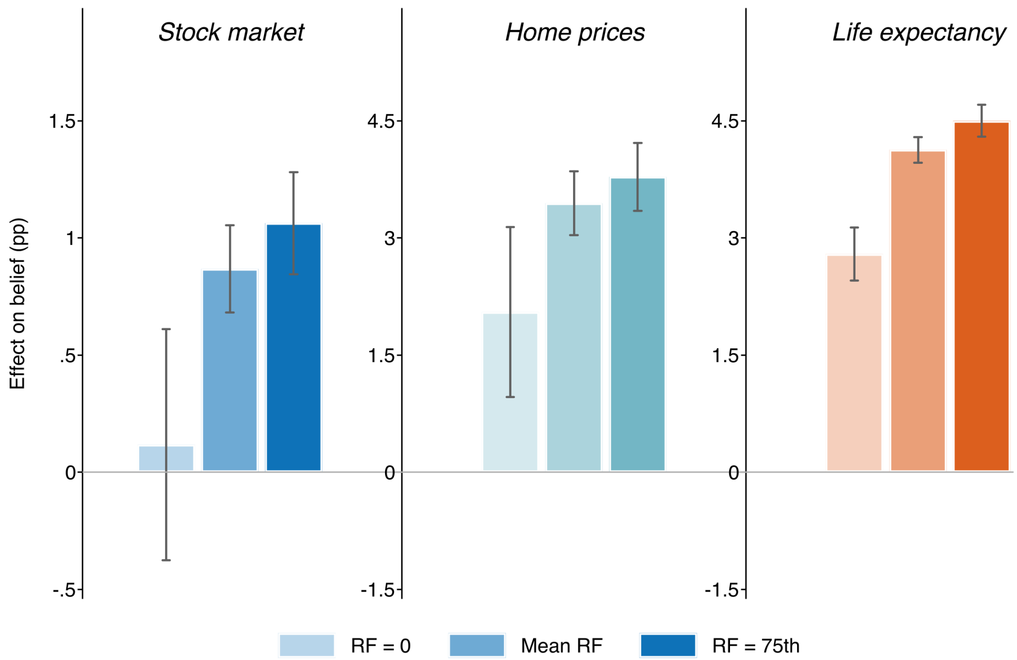
Table 1: Database Regressions for $\overline{s_{it}}$ and $cov(s_k, (s_k - s_{it})^2)$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Chance Stocks ↑		**Chance Home ↑**		**Chance Live10+**	
Cognition						
RF	.	0.002	.	-0.013	.	-0.003
	.	[0.005]	.	[0.010]	.	[0.003]
IQ	0.025***	0.025***	0.016***	0.016***	-0.019***	-0.019***
	[0.002]	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]
DS experiences						
$\overline{s_{it}}$ (γ_1)	0.000	0.001	0.027***	0.021***	0.029***	0.028***
	[0.001]	[0.003]	[0.002]	[0.006]	[0.001]	[0.002]
RF Interactions						
$RF * \overline{s_{it}}$ (γ_2)	0.005***	0.004***	0.004***	0.008***	0.007***	0.007***
	[0.000]	[0.001]	[0.001]	[0.003]	[0.000]	[0.001]
$RF * cov(s, (s - s_{it})^2)$ ($-\gamma_3$)	-0.004***	-0.004***	-0.030***	-0.030***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]
N	139345	139345	49972	49972	116262	116262
AR2	0.04	0.04	0.05	0.05	0.11	0.11
Demographic Controls	Y	Y	Y	Y	Y	Y
Cohort FE	N	N	N	N	Y	Y
Age FE	N	N	N	N	Y	Y

Notes: Each column reports a panel regression of subjective beliefs on Recall Fluency (RF), IQ, domain-specific (DS) experience variables ($\overline{s_{it}}$, cov$(s_k, (s_k - s_{it})^2)$), and their interactions with RF as shown in Equation 10. Demographic controls include age, gender, marital status, retirement status, income, and education. Columns 1–2 use stock market beliefs; columns 3–4 home-price beliefs; columns 5–6 health beliefs. Columns 2, 4, 6 additionally include the RF base effect. Standard errors in brackets; * p<0.12, ** p<0.05, *** p<0.01.

To quantify magnitudes, Figure 5 reports, for each domain, how strongly past DS experiences shape beliefs at three levels of recall fluency: zero, the average, and the 75th percentile. Bars show the experience effect in percentage points.[20]

Figure 5: Economic Magnitude of Experiences Across Belief Domains, by Recall Fluency Level.



Notes: Each bar is the marginal effect on beliefs of moving past experiences from their 25th to their 75th percentile, expressed in percentage points, evaluated at three levels of recall fluency: zero (no recall fluency), the sample mean, and the 75th percentile. For each of the three belief domains (stock market, home prices, life expectancy) the three bars trace how the experience effect grows with recall fluency. Because the three domains are on different scales, each cluster is read off its own vertical axis: the stock-market axis on the far left, the home-prices axis between the stock-market and home-prices clusters, and the life-expectancy axis between the home-prices and life-expectancy clusters. The three axes share a common zero and each is scaled to its own data. All continuous regressors are standardized by their sample interquartile range before estimation. Error bars are 95% confidence intervals. Specifications and samples match columns 2, 4, and 6 of Table 1.

In every domain the experience effect rises with RF, exactly as the model predicts: experiences that are more likely to be remembered shape beliefs more. For the stock market, past experiences barely move the subjective probability that stocks go up at zero RF (0.1 percentage points, 0.3% of its mean), but shift it by 0.9 percentage points at average RF

[20] These are marginal effects of $\bar{s}_{it}$ from columns 2, 4, and 6 of Table 1. All continuous regressors ($\bar{s}_{it}$, RF, IQ) are divided by their interquartile range prior to estimation, giving the response of beliefs to an interquartile increase in past experiences. The experience effect at recall-fluency level RF is $\hat{\gamma}_1 + \hat{\gamma}_2 \ \cdot$ RF,, where $\hat{\gamma}_1$ and $\hat{\gamma}_2$ are the coefficients on $\bar{s}_{it}$ and RF $\times$ $\bar{s}_{it}$; we evaluate it at RF=0, at its mean, and at its 75th percentile.

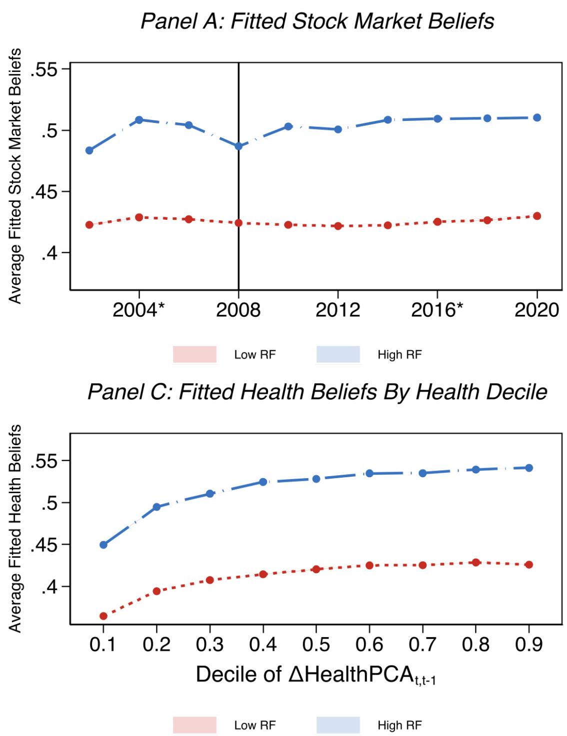
(1.9%) and by 1.1 percentage points at the 75th percentile of RF (2.3%). The same gradient holds for home prices —from 2.1 percentage points at zero RF (3.9% of the mean) to 3.4 at the average (6.5%) and 3.8 at the 75th percentile (7.2%), as well as for life expectancy—from 2.8 percentage points (5.9%) to 4.1 (8.7%) to 4.5 (9.5%)—where the direct experience effect is larger (arguably because respondents attend more to own home and health states).

Thus, recall fluency sizably amplifies the transmission from past experiences to beliefs across domains, most dramatically in the the stock market (at the 75th percentile of RF it is roughly nine times its value at zero RF), but also in housing and life expectancy (with 85% and 60% increases in the experience effect, respectively). The magnitudes remain similar when we estimate our regressions in different RF quartiles.

Figure D.1–Figure D.2 shows that the effect of RF is sizable compared to standard demographics. For the stock market, Table 1 implies that an interquartile shift in RF raises the subjective probability that stocks will go up by approximately 2.1 percentage points, equivalent to the effect of an interquartile shift in education (≈ 2.1 percentage points over its 3-year IQR), five times the effect of an interquartile shift in household income (≈ 0.4 percentage points over its $49K IQR), and about 40% the effect of gender (women are about 4.9 p.p. more optimistic than men). The same ordering carries through to home prices and life expectancy.

Using the regression estimates, we can go back to the main patterns in Section 2. Figure 6 reports fitted beliefs from Table 1 for the top and bottom RF quartile. In the stock market (Panel A), high-RF fitted beliefs exhibit a pronounced boom-bust cycle, mirroring Panel A of Figure 3: they rise to a pre-crisis high of 50.8 percent in 2004, fall by 2.2 percentage points to 48.7 percent in the wake of the 2008 crisis, and subsequently recover by 2.3 percentage points through 2020. Low-RF fitted beliefs, by contrast, decline by just 0.5 percentage points between 2004 and 2008 and recover by a comparable margin thereafter—consistent with the attenuated boom-bust pattern in the raw data. In housing (Panel B), high-RF fitted beliefs for home price appreciation rise by 11.6 percentage points from 2010 to their 2018 peak (from 37.4 to 49.1 percent), while low-RF fitted beliefs rise by 8.5 percentage points over the same period (from 36.1 to 44.7 percent), mirroring Panel B of Figure 3. In both the stock and housing markets, our model captures the differential sensitivity of the high and low RF groups, driven by the interaction of RF with the evolving database and cues.

Figure 6: Fitted Beliefs Over Time for High vs. Low Recall Fluency.



Notes: Each panel plots fitted beliefs from the full database regressions of Table 1 (Equation 10), which include the full set of demographic controls and the IQ measure; fitted values use each respondent's actual covariates. Fitted beliefs are shown for the bottom (red) and top (blue) quartile of Recall Fluency. Panel A shows fitted stock market beliefs over time (column 1 of Table 1); Panel B fitted home-price beliefs over time (column 3); Panel C fitted health beliefs by decile of $\Delta\text{HealthPCA}_{t,t-1}$ (column 5). Shaded bands are 95% confidence intervals. The counterpart that holds demographics and the IQ measure at their sample means—isolating the contribution of recall fluency, experiences, and cues—is reported in Appendix Figure C.12.

Panel C presents fitted health beliefs across deciles of current health, $\Delta\text{HealthPCA}_{t,t-1}$. As in Panel C of Figure 3, the gradient is steeper for high-RF respondents: survival expectations rise by 9.2 percentage points from the bottom to the top current health decile for high-RF people (from 44.9 to 54.1 percent), compared with 6.1 percentage points for their low-RF counterparts (from 36.5 to 42.6 percent). A level gap of about 11 percentage points on average in favour of high-RF people remains across current health states—widening from roughly 8 percentage points at the lowest health decile to 12 at the highest. These results confirm that the interaction of RF with the experience database and changing cues can help account for the higher sensitivity of beliefs by high RF people compared to low RF ones.

In sum, a memory parameter measured in abstract tasks systematically predicts beliefs: a high RF is associated with beliefs that are more sensitive to past experiences and to their similarity with current cues, in turn generating systematic differences in optimism.[21]

4.2 Non Domain Specific Experiences

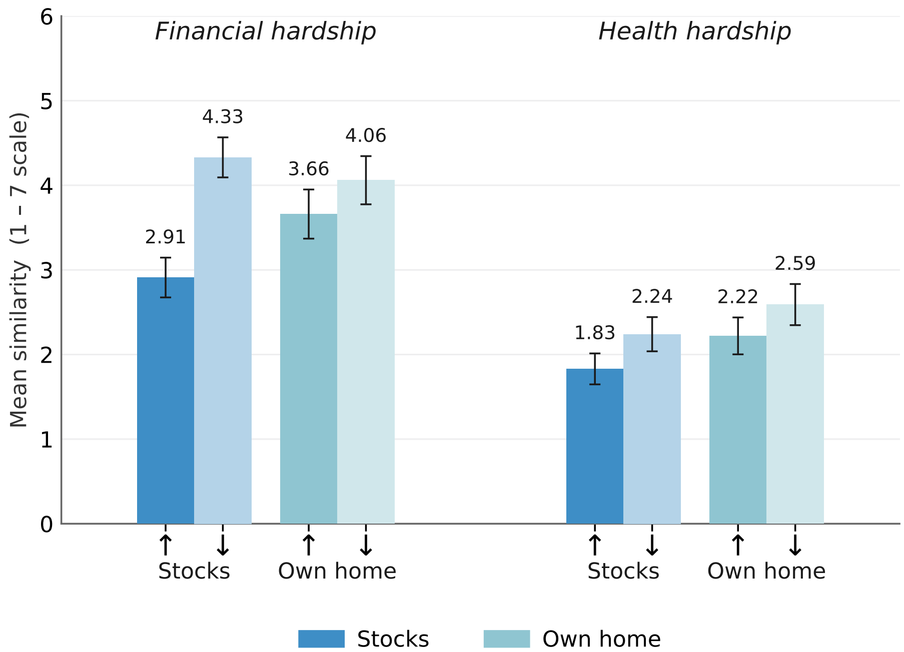
To test Prediction 2, for stock and home prices we use as NDS childhood health and socioeconomic status, denoted $ChHea$ and $ChSES$ respectively. These remote and personal experiences contain no information for aggregate outcomes like stocks, and do not matter in standard statistical models, whether rational or behavioral (including Bayesian learning from experiences, Malmendier and Nagel (2011, 2016)). With memory they could because NDS events can help imagine similar future states, as shown in Taubinsky et al. (2026) and Bordalo et al. (2026a). Building on the latter, we elicit similarity judgments of the childhood experiences $ChHea$ and $ChSES$ to an increase and a decrease in stock and own home prices.

Figure 7 shows that financial and health adversities are more similar to a decrease than to an increase in stock and own home prices. By Prediction 2, then, better childhood health and SES should prompt high RF people more optimism for stock and own home prices. Figure 7 also shows that financial adversities are more similar than health adversities to both stock and own home price declines (both in terms of levels and relative to increases), suggesting that $ChSES$ should have a stronger impact on beliefs, particularly for high RF people.[22]

[21] Table D.6 confirms the higher sensitivity the beliefs of high RF people for two aggregate outcomes for which we have limited time series dimension: the probability of a major economic depression within the next ten years (four waves, 2002-2008), and the probability that inflation will exceed five percent over the next ten years (two waves, 2006-2008). In both cases the role of RF is confirmed. The Appendix describes the analysis in detail.

[22] This survey was run on a sample of 400 US home owners in Prolific. Descriptive statistics are in Table D.5. The survey also assessed the perceived similarity of financial and health adversities to an *aggregate* increase in the price of homes. Contrary to the case for own home prices, home owners perceive increases of aggregate home prices as similar to adversities, particularly to financial ones. This helps reconcile our finding that positive NDS experiences drive optimism about own home prices with the finding in Bordalo et al. (2026a) that NDS adversities increases estimated aggregate home price growth.

Figure 7: Perceived Similarity Between Personal Hardships and Asset Outcomes.



Notes: Respondents rate, on a 1–7 scale, how similar a given personal hardship is to a state of the world in which each asset performs well or poorly. The left group conditions on a financial hardship and the right group on a health hardship. Within each, bars report mean perceived similarity to stock-market and housing outcomes, separated by whether the asset rises (↑) or falls (↓); darker bars refer to stock-market outcomes and lighter bars to own-home outcomes. Perceived similarity is highest for the asset movement that most naturally maps onto the hardship—for example, a financial hardship is rated most similar to a state in which stocks fall—consistent with the similarity-based recall mechanism used throughout the paper. Error bars are 95% confidence intervals.

For the stock market, childhood conditions are clearly an NDS, so they should play no role in a rational model. For own home prices, one cannot fully rule out a role of information: childhood experiences may be correlated with the respondent's current socioeconomic outcome and hence with the price of her home. To assuage this concern, we control for a battery of demographics, which include a respondent's income and region. In addition, the key prediction of memory is that NDS should matter through RF, not mechanically through the home price experiences the person faced in the past. Finding no effect of experiences "per se" would then further assuage omitted variables concerns. Finally, as NDS experiences for beliefs about life expectancy we use past aggregate stock and housing returns. According to Figure 7, higher stock and housing returns are less similar to negative health outcomes, and should therefore promote optimism about life expectancy. Again, conditioning on respondents' socio-demographics and focusing on their interaction with RF should allay endogeneity concerns.

We take the specification of Equation 10, and add to it two NDS regressors, yielding the estimating equation:

$$\begin{aligned} p_{X,it} \approx \gamma_0 + \gamma_1 \cdot \bar{s}_{it} + \gamma_2 \cdot \mathrm{RF}_i \cdot \bar{s}_{it} - \gamma_3 \cdot \mathrm{RF}_i \cdot cov\left[s, (s - s_{it})^2\right] \\ + \delta_1 \cdot nds_{it} + \delta_2 \cdot \mathrm{RF}_i \cdot nds_{it} + \varepsilon_{it}, \end{aligned} \tag{11}$$

where δ_1 captures the direct effect of NDS on beliefs at the bottom percentile of RF (no memory), and δ_2 captures memory's amplification. Since all regressors are IQR-normalised, each coefficient quantifies the belief change for a 25th-to-75th percentile shift in the corresponding variable.[23] By Prediction 2, NDS experiences should matter more for high RF individuals, $\delta_2 > 0$ (together with the usual DS effects, $\gamma_1, \gamma_2, \gamma_3$ positive).

Table 2 reports estimates of Equation 11. NDS experiences matter in all domains —but almost exclusively for higher-RF participants. Across all six columns the base NDS coefficient $\hat{\delta}_1$ is small and statistically indistinguishable from zero, while the memory-amplification term $\hat{\delta}_2$ is positive and significant throughout. NDS experiences do not shift beliefs for individuals near the bottom of the RF distribution; they become relevant only as recall fluency rises. The fact that NDS matters only through the RF interaction is consistent with the memory mechanism: these experiences are normatively irrelevant, and are "lost" in the large memory database of people, unless they are actively retrieved by high memory people and hence used to simulate future outcomes.[24] Compared to (Table 1), the coefficients on DS experiences and their interactions with RF are very stable, consistent with our regressors capturing orthogonal memory channels rather than unobserved individual heterogeneity in information or tastes.

[23]For recall fluency, after dividing by the interquartile range (which places most of the distribution between roughly -2 and $+2$), we add 2, so that $\mathrm{RF} = 0$ corresponds to the bottom of the recall-fluency distribution—a respondent with no recalled experiences—rather than to the average respondent.

[24]These results are robust to absorbing common time trends via survey-year fixed effects, as well as to including the RF base effect (Table D.3). They are also quantitatively similar when the childhood-health and childhood-SES databases are replaced with simpler, one-dimensional indices (Table D.4).

Table 2: NDS Database Regressions for $\overline{s_{it}}$ and $cov(s_k, (s_k - s_{it})^2)$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Chance Stocks ↑		**Chance Home ↑**		**Chance Live 10+**	
IQ	0.025***	0.024***	0.016**	0.015***	-0.018***	-0.021***
	[0.002]	[0.002]	[0.006]	[0.003]	[0.002]	[0.002]
DS Experiences						
$\overline{s_{it}}$ (γ_1)	0.001	0.001	0.027***	0.027***	0.028***	0.027***
	[0.001]	[0.001]	[0.007]	[0.002]	[0.002]	[0.002]
RF Interactions						
$RF * \overline{s_{it}}$ (γ_2)	0.004***	0.004***	0.004***	0.004***	0.007***	0.008***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
$RF * cov(s_k, (s_k - s_{it})^2)$ ($-\gamma_3$)	-0.003***	-0.004***	-0.030***	-0.030***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.008]	[0.001]	[0.000]	[0.000]
NDS Experiences						
nds (δ_1)	-0.001	-0.003	-0.003	-0.007	0.002	0.001
	[0.001]	[0.002]	[0.002]	[0.005]	[0.003]	[0.001]
$RF * nds$ (δ_2)	0.001**	0.005***	0.002*	0.006**	0.008***	0.005***
	[0.001]	[0.001]	[0.001]	[0.003]	[0.001]	[0.000]
N	134136	139342	49593	49971	116262	100979
AR2	0.04	0.04	0.05	0.05	0.11	0.12
NDS Var	ChHea	ChSES	ChHea	ChSES	$\Delta_L sp500$	$\Delta_L hpi$
Demographic Controls	Y	Y	Y	Y	Y	Y
Cohort FE	N	N	N	N	Y	Y
Age FE	N	N	N	N	Y	Y

Notes: Each column reports a panel regression of subjective beliefs on Recall Fluency (RF), IQ, domain-specific (DS) experience variables ($\overline{s_{it}}$ and $\text{cov}(s_k, (s_k - s_{it})^2)$), non-domain-specific (NDS) experiences, and their interactions with RF. NDS variables differ by domain: childhood health and SES index for stocks and home prices; cumulative lifetime log equity and home-price returns for health. All continuous regressors (RF, IQ, $\overline{s_{it}}$, cov, NDS) are divided by their within-sample IQR prior to estimation, so each coefficient represents the change in beliefs associated with a move from the 25th to the 75th percentile of the regressor. Demographic controls include age, gender, marital status, retirement status, income, and education. Standard errors in brackets; * p<0.10, ** p<0.05, *** p<0.01.

Overall, high-RF individuals are not simply better informed or more responsive to information. They use memory more, including of events that are not informative about the domain in question. The effect of NDS experiences is quantitatively large. Evaluated at the sample mean of RF, a one-IQR shift in NDS experiences shifts stock-market beliefs by approximately 0.5 percentage points (column 2) and health beliefs by 1.6 percentage points (column 5).[25]. The corresponding DS experience effect, from the same regression evaluated at mean RF, is 0.9 percentage points for stocks and 4.1 percentage points for health, so the NDS channel corresponds to roughly 40–60 percent of the DS channel in these two domains. For home prices, the NDS channel is weaker: a one-IQR shift in childhood SES raises the subjective probability of home price appreciation by only 0.3 percentage points (column 4), and childhood health is negligible at 0.1 percentage points (column 3)—each less than one-tenth of the corresponding DS experience effect of 3.5 percentage points. One possible explanation is that, relative to the stock market, people have a substantially larger database of home experiences, which reduces the effect of NDS. Figure D.3 illustrates these magnitudes in absolute terms (percentage points of the dependent variable) and further decomposes the heterogeneity generated by NDS databases relative to RF itself.

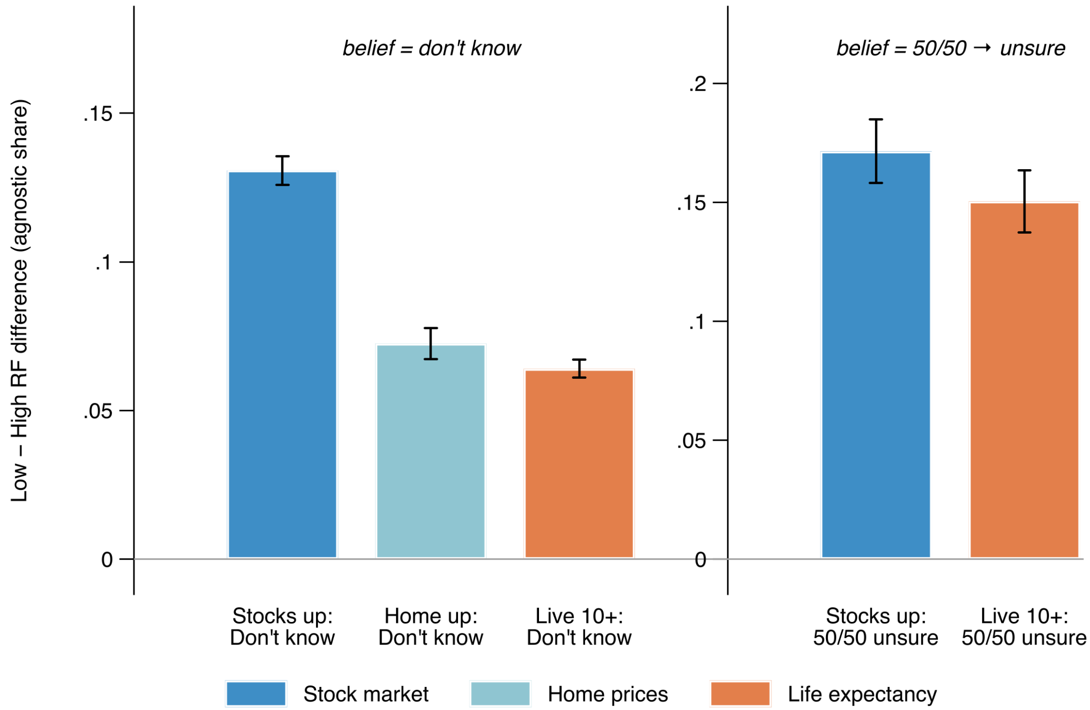
4.3 Agnosticism from Memory

Prediction 3 says that high RF people should recall more material to simulate the future and so should be less likely to give agnostic answers compared to low RF people, across all domains. This prediction rests on the centrality of memory for imagining the future, which is well established in cognitive science (Hassabis et al., 2007; Schacter et al., 2007).

We measure agnostic answers by the: i) share of people answering with "I do not know", and ii) share of people answering with "50-50" *and* stating that they are highly uncertain. In both cases, respondents are unsure how to think about the future. Figure 8 shows that Prediction 3 strongly holds in the data: people in the bottom RF quartile are more likely to give agnostic answers than people in the top RF quartile. The gaps are large. Relative to low-RF respondents, high-RF respondents are about 13pp less likely to answer "I do not know" about the stock market, 7pp about their own home, and 6pp about their own survival. Among those who answer 50-50, they are about 17 and 15 percentage points less likely to report being unsure for stocks and survival, respectively.

[25] The marginal effect of NDS experiences at mean RF is $\hat{\delta}_1 + \hat{\delta}_2\,\overline{\mathrm{RF}}^*$, where $\hat{\delta}_1$ and $\hat{\delta}_2$ denote the estimated coefficients on NDS_{it} and $\mathrm{RF} \times \mathrm{NDS}_{it}$ respectively, and $\overline{\mathrm{RF}}^* \approx 1.76$ is the post-standardisation sample mean of recall fluency, corresponding to an average respondent with raw recall-fluency index of zero. Analogously, the marginal effect of DS experiences at mean RF is $\hat{\gamma}_1 + \hat{\gamma}_2\,\overline{\mathrm{RF}}^*$.

Figure 8: Agnosticism and Recall Fluency: Low–High RF Difference.



Notes: Each bar is the difference between the bottom and top recall-fluency quartile in the share of respondents giving an agnostic answer. For each domain-question we restrict the sample to respondents in the bottom and top recall-fluency quartiles and estimate $\Pr(\text{agnostic}_i = 1) = \alpha + \beta\,\text{LowRF}_i + \varepsilon_i$, where LowRF_i equals one for the bottom quartile; the plotted bar is $\hat{\beta}$ (robust standard errors), the low-minus-high recall-fluency difference. A positive value means low-recall-fluency respondents are *more* agnostic. Each cluster is read off its own vertical axis: the Don't-Know cluster off the left-hand axis and the 50/50-unsure cluster off the axis between the two clusters; the two axes are scaled separately to their own data. The left cluster reports the difference in the share answering "Don't Know" for stock, home-price, and life-expectancy beliefs (whole sample). The right cluster reports the difference in the share who, having first answered 50/50, further state they are "unsure" rather than "equally likely"; this is computed only among respondents who answer 50/50, and only for stocks and life expectancy, since the home-price question has no 50/50 follow-up. Bars are colored by domain: stock market, home prices, and life expectancy. Error bars are 95% confidence intervals.

The link between RF and agnosticity suggests that answers like "I do not know" may not reflect lack of information but rather cognitive bounds on retrieval. Related answers like "50-50 and low confidence" have been cognitively traced to noise in signal perception, that causes people to stick to their prior (Enke and Graeber, 2023; Woodford, 2020). Memory offers a possible mechanism: the signal is *internally generated* through retrieval and simulation. In this mechanism, "noise" means that the signal fails to deliver a vivid image of the future. The DM then sticks to a belief that – unlike a Bayesian prior – does not reflect previous data. It is an agnostic default: nothing concrete comes to mind. [26] [27] Likewise, high confidence people are not necessarily more precise and hence accurate in their beliefs. They may overweight statistically uninformative events such as NDS ones.

5 Recall Fluency, Expectations and Choices

Is the role of RF limited to beliefs, or does it also predict economic choices? The RHS fortunately reports respondents' choices related to our three belief domains.

Stock Market. There are two relevant choice variables in this domain. The first is *New Stock Market Investments 2y*, a dummy capturing whether the respondent has made any new stock market investments in the last 2 years. The second is *% IRA in Stocks*, measuring the proportion of the respondents IRA that is invested in stocks/mutual funds. This variable is restricted to people that own an IRA. The belief B_{it} relevant for these choices is the assessed probability of stocks going up, which should raise both measures of stock investment.

Housing. The available variable is *Bought New Home 2y*, a dummy taking the value of one if the respondent bought a new home in the past two years. The relevant belief is the probability of the respondent's own home increasing in value, which should foster this choice.

Life Expectancy. Here there are three indicators of choice. The first is *Retired*, a dummy equal to one if the respondent is currently retired. The second is *% Income to Pension*, the percentage of monthly pay the respondent contributes to their pension (restricted to people who are currently working and have a defined contribution pension scheme). Finally, we also include *Work Past 70*, a variable from 0 to 100 indicating the respondent's expectation or plan to work after age 70 (higher value means higher probability. This variable is restricted to people who are currently working and younger than 70). The belief measure relevant to these choices

[26] This mechanism could also explain why low RF answers are more dispersed and take extreme values, as shown in Appendix Figure C.9, Figure C.10, and Figure C.11. The agnostic default may in fact vary with arbitrary anchors such as the response scale etc.

[27] One potential concern is that low RF people may just be less willing to exert effort, both in laboratory recall tasks, where they recall fewer words, and in forecast elicitations, where they give agnostic low effort answers. This account does not however explain why high RF people should rely on their own DS and NDS experiences in the way shown by our previous tests, and also why this differential sensitivity should predict real world choices.

is the probability attached to being alive in the next ten years, which should be associated with higher believed probability of working after 70, a lower probability of being currently retired, and a higher contribution to pensions.

We first check if beliefs predict choices by estimating, in each domain:

$$C_{it} = \alpha + \eta^M \mathrm{RF}_{it} + \eta^I IQ_{it} + \theta B_{it} + \beta X_{it} + \varepsilon_{it} \tag{12}$$

Here C_{it} is a choice recorded for respondent i at time t (such as new stock market investments), and B_{it} is the measured choice-relevant belief (such as belief about stock returns) of the same subject and the same time. X_{it} is our standard vector of controls. The results in Table 3 are reassuring: beliefs predict choices in the expected way. Beliefs are informative about what people do, consistent with much previous evidence (Bailey et al., 2019; D'Acunto et al., 2023; Giglio et al., 2021; Malmendier and Nagel, 2011, 2016).

Table 3: Choices on Measured Beliefs (Specification 12).

	(1)	(2)	(3)	(4)	(5)	(6)
	New Stock Market Inv.	% IRA in Stocks	Bought a New Home	Work Past 70	Retired	% Income to Pension
Cognition						
RF (1 sd) (κ^M)	0.017***	0.024***	0.004***	0.017***	-0.008***	0.001
	[0.001]	[0.003]	[0.001]	[0.002]	[0.001]	[0.001]
IQ (1 sd)	0.020***	0.044***	0.006***	0.010***	-0.003**	0.002*
	[0.001]	[0.003]	[0.001]	[0.002]	[0.001]	[0.001]
Beliefs (ϕ)						
B_{it} (θ)	0.022***	0.055***	0.006***	0.059***	-0.002**	0.000
	[0.001]	[0.002]	[0.001]	[0.002]	[0.001]	[0.001]
Avg DV	0.10	0.55	0.04	0.26	0.53	0.08
N	134545	36569	45746	36105	156907	7353
Demographic Controls	Y	Y	Y	Y	Y	Y
Fixed Effects	N	N	N	Age/Cohort	Age/Cohort	Age/Cohort

Notes: Each column estimates specification 12: a single choice outcome is regressed on the survey-measured belief relevant to that choice (B_{it}, θ), recall fluency (RF, κ^M), IQ, and demographic controls (age, gender, marital status, income, education; the household-retirement control is omitted for the health outcomes). The belief is the respondent's stated probability that stock prices rise over the next year (for the two stock outcomes), that the value of their own home rises (for home purchase), and of surviving at least ten more years (for the three health outcomes). All regressors are scaled to one standard deviation. Columns 1–3 (*New Stock Market Inv.*, *% IRA in Stocks*, *Bought a New Home*) are estimated by pooled OLS without fixed effects; columns 4–6 (*Work Past 70*, *Retired*, *% Income to Pension*) include age and birth-cohort fixed effects. Standard errors in brackets; * p<0.10, ** p<0.05, *** p<0.01.

Our analysis raises a deeper question: does RF shape choices by influencing the sensitivity of beliefs to experiences and cues? Standard economics traces choices to tastes and information. Tracing choices to memory implies that cognition is an important independent source of behavior. To assess this issue, we separating a respondent's fitted beliefs, from Equation 11, into three additive components:

$$\widehat{B}_{it} = B_{E_{it}} + B_{(\mathrm{RF}_{it} \cdot E_{it})} + B_{D_{it}}. \tag{13}$$

The first term, $B_{E_{it}}$, is a pure *experience* component, including both DS and NDS experiences, obtained as follows:

$$B_{E_{it}} = \widehat{\gamma}_1 \cdot \overline{s}_{it} + \widehat{\delta}_{1,hea} \cdot ChHea + \widehat{\delta}_{1,ses} \cdot ChSES. \tag{14}$$

where the respondent's DS experiences are weighted by the coefficient $\widehat{\gamma}_1$ estimated in Table 2, and the weights $\widehat{\delta}_{1,hea}$ and $\widehat{\delta}_{1,ses}$ on NDS experiences are estimated by including both the childhood health $ChHea$ and childhood socioeconomic status $ChSES$ as regressors (Δ_L S&P 500 and Δ_L HPI for the life-expectancy domain).

The second and key term, $B_{(\mathrm{RF}_{it} \cdot E_{it})}$, is memory's amplification of experiences: the contribution of recall fluency to the sensitivity of beliefs to past experiences and to their similarity with current cues. It collects the RF $\times$ experience and RF $\times$ cue-similarity interactions:

$$\begin{aligned} B_{(\mathrm{RF}_{it} \cdot E_{it})} = \widehat{\gamma}_2 \cdot \mathrm{RF}_i \cdot \overline{s}_{it} + \widehat{\delta}_{2,hea} \cdot \mathrm{RF}_i \cdot ChHea + \widehat{\delta}_{2,ses} \cdot \mathrm{RF}_i \cdot ChSES \\ + \widehat{\gamma}_3 \cdot \mathrm{RF}_i \cdot \mathrm{cov}\left[s, (s - s_{it})^2\right]. \end{aligned} \tag{15}$$

The sum is the total contribution from memory amplification, with higher values of RF or of experiences corresponding to higher predicted beliefs. The last term, $B_{D_{it}}$, is a pure *demographic*+IQ component.[28] To link choices to RF, we replace in Equation 12 actual beliefs with the three beliefs components capturing experiences, RF, demographics. We add out standard controls, which may affect choices independently.

[28]For parsimony we do not report this component in Table 4.

Table 4: Choice Regressions: Beliefs, Memory, and Economic Choices.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Stock/Home-Price Market Choices					
	New Stock Market Inv.		**% IRA in Stocks**		**Bought a New Home**	
IQ (1 sd)	0.009***	-0.001	0.030***	0.010***	0.006***	-0.002
	[0.001]	[0.001]	[0.004]	[0.004]	[0.001]	[0.002]
Beliefs (ϕ)						
$\widehat{B}_{it}$ (θ)	0.052***	.	0.067***	.	0.008***	.
	[0.003]	.	[0.006]	.	[0.001]	.
$B_{E_{it}}$ (γ)	.	-0.009***	.	-0.011***	.	0.002**
	.	[0.001]	.	[0.003]	.	[0.001]
$B_{(\mathrm{RF}_{it}\cdot E_{it})}$ (μ)	.	0.017***	.	0.022***	.	0.007***
	.	[0.001]	.	[0.002]	.	[0.001]
Avg DV	0.10	0.10	0.56	0.56	0.04	0.04
N	129529	124424	36078	35150	45249	44460
Demographic Controls	Y	Y	Y	Y	Y	Y
Risk-taking	N	Y	N	Y	N	Y
	Panel B: Health Choices					
	Work Past 70		**Retired**		**% of Income to Pension**	
IQ (1 sd)	0.018***	0.016***	-0.006***	-0.001	0.002	0.002
	[0.003]	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]
Beliefs (ϕ)						
$\widehat{B}_{it}$ (θ)	0.035***	.	-0.010***	.	0.003	.
	[0.004]	.	[0.002]	.	[0.002]	.
$B_{E_{it}}$ (γ)	.	0.016***	.	-0.016***	.	-0.002
	.	[0.004]	.	[0.002]	.	[0.002]
$B_{(\mathrm{RF}_{it}\cdot E_{it})}$ (μ)	.	0.014***	.	0.005***	.	0.004**
	.	[0.003]	.	[0.001]	.	[0.002]
Avg DV	0.26	0.26	0.64	0.63	0.08	0.08
N	20280	20265	100979	95419	4352	4349
Demographic Controls	Y	Y	Y	Y	Y	Y
Risk-taking	N	Y	N	Y	N	Y
Cohort/Age FE	Y	Y	Y	Y	Y	Y

Notes: Two-stage regressions linking beliefs to economic choices, HRS 2002–2020. Stage 1 predicts beliefs from RF, IQ, domain-specific (DS) experiences and their interactions with RF, the RF × experience-covariance interaction (consistent with Table 1), and non-domain-specific (NDS) experiences and their interactions with RF, using the same specifications as Table 2. The NDS experiences are childhood health and childhood SES for the stock- and home-price choices (Panel A), and lifetime aggregate stock and home-price returns (Δ_L S&P 500 and Δ_L HPI) for the life-expectancy choices (Panel B). Stage 2 regresses each choice on components of Stage 1 fitted beliefs. Odd columns (1, 3, 5) use total predicted belief $\widehat{B}_{it}$ (θ). Even columns (2, 4, 6) decompose fitted beliefs into three additive components: $B_{E_{it}}$ (experience-driven, γ); $B_{(\mathrm{RF}_{it}\cdot E_{it})}$ (μ), the total memory-amplified contribution to fitted belief, summing the Stage-1 fitted contributions of the RF × experience and RF × experience-covariance interactions; and $B_{D_{it}}$ (controls-driven). A direct Risk Taking index is also included. Panel A outcomes: *New Stock Market Inv.*, an indicator equal to one if the respondent made a new stock market investment since the prior survey wave; *% IRA in Stocks*, the share of IRA assets held in stocks (0–1); *Bought a New Home*, an indicator for home purchase since the prior wave; estimated by pooled OLS without fixed effects. Panel B outcomes: *Work Past 70*, the subjective probability of working past age 70 (0–100); *Retired*, an indicator for retirement status; *% of Income to Pension*, the share of income contributed to a pension plan (0–1); age and cohort fixed effects. Demographic controls (age, gender, marital status, income, education) in all columns. Coefficients scaled to 1 SD of each regressor. Standard errors in brackets; * p<0.10, ** p<0.05, *** p<0.01.

Table 4 reports, for each choice, the predictive value of fitted beliefs in the first column and the decomposition into their three components in the second column. In the second column, we also include the self-reported degree of risk aversion so as to benchmark the explanatory power of cognition to a standard measure of tastes.[29] Table 4 reports the results. Across the three domains, a higher fitted belief raises the relevant choice probability in the odd columns (1, 3, and 5), with the exception of the pension-contribution outcome, where the total-belief coefficient is not statistically distinguishable from zero. Decomposing fitted beliefs into their three components (columns 2, 4, and 6), the RF component enters positively and significantly for every outcome, and is the dominant belief-driven channel in all choices except the probability of working past 70 and retirement. The pure experience component has a heterogeneous, and sometimes negative, role across domains.

Stock Market. A one-standard-deviation (SD) increase in fitted stock market beliefs is associated with a 5.2 percentage-point (pp) rise in the probability of making a new stock investment (52% of the 10% mean), and with a 6.7 pp rise in the share of IRA assets held in stocks (12.0% of the 56% mean). Decomposing fitted beliefs (even columns), the memory-amplified-experience component (μ) is the operative channel: a one-SD increase in it raises new investment by 1.7 pp (17% of the mean) and the IRA share by 2.2 pp. The pure-experience component (γ) enters negatively for both stock outcomes (-0.9 pp and -1.1 pp), so it is the memory's amplification of the experience, not the raw experience, that maps fitted beliefs into investment behavior.

Housing. A one-SD increase in fitted home price beliefs is associated with a 0.8 pp increase in the probability of buying a new home in the past two years, a 20% increase relative to the 4% baseline purchase rate. Both belief components contribute: the pure-experience component (γ) accounts for 0.2 pp (5.7% of the mean) and the memory-amplified-experience component (μ) for 0.7 pp (16.3%). While the absolute magnitudes are modest, they are eco-

[29] To measure risk aversion, we take the standardized average of: (a) risk taking for employment (choose between a job with higher expected pay but more variance vs. one with lower pay and more certainty); (b) risk taking for business inheritance (allocate an inheritance into a safe asset or invest in a risky business); and (c) self-reported risk taking, measured on a scale of 0 to 10. Respondents missing a proxy are averaged over the proxies they do have.

nomically meaningful relative to the low base rate of home purchases in the older population.

Health and Retirement. Three choice outcomes are linked to survival beliefs. For the probability of expecting to work past age 70, a one-SD increase in fitted survival beliefs raises the outcome by 3.5 pp (13.5% of the 26% mean), with both components contributing: the pure-experience channel (γ) accounts for 1.6 pp (6.2% of the mean) and the memory-amplified-experience channel (μ) for 1.4 pp (5.4%). For retirement status, higher survival beliefs predict a lower probability of being retired: a one-SD increase in fitted beliefs reduces the probability of being retired by 1.0 pp (1.6% of the 64% baseline), driven by the pure-experience channel (-1.6 pp) and partially offset by a positive amplified-experience component (+0.5 pp). Finally, for the share of income contributed to a pension, the total-belief coefficient is not statistically distinguishable from zero, but the amplified-experience component enters positively and significantly at 0.4 pp (5% of the mean, $p < 0.05$), while the pure-experience component is not individually distinguishable from zero. The small sample for this outcome (approximately 4,300 observations) limits statistical power.

To address the possibility that RF affects choices directly—through channels such as general planning capacity or self-control, rather than through its role in shaping beliefs—Table D.7 in the Appendix repeats the specification with RF included as a direct second-stage regressor. The main belief coefficients remain significant and of comparable magnitude, confirming that the belief-mediation channel documented in Table 4 is not an artifact of a direct effect of RF on choices.[30]

A related concern is timing: choices can occur at any point in the two years since the previous interview, while beliefs are elicited in the same wave—so current beliefs may proxy for those that drove the decision, or instead reflect its aftermath. Table D.8 re-estimates the second stage using fitted beliefs from the previous wave, pre-determined relative to the choice. Results are consistent: beliefs generated by memory's amplification of experiences significantly

[30]The memory-amplified belief component remains individually significant for every choice once recall fluency enters the second stage directly, though it weakens for the share of an IRA held in stocks, where it is significant only at the 10% level.

drive choices in all three domains.[31]

6 Conclusion

Recall fluency, how many words a person can retrieve from a list, declines with age but varies sharply within cohorts. We showed that this trait is linked to a parameter of a standard mnemonic beliefs model: the interference a person faces at retrieval. By the model, then, recall fluency should govern how tightly expectations are influenced by the experiences a person has accumulated, informative or not, and the cues that select them. That is, performance in a task with no economic content should predict beliefs across different economic domains.

We show that, consistent with this prediction, people with high recall fluency are more optimistic about the stock market when they have lived through better returns, they become much more optimistic when today's return resembles the best returns in their past, and are more optimistic about stocks if they merely had a happy childhood — an experience carrying no information. Before 2008 they had grown highly optimistic, during the crisis they became very pessimistic, and then chased the recovery back up; low recall fluency people barely moved.

Remarkably, recall fluency does this work everywhere else we look: house prices, own life expectancy, inflation, and the odds of a depression. It also reaches behavior. The memory-amplified component of beliefs predicts buying stocks, buying a home, and planning to work longer, holding measured risk tolerance fixed. The same mnemonic model that elsewhere explains expectations from chancing cues, experiences and similarity (CITE) here yields new predictions about which people are most influenced by them.

These results provide a sharp confirmation of the importance of memory as a driver of beliefs and choices across different economic domains. They also open new issues, and we conclude by discussing two of them. First, remembering more is not knowing better. High recall fluency anchors beliefs more tightly to lived experiences, but it also makes them more

[31] Requiring two consecutive waves reduces the sample by roughly a fifth, more so for the share of income contributed to a pension. The one material change is retirement: μ is positive contemporaneously but turns negative under this pre-determined timing, which is arguably a more intuitive result, since θ, γ, and μ then all point the same way—greater survival optimism is associated with a lower probability of being retired.

extrapolative from cues and more contaminated by irrelevant material. This is key: no account in which recall fluency proxies for information, numeracy or engagement predicts that a happy childhood should weigh on a stock forecast. It also implies that effective cognition is not a slack computational or processing capacity constraint. High recall fluency people hold confident beliefs built from vivid and readily retrieved material, and are wrong anyway. Their fertile imagination is what makes them confident, not what makes them right. This means that effective cognition rests on at least two inputs: powerful retrieval and a focus on relevant data. This idea is consistent with a model of mental representations we presented elsewhere, and can be helpful to understand the determinants of decision quality and the interventions to improve it (which may differ for high and low recall fluency people).

Second, recall fluency is a new source of choice heterogeneity. Economics traces heterogeneity to tastes and information; recall fluency is purely cognitive, acting on the mnemonic component of representations. It helps understand disagreement along three margins. When a shock arrives, high fluency people move sharply, low fluency ones stay still, so disagreement widens during crises, policy surprises, etc. At a point in time, high fluency people are shaped by a cohort-specific or wholly personal past to a much greater extent than low fluency people, creating stable disagreement. Over time, aging societies remember less, so average beliefs and choices become less responsive to shocks and policy changes. Based on these forces, high fluency people will buy appreciating assets and dump depreciating ones, while low fluency people will stay put or even refrain from investing due to low confidence, potentially affecting prices and resource allocation. We have memory models, measuring recall fluency is easy, so these questions could be studied, even at scale.

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A Proofs

Proof of Proposition 1. Let $p_{it}(e) := f_{it}(e)/\mathbf{f}_{it}$ denote the frequency distribution over past experiences, with $\mathbf{f}_{it} = \sum_{z\in E} f_{it}(z)$ the total number of experiences of agent i at time t, and let

$$d(q_{X,it}) \;:=\; \sum_{e\in E} p_{it}(e)\, d(e, q_{X,it}),$$

be the p_{it}-average discrepancy to the cue. Define $\eta \;:=\; -\frac{S'(0)}{S(0)}$. By a first-order Taylor expansion of S at 0,

$$S\big(a\, d(X,e)\big) \;=\; S(0)\Big[1 - a\eta\, d(X,e)\Big] + O(a^2).$$

Substituting into the recall function $r(e \mid q_{X,it}, f_{it})$, and using $\mathbf{f}_{it}\, d(q_{X,it}) = \sum_z f_{it}(z)\, d(z, q_{X,it})$ in the denominator,

$$r(e \mid q_{X,it}, f_{it}) = \frac{1 - a\eta\, d(z, q_{X,it})}{1 - a\eta\, d(q_{X,it})}\, p_{it}(e) = p_{it}(e)\Big[1 + a\eta\big(d(X) - d(X,e)\big)\Big] + O(a^2).$$

To get beliefs, multiply by $\sigma(X,e)$ and summing over $e \in E$,

$$E_{it}[s_X] = \sum_e r(e \mid q_{X,it}, f_{it})\, \sigma(X,e) = \bar{\sigma}_{it}(X) + a\eta \sum_e p_{it}(e)\big[d(X) - d(X,e)\big]\sigma(X,e) + O(a^2).$$

In the limit of small a we get $S'(0)/S(0) = -1$, so $\eta = 1$ yielding the expression in the text. ■

Proof of Prediction 1. By definition, $E_{it}[s_X] = \sum_{e\in E} r(e)\, \sigma(X,e)$. Splitting the sum over $E = DS \cup NDS$ and writing $P(a) := \sum_{e\in DS} r(e)$ for the total recall weight on DS experiences,

$$E_{it}[s_X] = P(a)\, E_{DS}[s] \;+\; \big(1 - P(a)\big)\, E_{NDS}[s],$$

where $E_{DS}[s] = \frac{\sum_{e\in DS} S(e, q_{X,it}) f_{it}(e) \sigma_X(e)}{\sum_{e\in DS} S(e, q_{X,it}) f_{it}(e)}$ is the recall normalized within DS, and similarly for $E_{NDS}[s]$. Now we can apply Proposition 1 to each term directly. With discrepancy $(s - s_{it})^2$,

$$E_{DS}[s] \approx \bar{s}_X - a\eta\, \mathrm{Cov}_{DS}\big((s - s_{it})^2,\, s\big),$$

and similarly for $E_{NDS}[s]$. Now let's compute the recall-weighted share of DS experiences, which should increase in a. Let ρ denote the share of DS experiences. Then, with a similar logic to Proposition 1 we find:

$$P(a) \approx \rho + a\eta\kappa$$

where $\kappa = -\sum_e p_{it}(e)\big[d(X) - d(X,e)\big] > 0$. Keeping terms to first order in a:

$$P(a)E_{DS}[s] = \rho\bar{s}_X + a\kappa\,\bar{s}_X - a\rho\,\mathrm{Cov}_{DS}\big((s - s_{it})^2,\, s\big) + O(a^2),$$

as in the prediction. Note however that a similar expression holds for NDS experiences, whose recall also changes with a.

■

Proof of Prediction 2. Starting from the expression above:

$$E_{it}[s_X] = P(a)\,E_{DS}[s] \;+\; \big(1 - P(a)\big)\,E_{NDS}[s],$$

consider an increase in the frequency of $e_0 \in NDS$. We find:

$$\frac{\partial E_{NDS}}{\partial f(e_0)} = \frac{r_{NDS}(e_0)}{f(e_0)}\big[h_X(e_0) - E_{NDS}\big].$$

Since e_0 is valence-congruent, $d(X, e_0) = K$, while the NDS average discrepancy is $d_{-X} \approx K+V$ (dominated by valence-incongruent neutral experiences):

$$\frac{r_{NDS}(e_0)}{f(e_0)} \approx \frac{1}{|\mathbf{f}_{it,NDS}|}\Big[1 + a\big(d_{-X} - d(X,e_0)\big)\Big] \approx \frac{1}{|\mathbf{f}_{it,NDS}|}\big(1 + aV\big).$$

Moreover, since neutral experiences dominate NDS frequency, $E_{NDS} \approx \bar{\sigma}_{-X} \approx \delta_X$. Substituting into the equation above, we find:

$$\frac{\partial E_{it}[s_X]}{\partial f(e_0)} \approx \frac{1}{|\mathbf{f}_{it,NDS}|}(1 + aV)\big[h_X(e_0) - \delta_X\big].$$

In the limit where there are sufficiently many neutral NDS experiences, both DS and non-neutral NDS experiences become rare. Then $|\mathbf{f}_{it,NDS}| \to |\mathbf{f}_{it}|$, and the above expression converges to the prediction. $\blacksquare$

Proof of Prediction 3. The probability of retrieving a neutral experience is

$$r(e_n|q_{X,it}, f_{it}) = \frac{S(e_n, q_{X,it})f_{it}(e_n)}{\sum_e S(e, q_{X,it})f_{it}(e)}$$

To first order expansion in a this is equal to

$$r(e_n|q_{X,it}, f_{it}) = \frac{f_{it}(e_n)}{|\mathbf{f}_{it}|}\left(1 - a\left(K + V\right) + ad\left(q_{X,it}\right)\right)$$

with the first term coming from the lower similarity of the numerator, and the second term from the change in similarity in the denominator (which drops by the average discrepancy $d\left(q_{X,it}\right)$).

$\blacksquare$

B Survey Description and Variable Construction

Table B.1: Dependent Variable Survey Wording.

Variable	Exact HRS Survey Wording (by wave and HRS item code)
Chance Stock Market Up	**2002–2004 (P047):** "We are interested in how well you think the economy will do in the next year. By next year at this time, what is the percent chance that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more than they are today?" **2006–2014 (P047):** "We are interested in how well you think the economy will do in the future. By next year at this time, what is the percent chance that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more than they are today?" **2014 (P190, randomized branch):** "What do you think is the percent chance that the stock market will be higher in twelve months today?" **2016–2020 (P047):** "By next year at this time, what is the percent chance that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more than they are today?"
Chance Own Home Value Up	**2010 (P166):** "We are interested in how the value of your home will change in the future. On the same scale from 0 to 100, what do you think is the percent chance that by next year at this time your home will be worth more than it is today?" **2012–2020 (P166, randomized fill):** "We are interested in how the value of your home will change in the future. On the same scale from 0 to 100, what do you think is the percent chance that by next year at this time your home will be worth [more/less] than it is today?"
Chance Live 10+ Years	**2002–2004 (P029):** "(What is the percent chance) that you will live to be [X] or more?", where [X] is 80 if age 69 or younger, 85 if 70–74, 90 if 75–79, 95 if 80–84, and 100 if 85–89. **2006–2020 (P029):** "What is the percent chance that you will live to be [X] or more?", where [X] is 85 if under 65, 80 if 65–69, 85 if 70–74, 90 if 75–79, 95 if 80–84, and 100 if 85–89.
Chance Major Economic Depression	**2002–2008 (P034):** "What do you think are the chances that the U.S. economy will experience a major depression sometime during the next 10 years or so?"
Chance Cost of Living Rises >5%/yr	**2006–2008 (P116):** "Over the next 10 years what are the chances the cost of living will increase by 5 percent or more per year on average?"

Notes: This table reports the verbatim HRS Section P survey wording for each of the five dependent variables used in the paper, organized by estimation-sample wave and HRS item code. Wave scope for each DV is restricted to the waves in which the underlying item was fielded: *Chance Stock Market Up* covers 2002–2020; *Chance Own Home Value Up* covers 2010–2020 (P166 was introduced in 2010); *Chance Live 10+ Years* covers 2002–2020; *Chance Major Economic Depression* covers 2002–2008; and *Chance Cost of Living Rises >5%/yr* covers 2006–2008. In 2014 the stock-market question was administered under a randomized branch: half the sample (X504_4Random1_2 = 1) was asked the standard P047 wording, while the other half (X504_4Random1_2 = 2) was asked the alternative P190 wording referring to the stock market (rather than mutual funds in blue-chip stocks) and a twelve-month (rather than next-year-at-this-time) horizon. For *Chance Own Home Value Up*, 2012 onwards the fill phrase was randomized between "more" and "less" across respondents (variable X501 in 2012–2014; X083/P196 in 2016–2020); sign of the analysis variable is harmonized to the probability the home is worth more. For *Chance Live 10+ Years*, the target age fill depends on respondent age; in 2002–2004 the fill took five levels (80/85/90/95/100) while from 2006 onwards it took six levels (85/80/85/90/95/100), with the 85-year target added for respondents under age 65. The home-value and (2014-branch) stock-market questions are asked only to the relevant subsamples (homeowners; the X504_4Random1_2 = 2 branch). Source: HRS Section P questionnaires, hrsdata.isr.umich.edu.

Table B.2: Index Variable Construction.

Variable	Description	Min	Max	Mean
Panel 1: Recall Fluency Index				
Immediate Recall	Number of words recalled immediately from a 10-word list	0.00	10.00	5.40
Delayed Recall	Number of words recalled after a 5-minute delay	0.00	10.00	4.35
Retrieval Fluency	Number of unique animals named in 60 seconds, net of errors	0.00	40.00	16.09
Construction: Each component is standardized (demeaned, divided by s.d.) across the pooled sample. The index is the mean of the three standardized components. The index is then re-standardized to have mean zero and unit variance.				
Panel 2: IQ (Math) Index				
Counting Backwards	Number of correct serial-7 subtractions from 100	0.00	4.00	2.43
Number Series	Correct answers on number pattern completion (adaptive)	0.00	3.00	1.56
Numeracy	Correct answers on 3 arithmetic/probability questions	0.00	3.00	1.38
Construction: Each component is standardized (demeaned, divided by s.d.) across the pooled sample. The index is the mean of the three standardized components. The index is then re-standardized.				
Panel 3: Current Health PCA				
Self-Rated Health	Self-reported health on 5-point scale (poor to excellent)	1.00	5.00	2.91
Days in Bed	Days spent in bed due to illness in the past month *(inverted)*	-31.00	0.00	-0.77
Health Conditions (Full)	Count of all diagnosed health conditions *(inverted)*	-11.00	0.00	-2.55
Depressed	Indicator for depression diagnosis *(inverted)*	-1.00	0.00	-0.16
Health Change	Self-reported health change since last wave (3-point scale) *(inverted)*	-3.00	-1.00	-2.15
Health Conditions (Basic)	Count of 8 major diagnosed conditions *(inverted)*	-8.00	0.00	-2.15
New Heart Attack	New heart attack since last wave *(inverted)*	-1.00	0.00	-0.01
New/Worsening Severe	New or worsening severe health condition since last wave *(inverted)*	-1.00	0.00	-0.33
Sleep Quality	1st principal component of 4 sleep difficulty items *(inverted)*	-3.57	1.79	-0.00
Functional Limitations	Count of functional limitations (0–15 ADL/IADL scale) *(inverted)*	-15.00	0.00	-3.30
Has Helper	Indicator for receiving help with daily activities *(inverted)*	-1.00	0.00	-0.16
Tasks Helped With	Number of daily tasks receiving help (0–6) *(inverted)*	-6.00	0.00	-0.27
Construction: The first principal component is taken of the 12 components listed above. Components where a higher raw value indicates worse health are multiplied by -1 (marked *(inverted)*) so that higher values of every component, and of the resulting index, indicate better health. Missing values are imputed with the sample median.				
Panel 4: Childhood Health PCA				
Childhood Health Rating	Self-rated health before age 16 (5-point scale)	0.00	4.00	3.23
Missed School	Missed 1+ month of school due to health before age 16 *(inverted)*	-1.00	0.00	-0.11
Disabled as Child	Disabled for 6+ months before age 16 *(inverted)*	-1.00	0.00	-0.04
Childhood Conditions	Count of 16 childhood diseases/conditions *(inverted)*	-12.00	0.00	-0.63
Severe Conditions	Count of 5 severe childhood conditions *(inverted)*	-4.00	0.00	-0.21
Psychological Conditions	Count of 3 psychological conditions before 16 *(inverted)*	-3.00	0.00	-0.07

Continued on next page

Table B.2 – continued from previous page

Variable	Description	Min	Max	Mean
Construction: The first principal component is taken of the 6 subcomponents listed above. Childhood measures are asked once per respondent and carried forward across waves using the within-person mode. Components where a higher raw value indicates worse health are multiplied by -1 (marked *(inverted)*) so that higher values indicate better childhood health. Missing values are imputed with the sample median.				
Panel 5: Risk-Taking Index				
Subjective Risk Taking	Willingness to take risks, 0–10 self-report scale	0.00	10.00	5.38
Risk Taking (Employment)	Prefers risky high-pay job over safe lower-pay job	0.00	1.00	0.15
Risk Taking (Business)	Prefers risky business gamble over safe cash-out	0.00	1.00	0.28
Construction: Each component is standardized (demeaned, divided by s.d.); the statistics above are for the components as asked, before standardization. The subjective risk-taking item is asked from 2014; pre-2014 values are imputed with the respondent's modal response. The index is the mean of the three standardized components, each entering once; respondents missing a component are averaged over the components they do have, so the index is defined for more respondents than any single component.				
Panel 6: Current Socioeconomic Status PCA				
Education	Years of education completed	0.00	17.00	12.57
Income	Household income residualized on retirement status (millions USD)	-0.08	0.96	-0.00
Wealth	Total household wealth (millions USD)	0.00	35.50	0.18
Home Ownership	Indicator for owning a home	0.00	1.00	0.61
Not Unemployed	Indicator: not currently unemployed or laid off	0.00	1.00	0.97
Construction: The first principal component is taken of the 5 subcomponents listed above. Missing values are imputed with the sample median.				
Panel 7: Childhood Socioeconomic Status PCA				
Father's Education	Father's years of education	0.00	17.00	9.63
Mother's Education	Mother's years of education	0.00	17.00	9.88
Childhood Finances	Family financial status before 16 (3-point scale: 1=well-off, 3=poor) *(inverted)*	-3.00	-1.00	-1.77
Childhood Poor	Family was poor before age 16 *(inverted)*	0.00	1.00	0.69
Childhood Upper	Family was well-off before age 16	0.00	1.00	0.08
Father Unemployed	Father had extended unemployment before 16 *(inverted)*	0.00	1.00	0.79
Moved (Fin. Difficulty)	Family moved due to financial difficulty before 16 *(inverted)*	0.00	1.00	0.82
Family Received Aid	Family received financial aid before 16 *(inverted)*	0.00	1.00	0.85
Lived Rural	Lived in rural area before age 16 *(inverted)*	0.00	1.00	0.57
Spoke English	English spoken at home as a child	0.00	1.00	0.91
Mother Worked	Mother worked outside home during childhood *(inverted)*	0.00	1.00	0.44
Construction: The first principal component is taken of the 11 subcomponents listed above. Childhood measures are asked once per respondent and carried forward across waves using the within-person mode. Components where a higher raw value indicates lower childhood SES are multiplied by -1 (marked *(inverted)*) so that higher values indicate higher childhood SES. Missing values are imputed with the sample median.				

Notes: This table documents the construction of all index variables used in the paper. For each index, we list the component sub-variables, a brief description based on the underlying HRS survey item, and summary statistics (minimum, maximum, and mean) computed from the estimation sample. The *Construction* row at the foot of each panel describes how the index is aggregated from its components. Components marked *(inverted)* have been multiplied by -1 so that higher values indicate more favorable outcomes (better health, higher socioeconomic status), and the reported min, max, and mean reflect this inversion. Income and wealth are reported in millions of dollars.

Table B.3: Construction of the experience and cue-similarity regressors

Variable	Construction
Panel A. Stock-market beliefs (DV: subjective chance the stock market rises)	
$\overline{s}_{it}^{\text{stk}}$ Average experienced stock return	Mean of the experienced stock-return signals over the respondent's lifetime, $\overline{s}_{it}^{\text{stk}} = \frac{1}{K}\sum_k s_k$. The signal s_k is the trailing twelve-month log return on the S&P 500 price index, $s_k = \log P_k - \log P_{k-12}$, evaluated at every month k from the respondent's birth through the survey month. A higher value means the respondent has lived through higher average stock returns.
$cov^{\text{stk}}\big(s_k, (s_k - r_t)^2\big)$ Cue-similarity covariance	Within-window sample covariance between each experienced return s_k and its squared distance from the current cue, $cov^{\text{stk}} = \frac{1}{K}\sum_k \big(s_k - \overline{s}\big)\big(s_k - r_t\big)^2$, where r_t is the trailing one-year S&P 500 return as of the survey month. It is low (negative) when the returns the respondent experienced most often lie close to today's return – i.e. when the recalled past is similar to the current cue.
Panel B. House-price beliefs (DV: subjective chance home prices rise)	
$\overline{s}_{it}^{\text{hpi}}$ Average experienced house-price growth	Mean of the experienced house-price signals over the lifetime, $\overline{s}_{it}^{\text{hpi}} = \frac{1}{K}\sum_k s_k$. The signal s_k is the trailing four-quarter (one-year) log return on the regional house-price index, evaluated each quarter k from birth through the survey quarter. The index is the FHFA Census-division house-price index from 1975 onward, back-filled with the national Case–Shiller real return before 1975, and is matched to the respondent's *childhood* Census division.
$cov^{\text{hpi}}\big(s_k, (s_k - r_t)^2\big)$ Cue-similarity covariance	Within-window sample covariance between each experienced house-price return s_k and its squared distance from the current cue, $cov^{\text{hpi}} = \frac{1}{K}\sum_k \big(s_k - \overline{s}\big)\big(s_k - r_t\big)^2$, where r_t is the current trailing-year house-price return for the respondent's childhood Census division at the survey quarter. It is low (negative) when the house-price growth rates the respondent experienced most often lie close to today's growth rate – i.e. when the recalled past is similar to the current cue.
Panel C. Survival beliefs (DV: subjective chance of living ten or more years)	
$\overline{s}_{it}^{\text{hlth}}$ Average experienced health change	Mean of the respondent's experienced health changes, $\overline{s}_{it}^{\text{hlth}} = \frac{1}{K}\sum_k s_k$. The signal s_k is the wave-to-wave change in the respondent's current-health index, $s_k = \text{health}_k - \text{health}_{k-1}$, taken over all HRS waves k in which the respondent is observed, up to and including the survey wave. The current-health index is the first factor of a single-factor model fitted to a battery of current-health measures, as described in the factor-loadings table above. At the first observed wave – where no prior wave exists to difference – the change is the current-health index minus the childhood-health index, the analogous single-factor index over childhood-health measures, so the first wave still enters the window.
$cov^{\text{hlth}}\big(s_k, (s_k - r_t)^2\big)$ Cue-similarity covariance	Within-window sample covariance between each experienced health change s_k and its squared distance from the current cue, $cov^{\text{hlth}} = \frac{1}{K}\sum_k \big(s_k - \overline{s}\big)\big(s_k - r_t\big)^2$, where r_t is the respondent's current health change at the survey wave. It is low (negative) when the health changes the respondent experienced most often lie close to the current change – i.e. when the recalled past is similar to the current cue.

Notes. The table documents the two domain-specific regressors that enter Equation (8) for each belief domain: the average experienced signal $\overline{s}_{it}$ and the cue-similarity covariance $cov(s_k, (s_k - r_t)^2)$. In every domain the experience window runs from the respondent's birth (for stocks and house prices) or from the first observed HRS wave (for health) up to the survey period, $\{s_k\}$ collects the K period signals observed within that window, $\overline{s}$ denotes their within-window mean, and r_t is the contemporaneous signal that serves as the recall cue. Both regressors are divided by their interquartile range before estimation, so that a one-unit change corresponds to a 25th-to-75th-percentile move in the underlying variable.

Table B.4: Variable Summary Statistics

	Mean	St.d	IQR	P10	P25	P50	P75	P90
Cognition								
Recall Fluency	0.01	0.90	1.14	-1.16	-0.55	0.04	0.58	1.10
– Immediate Memory	5.40	1.74	3.00	3.00	4.00	5.00	7.00	8.00
– Delayed Memory	4.35	2.08	3.00	1.00	3.00	4.00	6.00	7.00
– Retrieval Fluency	16.09	6.92	10.00	8.00	11.00	16.00	21.00	25.00
IQ	-0.00	0.88	1.61	-1.24	-0.81	0.07	0.80	1.18
– Counting Backwards	2.43	1.56	3.00	0.00	1.00	2.00	4.00	4.00
– Number Series	1.56	1.06	2.00	0.00	1.00	1.00	3.00	3.00
– Numeracy	1.38	1.03	2.00	0.00	0.00	1.00	2.00	3.00
Experiences (DS)								
$\overline{s_{it}}^{STOCKS}$	0.03	0.01	0.01	0.02	0.03	0.03	0.03	0.04
$\overline{s_{it}}^{HOUSE}$	0.03	0.01	0.01	0.02	0.02	0.03	0.03	0.04
$\overline{s_{it}}^{HEALTH}$	-0.04	0.28	0.22	-0.34	-0.15	-0.02	0.08	0.21
$cov(s,(s-s_{it})^2)^{STOCKS}$	-0.00	0.01	0.01	-0.01	-0.01	-0.01	-0.00	0.01
$cov(s,(s-s_{it})^2)^{HOUSE}$	0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	0.00
$cov(s,(s-s_{it})^2)^{HEALTH}$	0.08	1.75	0.11	-0.29	-0.03	0.00	0.08	0.48
Experiences (NDS)								
Childhood Health PCA	-0.04	0.71	0.41	-0.95	-0.10	0.31	0.31	0.36
Childhood SES PCA	0.06	0.47	0.60	-0.63	-0.23	0.16	0.37	0.62
Δ_L S&P 500	1.71	0.54	0.90	0.90	1.24	1.85	2.13	2.31
Δ_L HPI	1.69	0.33	0.43	1.35	1.45	1.61	1.88	2.15
Beliefs								
Chance Stock Increase [0-1]	0.47	0.26	0.35	0.10	0.25	0.50	0.60	0.80
Chance Home Value Increase [0-1]	0.38	0.31	0.50	0.00	0.10	0.30	0.60	0.80
Chance Live 10+ Years [0-1]	0.48	0.32	0.55	0.00	0.20	0.50	0.75	0.93
Controls								
Age	67.61	11.42	17.00	54.00	59.00	67.00	76.00	83.00
Female [0,1]	0.59	0.49	1.00	0.00	0.00	1.00	1.00	1.00
Married [0,1]	0.63	0.48	1.00	0.00	0.00	1.00	1.00	1.00
Retired [0,1]	0.53	0.50	1.00	0.00	0.00	1.00	1.00	1.00
Income (1000s)	57.57	105.37	49.13	7.34	14.40	30.00	63.53	117.38
Years Education	12.57	3.28	3.00	8.00	12.00	12.00	15.00	17.00

Notes: HRS biennial waves 2002–2020. *Recall Fluency*: standardized mean of immediate recall (10-item list), delayed recall, and retrieval fluency (unique animals in 60s). *IQ*: standardized mean of Counting Backwards (serial subtraction of 7), Number Series, and Numeracy. DS experience variables $\bar{s}_{it}$: each respondent's lifetime average realized return (monthly S&P 500 for stocks, quarterly FHFA regional HPI for home prices, wave-to-wave changes in a health PCA for health). The covariance term $\text{cov}(s,(s-r_t)^2) \equiv \frac{1}{T_i}\sum_k (s_k - \bar{s}_i)(s_k - r_t)^2$ governs the direction of belief distortion under selective retrieval. NDS: *Childhood Health PCA* and *Childhood SES PCA* are first-principal-component summaries of retrospective childhood reports; Δ_L S&P 500 and Δ_L HPI are cumulative lifetime log returns on each index (the change in log price from childhood to the survey date). Beliefs are elicited on a 0–100 scale and rescaled to $[0,1]$: chance stocks rise next year, home values rise locally, and respondent survives 10+ more years. Controls measured at interview; income in 1000s USD; female indicator $=1$ if female, 0 if male. IQR denotes the interquartile range (P75 − P25).

C Recall Fluency and Beliefs: descriptive results

Table C.1: Correlation of Recall Fluency with the Components of IQ.

	IQ Index (overall)	Counting Backwards	Number Series	Numeracy
Recall Fluency	0.40***	0.33***	0.39***	0.37***
Observations	176,122	176,122	67,989	94,600

Notes: Each cell reports the pairwise correlation between Recall Fluency and a measure of IQ, pooled across all respondent-waves for which both items are non-missing. The first column uses the overall IQ (math) index; the remaining columns use its three individual components: counting backwards (serial-7 subtraction from 100), number series (number-pattern completion), and numeracy (arithmetic and probability questions); see Table B.2 for definitions. Observation counts differ across columns because the number-series and numeracy items are administered to restricted subsamples. Stars denote significance of the correlation: *** p<0.01, ** p<0.05, * p<0.1.

Table C.2: Variance Decomposition of Cognitive Indices and Sub-Components.

	Memory Index	Math Index	Immed. Mem.	Delayed Mem.	Named Animals	Count. Back.	Number Ser.	Numeracy
Variance								
$\text{Var}(y_{it})$	0.806	0.776	1.000	1.000	1.000	1.000	1.000	1.000
$\text{Var}_i(\overline{y}_i)$ (cross-section)	0.501	0.522	0.556	0.573	0.749	0.612	0.694	0.690
$\text{E}_i[\text{Var}_t(y_{it})]$ (over time)	0.305	0.254	0.444	0.427	0.251	0.388	0.306	0.310
Proportion								
$\text{Var}(y_{it})$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
$\text{Var}_i(\overline{y}_i)$ (cross-section)	0.622	0.673	0.556	0.573	0.749	0.612	0.694	0.690
$\text{E}_i[\text{Var}_t(y_{it})]$ (over time)	0.378	0.327	0.444	0.427	0.251	0.388	0.306	0.310

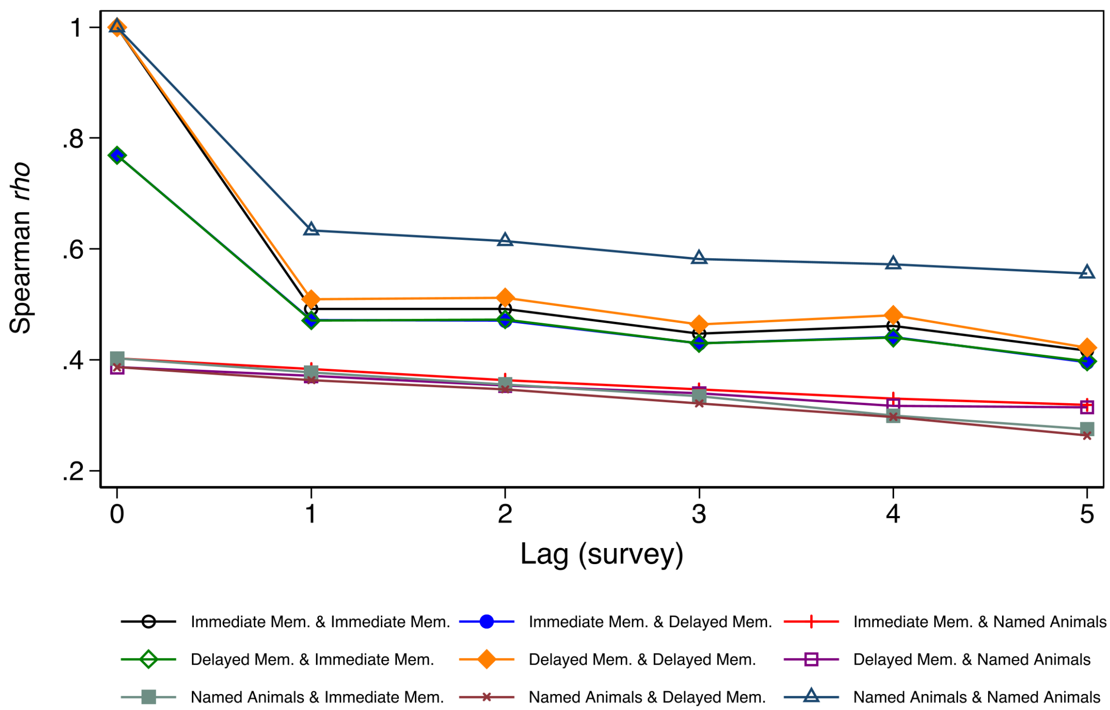
Notes: Variance decomposition of the Memory Index (Recall Fluency), the Math Index (IQ), and all individual cognitive sub-components across HRS waves 2002–2020. $\text{Var}(y_{it})$ is total variance. $\text{Var}_i(\overline{y}_i)$ is the cross-sectional (between-person) component, computed as the variance of individual-level means weighted by the number of non-missing observations per respondent. $\text{E}_i[\text{Var}_t(y_{it})]$ is the mean within-person variance over time. The proportion rows express each component as a share of total variance; by construction the two proportions sum to one. All sub-components are standardized (mean zero, unit variance) before inclusion in the indices.

Table C.3: Within- vs Between-Person Variance Decomposition of Experience Signals and Covariance Terms.

	Stocks		Home Prices		Health	
	$\overline{s_{it}}$	$\mathrm{cov}(s, (s - s_{it})^2)$	$\overline{s_{it}}$	$\mathrm{cov}(s, (s - s_{it})^2)$	$\overline{s_{it}}$	$\mathrm{cov}(s, (s - s_{it})^2)$
Total variance	1.000	1.000	1.000	1.000	1.000	1.000
$\mathrm{Var}_i(\overline{y}_i)$ (cross-section)	0.798	0.153	0.909	0.112	0.774	0.612
$\mathrm{E}_i[\mathrm{Var}_t(y_{it})]$ (over time)	0.202	0.847	0.091	0.888	0.226	0.388
$\mathrm{Corr}(\overline{s_{it}}, \mathrm{cov}(s, (s - s_{it})^2))$	0.214		0.094		0.296	

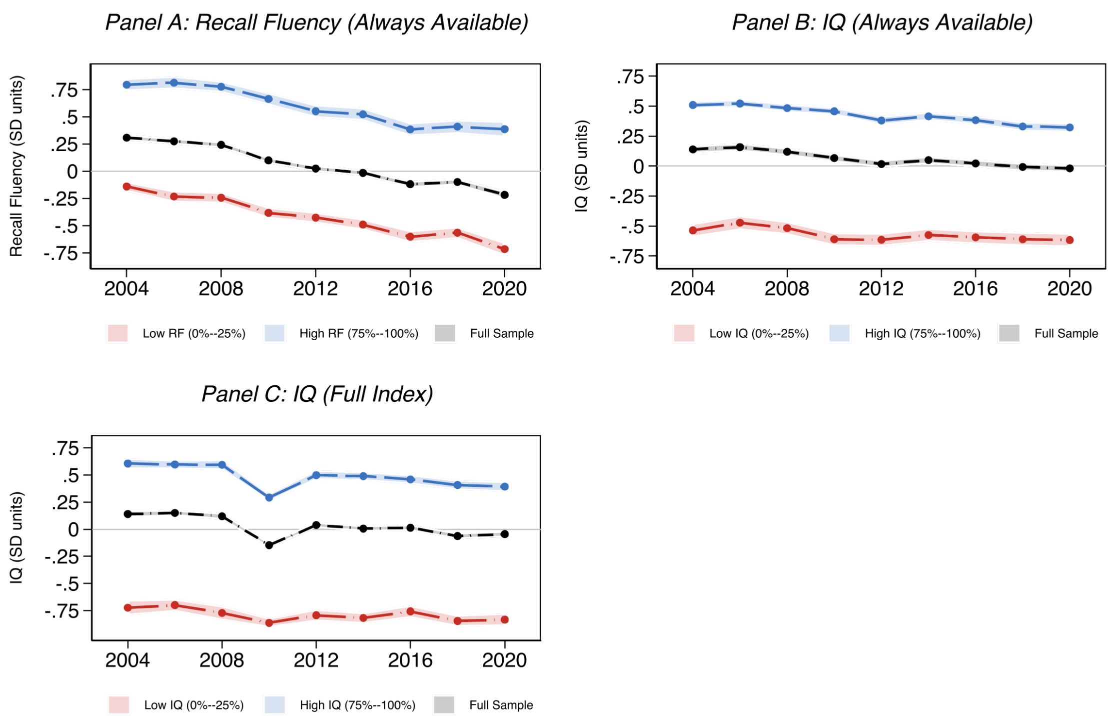
Notes: Proportional variance decomposition of the domain-specific experience signal $\overline{s_{it}}$ and the covariance term $\mathrm{cov}(s, (s - s_{it})^2)$ for stocks, home-price, and health. Parallels Table C.2 for the Memory and Math indices; raw variances suppressed here because the source series are on different native scales (monthly returns, quarterly HPI growth, health-PCA units). Rows report shares of total variance: $\mathrm{Var}_i(\overline{y}_i)$ is the cross-sectional (between-person) component, computed as the variance of individual-level means weighted by the number of non-missing observations per respondent; $\mathrm{E}_i[\mathrm{Var}_t(y_{it})]$ is the mean within-person variance over time. The between and within shares sum to one by construction. The bottom row reports the pooled person-wave correlation between $\overline{s_{it}}$ and the covariance term for each category. Stocks series are monthly returns; home-price series are quarterly HPI returns; health series are built from HRS-wave health indices.

Figure C.1: Memory Trait Stability: Spearman Correlation by Lag.



Notes: Each series plots the Spearman rank correlation ρ (y-axis) between a pair of memory sub-components at increasing survey lags (x-axis; lag 0 = same survey wave, lags 1–5 = up to ten years apart). The nine series correspond to all pairwise combinations of the three sub-components (Immediate Recall, Delayed Recall, Named Animals). High and persistent correlations across lags indicate that individual rankings in memory performance are stable over time. Sample: HRS respondents present in at least two waves, 2002–2020.

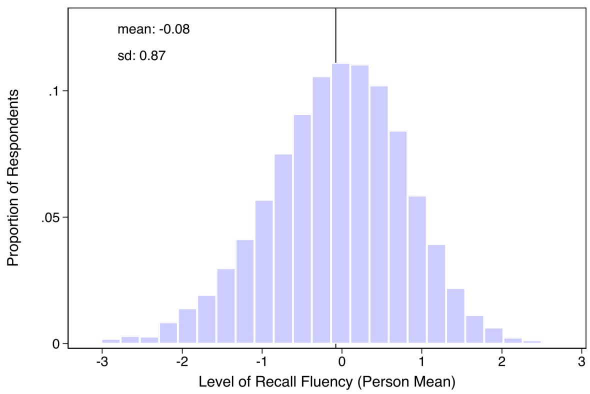
Figure C.2: Recall Fluency and IQ Over Time, by Quartile: Always-Available Indices



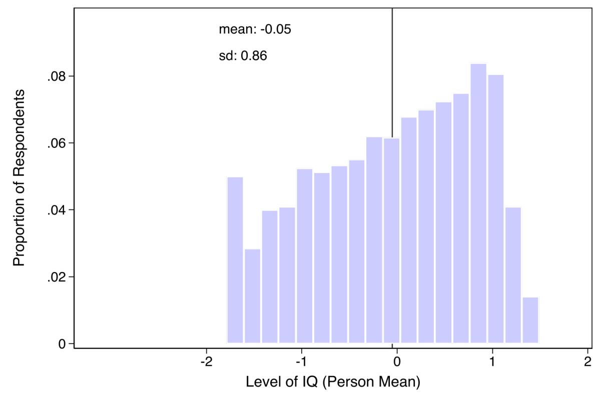
Notes: Each panel plots the average level of an index in each survey wave from 2004 to 2020, by quartile of that index in the first wave. Panel A plots Recall Fluency using only the immediate- and delayed-recall components, which are administered in every wave. Panel B plots IQ using only the counting-backwards task, the single IQ component administered in every wave. Panel C plots IQ using the full index, which additionally includes the number series and numeracy components (numeracy is not re-administered at re-interview). Blue lines show respondents in the top quartile of the respective index in the first wave; red lines show the bottom quartile; black lines show the full sample. Shaded bands are 95% confidence intervals. The sample is restricted to respondents present in all ten survey waves (2002–2020). The first wave is omitted as it is the base year for group assignment. Memory and IQ are expressed in standard deviation units.

Figure C.3: Distribution of Recall Fluency and IQ (Raw, Un-Residualized).

Panel A: Recall Fluency



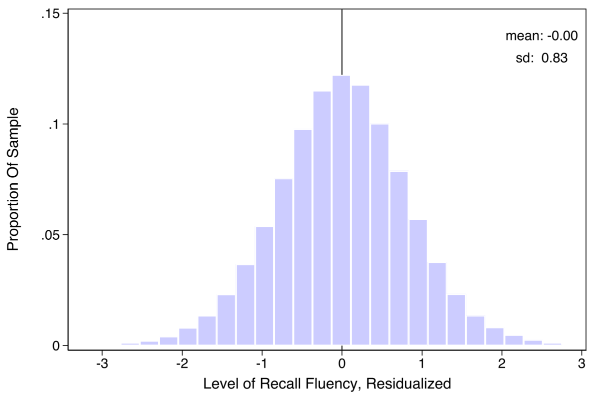
Panel B: IQ



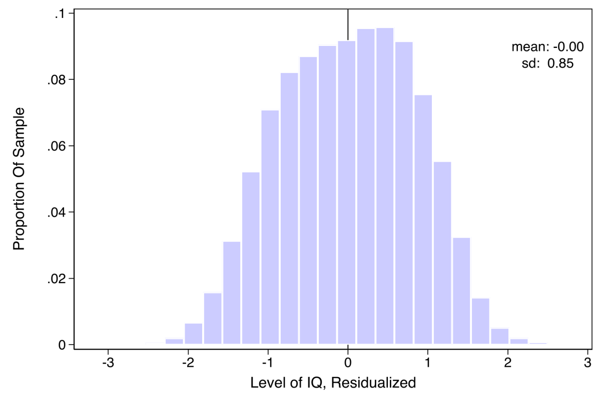
Notes: This is the raw (un-residualized) counterpart of Figure 1. Each panel plots the distribution across respondents of a person-level average, where for each respondent the relevant index is averaged over all survey waves in which they appear (one observation per respondent). Panel A shows person-level average Recall Fluency (RF); Panel B shows person-level average IQ. Both indices are constructed as the standardized mean of their components and are expressed in standard deviation units. Sample: HRS respondents, waves 2002–2020.

Figure C.4: Distribution of Recall Fluency and IQ (Pooled Person-Wave, Residualized).

Panel A: Recall Fluency (Residualized)



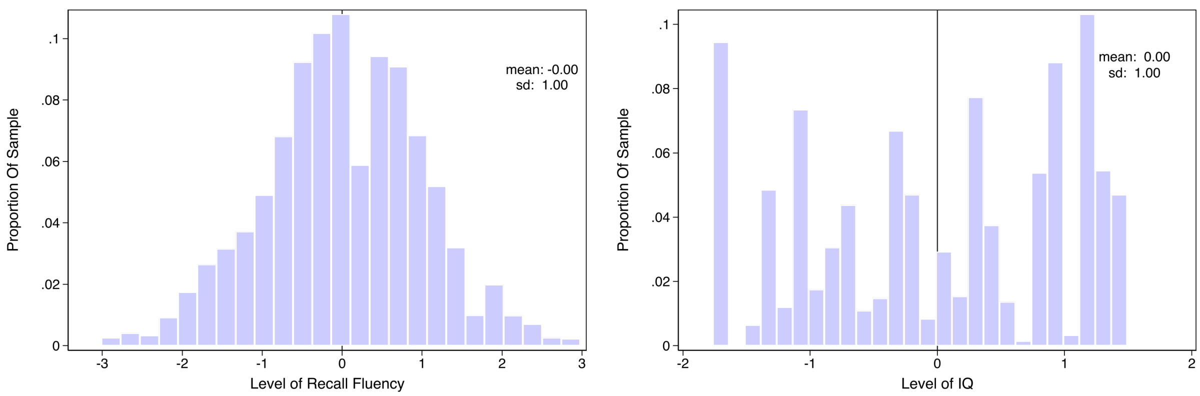
Panel B: IQ (Residualized)



Notes: This is the pooled (person-wave) residualized counterpart of Figure 1; here each index is taken at the person-wave level rather than averaged within respondent. Panel A shows the distribution of Recall Fluency (RF) after residualizing on IQ, age, income, education, gender, marital status, and retirement status. Panel B shows the distribution of IQ after residualizing on RF and the same demographics. Both indices are constructed as the standardized mean of their components and are expressed in standard deviation units. The cross-sectional standard deviations reported in the main text (Section 2) refer to this pooled sample. The raw (un-residualized) pooled distributions are reported in Figure C.5. Sample: HRS respondents, waves 2002–2020.

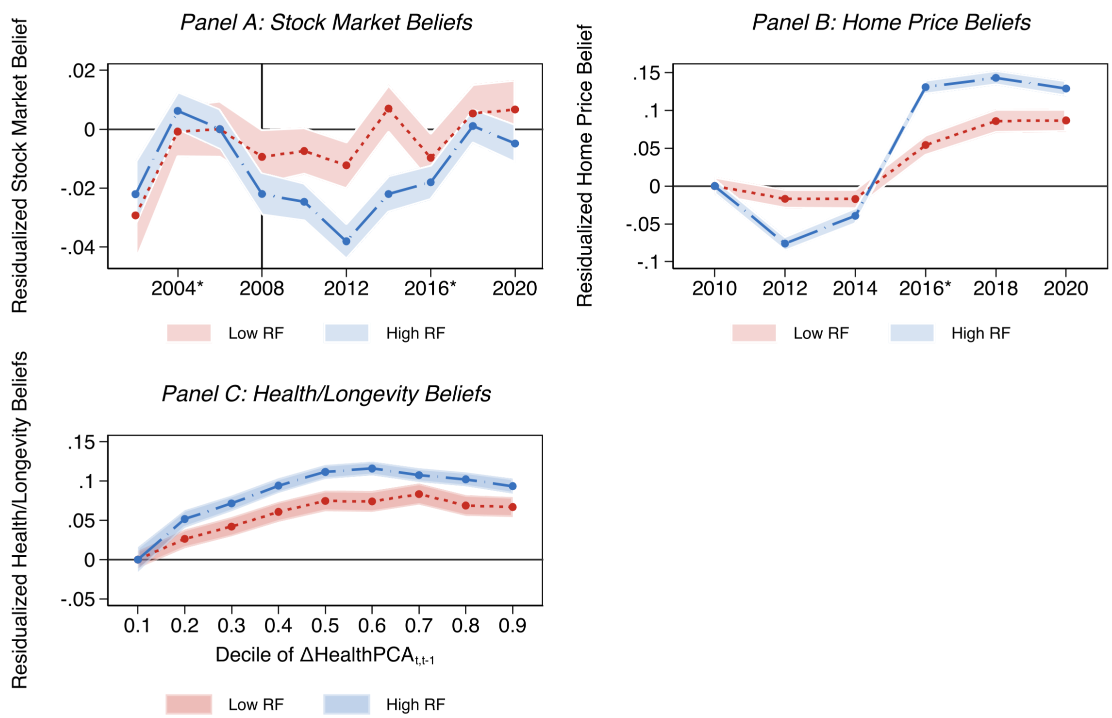
Figure C.5: Distribution of Recall Fluency and IQ (Pooled Person-Wave, Raw).

Panel A: Recall Fluency *Panel B: IQ*



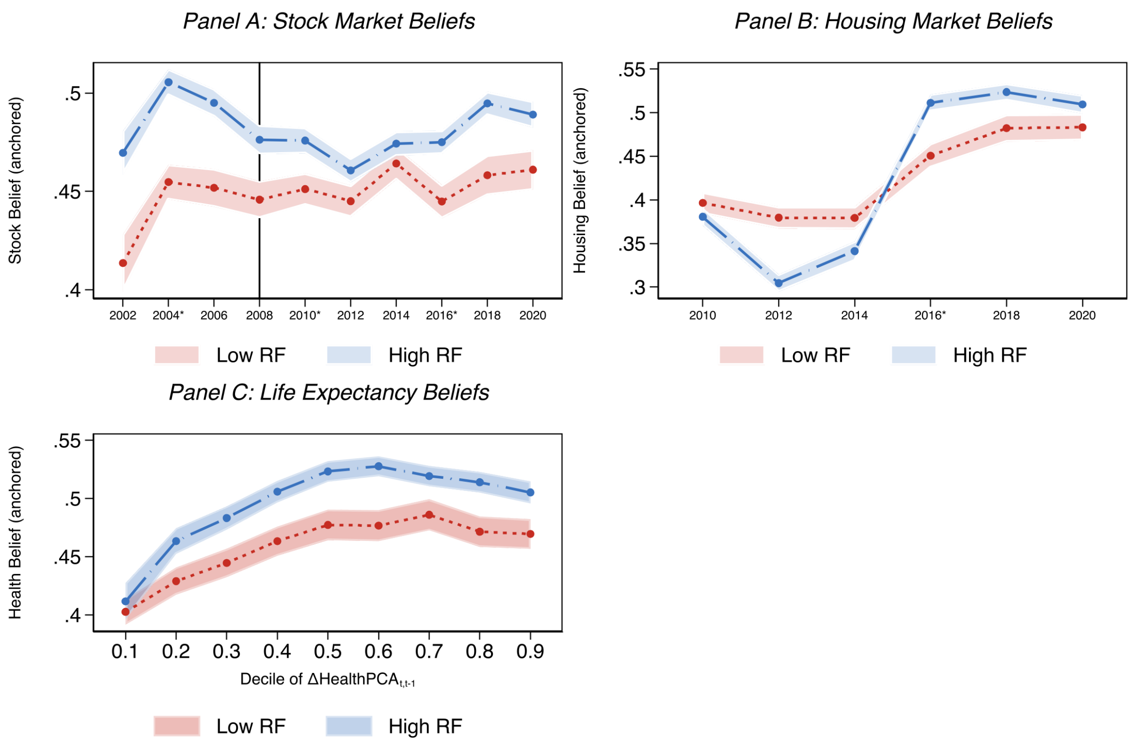
Notes: This is the raw (un-residualized) pooled (person-wave) counterpart of Figure 1. Panel A shows the raw distribution of Recall Fluency (RF) across all respondents and survey waves; Panel B shows the raw distribution of IQ. Both indices are constructed as the standardized mean of their components and are expressed in standard deviation units. The residualized pooled distributions are reported in Figure C.4. Sample: HRS respondents, waves 2002–2020.

Figure C.6: Residualized Beliefs Over Time, by Recall Fluency (Scaled).



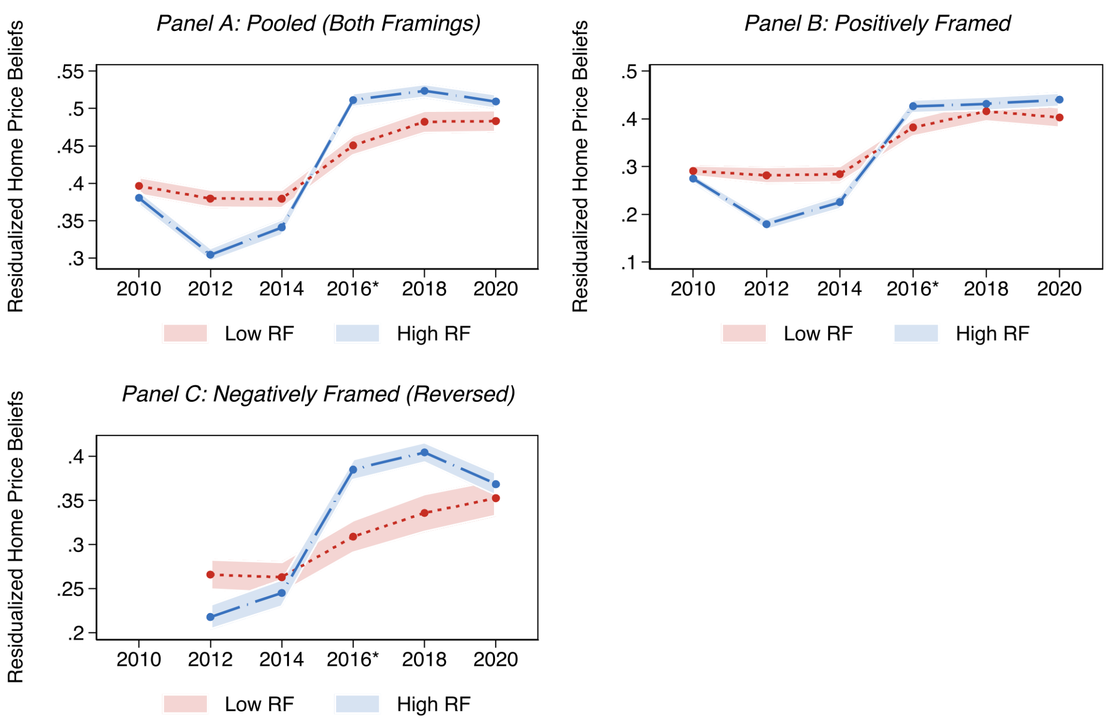
Notes: Each panel shows average residualized beliefs by Recall Fluency (RF) group. Panel A plots stock market beliefs ("chance stocks will be worth more in one year") by survey year (2002–2020). Panel B plots home-price beliefs ("chance home prices will go up") by survey year (2010–2020). Panel C plots longevity beliefs ("chance of surviving 10+ years") by decile of health change between survey waves. In all panels, beliefs are residualized on: age, gender, marital status, retirement status, income, education, and the Math Index (IQ). The stock market series additionally controls for whether the respondent actively follows the stock market. Each RF group is normalized to zero at its baseline: 2006 for stocks (just prior to the financial crisis), 2010 for home prices (first year the question was asked), and the lowest health-change decile for longevity. Low RF (High RF) is respondents in the bottom (top) quartile of the RF distribution. Shaded areas are 90% confidence intervals. Sample: HRS respondents, waves 2002–2020. * denotes years in which the HRS surveys only new entrants.

Figure C.7: Average Residualized Beliefs Over Time by Recall Fluency.



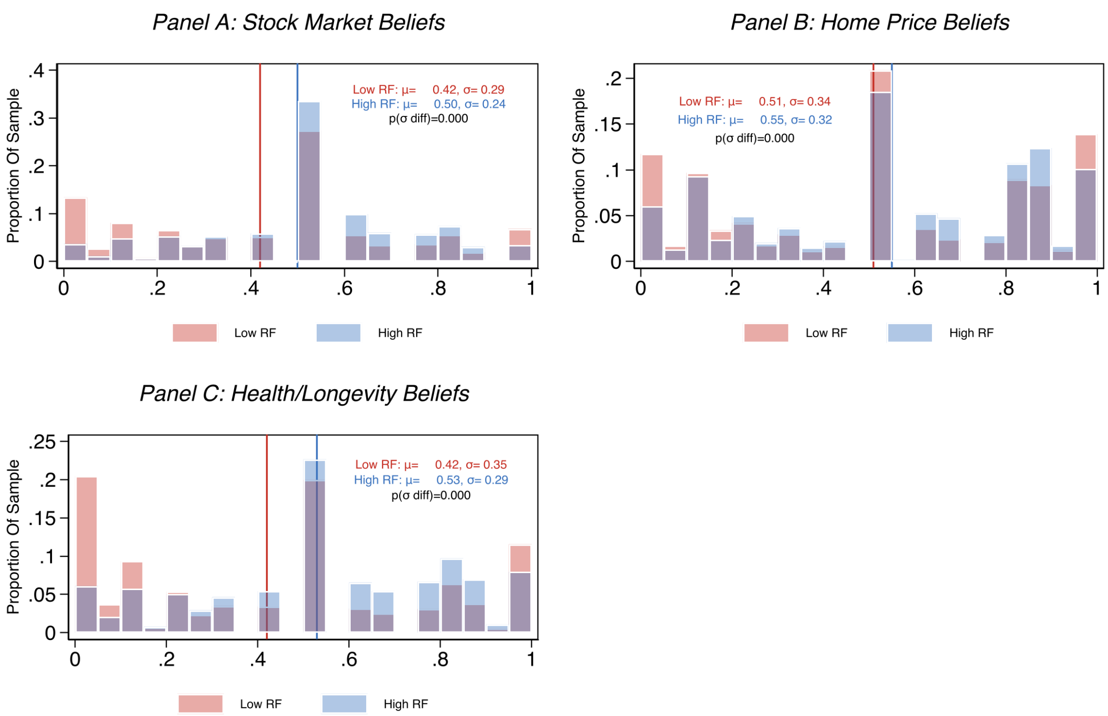
Notes: Each panel plots beliefs residualized on IQ, age, income, education, gender, marital status, and retirement status, then re-anchored to the overall raw sample mean so that the vertical axis is in interpretable belief units, for the top (blue) and bottom (red) quartile of Recall Fluency (RF). Panel A shows the average stock market belief ("chance stocks will be worth more in one year") by survey wave. Panel B shows the average home-price belief ("chance home will be worth more in one year") by survey wave from 2010 onward. Panel C shows the average life-expectancy belief ("chance live 10+ years") by decile of health change ($\Delta\text{HealthPCA}_{t,t-1}$). Shaded bands are 95% confidence intervals. Sample: HRS respondents, waves 2002–2020 (home prices 2010–2020). The dispersion of these residualized beliefs across RF groups is shown in Appendix Figure C.10; the corresponding raw (un-residualized) beliefs over time are shown in Figure 3.

Figure C.8: Home Price Beliefs by Question Framing, by Recall Fluency.



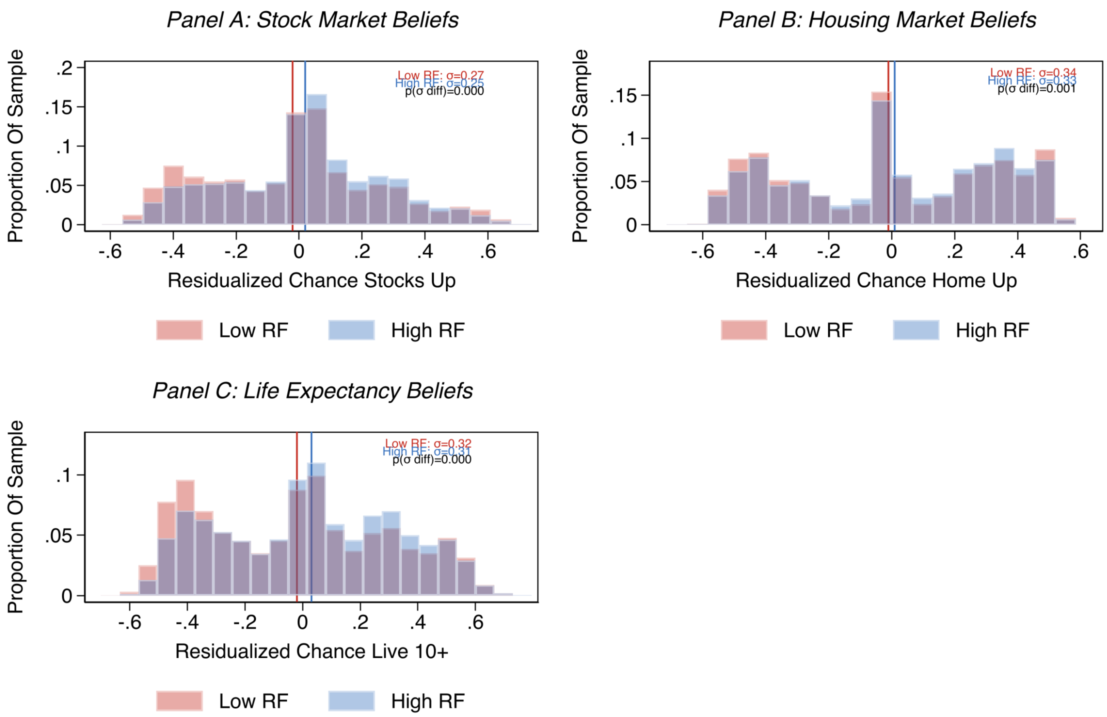
Notes: Each panel reproduces the home-price belief series of Panel B of Figure C.7 for a different subsample defined by how the home-price question was framed. Home-price beliefs are residualized on IQ, age, income, education, gender, marital status, and retirement status, then anchored to a subsample mean, by survey wave from 2010 onward, for the top (blue) and bottom (red) quartile of Recall Fluency. Negatively-framed responses (the probability the home loses value) are first reversed to the probability-of-increase scale, then additively level-shifted so that their mean matches the positively-framed mean; this level adjustment is applied wherever the negative frame appears (Panels A and C) and preserves all within-frame variation. Panel A pools both framings. Panel B uses only positively-framed respondents and is unaffected by the shift. Panel C uses only negatively-framed respondents, level-matched to the positive frame. Shaded bands are 95% confidence intervals. Sample: HRS homeowners, waves 2010–2020.

Figure C.9: Raw Belief Distributions, by Recall Fluency.



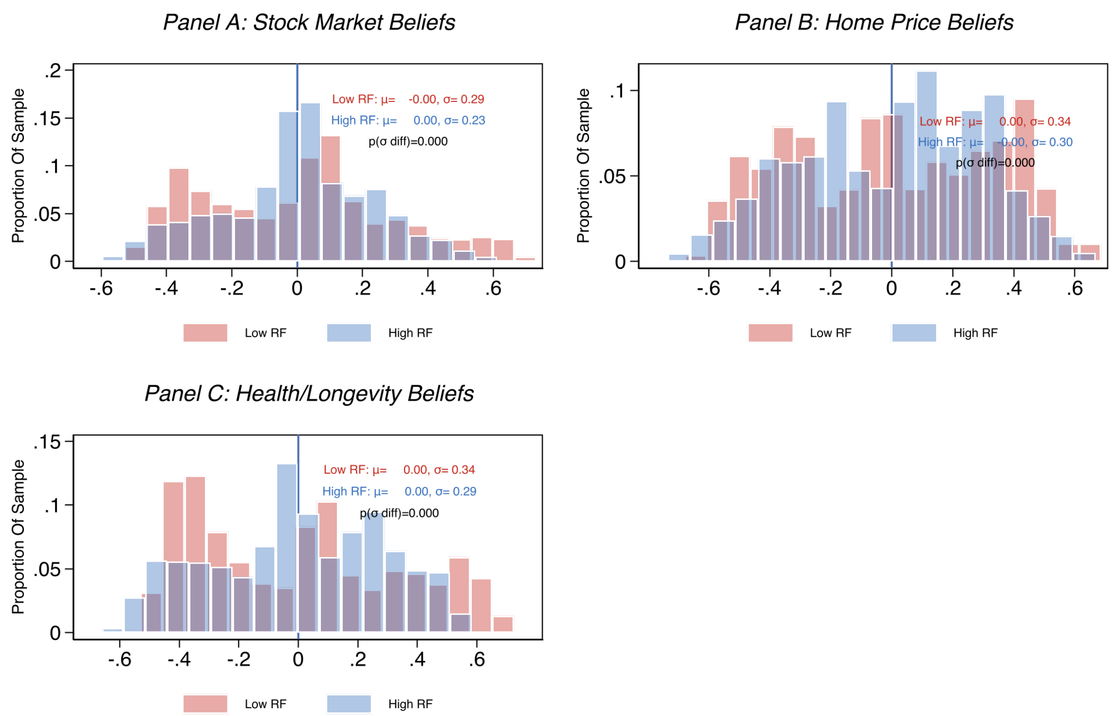
Notes: Each panel shows the distribution of raw (un-residualized) beliefs by Recall Fluency (RF) group. Panel A: stock market beliefs (). Panel B: home-price beliefs (; negative-framed responses reversed). Panel C: longevity beliefs (). Low RF (High RF) is respondents in the bottom (top) quartile of the raw RF distribution. Vertical lines show group means. Text on each panel reports group means (μ), standard deviations (σ), and the p-value for the Brown-Forsythe test of equality of variances. Sample: HRS respondents, waves 2002–2020.

Figure C.10: Dispersion of Residualized Beliefs, by Recall Fluency.



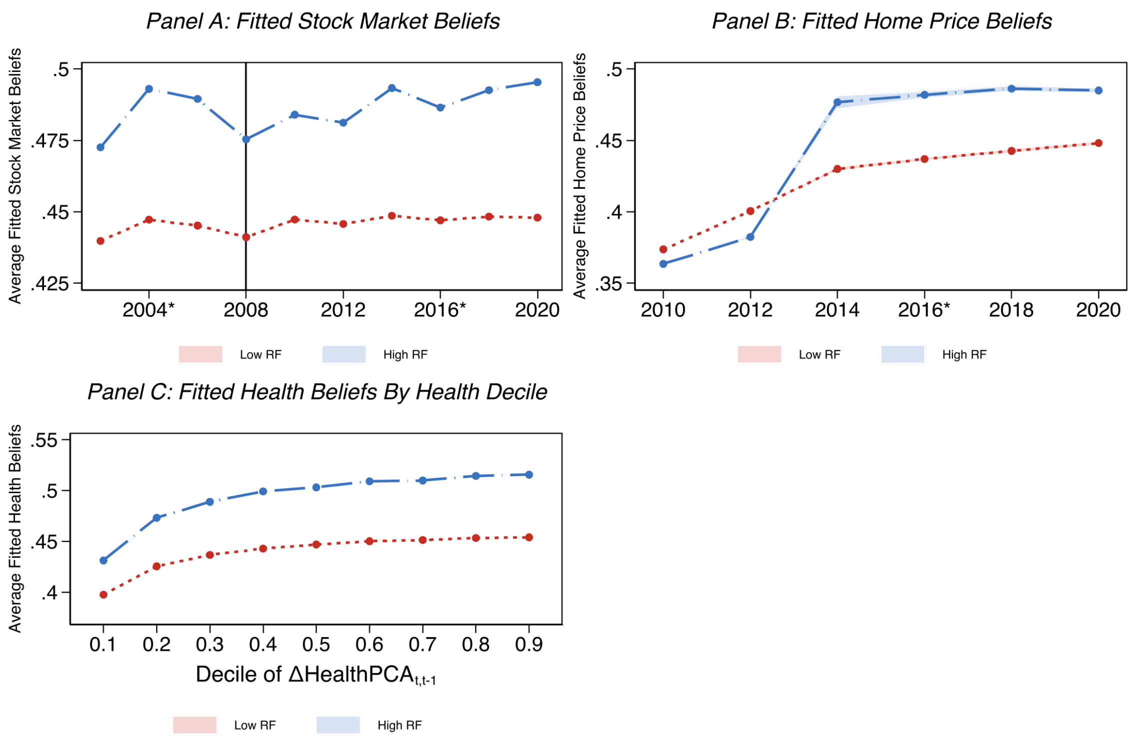
Notes: Each panel shows the distribution of beliefs residualized on IQ, age, income, education, gender, marital status, and retirement status, for the high (blue) and low (red) quartile of Recall Fluency (RF), plotted on a common bin grid; the inset reports each group's standard deviation and the p-value of an equality-of-variance test. Panel A: stock market beliefs ("chance stocks will be worth more in one year"). Panel B: home-price beliefs ("chance home will be worth more in one year"). Panel C: life-expectancy beliefs ("chance live 10+ years"). Sample: HRS respondents, waves 2002–2020. These demographic-residualized distributions sit between the raw distributions of Appendix Figure C.9 and the demographic- and time-residualized distributions of Appendix Figure C.11.

Figure C.11: Demographic- and Time-Residualized Belief Distributions, by Recall Fluency.



Notes: Each panel shows the distribution of beliefs residualized on both demographics and time. Panel A: stock market beliefs (). Panel B: home-price beliefs (; negative-framed responses reversed). Panel C: longevity beliefs (). Beliefs are first residualized on: age, gender, marital status, retirement status, income, education, and the Math Index (IQ); the stock market series additionally controls for stock market participation. The memory index is also residualized on the same demographics and used to form RF quartile groups. Beliefs are then further residualized on survey-year dummies separately within each RF group, removing common time variation. Vertical lines show group means. Text on each panel reports group means (μ), standard deviations (σ), and the p-value for the Brown-Forsythe test of equality of variances. Sample: HRS respondents, waves 2002–2020.

Figure C.12: Fitted Beliefs Over Time for High vs. Low Recall Fluency.



Notes: Fitted beliefs from the regressions in Table 1, with demographics and the IQ measure held at their sample means so the figure isolates the contribution of recall fluency, experiences, and cues; the counterpart that instead uses each respondent's actual covariates (the full-regression fitted values) is Figure 6. Each panel shows fitted beliefs for the bottom (red) and top (blue) quartile of Recall Fluency. Panel A shows fitted stock market beliefs over time from a regression of Equation 10 (column 1 of Table 1). Panel B shows fitted home-price beliefs over time using HPI moments (column 3 of Table 1). Panel C shows fitted health beliefs by decile of $\Delta\text{HealthPCA}_{t,t-1}$ (column 5 of Table 1). Shaded bands are 95% confidence intervals.

D Recall Fluency and Beliefs: regression analysis

Table D.1: DS Regressions With IQ × Experience and IQ × Signal Interactions.

	(1)	(2)	(3)	(4)	(5)	(6)
	Chance Stocks ↑		**Chance Home ↑**		**Chance Live10+**	
Cognition						
RF	.	0.003	.	-0.021*	.	0.001
	.	[0.006]	.	[0.012]	.	[0.003]
IQ	0.020**	0.019**	0.008	0.020	-0.035***	-0.035***
	[0.008]	[0.009]	[0.015]	[0.016]	[0.004]	[0.004]
DS Experiences						
$\overline{s_{it}}$ (γ_1)	-0.001	0.000	0.015**	0.009	0.022***	0.023***
	[0.003]	[0.003]	[0.006]	[0.007]	[0.002]	[0.002]
RF Interactions						
$RF * \overline{s_{it}}$ (γ_2)	0.005***	0.004**	0.003***	0.008***	0.006***	0.006***
	[0.000]	[0.002]	[0.001]	[0.003]	[0.000]	[0.001]
$RF * cov(s,(s-s_{it})^2)$ $(-\gamma_3)$	-0.003***	-0.003***	-0.007***	-0.007***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]
IQ Interactions						
$IQ * \overline{s_{it}}$ (κ_1)	0.001	0.001	-0.002	-0.005	0.006***	0.006***
	[0.002]	[0.002]	[0.004]	[0.004]	[0.001]	[0.001]
$IQ * s_{it}$ (κ_2)	-0.003***	-0.003***	0.063***	0.063***	0.002**	0.002**
	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]
N	118529	118529	44855	44855	113364	113364
AR2	0.04	0.04	0.07	0.07	0.11	0.11
Demographic Controls	Y	Y	Y	Y	Y	Y
Cohort FE	N	N	N	N	Y	Y
Age FE	N	N	N	N	Y	Y

Notes: Each column replicates the corresponding column of the main Table 1 with the addition of IQ × mean-experience and IQ × current-signal interactions (IQ $\times \overline{s_{it}}$ and IQ $\times s_{it}$). The signal is the most recent realized return that enters the covariance term. Its main effect is omitted by design; only its interaction with IQ enters. Dependent variables: cols 1–2 chance stocks rise; cols 3–4 chance home prices rise; cols 5–6 chance of living 10+ years. Columns 2, 4, 6 additionally include RF as a main effect. All regressors standardized by sample IQR prior to estimation. Demographic controls include age, gender, marital status, retirement status, income, and education; home-price regressions also include home ownership. Survey-year fixed effects are absorbed in every column; columns 5–6 additionally absorb age and birth-cohort fixed effects. Standard errors clustered by respondent in brackets. * p<0.12, ** p<0.05, *** p<0.01.

Table D.2: DS Regressions With Survey-Year Fixed Effects.

	(1)	(2)	(3)	(4)	(5)	(6)
	Chance Stocks ↑		**Chance Home ↑**		**Chance Live10+**	
Cognition						
RF	.	0.003	.	-0.042***	.	-0.002
	.	[0.005]	.	[0.010]	.	[0.003]
IQ	0.024***	0.024***	0.001	0.002	-0.020***	-0.020***
	[0.002]	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]
DS Experiences						
$\overline{s_{it}}$ (γ_1)	-0.004***	-0.003	0.005**	-0.015***	0.029***	0.029***
	[0.001]	[0.003]	[0.002]	[0.005]	[0.001]	[0.002]
RF Interactions						
$RF * \overline{s_{it}}$ (γ_2)	0.005***	0.004***	0.002***	0.013***	0.006***	0.007***
	[0.000]	[0.001]	[0.001]	[0.003]	[0.000]	[0.001]
$RF * cov(s,(s-s_{it})^2)$ $(-\gamma_3)$	-0.003***	-0.003***	-0.005***	-0.005***	-0.001***	-0.001***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]
N	139345	139345	49972	49972	116262	116262
AR2	0.04	0.04	0.10	0.10	0.11	0.11
Demographic Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Cohort FE	N	N	N	N	Y	Y
Age FE	N	N	N	N	Y	Y

Notes: Each column replicates the corresponding column of the main Table 1 with the addition of survey-year fixed effects throughout. Year fixed effects absorb aggregate time-series shocks—such as macroeconomic news or market-wide returns—that affect all respondents in the same survey wave simultaneously. Persistence of the RF × experience interactions (γ_2, γ_3) after absorbing year effects indicates that results reflect individual memory reactions to personal past experiences rather than common aggregate information. All other specification choices are identical to Table 1: dependent variables, regression specification, controls, and (non-year) fixed effects structure. Dependent variables: cols 1–2 chance stocks rise; cols 3–4 chance home prices rise; cols 5–6 chance of living 10+ years. Columns 2, 4, 6 additionally include RF as a main effect. Demographic controls include age, gender, marital status, retirement status, income, and education; home-price regressions also include home ownership. Standard errors clustered by respondent in brackets. * p<0.12, ** p<0.05, *** p<0.01.

Table D.3: NDS Database Regressions With Survey-Year Fixed Effects.

	(1)	(2)	(3)	(4)	(5)	(6)
	Chance Stocks ↑		**Chance Home ↑**		**Chance Live 10+**	
Cognition (η)						
RF	0.004	0.002	-0.046***	-0.042***	-0.002	-0.003
	[0.006]	[0.006]	[0.010]	[0.010]	[0.004]	[0.007]
IQ	0.024***	0.024***	0.002	0.001	-0.020***	-0.023***
	[0.002]	[0.002]	[0.003]	[0.003]	[0.002]	[0.002]
DS Experiences (θ)						
$\overline{s_{it}}$ (γ_1)	0.000	0.000	-0.017***	-0.015***	0.022***	0.025***
	[0.002]	[0.002]	[0.005]	[0.005]	[0.002]	[0.002]
RF Interactions (β)						
$RF \times \overline{s_{it}}$ (γ_2)	0.004***	0.004***	0.014***	0.012***	0.008***	0.007***
	[0.001]	[0.001]	[0.003]	[0.003]	[0.001]	[0.001]
$RF \times \text{cov}(s, (s - s_{it})^2)$ $(-\gamma_3)$	-0.003***	-0.002***	-0.005***	-0.005***	-0.000	-0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]
NDS Experiences (δ, τ)						
nds (δ_1)	0.001	0.001	-0.002	-0.004	0.046***	-0.003
	[0.001]	[0.001]	[0.002]	[0.005]	[0.005]	[0.004]
$RF \times nds$ (τ)	0.001**	0.005***	0.002	0.005**	0.014***	0.008***
	[0.001]	[0.001]	[0.001]	[0.003]	[0.002]	[0.002]
N	134136	139342	49593	49971	102724	88815
AR2	0.04	0.04	0.10	0.10	0.07	0.07
NDS Var	Chld.Health	Chld.SES	Chld.Health	Chld.SES	$\Delta_L sp500$	$\Delta_L hpi$
Demographic Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Cohort FE	N	N	N	N	Y	Y
Age FE	N	N	N	N	N	N

Notes: Replicates Table 2 adding survey-year fixed effects throughout. Year FE absorb common time trends; RF–experience interactions identify within-year, cross-person variation in belief sensitivity. Columns 5–6 therefore replace the age fixed effects used in the health columns of Table 2 with the survey-year dimension, since age is largely determined by survey year and birth cohort once both are absorbed; age remains a linear demographic control in every column. NDS variables: childhood health and SES for stocks and home prices; lifetime equity and home-price returns for health. All continuous regressors (RF, IQ, $\overline{s_{it}}$, $\text{cov}(s_k, (s_k - s_{it})^2)$, NDS) divided by within-sample IQR; coefficients represent a move from p25 to p75. Demographic controls: age, gender, marital status, retirement status, income, education. Standard errors in brackets; * p<0.10, ** p<0.05, *** p<0.01.

Table D.4: NDS Database Regressions: Robustness of Simple NDS Indexes.

NDS index components used in this version:

Childhood Health (4 vars): severe childhood conditions, disabled as a child, total childhood conditions, missed school for health.

Childhood SES (2 vars): father's education, mother's education.

	(1)	(2)	(3)	(4)	(5)	(6)
	Chance Stocks ↑		**Chance Home ↑**		**Chance Live 10+**	
Cognition						
IQ	0.025***	0.025***	0.016**	0.013***	-0.018***	-0.021***
	[0.002]	[0.002]	[0.006]	[0.003]	[0.002]	[0.002]
DS Experiences						
$\overline{s_{it}}$ (γ_1)	0.000	0.002*	0.027***	0.027***	0.028***	0.027***
	[0.001]	[0.001]	[0.007]	[0.002]	[0.002]	[0.002]
RF Interactions						
$RF * \overline{s_{it}}$ (γ_2)	0.004***	0.004***	0.004***	0.004***	0.007***	0.008***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
$RF * cov(s_k, (s_k - s_{it})^2)$ $(-\gamma_3)$	-0.003***	-0.003***	-0.030***	-0.030***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.008]	[0.001]	[0.000]	[0.000]
NDS Experiences						
nds (δ_1)	-0.001	0.000	-0.004	-0.007	0.002	0.001
	[0.001]	[0.002]	[0.002]	[0.005]	[0.003]	[0.001]
$RF * nds$ (δ_2)	0.002***	0.005***	0.002**	0.007***	0.008***	0.005***
	[0.001]	[0.001]	[0.001]	[0.003]	[0.001]	[0.000]
N	134136	124539	49593	46108	116262	100979
AR2	0.04	0.04	0.05	0.05	0.11	0.12
NDS Var	Chld.Health	Chld.SES	Chld.Health	Chld.SES	$\Delta_L sp500$	$\Delta_L hpi$
Demographic Controls	Y	Y	Y	Y	Y	Y
Cohort FE	N	N	N	N	Y	Y
Age FE	N	N	N	N	Y	Y

Notes: Robustness version of the main NDS table with simpler childhood indexes. The childhood-health index in columns 1 and 3 uses four objective components and drops psychological childhood conditions; the childhood-SES index in columns 2 and 4 uses parental education only. Columns 5 and 6 use the same lifetime stock-return and lifetime home-price-return NDS variables as the main table. Sample, demographic controls, fixed effects, IQR rescaling of all continuous regressors, and standard-error treatment otherwise match the main NDS table exactly. All continuous regressors (RF, IQ, the DS experience mean and covariance, and the NDS index) are divided by their within-sample IQR prior to estimation, so each coefficient is the change in beliefs associated with a P25-to-P75 move in the regressor. Demographic controls include age, gender, marital status, retirement status, income, and education. Standard errors in brackets; * p<0.10, ** p<0.05, *** p<0.01.

Table D.5: Descriptive statistics of similarity ratings, by between-subjects group.

Outcome	n	vs. Illness / accident	vs. Financial difficulties
Group 1: personally-scoped economic outcomes			
Own home price: future increase of 7% or more	199	2.22 (1.57)	3.66 (2.09)
Own home price: future decrease of 7% or more	199	2.59 (1.75)	4.06 (2.05)
U.S. economy: major depression in the next 10 years	199	3.60 (1.83)	5.75 (1.43)
Cost of living: increase of 5%+ per year over next 5 years	199	2.95 (1.73)	5.28 (1.60)
Group 2: macro-market outcomes			
General U.S. home prices: future increase of 7% or more	203	2.35 (1.55)	4.96 (1.59)
General U.S. home prices: future decrease of 7% or more	203	2.12 (1.54)	3.36 (1.96)
Blue-chip stocks (DJIA): increase of 7% or more	203	1.83 (1.33)	2.91 (1.71)
Blue-chip stocks (DJIA): decrease of 7% or more	203	2.24 (1.47)	4.33 (1.72)

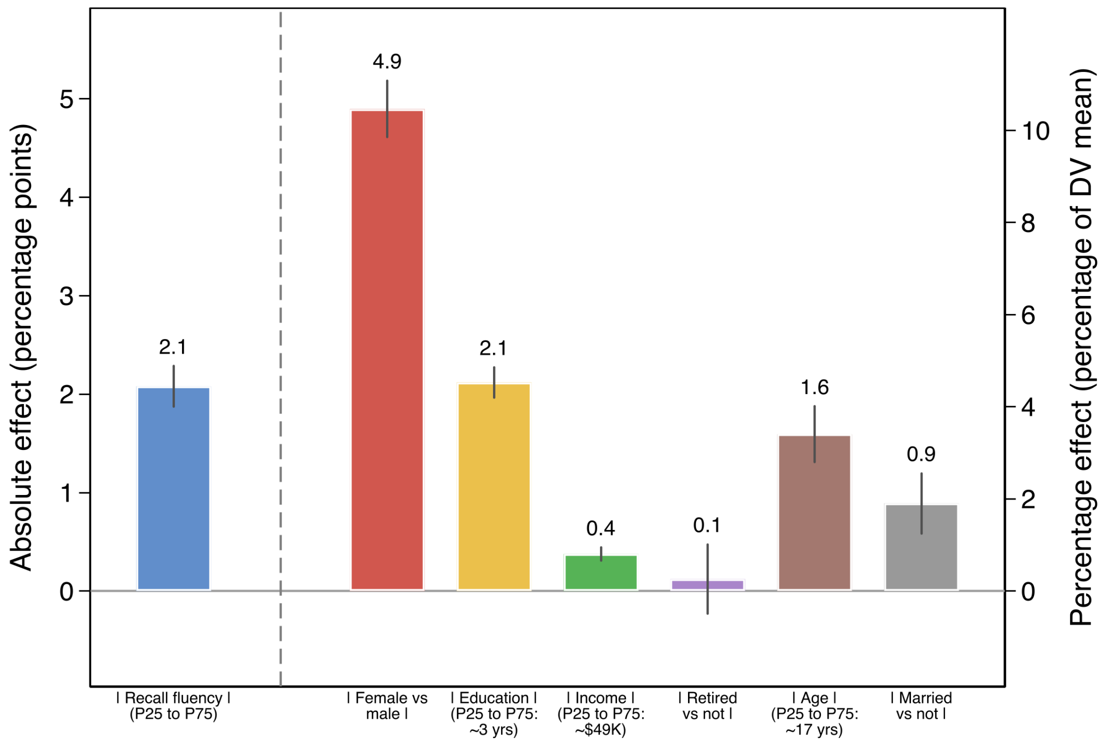
Notes: $N = 402$ U.S. homeowners (screened for owner-occupied housing). Each respondent was randomly assigned to one of two between-subjects groups ($n = 199$ and $n = 203$) and rated the four outcomes in their group. Similarity is measured on a 1–7 scale (1 = not similar at all, 7 = extremely similar). The two reference experiences are (a) a serious or chronic illness or accident, and (b) struggling with financial difficulties. Cell entries are mean perceived similarity, with the standard deviation in parentheses.

Table D.6: Database Regressions for Macroeconomic Beliefs: Baseline and Non-Domain-Specific Experiences.

	Chance Depression				**Chance Inflation > 5%**			
	Baseline		+ NDS		Baseline		+ NDS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cognition								
RF		-0.101***	-0.037	-0.097***		-0.035	-0.045	-0.036
		[0.022]	[0.025]	[0.022]		[0.099]	[0.100]	[0.099]
IQ	-0.028***	-0.028***	-0.028***	-0.028***	-0.000	-0.000	-0.001	0.000
	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]	[0.004]	[0.004]	[0.004]
DS experiences								
$\overline{s_{it}}$ (γ_1)	0.004**	-0.005**	0.002	-0.005*	-0.001**	-0.002	-0.002	-0.002
	[0.002]	[0.002]	[0.003]	[0.002]	[0.000]	[0.001]	[0.001]	[0.001]
RF Interactions								
$RF * \overline{s_{it}}$ (γ_2)	0.001***	0.006***	0.003*	0.006***	0.000***	0.000	0.000	0.000
	[0.000]	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]
$RF * cov(s,(s-s_{it})^2)$ ($-\gamma_3$)	-0.058***	-0.058***	-0.058***	-0.058***	-0.013***	-0.013***	-0.010***	-0.013***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
NDS experience								
nds (δ_1)			-0.004***	0.001			-0.002*	0.007
			[0.001]	[0.004]			[0.001]	[0.005]
$RF * nds$ (δ_2)			-0.000	-0.007***			-0.000	-0.006**
			[0.000]	[0.002]			[0.001]	[0.003]
NDS Var	—	—	Chld.Health	Chld.SES	—	—	Chld.Health	Chld.SES
N	46576	46576	42984	46576	29682	29682	28452	29682
AR2	0.05	0.05	0.06	0.05	0.01	0.01	0.01	0.01
Min year	2002	2002	2002	2002	2006	2006	2006	2006
Max year	2008	2008	2008	2008	2008	2008	2008	2008
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y

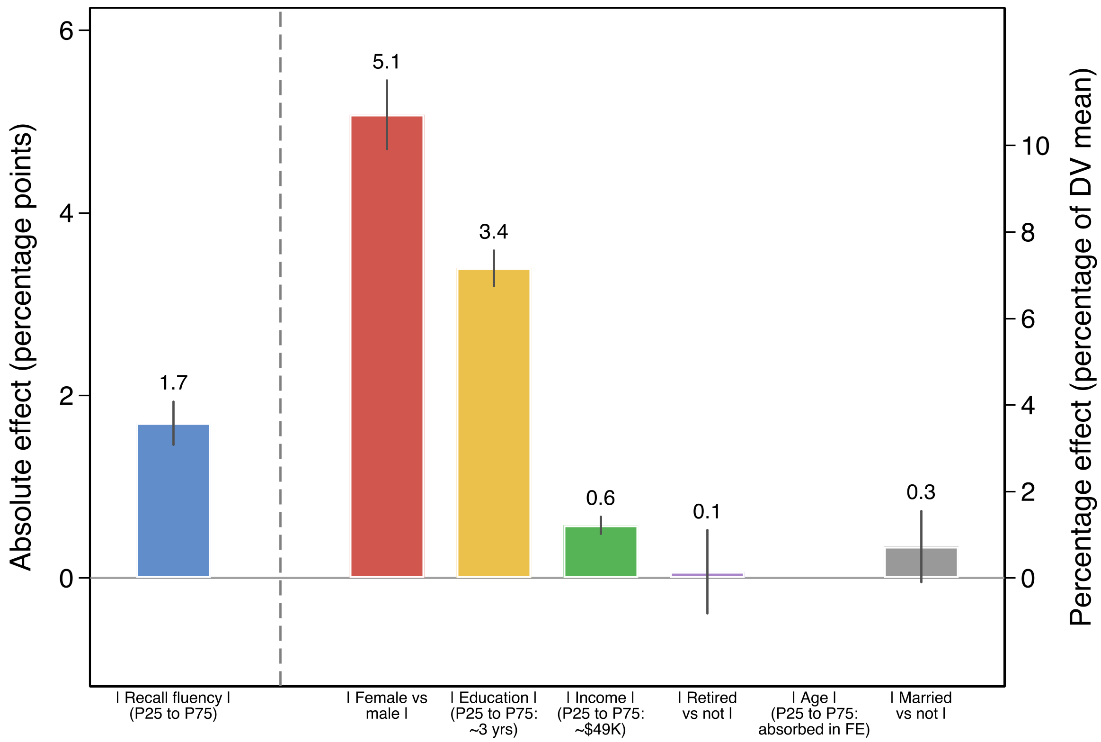
Notes: Each column reports a panel regression of subjective macroeconomic beliefs on Recall Fluency (RF), IQ, domain-specific (DS) experience variables ($\overline{s_{it}}$ and $cov(s,(s-s_{it})^2)$), and their RF interactions, mirroring Table 1. For each outcome the first two (*Baseline*) columns add cognition and RF interactions without and then with the RF base effect; the next two (*+ NDS*) columns add a single non-domain-specific experience entered directly (δ_1) and interacted with RF (δ_2), using childhood health and then childhood socioeconomic-status (SES), as reported in the *NDS Var* row. Childhood health and childhood SES are never included in the same regression. **Chance Depression** is the subjective probability that the U.S. economy will experience a major depression within the next 10 years, paired with lifetime NBER recession experience. **Chance Inflation > 5%** is the subjective probability that the cost of living will rise by more than 5% on average over the next 10 years, paired with lifetime inflation experience. All continuous regressors are divided by their within-sample IQR prior to estimation. Min/Max year report the earliest and latest HRS wave year in each column's estimation sample. Standard errors in brackets; * p<0.12, ** p<0.05, *** p<0.01.

Figure D.1: Economic Magnitude of Recall Fluency Versus Main Demographic Controls: Chance Stocks Will Go Up.



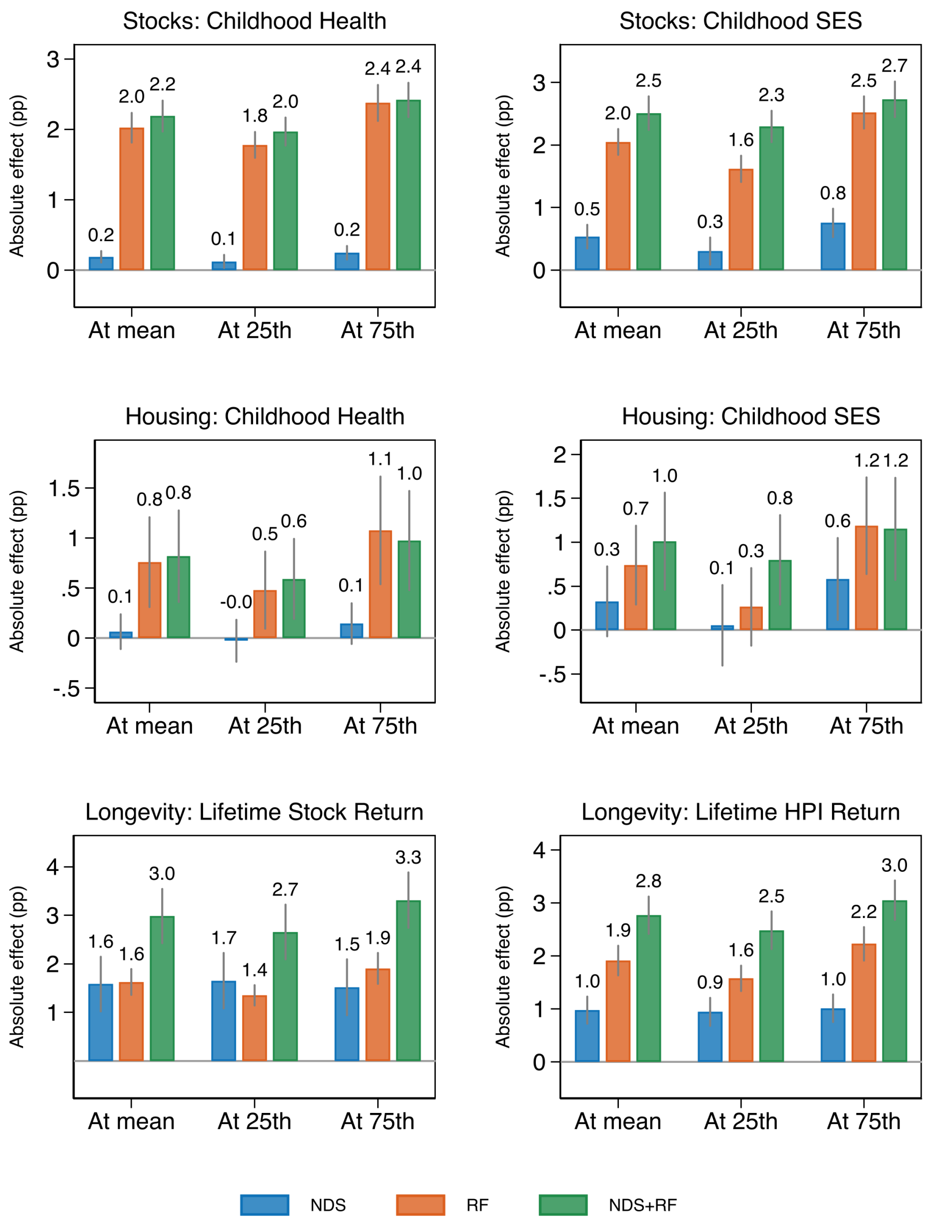
Notes: Bars show the absolute change in the predicted belief (in percentage points) implied by moving each regressor by a pre-specified amount, holding all other regressors fixed, in column 1 of Table 1 (subjective-belief outcome: Chance Stocks Will Go Up; N = 139,345). For continuous regressors (recall fluency, education, income, age) the bar is the predicted change from a P25-to-P75 move in the estimation sample; for binary regressors (gender, retired, married) it is a 0-to-1 change. Gender is plotted as female relative to male. The recall-fluency bar is $\hat{\gamma}_2 \cdot \bar{s}_{it}$ evaluated at the sample mean of $\bar{s}_{it}$, following Equation 10. Interquartile ranges (continuous variables only): education $\approx$ 3 years; household income $\approx$ \$49K; age $\approx$ 17 years. Error bars are 95% confidence intervals.

Figure D.2: Economic Magnitude of Recall Fluency Versus Main Demographic Controls: Chance of Living 10+ Years.



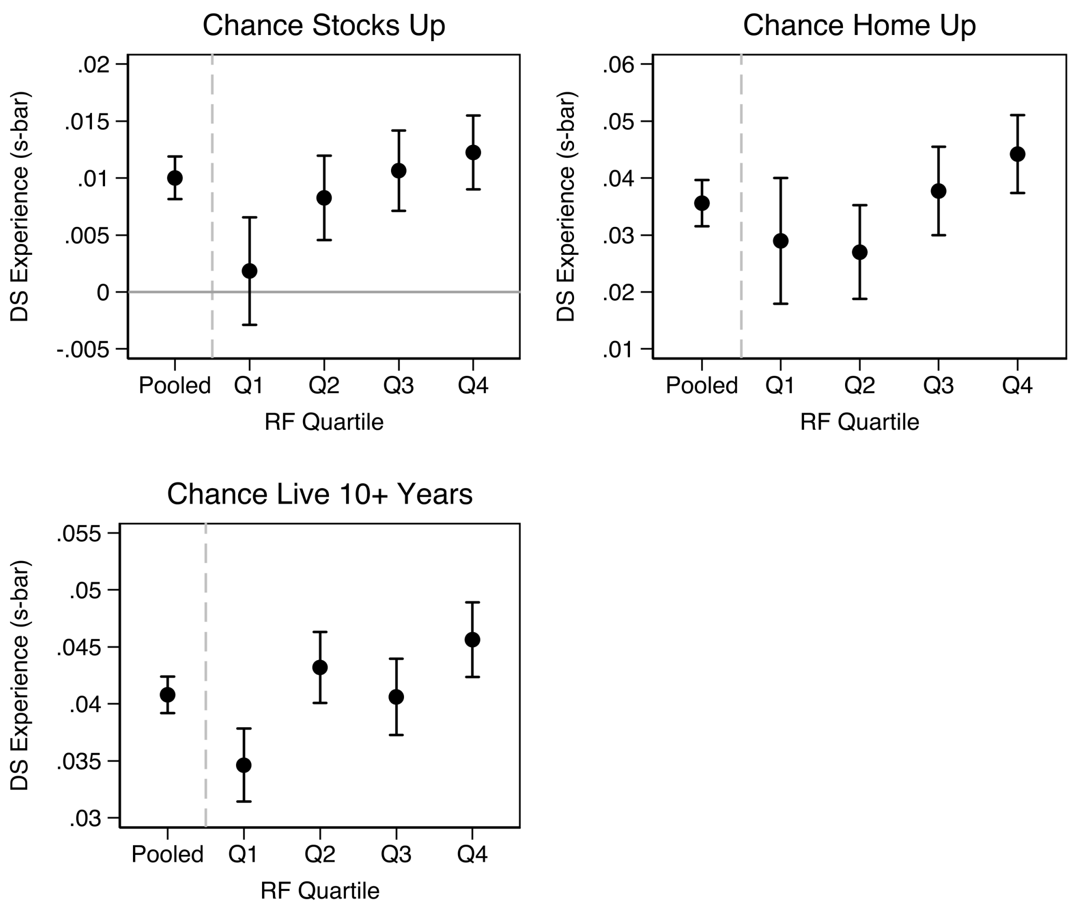
Notes: Bars show the absolute change in the predicted belief (in percentage points) implied by moving each regressor by a pre-specified amount, holding all other regressors fixed, in column 5 of Table 1 (subjective-belief outcome: Chance of Living 10+ Years; $N = 116{,}262$). For continuous regressors (recall fluency, education, income, age) the bar is the predicted change from a P25-to-P75 move in the estimation sample; for binary regressors (gender, retired, married) it is a 0-to-1 change. Gender is plotted as female relative to male. The recall-fluency bar is $\hat{\gamma}_2 \cdot \bar{s}_{it}$ evaluated at the sample mean of $\bar{s}_{it}$, following Equation 10. Interquartile ranges (continuous variables only): education $\approx$ 3 years; household income $\approx$ \$49K; age is absorbed in the column fixed effects. Error bars are 95% confidence intervals.

Figure D.3: NDS Impact Coefficient Sizes: Stock, Home-Price, and Longevity Beliefs.



Notes: Each panel reports the absolute marginal effect, in percentage points of the dependent variable, at three evaluation points—*At mean*, *At 25th*, *At 75th*—denoting where all four covariates (RF, NDS, IQ, Experiences) are held when computing marginal effects. Within each group, three bars: NDS = marginal effect of the non-domain-specific experience holding RF constant; RF = marginal effect of recall fluency holding NDS constant; NDS+RF = combined effect of moving both NDS and RF from the 25th to the 75th percentile. Rows correspond to the three dependent variables (chance stocks rise; chance home prices rise; chance of living 10+ years). The two columns within each row report the two non-domain-specific experience measures used for that outcome: childhood health and childhood SES indices for the stock and home-price outcomes, and lifetime S&P 500 and HPI returns for longevity. Error bars: 95% CIs. Variables standardized by sample IQR.

Figure D.4: Non-Parametric RF-Quartile Experience Coefficients, by Domain.



Notes: Each panel reports, for one belief domain (top-left: stock market; top-right: home prices; bottom: health/longevity), the DS experience coefficient ($\hat{\gamma}_1$ on $\bar{s}_{it}$) and its 95% confidence interval from the column 1/3/5 specification of Table 1, estimated separately within each recall-fluency (RF) quartile; the RF $\times$ Experience interaction is omitted so the figure isolates the pure experience effect within each quartile. The Pooled group gives the full-sample estimate. All continuous regressors are IQR-standardized within each subsample. Demographic controls included throughout.

Table D.7: Robustness: Choice Regressions Including RF Directly in Second Stage.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Stock/Home-Price Market Choices					
	New Stock Market Inv.		**% IRA in Stocks**		**Bought a New Home**	
Cognition						
RF (1 sd) (κ^M)	0.006***	0.011***	0.015***	0.019***	0.003**	0.003**
	[0.002]	[0.002]	[0.005]	[0.005]	[0.001]	[0.001]
IQ (1 sd)	0.011***	-0.002	0.037***	0.009**	0.005***	-0.002
	[0.001]	[0.001]	[0.004]	[0.004]	[0.001]	[0.002]
Beliefs *(ϕ)*						
$\widehat{B_{it}}$ (θ)	0.040***	.	0.037***	.	0.008***	.
	[0.004]	.	[0.011]	.	[0.001]	.
$B(E)$ (γ)	.	-0.011***	.	-0.014***	.	0.002**
	.	[0.001]	.	[0.003]	.	[0.001]
$B(RF \times E)$ (μ)	.	0.008***	.	0.007*	.	0.006***
	.	[0.002]	.	[0.004]	.	[0.001]
Avg DV	0.10	0.10	0.56	0.56	0.04	0.04
N	129529	124424	36078	35150	45249	44460
Demographic Controls	Y	Y	Y	Y	Y	Y
Risk-taking	N	Y	N	Y	N	Y
	Panel B: Health Choices					
	Work Past 70		**Retired**		**% of Income to Pension**	
Cognition						
RF (1 sd) (κ^M)	0.006**	0.008**	-0.004***	-0.013***	-0.001	-0.004**
	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
IQ (1 sd)	0.016***	0.014***	-0.005***	0.002	0.002	0.003*
	[0.003]	[0.003]	[0.001]	[0.001]	[0.002]	[0.002]
Beliefs *(ϕ)*						
$\widehat{B_{it}}$ (θ)	0.032***	.	-0.009***	.	0.004	.
	[0.004]	.	[0.002]	.	[0.002]	.
$B(E)$ (γ)	.	0.019***	.	-0.018***	.	-0.004*
	.	[0.004]	.	[0.002]	.	[0.003]
$B(RF \times E)$ (μ)	.	0.008**	.	0.012***	.	0.007***
	.	[0.004]	.	[0.002]	.	[0.002]
Avg DV	0.26	0.26	0.64	0.63	0.08	0.08
N	20280	20265	100979	95419	4352	4349
Demographic Controls	Y	Y	Y	Y	Y	Y
Risk-taking	N	Y	N	Y	N	Y
Cohort/Age FE	Y	Y	Y	Y	Y	Y

Notes: Robustness version of Table 4. The two-stage structure is identical: Stage 1 predicts beliefs from RF, IQ, experience interactions, and the RF × experience-covariance interaction (same specification as Table 2). Stage 2 decomposes fitted beliefs into three additive components: experience ($B(E)$, γ); total memory-amplified contribution to fitted belief ($B(RF \times E)$, μ), summing the Stage-1 fitted contributions of the RF × experience and RF × experience-covariance interactions; and a controls component ($B(Dems)$). The only difference from Table 4 is that RF (Recall Fluency) is also included as a direct second-stage regressor (κ^M), allowing it to affect choices through channels beyond its belief-shaping effect. Odd columns (1, 3, 5): total predicted belief $\widehat{B}_{it}$ (θ). Even columns (2, 4, 6): full decomposition with risk taking. Panel A outcomes: *New Stock Market Inv.*, an indicator equal to one if the respondent made a new stock market investment since the prior survey wave; *% IRA in Stocks*, the share of IRA assets held in stocks (0–1); *Bought a New Home*, an indicator for home purchase since the prior wave; estimated by pooled OLS without fixed effects. Panel B outcomes: *Work Past 70*, the subjective probability of working past age 70 (0–100); *Retired*, an indicator for retirement status; *% of Income to Pension*, the share of income contributed to a pension plan (0–1); age and cohort fixed effects. Demographic controls in all columns. Coefficients scaled to 1 SD of each regressor. Standard errors in brackets; * p<0.10, ** p<0.05, *** p<0.01.

Table D.8: Robustness: Choice Regressions Using Previous-Wave Fitted Beliefs.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Stock/Home-Price Market Choices					
	New Stock Market Inv.		**% IRA in Stocks**		**Bought a New Home**	
IQ (1 sd)	0.016***	0.015***	0.038***	0.036***	0.007***	0.005***
	[0.001]	[0.001]	[0.003]	[0.003]	[0.001]	[0.001]
Lagged Beliefs **(ϕ)**						
$\widehat{B}_{i,t-2}$ (θ)	0.051***	.	0.063***	.	0.006***	.
	[0.002]	.	[0.005]	.	[0.001]	.
$B_{E_{i,t-2}}$ (γ)	.	-0.009***	.	-0.011***	.	0.001
	.	[0.001]	.	[0.003]	.	[0.001]
$B_{(\mathrm{RF}_{i,t-2} \cdot E_{i,t-2})}$ (μ)	.	0.014***	.	0.019***	.	0.005***
	.	[0.001]	.	[0.003]	.	[0.001]
Avg DV	0.11	0.11	0.55	0.56	0.03	0.03
N	106696	103113	33103	32292	36611	36233
Demographic Controls	Y	Y	Y	Y	Y	Y
Risk-taking	N	Y	N	Y	N	Y
Beliefs Lagged One Wave	Y	Y	Y	Y	Y	Y
	Panel B: Health Choices					
	Work Past 70		**Retired**		**% of Income to Pension**	
IQ (1 sd)	0.012***	0.009***	-0.006***	-0.011***	0.003	0.003
	[0.003]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
Lagged Beliefs **(ϕ)**						
$\widehat{B}_{i,t-2}$ (θ)	0.030***	.	-0.025***	.	0.006**	.
	[0.004]	.	[0.002]	.	[0.003]	.
$B_{E_{i,t-2}}$ (γ)	.	0.017***	.	-0.018***	.	-0.003
	.	[0.004]	.	[0.002]	.	[0.003]
$B_{(\mathrm{RF}_{i,t-2} \cdot E_{i,t-2})}$ (μ)	.	0.013***	.	-0.004**	.	0.005***
	.	[0.003]	.	[0.002]	.	[0.002]
Avg DV	0.26	0.26	0.70	0.70	0.09	0.09
N	14919	14917	79270	75860	3029	3028
Demographic Controls	Y	Y	Y	Y	Y	Y
Risk-taking	N	Y	N	Y	N	Y
Cohort/Age FE	Y	Y	Y	Y	Y	Y
Beliefs Lagged One Wave	Y	Y	Y	Y	Y	Y

Notes: Timing robustness version of Table 4. Stage 1 is identical: beliefs are predicted from RF, IQ, domain-specific (DS) experiences and their interactions with RF, the RF × experience-covariance interaction, and the non-domain-specific (NDS) experiences and their interactions with RF. The NDS experiences are childhood health and childhood SES for the stock- and home-price choices (Panel A), and cumulative lifetime log equity and home-price returns for the life-expectancy choices (Panel B). The single change is the timing of Stage 2: each choice recorded at survey wave t is regressed on the fitted-belief components constructed from that respondent's *previous* survey wave, two years earlier ($t-2$), so that the belief is pre-determined relative to the recorded choice. This addresses the fact that each of these choices may be realised at any point in the two years between interviews, whereas in Table 4 the belief is elicited in the same wave as the choice. Demographic controls, IQ, the risk-taking index, and fixed effects are all measured at wave t, contemporaneous with the choice. Odd columns (1, 3, 5) use the total lagged predicted belief $\widehat{B}_{i,t-2}$ (θ). Even columns (2, 4, 6) decompose it into an experience-driven component ($B_{E_{i,t-2}}$, γ); the total memory-amplified contribution ($B_{(\mathrm{RF}_{i,t-2} \cdot E_{i,t-2})}$, μ), summing the Stage-1 fitted contributions of the RF × experience and RF × experience-covariance interactions; and a demographic component, which enters the regression but is not reported. Panel A outcomes: *New Stock Market Inv.*, an indicator equal to one if the respondent made a new stock market investment since the previous survey wave; *% IRA in Stocks*, the share of IRA assets held in stocks (0–1); *Bought a New Home*, an indicator for home purchase since the previous wave; estimated by pooled OLS without fixed effects. Panel B outcomes: *Work Past 70*, the subjective probability of working past age 70 (0–100); *Retired*, an indicator for retirement status; *% of Income to Pension*, the share of income contributed to a pension plan (0–1); age and birth-cohort fixed effects. Sample sizes are smaller than in Table 4 because the specification requires each respondent to be observed in two consecutive waves. Coefficients scaled to 1 SD of each regressor. Standard errors in brackets; * p<0.10, ** p<0.05, *** p<0.01.

Table D.9: Stock-Market Belief Regressions, by Whether Respondent Follows the Stock Market.

	(1)	(2)	(3)	(4)
	Follow Stocks		**Don't Follow Stocks**	
Cognition				
RF	.	0.005	.	-0.005
	.	[0.008]	.	[0.008]
IQ	0.018***	0.018***	0.017***	0.017***
	[0.002]	[0.002]	[0.002]	[0.002]
DS Experiences				
$\overline{s_{it}}$ (γ_1)	0.006***	0.008**	0.000	-0.002
	[0.002]	[0.004]	[0.002]	[0.003]
RF Interactions				
$RF * \overline{s_{it}}$ (γ_2)	0.004***	0.003	0.004***	0.005***
	[0.000]	[0.002]	[0.000]	[0.002]
$RF * cov(s, (s - s_{it})^2)$ $(-\gamma_3)$	-0.004***	-0.004***	-0.003***	-0.003***
	[0.000]	[0.001]	[0.001]	[0.001]
N	71080	71080	67730	67730
AR2	0.03	0.03	0.02	0.02
Demographic Controls	Y	Y	Y	Y

Notes: Each column reports a panel regression of the subjective probability that the stock market will rise on Recall Fluency (RF), IQ, stock-return experience variables ($\overline{s_{it}}$, $cov(s_k, (s_k - s_{it})^2)$), and their interactions with RF. The specification mirrors columns 1–2 of Table 1: within each sample split, column (1)/(3) omits the RF main effect, and column (2)/(4) adds it back. Columns 1–2 restrict the sample to respondents who report following the stock market; columns 3–4 restrict to respondents who do not. Demographic controls include age, gender, marital status, retirement status, income, and education. All regressors IQR-standardized within the estimation sample. Standard errors in brackets; * p<0.12, ** p<0.05, *** p<0.01.