Fading-Memory Expectations in Equity Markets

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ABSTRACT

We study how investors update their beliefs and how these updates shape their decisions. Using a randomized information experiment with 2,800 investors across seven regions, we exploit the variation in the horizon of historical index returns shown to each investor to examine how the scope of information affects expectations. Investors revise their beliefs in the direction of the returns they see, with larger adjustments among those who are initially more uncertain. The sensitivity to information rises with the length of the return history and is highest when ten-year average returns are disclosed. These patterns are inconsistent with full-information rational expectations or simple extrapolation. Instead, they support a fading-memory learning model in which investors use longer histories to infer the long-run average return. This mechanism provides a structural explanation for the extrapolative expectations commonly observed in financial markets.

Key words: Expectation formation, Information frictions, Updating.

JEL classification: D12, D14, D83, D84

I Introduction

Investor expectations about future asset returns are central to decision-making in financial markets. They determine how households allocate their savings, how much risk they take in their portfolios, and ultimately how prices in financial markets are formed. Yet despite their foundational role in finance, we know relatively little about how individual investors form these beliefs, how they respond to new information, and whether belief revisions translate into meaningful shifts in investment attitudes. This paper examines three fundamental questions. First, do investors draw on both their local and international return experiences when forming expectations about future equity market performance? Second, are past realized returns of major indices, such as S&P 500, part of households' information sets? Third, do households adjust their attitudes towards portfolios in response to changes in their expectations about aggregate market returns?

Correlational evidence on these questions is difficult to interpret because information, beliefs, and portfolio choices are jointly determined and confounded by omitted variables, reverse causality, and measurement errors. To address these challenges, we follow a growing literature that uses information-provision experiments embedded in surveys to study how people update their beliefs when exposed to exogenous signals about macroeconomic and financial outcomes.[1] These experiments treat information as an exogenous shock to beliefs and causally examine how posteriors and behavior change when respondents learn about inflation, unemployment, or asset returns (e.g., Cavallo et al. (2017), Coibion et al. (2018), Roth and Wohlfart (2020)). In parallel, household-finance studies that link beliefs to actual portfolios find that investors with higher expected stock returns hold riskier portfolios, but the pass-through from beliefs to portfolio shares is modest on average and varies strongly across investors and contexts (Ameriks et al. (2020), Giglio et al. (2021)). Taken together, this research demonstrates that beliefs matter, and that information changes beliefs, but it leaves open fundamental questions about how investors map histories of asset returns into

[1] See the recent survey by Haaland et al. (2023) for a review.

expectations and how these expectations evolve across different horizons.

In this paper, we address these questions using data from a large-scale randomized survey experiment with 2,800 individual investors across seven geographic regions conducted by a global commercial bank. Respondents report their expectations and uncertainty about the next one-year return for both the U.S. and local equity indices they closely follow. The survey also collects detailed portfolio information, including asset-class shares and recent realized portfolio performance. After reporting their prior beliefs, each investor is randomly assigned to view a concise summary of the historical performance for their chosen indices over one of three horizons: past one-year, five-year, or ten-year average annual returns. This design generates exogenous variation in the scope of return history made salient to the respondents. Immediately after the information treatment, participants again report their expected next one-year return for the same index, allowing us to measure belief updates at individual level. Finally, respondents evaluate a simple hypothetical portfolio decision—whether they would invest 50% or more of their portfolio in bonds or a fixed-income fund over the next 12 months—and rate the attitude, risk, and benefits of that decision.

Our first set of results examines how pre-treatment beliefs relate to investors‘ own return histories/experiences. Each participant selected two indices, one from the eight local markets and one from the three U.S. indices, and for each chosen index we construct experienced returns by aggregating annual index performance from the calendar year the investor turned 25 through 2023, applying an exponential decay to weight recent realizations more heavily. We find that one-year-ahead expected returns for both local and U.S. indices are strongly positively related to these experienced-return measures: investors who have lived through better realized stock market performance expect higher future returns. The relationship is robust to controlling for demographics, past portfolio returns, and macro conditions, and we estimate that specifications with decaying weights fit the data substantially better than equal-weight or extreme-recency benchmarks. We also find evidence of cross-market learning: experienced returns in the local market help explain beliefs about U.S. index returns and vice versa. Finally, recent portfolio performance matters over and above index histories; investors whose portfolios performed better in the previous year hold more optimistic beliefs even after conditioning on aggregate returns. These patterns generalize and refine the experience-based evidence in Malmendier and Nagel (2011).

Our second set of results studies how investors update their beliefs when confronted with historical return information of different horizons. We define shock as the difference between the disclosed historical average return (the signal) and the investor's prior expectation for the same index. We then estimate learning rates by regressing the update on the shock, where the update is defined as the difference between posterior and prior expectations. We find three key facts. First, belief revisions move strongly in the direction of the signal: on average, investors adjust a large fraction of the shock, yielding sizable learning rates, in line with other information-provision experiments (see Table I). Second, updating is stronger among respondents with higher uncertainty, consistent with Bayes rule. Third, and most strikingly, sensitivity to information increases with the horizon of the disclosed history: the estimated learning coefficients satisfy $\beta_{10} > \beta_5 > \beta_1$. These patterns are difficult to reconcile with standard models in which rational investors, facing aggregate index returns that exhibit little persistence, should place essentially zero weight on signals about past performance.

Our third set of results links belief changes to investment attitudes. Using the bond-allocation vignette, we estimate how the equity-return information shock affects respondents' stated likelihood of investing 50% or more of their portfolio in bonds, as well as their perceived risk and benefits of this decision. A positive shock to expected equity returns—induced by favorable historical performance—significantly reduces the likelihood that investors say they would take a 50% bond position and lowers the perceived benefits of doing so. In contrast, perceived risk of the bond strategy moves little in response to the equity-return signal. These findings indicate that belief changes about aggregate stock-market performance translate into meaningful shifts in portfolio attitudes, primarily through perceived payoff and attractiveness rather than through perceived risk.

To interpret these empirical patterns, we develop a simple belief-formation framework that nests several prominent expectations models. We start from a full-information rational-expectations benchmark in which the historical averages shown in the experiment are deterministic functions of returns already in investors' information sets; in that case, learning from our treatments should be negligible, contrary to the large updating we document. We then consider the AR(1)-based expectations in which investors treat the most recent return as a sufficient statistic for the conditional mean; in that environment, averages over longer horizons are less informative than the latest realization and the model implies $\beta_1 \geq \beta_5 \geq \beta_{10}$, which is violated by our finding that $\beta_{10} > \beta_5 > \beta_1$. A Bayesian model of learning about an unknown unconditional mean can generate increasing β_m in the horizon of the signal, but with homogeneous precision and no forgetting, it delivers priors that are too close to equal-weight averages of history relative to what we estimate from experienced returns. We then incorporate fading memory: investors' recall of past returns deteriorates over time, making their priors recency-weighted averages of historical outcomes and generating learning coefficients that rise with the horizon of the signal. This structure implies that their beliefs can be expressed as extrapolative rules that overweight recent returns, providing a microfoundation for the extrapolative expectations widely used in macro-finance and behavioral asset-pricing models.

The remainder of the paper is organized as follows. Section II discusses the related literature in more detail. Section III describes the survey, sample, and experimental design. Section IV presents evidence on prior beliefs and experienced returns. Section V analyzes belief updating in response to the information treatments. Section VI studies how belief changes map into post-treatment portfolio allocation decisions. Section VII develops the expectations framework embedded with fading-memory assumption and relates it to our empirical results. Section VIII concludes.

II Related Literature

Our paper contributes to three strands of literature. First and foremost, it adds to a growing literature that measures investors' beliefs and studies how those beliefs relate to portfolio choices. Large-scale survey evidence documents substantial cross-sectional dispersion and persistence in expected returns and risk assessments, and connects those beliefs to allocations and trading (Adam and Nagel, 2023). A central takeaway is that the belief heterogeneity is economically large and helps account for variation in household portfolios and rebalancing behavior (Giglio et al., 2021; Greenwood and Shleifer, 2014). Additional evidence using professional and high–net-worth investors highlights dispersion in perceived return drivers and motives for allocation (Bender et al., 2022; Dahlquist and Ibert, 2024). Our design follows this tradition by eliciting full predictive return distributions and the expected one-year-ahead returns, and extends it to an international context in which each respondent reports beliefs for both a U.S. index and a local benchmark, enabling direct comparisons across indices and environments. Finally, our approach is closely connected to research using survey expectations to study information frictions and heterogeneous updating (Coibion and Gorodnichenko, 2012, 2015).

A second strand uses randomized information provision embedded in surveys to study belief updating. These experiments show that providing credible signals about macroeconomic or financial outcomes shifts posteriors toward the provided information, typically with partial learning rates (Cavallo et al., 2017; Coibion et al., 2018). Responsiveness varies with the informational environment and respondent characteristics: treatments fielded in different economic regimes or using different frames generate heterogeneous updating that is difficult to reconcile with frictionless full-information benchmarks (Armantier et al., 2016; Coibion et al., 2021). In macro-expectations settings, people update more when the information they receive is highly informative compared to their noisy prior beliefs, and changes in beliefs tend to be more persistent when the macro environment makes the treated outcome particularly salient (Roth and Wohlfart, 2020). Firm-level surveys further show that managers' macro expectations are systematically related to planning and investment, and that structured elicitation can recover informative belief distributions (Coibion et al., 2018). These studies underscore the value of anchoring belief questions to concrete objects and of documenting the connection between beliefs and decisions. We build on this information-experiment approach by delivering index-specific and horizon-varying historical return averages to the respondents. This design clarifies the object of learning, permits a clean test of horizon effects in belief updating, and complements recent causal designs that link information provision to financial behavior and (hypothetical) portfolio outcomes (Armona et al., 2018; Beutel and Weber, 2025; Roth and Wohlfart, 2020).

Third, our paper relates to the strand of research on experience-based beliefs, memory, and expectations formation. A large literature emphasizes that investor beliefs are shaped by personally experienced outcomes and by how those experiences are stored in memory. Experience-based learning models show that cohorts who have lived through higher stock returns hold more optimistic beliefs and choose riskier portfolios, and that age-weighted experienced return measures help explain cross-sectional variation in expectations and portfolio choice (e.g., Malmendier and Nagel, 2011, 2015; Malmendier et al., 2020). Memory-based models further stress that agents do not aggregate the full history but retrieve a small set of salient, context-similar episodes when forming valuations and beliefs (Bordalo et al., 2020, 2024), and recent evidence shows that distorted recall of past returns predicts biased beliefs and trading in financial markets (Charles, 2024; Gödker et al., 2025). We build on this work in two steps. First, we construct investor-specific experienced returns for both local and U.S. indices and show that expected one-year-ahead returns are tightly linked to recency-weighted histories, with intermediate decay parameters fitting the data best and with clear evidence of cross-learning across markets. Second, we relate these findings to expectations-formation models and show that a fading-memory learning model, in which the precision of recalled returns declines with age, can jointly match the recency-weighted structure of priors and the increasing sensitivity to longer-horizon signals in our experiment. This provides a microfoundation for extrapolative belief dynamics commonly used in asset-pricing models.

III Data and Experimental Design

In this section, we describe the survey administration, explain the structure of main survey and present the experimental design. The survey was commissioned by Standard Chartered bank and conducted by Agility Research & Strategy in January 2024. They surveyed 2,800 investors (400 per region) across 7 regions.[2] Within each region, they imposed fixed quotas across three asset-under-management (AUM) bands: 100 "emerging affluent" investors (AUM below $100,000), 200 "affluent" investors (AUM between $100,000 and $1,000,000), and 100 "high-net-worth" investors (AUM above $1,000,000). Invitations were issued in waves and reminders sent as needed until regional targets were met.[3]

A Survey

The survey comprised three sections. The first section gathered information on investor characteristics, including demographics (age, gender, job title), financial position (AUM, income, portfolio composition), and decision structure (self-directed investing v.s. delegation to professionals, and use of advice). It also collected details on participants' information sources and market attention.

The second section involved the randomized information treatment which in turn consists of three stages: (1) prior elicitation, (2) treatment, (3) posterior elicitation. To elicit the prior expectation, they first asked participants to select the U.S. equity index they track most closely from the S&P 500, Nasdaq Composite, and Dow Jones Industrial Average. Similarly, participants also selected a local index they follow closely from a list of eight indices covering the markets in our sample: BSE Sensex, FTSE Bursa Malaysia KLCI, Hang Seng Index, Jakarta Composite Index, KOSPI, Nikkei 225, SSE Composite, and Straits Times Index. For their chosen indices (for both U.S. and local index), they elicited participants' subjective return distribution for next year (2024) using the following question:

Consider the annual return (including dividends) of [the chosen index] in 2024. What is your assessment of the probability (in percentage terms) for each of the ranges below?

Respondents allocated a total of 100 probability points across seven bins: $< -20\%$, $[-20\%, -10\%)$, $[-10\%, 0)$, $[0, 10\%)$, $[10\%, 20\%)$, $[20\%, 30\%)$, and $> 30\%$.

[2] Hong Kong, India, Indonesia, Mainland China, Malaysia, Singapore, South Korea.

[3] To minimize panel conditioning and fatigue, invitees are limited to at most three surveys per year.

	Probability (%)
More than 30%	
From 20% to 30%	
From 10% to 20%	
From 0% to 10%	
From -10% to 0%	
From -20% to -10%	
Less than -20%	
Total	100

After the prior elicitation, respondents then selected their most followed index from all 11 indices, and the survey randomized respondents into one of three information arms. Each arm displayed a factual summary of the historical average return of the respondent's chosen index, computed over a specific horizon: the past one year, the past five years, or the past ten years. Specifically, three treatments (T) are

- T1: Last year (2023), the annual return of [the index the participant selected as the most followed index] was X1.
- T2: Over the last 5 years (2019-2023), the average annualised return of [the index the participant selected as the most followed index] was X2.
- T3: Over the last 10 years (2014 -2023), the average annualised return of [the index the participant selected as the most followed index] was X3.

As mentioned above, X1, X2, and X3 were the actual return values of the respondent's selected index over the relevant horizons.

After the treatments, they elicited respondents' posterior expectations as a point forecast for the 2024 return of their chosen index. The survey design generates, at the individual level, a shock equal to the difference between the displayed statistic and the prior, and an update equal to the difference between the posterior and the prior of the chosen index.

The third section of the survey focused on intended behavior after information treatment.

Respondents were asked to consider the following investment scenario: Invest 50% or more of your investment portfolio in bonds or a fixed-income fund, and to report their attitude, perceived risk, and perceived benefits regarding this scenario. Specifically, they were asked:

- Risk attitudes. Please indicate how likely you are to engage in this activity over the next 12 months on the scale of 1 (Very unlikely) to 5 (Very likely).
- Risk Perceptions. People often see risk in situations that contain uncertainty about what the outcome or consequences will be, and for which there is the possibility of "bad" consequences. However, riskiness is a very personal and intuitive notion, and we are interested in your gut-level assessment of how risky this situation is. Please indicate how risky you perceive this activity on the scale of 1 (Not at all risky) to 5 (Extremely risky).
- Expected Benefits. Please indicate the benefits you would obtain from engaging in this activity on a scale of 1 (No benefits) to 5 (Great benefits).

A key advantage of this survey design lies in the intentional construction of belief elicitation questions to directly inform asset pricing theories, allowing us to generate insights that speak to foundational models of expectation formation and portfolio choice. The surveyed respondents are relatively wealthy and experienced investors, which enhances the economic relevance of the findings, particularly for settings where stock market participation and financial sophistication are essential. We have information on the entire financial portfolio of the participants. Besides, the survey anchors beliefs to indices that respondents actually follow, tightening the connection between subjective expectations and objective histories. And it pairs belief and portfolio measures with a randomized, index-consistent information intervention, allowing us to go beyond descriptive facts and identify how investors revise expectations and shift intended allocations when presented with precise, transparent signals. However, a limitation of our approach is that the data are cross-sectional, capturing a single snapshot in time. While this allows for causal inference in the short run, it does not permit us to study the persistence of beliefs or dynamic learning across time, which remains an important avenue for future research. Another limitation is that portfolio holdings are self-reported, which may introduce noise from recall or reporting bias and slightly reduce the precision of estimated belief–portfolio relationships.

B Sample

This subsection characterizes the participants in our study, summarizes main cross-sectional features of their beliefs and portfolios, and benchmarks our sample against investor and household datasets used in related studies.

Table II presents the summary statistics for the full sample of survey respondents. The average respondent is approximately 40 years old, with a wide dispersion in age reflecting a diverse investor base. Investors under 45 account for roughly three quarters of the sample (19.0% are aged below 34 and 56.3% are aged between 35 and 44), with smaller mass at older ages. Less than 5% of our respondent are aged above 55. The sample is predominantly male. This gender composition is broadly in line with patterns observed in retail trading platforms and private banking clients. By construction, the AUM distribution is well populated at both the lower and upper ends within each market, with high-net-worth investors supplying mass in the right tail and emerging-affluent investors ensuring coverage below $100,000. In 2023, portfolio performance among survey participants was generally strong: roughly 99% of respondents reported non-negative portfolio returns, with substantial heterogeneity across return brackets.

Respondents reported current portfolio shares across a comprehensive set of categories: Cash; CDs/Money market funds; Local government bonds; Other local bonds (e.g., Munis, Corp. bonds); International bonds; Local stocks; International stocks; Hedge funds/Venture capital (VC)/Private equity (PE); Mutual funds; Structured products (e.g. Equity Linked Notes (ELNs)); Real estate investments (excl. primary residence); Commodities/Futures/Options; and Other. We define the portfolio equity share as the sum of share in local stocks, international stocks, mutual funds, and hedge funds/VC/PE. Figure I shows the cross-sectional distribution of respondents' portfolio equity shares; the median is 30%, which is comparable to the levels reported in Calvet et al. (2023).

Overall, these summary statistics suggest that the sample consists of demographically diverse, financially experienced and actively engaged investors, making it well suited for investigating belief formation and behavioral responses to information treatments.

Table III shows the comparison of our sample and other studies in terms of age, gender, AUM, and portfolio shares. Relative to the investor panels in Bender et al. (2022) and the Vanguard–based sample in Giglio et al. (2021), our sample is markedly younger and less male-skewed. Average age is 40.3 in our data versus 60.1 in Giglio et al. (2021) (median 40.0 vs 63.0), with only 0.1% of our respondents aged 65 or above compared with roughly 52% and 58% in the "One-off" and "Quarterly" surveys in Bender et al. (2022). The wealth distribution also differs: 75% of our investors report AUM under $1 million, whereas the Bender et al. (2022) panels are concentrated in $1 million to $2 million (47%) and $2 million to $5 million (31%) brackets, with over 20% of respondents holding more than $5 million in investable financial assets. By contrast, essentially none of our respondents report AUM above $5 million. Giglio et al. (2021) report on-platform wealth at Vanguard, which leads to a lower mean of AUM compared to our sample.

In terms of portfolio shares, our respondents hold substantially less equity and much more in cash and "other" assets, yielding a markedly different portfolio mix . The mean equity share in our sample is 33.7%, roughly 20 percentage points below the Bender et al. (2022) "Quarterly" investor panel (53.3%) and 34 percentage points below Giglio et al. (2021) (67.5%). Fixed income is comparable to the "Quarterly" panel (14.9% vs. 15.4%) but well below Giglio et al. (2021) (20.9%). The most striking difference is in "other" category: our investors hold 27.6% in "other" (vs. 11.2% in Bender et al. (2022) and 1.6% in Giglio et al. (2021)).[4] The elevated "other" share is consistent with heavier real-estate and structured-product exposure in our markets, whereas Giglio et al. (2021) measures platform wealth at

[4]Our sample consists primarily of rich households in Asia, many of whom own or actively manage private businesses. A substantial share of the "other" category thus reflects stakes in closely held firms, or partnership interests—assets that are typically absent from brokerage-based datasets such as Giglio et al. (2021).

Vanguard, where property and many off-platform assets are absent and thus mechanically depress the "other" category.

Taken together, our sample consists of relatively young, mass-affluent individual investors, with more diversified balance sheets and a heavier tilt toward non-equity, non-bond assets than is typical in U.S. investor studies. These contrasts imply that reallocations in our setting operate against a lower equity baseline and along wider cash/real-asset margins than in the U.S. investor samples used in prior work, a context that helps interpret both the pass-through from beliefs to equity exposure and the hypothesized bond investment results that follow.

Prior Expectation. In the survey, respondents first identified the stock market index they actively followed. For the United States, respondents could choose among the S&P 500, Nasdaq Composite, and Dow Jones Industrial Average. For the local market, the index list included BSE Sensex, FTSE Bursa Malaysia KLCI, Hang Seng Index, Jakarta Composite Index, KOSPI, Nikkei 225, SSE Composite, and Straits Times Index. They could also choose a "do not follow" option if they did not follow these indices. After choosing the index they followed, respondents were asked to distribute a total probability mass of 100 points across 7 bins ranging from a 20% or more decrease to a 30% or more increase (with a bin width of 10 percentage points) as described in Section III.

We construct the mean and standard deviation implied by an individual's subjective probability distribution using the midpoints of each bin and weighting each bin by the probability assigned by the individual. For the open-ended upper and lower bins of *a 30% or more increase* and *a 20% or more decrease*, we use values of 35% and -25%, respectively. We compute the *expected return* and *subjective volatility* implied by the subjective probability distribution as:

$$\mu_{i,j} \equiv E_i[R_j] = \sum_{k=1}^{7} p_{i,j,k} \cdot r_k$$

$$\mathrm{Var}_i[R_j] = \sum_{k=1}^{7} p_{i,j,k} \, (r_k - \mu_{i,j})^2 \qquad \sigma_{i,j} \equiv \sqrt{\mathrm{Var}_i[R_j]}.$$

$E_i[R_j]$ is the 1-year expected return of investor i for index j. $p_{i,j,k}$ denotes the probability assigned by investor i for index j to return bin k. r_k denotes the midpoint of return bin k. $\sigma_{i,j}$ is the subjective volatility for 1-year expected return of investor i for index j.

Figure II plots the cross-sectional distribution of one-year expected stock returns. Panel A uses the full sample of investors who reported following one of the listed local or U.S. indices. The mean one-year expected return across all investors is approximately 13%, with a cross-sectional standard deviation of 8.5 percentage points. The distribution is wide: the 10th percentile of the expected return is 2.5%, while the 90th percentile is 24.5%. Panel B restricts the sample to respondents who follow a U.S. index (S&P 500, Nasdaq Composite, or Dow Jones Industrial Average). For this group, the mean expected one-year U.S. stock return is 13.8%, with a standard deviation of 8.8 percentage points and a 10th–90th percentile range from 3.5% to 25.0%. These expectations are higher than the historical average annual U.S. stock market return of about 11.8% between 1927 and 2024 and substantially above the average one-year expectation of roughly 4.6% reported by Giglio et al. (2021), indicating that investors in our sample are, on average, quite optimistic about near-term equity returns. Besides, the difference in our one-year U.S. stock return expectations relative to Giglio et al. (2021) likely reflects the different return histories immediately preceding the respective survey administrations.

Among respondents who follow a U.S. index, the probability mass allocated to extreme outcomes is also asymmetric. On average, they assign about 5.6% probability to a one-year loss worse than -20% and 16.9% probability to a gain above 30%. Thus, investors place considerably more weight on very large positive than on very large negative returns, consistent with a positively skewed view of the return distribution.

Figure III summarizes the cross-sectional distribution of subjective uncertainty about one-year stock returns. Panel A shows that, for the full sample, the mean perceived standard deviation of annual stock returns is 12.5%. Panel B reports analogous statistics for U.S. index followers; their average subjective volatility is 12.0%. Taken together, Figures II and III indicate that respondents hold optimistic beliefs about equity returns while perceiving substantial uncertainty about the dispersion of possible outcomes.

Information treatment. To ensure the credibility of the experimental design, we first assess the success of the random assignment across treatment groups. We compare a broad set of investor characteristics—including demographics (region of residence, gender, age), financial status (monthly income, portfolio return, AUM), and investment-related features (preferred index)—across participants assigned to the 1-year, 5-year, and 10-year return treatments. Table IV shows that, along all observable dimensions, we find no statistically significant differences across treatment arms. These results indicate that randomization was implemented effectively and that the treatment groups are statistically comparable ex ante.

We also examine balance in key pre-treatment variables central to our empirical analysis: investors' prior beliefs about 1-year expected returns and their subjective uncertainty. Again, we find no evidence of systematic differences across treatment groups, as shown in Table V. Balance in both observable characteristics and baseline beliefs supports the internal validity of our empirical design and implies that any subsequent differences in posterior beliefs or investment attitudes can be causally attributed to the information treatment rather than to selection or latent heterogeneity.

IV Prior Beliefs

This section examines the relationship between respondents' beliefs and their experienced returns. A natural concern is that reported beliefs may reflect noise rather than meaningful heterogeneity. We address this by testing whether participants' beliefs are systematically correlated with the realized returns they have personally experienced in both their local and U.S. stock markets.

A Beliefs and Experienced returns

To investigate the determinants of investors' prior return expectations, we examine whether these beliefs are systematically related to measures of experienced market performance. This approach is motivated by evidence that individuals' economic expectations are shaped by their personal histories with macroeconomic and financial conditions. In particular, Malmendier and Nagel (2011) show that individuals who have lived through periods of low stock returns tend to expect lower future returns and have lower willingness to participate in equity markets. Building on this insight, we assess whether similar patterns hold in our sample.

To this end, we construct a measure of "experienced return" for each respondent, defined as the average annual return of the investor i's self-selected index j, which can be either a U.S. or a local benchmark, over the period from the year in which the respondent turned 25 through the end of 2023. This is the average historical return an investor would have experienced with a fading memory ($\alpha = 0.75$).

$$R_{i,j}^{\text{WtExperienced}} = \exp\left(\sum_{t}^{2023} \tilde{w}_t \cdot \log(1 + r_{j,t})\right) - 1, \text{where} \quad \tilde{w}_t = \frac{\alpha^{2023-t}}{\sum_s \alpha^{2023-s}}.$$

This personalized measure captures the historical return path an investor would have observed over their adult investment life, abstracting from individual portfolio choices while conditioning on the investor's preferred index. By linking this experienced return measure to respondents' stated beliefs about the future one-year returns, we test whether longer-term return histories influence expectations in a manner consistent with extrapolative or experience-based learning models.

Table VI reports regression estimates that relate investors' experienced returns to their one-year-ahead return expectations. In Panel A, we focus on expectations about the U.S. index. Column (1) shows that investors' expectations for the U.S. index are strongly related to the historical returns they personally experienced for the same index, replicating the core finding of Malmendier and Nagel (2011). We then go a step further and ask whether they also draw on their local market experiences when forming expectations about the U.S. market. Malmendier and Nagel (2011) argue that investors exhibit context dependence in learning, i.e., experiences with one asset class (stocks or bonds) do not spill over to the expectations about another. In our setting, we test whether a similar pattern of "context-bound" learning holds across geographic markets. Columns (2)–(4) examine whether investors who have experienced higher local-market returns also become more optimistic about future U.S. returns compared to investors who experienced lower local-market returns.

We find evidence of significant cross-learning: investors appear to use salient local history performance as a cue when thinking about global markets. The inclusion of birth-year fixed effects ensures that identification comes from differences in local experiences among investors of the same birth cohort, thereby isolating variation in beliefs not driven by age or macroeconomic conditions. Together, these results suggest that investors' belief formation is partly shaped by associative learning across contexts—when local markets perform well, optimism extends beyond domestic assets to U.S. equities as well.

Across all specifications, experienced returns emerge as a statistically and economically significant predictor of return expectations. We estimate that a one percentage point increase in the historical average return of an investor's preferred U.S. index is associated with a 40 basis point increase in their expected future returns. While meaningful, this coefficient is smaller than those documented in prior U.S.-focused studies, such as Malmendier and Nagel (2011), who report response coefficients in the range of 0.5 to 0.6. This attenuated response likely reflects differences in sample composition, as our survey targets relatively wealthy and financially sophisticated investors who may rely on more diversified information sets and exhibit weaker extrapolative biases compared to the general U.S. retail investor population.

Panel B reports the expectations for the local index. The results are qualitatively very similar. Again, there is significant cross learning from experienced returns in U.S. index to local index.

In addition to index-level experience, we also consider the role of personal portfolio performance in shaping expectations. We find that portfolio returns from the previous calendar year (2023) are strongly associated with forward-looking beliefs (in Table VI columns (3) and (4)). This relationship is robust across model specifications and remains significant after controlling for experienced index returns, indicating that investors update their expectations based not only on aggregate market experience but also on individual feedback. Figure IV plots the relation between last year's portfolio return and expected 1-year return. Overall, the evidence supports a model of belief formation that incorporates both long-run experience and recent performance feedback.

To assess the robustness of our findings and to explore how investors weight past returns over time, we conduct a sensitivity analysis using alternative memory-decay parameters. Specifically, we reconstruct the experienced return as an exponentially weighted average of past annual index returns, where the weight on each observation decays geometrically at rate α. A value of $\alpha = 1.0$ corresponds to equal weighting of all past returns (no memory decay), while lower values of α place progressively more weight on more recent realizations, capturing the extent of recency bias in belief formation.

We re-estimate the belief-formation regression separately for each value of α from 0.0 to 1.0 in increments of 0.05 and plot the resulting R^2 in Figure V. For expectations about local index returns, the explanatory power of experienced returns peaks at $\alpha = 0.75$, indicating that investors appear to integrate a long history of returns with a modest tilt toward more recent outcomes. A similar pattern emerges for expectations of U.S. index returns. In both panels, specifications that put almost all weight on the most recent year (α close to zero) or treat all past years nearly equally (α close to one) fit the data worse than intermediate values, pointing to a fading-memory structure rather than pure recency or equal-weight averaging.

B Beliefs and Portfolios

The importance of subjective beliefs crucially depends on their pass-trough to investors portfolios. To estimate the sensitivity of portfolio shares to beliefs, we run the following regression:

$$\text{EquityShare}_i = \alpha + \beta E_i[R_{1y}] + \epsilon_i \tag{1}$$

This is a cross sectional regression in which the dependent variable is respondent i's equity share at the time of the survey. Equity share is defined as

$$\begin{aligned}\text{Equity Share} = \text{Weight in Local stocks} + \text{International stocks} + \\ \text{Mutual funds} + \text{Hedge funds/Venture Capital/Private Equity.}\end{aligned}$$

Our main independent variable is the investor's one-year-ahead expected stock return. We elicit expectations for both the local and the U.S. index chosen in the survey. To capture the average belief relevant for the equity portion of the portfolio, we construct a portfolio-weighted expected return,

$$E_i^W[R_{1y}] = \frac{w_{\text{LocalStock}} \times E_{i,j}[R_{1y}^{Local}] + w_{\text{InternationalStock}} \times E_{i,j}[R_{1y}^{US}]}{w_{\text{LocalStock}} + w_{\text{InternationalStock}}},$$

where $E_{i,j}[R_{1y}^{Local}]$ and $E_{i,j}[R_{1y}^{US}]$ denote respondent i's expectation, for index j, of the one-year return in 2024 on the local and U.S. indices selected in the survey, respectively. The variable of interest is β, which captures the increase in an individual's equity share for each percentage point increase in the expected return.

Table VII presents the results. Column (1) includes separate expectations for the local and U.S. indices and shows that only expected U.S. returns are significantly related to the equity share: an extra percentage point of U.S. expected stock return is associated with a 0.16 percentage point increase in respondents' equity shares. This magnitude is smaller than the estimate found in other studies (e.g., Giglio et al. (2021)) in which the estimate is close to 0.7. Column (2) replaces the two expectations with the composite measure $E_i^W[R_{1y}]$, whose coefficient implies a similar sensitivity. Column (3) adds the experienced–return measures; their coefficients are positive and the local experience term is marginally significant, implying that past realized performance has some incremental explanatory power beyond current beliefs. Column (4) further includes the interaction between $E_i^W[R_{1y}]$ and uncertainty. The negative and significant interaction coefficient suggests that low uncertainty increases the sensitivity of expected returns with equity share. This is consistent with benchmark theory models in which, for a power-utility investor:

$$\text{Equity Share} = \frac{E_i[R] - R_f}{\gamma Var_i[R]}.$$

V Belief Updating

Now, we examine the effect of information treatment on people's beliefs. Simple Bayesian updating predicts:

$$\text{Posterior}_i = (1 - G)\,\text{Prior}_i + G \times \text{Signal},$$

where G will be large when the signal is credible and informative, and small otherwise. This equation can be rewritten as

$$\underbrace{\text{Posterior}_i - \text{Prior}_i}_{\equiv Update_i} = G \times (\underbrace{\text{Signal} - \text{Prior}_i}_{\equiv Shock_i}).$$

We will run a regression of this form to infer G. Specifically, let $\text{Update}_{i,j,g} = \text{Post}_{i,j,g} - \text{Prior}_{i,j,g}$ denote the belief update (i.e., difference between respondent's posterior and prior) for individual i following index j in treatment group g, and let $\text{Signal}_{j,g}$ represent the return signal for index j shown to participants in group g. The signal shock is constructed as the difference between the return signal and the investor's prior expectation, i.e., $\text{Shock}_{i,j,g} \equiv \text{Signal}_{j,g} - \text{Prior}_{i,j,g}$. We estimate the following linear regression model:

$$\text{Update}_{i,j,g} = \alpha + \beta_1 \text{Shock}_{i,j,g} + \beta_2 \text{Prior}_{i,j,g} + \Pi^T \mathbf{X}_i + u_{i,j,g}, \tag{2}$$

In this specification, β_1 captures the average weight that investors place on the return signal when revising their expectations, with $\beta_1 = 0$ reflecting the complete inattention or disregard of the signal. The intercept β_0 captures systematic shifts in posterior beliefs unrelated to the shock magnitude, and $u_{i,j,g}$ is the idiosyncratic error term.

Table VIII shows the results. We estimate a highly significant coefficient of $\beta_1 = 0.76$, indicating that investors place considerable weight on the signal when forming posterior expectations. The size of the estimated learning rate implies that the respondents found that the past realized returns contain some relevant information that was not already incorporated into their priors.

Are changes in expectations consistent with Bayesian updating? First, Bayesian updating predicts that respondents should adjust their expectations partially towards new signals that they find informative, i.e., that learning rates should lie in the interval [0, 1]. Second, Bayesian updating implies that respondents who are less confident in their prior belief should react more strongly to new signals. We find evidence consistent with that. When we interact shock with prior uncertainty, we find that the coefficient for this interaction is positive and significant, as shown in Table IX.

Heterogeneous updating across treatment groups. Do respondents update their return expectations after receiving information about the performance of their chosen index over the past 1, 5, or 10 years? To examine whether investors respond differently to return signals of varying horizons, we test for heterogeneity in belief updating across the 1-year, 5-year, and 10-year treatment arms. Specifically, we estimate an interaction regression that allows the updating coefficient to vary by signal horizon:

$$\text{Update}_{i,j,g} = \alpha + \beta_1 \text{Shock}_{i,j,g} + \beta_2 \text{Shock}_{i,j,g} \times \mathbb{1}_{i,1\text{yr}} + \beta_3 \text{Shock}_{i,j,g} \times \mathbb{1}_{i,10\text{yr}} + \Pi^T \mathbf{X}_i + u_{i,j,g}, \quad (3)$$

where $\mathbb{1}_{i,1\text{yr}}/\mathbb{1}_{i,10\text{yr}}$ is 1 if respondent i is given the 1-year/10-year signal and 0 otherwise. β_1 represents the baseline updating coefficient for 5-year signal group, while β_2 and β_3 capture the incremental responsiveness for the 1-year and 10-year signal groups, respectively.

Estimation results of Equation (3), reported in Table X, show that β_2 is negative and statistically significant, while β_3 is positive and statistically significant. This indicates that investors place greater weight on signals that summarize longer return histories. Specifically, the highest updating coefficient is observed for respondents exposed to the 10-year return signal, followed by those in the 5-year treatment, and then the 1-year group.

VI Causal Effect on Behavior

After beliefs are elicited and the information signal is shown, we measure portfolio intentions using a hypothetical portfolio decision. Respondents evaluate the option "Invest 50% or more of your investment portfolio in bonds or a fixed income fund." For this scenario, the survey records three outcomes, each on a 1–5 scale: a likelihood rating (attitude), a perceived risk rating, and a perceived benefits rating. These outcomes are designed to move in opposite directions for equity-tilting versus bond-tilting intentions and allow us to separate risk from benefit channels.

To study how information translates into portfolio intentions, we regress each outcome on the individual-specific information shock,

$$\mathrm{y}_{i,j,g} = \alpha + \beta_1 \mathrm{Shock}_{i,j,g} + \beta_2 \mathrm{Prior}_{i,j,g} + \Pi^T \mathbf{X}_i + u_{i,j,g}, \tag{4}$$

where $y_{i,j,g}$ is Attitude, Perceived Risk, or Perceived Benefits for individual i following index j in treatment arm g; $\mathrm{Shock}_{i,j,g}$ is the difference between the displayed index statistic and the respondent's prior for that index; $\mathrm{Prior}_{i,j,g}$ is the corresponding prior expectation; and $\mathbf{X}_i$ denotes the vector of pre-treatment controls.

Table XI display the regression results. The estimates indicate a clear substitution away from bonds when the stock-market news the respondent received during the experiment is favorable. A one–standard-deviation increase in the shock reduces the stated likelihood of allocating 50% or more to bonds by 0.071 points on the 1–5 scale. Perceived benefits fall by 0.094 points, while the perceived risk rating does not move significantly. These behavioral responses line up with the belief-updating results reported earlier. Participants meaningfully revise their expectations toward the signal and shift away from bonds when the signal is favorable for equities. Taken together, the pattern is consistent with respondents revising their assessment of the payoffs from bonds rather than changing risk perceptions per se.

VII Theoretical Framework

This section examines how investors form expectations about stock returns and how they update when confronted with new signals. Our empirical analysis so far documents two central patterns. First, pre-treatment expectations about one-year index returns are closely related to experienced returns constructed from each participant's own index history, with recency bias, i.e., recent experiences have a stronger impact on individual expectations than experiences made earlier in life. Second, when we experimentally disclose historical average returns over different horizons (one, five, and ten years), participants revise their beliefs substantially, and the strength of updating increases with the horizon of the signal, i.e., $\beta_{10} > \beta_5 > \beta_1$. We develop a simple belief-based framework to interpret these patterns.

Let j denote an equity index (for instance, the local market index chosen by a respondent), and let t denote time. For each index j, we denote by

$$H_{j,t} = \{R_{j,s} : t - k + 1 < s \leq t\}$$

the history of realized annual total returns observed up to time t.

In the experiment, we disclose to each investor an index-specific historical return statistic

$$S_{j,m} = g_m(H_{j,t}) = \overline{R}^{(m)}_{j,t} = \frac{1}{m}\sum_{h=0}^{m-1} R_{j,t-h}, \qquad m \in \{1, 5, 10\},$$

constructed as the average of past annual returns over the last m years for index j. By construction, $S_{j,m}$ is a deterministic function of the return history H_t and therefore of all information available to an econometrician at time t. From the investor's perspective, the statistic is a noisy signal of the one-year-ahead return $R_{j,t+1}$, whose informativeness depends on the model under consideration. After seeing $S_{j,m}$, agent i forms a posterior belief $\mathbb{E}^{\text{post}}_{i,j,t}$ about the one-year-ahead return of index j accordingly.

Let $\mathcal{I}_{i,t}$ be investor i's information set at time t. We define

$$\mu^{-}_{i,j,t} \equiv \mathbb{E}^{\text{prior}}_{i,j,t} = \mathbb{E}\big[R_{j,t+1} \mid \mathcal{I}_{i,t}\big]$$

for the prior forecast of the one–year–ahead return on index j. After observing the given statistic $S_{j,m}$, investor i forms a posterior forecast

$$\mu^{+}_{i,j,t} \;\equiv\; \mathbb{E}^{\text{post}}_{i,j,t} = \mathbb{E}\big[R_{j,t+1} \mid \mathcal{I}_{i,t}, S_{j,m}\big].$$

We define the belief revision and the experimental shock at horizon m as

$$\text{Update}_{i,j,m} \equiv \mu^{+}_{i,j,t} - \mu^{-}_{i,j,t},$$
$$\text{Shock}_{i,j,m} \equiv S_{j,m} - \mu^{-}_{i,j,t}.$$

Our empirical regressions estimate the linear projection of updates on shocks, and by the usual projection formula, we have

$$\beta_m = \frac{\text{Cov}(\text{Update}_{i,j,m}, \text{Shock}_{i,j,m})}{\text{Var}(\text{Shock}_{i,j,m})}. \tag{5}$$

We interpret β_m as the *learning coefficient* at horizon m: it measures how strongly investors' expectations move, on average, in response to the given experimental statistic.

In what follows, we take this empirical framework as given and examine, in turn, alternative specifications that map return histories into prior beliefs and prescribe corresponding updating rules.[5] For each specification, we address two questions: (i) how prior expectations depend on past returns, and (ii) what the model implies for the coefficients β_m in (5) when agents are exposed to our one–year, five–year, and ten–year historical signals.

A AR(1) expectations with noisy information

We now consider an economy where the agent believes that returns follow an AR(1) process with mean μ and persistence α:

$$R_{t+1} = \mu + \alpha\big(R_t - \mu\big) + \varepsilon_{t+1}, \qquad \varepsilon_{t+1} \sim \mathcal{N}(0, \sigma^2_{\varepsilon}). \tag{6}$$

[5] To simplify notation, we suppress the index j and write R_t, S_m, $\mu^{-}_{i,t}$, and so on.

At date t, the agent does not recall past returns R_{t-h} fully but instead sees a noisy signal for $h = 0, \ldots, k-1$:

$$S_{i,t-h} = R_{t-h} + \eta_{i,t-h}, \qquad \eta_{i,t-h} \sim \mathcal{N}(0, \sigma_\eta^2).$$

The shocks ε_t and $\eta_{i,t}$ are independent over time and across agents and mutually independent. The agent's information set at date t is $\mathcal{I}_{i,t} = \{S_{i,t}, S_{i,t-1}, \ldots, S_{i,t-k+1}\}$. It is convenient to summarize the overall quality of information about past returns using

$$\gamma \equiv \frac{\text{Var}(\mathbb{E}[R_{t-h} \mid \mathcal{I}_{i,t}])}{\text{Var}(R_{t-h})} \in (0, 1), \tag{7}$$

Intuitively, γ captures how well agents recall past information. Now suppose the agent is given the last-year return $S_1 \equiv R_t$. After observing S_1 the posterior expectation becomes

$$\mathbb{E}_i^{\text{post}}[R_{t+1}] = \mu + \alpha(R_t - \mu)$$

In this model with noisy signals about past returns described above, the coefficient on the one-year shock in Equation (5) is

$$\beta_1 = \frac{\text{Cov}(\text{Update}_{i,1}, \text{Shock}_{i,1})}{\text{Var}(\text{Shock}_{i,1})} = \frac{\alpha(1-\gamma)}{1 - \alpha\gamma(2-\alpha)}. \tag{8}$$

We now extend the analysis to the case where the agent is given the five-year historical signal used in the experiment. The disclosed statistic is

$$S_5 \equiv \frac{1}{5} \sum_{h=0}^{4} R_{t-h},$$

that is, the average of the last five annual returns. The prior expectation of the one-year-ahead return under the AR(1) belief remains

$$\mathbb{E}_{i,t}^{\text{prior}}[R_{t+1}] = \mu + \alpha \left(\mathbb{E}(R_t | \mathcal{I}_{i,t}) - \mu\right)$$

Because the model is linear and Gaussian, the pair (R_t, S_5) is jointly normal conditional on $\mathcal{I}_{i,t}$. The following proposition shows the regression coefficient of shock on update in this specificiation.

Proposition 1: *In the AR(1) expectations model with noisy signals about past returns described above, the coefficient on the five-year shock in Equation* (5) *is*

$$\beta_5 = \frac{5\alpha\big(\alpha^4 + \alpha^3 + \alpha^2 + \alpha + 1\big)(1-\gamma)}{2\alpha^4 + 4\alpha^3 + 6\alpha^2 + 8\alpha + 5 - 5\alpha\gamma\big(2\alpha^2(\alpha^2 + \alpha + 1) - 3\alpha + 2\big)}, \tag{9}$$

and satisfies

$$\beta_5 \; < \; \beta_1 \qquad \textit{for all } \alpha \in (0,1),\; \gamma \in (0,1), \tag{10}$$

where β_1 *is given by Equation* (8) *and* γ *is given by Equation* (7)*.*

Proof. See Appendix A.3. □

Within this AR(1) expectations model with noisy information, the one-year signal is always more effective at shifting beliefs about next year's return than the five-year average, once we account for the relative variances of the signals. Intuitively, under AR(1) dynamics, the last realized return R_t is the sufficient statistic for predicting R_{t+1}, while the five-year average S_5 dilutes this information by mixing R_t with older, less relevant realizations. Consequently, the model restricts the learning coefficients to satisfy $\beta_5 < \beta_1$. This restriction is violated in our data, where we estimate $\beta_{10} > \beta_5 > \beta_1$ and hence we reject this specification.

B Learning the Unconditional Mean with Constant Memory

Suppose the agent believe that returns follow an independent and identically distributed (i.i.d) process around an unknown unconditional mean μ:

$$R_{t+1} = \mu + \varepsilon_{t+1}, \qquad \mathbb{E}[\varepsilon_t] = 0, \quad Var(\varepsilon_t) = \sigma_\varepsilon^2. \tag{11}$$

but she is learning about μ from past data. Assume agents form beliefs based on all the information from the past k years. However, she does not recall past returns perfectly when estimating the unconditional mean. For each past year $h = 0, \ldots, k-1$ she recalls a noisy signal of the corresponding return,

$$S_{i,t-h} = R_{t-h} + \eta_{i,t-h} = \mu + \underbrace{\varepsilon_{t-h} + \eta_{i,t-h}}_{\xi_{i,t-h}}, \qquad \mathbb{E}[\eta_{i,t}] = 0, \quad Var(\eta_{i,t}) = \sigma_\eta^2,$$

with ε_t and $\eta_{i,t}$ mutually independent over time and across agents. At date t the agent's information set is $\mathcal{I}_{i,t} = \{S_{i,t}, S_{i,t-1}, \ldots, S_{i,t-k+1}\}$. It is convenient to define the signal noise variance $\sigma_\xi^2 \equiv \sigma_\varepsilon^2 + \sigma_\eta^2$ and the corresponding precisions $\tau_\varepsilon \equiv \sigma_\varepsilon^{-2}$, $\tau_\eta \equiv \sigma_\eta^{-2}$, and

$$\tau_\xi \equiv \frac{1}{\sigma_\xi^2} = \frac{1}{\sigma_\varepsilon^2 + \sigma_\eta^2} = \frac{\tau_\varepsilon \, \tau_\eta}{\tau_\varepsilon + \tau_\eta}.$$

Prior. At date t the agent cares about forecasting next year's return R_{t+1}. Given the information set $\mathcal{I}_{i,t} = \{S_{i,t}, \ldots, S_{i,t-k+1}\}$, we denote her prior forecast by

$$\mu_{i,t}^{-} \ \equiv \ \mathbb{E}[R_{t+1} \mid \mathcal{I}_{i,t}].$$

Under the i.i.d. DGP in (11) and a diffuse pre-sample prior on μ, this forecast coincides with the posterior mean of μ and is simply the average of the k signals in agent's information set $\mathcal{I}_{i,t}$:

$$\mu_{i,t}^{-} = \mathbb{E}[\mu \mid \mathcal{I}_{i,t}] = \frac{1}{k} \sum_{h=0}^{k-1} S_{i,t-h}.$$

New Signal. Now, the agent is given new information i.e., the average return of the past m ($m < k$) years:

$$X_{m,t} = \overline{R}_t^{(m)} = \frac{1}{m} \sum_{h=0}^{m-1} R_{t-h}$$

Proposition 2: *In the constant-memory environment described in Section B, the coefficient on the m-year shock in Equation* (5) *is given by*

$$\beta_m = \frac{1}{1 + \left(\frac{k}{m} - 1\right) \frac{\sigma_\varepsilon^2}{\sigma_\eta^2}}. \tag{12}$$

Fix $(k, \sigma_\varepsilon^2, \sigma_\eta^2)$. *Then* β_m *in* (12) *is strictly increasing in m.*

Proof. See Appendix A.5. □

Equation (12) makes clear that, for fixed (k, γ), β_m increases with the horizon m: signals that average over a longer window put more weight on the true return innovation ε_t relative to idiosyncratic noise $\eta_{i,t}$ and therefore induce larger belief revisions.

However, this model implies that agents form priors by giving equal weight to all past signals—that is, the decay parameter in Section IV should be one. Empirically, fitting expectations to realized returns yields a decay rate of roughly 0.75 (Figure V). Thus, the model is rejected by the data.

C Learning the Unconditional Mean with Fading Memory

Next, we study the model in which agents have fading memory, i.e., the agent recalls recent observations better than distant observations. In other words, we assume that, at time t, for each past year $h = 0, \ldots, k-1$ she recalls a noisy signal of the corresponding return,

$$S_{i,t-h} = R_{t-h} + \eta_{i,t-h} = \mu + \underbrace{\varepsilon_{t-h} + \eta_{i,t-h}}_{\xi_{i,t-h}}, \qquad \mathbb{E}[\eta_{i,t}] = 0, \quad \mathrm{Var}(\eta_{i,t}) = \lambda^h \sigma_\eta^2 \text{ for a given } \lambda > 1,$$

where $\{\eta_{i,t}\}$ are i.i.d. across time and agents, independent of $\{\varepsilon_t\}$. The parameter λ governs the rate at which agents' memory fades. At date t the agent's information set is $\mathcal{I}_{i,t} = \{S_{i,t}, S_{i,t-1}, \ldots, S_{i,t-k+1}\}$.

Let $v_h \equiv \mathrm{Var}(S_{i,t-h} - \mu) = \sigma_\varepsilon^2 + \lambda^h \sigma_\eta^2$ and define per-signal precisions

$$\tau_h \equiv \frac{1}{v_h} = \frac{1}{\sigma_\varepsilon^2 + \lambda^h \sigma_\eta^2}, \qquad T \equiv \sum_{h=0}^{k-1} \tau_h, \qquad T_m \equiv \sum_{h=0}^{m-1} \tau_h, \qquad W_m \equiv \frac{T_m}{T}.$$

Prior. With a diffuse pre-sample prior on μ, the expectation based on the last k signals, i.e., $\mathcal{I}_{i,t} = \{S_{i,t}, \ldots, S_{i,t-k+1}\}$, is

$$\mu_{i,t}^- \equiv \mathbb{E}[\mu \mid \mathcal{I}_{i,t}] = \sum_{h=0}^{k-1} \theta_h S_{i,t-h}, \quad \theta_h \equiv \frac{\tau_h}{T}, \quad \sum_{h=0}^{k-1} \theta_h = 1,$$

The prior based on $\mathcal{I}_{i,t}$ is the precision-weighted sum of past k signals. This rationalizes the fading memory we observed in the regression of agents' prior expected return on the experienced return with recency bias.

New Signal. Now, same as the above, the agent is given a new statistic about μ, i.e., the average return of the past m ($m < k$) years:

$$X_{m,t} = \overline{R}_t^{(m)} = \frac{1}{m}\sum_{h=0}^{m-1} R_{t-h}$$

Hence $\mathbb{E}[X_{m,t} \mid \mu] = \mu$ and $\text{Var}(X_{m,t} - \mu) = \frac{\sigma_\varepsilon^2}{m}$. Because the same innovations $\{\varepsilon_{t-h}\}_{h=0}^{m-1}$ enter $\mu_{i,t}^-$ and $X_{m,t}$, the two measurements are correlated.

Proposition 3: *In the fading-memory environment described in Section C, the coefficient on the m-year shock in Equation* (5) *is given by*

$$\beta_m = \frac{\frac{1}{T} - \frac{\sigma_\varepsilon^2}{m} W_m}{\frac{1}{T} + \frac{\sigma_\varepsilon^2}{m} - 2\,\frac{\sigma_\varepsilon^2}{m} W_m}. \tag{13}$$

Let $\tau_h \equiv \frac{1}{v_h} = \frac{1}{\sigma_\varepsilon^2 + \lambda^h \sigma_\eta^2}$ *be the per–signal precision,* $T = \sum_{h=0}^{k-1} \tau_h$*,* $T_m = \sum_{h=0}^{m-1} \tau_h$*, and* $W_m = \frac{T_m}{T}$*. If* $\lambda \geq 1$*, the precision sequence is weakly decreasing in time, i.e.,* $\tau_t \geq \tau_{t-1} \geq \cdots \geq \tau_{t-k+1}$ *, then for all* $m \leq k-1$*,*

$$\beta_{m+1} \;\geq\; \beta_m.$$

Proof. See Appendix A.7. □

Taken together, these results show that the framework can jointly capture the cross-sectional link between beliefs and experienced returns, as well as the horizon pattern in the experimental learning coefficients.

VIII Conclusion

We have used a large-scale survey and information-provision experiment with mass-affluent investors across seven markets to study how expectations about equity returns are formed, updated, and mapped into portfolio attitudes. On the belief side, we document that one-year-ahead expected returns are tightly linked to investors' own experienced index histories, with a recency-weighted, fading-memory structure and meaningful cross-market spillovers between the local and U.S. indices. In the experiment, investors react strongly—but not fully—to historical return information, with learning rates that rise with the horizon of the disclosed history and are larger when prior uncertainty is higher. On the behavior side, favorable equity-return information reduces the stated likelihood of shifting half of the portfolio into bonds and lowers the perceived benefits of a bond-heavy allocation, while leaving perceived risk almost unchanged. These facts jointly show that return histories are partially in investors' information sets, that they are processed in a horizon-dependent way, and that belief shifts translate into economically meaningful changes in investment attitudes.

We interpret these patterns through an expectations framework with fading memory. Full-information rational expectations and AR(1)-based models either predict negligible learning from historical summaries or the opposite horizon ranking of learning coefficients that we find in the data, while constant-memory learning overweights distant history relative to our experienced-return regressions. A fading-memory specification, in which the precision of remembered signals declines with age, can simultaneously rationalize the cross-sectional link between beliefs and experienced returns, the horizon profile of experimental learning. Recasting its forecasts as extrapolative rules provides a microfoundation for extrapolative expectations widely used in asset-pricing and macro-finance. More broadly, our evidence underscores the value of combining rich survey elicitations with randomized information treatment in diverse investor populations to test models of belief formation, and it points to fading memory as a key ingredient in understanding how financial histories shape expectations and risk-taking.

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Table I: Selected Experimental Evidence on Belief Updating (Learning Rates)

This table provides an overview of estimated learning rates in published papers that study how individuals update their beliefs in response to the provision of quantitative information and that calculate learning rates. The table shows the immediate learning rate (LR) measured in the main survey. Journal abbreviations are defined as follows: AEJ: Macro is the American Economic Journals: Macroeconomics; the AER is the American Economic Review; AER:I is the American Economic Review: Insights; JPubEc is the Journal of Public Economics; QJE is the Quarterly Journal of Economics; REStat is the Review of Economics and Statistics; and REStud is the Review of Economic Studies.

Authors (year) / Journal	**Context**	**Type of information**	**LR**
Macro Environment (Firms)			
Coibion and Gorodnichenko (2015)			
AER	Inflation, unemployment, & GDP growth	Professional forecasts; central bank target	0.35–0.66
Coibion et al. (2021)			
QJE	Inflation	Average first- and higher-order beliefs of other firms	0.31–0.88
Macro Environment (Households)			
Armantier et al. (2016)			
REStat	Inflation	Average professional forecast (SPF)	0.39
Cavallo et al. (2017)			
AEJ: Macro	Inflation	Current inflation rate or selected product price changes	0.43–0.84
Roth and Wohlfart (2020)			
REStat	Recession	Individual professional forecasts (SPF)	0.32
Roth et al. (2022a)			
Journal of Econometrics	Debt-to-GDP ratio	Factual information	0.62
Roth et al. (2022b)			
AER: Insights	Perceived unemployment risk (next recession)	Change in unemployment rate in own demographic group	0.49
Bottan and Perez-Truglia (2022)			
REStat	Income rank; cost of living	Tailored statistics from ACS/CPS	0.87–0.88
Housing / Real Estate			
Armona et al. (2018)			
REStud	House-price expectations	Past 1y and 5–10y local house-price growth	0–0.18
Fuster et al. (2022)			
REStat	House-price expectations	Choice among expert forecast / past 1-year / past 10-year growth	0.38
Education / Human Capital			
Wiswall and Zafar (2014)			
REStud	Own earnings by college major	Population earnings by major	0.08
Wiswall and Zafar (2015)			
Journal of Human Capital	Own earnings by college major	Population earnings by major	0.34
Bleemer and Zafar (2018)			
JPubEc	Perceived college returns/cost (own child)	Population-level returns/cost	0.18–0.35

Source: Haaland et al. (2023).

Table II: Summary Statistics

This table reports descriptive statistics for the survey sample (N = 2,800) drawn from seven regions (400 respondents per region). Panel A presents the distribution of respondents by gender, age, job title, portfolio return, monthly pre-tax income, and overall value of household's assets (AUM). Panel B reports, for each asset class, the mean and standard deviation of portfolio weights (percent of portfolio) and the percentage of respondents with a positive allocation.

Panel A: Demographics

	Respondents (%)
Gender	
Male	62.71
Age	
25-34	18.96
35-44	56.29
45-54	20.57
55-64	4.11
65+	0.07
Job Title	
Business owner	10.82
C-Level (e.g., CEO, CFO)	22.96
Director	20.21
Manager	37.07
Analyst/professional without managerial responsibilities	2.64
Independent professional	4.61
Retired	0.54
Other	1.14
2023 Portfolio Return	
Negative	1.39
Between 0% to < 2%	7.89
Between 2% to < 5%	29.39
Between 5% to < 7%	32.82
Between 7% to < 10%	21.29
Over 10%	7.21
Monthly personal income before tax	
Less than USD 10,000	58.46
USD 10,000 to < USD 20,000	14.29
USD 20,000 to < USD 30,000	9.32
USD 30,000 to < USD 50,000	8.07
USD 50,000 to < USD 100,000	9.07
USD 100,000 or more	0.79
AUM	
USD 50,000 to < 100,000	25.00
USD 100,000 to < 150,000	8.32
USD 150,000 to < 200,000	5.54
USD 200,000 to < 250,000	5.64
USD 250,000 to < 500,000	9.79
USD 500,000 to < 750,000	6.61
USD 750,000 to < 1 million	14.11
USD 1 million to < 2 million	9.29
USD 2 million to < 3 million	8.46
USD 3 million to < 5 million	7.25

Table II: Summary Statistics *(continued)*

This table reports descriptive statistics for the survey sample (N = 2,800) drawn from seven regions (400 respondents per region). Panel A presents the distribution of respondents by gender, age, job title, portfolio return, monthly pre-tax income, and overall value of household's assets (AUM). Panel B reports, for each asset class, the mean and standard deviation of portfolio weights (percent of portfolio) and the percentage of respondents with a positive allocation.

Panel B: Portfolio Shares

	Mean (%)	Std (%)	HasPositive (%)
Cash	16.59	14.84	90.43
CDs / Money market funds	7.31	9.91	56.46
Fixed Income			
Local government bonds	6.40	8.11	57.11
Other local bonds	3.96	6.25	41.86
International bonds	4.50	7.02	44.04
Equity			
Local stocks	11.88	12.85	75.54
International stocks	8.19	10.71	61.14
Hedge funds / Venture capital / Private equity	2.49	5.67	22.57
Mutual funds	11.13	12.80	63.46
Others			
Structured products	6.93	8.77	55.36
Real estate investments	13.22	13.21	73.36
Commodities / Futures / Options	6.42	8.26	55.82
Other	0.99	4.39	10.04

Table III: Sample Comparison vs. Other Studies

This table compares our sample with selected prior studies. Columns report the percent distribution by age, gender, assets under management (AUM), and average portfolio weights across equity, fixed income, cash, and other.

	Quarterly[a]	One-off[a]	SCF (rich)[b]	SCF (all)[b]	FiveFacts[c]	Our Sample[d]
Age						
< 34	1.1%	1.7%	1.4%	21.5%	–	19.0%
35–44	3.2%	3.8%	6.3%	16.8%	–	56.3%
45–54	8.5%	11.9%	16.4%	18.0%	–	20.6%
55–64	29.3%	31.0%	34.3%	19.4%	–	4.1%
≥ 65	57.8%	51.6%	41.7%	24.3%	–	0.1%
Mean	–	–	–	–	60.1	40.4
Median	–	–	–	–	63.0	40.0
Gender						
Male	72.1%	72.7%	69.9%	47.5%	69.0%	62.71%
AUM						
\$0 to < \$1m	0.0%	0.0%	0.0%	93.1%	–	75.0%
\$1m to < \$2m	46.9%	57.2%	50.8%	3.5%	–	9.3%
\$2m to < \$5m	31.4%	33.3%	32.3%	2.2%	–	15.7%
\$5m to < \$10m	16.6%	7.2%	10.8%	0.7%	–	0.0%
\$10m+	5.1%	2.3%	6.2%	0.4%	–	0.0%
Mean (\$)	–	–	–	–	520,000	893,857
Median (\$)	–	–	–	–	227,800	375,000
Portfolio Shares (Mean)						
Equity	53.3%	–	–	–	67.5%	33.7%
Fixed income	15.4%	–	–	–	20.9%	14.9%
Cash	20.1%	–	–	–	10.1%	23.9%
Other	11.2%	–	–	–	1.6%	27.6%
Total	100.0%	–	–	–	100.0%	100.0%

[a] Bender et al. (2022). AUM refers to investable financial assets. Equity includes U.S. stocks, International stocks, and Hedge funds/Venture capital/Private equity. Fixed Income includes Government bonds, Other U.S. bonds, and International bonds. Cash includes Cash and CDs/Money market funds. Other includes Structured products, Real estate investments (excluding own home), and Commodities/futures/options.
[b] "SCF (rich)" = 2016 Survey of Consumer Finances (SCF) respondents with > \$1 m investable assets; "SCF (all)" = Full 2016 SCF.
[c] Giglio et al. (2021). AUM refers to total wealth at Vanguard measured as of June 2019.
[d] AUM in our sample is household total assets (including non-primary property, pensions, etc.). The mean and median of AUM are computed using bin midpoints. Portfolio categories are defined as follows: Equity includes Local stocks, International stocks, Mutual funds, and Hedge funds/Venture capital/Private equity; Fixed Income includes Local government bonds, Other local bonds and International bonds; Other includes Structured products, Real estate investments (excluding own home), and Commodities/futures/options.

Table IV: Balance Check on Categorical Variables

This table reports the percentage distribution of respondents across key categorical characteristics by information treatment arm: the 1-year signal group, 5-year signal group, and 10-year signal group. For each characteristic, each entry reports the percentage of respondents within a given treatment arm who fall into the indicated category.

Variable	1-year Signal	5-year Signal	10-year Signal
Residence			
Mainland China	16.2	14.6	12.4
Hong Kong	12.4	14.4	13.9
India	12.4	14.6	15.3
Indonesia	15.6	12.6	15.4
Malaysia	13.8	14.8	15.8
Singapore	13.8	13.3	13.7
South Korea	15.8	15.7	13.5
Gender			
Male	63.7	62.9	61.9
Age			
25–34	19.0	18.8	19.6
35–44	55.5	57.1	56.9
45–54	22.0	20.2	18.8
55–64	3.5	3.9	4.5
65+	0.0	0.0	0.2
2023 Portfolio Return			
Negative	1.7	0.9	1.9
Between 0% to < 2%	8.3	8.2	7.7
Between 2% to < 5%	30.0	29.9	29.9
Between 5% to < 7%	33.0	32.1	34.3
Between 7% to < 10%	21.0	21.5	18.8
Over 10%	6.0	7.6	7.4
Monthly Personal Income Before Tax			
Less than USD 10,000	58.1	59.0	60.0
USD 10,000 to < USD 20,000	13.8	14.3	12.4
USD 20,000 to < USD 30,000	8.7	8.5	10.7
USD 30,000 to < USD 50,000	8.2	7.9	7.8
USD 50,000 to < USD 100,000	10.5	9.5	8.3
USD 100,000 or more	0.8	0.7	0.9
AUM			
USD 50,000 to < 100,000	26.5	25.4	26.0
USD 100,000 to < 150,000	8.2	8.2	8.0
USD 150,000 to < 200,000	5.4	5.4	5.8
USD 200,000 to < 250,000	4.5	6.5	6.0
USD 250,000 to < 500,000	10.1	10.4	9.1
USD 500,000 to < 750,000	7.1	7.1	6.1
USD 750,000 to < 1 million	13.6	12.7	13.2
USD 1 million to < 2 million	8.5	9.9	9.5
USD 2 million to < 3 million	8.5	8.3	8.8
USD 3 million to < 5 million	7.8	6.3	7.5

Table IV: Balance Check on Categorical Variables *(continued)*

This table reports the percentage distribution of respondents across key categorical characteristics by information treatment arm: the 1-year signal group, 5-year signal group, and 10-year signal group. For each characteristic, each entry reports the percentage of respondents within a given treatment arm who fall into the indicated category.

Variable	1-year Signal	5-year Signal	10-year Signal
Index			
BSE	8.0	9.2	7.3
Dow	9.7	9.9	7.8
FTSE	6.8	8.9	6.3
HS	9.2	9.0	11.3
JKT	11.6	10.5	10.1
KOSPI	12.8	10.0	10.1
NASDAQ	10.8	11.8	11.9
Nikkei	4.4	3.9	4.0
SP	10.8	10.6	11.3
SSE	12.2	12.9	15.4
ST	3.7	3.3	4.5

Table V: Balance Check on Beliefs

This table presents summary statistics for prior beliefs about one-year stock returns across the three information treatment arms: the 1-year signal group, 5-year signal group, and 10-year signal group. Prior belief is the expected one-year return, in percent, implied by respondents' subjective probability distributions. Prior uncertainty is the subjective volatility of the same belief distribution. For each belief measure and treatment arm, the table reports the share of respondents in the experimental sample and the corresponding summary statistics.

	% of Respondents	Mean	Std	Min	Median	Max
Prior Belief (Expected 1-Year Return, %)						
1-year Signal	32.9	12.9	8.6	-10.0	12.0	33.0
5-year Signal	33.5	12.9	8.4	-10.0	12.5	33.0
10-year Signal	33.6	12.3	8.4	-10.5	12.0	33.0
Prior Uncertainty (Subjective Volatility, %)						
1-year Signal	32.9	12.3	6.0	0.0	12.1	26.7
5-year Signal	33.5	12.3	6.2	0.0	12.0	25.2
10-year Signal	33.6	12.7	6.1	0.0	12.4	24.7

Table VI: Explain Stock Market Expectation with Experienced Return

This table presents the results of regressing participants one-year-ahead expected stock returns on their experienced returns. For each respondent i, the experience-based return is the weighted geometric mean of annual index returns observed from the year in which the respondent turned 25 through 2023. The weights have the exponentially–decayed structure. We set weights $w_t \propto \alpha^{T-t}$ with $\alpha = 0.75$ and $\sum_t w_t = 1$, and compute $R_i^{\text{WtExp}} = \exp\big(\sum_t w_t \log(1 + r_t)\big) - 1$, where $r_{j,t}$ denotes the annual total return (including dividends when available) of index j in year t. Panel A (U.S.) uses the U.S. index the respondent selected; Panel B (Local) uses the respondent's chosen local index. We control for participants' characteristics, including residence, gender, age, job title, AUM, and relationship status; as well as main source of financial news, last year's (2023) portfolio return, delegation behavior, and trading frequency. Expected returns are winsorized at the 1% tails. Standard errors, shown in parentheses, are robust to heteroskedasticity. * p<0.1, ** p<0.05, ***p<0.01.

Panel A: U.S. Expectation

	$\text{E}_{i,j}[\text{R}_{1y}^{US}]$	$\text{E}_{i,j}[\text{R}_{1y}^{US}]$	$\text{E}_{i,j}[\text{R}_{1y}^{US}]$	$\text{E}_{i,j}[\text{R}_{1y}^{US}]$
$R_i^{\text{WtExperienced, US}}$	0.241**	0.399***	0.399***	
	(0.106)	(0.102)	(0.102)	
$R_i^{\text{WtExperienced, Local}}$		0.081**	0.081**	0.079**
		(0.034)	(0.034)	(0.035)
$R_{i,2023}^{\text{Portfolio}}$			0.683*	0.790**
			(0.387)	(0.401)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	USIndex	BirthYear	BirthYear	BirthYear-USIndex
R-squared	0.119	0.139	0.139	0.169
N	1952	1952	1952	1952

Panel B: Local Expectation

	$\text{E}_{i,j}[\text{R}_{1y}^{Local}]$	$\text{E}_{i,j}[\text{R}_{1y}^{Local}]$	$\text{E}_{i,j}[\text{R}_{1y}^{Local}]$	$\text{E}_{i,j}[\text{R}_{1y}^{Local}]$
$R_i^{\text{WtExperienced, US}}$		0.316***	0.316***	0.261**
		(0.103)	(0.103)	(0.115)
$R_i^{\text{WtExperienced, Local}}$	0.376*	0.123***	0.123***	
	(0.219)	(0.033)	(0.033)	
$R_{i,2023}^{\text{Portfolio}}$			1.355***	1.428***
			(0.350)	(0.395)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	LocalIndex	BirthYear	BirthYear	BirthYear-LocalIndex
R-squared	0.170	0.162	0.162	0.300
N	1952	1952	1952	1952

Table VII: Portfolio Equity Share and Expected Return

This table presents the results of estimating Equation (1). The dependent variable is the portfolio equity share, defined as the fraction of the respondent's portfolio invested in local stocks, international stocks, mutual funds, and hedge funds/venture capital/private equity. $E_{i,j}[R_{1y}^{\text{Local}}]$ and $E_{i,j}[R_{1y}^{\text{US}}]$ denote investor i's expected one-year return for 2024 on their chosen local index and U.S. index, respectively. The experience-based returns $R_i^{\text{WtExperienced,Local}}$ and $R_i^{\text{WtExperienced,US}}$ are constructed as weighted geometric means of past annual index returns observed from the year in which the respondent turned 25 through 2023. We use exponentially decaying weights $w_t \propto \alpha^{T-t}$ with $\alpha = 0.75$ and $\sum_t w_t = 1$, and compute $R_i^{\text{WtExp}} = \exp\big(\sum_t w_t \log(1 + r_t)\big) - 1$, where $r_{j,t}$ denotes the annual total return (including dividends when available) of index j in year t. $\text{E}_i^W[R_{1y}]$ is the weighted average of $E_{i,j}[R_{1y}^{\text{Local}}]$ and $E_{i,j}[R_{1y}^{\text{US}}]$, and $E_i^W[R_{1y}] \times$ Uncertainty captures the interaction between this weighted expectation and the investor's subjective uncertainty calculated from belief probability distribution. We control for participants' characteristics, including residence, gender, age, job title, AUM, and relationship status; as well as main source of financial news, last year's (2023) portfolio return, delegation behavior, and trading frequency. Expected returns are winsorized at the 1% tails. Standard errors, shown in parentheses, are robust to heteroskedasticity. * p<0.1, ** p<0.05, ***p<0.01.

	(1)	(2)	(3)	(4)
$\text{E}_{i,j}[R_{1y}^{Local}]$	-0.105			
	(0.076)			
$\text{E}_{i,j}[R_{1y}^{US}]$	0.159**			
	(0.072)			
$\text{E}_i^W[R_{1y}]$		0.165***	0.148**	0.270***
		(0.058)	(0.059)	(0.079)
$R_i^{\text{WtExperienced, US}}$			0.066	
			(0.294)	
$R_i^{\text{WtExperienced, Local}}$			0.117*	
			(0.066)	
$\text{E}_i^W[R_{1y}] \times$Uncertainty				-0.013**
				(0.006)
R-squared	0.017	0.025	0.026	0.027
N	2081	1748	1748	1748

Table VIII: Updating Behavior

This table presents the results of estimating Equation (2). The dependent variable is the change in investor i's expected one–year return for their chosen index between the posterior and prior elicitation. *Shock* is defined as the difference between the historical return signal shown in the survey and the investor's prior expected one–year return. *Prior* is the pre–treatment expected one–year return for 2024. We control for agents characteristics, including their residence, gender, age, job title, AUM, relationship status, source of financial news, 2023 portfolio return, delegation, and trading frequency. Prior and posterior return expectations are winsorized at their 1% tails. Standard errors, shown in parentheses, are robust to heteroskedasticity. * p<0.1, ** p<0.05, ***p<0.01.

	(1)	(2)	(3)
Shock	0.759***	0.751***	0.660***
	(0.018)	(0.027)	(0.028)
Prior	-0.143***	-0.143***	-0.238***
	(0.021)	(0.030)	(0.030)
Controls	Yes	Yes	Yes
FE	None	Index	Index-Horizon
R-squared	0.823	0.834	0.841
N	2447	2447	2447

Table IX: Update on Shock by Uncertainty

This table reports estimates from regressions of belief updates on information shocks, prior beliefs, and prior uncertainty. The dependent variable is the change in investor i's expected one–year return for their chosen index between the posterior and prior elicitation. *Shock* is defined as the difference between the historical return signal shown in the survey and the investor's prior expected one–year return. *Prior* is the pre–treatment expected one–year return for 2024. *Uncertainty* is the investor's subjective uncertainty calculated from belief probability distribution. We control for agents characteristics, including their residence, gender, age, job title, AUM, relationship status, source of financial news, 2023 portfolio return, delegation, and trading frequency. Prior and posterior return expectations are winsorized at their 1% tails. Standard errors, shown in parentheses, are robust to heteroskedasticity. * p<0.1, ** p<0.05, ***p<0.01.

	(1)	(2)	(3)	(4)
Shock	0.707***	0.678***	0.697***	0.607***
	(0.034)	(0.034)	(0.039)	(0.039)
Uncertainty	0.085***	0.088***	0.075***	0.079***
	(0.021)	(0.021)	(0.021)	(0.020)
Shock × Uncertainty	0.004*	0.004*	0.004**	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Prior	-0.118***	-0.146***	-0.121***	-0.216***
	(0.022)	(0.022)	(0.030)	(0.031)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	None	Horizon	Index	Index-Horizon
R-squared	0.825	0.830	0.836	0.842
N	2447	2447	2447	2447

Table X: Horizon Effect in Updating Behavior

This table presents the results of estimating Equation (3). The dependent variable is the change in investor i's expected one–year return for their chosen index, measured as the posterior expectation minus the prior (in percentage points). *Shock* is defined as the difference between the historical average return signal shown in the survey and the investor's prior one–year expected return. Respondents are randomly assigned to receive a 1-year, 5-year, or 10-year historical average; the 5-year signal group serves as the reference category. $\mathbb{1}_{i,1\text{yr}}$ ($\mathbb{1}_{i,10\text{yr}}$) equals 1 if respondent i is assigned to the 1-year (10-year) signal group, and 0 otherwise. *Prior* denotes the pre-treatment expected one–year return for 2024. We control for agents characteristics, including their residence, gender, age, job title, AUM, relationship status, source of financial news, 2023 portfolio return, delegation, and trading frequency. Prior and posterior return expectations are winsorized at their 1% tails. Standard errors, shown in parentheses, are robust to heteroskedasticity. * p<0.1, ** p<0.05, ***p<0.01.

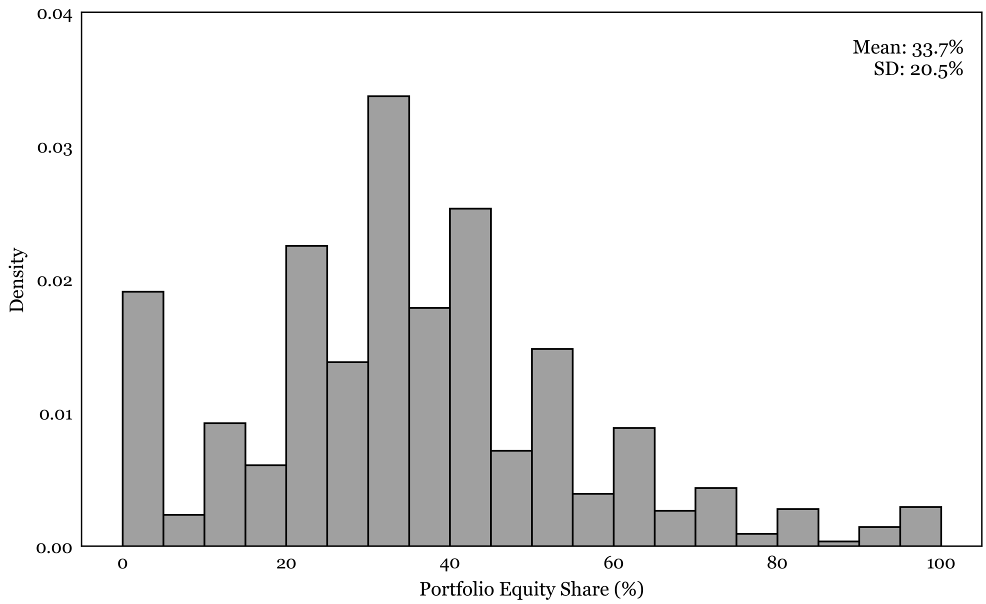
	(1)	(2)	(3)
Shock	0.805***	0.862***	0.855***
	(0.019)	(0.034)	(0.034)
$\text{Shock}_{i,j,g} \times \mathbb{1}_{i,1\text{yr}}$	-0.073***	-0.105***	-0.100***
	(0.022)	(0.024)	(0.023)
$\text{Shock}_{i,j,g} \times \mathbb{1}_{i,10\text{yr}}$	0.083***	0.083***	0.078***
	(0.019)	(0.018)	(0.018)
Prior	-0.099***	-0.033	-0.049
	(0.022)	(0.035)	(0.035)
Controls	Yes		Yes
FE		Index	Index
N	2447	2447	2447
R-squared	0.826	0.830	0.838

Table XI: Attitude on Bond Investment After Information Treatment

This table presents the results of estimating Equation (4). Outcomes are elicited for a hypothetical investment scenario: *"Invest 50% or more of your investment portfolio in bonds or a fixed income fund."* Respondents select 1–5 values on three dimensions: (i) Attitude, likelihood of engaging in the activity over the next 12 months (1 = Very unlikely, 5 = Very likely); (ii) Risk perception, the perceived risk of the situation (1 = Not at all risky, 5 = Extremely risky); and (iii) Perceived benefits, the anticipated benefits from engaging in the activity (1 = No benefits at all, 5 = Great benefits). Dependent variables include investors' pre-treatment expected 1-year return, and shock, which is defined as the signal respondents are given minus their prior. *Shock* and *Prior* are standardized. We control for agents characteristics, including their residence, gender, age, job title, AUM, relationship status, source of financial news, 2023 portfolio return, delegation, and trading frequency. Prior and posterior return expectations are winsorized at their 1% tails. Standard errors, shown in parentheses, are robust to heteroskedasticity. * p<0.1, ** p<0.05, ***p<0.01.

	Attitude	Risk Perception	Perceived Benefits
Shock	-0.071***	-0.014	-0.094***
	(0.026)	(0.030)	(0.025)
Prior	-0.122***	-0.055*	-0.017
	(0.028)	(0.031)	(0.026)
Controls	Yes	Yes	Yes
R-squared	0.091	0.069	0.107
N	2447	2447	2447

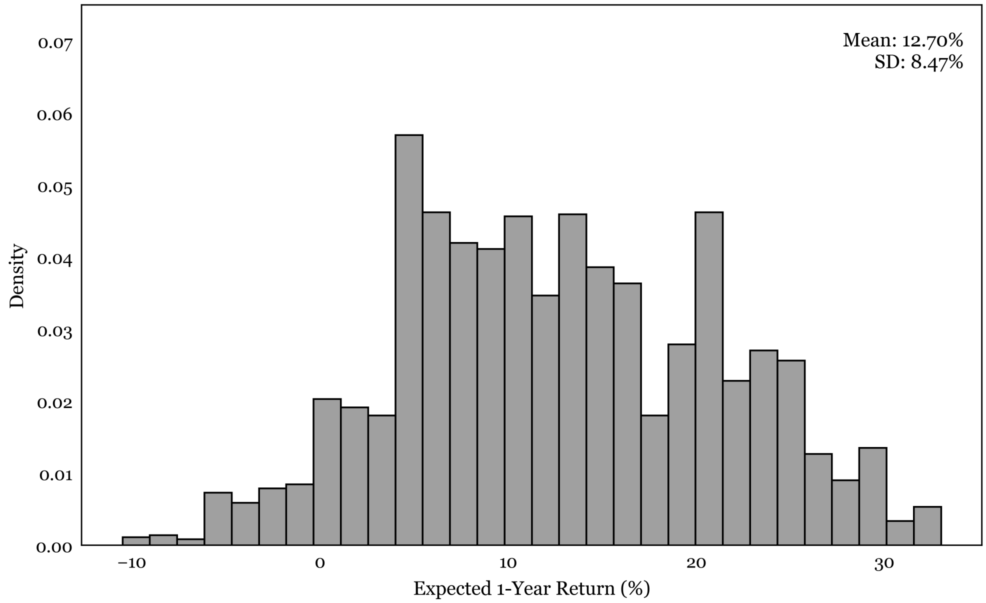
Figure I: Distribution of Portfolio Equity Share



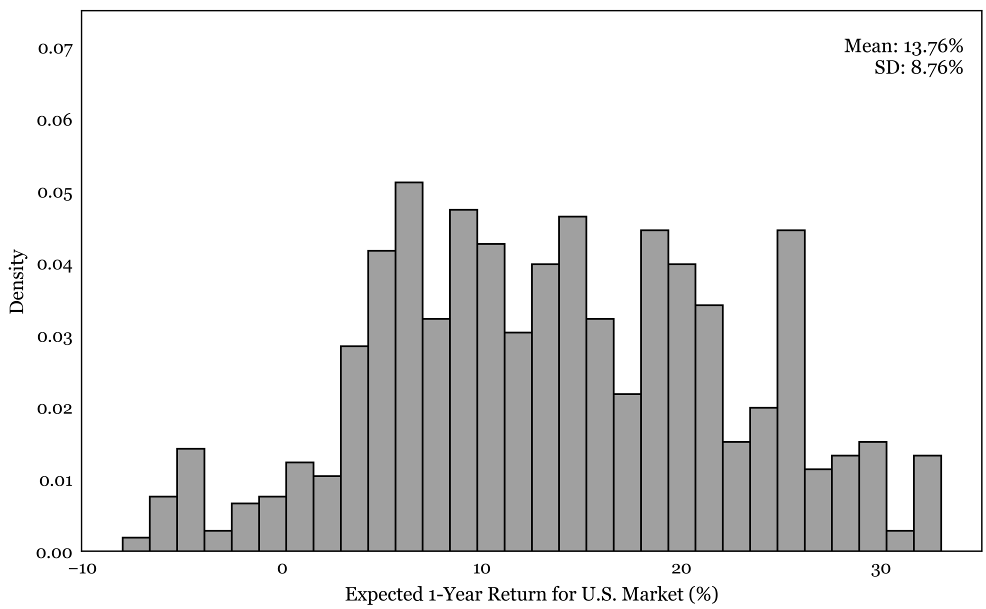
Notes: This figure plots a histogram of respondents' portfolio equity share, defined as the percentage of their financial portfolio invested in local stocks, international stocks, mutual funds, and hedge funds/venture capital/private equity.

Figure II: Distribution of 1-Year Expected Stock Returns

Panel A: All Indices



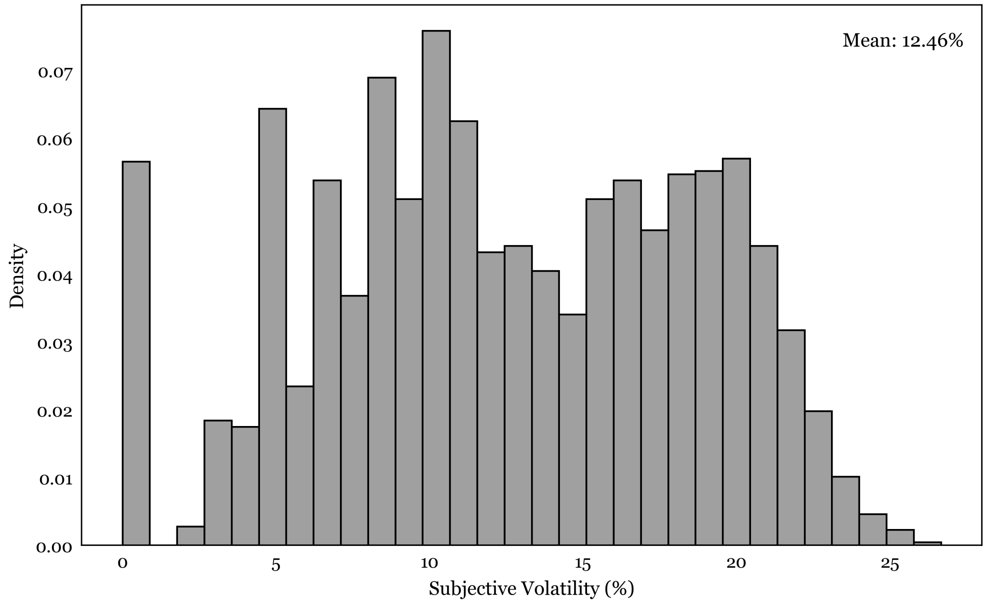
Panel B: U.S. Indices



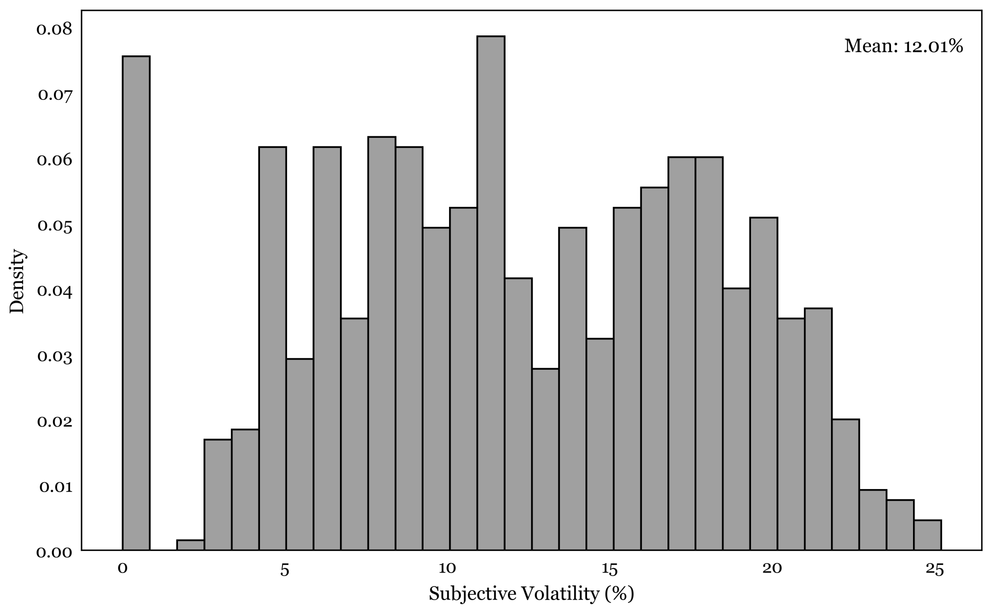
Notes: This figure plots histograms of one-year expected stock returns, $\mu_{i,j}$, for survey respondents and the stock market index j that they report following most closely. For each respondent i and index j, $\mu_{i,j}$ is constructed from the respondent's subjective probability distribution over seven return bins for 2024, using the bin midpoints; we assign 35% and −25% to the open-ended bins *More than* 30%*"* and *Less than* −20%*"*, respectively. Panel A uses the full sample of respondents who selected one of the listed local or U.S. stock indices. Panel B restricts the sample to respondents who follow a U.S. index (S&P 500, Nasdaq Composite, or Dow Jones Industrial Average) and plots their corresponding one-year expected return for that U.S. market index. Returns are expressed in percent, and each histogram is scaled so that the total area under the bars equals one.

Figure III: Distribution of Subjective Uncertainty About 1-Year Stock Returns

Panel A: All Indices

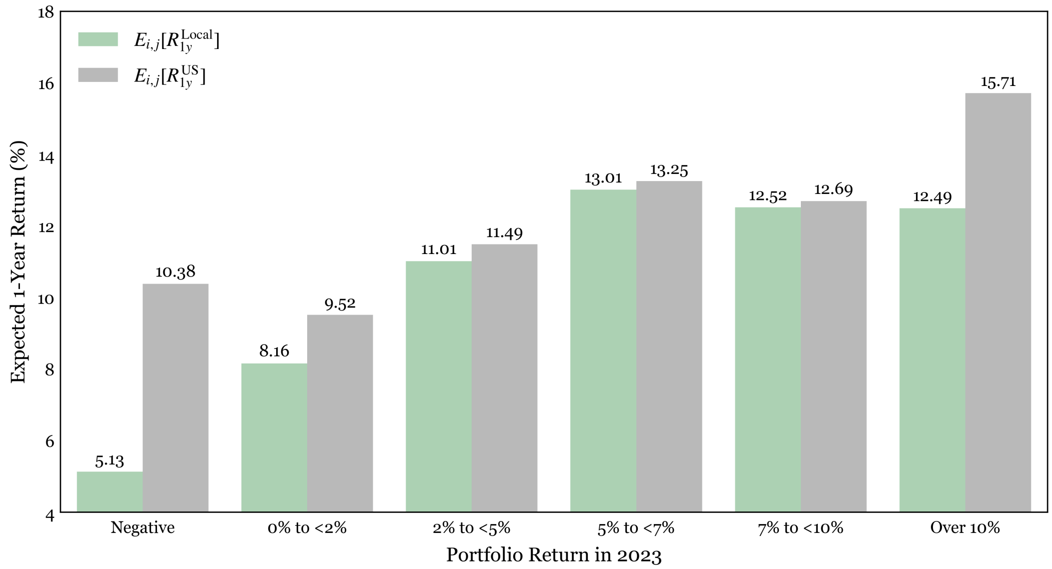


Panel B: U.S. Indices



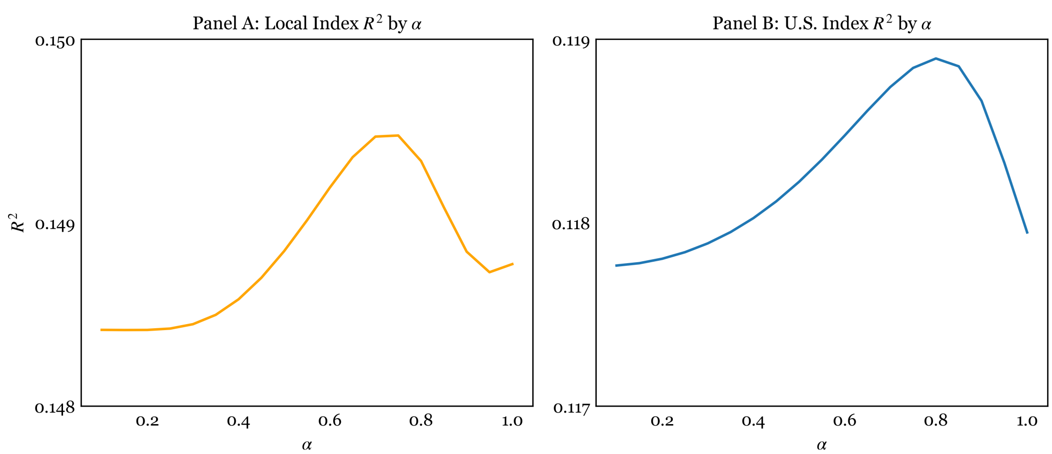
Notes: This figure plots histograms of investors' subjective uncertainty about one-year stock returns, measured by the subjective volatility $\sigma_{i,j}$. For each respondent i and followed index j, $\sigma_{i,j}$ is the standard deviation implied by the respondent's subjective probability distribution over seven return bins for 2024, constructed using the bin midpoints, with 35% and −25% assigned to the open-ended bins *"More than* 30%*"* and *"Less than* −20%*"*. Panel A includes all respondents who selected one of the listed local or U.S. indices and whose reported probabilities across bins sum to 100%. Panel B restricts the sample to respondents who follow a U.S. index (S&P 500, Nasdaq Composite, or Dow Jones Industrial Average). Volatility are expressed in percent, and each histogram is scaled so that the total area under the bars equals one.

Figure IV: Expected 1-Year Returns by 2023 Portfolio Performance



Notes: This figure plots average one-year expected stock returns by self-reported 2023 portfolio performance. The horizontal axis displays the six response options on 2023 portfolio returns: Negative, 0% to <2%, 2% to <5%, 5% to <7%, 7% to <10%, and Over 10%. For each category, the bars report the mean expected 1-year return for the respondent's chosen local index, $E_{i,j}[R_{1y}^{\text{Local}}]$, and for the U.S. index they follow, $E_{i,j}[R_{1y}^{\text{US}}]$. Expected returns are constructed from respondents' subjective probability distributions over seven return bins, and are expressed in percentage points.

Figure V: Expected Return and Weighted Experienced Return



Notes: This figure plots the R^2 from the belief–formation regression as a function of the memory–decay parameter α. For each value of α between 0 and 1, in increments of 0.05, we construct investors' experienced returns as an exponentially weighted average of past annual index returns, using weights $w_t \propto \alpha^{2023-t}$ normalized to sum to one, and estimate the regression of one–year–ahead expected returns on experienced returns with the full set of controls described in Table VI. The curve reports the resulting R^2 statistics.

Appendix

A Derivations in the Model

A.1 Derivation of Equation (8)

Standard properties of conditional expectations imply

$$\mathbb{E}[\hat{X}_{i,t}] = \mathbb{E}[e_{i,t}] = 0, \qquad \mathrm{Cov}(\hat{X}_{i,t}, e_{i,t}) = 0,$$

and we can decompose the variance of X_t as

$$\mathrm{Var}(X_t) = \sigma_R^2 = \mathrm{Var}(\hat{X}_{i,t}) + \mathrm{Var}(e_{i,t}) = \gamma\sigma_R^2 + (1-\gamma)\sigma_R^2.$$

From the expressions

$$\mathrm{Update}_{i,1} = \alpha e_{i,t}, \qquad \mathrm{Shock}_{i,1} = (1-\alpha)\hat{X}_{i,t} + e_{i,t},$$

we obtain

$$\mathrm{Cov}(\mathrm{Update}_{i,1}, \mathrm{Shock}_{i,1}) = \alpha\,\mathrm{Cov}(e_{i,t}, (1-\alpha)\hat{X}_{i,t} + e_{i,t}) = \alpha\,\mathrm{Var}(e_{i,t}) = \alpha(1-\gamma)\sigma_R^2.$$

The variance of the shock is

$$\mathrm{Var}(\mathrm{Shock}_{i,1}) = (1-\alpha)^2\mathrm{Var}(\hat{X}_{i,t}) + \mathrm{Var}(e_{i,t}) = \big[(1-\alpha)^2\gamma + 1 - \gamma\big]\sigma_R^2.$$

Dividing and simplifying the denominator,

$$(1-\alpha)^2\gamma + 1 - \gamma = 1 - 2\alpha\gamma + \alpha^2\gamma = 1 - \alpha\gamma(2-\alpha),$$

yields

$$\beta_1 = \frac{\mathrm{Cov}(\mathrm{Update}_{i,1}, \mathrm{Shock}_{i,1})}{\mathrm{Var}(\mathrm{Shock}_{i,1})} = \frac{\alpha(1-\gamma)}{1-\alpha\gamma(2-\alpha)},$$

which is (8). □

A.2 Derivation of Equation (9)

For the five-year signal,

$$S_5 = \frac{1}{5}\sum_{h=0}^{4} X_{t-h},$$

the vector $(X_t, X_{t-1}, \ldots, X_{t-4})$ is jointly normal with AR(1) autocovariances

$$\mathrm{Cov}(X_{t-h}, X_{t-k}) = \alpha^{|h-k|}\,\sigma_R^2,$$

where $\sigma_R^2 \equiv \mathrm{Var}(X_t)$ denotes the unconditional variance of X_t. Under stationarity and

$$X_{t+1} = \alpha X_t + \varepsilon_{t+1}, \qquad \mathbb{E}[X_t] = 0, \qquad \mathrm{Var}(\varepsilon_{t+1}) = \sigma_\varepsilon^2,$$

we have

$$\sigma_R^2 = \mathrm{Var}(X_t) = \alpha^2\sigma_R^2 + \sigma_\varepsilon^2 \quad \Rightarrow \quad \sigma_R^2 = \frac{\sigma_\varepsilon^2}{1-\alpha^2}.$$

It follows that

$$\mathrm{Cov}(X_t, S_5) = \frac{1}{5}\sum_{h=0}^{4}\mathrm{Cov}(X_t, X_{t-h}) = \frac{\sigma_R^2}{5}\sum_{h=0}^{4}\alpha^h = \frac{\sigma_R^2}{5}\big(1 + \alpha + \alpha^2 + \alpha^3 + \alpha^4\big),$$

and

$$\mathrm{Var}(S_5) = \mathrm{Var}\left(\frac{1}{5}\sum_{h=0}^{4} X_{t-h}\right) = \frac{1}{25}\mathrm{Var}\left(\sum_{h=0}^{4} X_{t-h}\right) = \frac{1}{25}\sum_{h=0}^{4}\sum_{k=0}^{4}\mathrm{Cov}(X_{t-h}, X_{t-k}) = \frac{\sigma_R^2}{25}\big(2\alpha^4 + 4\alpha^3 + 6\alpha^2 + 8\alpha + 5\big),$$

where we have used

$$\mathrm{Cov}(X_{t-h}, X_{t-k}) = \alpha^{|h-k|}\,\sigma_R^2, \quad \sum_{h=0}^{4}\sum_{k=0}^{4}\alpha^{|h-k|} = 2\alpha^4 + 4\alpha^3 + 6\alpha^2 + 8\alpha + 5.$$

Let

$$B_5(\alpha) \equiv 1 + \alpha + \alpha^2 + \alpha^3 + \alpha^4, \qquad V_5(\alpha) \equiv 2\alpha^4 + 4\alpha^3 + 6\alpha^2 + 8\alpha + 5,$$

so that

$$\mathrm{Cov}(X_t, S_5) = \sigma_{X_t,S_5} = \frac{\sigma_R^2}{5}B_5(\alpha), \qquad \mathrm{Var}(S_5) = \sigma_{S_5}^2 = \frac{\sigma_R^2}{25}V_5(\alpha). \tag{14}$$

We next describe how the investor's information set $\mathcal{I}_{i,t}$ affects the relation between X_t and S_5. We decompose the return as

$$X_t = \hat{X}_{i,t} + e_{i,t}, \qquad \hat{X}_{i,t} = \mathbb{E}[X_t \mid \mathcal{I}_{i,t}], \qquad \mathbb{E}[e_{i,t} \mid \mathcal{I}_{i,t}] = 0,$$

so that $\hat{X}_{i,t}$ is the predictable component and $e_{i,t}$ is the innovation orthogonal to $\mathcal{I}_{i,t}$. Let

$$\sigma_R^2 \equiv \mathrm{Var}(X_t), \qquad \sigma_{\hat{X}}^2 \equiv \mathrm{Var}(\hat{X}_{i,t}) = \mathrm{Var}\big(\mathbb{E}[X_t \mid \mathcal{I}_{i,t}]\big).$$

We define

$$\gamma \equiv \frac{\sigma_{\hat{X}}^2}{\sigma_R^2} = \frac{\mathrm{Var}(\mathbb{E}[X_t \mid \mathcal{I}_{i,t}])}{\mathrm{Var}(X_t)} \in (0,1),$$

so that

$$\mathrm{Var}(\hat{X}_{i,t}) = \gamma\,\sigma_R^2, \qquad \mathrm{Var}(e_{i,t}) = (1-\gamma)\,\sigma_R^2.$$

We also write the decomposition for S_5:

$$S_5 = m_{i,t} + u_{i,t}, \qquad m_{i,t} = \mathbb{E}[S_5 \mid \mathcal{I}_{i,t}], \qquad u_{i,t} = S_5 - m_{i,t}, \qquad \mathbb{E}[u_{i,t} \mid \mathcal{I}_{i,t}] = 0.$$

Let

$$\sigma_{X_t,S_5} \equiv \mathrm{Cov}(X_t, S_5), \qquad \sigma_{S_5}^2 \equiv \mathrm{Var}(S_5).$$

Because (X_t, S_5) are jointly normal, the best linear predictor of S_5 based on X_t is

$$\mathbb{E}[S_5 \mid X_t] = a + bX_t, \qquad b = \frac{\mathrm{Cov}(X_t, S_5)}{\mathrm{Var}(X_t)} = \frac{\sigma_{X_t,S_5}}{\sigma_R^2}.$$

Applying the law of iterated expectations,

$$m_{i,t} = \mathbb{E}[S_5 \mid \mathcal{I}_{i,t}] = \mathbb{E}\big[\mathbb{E}[S_5 \mid X_t] \,\big|\, \mathcal{I}_{i,t}\big] = a + b\,\mathbb{E}[X_t \mid \mathcal{I}_{i,t}] = a + b\,\hat{X}_{i,t}.$$

It follows that

$$\mathrm{Var}(m_{i,t}) = b^2\,\mathrm{Var}(\hat{X}_{i,t}) = \left(\frac{\sigma_{X_t,S_5}}{\sigma_R^2}\right)^2 \gamma\sigma_R^2 = \gamma\,\frac{\sigma_{X_t,S_5}^2}{\sigma_R^2}, \tag{15}$$

and

$$\mathrm{Cov}(\hat{X}_{i,t}, m_{i,t}) = \mathrm{Cov}\big(\hat{X}_{i,t}, a + b\hat{X}_{i,t}\big) = b\,\mathrm{Var}(\hat{X}_{i,t}) = \frac{\sigma_{X_t,S_5}}{\sigma_R^2}\,\gamma\sigma_R^2 = \gamma\,\sigma_{X_t,S_5}. \tag{16}$$

By the law of total covariance and variance,

$$\mathrm{Cov}(X_t, S_5 \mid \mathcal{I}_{i,t}) = \mathrm{Cov}(X_t, S_5) - \mathrm{Cov}(\hat{X}_{i,t}, m_{i,t}) = (1-\gamma)\,\sigma_{X_t,S_5},$$

$$\mathrm{Var}(S_5 \mid \mathcal{I}_{i,t}) = \mathrm{Var}(S_5) - \mathrm{Var}(m_{i,t}) = \sigma_{S_5}^2 - \gamma\,\frac{\sigma_{X_t,S_5}^2}{\sigma_R^2}. \tag{17}$$

Intuitively, γ measures how much of the variation in X_t and S_5 is already absorbed by the predictable components $(\hat{X}_{i,t}, m_{i,t})$, while the remaining fraction $(1-\gamma)$ is contained in the innovations $(e_{i,t}, u_{i,t})$ that drive learning from the signal.

As in the main text, we represent the conditional expectation of X_t given the signal S_5 as

$$\mathbb{E}[X_t \mid \mathcal{I}_{i,t}, S_5] = \hat{X}_{i,t} + \kappa_5\big(S_5 - \mathbb{E}[S_5 \mid \mathcal{I}_{i,t}]\big),$$

where $\hat{X}_{i,t} \equiv \mathbb{E}[X_t \mid \mathcal{I}_{i,t}]$. The coefficient κ_5 is the Kalman gain, i.e. the regression coefficient of X_t on S_5 conditional on $\mathcal{I}_{i,t}$:

$$\kappa_5 = \frac{\mathrm{Cov}(X_t, S_5 \mid \mathcal{I}_{i,t})}{\mathrm{Var}(S_5 \mid \mathcal{I}_{i,t})} = \frac{(1-\gamma)\,\sigma_{X_t,S_5}}{\sigma_{S_5}^2 - \gamma\,\dfrac{\sigma_{X_t,S_5}^2}{\sigma_R^2}}.$$

We now relate this to the belief revision about X_{t+1}. Under the AR(1) structure, investor i's posterior expectation of next period's return is

$$\mathbb{E}_{i,t}^{\text{post}}[X_{t+1}] = \mathbb{E}[X_{t+1} \mid \mathcal{I}_{i,t}, S_5] = \alpha\,\mathbb{E}[X_t \mid \mathcal{I}_{i,t}, S_5] = \alpha\left[\hat{X}_{i,t} + \kappa_5\big(S_5 - \mathbb{E}[S_5 \mid \mathcal{I}_{i,t}]\big)\right],$$

while the prior expectation is

$$\mathbb{E}_{i,t}^{\text{prior}}[X_{t+1}] = \alpha\,\hat{X}_{i,t}.$$

Hence the belief revision and the experimental shock at the five-year horizon can be written as

$$\begin{aligned}
\text{Update}_{i,5} &= \mathbb{E}_{i,t}^{\text{post}}[X_{t+1}] - \mathbb{E}_{i,t}^{\text{prior}}[X_{t+1}] = \alpha\,\kappa_5\big(S_5 - \mathbb{E}[S_5 \mid \mathcal{I}_{i,t}]\big),\\
\text{Shock}_{i,5} &= S_5 - \mathbb{E}_{i,t}^{\text{prior}}[X_{t+1}] = S_5 - \alpha\hat{X}_{i,t}.
\end{aligned}$$

Using $S_5 = m_{i,t} + u_{i,t}$ with $u_{i,t} = S_5 - \mathbb{E}[S_5 \mid \mathcal{I}_{i,t}]$, we can rewrite

$$\text{Update}_{i,5} = \alpha\kappa_5 u_{i,t}, \qquad \text{Shock}_{i,5} = m_{i,t} + u_{i,t} - \alpha\hat{X}_{i,t}.$$

We now compute the covariance and variance that define β_5:

$$\beta_5 = \frac{\mathrm{Cov}(\text{Update}_{i,5}, \text{Shock}_{i,5})}{\mathrm{Var}(\text{Shock}_{i,5})}.$$

First, using orthogonality between innovations and predictable components,

$$\begin{aligned}
\mathrm{Cov}(\text{Update}_{i,5}, \text{Shock}_{i,5}) &= \mathrm{Cov}\big(\alpha\kappa_5 u_{i,t},\ m_{i,t} + u_{i,t} - \alpha\hat{X}_{i,t}\big)\\
&= \alpha\kappa_5\,\mathrm{Var}(u_{i,t})\\
&= \alpha\,\mathrm{Cov}(e_{i,t}, u_{i,t})\\
&= \alpha(1-\gamma)\,\sigma_{X_t,S_5}.
\end{aligned}$$

Second, the variance of the shock is

$$\begin{aligned}
\mathrm{Var}(\text{Shock}_{i,5}) &= \mathrm{Var}(m_{i,t} + u_{i,t} - \alpha\hat{X}_{i,t})\\
&= \mathrm{Var}(m_{i,t}) + \mathrm{Var}(u_{i,t}) + \alpha^2\mathrm{Var}(\hat{X}_{i,t}) - 2\alpha\,\mathrm{Cov}(\hat{X}_{i,t}, m_{i,t})\\
&= \sigma_{S_5}^2 + \alpha^2\gamma\sigma_R^2 - 2\alpha\gamma\sigma_{X_t,S_5}.
\end{aligned}$$

Combining these expressions, we obtain

$$\beta_5 = \frac{\mathrm{Cov}(\text{Update}_{i,5}, \text{Shock}_{i,5})}{\mathrm{Var}(\text{Shock}_{i,5})} = \frac{\alpha(1-\gamma)\,\sigma_{X_t,S_5}}{\sigma_{S_5}^2 + \alpha^2\gamma\sigma_R^2 - 2\alpha\gamma\sigma_{X_t,S_5}}. \tag{18}$$

Using (14), this can be written as

$$\beta_5 = \frac{5\alpha(1-\gamma)\,B_5(\alpha)}{V_5(\alpha) + 25\alpha^2\gamma - 10\alpha\gamma B_5(\alpha)}.$$

Substituting the explicit forms of $B_5(\alpha)$ and $V_5(\alpha)$ and simplifying the denominator gives

$$\beta_5 = \frac{5\alpha\big(\alpha^4+\alpha^3+\alpha^2+\alpha+1\big)(1-\gamma)}{2\alpha^4+4\alpha^3+6\alpha^2+8\alpha+5-5\alpha\gamma\big(2\alpha^2(\alpha^2+\alpha+1)-3\alpha+2\big)},$$

which is equation (9). □

A.3 Proof of Proposition 1

We already show the derivation of Equation (9) in Appendix A.2. To compare β_5 and β_1, recall from Equation (8), learning coefficient at the one-year horizon is

$$\beta_1 = \frac{\alpha(1-\gamma)}{1-\alpha\gamma(2-\alpha)},$$

and from Equation (9) (using the shorthand $B_5(\alpha)$ and $V_5(\alpha)$ introduced in (14)),

$$\beta_5 = \frac{5\alpha(1-\gamma)\,B_5(\alpha)}{V_5(\alpha) - 5\alpha\gamma\big(2\alpha^2(\alpha^2+\alpha+1)-3\alpha+2\big)}.$$

Let $D_1(\alpha,\gamma) \equiv 1-\alpha\gamma(2-\alpha)$, and $D_5(\alpha,\gamma) \equiv V_5(\alpha) - 5\alpha\gamma\big(2\alpha^2(\alpha^2+\alpha+1)-3\alpha+2\big)$, so that $\beta_1 = \alpha(1-\gamma)/D_1$ and $\beta_5 = 5\alpha(1-\gamma)B_5/D_5$.

Step 1: Denominators are positive.

For $0 < \alpha < 1$ and $0 \le \gamma < 1$,

$$D_1(\alpha,\gamma) = 1-\alpha\gamma(2-\alpha) > 1-\gamma \max_{\alpha\in[0,1]} \alpha(2-\alpha) = 1-\gamma > 0,$$

because $\max_{\alpha\in[0,1]} \alpha(2-\alpha) = 1$ and $\gamma < 1$.

For D_5, define

$$G_5(\alpha) \equiv 2\alpha^2(\alpha^2+\alpha+1) - 3\alpha + 2.$$

Then

$$D_5(\alpha,\gamma) = V_5(\alpha) - 5\alpha\gamma G_5(\alpha) = \big[V_5(\alpha) - 5\alpha G_5(\alpha)\big] + 5\alpha(1-\gamma)G_5(\alpha).$$

A direct algebraic simplification gives

$$V_5(\alpha) - 5\alpha G_5(\alpha) = (1-\alpha)\big(10\alpha^4+18\alpha^3+24\alpha^2+3\alpha+5\big).$$

For $0 < \alpha < 1$, we have $1-\alpha > 0$ and the polynomial in parentheses is strictly positive, so $V_5(\alpha) - 5\alpha G_5(\alpha) > 0$. Moreover, $G_5(\alpha) = 2\alpha^4+2\alpha^3+2\alpha^2-3\alpha+2 \;\ge\; 2\alpha^2-3\alpha+2 > 0$ for all α. Hence $G_5(\alpha) > 0$ for all $0 < \alpha < 1$. Thus, we have $5\alpha(1-\gamma)G_5(\alpha) \ge 0$. It follows that $D_5(\alpha,\gamma) > 0$ for all $0 < \alpha < 1$, $0 \le \gamma < 1$. Hence $D_1 > 0$ and $D_5 > 0$ on the parameter region of interest.

Step 2: Sign of $\beta_1 - \beta_5$.

Because $\alpha > 0$, $1-\gamma \ge 0$ and $D_1, D_5 > 0$, the sign of $\beta_1 - \beta_5$ is the sign of

$$\Delta(\alpha,\gamma) \equiv \alpha(1-\gamma)D_5(\alpha,\gamma) - 5\alpha(1-\gamma)B_5(\alpha)D_1(\alpha,\gamma).$$

After simplification, we have

$$\Delta(\alpha,\gamma) = \alpha^2(1-\alpha)(1-\gamma)\,H(\alpha,\gamma), \tag{19}$$

where

$$H(\alpha,\gamma) = 5\alpha^4\gamma + 10\alpha^3\gamma + 15\alpha^2\gamma + 3\alpha^2 + 20\alpha\gamma + 4\alpha + 3.$$

Every term in $H(\alpha,\gamma)$ is non-negative for $\alpha \in (0,1)$, $\gamma \in [0,1)$, and the constant term 3 implies $H(\alpha,\gamma) > 0$ on this region.

Moreover, $\alpha^2 > 0$, $1-\alpha > 0$, and $1-\gamma > 0$. Therefore, (19) implies

$$\Delta(\alpha,\gamma) > 0 \qquad \text{for all } 0<\alpha<1,\ 0\le\gamma<1.$$

Since $D_1(\alpha,\gamma)D_5(\alpha,\gamma) > 0$, we conclude that

$$\beta_1 - \beta_5 = \frac{\Delta(\alpha,\gamma)}{D_1(\alpha,\gamma)D_5(\alpha,\gamma)} > 0,$$

that is,

$$\beta_5 < \beta_1 \qquad \text{for all } 0<\alpha<1,\ 0\le\gamma<1.$$

This proves Proposition (1). □

A.4 Derivation of Equation (12)

Define

$$e^- \equiv \mu - \mu_{i,t}^-, \qquad e^+ \equiv \mu - \mu_{i,t}^+, \qquad \text{Update} \equiv \mu_{i,t}^+ - \mu_{i,t}^-, \qquad \text{Shock} \equiv X_m - \mu_{i,t}^-.$$

By construction,

$$e^- = (\mu - \mu_{i,t}^+) + (\mu_{i,t}^+ - \mu_{i,t}^-) = e^+ + \text{Update}. \tag{20}$$

Given Gaussian shocks and a diffuse prior, the posterior mean $\mu_{i,t}^+$ is the linear projection of μ on the linear span of the signals $\{S_t,\dots,S_{t-k+1},X_m\}$. Hence the posterior error $e^+ = \mu - \mu_{i,t}^+$ is orthogonal to each signal and therefore to any linear combination of them. In particular,

$$\text{Cov}(e^+, \text{Shock}) = 0,$$

because $\text{Shock} = X_m - \mu_{i,t}^-$ is itself a linear combination of $\{S_t,\dots,S_{t-k+1},X_m\}$.

Taking covariance of (20) with Shock and using the linearity of covariance, we obtain

$$\begin{aligned}\text{Cov}(\mu - \mu_{i,t}^-,\ X_m - \mu_{i,t}^-) &= \text{Cov}(e^-, \text{Shock}) = \text{Cov}(e^+ + \text{Update}, \text{Shock}) \\ &= \text{Cov}(e^+, \text{Shock}) + \text{Cov}(\text{Update}, \text{Shock}) \\ &= \text{Cov}(\text{Update}, \text{Shock}).\end{aligned}$$

Since $\text{Shock} = X_m - \mu_{i,t}^-$, Equation (5) can be written as

$$\beta_m = \frac{\text{Cov}(\text{Update}_{i,j,t}, \text{Shock}_{i,j,t})}{\text{Var}(\text{Shock}_{i,j,t})} = \frac{\text{Cov}(\mu - \mu_{i,t}^-,\ X_m - \mu_{i,t}^-)}{\text{Var}(X_m - \mu_{i,t}^-)}. \tag{21}$$

Thus it suffices to compute the covariance and variance on the right-hand side of (22).

Because both $\mu_{i,t}^-$ and $X_{m,t}$ load on $\{\varepsilon_{t-h}\}_{h=0}^{m-1}$,

$$\begin{aligned}\text{Cov}\left(\mu_{i,t}^- - \mu,\ X_{m,t} - \mu\right) &= \text{Cov}\Big(\frac{1}{k}\sum_{h=0}^{k-1}(\varepsilon_{t-h} + \eta_{t-h}),\ \frac{1}{m}\sum_{h=0}^{m-1}\varepsilon_{t-h}\Big) \\ &= \frac{1}{km}\sum_{h=0}^{k-1}\sum_{l=0}^{m-1}\text{Cov}(\varepsilon_{t-h}, \varepsilon_{t-l}) = \frac{\sigma_\varepsilon^2}{k}.\end{aligned}$$

For shorthand, define

$$V_1 \equiv \text{Var}(\mu_{i,t}^- - \mu) = \frac{\sigma_\varepsilon^2}{k} + \frac{\sigma_\eta^2}{k}, \quad V_2 \equiv \text{Var}(X_{m,t} - \mu) = \frac{\sigma_\varepsilon^2}{m}, \quad C \equiv \text{Cov}(\mu_{i,t}^- - \mu,\ X_{m,t} - \mu) = \frac{\sigma_\varepsilon^2}{k}.$$

with

$$\beta_m = \frac{\text{Cov}(\mu - \mu_{i,t}^-,\ X_{m,t} - \mu_{i,t}^-)}{\text{Var}(X_{m,t} - \mu_{i,t}^-)}. \tag{22}$$

$$\mathrm{Cov}(\mu - \mu_{i,t}^{-},\, X_{m,t} - \mu_{i,t}^{-}) = \mathrm{Cov}\big(-(\mu_{i,t}^{-} - \mu),\, (X_{m,t} - \mu) - (\mu_{i,t}^{-} - \mu)\big)$$
$$= \underbrace{\mathrm{Var}(\mu_{i,t}^{-} - \mu)}_{V_1} - \underbrace{\mathrm{Cov}(\mu_{i,t}^{-} - \mu,\ X_{m,t} - \mu)}_{C} = V_1 - C = \frac{\sigma_\eta^2}{k},$$

$$\mathrm{Var}(X_{m,t} - \mu_{i,t}^{-}) = \mathrm{Var}(X_{m,t} - \mu) + \mathrm{Var}(\mu_{i,t}^{-} - \mu) - 2\,\mathrm{Cov}(\mu_{i,t}^{-} - \mu,\ X_{m,t} - \mu)$$
$$= V_2 + V_1 - 2C = \frac{\sigma_\eta^2}{k} + \sigma_\varepsilon^2\left(\frac{1}{m} - \frac{1}{k}\right).$$

Substituting the above into (22) gives:

$$\beta_m = \frac{\frac{\sigma_\eta^2}{k}}{\frac{\sigma_\eta^2}{k} + \sigma_\varepsilon^2\big(\frac{1}{m} - \frac{1}{k}\big)} = \frac{1}{1 + \left(\frac{k}{m} - 1\right)\frac{\sigma_\varepsilon^2}{\sigma_\eta^2}} \in (0,1). \tag{23}$$

Substituting these expressions into (22) yields

$$\beta_m = \frac{\dfrac{\sigma_\eta^2}{k}}{\dfrac{\sigma_\eta^2}{k} + \sigma_\varepsilon^2\big(\frac{1}{m} - \frac{1}{k}\big)} = \frac{1}{1 + \left(\frac{k}{m} - 1\right)\frac{\sigma_\varepsilon^2}{\sigma_\eta^2}}, \tag{24}$$

which is Equation (12).

A.5 Proof of Proposition 2

We already show the derivation of Equation (12) in Appendix A.4.

Since $\sigma_\varepsilon^2 > 0$, $\sigma_\eta^2 > 0$, and $1 \le m \le k$, we have

$$\left(\frac{k}{m} - 1\right)\frac{\sigma_\varepsilon^2}{\sigma_\eta^2} \ge 0,$$

which implies $0 < \beta_m \le 1$, with strict inequality $\beta_m < 1$ whenever $m < k$. Setting $m = 1$ yields

$$\beta_1 = \frac{1}{1 + (k-1)\,\frac{\sigma_\varepsilon^2}{\sigma_\eta^2}},$$

as stated in the proposition. □

A.6 Derivation of Equation (13)

Let

$$V_1 \equiv \mathrm{Var}(\mu_{i,t}^{-} - \mu), \quad V_2 \equiv \mathrm{Var}(X_{m,t} - \mu), \quad C \equiv \mathrm{Cov}(\mu_{i,t}^{-} - \mu,\ X_{m,t} - \mu).$$

From the expressions in the main text we have

$$V_1 = \frac{1}{T}, \qquad V_2 = \frac{\sigma_\varepsilon^2}{m}, \qquad C = \frac{\sigma_\varepsilon^2}{m}\,W_m = \frac{\sigma_\varepsilon^2}{m}\sum_{h=0}^{m-1}\theta_h. \tag{25}$$

We have shown in Appendix (A.4) that

$$\beta_m = \frac{\mathrm{Cov}(\mathrm{update}_{i,t}(m), \mathrm{shock}_{i,t}(m))}{\mathrm{Var}(\mathrm{shock}_{i,t}(m))} = \frac{\mathrm{Cov}(\mu - \mu_{i,t}^-,\, X_{m,t} - \mu_{i,t}^-)}{\mathrm{Var}(X_{m,t} - \mu_{i,t}^-)}. \tag{26}$$

$$\begin{aligned}\mathrm{Cov}(\mu - \mu_{i,t}^-,\, X_{m,t} - \mu_{i,t}^-) &= \mathrm{Cov}\big(-(\mu_{i,t}^- - \mu),\, (X_{m,t} - \mu) - (\mu_{i,t}^- - \mu)\big) \\ &= \underbrace{\mathrm{Var}(\mu_{i,t}^- - \mu)}_{V_1} - \underbrace{\mathrm{Cov}(\mu_{i,t}^- - \mu,\; X_{m,t} - \mu)}_{C} = V_1 - C,\end{aligned}$$

$$\begin{aligned}\mathrm{Var}(X_{m,t} - \mu_{i,t}^-) &= \mathrm{Var}(X_{m,t} - \mu) + \mathrm{Var}(\mu_{i,t}^- - \mu) - 2\,\mathrm{Cov}(\mu_{i,t}^- - \mu,\; X_{m,t} - \mu) \\ &= V_2 + V_1 - 2C.\end{aligned}$$

Substituting into β_m yields the generic expression

$$\beta_m = \frac{\mathrm{Cov}(\mu - \mu_{i,t}^-,\, X_{m,t} - \mu_{i,t}^-)}{\mathrm{Var}(X_{m,t} - \mu_{i,t}^-)} = \frac{V_1 - C}{V_1 + V_2 - 2C}. \tag{27}$$

Therefore, we have

$$\begin{aligned}\beta_m &= \frac{V_1 - C}{V_1 + V_2 - 2C} = \frac{\frac{1}{T} - \frac{\sigma_\varepsilon^2}{m} W_m}{\frac{1}{T} + \frac{\sigma_\varepsilon^2}{m} - 2\,\frac{\sigma_\varepsilon^2}{m} W_m} = \frac{1 - \frac{\sigma_\varepsilon^2}{m} T_m}{1 + \frac{\sigma_\varepsilon^2}{m} T - 2\,\frac{\sigma_\varepsilon^2}{m} T_m} \\ &= \frac{1 - \frac{1}{m}\sum_{h=0}^{m-1} q_h}{1 + \frac{1}{m}\left(\sum_{h=m}^{k-1} q_h - \sum_{h=0}^{m-1} q_h\right)} = \frac{m - \sigma_\varepsilon^2 T_m}{m + \sigma_\varepsilon^2\,(T - 2T_m)}, \quad \text{where } q_h \equiv \sigma_\varepsilon^2 \tau_h = \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \lambda^h \sigma_\eta^2}\end{aligned} \tag{28}$$

A.7 Proof of Proposition 3

We already show the derivation of Equation (13) in Appendix A.6.

Recall from (28) that

$$\beta_m = \frac{1 - \frac{1}{m}\sum_{h=0}^{m-1} q_h}{1 + \frac{1}{m}\left(\sum_{h=m}^{k-1} q_h - \sum_{h=0}^{m-1} q_h\right)}, \qquad q_h \equiv \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \lambda^h \sigma_\eta^2} \in (0,1).$$

Define cumulative sums

$$Q_m \equiv \sum_{h=0}^{m-1} q_h, \qquad S \equiv \sum_{h=0}^{k-1} q_h, \qquad L_m \equiv S - Q_m = \sum_{h=m}^{k-1} q_h.$$

Then

$$\beta_m = \frac{1 - \frac{Q_m}{m}}{1 + \frac{S - 2Q_m}{m}} = \frac{m - Q_m}{m + S - 2Q_m}.$$

For convenience, write

$$N_m \equiv m - Q_m, \qquad D_m \equiv m + S - 2Q_m,$$

so that $\beta_m = N_m/D_m$. Note that each $q_h \in (0,1)$ implies $0 < Q_m < m$ and hence $N_m > 0$. Moreover,

$$D_m = N_m + L_m > 0,$$

because $L_m \geq 0$.

To show β_m is increasing in m, it suffices to prove

$$\beta_{m+1} > \beta_m \quad \iff \quad N_{m+1}D_m - N_m D_{m+1} > 0, \qquad m = 1, \ldots, k,$$

since all denominators are positive. Using $Q_{m+1} = Q_m + q_m$ we have

$$N_{m+1} = (m+1) - Q_{m+1} = N_m + (1 - q_m), \qquad D_{m+1} = (m+1) + S - 2Q_{m+1} = D_m + (1 - 2q_m).$$

Hence

$$\begin{aligned} N_{m+1}D_m - N_m D_{m+1} &= (N_m + 1 - q_m)D_m - N_m(D_m + 1 - 2q_m) \\ &= (1 - q_m)D_m - N_m(1 - 2q_m). \end{aligned}$$

Substituting $D_m = N_m + L_m$ gives

$$\begin{aligned} N_{m+1}D_m - N_m D_{m+1} &= (1 - q_m)(N_m + L_m) - N_m(1 - 2q_m) \\ &= q_m N_m + (1 - q_m)L_m. \end{aligned}$$

By construction $q_m \in (0, 1)$, $N_m > 0$, and $L_m \geq 0$, so

$$q_m N_m > 0, \qquad (1 - q_m)L_m \geq 0,$$

and therefore

$$N_{m+1}D_m - N_m D_{m+1} = q_m N_m + (1 - q_m)L_m > 0.$$

Since $D_m D_{m+1} > 0$, it follows that $\beta_{m+1} > \beta_m$ for all $m < k$. Thus β_m is strictly increasing in m.