

Uncertain Uncertainty

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Abstract

Total returns and average annual returns are mathematically equivalent, yet when asked about one versus the other, the same individual's implied variance ratios differ by a factor of 25. We hypothesize that most individuals do not reliably scale uncertainty across horizons, compressing their near- and long-term estimates. This compression produces implausibly strong negative risk-horizon relations when individuals are asked about total returns and implausibly strong positive relations when they are asked about average annual returns. Evidence from five datasets supports the hypothesis and helps explain several puzzling findings about subjective risk perceptions.

JEL classifications: C90, D10, D83, D84, G11, G30, G41, G51, G53

Key words: Expectations, Variance ratios, Miscalibration, Parameter uncertainty, Mean-reversion, Long-run risk, Risky share, Target date funds

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1 Introduction

Total returns and average annual returns are mathematically equivalent ways of expressing the same information about long-horizon uncertainty. Yet when the same person is asked about each, their implied variance ratios differ by a factor of 25. The same person cannot simultaneously believe that time nearly eliminates stock market risk over the coming decade *and* that it sharply magnifies that risk over the same decade, yet that is precisely what individuals appear to do when answering these questions. This is not a statistical artifact—the results hold over five datasets (spanning business school students, retail investors, CFOs, and representative samples of Americans), three different elicitation methods, and variation in elicitation parameters. The culprit is a single design choice: whether the long-horizon return question is framed in terms of total cumulative returns or average annual returns. When asked about cumulative returns—where variance increases with horizon—respondents report beliefs that imply an implausibly strong *negative* relation between risk and horizon. When asked about average annual returns—where variance decreases with horizon—the same respondents report beliefs that imply an implausibly strong *positive* relation. The resulting implied optimal equity allocations are, respectively, 255% and 5.7% of wealth for an investor with a 10-year horizon versus the 37.5% the standard model (Merton (1969)) prescribes.¹ Investor beliefs are highly implausible in opposing directions relative to the standard model, and generated by respondents answering what is, mathematically, the same question.

This unit-dependency (cumulative versus average annual returns) cuts to the heart of a long-standing debate in finance and economics about how economic agents should, and do, perceive the relation between risk and horizon. The interpretation of both theory and empirical evidence that considers economic agents’ perceptions of uncertainty relies, explicitly or implicitly, on the assumption that agents’ near- and long-term beliefs are linked by a consistent distributional logic. Our central finding is that they are not. Moreover, this failure helps explain a puzzling set of empirical results across multiple literatures that have resisted a common interpretation. First, CFOs appear to perceive risk as increasing with horizon (Pástor and Stambaugh (2012)) while individuals appear to perceive risk as decreasing with horizon (Sias, Starks, and Turtle (2026)). Second, not only do these estimates diverge in opposite directions, both are individually implausible by any

¹These values are based on a continuous annual equity risk premium of 6%, an annual market volatility of 20% (both approximate historical values), and a coefficient of relative risk aversion (γ) of 4 (following Giglio, Maggiori, Stroebel, and Utkus (2021)). Thus, an investor with a 1-year horizon holds 37.5% of their wealth in equities (i.e., $(E(r_k) - r_{f,k})/(\gamma\sigma^2(r_k)) = 0.06/(4 \times 0.20^2)$). An investor with a 10-year horizon holds $0.06/(4 \times 0.20^2 \times VR_{10,i})$, where the 10-year variance ratio ($VR_{10,i}$) is 1.0 (when returns are *iid* and there is no parameter uncertainty), 0.147 (the median variance ratio for American Life Panel respondents answering their total return questions), or 6.61 (the median variance ratio for CFOs answering the Duke survey’s average return questions).

reasonable theoretical benchmark. The median CFO variance ratio of 6.6 is six times the Pástor and Stambaugh (2012) estimate (of 1.1) that accounts for parameter uncertainty using “realistic” parameters. The median individual’s variance ratio of 0.147 implies effectively zero probability of a negative 10-year market return, inconsistent with even the most extreme mean-reversion estimates in the empirical literature.² Third, CFOs exhibit severely miscalibrated near-term uncertainty estimates but appear much less miscalibrated at long horizons (Ben-David, Graham, and Harvey (2013)). The mechanism driving this asymmetry, however, remains unclear. Fourth, the empirical relation between perceived subjective uncertainty and portfolio allocation is less than one-tenth the theoretical value—the “attenuation puzzle” (Amromin and Sharpe (2014)). Fifth, qualitative measures of perceived risk better explain investor behavior than quantitative model primitives (Nosić and Weber (2010), Kapteyn and Teppa (2011)).

We hypothesize that respondents’ compression of near- and long-term uncertainty estimates is the central mechanism underlying these results. A growing literature (discussed in the next section) demonstrates that when decisions or judgments require aggregating information over multiple periods or dimensions, individuals’ responses exhibit insufficient sensitivity to the scope parameter (relative to objective values) whether that parameter is the number of periods, length of a time delay, or the magnitude of a probability. Applied to equity return distributions, compression has the opposite implications depending on the return unit. Specifically, (1) because *total* return uncertainty increases with horizon, compression pulls long-term total return estimates insufficiently far from near-term values, generating implausibly low variance ratios, and (2) because *average annual* return uncertainty decreases with horizon, compression pulls long-term average return estimates insufficiently far from near-term values in the opposite direction, generating implausibly high variance ratios. In short, the same compression produces opposite apparent beliefs depending on the return unit asked about.

Using five datasets—the American Life Panel (ALP), the Health and Retirement Study (HRS), the Duke CFO surveys, the Understanding America Study (UAS), and a series of surveys to undergraduate business students over five semesters—we find strong and consistent support for our hypothesis. When ALP and HRS respondents are asked about total return uncertainty over the next decade, their median implied variance ratios are 0.147 and 0.145, respectively. When CFOs are asked about average annual return uncertainty over the same horizon, the median implied variance ratio is 6.6. When the same business school students are asked both question formats two

²Given the historical 10-year (continuous) market return of 97%, ALP respondents’ inferred 10-year standard deviation of 29.1% implies a 0.04% chance of a negative market return over a 10-year horizon.

weeks apart, 95% generate a larger variance ratio from the average return questions, with a median difference of 8.71—versus a value of zero for any agent with a consistent distributional model of how risk evolves with horizon.

Additional tests show the compression is robust. The clearest evidence comes from the return unit itself. Asking the same students about average annual versus cumulative returns flips the median variance ratio from well above one to well below it, and it does so under both standard elicitation methods—whether we give students a probability and ask for the corresponding return (quantile elicitation) or give them a return threshold and ask for the likelihood (probability elicitation). It is the return unit driving the result, not the way the question is posed. For example, under probability elicitation, the median 10-year variance ratio falls from above 4.5 when students are asked about average annual returns to below 0.4 when asked about cumulative returns. Although the return unit determines whether respondents appear to view risk as increasing or decreasing with horizon, the levels they report are themselves fragile and far more so than the compression. For instance, switching ALP respondents to a balls-and-bins format cuts their reported standard deviations by more than 60% at both the 1- and 10-year horizons, yet their median variance ratio is essentially unchanged. Varying the probability level, the return threshold, the confidence interval width, the bin structure, and seed values all move the reported numbers while leaving the compression in place. The pattern worsens with horizon, as the underlying calculation grows more complex, and it holds when students are asked about historical rather than forward-looking distributions, which rules out overconfidence in their own forecasting ability. Heterogeneity across respondents tells the same story: more financially sophisticated respondents produce more reasonable, yet still implausible, variance ratios. Respondents who exhibit greater compression in eight unrelated personal events, such as their estimated chance of a car accident over the next one versus five years, also exhibit greater compression in equity markets.

The implications are broad. If investors’ quantitative answers about long-horizon risk are artifacts of how the question is posed rather than stable underlying objects, then the survey measures used throughout household finance may be capturing far less than is assumed. Lifecycle and target-date funds, for instance, presume investors hold well-specified quantitative risk perceptions and understand how risk evolves with horizon; if those perceptions are not stable underlying objects, the risk profiling that drives these allocations may not effectively capture objective investment risks, or related risk tolerances. Regulation embeds the same assumption: the safe-harbor treatment of target-date funds as default retirement investments institutionalizes horizon-based risk management on behalf of investors who may not hold the very beliefs the framework presumes. In corporate fi-

nance, if the typical CFO cannot reliably scale risk across horizons, the well-documented preference for simple decision rules such as payback period (Graham (2022)) may be a natural response to that difficulty. More broadly, theory, measurement, and policy often presume that economic agents understand how risk evolves with horizon and that surveys can elicit what they understand. Our results suggest that, for most people, that understanding is far weaker, and far harder to measure, than the presumption requires.

The same mechanism also helps explain the five disparate puzzles detailed above. The apparent contradiction between CFOs and individuals dissolves: both compress, but in opposite directions because they are asked about different return units. The implausible magnitudes follow directly from the severity of this compression. The asymmetry between CFOs’ near- and long-term miscalibration follows too, as compression pulls the two estimates toward each other and mechanically narrows the gap at the more distant horizon. And the attenuation puzzle and the superior performance of qualitative risk measures both reflect the same fragility: if elicited quantities are format-dependent proxies for the qualitative beliefs that actually govern behavior, then the measured link between perceived risk and allocation will be weak, and qualitative measures that sidestep the format problem may better predict behavior.

More broadly, our study builds on a growing literature (discussed in the next section) showing that reported beliefs about return distributions are a function of how questions are framed. This work shows framing can move a given estimate; our finding is different. What is frame-dependent here is not the level of any single estimate but the relation between near- and long-term estimates, so that the same person reports opposite views of how risk evolves with horizon depending only on the unit of measurement.

2 Background

Theory and empirical work often rely (implicitly or explicitly) on the assumption that economic agents understand the relation between horizon and uncertainty. For instance, both the classic Merton (1969) model and the growing literature that focuses on the relation between horizon and uncertainty solves for the optimal risky share for an investor who understands how uncertainty evolves with horizon.³ Similarly, the interpretation of empirical evidence often relies on this as-

³A partial list of the studies that focus on the important question of how predictive risk varies with horizon for a forward looking investor includes Samuelson (1969), Merton (1969), Barberis (2000), Campbell and Viceira (2002), Pettenuzzo and Timmermann (2011), Pástor and Stambaugh (2012), Hoevenaars, Molenaar, Schotman, and Steenkamp (2014), Johannes, Korteweg, and Polson (2014), Siegel (2014), Müller and Watson (2016), Avramov, Cederburg, and Lučivjanská (2018), Carvalho, Lopes, and McCulloch (2018), Zhang, Zhu, and Zhu (2020), and

sumption. Pástor and Stambaugh (2012) conclude, based on the Duke surveys, that CFOs view stocks as “more volatile at long horizons” and both explanations Ben-David, Graham, and Harvey (2013) offer for CFOs’ near- versus long-term miscalibration asymmetry (parameter uncertainty and expectations of increases in future market volatility) implicitly assume CFOs understand how uncertainty evolves with horizon.⁴ Correspondingly, labeling the weak empirical relation between perceived uncertainty and portfolio allocation the attenuation “puzzle” implicitly assumes investors know and use variance (or something highly correlated) and, assuming many have expected holding periods other than one year, understand the relation between horizon and risk.⁵

2.1 Measuring perceived distributions

Most work takes one of three approaches to measuring economic agents’ perceptions of a return distribution. The first approach, quantile elicitation, gives respondents a probability and asks them to report the corresponding return. For example, the Duke CFO surveys ask respondents for their 10th and 90th return percentiles, generating an 80% confidence interval. The second approach, probability elicitation, gives respondents a return threshold and asks them to report the corresponding likelihood. The ALP and HRS surveys, for instance, ask respondents to estimate the likelihood that markets will gain more than 20% over the next year. The third approach, distributional elicitation, gives respondents a set of return bins and asks them to allocate balls across bins in proportion to their perceived likelihoods. Although the focus of our study is on the relation between near- and long-horizon perceptions holding the elicitation approach constant, a growing literature demonstrates that elicitation approach impacts responses. For instance, respondents tend to report similar confidence intervals regardless of the probability level asked about (Hartzmark and Sussman (2026)).

Regardless of elicitation approach, surveys of long-horizon beliefs must also choose between asking about cumulative or average annual returns. For instance, the Duke CFO surveys use quantile elicitation framed in average annual returns (e.g., there is a 1-in-10 chance annual returns over the next decade will average less than ___), while the ALP surveys use probability elicitation framed in cumulative returns (e.g., what are the chances equity markets will have fallen in value

Jondeau, Zhang, and Zhu (2021).

⁴Barrero (2022) and Boutros, Ben-David, Graham, Harvey, and Payne (2025) also find corporate managers exhibit near-term miscalibration.

⁵For instance, [Jay Clayton \(former Chairperson Securities Exchange Commission\)](#) claims, “Put simply, they are investing for the long term and it’s their money that’s in our markets as they save for retirement and other life events. We think about them every day at the Commission and they’re not investing for next week, they’re not investing for next year. Predominately they’re investing for something 10, 20, 30 years away and they expect their money to be managed that way.”

by more than 20% in 10 years?). Crucially, all three elicitation approaches can be framed in either cumulative or average annual long-horizon returns—a choice that, as we demonstrate, has first-order consequences for the variance ratios implied by respondents’ answers.

2.2 Compression and hypotheses

Understanding why elicitation format generates such dramatically different variance ratio estimates requires first recognizing the mathematical complexity of the relation between horizon and uncertainty—given the variance of k -year returns is k^2 times the variance of the average annual return over k years (i.e., $\sigma^2(r_k) = \sigma^2(k\bar{r}_k) = k^2\sigma^2(\bar{r}_k)$), the k -period variance ratio (denoted VR_k), regardless of the level of parameter uncertainty or return predictability, satisfies:

$$VR_k = \frac{\sigma^2(r_k)}{k\sigma^2(r_1)} = \frac{k\sigma^2(\bar{r}_k)}{\sigma^2(r_1)}. \quad (1)$$

Even in the simplest case where there is no parameter uncertainty and returns are *iid* (the “base” case where $VR_k = 1 \forall k$), the variance of 10-year total returns is 10 times the 1-year return variance, the variance of average annual returns over 10 years is $1/10^{\text{th}}$ the 1-year return variance, and the 10-year total return variance is 100 times the 10-year average return variance.⁶ Adding uncertainty regarding the return generating process and expectations of mean-reversion or other forms of predictability only further complicates the estimation of these values (e.g., see equation (12) in Pástor and Stambaugh (2012)).

A growing literature demonstrates that when people make complex quantitative judgments, they are insufficiently sensitive to the input that should scale their answer—such as the horizon, probability, or magnitude involved—so their estimates are compressed. Enke and Graeber (2023) show that this compression appears across choice under risk, belief updating, and economic forecasting, with respondents’ estimates behaving as attenuated functions of objective values.⁷ The same pattern accounts for probability weighting in lotteries, base-rate insensitivity and conservatism in belief updating, overestimation of low-probability events, and the weak transmission from beliefs to behaviors (Enke and Graeber (2023), Charles, Frydman, and Kilic (2024)). For instance, Oprea (2024) finds that classic lottery anomalies are equally apparent in deterministic “mirrors”

⁶Equivalently, the standard deviation of 10-year returns is $\sqrt{10}$ times the standard deviation of 1-year returns, the standard deviation of the average return over 10 years is $1/\sqrt{10}$ times the standard deviation of 1-year returns, and the standard deviation of 10-year returns is 10 times the standard deviation of the average return over 10 years in the base case.

⁷This compression is related to the Tversky and Kahneman (1974) anchoring and adjustment heuristic, in which individuals form estimates with an insufficient adjustment from an anchor. See Woodford (2020) and Gabaix (2019) for related models and reviews.

of those lotteries, supporting the hypothesis that the complexity of the evaluation, rather than risk preferences, drives these patterns.

A closely related body of work documents compression across time, where measured discount rates over money violate exponential discounting (for a review, see Cohen, Ericson, Laibson, and White (2020)). This research argues that the appearance of hyperbolic discounting arises from compression of estimates over different horizons rather than from non-standard preferences (Enke, Graeber, and Oprea (2025), Gabaix and Laibson (2022), Gershman and Bhui (2020)). Enke, Graeber, and Oprea (2025), for example, document that hyperbolic discounting is equally apparent when the same questions are posed in a way that removes the time dimension entirely.⁸ Khaw, Li, and Woodford (2021) attribute these patterns to the imprecision in how people mentally represent magnitudes, and Gabaix and Laibson (2022) show that when estimates of the future grow noisier at longer horizons, people lean on a default value, producing behavior that mimics discounting even absent true impatience.

Applied to our setting, this mechanism predicts that subjective estimates of uncertainty are compressed relative to the benchmark implied by respondents’ own near-term uncertainty estimates—which has opposite implications depending on the return unit. Because total return uncertainty increases with horizon, compression pulls long-term total return estimates insufficiently far from near-term values. Specifically, if a respondent’s estimates are compressed, their inferred long-term variance ($\hat{\sigma}^2(r_k)$) will be too small relative to their near-term estimate when asked about cumulative returns:⁹

$$\hat{\sigma}^2(r_1) < \hat{\sigma}^2(r_k) < (k \times \hat{\sigma}^2(r_1)). \quad (2)$$

Correspondingly, because average annual return uncertainty decreases with horizon, compression pulls long-term average return estimates insufficiently far from near-term values in the other direction and, as a result, the inferred long-term average annual variance ($\hat{\sigma}^2(\bar{r}_k)$) will be too large relative to their near-term estimate:¹⁰

$$\hat{\sigma}^2(r_1) > \hat{\sigma}^2(\bar{r}_k) > (\hat{\sigma}^2(r_1)/k). \quad (3)$$

⁸The authors reframe the question as an “atemporal mirror,” e.g., asking a person to value “\$50 shrunk 12 times, each time by 4%.”

⁹To reduce notational clutter, equations (2) and (3) are base case scenarios where the k -period variance ratio is 1. In the more general case, the last term in both equations is multiplied by the k -period variance ratio (VR_k).

¹⁰Consider a simple example: If the individual perceives the standard deviation of annual returns is 20% (i.e., the approximate historical value), then, in the base case, the objective standard deviation of total 10-year returns is 63% (i.e., $(0.2^2 \times 10)^{0.5}$) and the objective standard deviation of the average annual return over the 10 years is 6.3% (i.e., $(0.2^2/10)^{0.5}$).

In short, compression implies the perceived long-term variance will be too close to the perceived near-term variance regardless of whether respondents are asked about cumulative returns (resulting in variance ratios that are too small; equation (2)) or average annual returns (resulting in variance ratios that are too large; equation (3)).

3 Data

We use five datasets to examine respondents’ near- and long-term perceived return distributions—the American Life Panel, the Health and Retirement Study, the Duke CFO surveys, the Understanding America Study, and a series of surveys given to undergraduate business students at two public universities.

3.1 The American Life Panel

The ALP is an ongoing nationally representative panel of Americans that has grown from approximately 2,000 participants in 2003 to more than 6,000 today. Between November 2008 and January 2016, ALP executed 61 “effects of the financial crisis” surveys in either long-form (29 surveys) or short-form (32 surveys) formats. The long-form surveys asked respondents six questions regarding both near- and long-term perceived stock market return distributions:

We are interested in how well you think the economy will do in the future. By next year at this time, what is the percent chance that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more than they are today?

By next year at this time, what is the percent chance that mutual fund shares invested in blue-chip stocks like those in the Dow Jones Industrial Average will have

-gained in value by more than 20 percent compared to what they are worth today?

-fallen in value by more than 20 percent compared to what they are worth today?

Now please think about how the stock market will change over the next 10 years: What are the chances that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more in 10 years than they are today?

What are the chances that mutual fund shares invested in blue-chip stocks like those in the Dow Jones Industrial Average will have

-increased in value by more than 20 percent in 10 years compared to what they are worth today?

-fallen in value by more than 20 percent in 10 years compared to what they are worth today?

The 32 short-form surveys asked the first four questions but not the final two. Because estimation of the long-term variance requires the final two questions, we limit our sample to the 29 long-form surveys. In 18 of the 29 long-form waves, roughly half of respondents were randomly assigned to a distributional (balls-and-bins) elicitation of the market expectations questions rather than the standard probability format. We exclude these respondents from our primary tests and analyze their variance ratios separately in our tests of the robustness of compression to elicitation format.¹¹

Following previous work (Dominitz and Manski (2007), Kézdi and Willis (2011), Ben-David, Graham, and Harvey (2013), Boutros, Ben-David, Graham, Harvey, and Payne (2025)), we infer the near-term (long-term) perceived return variance for each respondent at each point in time by assuming continuously compounded returns are normally distributed and solving for the parameters that fit the respondent’s reported likelihoods that markets rise or fall 20% in the next year (decade).¹² Estimation requires that respondents’ beliefs about the sum of the tail probabilities does not exceed 100% and that neither tail probability is zero.¹³ We are able to infer variances for 69% of surveys where respondents report near-term tail probabilities and 62% where respondents report long-term tail probabilities. Because our variable of interest is the variance ratio, we limit the sample to observations with both near- and long-term variance estimates, and winsorize variance ratios and inferred volatility estimates at the 5th and 95th percentiles. Our final sample consists of 22,745 pooled cross-sectional time-series observations from 3,022 individuals, with the average respondent participating in more than 7.5 of the 29 long-form surveys.

The panel structure of the ALP enables tests that are unavailable in most traditional survey datasets. Because we observe the same individuals across multiple waves, we can estimate individual-level beliefs about mean-reversion in equity markets—allowing us to examine heterogeneity in mean-reversion beliefs in a way that most surveys (e.g., those where the sample changes each period or respondents are not uniquely identified) cannot. More broadly, the panel structure allows us to construct a rich set of individual-level measures including expected future economic conditions, overconfidence, financial literacy, and numeracy, which we exploit to investigate the sources of variance ratio heterogeneity. The Internet Appendix reports descriptive statistics of

¹¹Twenty-three observations with valid responses to both question formats in the same wave are excluded from both samples. In addition, wave 44 was split into two portions and only respondents to wave 44.1 were asked the long-horizon tail probability questions.

¹²Following the variance ratio literature (e.g., Poterba and Summers (1987), Lo and MacKinlay (1988)), we focus on continuously compounded returns. Because we focus on continuously compounded returns, we convert arithmetic returns to continuously compounded returns via a log transformation before estimating perceived distributions.

¹³The substantial number of observations that violate probability laws is consistent with previous work (e.g., de Bruin, Fischhoff, Millstein, and Halpern-Felsher (2000), Merkoulova and Veld (2022)). See Internet Appendix for additional detail.

respondent characteristics and details of these additional ALP variables.

3.2 The Health and Retirement Study

The Health and Retirement Study (HRS) is a longitudinal panel of individuals ages 50 and older. In 2009, HRS executed an off-year internet survey to a random subset of participants asking the same six probability elicitation questions as the ALP long-form survey. We apply the same sample restrictions and variance inference procedure as for the ALP, yielding 1,252 respondents with implied variance ratios. Variance ratios and volatility estimates are winsorized at the 5th and 95th percentiles.

3.3 CFO survey data

The Duke CFO surveys use quantile elicitation, asking respondents to fill in the blanks:

Over the next 10 years, I expect the average annual S&P 500 return will be:

There is a 1-in-10 chance it will be less than ____

Expected return ____

There is a 1-in-10 chance it will be greater than ____

Over the next year, I expect the S&P 500 return will be:

There is a 1-in-10 chance it will be less than ____

Expected return ____

There is a 1-in-10 chance it will be greater than ____

For 63 quarters between 2004 and 2019, we gather the mean and median answers published at the Duke CFO survey website (cfosurvey.fuqua.duke.edu), computed from an average of approximately 400 CFOs per quarter (ranging from 186 to 781).¹⁴ Following Pástor and Stambaugh (2012), we infer variance from the reported median and mean 10th and 90th return percentiles for the S&P 500 over the next year and next decade, based on continuously compounded returns.

3.4 Student surveys

In spring and fall 2024, undergraduate business students at two large public universities were given both the ALP probability elicitation questions (Section 3.1) and the CFO quantile elicitation questions (Section 3.3), framed in total and average annual returns respectively, two weeks apart.¹⁵

¹⁴Data were not available for the first quarter of 2019.

¹⁵The order of the two surveys was varied across sections. As detailed in the Internet Appendix, survey order did not materially influence the results.

We limit the sample to students whose answers follow probability laws and infer near- and long-term variances assuming normally distributed continuously compounded returns. Our spring and fall 2024 sample consists of 322 students with variance ratios based on the probability elicitation total return questions, 673 based on the quantile elicitation average return questions, and 241 with variance ratios based on both.

The fall 2024 surveys also included a historical returns component designed to distinguish compression from greater overconfidence in near-term predictive ability. Specifically, fall 2024 students were first given the forward-looking ALP probability elicitation questions and a backward-looking version of the CFO quantile elicitation questions reframed around historical returns. Two weeks later, the same students were given the forward-looking CFO quantile elicitation questions and a backward-looking version of the ALP probability elicitation questions reframed around historical returns. This design yields 251 students with variance ratios based on the historical probability elicitation questions and 290 based on the historical quantile elicitation questions.

In spring 2025, fall 2025, and spring 2026, we administered additional surveys to new groups of introductory finance students at both universities, varying elicitation approach (probability versus quantile), return unit (cumulative versus average annual), horizon (5, 10, or 15 years), and whether respondents were asked about historical or expected future returns. This sample consists of 1,368 students. Variance ratios and volatility estimates are winsorized at the 5th and 95th percentiles throughout. The Internet Appendix provides additional details regarding all student surveys.

3.5 Understanding America Study

The Understanding America Study (UAS) is a national panel of approximately 14,700 US households managed by the USC Dornsife Center for Economic and Social Research. In January 2025, UAS administered the six ALP probability elicitation total return questions to 9,455 respondents; we limit the sample to the 3,644 whose answers do not violate probability laws. In May–June 2019, UAS administered quantile elicitation questions about 10-year average annual returns and historical annual return distributions to 2,461 respondents; after applying probability law restrictions, 1,439 remain.¹⁶ Inferred standard deviations and variance ratios are winsorized at the 5th and 95th percentiles.

¹⁶The UAS CFO-style 1-year questions differ from the Duke CFO survey in that they ask about historical rather than expected returns, and rephrase the 10th and 90th percentile question as the six lowest and six highest years over the past 60 years. Note that the ALP-style and CFO-style UAS surveys were administered six years apart, a limitation we discuss further when presenting the UAS results. See Internet Appendix for details.

4 The Perceived Relation between Horizon and Uncertainty

4.1 ALP respondents' variance ratios

Table I reports descriptive statistics for ALP respondents' perceived return distributions. Consistent with previous work, respondents tend to hold pessimistic near-term beliefs as the median respondent reports only a 40% likelihood markets rise in the next year despite markets rising approximately three out of every four years historically.¹⁷ The bottom row of Panel A, however, reveals that the median ALP respondent's inferred 1-year standard deviation of 20.7% is almost identical to the historical value of 20%.

[Insert Table I about here]

Panel B shows the typical individual severely underestimates, relative to historical values, long-term expected returns when responding to the ALP survey questions—the median respondent's inferred 10-year expected return is only 4.3% (0.43% annually). More importantly, for our purposes, the median respondent's beliefs imply a 10-year standard deviation of only 29%—less than half the 65% value implied by their own near-term uncertainty estimates under serial independence (i.e., the 20.7% 1-year median standard deviation times $\sqrt{10}$; see equation 2). Nearly three out of four respondents report beliefs that generate a long-term variance less than the historical average.¹⁸

Because near- and long-term variance estimates are compressed toward each other, the implied variance ratios are implausibly small. Panel C reports the distribution of implied variance ratios. The historical 10-year variance ratio for the CRSP value-weighted index is 0.542, reflecting the mean reversion in US equity markets. The median ALP respondent's implied variance ratio of 0.147 is far below even this historically mean-reverting value—a value only possible if equity markets exhibit unprecedented levels of mean reversion and ALP respondents have essentially no parameter uncertainty. Moreover, 89% of respondent-survey observations imply variance ratios below unity and 82% fall below the historical value of 0.542.

Figure 1 illustrates the compression pattern by plotting the implied distributions for near-term and long-term beliefs, recentered at zero to remove mean beliefs. The figure reports the distribution for the median ALP respondent's near-term uncertainty (red line), long-term uncertainty (blue line), and the long-term uncertainty implied by their near-term beliefs under serial independence (orange

¹⁷Other studies suggesting respondents tend to hold pessimistic near-term beliefs include Hurd (2009), Hurd, Van Rooij, and Winter (2011), Kuhnen and Miu (2017), Das, Kuhnen, and Nagel (2020), Giglio, Maggiori, Stroebel, and Utkus (2021), and Sias, Starks, and Turtle (2023).

¹⁸The 1- and 10-year return distributions implied by median ALP respondent beliefs are reported in Figure IA-1 of the Internet Appendix.

line) described in equation (2). The ALP total return long-term uncertainty estimate (blue) lies between the near-term estimate (red) and the independence-implied value (orange). In fact, the compression is so great that the long-term estimate is far closer to the near-term estimate than the estimate under independence, thus generating variance ratios well below one.

[Insert Figure 1 about here]

4.2 HRS respondents' variance ratios

Panels D, E, and F of Table I report analogous statistics for HRS respondents. The results are nearly identical to corresponding values for the ALP sample. Specifically, HRS respondents exhibit both near- and long-term bearishness. HRS respondents' near-term uncertainty is close to the historical value but their long-term uncertainty estimates tend to be substantially smaller than the historical value. As a result, 88% of the HRS participants' imputed variance ratios are less than unity and 80% are less than the historical CRSP value-weighted index's variance ratio. The median variance ratios for the ALP and HRS samples are nearly identical at 0.147 and 0.145, respectively.

4.3 CFO variance ratios

Table II reports the time-series descriptive statistics of the quarterly CFO surveys between 2004 and 2019 ($n=63$ quarters) for the cross-sectional mean (columns 2-5) and median (columns 6-9) CFO beliefs. Panel A reports CFO expectations for 1-year horizons, Panel B reports corresponding values for 10-year horizons, and Panel C reports variance ratios.

[Insert Table II about here]

Consistent with Ben-David, Graham, and Harvey (2013) and Boutros, Ben-David, Graham, Harvey, and Payne (2025), CFOs exhibit substantial near-term miscalibration—the mean (median) CFO's inferred 1-year standard deviation averages 4.7% (3.3%) compared to the historical value of 20%, and in every quarter the inferred mean and median CFO near-term standard deviations fall below the historical value. In sharp contrast to ALP respondents, CFOs are severely miscalibrated in the near-term.

Panel B reveals that CFOs' long-term beliefs are also miscalibrated, but far less so than their near-term beliefs. In the base case, the standard deviation of average annual returns over 10 years should be only 32% ($1/\sqrt{10}$) of the annual standard deviation. Given the mean CFO's 1-year standard deviation of 4.7%, the implied base case average annual 10-year standard deviation is

only 1.5%. Empirically, however, CFOs’ average annual 10-year standard deviation is more than twice that value at 3.3%—still miscalibrated, but far less so than at the 1-year horizon. To allow direct comparison to ALP respondents’ long-term beliefs (which are expressed in total return units), Panel B also reports the total return standard deviation over 10 years—simply 10 times the average annual return standard deviation. The mean (median) CFO’s implied 10-year total return standard deviation is 33.3% (26.7%), compared to the historical value of 46.5%.¹⁹

Because long-term beliefs are less miscalibrated than near-term beliefs, the implied variance ratios are implausibly large. Panel C reports that the time-series average variance ratio is 6.6 based on median CFO beliefs and 5.1 based on mean CFO beliefs—more than five times the value implied by serial independence and nearly 10 times the historical value of 0.542. As pointed out by Pástor and Stambaugh (2012) and Ben-David, Graham, and Harvey (2013), a variance ratio greater than one is consistent with CFOs perceiving that parameter uncertainty increases per period risk at longer horizons. The magnitude, however, is far greater than that suggested by the Pástor and Stambaugh (2012) model, who report a 10-year forward-looking variance ratio of approximately 1.1 with “realistic” parameters.²⁰ A variance ratio of 5 to 6 would require the impact of parameter uncertainty to be four to five times larger than that implied by the Pástor and Stambaugh (2012) model. Moreover, the results are hard to reconcile with parameter uncertainty as the sole explanation because CFOs’ expected long-term variance remains below the historical value.

Figure 2 plots the median CFO’s implied distribution for near-term uncertainty (red line), uncertainty in average annual long-term returns (blue line), and the average annual long-term return uncertainty implied by their near-term beliefs under serial independence (orange line), all recentered at zero. Because CFOs are asked about average annual long-term returns, all values are expressed in average annual return units. Consistent with equation (3), the long-term estimate (blue) lies between the near-term estimate (red) and the independence-implied value (orange)—but far closer to the near-term estimate, generating variance ratios well above one. The pattern is the mirror image of that for ALP respondents in Figure 1.

[Insert Figure 2 about here]

¹⁹The 1-year and 10-year return distributions implied by median CFO beliefs are reported in Figure IA-2 of the Internet Appendix.

²⁰The authors’ Figure 6 reports 1- and 10-year annualized variances of approximately 0.029 and 0.032, respectively, implying a variance ratio of 1.1 (i.e., $\frac{\sigma^2(r_{10})/10}{\sigma^2(r_1)} = 0.032/0.029$).

4.4 Business students' variance ratios

Although the analysis suggests that both CFOs and individuals struggle in their understanding of the relation between horizon and uncertainty, the dramatic difference in variance ratios could reflect differences in samples rather than differences in return units. CFOs, for instance, are presumably more financially sophisticated than the typical individual and therefore are perhaps more overconfident in their ability to forecast market returns and, for some reason, their overconfidence is especially strong for near-term forecasts. To rule this out, we give both the probability elicitation total return questions and the quantile elicitation average return questions to the same undergraduate business students at two large public universities two weeks apart.

Panels A, B, and C of Table III report results for students answering the probability elicitation total return questions. The results mirror the ALP findings as students hold bearish near- and long-term expected returns, show no systematic near-term overprecision (only 28% of forecasts imply a 1-year standard deviation below the historical value), and generate implausibly small variance ratios. Specifically, the median student variance ratio of 0.238 is low, 81% of student variance ratios are below unity, and 70% are below the historical value of 0.542. Panel A of Figure 3 confirms the compression pattern: identical to the pattern for ALP respondents and consistent with equation 2, the long-term uncertainty estimate (blue line) lies between the near-term estimate (red line) and the independence-implied value (orange line), closely tracking the near-term estimate.

[Insert Table III and Figure 3 about here]

Panels D, E, and F in Table III report results for students answering the quantile elicitation average return questions. The same students now exhibit severe near-term overprecision with a median implied 1-year standard deviation of 4.3% (nearly identical to the CFO mean of 4.7%) and generate implausibly large variance ratios. Specifically, the median student variance ratio is 9.32 and 90% of student estimates imply a variance ratio greater than one. Panel B of Figure 3 confirms the mirror-image compression pattern: identical to the pattern for CFOs and consistent with equation 3, the long-term estimate (blue line) lies between the near-term estimate (red line) and the independence implied value (orange line), but far closer to the near-term estimate.

Panel G reports the key within-person result. For the 241 students who answer both sets of questions, the median student's quantile elicitation average return variance ratio is 25 times their probability elicitation total return variance ratio, the median difference is 8.71 (versus a value of zero for any agent with a consistent distributional model of risk), and 95% of students generate a larger

variance ratios from the average return questions. The results leave little room for a sample-based explanation for these patterns: the same students, answering mathematically equivalent questions two weeks apart, generate variance ratios that are orders of magnitude apart depending solely on whether the question asks about cumulative or average annual returns.

4.5 Understanding America Study

The UAS data allow us to investigate the compression pattern in a nationally representative sample and, for the subset of respondents who completed both surveys, to replicate the within-person comparison from the student analysis. The UAS data differ from the student sample, however, in three respects: (1) the probability elicitation total return questions and the quantile elicitation average annual return questions were administered six years (rather than two weeks) apart, (2) the quantile elicitation 10-year questions are phrased slightly differently than the Duke CFO survey questions, and (3) the quantile elicitation 1-year questions ask about historical returns rather than expected returns. Despite these differences, the results are fully consistent with our hypothesis. The median probability elicitation variance ratio for the 3,644 UAS respondents who answer the total return questions in 2025 is 0.187—comparable to the ALP median of 0.147. Correspondingly, the median quantile elicitation variance ratio for the 1,439 respondents who answer the average annual return questions in 2019 is 2.60. For the 469 respondents who complete both surveys, 79% generate a larger variance ratio from the average annual return questions, with a median CFO-style average return variance ratio nearly ten times the median ALP-style total return variance ratio. The Internet Appendix provides complete details of the UAS analysis.

5 The Persistence of Compression

The results in Section 4 demonstrate uniform evidence of compression in near- and long-term uncertainty estimates. In this section, we investigate the robustness of this finding by varying the elicitation style, the horizon, the probability level or return threshold, and whether questions ask about historical or future returns. Although variation in these dimensions produce substantial shifts in the inferred near- and long-term estimated uncertainty, the compression signature persists and the impact on variance ratio remains remarkably stable.

5.1 Return unit versus elicitation style

The ALP and CFO-style surveys used in the previous section differ along two dimensions: the elicitation style (probability versus quantile elicitation) and the return unit (average annual versus cumulative). To ensure that the return unit, rather than the elicitation style, is the primary driver of the variance ratio patterns, we begin by varying both return unit and elicitation style. Specifically, in spring 2025, fall 2025, and spring 2026 we fielded new surveys to new sets of introductory finance students at both universities. For half the respondents, the CFO-style quantile elicitation surveys reframed the average annual return questions into cumulative returns (e.g., there is a 1-in-10 chance the total (cumulative) return over the next 10 years will be less than ___%) and the ALP probability elicitation surveys reframed the total return questions as average annual returns (e.g., what are the chances that the US stock market will average an annual return of at least 10% per year over the next 10 years?). The other half of student respondents answered average annual return questions for the CFO-style quantile elicitation surveys and cumulative return questions for the ALP-style probability elicitation survey (i.e., the original structure of both surveys).

The results of the surveys are summarized in Tables IV and V. Each table crosses return unit with elicitation style within the same student sample: Table IV presents ALP-style probability elicitation questions about both average annual and cumulative returns; Table V does the same for CFO-style quantile elicitation questions. Rows 1-4 of each table ask about average annual returns at 5-, 10-, and 15-year horizons; rows 5-8 ask about cumulative returns at the same horizons. Beyond return unit, the design also varies horizon, whether questions ask about past or future returns, and the probability level or return threshold.

[Insert Tables IV and V about here]

The results are unambiguous as the compression is determined entirely by return unit rather than elicitation style. In Table IV, the median variance ratio implied by the ALP-style probability elicitation questions ranges from 4.53 to 11.16 for the average-annual return variants (rows 1-4) versus 0.21 to 0.47 for the cumulative return variants (rows 5-8). The corresponding values in Table V for the CFO-style quantile elicitation questions range from 5.96 to 18.40 for the four average-annual return variants (rows 1-4) and from 0.14 to 0.41 for the four cumulative return variants (rows 5-8). In both tables every average-annual return question produces a median variance ratio above one and every cumulative return question produces a median variance ratio less than one. The Z -statistics (reported in Panel B for both Tables IV and V) for the return-unit comparison

exceed 13 in every case (statistically significant at the 1% level) whether the comparison is pooled (row 9), restricted to future returns (row 10), or restricted to historical returns (row 11).

5.2 Compression and horizon

The compression mechanism predicts that variance ratios should become more extreme as the horizon increases. Moreover, because the return unit determines the sign of the compression’s effect on the variance ratio, the impact of a longer horizon will generate opposite signs across the two return units: an increase in variance ratios for average-annual return questions and a decrease in variance ratios for cumulative return questions. The results in both tables support our hypothesis. Specifically, the average annual return 15-year horizon variance ratio (row 4) is more than twice the magnitude of the 5-year horizon variance ratio (row 3) in both tables. Correspondingly, the cumulative return 5-year variance ratio (row 7) is at least twice the magnitude of the 15-year value (row 8) in both tables. The Z -statistics reported in rows 12-13 of both tables have the predicted sign and are statistically significant at the 1% level in all four comparisons. In sum, longer horizons amplify the effects of compression, pushing average-annual return variance ratios higher and cumulative return variance ratios lower.

5.3 Scope insensitivity

Hartzmark and Sussman (2026) show that for CFO-style confidence interval questions, respondents’ 1-year uncertainty estimates are largely insensitive to the interval. For example, respondents report nearly identical quantiles when changing the probability level from a 1-in-5 chance (i.e., a 60% confidence interval) to a 1-in-20 chance (i.e., a 90% confidence interval). We examine how this insensitivity extends to long-horizon estimates, the ALP-style probability elicitation approach, and most importantly, the variance ratio.

Rows 5 and 6 in Table IV report values for ALP-style cumulative return questions that are identical in every dimension except the return threshold ($\pm 10\%$ versus $\pm 30\%$).²¹ The raw responses are nearly identical across the two variants: the median 1-year upside response is 25% versus 20%, and the median 1-year downside response is 20% in both cases. The long-term responses are similarly stable: median upside 70% versus 60%, median downside 10% versus 12%. Yet because the threshold being asked about changes from $\pm 10\%$ to $\pm 30\%$, the inferred 1-year standard deviation

²¹The ALP-style probability elicitation questions ask about the likelihood of returns above or below a fixed threshold. For cumulative return questions this threshold can be easily varied (e.g., $\pm 10\%$ versus $\pm 30\%$). We did not run an experiment for variation in the ALP-style probability elicitation method when using the CFO-style average annual returns.

more than doubles from 16.7% to 40.3%. The inferred 10-year standard deviation, however, also more than doubles from 33.1% to 79.6%. As a result, despite these large swings in estimated uncertainty levels, the median variance ratio remains largely stable (shifting less than 3% from 0.367 to 0.358) and the Z -statistic reported in row 14 reveals no evidence of a meaningful shift in the distributions of variance ratios.

The CFO-style results in Table V tell the same story. Shifting from a 90% confidence interval (i.e., 1-in-20 chance) to a 60% confidence interval (i.e., 1-in-5 chance) has little impact on the median response for either average annual returns (rows 1 and 2) or cumulative returns (rows 5 and 6) at either the 1- or 10-year horizon. As a result, the inferred 1- and 10-year standard deviations based on both average annual returns and cumulative returns strongly rise when moving from a 1-in-20 likelihood to a 1-in-5 likelihood. Once again, however, because both near- and long-term estimates rise, the impact on variance ratios is small. For instance, the Z -statistics reported in rows 14 (for average annual return differences) and 15 (for cumulative return differences) are, respectively, 1.66 (marginally significant at the 10% level) and -0.66.

Across both elicitation styles, the pattern is the same: raw responses are largely insensitive to the specific parameter being asked about; and because the inferred standard deviation depends mechanically on that parameter, the insensitivity produces large swings in estimated uncertainty levels. In contrast, the compression signature remains stable and, as a result, the variance ratios change little.

5.4 Stable compression and unstable levels: balls and bins approach

Hartzmark and Sussman (2026) show that the distributional elicitation approach (where respondents report their perceived return distribution by placing “balls” in “bins”) produces more accurate estimates of both 1-year expected returns and uncertainty. This raises the question of whether the compression pattern documented in Sections 4 and 5 is an artifact of the probability or quantile elicitation format, or whether it persists under the balls-and-bins approach. As noted above (see Section 3.1), in 18 of the 29 ALP long-form surveys, approximately half of the respondents answered the standard probability elicitation questions that form our primary sample; the other half answered the same 1- and 10-year horizon questions using the balls-and-bins format. Thus the two groups were drawn from the same surveys, faced questions about the same return horizons at the same point in time, and differed only in elicitation format.

Following the Hartzmark and Sussman (2026) method to infer the expected return and standard

deviations from the balls-and-bins approach, Table VI reports statistics for inferred 1- and 10-year distributions and variance ratios.²² The impact of shifting to the balls-and-bins approach on estimated volatility is large. Panel A shows that the median 1-year standard deviation is 7.2% under the balls-and-bins approach versus the 20.7% from the standard ALP probability elicitation questions (see Table I). The median 10-year standard deviation falls from 29.1% (Table I) to 9.6% when using the balls-and-bins approach. These differences are large: switching elicitation method nearly triples the inferred 1-year uncertainty estimate and more than triples the 10-year estimate. The fraction of respondents with variance ratios below one falls modestly from 89% under standard probability elicitation to 74% under the balls-and-bins approach, suggesting that the overwhelming majority of respondents exhibit compression regardless of format.

[Insert Table VI about here]

Despite the dramatic shifts in levels, the compression signature persists. The median variance ratio from the balls-and-bins approach is 0.175 versus 0.147 from the standard ALP questions. That is, despite a 300% shift in the volatility estimates, the median variance ratio shifts by less than 20%.

5.5 Respondents lack stable quantitative distributions

The instability of volatility level estimates documented in Tables I-VI across elicitation formats, horizons, and parameters suggests the variation reflects the absence of a stable belief distribution rather than measurement noise around a fixed variance ratio (of 1, or 0.542, for example). The evidence in this section provides further support for the absence of a stable underlying distribution. When elicitation cues shift, estimated beliefs change in ways that appear inconsistent with respondents holding fixed internal beliefs, even among sophisticated respondents with strong professional incentives to hold well-formed beliefs.

The [2011 Q1 Duke CFO survey](#) offers a striking illustration. In addition to the standard 80% confidence interval questions, CFOs were asked directly: “In 2010, the volatility of S&P 500 returns was 12.6%. What do you think the volatility of S&P 500 returns will be: ___% in 2011?” The survey’s statement appears to be an error—annualized daily volatility was 18.1% and the VIX averaged 22.5%.²³ Yet the median CFO response was clustered around 11% (median=11%; cross-sectional standard deviation= 3.9%)—anchored closely to the erroneous seed value (12.6%) and

²²Specifically, we use the bin probability and midpoints. For the extreme (open-ended) bins, we use the CRSP calibrated conditional expectations.

²³The 12.6% figure does match the S&P 500’s 2010 price return (i.e., excluding dividends).

far from (1) their own confidence interval implied value (3.7%) *in the same survey*, (2) the actual 2010 volatility, and (3) the long-run historical average volatility (20.1%).²⁴ In sum, the results appear inconsistent with the hypothesis that the typical CFO holds, and reports, a stable internal estimate. Rather they appear to anchor on the cue provided, even an incorrect one.

Hartzmark and Sussman (2026) provide independent experimental confirmation of this pattern. In their experimental framework, respondents view a 100 year sequence of either US or Japanese annual returns and then report the distribution using bins calibrated to either US or (more volatile) Japanese data. When bins match the data (e.g., Japanese bins with Japanese data), the average respondent accurately replicates the underlying distribution. When the bins do not match the data (e.g., Japanese data with U.S. bins), respondents anchor on the bin structure. As a result, estimated distributions more closely resemble the distribution used for the bin structure than the actual data.²⁵ That is, despite attempting to replicate what they saw, when bins and data conflict, the bins are more important than the data. The results are consistent with the explanation that quantitative estimates are assembled from the available structural cues rather than retrieved from a stable internal representation.

5.6 Ruling out overconfidence

A potential alternative explanation for the compression pattern in the CFO-style quantile elicitation surveys is overconfidence in forecasting ability (Ben-David, Graham, and Harvey (2013), Boutros, Ben-David, Graham, Harvey, and Payne (2025)).²⁶ Respondents may know the historical distribution but believe they can predict market returns well enough to narrow the distribution of expected outcomes. We cannot directly test this explanation for the CFO evidence, but we can rule it out in our student sample by reframing the questions as perceived historical, rather than forward-looking, return estimates.²⁷ That is, students reporting perceptions of how markets have historically performed have no forecasting ability to be overconfident about. Thus, if overconfidence drives the small 1-year standard deviation estimate in the CFO-style quantile elicitation questions, it should be absent in the historical framing.

The results (detailed in Section IA-5 of the Internet Appendix) suggest overconfidence in fore-

²⁴Given the mean estimate (12.1%) and the cross-sectional standard deviation (3.9%), assuming normality, 97% of CFOs reported a 2011 volatility estimate exceeding the 3.7% inferred from their own confidence interval responses.

²⁵Internet Appendix Figures IA-5A and IA-5B illustrate these results.

²⁶This explanation, however, is inconsistent with the evidence from the ALP-style cumulative return questions that generally produce 1-year estimates near or above historical values (see Tables I and III).

²⁷For example, “Historically, over a 1-year period, I think the S&P 500 has had a 1-in-10 chance of being less than ____%.”

casting ability plays little role in the estimates. Specifically, the median student 1-year inferred standard deviation is 4.1% when the question is framed as historical returns versus 4.3% when framed as future returns (see Table III). In fact, the historical versus forward-looking values are nearly identical for 1- and 10-year horizons for both the CFO-style quantile elicitation and ALP-style probability elicitation questions. As a result, for both the CFO-style and ALP-style questions, the compression produces the same patterns in variance ratios whether the question asks about future or historical returns. For instance, the median CFO-style variance ratio is 9.32 under the forward-looking framing and 11.45 under the historical framing.

6 Cross-sectional Variance Ratio Heterogeneity

Most inferred variance ratios, regardless of question format, are far from reasonable theoretical and historical values. Despite the implausible levels, cross-sectional variation in both near- and long-term perceived volatility (and therefore variance ratios) appears to matter. For instance, Ben-David, Graham, and Harvey (2013) find that both near- and long-term miscalibration play important roles in explaining heterogeneity in firms' financial decisions and Sias, Starks, and Turtle (2026) find that near- and long-term expectations both play meaningful roles in individuals' equity market participation and risky share decisions. We therefore exploit the panel structure of the ALP dataset to examine what drives cross-sectional heterogeneity in variance ratios.

6.1 Respondent characteristics and variance ratio heterogeneity

Both theory and prior work suggest variance ratios should be related to respondent characteristics. Ben-David, Graham, and Harvey (2013) argue that the unreasonably small 1-year volatility inferred from the Duke surveys reflects CFOs' overconfidence in their ability to predict market returns, with overconfidence larger at the 1-year horizon. They also propose two mechanisms that may help explain why near-term miscalibration exceeds long-term miscalibration: (1) CFOs expect markets to be more volatile in the future, and (2) CFOs recognize that parameter uncertainty increases long-run risk. Pástor and Stambaugh (2012) formalize the latter argument, showing theoretically that parameter uncertainty disproportionately increases risk as the horizon extends. Using the Duke survey responses, they also compute variance ratios above one, which they interpret as evidence that economic agents recognize this effect.

This prior work generates three hypotheses for the ALP cumulative-return variance ratios. First, if overconfidence bears more heavily on near-term estimates, ALP respondents with greater

overconfidence should exhibit larger variance ratios. Second, if expectations of future changes in market volatility contribute to variance ratio heterogeneity, respondents who expect improved economic conditions should exhibit lower variance ratios. Third, if parameter uncertainty drives variance ratios higher, then less financially sophisticated respondents—who plausibly face greater parameter uncertainty—should exhibit larger variance ratios, implying an inverse relation between sophistication and variance ratios.²⁸ Cross-sectional variation in compression generates the *opposite* prediction: more financially sophisticated respondents should be better able to apply the horizon transformation and therefore exhibit larger variance ratios. The sign of the coefficients associated with the sophistication metrics therefore reflects which effect (parameter uncertainty versus compression) dominates. Finally, we hypothesize that respondents with strong beliefs in mean-reversion will exhibit lower variance ratios.

To examine how these characteristics relate to variance ratio heterogeneity, we estimate panel regressions of ALP respondents’ variance ratios on wave fixed effects, respondent demographic controls (age, and indicators for gender, White ethnicity, married, working, and retired), and each of the following characteristics: education, income, stock market participation, self-rated understanding of equity markets, numeracy, financial literacy, overconfidence, perceptions of expected changes in financial position, and mean-reversion beliefs. Except for the binary stock market participation indicator and the expected changes in financial position variable (which take the values of 1, 0, or -1), all characteristics are standardized to allow direct comparison of coefficient magnitudes. Table VII reports the estimates (standard errors clustered at the respondent level).²⁹ Columns (10) and (11) report joint regression results; in column (10) we exclude numeracy, financial literacy, and overconfidence because these variables substantially limit sample sizes.

[Insert Table VII about here]

The results are easily summarized. First, all six financial sophistication measures are positively related to variance ratios, consistent with the hypothesis that greater sophistication attenuates compression. The results are also inconsistent with the joint hypothesis that less sophisticated investors recognize they have greater parameter uncertainty and that cross-sectional heterogeneity

²⁸Specifically, under the greater near-term overconfidence explanation, the 1-year volatility in the denominator is reduced, increasing the variance ratio. Under the changing-volatility explanation, respondents who expect higher future volatility have a relatively larger 10-year volatility in the numerator, also increasing the variance ratio; respondents who expect improved conditions (lower future volatility) therefore exhibit lower variance ratios. Under the parameter-uncertainty explanation, greater parameter uncertainty likewise enlarges the numerator and increases the variance ratio.

²⁹In the Internet Appendix, we present results for respondent sorts into high and low groups by these characteristics.

in parameter uncertainty helps explain variance ratio heterogeneity.³⁰ Second, we find no support for the hypothesis that overconfidence is meaningfully associated with variance ratio heterogeneity. Third, we find no support for the hypothesis that expectations of rising volatility generate larger variance ratios. Although the coefficient is statistically significant before controlling for other characteristics, it has the wrong sign.³¹ Finally, consistent with the mean-reversion hypothesis, respondents who believe markets are more likely to mean revert exhibit lower variance ratios.

Although financial sophistication and mean-reversion beliefs contribute meaningfully to cross-sectional heterogeneity in variance ratios, these effects are an order of magnitude smaller than the effects documented in Sections 4 and 5. The largest single-variable effect in Table VII is the stock market participation coefficient in column (3), which implies participants exhibit a 0.132 larger variance ratio than non-participants. In contrast, Panel G of Table III shows that the median student variance ratio from CFO-style questions exceeds the median from ALP-style questions by 8.71—an effect 66 times larger. In short, how you ask matters much more than who you ask.

6.2 Long-term risk perceptions and variance ratios

In our fall 2024 student surveys, we asked respondents directly how they viewed the relation between risk and investment horizon, offering four choices ranging from long-term investing being more risky to less risky than short-term investing.³² Of the 455 responses, 62% viewed long-run investing as less risky, 21% as more risky, 13% as independent of horizon, and 4% had no idea. Despite the majority view that long-run investing is safer, stated beliefs about long-run riskiness are not associated with variance ratios. The median CFO-style quantile elicitation variance ratios were 9.66 and 10.00 for students who view long-horizon investing as less and more risky, respectively, and the corresponding ALP-style probability elicitation variance ratios were 0.27 and 0.16. In neither case is the difference statistically significant at the 5% level (Wilcoxon rank sum test).³³

³⁰A potential alternative interpretation is that more financially sophisticated respondents understand, and adjust for, parameter uncertainty while less financially sophisticated respondents do not.

³¹Because beliefs of an improving financial situation are positively correlated with education, income, understanding of markets, numeracy, and financial literacy (which are in turn associated with less compression), a likely explanation is that optimistic respondents exhibit less compression and therefore higher variance ratios, rather than any direct effect of volatility expectations.

³²Specifically, students selected one of: (a) investing for the long-term (e.g., 10 years) is more risky than investing for the near-term (e.g., 1 year); (b) investing for the long-term is less risky; (c) riskiness does not depend on holding period; or (d) no idea. The Internet Appendix provides complete details.

³³This result need not be inconsistent with our earlier finding that mean-reversion beliefs are associated with lower variance ratios: a respondent may believe long-term investing is safer without understanding or invoking mean-reversion as the reason. Such an interpretation is consistent with Bodie (2021) and Choi (2022), who document that most financial experts and individuals believe markets are less risky in the long run even absent a formal understanding of mean-reversion.

6.3 Compression in non-financial probability estimates

If compression reflects how respondents construct quantitative answers to scope-sensitive questions more broadly, rather than something specific to equity return distributions, (1) compression should appear outside financial domains, and (2) respondents who compress more in a non-financial setting should also compress more in financial settings. We test both predictions using an ALP survey completed between August 2006 and November 2007, in which respondents estimated the likelihood of eight personal events over both the next year and the next five years (the likelihood of including getting into a car accident, having a cavity filled, dying, having something stolen, moving, dying in a terrorist attack, experiencing a break-in, and visiting the dentist).³⁴

The first prediction is strongly supported. Under independence, a respondent's 1-year estimate implies a specific 5-year likelihood (i.e., $P(5_{yr}) = 1 - (1 - P(1_{yr}))^5$). If respondents compress their estimates, the 5-year likelihood will be too close to their 1-year likelihood. For instance, the median respondent reports a 20% chance of a car accident in the next year, implying a 5-year likelihood of 67.2% under independence; yet the typical respondent estimates only a 30% 5-year likelihood. Across all eight questions, 87% of respondents' 5-year estimates fall below the value implied by their 1-year estimate under independence.³⁵ In sum, the same compression pattern that characterizes equity variance ratios appears in entirely unrelated personal probability judgments.

The second prediction is also supported. For each respondent and question, we compute the compression error as the difference between the independence-implied 5-year likelihood and the respondent's actual 5-year estimate. Thus, larger values indicate greater compression.³⁶ Because ALP total return questions generate smaller variance ratios when respondents compress more, the predicted relation between compression errors in the non-financial questions and variance ratios is negative. Table VIII reports the results of panel regressions of ALP respondents' perceived variance ratios on their standardized (for ease of interpretation) compression errors (standard errors are clustered at the respondent level), wave fixed effects, and respondent demographics.

[Insert Table VIII about here]

The coefficient on compression errors is negative and statistically significant at the 5% level or better for each of the eight questions. An individual with a one standard deviation higher compression error for the car accident question has a 4.9% lower variance ratio: nearly a 10%

³⁴See Internet Appendix for question details.

³⁵We exclude observations where individuals report zero or 100% likelihoods for either horizon. For instance, 90% of respondents report a 100% likelihood of visiting a dentist in the next five years.

³⁶For instance, in the above example, the compression error is 37.2% (=67.2% - 30%).

standard deviation change given the standard deviation of ALP variance ratios is 0.586 (Table I, Panel C). The result holds across all event types. Respondents who compress more in personal risk domains also compress more when constructing equity variance ratios—compression is correlated across domains.

7 Conclusions

Even in the simplest possible setting—where returns are *iid* and there is no parameter uncertainty—understanding how risk evolves with horizon requires recognizing that 10-year total return variance is 10 times 1-year variance while 10-year average annual return variance is only $1/10^{th}$ the annual variance. These relations are cognitively challenging for even financially sophisticated individuals and introducing return predictability or parameter uncertainty into the return generating process only compounds the difficulty. Traditional models implicitly assume economic agents have a reasonable understanding of this relation. We find little evidence to support this assumption. Across representative samples of Americans, CFOs, and business school students, perceived variance ratios are far from theoretical and historical benchmarks—and in opposite directions depending on how uncertainty is elicited.

Our evidence suggests that most respondents do not hold stable belief distributions that surveys can reliably capture. The clearest evidence is the return unit: asking the same person about cumulative versus average annual long-horizon returns—mathematically equivalent ways of expressing the same information—flips the implied relation between risk and horizon from strongly negative to strongly positive with an effect size that dwarfs that of any respondent characteristic we consider. Other elicitation cues (e.g., probability levels, confidence interval widths, bin structure, and seed values) also move the implied estimates, reinforcing that respondents’ reported values are meaningfully shaped by question structure rather than reflecting stable underlying beliefs. The systematic component is compression: insufficient sensitivity to the scope parameter that leaves long-horizon estimates too close to near-horizon estimates regardless of the elicited return unit.

This compression provides a unifying explanation for a disparate set of empirical regularities across multiple literatures. CFOs and individuals appear to hold diametrically opposed views about whether risk rises or falls with horizon, but both groups are subject to the same compression, which operates in opposite directions because they are asked about different return units. The implausible magnitude of both sets of estimates, the asymmetry between CFOs’ severe near-term miscalibration and their mild long-term miscalibration, the attenuated empirical relation between perceived un-

certainty and risky share, and the tendency of qualitative risk measures to outperform quantitative metrics all follow from the same logic: respondents do not apply a principled transformation linking near- and long-term uncertainty, so quantitative survey answers are format-dependent proxies for the qualitative beliefs that govern behavior.

None of our results suggest that elicited beliefs are uninformative. CFO miscalibration predicts corporate financing and investment decisions (Ben-David, Graham, and Harvey (2013)), and individuals' near- and long-horizon beliefs help explain their equity market participation and portfolio allocations (Sias, Starks, and Turtle (2026)). Survey-based measures should be carefully interpreted, with recognition of the process by which beliefs are constructed, not discarded. But the central implication is more fundamental: most people, including financially sophisticated CFOs and business school students, do not appear to have a stable, well-anchored sense of how equity risk scales with horizon.

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TABLE I – INDIVIDUALS’ BELIEFS REGARDING NEAR- AND LONG-TERM STOCK RETURNS
Panels A, B, and C report descriptive statistics for the pooled cross-sectional time-series of American Life Panel Survey data between 2008 and 2016. Panels D, E, and F report cross-sectional descriptive statistics from the 2009 Health and Retirement Study Internet Survey. Both surveys use probability elicitation: respondents report the likelihood that markets will rise, rise by at least 20%, and fall by at least 20% over the next year (Panels A and D) and next decade (Panels B and E). Expected returns and standard deviations reported in the bottom two rows of Panels A, B, D, and E are inferred from the reported likelihoods markets rise or fall at least 20% assuming normally distributed continuously compounded returns. The penultimate column reports the historical average (computed from the CRSP value-weighted index between 1926 and 2024). The final column reports the fraction of observations below the historical average.

Description	N	Mean	25 th	Median	75 th	Std Dev.	Hist.	%<Hist
Panel A: American Life Panel stock market expectations over next year								
P(market>0)	22,722	0.406	0.200	0.400	0.600	0.248	0.747	0.863
P(market>20%)	22,745	0.201	0.100	0.150	0.300	0.155	0.336	0.822
P(market<-20%)	22,745	0.183	0.100	0.150	0.250	0.142	0.060	0.219
$E_{i,t}(r_{1year})$	22,745	-0.010	-0.046	-0.020	0.027	0.092	0.095	0.887
$\sigma_{i,t}(r_{1year})$	22,745	0.274	0.158	0.207	0.301	0.191	0.200	0.491
Panel B: American Life Panel stock market expectations over next decade								
P(market>0)	22,733	0.515	0.250	0.500	0.750	0.287	0.960	0.976
P(market>20%)	22,745	0.347	0.150	0.300	0.500	0.236	0.932	0.996
P(market<-20%)	22,745	0.169	0.060	0.100	0.250	0.132	0.013	0.030
$E_{i,t}(r_{10years})$	22,745	0.134	-0.020	0.043	0.182	0.253	0.969	0.970
$\sigma_{i,t}(r_{10years})$	22,745	0.414	0.179	0.291	0.505	0.353	0.465	0.721
Panel C: American Life Panel variance ratios								
Variance ratios	22,745	0.391	0.100	0.147	0.373	0.586	0.542	0.819
%Variance ratio<1	22,745	0.892						
Panel D: Health and Retirement Study stock market expectations over next year								
P(market>0)	1,250	0.370	0.200	0.300	0.500	0.231	0.747	0.897
P(market>20%)	1,252	0.241	0.100	0.200	0.300	0.181	0.336	0.758
P(market<-20%)	1,252	0.176	0.100	0.100	0.250	0.134	0.060	0.181
$E_{i,t}(r_{1year})$	1,252	0.016	-0.020	-0.020	0.065	0.117	0.095	0.800
$\sigma_{i,t}(r_{1year})$	1,252	0.284	0.158	0.225	0.316	0.180	0.200	0.423
Panel E: Health and Retirement Study stock market expectations over next decade								
P(market>0)	1,249	0.525	0.300	0.500	0.750	0.261	0.960	0.990
P(market>20%)	1,252	0.386	0.200	0.300	0.600	0.246	0.932	0.999
P(market<-20%)	1,252	0.158	0.100	0.100	0.200	0.115	0.013	0.014
$E_{i,t}(r_{10years})$	1,252	0.193	-0.020	0.065	0.256	0.302	0.969	1.000
$\sigma_{i,t}(r_{10years})$	1,252	0.424	0.191	0.301	0.521	0.320	0.465	0.698
Panel F: Health and Retirement Study variance ratios								
Variance ratios	1,252	0.434	0.100	0.145	0.400	0.664	0.542	0.795
%Variance ratio<1	1,252	0.875						

TABLE II – CFOs’ BELIEFS REGARDING NEAR- AND LONG-TERM STOCK RETURNS

The table reports summary statistics for the time series of the mean and median Duke CFO survey over the sample period from March 2004 to December 2019 ($n=63$ quarters). The survey uses quantile elicitation: respondents report the 10th and 90th percentile returns (P10 and P90) and their expected return for the next year (Panel A) and average annual return over the next decade (Panel B). Standard deviations are inferred from the reported percentiles assuming normally distributed continuously compounded returns. Column (1) reports historical results for the CRSP value-weighted index between 1926 and 2024. Columns (2) through (5) report results based on mean CFO beliefs for the next year (Panel A), the next decade (Panel B), and the associated variance ratios (Panel C). Columns (6) to (9) report analogous results for median CFO beliefs. Panel B reports two measures of long-term uncertainty: the standard deviation of average annual returns ($\sigma_t(\bar{r}_{10years})$), which is the quantity directly elicited by the quantile elicitation questions, and the standard deviation of total returns ($\sigma_t(r_{10years})$), which equals 10 times the former and is directly comparable in units to the long-term standard deviation reported for ALP and HRS respondents in Table I.

Description	Historical (1)	Cross-sectional mean CFO beliefs				Cross-sectional median CFO beliefs			
		Mean (2)	Minimum (3)	Maximum (4)	%<Hist (5)	Mean (6)	Minimum (7)	Maximum (8)	%<Hist (9)
Panel A: CFOs' stock market expectations over the next year									
$P90(r_{1year})$	0.302	0.098	0.069	0.129	1	0.089	0.058	0.113	1
$P10(r_{1year})$	-0.138	-0.023	-0.090	0.008	0	0.003	-0.051	0.030	0
$E_t(r_{1year})$	0.095	0.052	0.022	0.075	1	0.048	0.020	0.070	1
$\sigma_t(r_{1year})$	0.200	0.047	0.037	0.073	1	0.033	0.023	0.046	1
Panel B: CFOs' stock market expectations over the next decade									
$P90(\bar{r}_{10years})$	0.152	0.103	0.084	0.125	1	0.093	0.077	0.113	1
$P10(\bar{r}_{10years})$	0.035	0.018	-0.004	0.041	0.952	0.025	0.010	0.039	0.857
$E_t(r_{10years})$	0.969	0.682	0.554	0.861	1	0.616	0.488	0.770	1
$\sigma_t(\bar{r}_{10years})$	0.047	0.033	0.025	0.041	1	0.027	0.022	0.033	1
$\sigma_t(r_{10years})$	0.465	0.333	0.246	0.413	1	0.267	0.219	0.326	1
Panel C: CFOs' variance ratios									
Variance ratios	0.542	5.113	2.675	9.003	0	6.606	3.895	11.783	0
%Variance ratio<1		0				0			

TABLE III – STUDENTS’ BELIEFS REGARDING NEAR- AND LONG-TERM STOCK RETURNS
Panels A, B, and C report descriptive statistics for 322 undergraduate students based on probability elicitation cumulative return questions: respondents report the likelihood markets rise, rise by at least 20%, and fall by at least 20% over the next year and decade. Panels D, E, and F report descriptive statistics for 673 students based on quantile elicitation average annual return questions: respondents report the 10th and 90th percentile returns and expected return for the next year and average annual return over the next decade. Standard deviations are inferred from the reported percentiles or likelihoods assuming normally distributed continuously compounded returns. Panel E reports two measures of long-term uncertainty: the standard deviation of average annual returns ($\sigma_{i,t}(\bar{r}_{10years})$), which is the quantity directly elicited, and the standard deviation of total returns ($\sigma_{i,t}(r_{10years})$), which equals 10 times the former and is directly comparable to the long-term standard deviation in Panel B. Panel G summarizes variance ratio differences for the 241 students with sufficient data to compute variance ratios based on both sets of questions. Students were surveyed during the spring and fall 2024 semesters. The Internet Appendix provides details of the student surveys.

Description	N	Mean	25 th	Median	75 th	Std Dev.	Hist.	%<Hist
Panel A: Students’ stock market expectations over next year (probability elicitation, cumulative returns)								
P(market>0)	322	0.659	0.500	0.700	0.800	0.189	0.747	0.581
P(market>20%)	322	0.298	0.150	0.250	0.400	0.185	0.336	0.646
P(market<-20%)	322	0.216	0.100	0.200	0.300	0.149	0.060	0.118
$E_{i,t}(r_{1year})$	322	0.049	-0.041	0.001	0.107	0.184	0.095	0.736
$\sigma_{i,t}(r_{1year})$	322	0.433	0.191	0.297	0.521	0.361	0.200	0.276
Panel B: Students’ stock market expectations over next decade (probability elicitation, cumulative returns)								
P(market>0)	322	0.757	0.600	0.850	0.950	0.244	0.960	0.814
P(market>20%)	322	0.544	0.360	0.600	0.750	0.241	0.932	0.994
P(market<-20%)	322	0.169	0.050	0.100	0.250	0.143	0.013	0.068
$E_{i,t}(r_{10years})$	322	0.428	0.050	0.282	0.680	0.475	0.969	0.907
$\sigma_{i,t}(r_{10years})$	322	0.673	0.297	0.505	0.922	0.500	0.465	0.432
Panel C: Students’ variance ratios (probability elicitation, cumulative returns)								
“ALP” variance ratio	322	0.712	0.086	0.238	0.639	1.154	0.542	0.696
%Variance ratio<1	322	0.807						
Panel D: Students’ stock market expectations over next year (quantile elicitation, average annual returns)								
$P90(r_{1year})$	673	0.273	0.113	0.182	0.405	0.254	0.302	0.697
$P10(r_{1year})$	673	0.092	0.030	0.049	0.095	0.109	-0.138	0.001
$E_{i,t}(r_{1year})$	673	0.202	0.077	0.113	0.262	0.198	0.095	0.315
$\sigma_{i,t}(r_{1year})$	673	0.065	0.023	0.043	0.087	0.057	0.200	0.942

TABLE III –
STUDENTS' REPORTED BELIEFS REGARDING NEAR- AND LONG-TERM STOCK RETURNS (CONT.)

Panel E: Students' stock market expectations over next decade (quantile elicitation, average annual returns)								
$P90(\bar{r}_{10years})$	673	0.205	0.095	0.140	0.262	0.169	0.152	0.554
$P10(\bar{r}_{10years})$	673	0.067	0.020	0.049	0.095	0.102	0.035	0.407
$E_{i,t}(r_{10years})$	673	1.439	0.583	0.953	1.823	1.350	0.969	0.574
$\sigma_{i,t}(\bar{r}_{10years})$	673	0.051	0.019	0.035	0.068	0.042	0.047	0.575
$\sigma_{i,t}(r_{10years})$	673	0.512	0.187	0.355	0.680	0.417	0.465	0.575
Panel F: Students' variance ratios (quantile elicitation, average annual returns)								
"CFO" variance ratio	673	13.570	2.988	9.318	13.596	17.694	0.542	0.067
%Variance ratio<1	673	0.098						
Panel G: Students' differences in variance ratios								
"ALP" variance ratio	241	0.789	0.100	0.241	0.745	1.250	0.542	0.680
"CFO" variance ratio	241	13.541	3.365	9.462	13.742	17.148	0.542	0.066
("CFO")/("ALP")	241	119.765	6.552	25.235	117.004	275.326		
"CFO" - "ALP"	241	12.752	2.712	8.706	13.483	16.954		
("CFO" - "ALP")> 0	241	0.946						

TABLE IV – THE IMPORTANCE OF AVERAGE ANNUAL VERSUS CUMULATIVE RETURNS: ALP-STYLE PROBABILITY ELICITATION

Panel A reports the median upside and downside responses at the one-year and long-term horizons, the median inferred 1-year standard deviation (σ_1), the median inferred long-horizon standard deviation (σ_{LT}), and the median implied variance ratio for samples of students answering ALP-style probability elicitation questions. The upside (downside) response is the median reported probability that the return exceeds (falls below) the corresponding threshold. Rows 1–4 ask about average annual returns; rows 5–8 ask about cumulative returns. Panel B reports Z -statistics for comparisons of median variance ratios across the indicated groups. The sample is based on surveys given to undergraduate business students in the spring 2025, fall 2025, and spring 2026 semesters. Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: ALP-style probability elicitation questions													
Row no.	Returns	Horizon	Past/ future	Above	Below	Upside 1-year median	Downside median	Upside LT median	Downside	Median σ_1	Median σ_{LT}	N	Var. ratio
1	Avg. annual	10	Future	$\geq 10\%$	$\leq -5\%$	30%	25%	40%	10%	14.3%	95.5%	133	5.813
2	Avg. annual	10	Future	$\geq 10\%$	$\leq -5\%$	30%	30%	40%	10%	17.4%	107.3%	129	4.555
3	Avg. annual	5	Past	$\geq 10\%$	$\leq -5\%$	25%	20%	40%	10%	10.7%	55.6%	144	4.531
4	Avg. annual	15	Past	$\geq 10\%$	$\leq -5\%$	30%	20%	40%	10%	13.4%	158.0%	134	11.164
5	Cumulative	10	Future	$\geq 10\%$	$\leq -10\%$	25%	20%	70%	10%	16.7%	33.1%	77	0.367
6	Cumulative	10	Future	$\geq 30\%$	$\leq -30\%$	20%	20%	60%	12%	40.3%	79.6%	143	0.358
7	Cumulative	5	Past	$\geq 20\%$	$\leq -20\%$	16%	15%	38%	10%	20.0%	34.1%	168	0.466
8	Cumulative	15	Past	$\geq 20\%$	$\leq -20\%$	20%	13%	50%	10%	21.6%	41.8%	113	0.205

Panel B: ALP-style probability elicitation questions—Test statistics				
	Compare	Sample	Group 1 vs. Group 2	Z-stat
9	Avg. annual vs. cum.	Both	1–4 vs. 5–8	20.369***
10	Avg. annual vs. cum.	Future	1–2 vs. 5–6	13.155***
11	Avg. annual vs. cum.	Past	3–4 vs. 7–8	15.621***
12	5y vs. 15y horizon	Avg annual	3 vs. 4	−4.313***
13	5y vs. 15y horizon	Cumulative	7 vs. 8	3.230***
14	$\pm 10\%$ vs. $\pm 30\%$	Cumulative	5 vs. 6	0.705

TABLE V – THE IMPORTANCE OF AVERAGE ANNUAL VERSUS CUMULATIVE RETURNS: CFO-STYLE QUANTILE ELICITATION
Panel A reports the median upside and downside responses at the one-year and long-term horizons, the median inferred 1-year standard deviation (σ_1), the median inferred long-horizon standard deviation (σ_{LT}), and the median implied variance ratio for samples of students answering CFO-style quantile elicitation questions. The upside (downside) response is the median reported upper (lower) bound of the corresponding confidence interval. Rows 1–4 ask about average annual returns; rows 5–8 ask about cumulative returns. Panel B reports Z-statistics for comparisons of median variance ratios across the indicated groups. The sample is based on surveys given to undergraduate business students in the spring 2025, fall 2025, and spring 2026 semesters. Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Panel A: CFO-style quantile elicitation questions												
Row no.	Returns	Horizon	Past/future	Like-lihood	Upside 1-year median	Downside median	Upside LT median	Downside LT median	Median σ_1	Median σ_{LT}	N	Var. ratio
1	Avg. annual	10	Past	1 in 20	15%	4%	20%	5%	3.1%	40.6%	157	18.403
2	Avg. annual	10	Past	1 in 5	17%	5%	25%	10%	5.4%	76.0%	169	11.437
3	Avg. annual	5	Future	1 in 10	13%	4%	15%	5%	3.3%	17.8%	248	5.963
4	Avg. annual	15	Future	1 in 10	14%	5%	15%	5%	2.9%	50.9%	256	16.893
5	Cumulative	10	Past	1 in 5	15%	5%	20%	5%	5.2%	7.6%	162	0.135
6	Cumulative	10	Past	1 in 20	20%	5%	30%	5%	3.8%	5.0%	170	0.165
7	Cumulative	5	Future	1 in 10	14%	4%	23%	5%	3.6%	5.1%	236	0.409
8	Cumulative	15	Future	1 in 10	15%	4%	35%	10%	3.6%	6.4%	272	0.205
Panel B: CFO-style quantile elicitation questions—Test statistics												
	Compare	Sample	Group 1 vs. Group 2		Z-stat							
9	Avg. annual vs. cum.	Both	1–4 vs. 5–8		29.943***							
10	Avg. annual vs. cum.	Future	3–4 vs. 7–8		23.250***							
11	Avg. annual vs. cum.	Past	1–2 vs. 5–6		18.699***							
12	5y vs. 15y horizon	Avg annual	3 vs. 4		−8.189***							
13	5y vs. 15y horizon	Cumulative	7 vs. 8		4.088***							
14	1-in-20 vs. 1-in-5	Avg annual	1 vs. 2		1.660*							
15	1-in-5 vs. 1-in-20	Cumulative	5 vs. 6		−0.658							

TABLE VI – BELIEFS FROM THE ALP BINS-AND-BALLS FORMAT

This table reports descriptive statistics for ALP respondents assigned to the bins-and-balls elicitation format. Following Hartzmark and Sussman (2026), we compute the mean and standard deviation from the full distribution of ball allocations across all bins, using CRSP-calibrated conditional expectations for the open-ended tails. Panels A and B report perceptions of stock market returns over the next year and next decade, respectively. Panel C reports the implied variance ratios. The penultimate column reports the historical average (computed from the CRSP value-weighted index between 1926 and 2024). The final column reports the fraction of observations below the historical average.

Description	N	Mean	25 th	Median	75 th	Std Dev.	Hist.	%<Hist
Panel A: Stock market expectations over next year								
$E_{i,t}(r_{1year})$	25,504	0.016	-0.008	0.007	0.051	0.059	0.095	0.906
$\sigma_{i,t}(r_{1year})$	25,504	0.082	0.050	0.072	0.105	0.037	0.200	1.000
Panel B: Stock market expectations over next decade								
$E_{i,t}(r_{10years})$	25,504	0.130	-0.001	0.066	0.202	0.185	0.969	1.000
$\sigma_{i,t}(r_{10years})$	25,504	0.193	0.050	0.096	0.371	0.160	0.465	1.000
Panel C: Variance ratios								
Variance ratios	25,504	0.895	0.094	0.175	1.069	1.385	0.542	0.645
%Variance ratio<1	25,504	0.738						

TABLE VII – VARIANCE RATIOS AND RESPONDENT CHARACTERISTICS

This table reports coefficients from panel regressions of ALP respondents' variance ratios on their characteristics. Control variables include wave fixed effects, respondent age, and indicators for gender, White race, married, working, and retired. All reported explanatory variables, except the indicator variables for holding equity and the expected change in financial position (better next year) are standardized (rescaled to zero mean and unit variance). Larger mean reversion values indicate stronger beliefs about mean reversion. Standard errors are clustered at the respondent level. Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Description	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Years education	0.053***									0.020***	0.012
Income		0.054***								0.017**	-0.005
Holds equity indicator			0.132***							0.066***	0.052*
Understands market				0.094***						0.069***	0.069***
Numeracy					0.096***						0.054***
Financial literacy						0.130***					0.048***
Overconfidence							0.013				0.015
Better next year								0.034***		0.021**	0.016
Mean reversion									-0.037***	-0.031***	-0.047**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,690	22,617	22,681	22,626	11,465	8,164	8,143	22,542	21,506	21,308	6,900

TABLE VIII – VARIANCE RATIOS AND COMPRESSION ERRORS IN OTHER DOMAINS

This table reports coefficients from panel regressions of ALP respondents' perceived variance ratios on the difference between the implied 5-year likelihood (assuming independence given their reported 1-year likelihood) and their reported 5-year event likelihood (i.e., their compression error). Control variables include wave fixed effects, respondent age, and indicators for gender, White race, married, working, and retired. All variables are standardized (rescaled to zero mean and unit variance) and standard errors are clustered at the respondent level. Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
P(car accident)	-0.049***							
P(cavity filled)		-0.068***						
P(die)			-0.048***					
P(theft victim)				-0.038**				
P(move)					-0.060***			
P(die terrorism)						-0.060***		
P(break in victim)							-0.071***	
P(visit dentist)								-0.047**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>N</i>	7,851	5,927	7,773	7,583	3,910	5,764	7,470	1,704

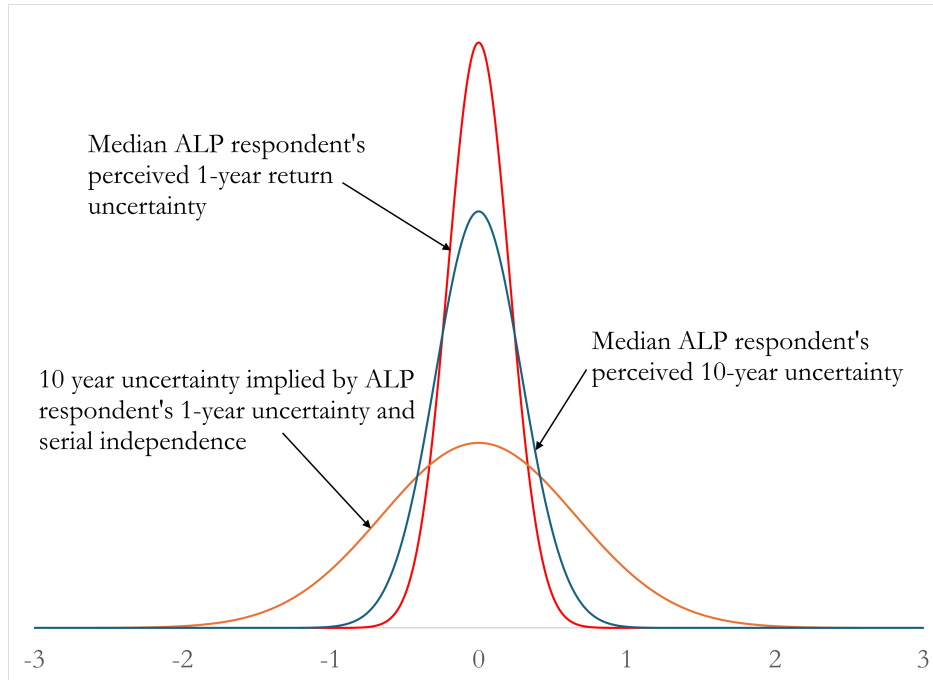


FIGURE 1 – NEAR- AND LONG-TERM UNCERTAINTY FOR ALP RESPONDENTS. The figure presents the perceived return distributions for the median ALP respondent for three measures of uncertainty after recentering at zero. The solid red line reflects the 1-year imputed uncertainty. The solid blue line represents the 10-year total return imputed uncertainty. The solid orange line reflects the 10-year total return uncertainty implied by the median respondent's 1-year beliefs under serial independence. Uncertainty estimates are based on ALP-style probability elicitation questions: respondents report the likelihood markets rise, rise by at least 20%, and fall by at least 20% over the next year and decade. All distributions are based on continuously compounded returns.

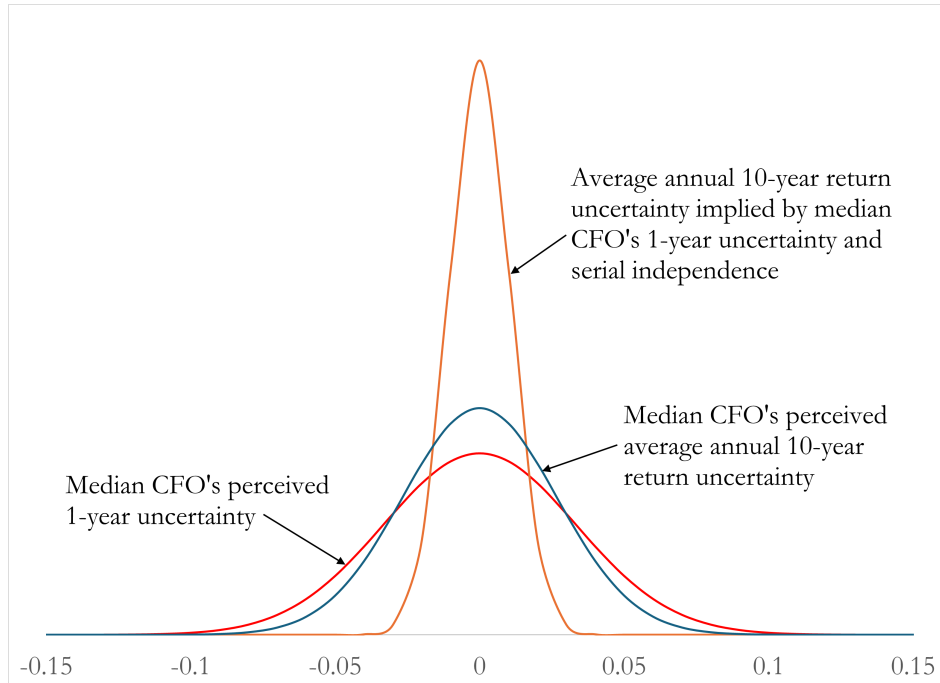
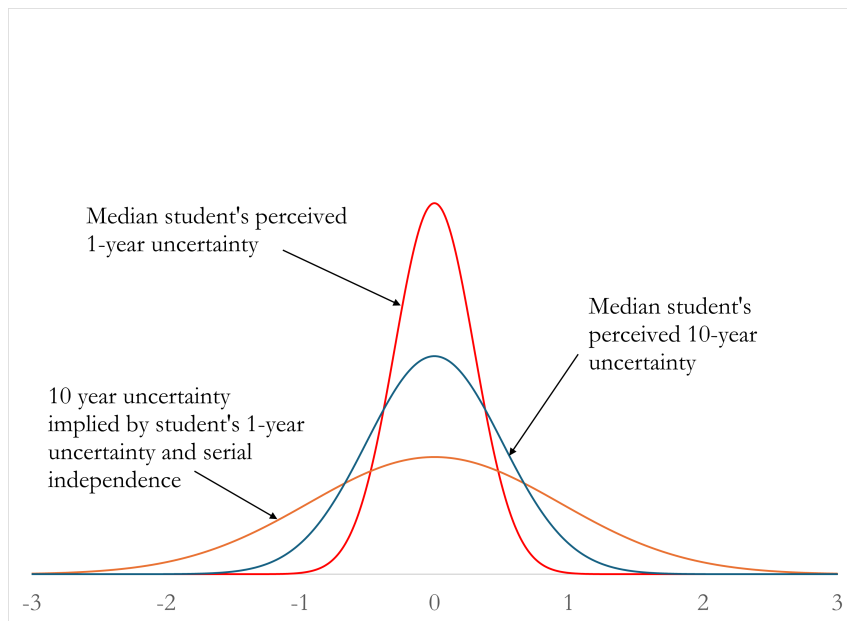
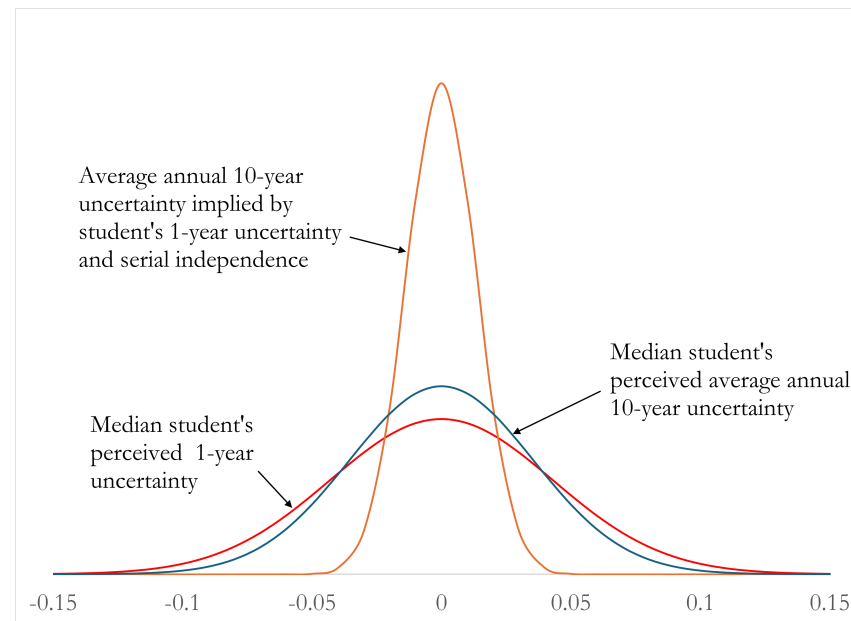


FIGURE 2 – NEAR- AND LONG-TERM UNCERTAINTY FOR CFOs. The figure presents the perceived return distributions for the median CFO respondent for three measures of uncertainty after recentering at zero. The solid red line reflects the 1-year imputed uncertainty. The solid blue line represents the imputed uncertainty in average annual returns over 10 years. The solid orange line reflects the average annual 10-year return uncertainty implied by the median CFO's 1-year beliefs under serial independence. Uncertainty estimates are based on CFO-style quantile elicitation questions: respondents report the 10th and 90th percentile returns and expected return for the next year and average annual return over the next decade. All distributions are based on continuously compounded returns. Because CFOs are asked about average annual long-term returns, the blue and orange lines are expressed in terms of average annual returns rather than total returns.



(A) Median student's 1- and 10-year uncertainty based on probability elicitation total return questions



(B) Median student's 1- and 10-year uncertainty based on quantile elicitation average annual return questions

FIGURE 3 – NEAR- AND LONG-TERM UNCERTAINTY FOR STUDENTS. Panel A presents the perceived return distributions for the median student respondent for three measures of uncertainty after recentering at zero. The solid red line reflects the 1-year imputed uncertainty. The solid blue line represents the 10-year total return imputed uncertainty. The solid orange line reflects the 10-year total return uncertainty implied by the median student's 1-year beliefs under serial independence. Uncertainty estimates are based on ALP-style probability elicitation questions: respondents report the likelihood markets rise, rise by at least 20%, and fall by at least 20% over the next year and decade. Panel B presents analogous distributions based on CFO-style quantile elicitation questions: respondents report the 10th and 90th percentile returns for the next year and for the average annual return over the next decade. The blue and orange lines in Panel B are expressed in terms of average annual returns rather than total returns. All distributions are based on continuously compounded returns.

Internet Appendix for “Uncertain Uncertainty”

Contents

IA-1	American Life Panel—additional detail	A2
IA-2	ALP, CFO, and student near- and long-term distributions	A2
IA-3	Spring and fall 2024 student surveys—additional detail	A3
IA-4	Student surveys—question order	A3
IA-5	Students’ perceived historical return distributions	A4
IA-6	Spring 2025, fall 2025, and spring 2026 student surveys—additional detail	A4
IA-7	Understanding America Survey	A4
IA-8	Respondent characteristic sorts and variance ratio heterogeneity	A6
IA-9	Correlations between explanatory variables	A7
IA-10	Compression in other domains	A7
IA-11	Anchoring in the ball and bin approach—evidence from Hartzmark and Sussman (2026)	A8
IA-12	Variable details	A9

IA-1 American Life Panel—additional detail

We use all 61 short- and long-form ALP surveys (not just the 29 long-form surveys used in our main analysis) to estimate each individual’s mean-reversion beliefs. Specifically, for each respondent, we estimate a time-series regression of their perceived likelihood markets rise in the next decade (which is asked in all 61 surveys) on the market return over the previous 12 months. For ease of interpretation, we standardize lagged returns by the standard deviation of the annual CRSP value-weighted market return, so the coefficient reflects the change in the perceived likelihood markets rise in the next decade associated with a one standard deviation higher lagged annual return. To facilitate reporting, we define the mean reversion variable as the estimated regression coefficient times -1, so that larger positive values suggest greater mean reversion. We require that respondents have at least 10 observations (from the 61 surveys) to estimate their mean-reversion beliefs. To ensure outliers do not drive the results, we winsorize the estimated coefficients at the 5th and 95th percentiles.

We hypothesize that individuals who expect their personal financial situation to worsen also perceive greater future economic uncertainty and riskier equity markets. Based on this hypothesis, we use the answer to the question *Now looking ahead – do you think a year from now you will be better off financially, worse off, or about the same as now?* as a proxy for expected future changes in market volatility. Consistent with our hypothesis, in two ALP surveys not in our main sample (ALP surveys 17 and 61; fielded in December 2007–April 2008 and January–March 2009, respectively), respondents were asked this question alongside their expectations for business conditions (*And how about a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?*) and unemployment (*How about people out of work during the coming 12 months – do you think that there will be more unemployment than now, about the same or less?*). We reverse score the unemployment variable (such that higher values indicate expected lower unemployment) so expected correlations are all positive. Sample sizes for these questions range from 501 to 555 per survey. The six correlations between the three metrics are statistically significant at the 1% level and range from 0.22 to 0.47, consistent with the hypothesis that expected changes in personal financial situation proxy for expected changes in market volatility (e.g., Hamilton and Lin (1996)).

The ALP surveys also collect data regarding respondents’ gender, race, marital status, employment status, retirement status, age, years of education, income, stock market participation, as well as measures of numeracy, financial literacy, and overconfidence, which we use in Section 5 (see Section IA-12 for variable construction details).

Table IA-I reports descriptive statistics of ALP respondent characteristics for our pooled cross-sectional time-series of 22,745 observations from 3,022 individuals (the average respondent participates in more than 7.5 long-form surveys). Our ALP sample is 58% female, 88% White race, 66% married, 61% working, and 23% retired. As shown in the bottom row of Table IA-I, approximately two-thirds of observations reveal a belief in mean-reversion.

[Insert Table IA-I about here]

IA-2 ALP, CFO, and student near- and long-term distributions

Figure IA-1 displays the inferred and historical near- and long-term return distributions for ALP respondents (these inferred distributions underlie Figure 1). In Panel A, the dashed red line reports the historical distribution for continuously compounded 1-year U.S. equity returns, based on the mean and standard deviation of the CRSP value-weighted index. The solid red line reflects the median estimated ALP respondent’s perceived near-term distribution, based on their inferred expected return and standard deviation. Although the typical ALP respondent holds a bearish

near-term view, their inferred near-term uncertainty is close to the historical average. Panel B presents the corresponding long-term distributions.

Figure IA-2 displays the analogous distributions for CFO respondents (these inferred distributions underlie Figure 2). In Panel A, the dashed red line reflects the historical 1-year return distribution from the CRSP value-weighted index, while the solid red line reflects the inferred 1-year distribution based on the mean CFO's expected return and variance. Similar to ALP and HRS respondents, CFOs tend to exhibit near-term expected returns below the historical market average. Unlike ALP and HRS respondents, however, CFO beliefs imply 1-year standard deviations substantially below historical values. Panel B presents the corresponding long-term distributions, with the solid and dashed blue lines reflecting mean CFO beliefs and the CRSP value-weighted index, respectively.

Figures IA-3 and IA-4 present the inferred and historical near- and long-term return distributions for students answering the ALP-style and CFO-style questions, respectively (these inferred distributions underlie Figure 3). In each figure, Panel A presents the 1-year distributions and Panel B presents the 10-year distributions, with solid lines reflecting median student beliefs and dashed lines reflecting the historical CRSP value-weighted index. The patterns mirror those of their survey-design counterparts. When answering the ALP-style total return question, the median student's inferred 1-year standard deviation is close to the historical value. When answering the same question reframed in the CFO style, students exhibit, similar to CFOs, substantial miscalibration—implying a 1-year standard deviation well below the historical average.

IA-3 Spring and fall 2024 student surveys—additional detail

The results in Table III and Figure 3 are based on surveys given in the spring and fall of 2024. A total of 828 students completed all four probability elicitation questions required to estimate variance ratios (i.e., chance market rises at least 20% in next year or decade; chance market falls at least 20% in next year or decade). To estimate variances, we require: (1) the sum of the perceived likelihoods that markets rise and fall at least 20% in the next year (decade) must be less than 100%, and (2) none of the perceived likelihoods can be zero. Of the 828 students, 238 report values that sum to exactly 100%, 193 report values that sum to greater than 100%, and 75 report a 0% likelihood for at least one of the four required probabilities. Panels A and B of Table IA-II report descriptive statistics for the perceived return likelihoods for the complete sample ($n=828$), analogous to the first three rows of Panels A and B in Table III. The results, based on raw (i.e., unwinsorized) data, exhibit the same patterns as reported in Table III.

[Insert Table IA-II about here]

A total of 824 students completed all four quantile elicitation questions required to estimate near- and long-term variances (i.e., 10th and 90th return percentiles for the next year and average annual return percentiles for the next decade). Estimation requires that the 10th percentile return is less than the 90th percentile return; 151 students violate this constraint. Panels C and D of Table IA-II report descriptive statistics for the perceived returns for the complete sample ($n=824$), analogous to the first three rows of Panels D and E in Table III. The results, based on raw (i.e., unwinsorized) data, exhibit the same patterns as reported in Table III.

IA-4 Student surveys—question order

Both the probability elicitation and quantile elicitation survey questions were given to undergraduate business students enrolled in introductory finance courses at two large public universities. In the Fall 2024 semester, one section of students at University A were first given the quantile elicitation

questions then two weeks later given the probability elicitation questions. Students in the second section at University A were first given the probability elicitation questions then two weeks later given the quantile elicitation questions. Table IA-III reports the distribution of inferred variance ratios for each section (analogous to Panels C and F in Table III). The results reveal the same pattern in both sections. Specifically, median variance ratios based on the probability elicitation questions were 0.198 and 0.140 in the two sections; a Mood’s median test reveals no evidence the medians differ across sections (p -value=0.82). Correspondingly, the median variance ratios based on the quantile elicitation questions were 9.81 and 7.15, and a Mood’s median test again fails to reject equality of the medians (p -value=0.55).

[Insert Table IA-III about here]

IA-5 Students’ perceived historical return distributions

As detailed in Section 5.6, we repeat our base student tests replacing forward-looking return questions with historical return questions. Table IA-IV reports descriptive statistics for students’ estimates of the historical 1- and 10-year return distributions, including their reported likelihoods, inferred standard deviations, and implied variance ratios based on the probability elicitation (total return) and quantile elicitation (average return) questions. Consistent with the forward-looking results in Table III, the patterns are nearly identical regardless of whether students are asked about historical or expected future returns—the total return probability elicitation questions generate unrealistically small variance ratios while the average annual return quantile elicitation questions generate unrealistically large variance ratios.

[Insert Table IA-IV about here]

IA-6 Spring 2025, fall 2025, and spring 2026 student surveys—additional detail

The results in Tables IV and V are based on student surveys given in spring 2025, fall 2025, and spring 2026. Students were randomly assigned to one of four survey versions, with each student completing two surveys two weeks apart. In one survey, students were assigned probability elicitation questions about either average annual or cumulative returns paired with quantile elicitation questions about either average annual or cumulative historical returns. In the other survey, students were assigned quantile elicitation questions about average annual or cumulative future returns paired with probability elicitation questions about average annual or cumulative historical returns. Note that the surveys in rows 1 and 2 of Table IV use identical question formats but represent two distinct randomly assigned groups. In each survey, between the two sets of questions, students were asked several financial literacy questions as a palate cleanser to reduce carry-over effects.

IA-7 Understanding America Survey

Our UAS sample is based on data from two surveys executed six years apart. In January 2025 (UAS survey 685), 9,455 individuals completed the six probability elicitation total return questions (see Section 3.1). We limit the sample to the 3,644 individuals whose answers allow us to calculate perceived variances (i.e., the sum of the probability of a return less than 20% and a return greater than 20% is less than 100%, and neither probability is zero). Panels A, B, and C of Table IA-V (directly analogous to Panels A, B, and C of Table III) report summary statistics for UAS respondents’ answers, inferred expected returns, inferred standard deviations, and variance ratios based on the probability elicitation total return questions. The results are nearly identical to the corresponding results for ALP participants (Table I) and students (Table III). For example, the

median UAS probability elicitation variance ratio of 0.187 is between the median value for ALP participants (0.147; Panel C of Table I) and students (0.238; Panel C of Table III).

[Insert Table IA-V about here]

In UAS survey 184—in the field between May and June 2019—UAS respondents were asked about average annual returns using quantile elicitation. Specifically, respondents were first asked about their expectations for returns over the next decade:

Please answer the next questions based on your best guess on how the stock market will perform over the next 10 years. Here is an example of what we mean by average annual (yearly) return: It is a simple average of each year's return. So if in the first year the stock market goes up by 2% and in the second year market goes up by 4%, the average annual return over two years is 3% - we want your own best guess, so please do not look anything up.

I expect the average annual return over the next 10 years will be ____

I believe that there is a small (1-in-10, or 10 percent) chance the actual return over 10 years will be less than ____

I believe that there is a small (1-in-10 or 10 percent) chance the actual return over 10 years will be greater than ____

UAS respondents were then asked (in the same survey) about their perceptions of annual returns over the previous 60 years:

We are interested in finding out what people know and do not know about the history of stock market returns. The next question asks about what you think about historical stock market returns over the past 60 years in the S&P 500. Over that time, there were some years, or periods of years, where returns were much higher, or much lower, than the average over the whole time period.

Please answer the next questions about the last 60 years of the stock market history (from 1959 to 2018), as measured by S&P 500 index. If you are not sure, we would like your best guess - please do not look up any answers.

I believe that the average annual return over the past 60 years was ____

During the 6 lowest years of the market over that time, returns were less than ____

During the 6 highest years of the market over that time, returns were greater than ____

The 1-year horizon questions differ from the Duke CFO survey questions in two respects: (1) they ask about historical rather than expected returns, and (2) they rephrase the 10th and 90th percentile question as the six lowest and six highest years over the past 60 years. A total of 2,461 UAS respondents answered all six questions from the May–June 2019 survey; after applying probability law restrictions (e.g., excluding respondents who report a 90th percentile equal to their 10th percentile), 1,439 remain. Panels D, E, and F of Table IA-V (directly analogous to Panels D, E, and F of Table III) report summary statistics for UAS respondents' answers, inferred expected returns, inferred standard deviations, and variance ratios based on the quantile elicitation average annual return questions. The results are fully consistent with the patterns for both CFOs and students. For instance, the median inferred UAS 1-year standard deviation, based on estimates of 10th and 90th percentile returns, is 0.036 versus 0.033 for CFOs (Table II) and 0.043 for students (Table III).³⁷ Similarly, based on the quantile elicitation average annual return questions, the vast

³⁷UAS respondents appear more miscalibrated than either students or CFOs about long-term returns—the median 10-year 90th percentile average annual return for UAS respondents, students, and CFOs are, respectively, 9.5%, 14%, and 13% (versus a historical value of 15%). As a result, long-term inferred variances are lower for UAS participants

majority of variance ratios for UAS participants (82%, see Table IA-V), students (93%, see Table III), and the median CFO (100%, see Table II) exceed the historical market variance ratio.

Panel G of Table IA-V (directly analogous to Panel G of Table III) reports descriptive statistics for the 469 UAS respondents who completed both the 2019 and 2025 surveys. For this subset, the vast majority of both UAS respondents (79%) and students (95%) generate a larger variance ratio when asked about average annual returns (denoted “CFO variance ratio”) than total returns (denoted “ALP variance ratio”). In sum, despite differences in question wording, the use of historical rather than forward-looking 1-year returns, and the six-year gap between the two surveys, the UAS results are fully consistent with our hypothesis.

IA-8 Respondent characteristic sorts and variance ratio heterogeneity

We sort ALP respondents into two groups by each of the characteristics investigated in Table VII. In each of the 29 ALP survey waves, we compute the cross-sectional median variance ratio as well as the fraction of variance ratios less than 1 and the fraction less than the historical market variance ratio (0.542). Finally, for each group and wave, we test whether the fraction of variance ratios less than 1, or less than 0.542, differs meaningfully from 50%. In total, we examine 1,044 tests (i.e., 9 characteristics $\times$ 2 groups $\times$ 29 waves $\times$ 2 tests) of whether the variance ratio is less than 1, or less than 0.542. The first two rows of each panel in Table IA-VI report the time-series averages of the cross-sectional median variance ratios and cross-sectional average fraction of variance ratios less than 1 or less than 0.542.

[Insert Table IA-VI about here]

The results in Table IA-VI reveal that unrealistically small variance ratios in the ALP sample are ubiquitous. The largest reported (cross-sectional average of time-series median) variance ratio in Table IA-VI is 0.229 for high numeracy individuals in Panel E. In addition, the fraction of variance ratios less than 0.542, and less than 1, are always meaningfully greater than 50%. That is, all 1,044 tests summarized in the last two columns are statistically significant at the 1% level.

Panels A-F in Table IA-VI report the variance ratios for the financial sophistication proxies (in each case, the top row represents the ‘more’ sophisticated group). The third row reports the difference in variance ratios and indicates whether the value differs meaningfully from zero (based on a paired t -test of the time-series of the 29 cross-sectional medians). If variance ratio heterogeneity were driven primarily by variation in perceived parameter uncertainty, more sophisticated respondents—who should face less parameter uncertainty—would exhibit smaller variance ratios. Instead, the differences in Panels A-F are all positive and statistically significant at the 1% level: more sophisticated respondents exhibit larger, more reasonable variance ratios, the opposite of what the parameter uncertainty explanation predicts.

The results in Panels G and H reveal no support for the hypotheses that individuals with greater overconfidence or individuals who expect economic risk to increase in the future exhibit larger variance ratios (i.e., both results have the “wrong” sign). The results in Panel I, however, support the hypothesis that heterogeneity in variance ratios results, in part, from heterogeneity in mean-reversion beliefs as individuals who exhibit stronger mean-reversion beliefs also exhibit significantly (at the 1% level) smaller variance ratios.

relative to CFOs and students. In all three cases, however, long-term inferred variances are too large relative to near-term inferred values, generating implausibly large variance ratios when asked the quantile elicitation average annual return questions.

IA-9 Correlations between explanatory variables

Table IA-VII reports correlations between the explanatory variables for the Table VII panel regressions including Years education, Income, Holds equity, Understands markets, Numeracy, Financial literacy, Overconfidence, Mean reversion, and Better next year for our pooled cross-sectional time-series of 22,745 observations (from 3,022 individuals).

[Insert Table IA-VII about here]

IA-10 Compression in other domains

As detailed in the manuscript, ALP respondents were asked a series of questions regarding the likelihood of an event in the next year. Specifically, respondents were asked, “What is the percent chance that ___ during the next year?” where the blank was filled with:

- ...you will get into a car accident...
- ...you will have a cavity filled...
- ...you will die (from any cause – crime, illness, accident, and so on)...
- ...someone will steal something from you...
- ...you will move your permanent address to another state some time...
- ...you will die in a terrorist attack...
- ...someone will break into your home and steal something from you...
- ...you will visit a dentist, for any reason,...

Respondents were then asked the same set of questions regarding the next five years, i.e., “What is the percent chance that ___ during the next 5 years?”

Columns (2) and (3) in Table IA-VIII report the median reported likelihood for each question over the next year and the corresponding implied 5-year likelihood calculated assuming independence. Column (4) reports the median respondent-reported 5-year likelihood and column (5) reports the difference in medians between the 5-year likelihood assuming independence and the reported 5-year likelihood. Columns (6)-(9) report analogous mean values.

[Insert Table IA-VIII about here]

If respondents compress their annual and 5-year forecasts toward each other, the differences between their 5-year likelihoods implied by their 1-year forecasts and their elicited 5-year likelihoods will be positive (columns 5 and 9). The final column reveals the fraction of respondents with a positive difference averages 87% across the eight questions and ranges from 68% (for the likelihood one moves out of state) to 94% (for the likelihood one is a theft victim). For instance, the median respondent reports a 20% chance of a car accident in the next year. Assuming that, on average, respondents’ car crash risk is approximately independent over the next five years, the 5-year likelihood should be 67.2% (i.e., $1 - (0.8^5)$). Yet the typical respondent estimates only a 30% 5-year likelihood—remarkably, less than the 36% implied 2-year likelihood (i.e., $1 - (0.8^2)$), let alone the 67.2% implied 5-year value. In short, the results are uniformly consistent with most individuals compressing their judgments regarding the relation between horizon and likelihood. Specifically, as shown in the final column of Table IA-VIII, we can reject the hypothesis that the difference between implied 5-year likelihoods and estimated 5-year likelihoods is as likely to be positive as negative at the 1% level in every case.

IA-11 Anchoring in the ball and bin approach—evidence from Hartzmark and Sussman (2026)

As discussed in Section 5.5, in the Hartzmark and Sussman (2026) distribution elicitation experiment, respondents viewed either 100 years of US stock returns (with $\mu_{US}=7.97\%$ and $\sigma_{US}=18.35\%$) or 100 years of Japanese returns (with $\mu_{Japan}=10.21\%$ and $\sigma_{Japan}=27.24\%$). Regardless of which set of returns viewed, respondents were then asked to place 100 balls in nine bins where the “bin distribution” was based on either historical Japanese or US returns (bin width was based on 0.5 standard deviations). Specifically, the bin distribution based on US and Japanese data were, respectively:

US bins:	$<-23\%$, -23% to -15% , -14% to -6% , -5% to 3% , 4% to 12% , 13% to 21% , 22% to 30% , 31% to 39% , $> 39\%$
Japan bins:	$<-42\%$, -42% to -28% , -27% to -13% , -12% to 2% , 3% to 17% , 18% to 32% , 33% to 47% , 48% to 62% , $> 62\%$

Thus, a given individual viewing Japanese historical data may face either “Japanese bins” or “US bins.” Correspondingly, an individual viewing US historical data may face either US bins or Japanese bins. If, just after viewing 100 years of historical data, individuals have a good understanding of the distribution, then the standard deviation implied by their ball and bin experiment should largely be invariant to whether balls are placed in Japanese or US bins. Alternatively, if respondents have little understanding of the distribution they just viewed, then we hypothesize they will place balls to largely mimic a normal distribution of the bins (US or Japanese) they view.

The solid lines in Figure IA-5A report implied distribution (recentered at zero for ease of comparison) based on historical Japanese (solid red line) or US (solid blue line) volatility.³⁸ The broken red line reports the implied distribution based on respondents who viewed Japanese data and Japanese bins. The broken blue line reports the implied distribution based on respondents who viewed *the same Japanese data* but US bins. Consistent with the typical CFO providing an estimate closely anchored to the seed value (Section 5), the average respondent in the Hartzmark and Sussman (2026) sample essentially distributed the balls to approximate a normal distribution centered on whichever bin structure they faced. That is, despite viewing the same Japanese stock returns, respondents using Japanese bins essentially returned the Japanese distribution (i.e., solid and broken red lines closely track) while those using US bins essentially returned the US distribution (i.e., the solid and broken blue lines closely track).

[Insert Figure IA-5 about here]

Figure IA-5B reports analogous results for respondents who viewed US data. When faced with US bins, respondents effectively replicated the US distribution (the solid blue line is based on $\sigma_{US}=18.35\%$ while the dashed blue line, which is largely covered by the solid blue line, reflects the average inferred standard deviation of 18.32%). When faced with the Japanese bins, however, the average estimated standard deviation (23.06%) is closer to the Japanese historical value (27.24%) than the US historical value (18.35%). In short, the results suggest that the average respondent largely places balls to generate something close to a normal distribution *of the bins* regardless of the distribution of the underlying data.

³⁸Values in Figure IA-5 are based on the authors’ Table A10 for bins centered at the historical means. Nonetheless, as shown in the authors’ Table A10, the same pattern occurs when returns are centered at zero.

IA-12 Variable details

Variable construction follows Sias, Starks, and Turtle (2024) and Sias, Starks, and Turtle (2026). As a result, this appendix contains identical descriptions to their appendices. For many questions, respondents are prompted if they do not initially respond to a question. For instance, if respondents do not respond to the question regarding direct stock holdings, they are prompted, “[You did not answer. Your answers are important to us. Please answer the question to the best of your ability.] In the next set of questions we will ask you about stock holdings besides those that you may have already told us about. Do [you (and/or your husband/wife/partner)] have any shares of stock or stock mutual funds besides stock holdings that are part of an IRA, 401(k), Keogh or similar retirement accounts?” These responses generally show up as a second variable (e.g., no value for ST001, but a value for ST001_NR_DK) that we include in our analysis.

Variable	Description
Female	Gender is identified in the pre-loaded demographic data for each “effects of the financial crisis” survey.
White race	Ethnicity is identified in the pre-loaded demographic data for each “effects of the financial crisis” survey.
Married	Current living situation is asked in each survey. Those who respond, “Married or living with a partner” are classified as married. All others (e.g., separated, divorced, widowed, never married) are classified as non-married.
Working	Current job status is identified in each survey. Respondents who report, “working now” are classified as working.
Retired	Current job status is identified in each survey. Respondents who report “retired” are classified as retired.
Age	Respondent age is reported in each survey. Respondents 50 and younger are classified as young while those older than 50 are classified as old.
Years Education	Respondents report 16 possible answers for “What is the highest level of school you have completed or the highest degree you have received?” We assign the following years of education for each answer (1) less than 1st grade=0, (2) 1st, 2nd, 3rd or 4th grade=2.5, (3) 5th or 6th grade=5.5, (4) 7th or 8th grade=7.5, (5) 9th grade=9, (6) 10th grade=10, (7) 11th grade=11, (8) 12 grade no diploma=12, (9) high school graduation=12, (10) some college but no degree=13, (11) associate degree in college occupational/vocational program=14, (12) associate degree in college academic program=14, (13) bachelor’s degree=16, (14) master’s degree=18, (15) professional school degree (e.g., MD, DDS, DVM, LLB, JD)=22, (16) Doctorate degree (e.g., PhD EdD)=22. We classify respondents with at least 13 years of education as “more” education.

Income	Respondents report values for family income questions. The first question, “family income” reports 14 possible income buckets—with the final bucket indicating income greater than \$75,000. “Family income part 2” asks those who report family income greater than \$75,000 to report income in four additional buckets. The 14 family income buckets are: $\text{inc} < \\$5\text{k}$, $\\$5\text{k} \leq \text{inc} < \\7.499k, $\\$7.5\text{k} \leq \text{inc} < \\9.999k, $\\$10\text{k} \leq \text{inc} < \\12.499k, $\\$12.5\text{k} \leq \text{inc} < \\14.999k, $\\$15\text{k} \leq \text{inc} < \\19.999k, $\\$20\text{k} \leq \text{inc} < \\24.999k, $\\$25\text{k} \leq \text{inc} < \\29.999k, $\\$30\text{k} \leq \text{inc} < \\34.999k, $\\$35\text{k} \leq \text{inc} < \\39.999k, $\\$40\text{k} \leq \text{inc} < \\49.999k, $\\$50\text{k} \leq \text{inc} < \\59.999k, $\\$60\text{k} \leq \text{inc} < \\74.999k, $\\$75\text{k} \leq \text{inc}$. The family income part 2 groupings are: $\\$75\text{k} \leq \text{inc} < \\99.999k, $\\$100\text{k} \leq \text{inc} < \\124.999k, $\\$125\text{k} \leq \text{inc} < \\199.999k, $\\$200\text{k} \leq \text{inc}$. For respondents who report income less than \$75K, we use the bucket midpoint. For respondents who report income of at least \$75k, but less than \$200k, we use the bucket midpoint of family income part 2. For respondents who report income greater than \$200k, we assume income is \$250k. We classify respondents with income of at least \$75,000 as “higher” income.
Numeracy	ALP survey 32 (in the field from 5-27-2008 to 6-30-2008) included a series of 17 questions used to compare measures of numeracy in Weller, Dieckmann, Tusler, Mertz, Burns, and Peters (2013). The authors conclude that the eight-item Rasch-based numeracy measure generally performed better than other measures. The Rasch metric consists of a series of increasingly difficult problems to better discriminate numeracy. The authors provide (via the ALP website for registered users; scores.xlsx), the Rasch based score for ALP survey 32 participants. We classify respondents with Rasch numeracy score greater than 4 as high numeracy and those with score of 4 or less as low numeracy.
Understand market	In 14 of the financial crisis waves (1, 2, 11, 14, 24, 38, 41, 50, 54, 55, 58, 59, 60, and 61) respondents are asked “How would you rate your understanding of the stock market with scores from 1 (extremely good) to 6 (extremely poor). We reverse score the variable (so higher values indicate greater understanding) and average the score of all waves for which the respondent answers this question. Those with an average score of at least 3 (understands the market extremely good, very good, somewhat good) are classified as high self-rated understanding of the market. Those with average scores less than 3 (somewhat poor, very poor, extremely poor) are classified as low self-rated understanding of the market.
Financial literacy	ALP survey 5 (in the field from 5-8-2006 to 11-1-2007) asked respondents a series of 13 financial literacy questions. The survey is described in Parker, de Bruin, Yoong, and Willis (2012). We compute the fraction of the 13 questions correctly answered and classify respondents who correctly answered more than 75% (i.e., at least 10) of the questions as high financial literacy.
Overconf.	ALP survey 6 (in the field from 8-14-2006 to 11-20-2007) asked respondents 14 true/false general knowledge questions (e.g., alcohol causes dehydration). Respondents are also asked their confidence in each answer ranging from 50% (just guessing) to 100% (absolutely sure). Following Parker, de Bruin, Yoong, and Willis (2012), overconfidence is computed as the difference between the average confidence in their answer and fraction of correct answers. We classify respondents with positive differences as overconfident and those with negative (or no) differences as not overconfident.

Holds equities	In the first two waves of the financial crisis surveys (both long-form), respondents (ST001) are asked, “Do [you (or your husband/wife/partner)] have any shares of stock or stock mutual funds? Please include stocks that [you (or your husband/wife/partner)] hold in an employer pension account.” Thus, in the first two waves, respondents are classified as equity market participants based on this question. In all subsequent waves, respondents are asked (ST001), “In the next set of questions we will ask you about stock holdings. Please, do not include stock holdings that are part of an IRA, 401(k), Keogh or similar retirement accounts. Do [you(and/or your husband/wife/partner)] have any shares of stock or stock mutual funds?” In short-form wave 3 and all subsequent long-form waves, respondents who report having retirement account (RA001) are asked (RA006), “Are any of these retirement accounts invested in stocks or stock mutual funds, either fully or partially?” In these waves, we classify respondents who report owning stocks (either directly or in retirement account) as equity holders. Respondents who answer they do not have money in stock directly and either report no retirement stock or do not have a retirement account are classified as non-participants.
Better next year	In the 29 long-form surveys, respondents are asked, “Now looking ahead - do you think that a year from now you will be better off financially, worse off, or about the same as now?” We code respondents as 1 if they believe they will be better off in a year, -1 if they believe they will be worse off, and 0 if they believe they will be about the same. For the sorts, those who believe they will be better off are compared to those who believe they will be worse off.
Mean- reversion	In all 61 effects of the financial crisis surveys, respondents are asked “What are the chances that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more in 10 years than they are today?” For respondents who answer this question in at least 10 surveys, we regress the time-series of respondents’ perceived likelihood markets rise in the next decade on scaled lagged 12 month returns. Specifically, to ease in interpretation, we divide raw lagged 12 month return by the standard deviation of CRSP 12-month returns such that the coefficient reflects the expected change in the likelihood markets rise in the next decade given a one standard deviation higher lagged 12-month return. For the sorts, we classify those with a negative relation between lag returns and future expected long-term returns as the mean-reversion sample and those with non-negative coefficients as the no mean-reversion sample. To facilitate reporting, we define the mean reversion variable as the estimated regression coefficient x -1, so that larger positive values suggest greater mean reversion.

TABLE IA-I – DESCRIPTIVE STATISTICS FOR ALP

This table reports descriptive statistics for American Life Panel respondents' characteristics including Female, White race, Married, Working, Retired, Age, Years education, Income, Holds equity, Understands markets, Numeracy, Financial literacy, Overconfidence, Better next year, Mean reversion, and Mean reversion >0 . Characteristics are based on the pooled cross-sectional time-series of 22,745 observations (from 3,022 individuals; the average respondent participates in more than 7.5 long-form surveys) that include any individual-survey wave observation where the respondent's variance ratio can be estimated. Detailed variable descriptions are provided in Section IA-12.

Description	N	Mean	25 th	Median	75 th	Std Dev.
Female	22,695	0.580	0.000	1.000	1.000	0.493
White race	22,745	0.878	1.000	1.000	1.000	0.327
Married	22,745	0.662	0.000	1.000	1.000	0.473
Working	22,744	0.609	0.000	1.000	1.000	0.488
Retired	22,744	0.229	0.000	0.000	0.000	0.420
Age	22,745	51.658	40.000	54.000	62.000	14.782
Years education	22,693	14.963	13.000	14.000	16.000	2.678
Income	22,620	71,511	37,500	55,000	87,500	51,672
Holds equity	22,732	0.589	0.000	1.000	1.000	0.492
Understand markets	22,677	3.194	2.444	3.286	4.000	1.076
Numeracy	11,467	4.496	3.000	5.000	6.000	1.764
Financial literacy	8,164	0.775	0.654	0.846	0.923	0.199
Overconfidence	8,143	-0.056	-0.114	-0.057	-0.007	0.095
Better next year	22,592	0.159	0.000	0.000	1.000	0.591
Mean reversion	21,546	1.451	-0.971	1.348	4.042	4.747
Mean reversion > 0	21,546	0.657				

TABLE IA-II – ADDITIONAL DETAIL ON STUDENTS’ BELIEFS

The table reports descriptive statistics for all respondents who provide estimates including those whose estimates violate probability laws for the spring and fall 2024 semesters (i.e., the sample for Table III). Panels A and B report, based on raw (i.e., unwinsorized) data, descriptive statistics for all 828 student respondents who answered the four ALP-style probability elicitation questions necessary to compute estimated variances over the next year or decade (i.e., chance market rises at least 20% in next year or decade; chance market falls at least 20% in next year or decade). Panels C and D report, based on raw (i.e., unwinsorized) data, beliefs for the 824 students who complete all four CFO-style quantile elicitation questions required to estimate near- and long-term variances (i.e., 10th and 90th return percentiles for the next year and average annual return percentiles for the next decade).

Description	N	Mean	25 th	Median	75 th	Std Dev.	Hist.	%<Hist
Panel A: Probability elicitation questions, next year								
P(market>0)	828	0.658	0.500	0.700	0.800	0.198	0.747	0.574
P(market>20%)	828	0.388	0.200	0.400	0.500	0.226	0.336	0.459
P(market<-20%)	828	0.317	0.130	0.300	0.500	0.220	0.060	0.110
Panel B: Probability elicitation questions, next decade								
P(market>0)	828	0.774	0.650	0.850	0.970	0.234	0.960	0.746
P(market>20%)	828	0.645	0.500	0.700	0.800	0.244	0.932	0.885
P(market<-20%)	828	0.273	0.100	0.200	0.400	0.225	0.013	0.094
Panel C: Quantile elicitation questions, next year								
$E_t(r_{1year})$	824	0.201	0.077	0.113	0.262	0.193	0.095	0.326
$P90(r_{1year})$	824	0.256	0.095	0.170	0.372	0.242	0.302	0.712
$P10(r_{1year})$	824	0.114	0.030	0.055	0.140	0.137	-0.138	0.001
Panel D: Quantile elicitation questions, next decade								
$E_t(r_{10years})$	824	1.493	0.583	0.953	1.823	1.407	0.969	0.562
$P90(\bar{r}_{10years})$	824	0.198	0.086	0.140	0.262	0.167	0.152	0.567
$P10(\bar{r}_{10years})$	824	0.088	0.020	0.049	0.095	0.124	0.035	0.351

TABLE IA-III – SURVEY ORDER ROBUSTNESS TESTS

The table reports results for two samples of undergraduate business students enrolled in an introductory finance course at a large public university in spring 2024. Students in Section 1 were given the CFO-style quantile elicitation average annual return questions and then the ALP-style probability elicitation cumulative return questions two weeks later. Students in Section 2 were given the ALP-style probability elicitation questions initially, and the CFO-style quantile elicitation questions two weeks later. Panels A and B report summary statistics for the distribution of probability elicitation and quantile elicitation variance ratios, respectively, for each section. Mood's median tests are reported in the final row of each panel.

Description	N	Mean	25 th	Median	75 th	Std Dev.	Hist.	%<Hist
Panel A: Probability elicitation variance ratio results								
Section 1								
“ALP” variance ratio	37	0.898	0.079	0.198	0.789	1.379	0.542	0.622
%ALP variance ratio<1	37	0.757						
Section 2								
“ALP” variance ratio	37	0.531	0.061	0.140	0.400	1.044	0.542	0.784
%ALP variance ratio<1	37	0.892						
	<i>Z</i>	<i>p</i> -value						
Mood's median test	0.231	0.817						
Panel B: Quantile elicitation variance ratio results								
Section 1								
“CFO” variance ratio	67	14.495	4.071	9.814	14.249	19.289	0.542	0.060
%CFO variance ratio<1	67	0.104						
Section 2								
“CFO” variance ratio	66	12.242	1.920	7.154	13.087	15.838	0.542	0.076
%CFO variance ratio<1	66	0.136						
	<i>Z</i>	<i>p</i> -value						
Mood's median test	-0.605	0.545						

TABLE IA-IV – STUDENTS’ PERCEPTIONS OF HISTORICAL RETURN DISTRIBUTIONS

Panels A, B, and C report descriptive statistics for 251 undergraduate students who have sufficient data to compute their inferred variance ratio based on their perceived likelihood that, historically, markets have risen or fallen by at least 20% over 1- and 10-year periods (i.e., the probability elicitation questions reframed as perceived historical return distributions). Panels D, E, and F report descriptive statistics for 290 students who have sufficient data to compute their inferred variance ratio based on their perceived 10th and 90th percentiles of historical 1-year returns and historical average annual 10-year returns (i.e., the quantile elicitation questions reframed as perceived historical return distributions). Panel E reports two measures of long-term uncertainty: the standard deviation of average annual returns ($\sigma_{i,t}(\bar{r}_{10years})$), which is the quantity directly elicited by the quantile elicitation questions, and the standard deviation of total returns ($\sigma_{i,t}(r_{10years})$), which equals 10 times the former and is directly comparable in units to the long-term standard deviation reported in Panel B. Panel G summarizes the variance ratio information and presents differences for students with sufficient data to compute variance ratios based on both sets of questions. The sample is based on students surveyed in the fall 2024 semester.

Description	N	Mean	25 th	Median	75 th	Std Dev.	Hist.	%<Hist
Panel A: Student perceptions of historical 1-year stock market return (ALP questions)								
P(market>0)	251	0.643	0.500	0.700	0.800	0.251	0.747	0.562
P(market>20%)	251	0.246	0.100	0.200	0.350	0.179	0.336	0.737
P(market<-20%)	251	0.185	0.100	0.150	0.280	0.147	0.060	0.227
$E_{i,t}(r_{1year})$	251	0.029	-0.020	0.001	0.050	0.147	0.095	0.821
$\sigma_{i,t}(r_{1year})$	251	0.325	0.158	0.237	0.387	0.249	0.200	0.430
Panel B: Student perceptions of historical 10-year stock market return (ALP questions)								
P(market>0)	251	0.678	0.500	0.800	0.900	0.295	0.960	0.841
P(market>20%)	251	0.414	0.200	0.400	0.600	0.254	0.932	0.972
P(market<-20%)	251	0.183	0.050	0.150	0.260	0.142	0.013	0.072
$E_{i,t}(r_{10years})$	251	0.216	-0.020	0.065	0.357	0.355	0.969	0.932
$\sigma_{i,t}(r_{10years})$	251	0.508	0.225	0.362	0.601	0.418	0.465	0.614
Panel C: Students’ variance ratios (based on reframed ALP questions)								
“ALP” variance ratio	251	0.599	0.086	0.199	0.618	0.939	0.542	0.729
%Variance ratio<1	251	0.825						
Panel D: Student perceptions of historical 1-year stock market return (CFO questions)								
$P90(r_{1year})$	290	0.231	0.104	0.182	0.262	0.184	0.302	0.783
$P10(r_{1year})$	290	0.085	0.020	0.049	0.095	0.111	-0.138	0.003
$E_{i,t}(r_{1year})$	290	0.148	0.068	0.095	0.182	0.148	0.095	0.486
$\sigma_{i,t}(r_{1year})$	290	0.054	0.021	0.041	0.076	0.042	0.200	1.000

TABLE IA-IV – STUDENTS PERCEPTIONS OF HISTORICAL RETURN DISTRIBUTIONS (CONT.)

Panel E: Student perceptions of historical 10-year stock market return (CFO questions)								
$P90(\bar{r}_{10years})$	290	0.329	0.140	0.223	0.470	0.286	0.152	0.359
$P10(\bar{r}_{10years})$	290	0.140	0.049	0.095	0.182	0.146	0.035	0.117
$E_{i,t}(r_{10years})$	290	2.583	0.953	1.398	3.716	2.560	0.969	0.383
$\sigma_{i,t}(\bar{r}_{10years})$	290	0.074	0.026	0.048	0.094	0.079	0.047	0.483
$\sigma_{i,t}(r_{10years})$	290	0.675	0.257	0.481	0.941	0.555	0.465	0.483
Panel F: Students' variance ratios (based on reframed CFO questions)								
"CFO" variance ratio	290	50.836	5.811	11.454	40.831	86.681	0.542	0.034
%Variance ratio<1	290	0.066						
Panel G: Students' differences in variance ratios (historical return distributions)								
"ALP" variance ratio	139	0.681	0.086	0.199	0.624	1.044	0.542	0.712
"CFO" variance ratio	139	43.510	7.432	11.527	38.928	71.989	0.542	0.007
("CFO")/("ALP")	139	435.357	16.662	88.294	210.344	1593.260		
"CFO" - "ALP"	139	42.829	6.363	10.844	38.791	71.954		
("CFO" - "ALP")> 0	139	0.978						

TABLE IA-V – UNDERSTANDING AMERICA SURVEYS

Panels A, B, and C report descriptive statistics for 3,644 individuals from the Understanding America Survey (UAS) who have sufficient data to compute their inferred variance ratio in January 2025 (UAS survey 685) based on their perceived likelihood markets rise or fall 20% over the next year or decade (i.e., the probability elicitation total return questions). Panels D, E, and F report descriptive statistics for 1,439 individuals from the 2019 UAS survey (UAS survey 184) who have sufficient data to compute their inferred variance ratio based on their perceived *historical* 10th and 90th percentiles of annual returns over the previous 60 years, and their perceived *forward-looking* 10th and 90th percentiles of average annual returns over the next decade (i.e., the quantile elicitation average annual return questions). Panel E reports two measures of long-term uncertainty: the standard deviation of average annual returns ($\sigma_{i,t}(\bar{r}_{10years})$), which is the quantity directly elicited by the quantile elicitation questions, and the standard deviation of total returns ($\sigma_{i,t}(r_{10years})$), which equals 10 times the former and is directly comparable in units to the long-term standard deviation reported in Panel B. Panel G summarizes the variance ratio information and presents differences for individuals with sufficient data to compute variance ratios based on both the 2019 quantile elicitation average annual return questions and the 2025 probability elicitation total return questions.

Description	N	Mean	25 th	Median	75 th	Std Dev.	Hist.	%<Hist
Panel A: UAS participants' stock market expectations over next year (ALP total return questions, 2025 survey)								
P(market>0)	3,644	0.442	0.230	0.470	0.610	0.254	0.747	0.837
P(market>20%)	3,644	0.272	0.100	0.240	0.400	0.197	0.336	0.667
P(market<-20%)	3,644	0.294	0.110	0.250	0.440	0.212	0.060	0.111
$E_{i,t}(r_{1year})$	3,644	-0.062	-0.126	-0.020	0.072	0.718	0.095	0.780
$\sigma_{i,t}(r_{1year})$	3,644	0.746	0.204	0.316	0.601	1.647	0.200	0.243
Panel B: UAS participants' stock market expectations over next decade (ALP total return questions, 2025 survey)								
P(market>0)	3,644	0.564	0.350	0.520	0.800	0.281	0.960	0.911
P(market>20%)	3,644	0.436	0.250	0.430	0.600	0.242	0.932	0.984
P(market<-20%)	3,644	0.249	0.100	0.200	0.370	0.179	0.013	0.027
$E_{i,t}(r_{10years})$	3,644	0.285	-0.034	0.065	0.381	1.110	0.969	0.904
$\sigma_{i,t}(r_{10years})$	3,644	1.172	0.287	0.505	1.040	2.177	0.465	0.460
Panel C: UAS participants' variance ratios (ALP total return questions, 2025 survey)								
"ALP" variance ratio	3,644	1.003	0.076	0.187	0.711	1.983	0.542	0.709
%Variance ratio<1	3,644	0.837						

TABLE IA-V – UNDERSTANDING AMERICA SURVEYS (CONT.)

Panel D: UAS participants' historical perceived annual return distributions (CFO average annual return questions, 2019 survey)								
$P90(r_{1year})$	1,439	0.165	0.095	0.122	0.182	0.161	0.302	0.904
$P10(r_{1year})$	1,439	0.031	0.010	0.020	0.039	0.070	-0.138	0.008
$E_{i,t}(r_{1year})$	1,439	0.132	0.049	0.077	0.113	0.266	0.095	0.570
$\sigma_{i,t}(r_{1year})$	1,439	0.048	0.025	0.036	0.063	0.034	0.200	1.000
Panel E: UAS participants' stock market expectations over next decade (CFO average annual return questions, 2019 survey)								
$P90(\bar{r}_{10years})$	1,439	0.120	0.058	0.095	0.122	0.124	0.152	0.831
$P10(\bar{r}_{10years})$	1,439	0.045	0.020	0.030	0.049	0.061	0.035	0.525
$E_{i,t}(\bar{r}_{10years})$	1,439	0.765	0.392	0.583	0.770	1.304	0.969	0.883
$\sigma_{i,t}(\bar{r}_{10years})$	1,439	0.026	0.011	0.018	0.032	0.024	0.047	0.856
$\sigma_{i,t}(r_{10years})$	1,439	0.259	0.111	0.181	0.318	0.240	0.465	0.856
Panel F: UAS participants' variance ratios (CFO average annual return questions, 2019 survey)								
"CFO" variance ratio	1,439	6.805	0.867	2.595	7.277	10.476	0.542	0.180
%Variance ratio<1	1,439	0.270						
Panel G: UAS participants' differences in variance ratios								
"ALP" variance ratio	469	1.195	0.100	0.255	0.908	2.162	0.542	0.674
"CFO" variance ratio	469	19.843	0.892	2.546	7.146	98.559	0.542	0.171
("CFO")/("ALP")	469	375.177	1.474	7.654	51.415	4401.810		
"CFO" - "ALP"	469	18.648	0.078	1.905	6.214	98.677		
("CFO" - "ALP")> 0	469	0.785						

TABLE IA-VI – VARIANCE RATIO BY RESPONDENT CHARACTERISTICS

We sort respondents by characteristic (education level, income, stock market participation, understanding of the stock market, numeracy, financial literacy, overconfidence, economic expectations, and beliefs about mean-reversion) for each of 29 long-form waves. The initial two rows of the first column report the time-series mean of the 29 cross-sectional median variance ratio for respondents in that group. Columns 2 and 3 present the time-series average (across the 29 waves) of the cross-sectional mean percentage of variance ratios less than 1 and the historical average for US equity markets (0.542), respectively. For each wave and sample, we test the hypothesis that the fraction of variance ratios less than 1 or 0.542, respectively, does not differ from 50%. † indicates that we can reject the hypothesis at the 1% level for all 29 waves. The third row in each panel reports the difference in median variance ratios and associated statistical significance (1%, 5%, and 10% levels are indicated by ***, **, and *, respectively) associated with a paired t -test ($N=29$) of the null hypothesis that the difference is zero.

Variable	Variance Ratio (median)	%Variance Ratio<1	%Variance Ratio<0.542
Panel A: Education			
More education	0.169	0.874 [†]	0.790 [†]
Less education	0.125	0.921 [†]	0.865 [†]
Difference	0.045***		
Panel B: Income			
High income	0.183	0.868 [†]	0.777 [†]
Low income	0.134	0.906 [†]	0.843 [†]
Difference	0.049***		
Panel C: Stock market participation			
Holds equity	0.176	0.870 [†]	0.782 [†]
No equity	0.119	0.925 [†]	0.874 [†]
Difference	0.057***		
Panel D: Self-rated understanding of stock market			
High understanding	0.172	0.869 [†]	0.783 [†]
Low understanding	0.120	0.931 [†]	0.880 [†]
Difference	0.052***		
Panel E: Numeracy			
High numeracy	0.229	0.836 [†]	0.728 [†]
Low numeracy	0.131	0.914 [†]	0.853 [†]
Difference	0.098***		
Panel F: Financial literacy			
High financial literacy	0.218	0.835 [†]	0.731 [†]
Low financial literacy	0.114	0.939 [†]	0.893 [†]
Difference	0.104***		

Panel G: Overconfidence			
Overconfident	0.149	0.881 [†]	0.810 [†]
Not overconfident	0.173	0.868 [†]	0.779 [†]
Difference	-0.024***		
Panel H: Expectations for a year from now			
Better	0.155	0.883 [†]	0.804 [†]
Worse	0.142	0.896 [†]	0.825 [†]
Difference	0.013**		
Panel I: Mean-reversion beliefs			
Mean-reversion belief	0.144	0.898 [†]	0.828 [†]
No mean-reversion	0.162	0.884 [†]	0.804 [†]
Difference	-0.019***		

TABLE IA-VII – CORRELATION MATRIX OF PANEL REGRESSION EXPLANATORY VARIABLES

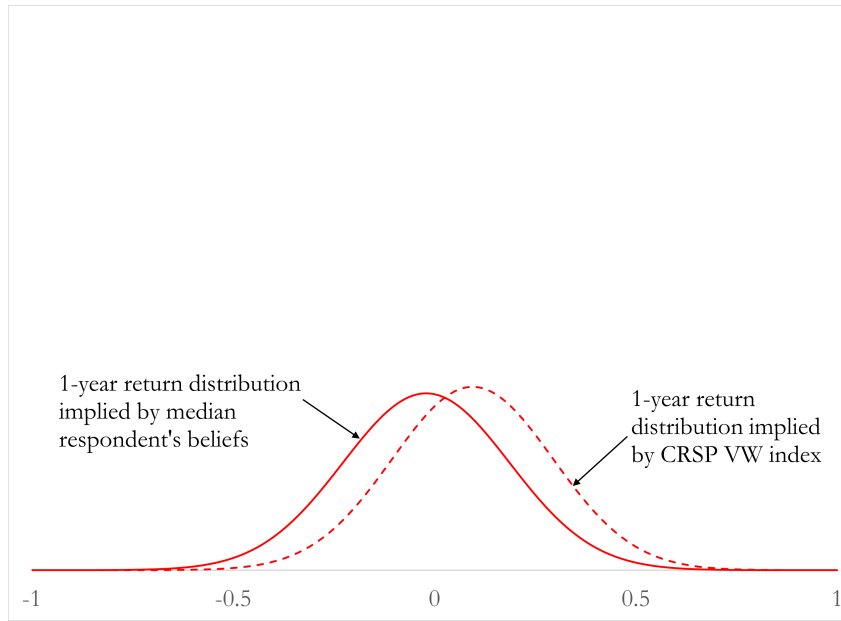
The table reports correlations between the panel regression (see Table VII) explanatory variables including Years education, Income, Holds equity, Understands markets, Numeracy, Financial literacy, Overconfidence, Mean reversion, and Better next year. Data includes the pooled cross-sectional time-series of 22,745 observations (from 3,022 individuals) that include any individual-survey wave observation with an estimable variance ratio. Variable descriptions are provided in the Internet Appendix, Section IA-12. Significance at the 1, 5, and 10% levels are indicated by ***, **, and *, respectively.

	Years education	Income	Holds equity	Understands markets	Numeracy	Financial literacy	Overconfidence	Mean reversion	Better next year
Years education	1.000								
Income	0.404***	1.000							
Holds equity	0.321***	0.397***	1.000						
Understands markets	0.332***	0.329***	0.410***	1.000					
Numeracy	0.405***	0.313***	0.328***	0.409***	1.000				
Financial literacy	0.340***	0.337***	0.428***	0.583***	0.521***	1.000			
Overconfidence	-0.014	-0.024**	-0.033***	0.019*	-0.031***	0.015	1.000		
Mean reversion	-0.029***	-0.056***	-0.026***	-0.034***	-0.080***	-0.102***	0.004	1.000	
Better next year	0.058***	0.036***	-0.017***	0.015**	0.024**	0.037***	0.032***	-0.002	1.000

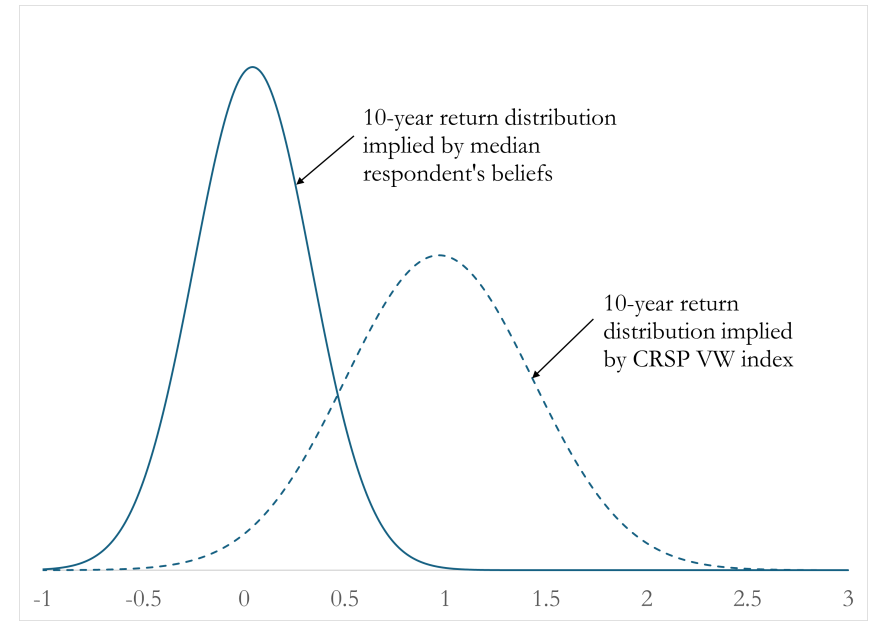
TABLE IA-VIII – UNCERTAINTY AND TIME

This table reports descriptive statistics for ALP survey results between August 2006 and November 2007 regarding respondents' uncertainty beliefs around different events in the next year or 5 years. Events considered include the likelihood of a car accident, having a cavity filled, dying, being a victim of theft, moving, dying from terrorism, having their home broken into, or visiting the dentist. Sample sizes for each event are reported in column (1). Median respondents' beliefs about event risk are reported in columns (2) through (5). Beliefs for the next year and 5 years are given in columns (2) and (4), respectively. Column (3) reports the implied 5-year probability given independence and the reported 1-year probability response. Column (5) reports the difference between the median implied and median reported 5-year probabilities. Columns (6) through (9) report analogous results for mean beliefs. Column (10) reports the fraction of respondents with a positive difference between the implied and reported 5-year probabilities. Significance at the 1% level is indicated by *** for the test that the fraction reported in column (10) does not differ from 50%.

	N	Median				Mean				%>0
		P(1-year)	Implied P(5-year)	P(5-year)	Difference	P(1-year)	Implied P(5-year)	P(5-year)	Difference	
Description	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
P(car accident)	859	0.200	0.672	0.300	0.372	0.278	0.673	0.352	0.321	0.934***
P(cavity filled)	642	0.200	0.672	0.500	0.172	0.302	0.665	0.492	0.173	0.815***
P(die)	838	0.100	0.410	0.200	0.210	0.207	0.523	0.279	0.244	0.870***
P(theft victim)	818	0.250	0.763	0.300	0.463	0.306	0.676	0.355	0.321	0.941***
P(move)	390	0.100	0.410	0.200	0.210	0.153	0.393	0.312	0.081	0.679***
P(die terrorism)	610	0.050	0.226	0.100	0.126	0.107	0.326	0.146	0.180	0.931***
P(break in victim)	813	0.100	0.410	0.150	0.260	0.154	0.443	0.220	0.223	0.888***
P(visit dentist)	190	0.500	0.969	0.750	0.219	0.560	0.851	0.670	0.180	0.932***



(A) ALP median respondent's 1-year return distribution



(B) ALP median respondent's 10-year total return distribution

FIGURE IA-1 – HISTORICAL AND PERCEIVED RETURN DISTRIBUTIONS FOR ALP RESPONDENTS. Panel A reports the distribution of 1-year returns implied by the first two moments of the CRSP value-weighted annual return over the 1926–2024 period (dashed red line) and the imputed 1-year distribution based on the median ALP respondent's beliefs over the 2008–2016 period (solid red line). Panel B reports the distribution of 10-year total returns implied by the first two moments of the CRSP value-weighted index 10-year return over the 1926–2024 period (dashed blue line) and the implied 10-year total return distribution based on the median ALP respondent's beliefs over the 2008–2016 period (solid blue line). The compression of near- and long-term uncertainty implied by these distributions is summarized in Figure 1 of the main text.

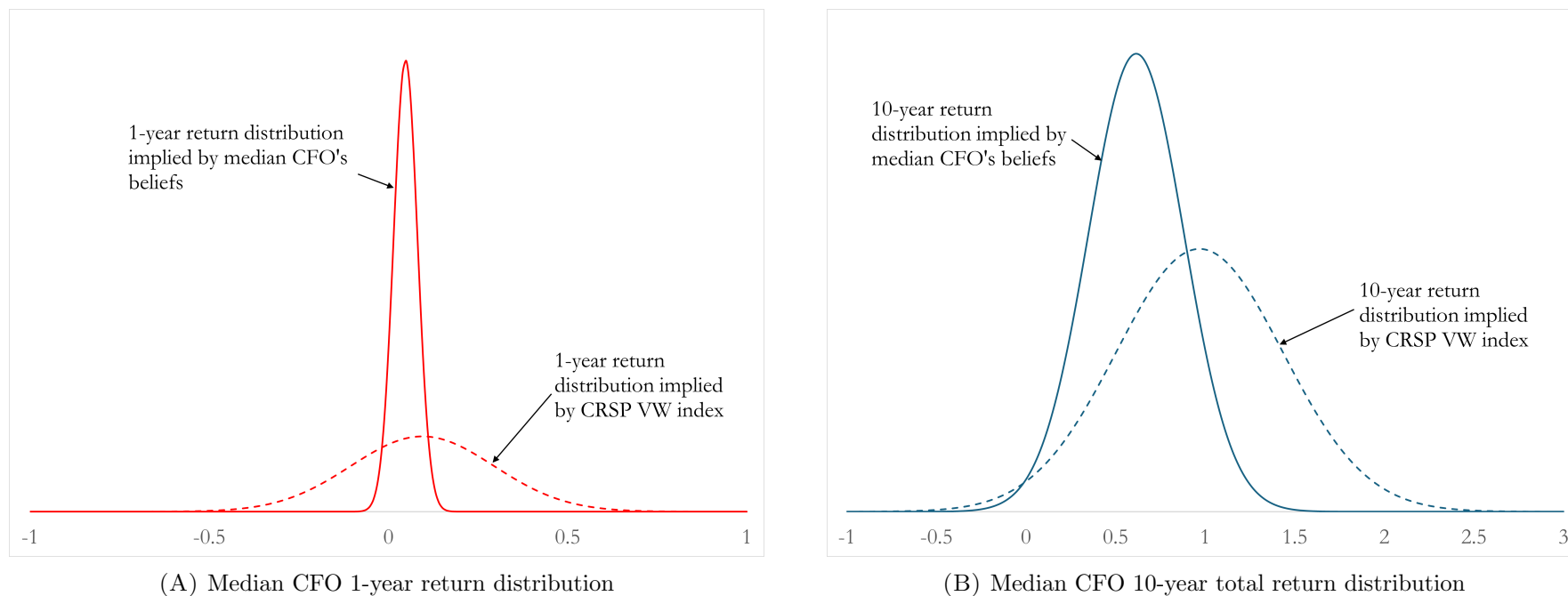


FIGURE IA-2 – HISTORICAL AND PERCEIVED RETURN DISTRIBUTIONS FOR CFOs. Panel A reports the distribution of 1-year returns implied by the first two moments of the CRSP value-weighted annual return over the 1926–2024 period (dashed red line) and the imputed 1-year distribution based on the median CFO’s beliefs over 2004–2019 (solid red line). Panel B reports the distribution of 10-year total returns implied by the first two moments of the CRSP value-weighted index 10-year return over the 1926–2024 period (dashed blue line) and the implied 10-year total return distribution based on the median CFO’s beliefs over 2004–2019 (solid blue line). The compression of near- and long-term uncertainty implied by these distributions is summarized in Figure 2 of the main text.

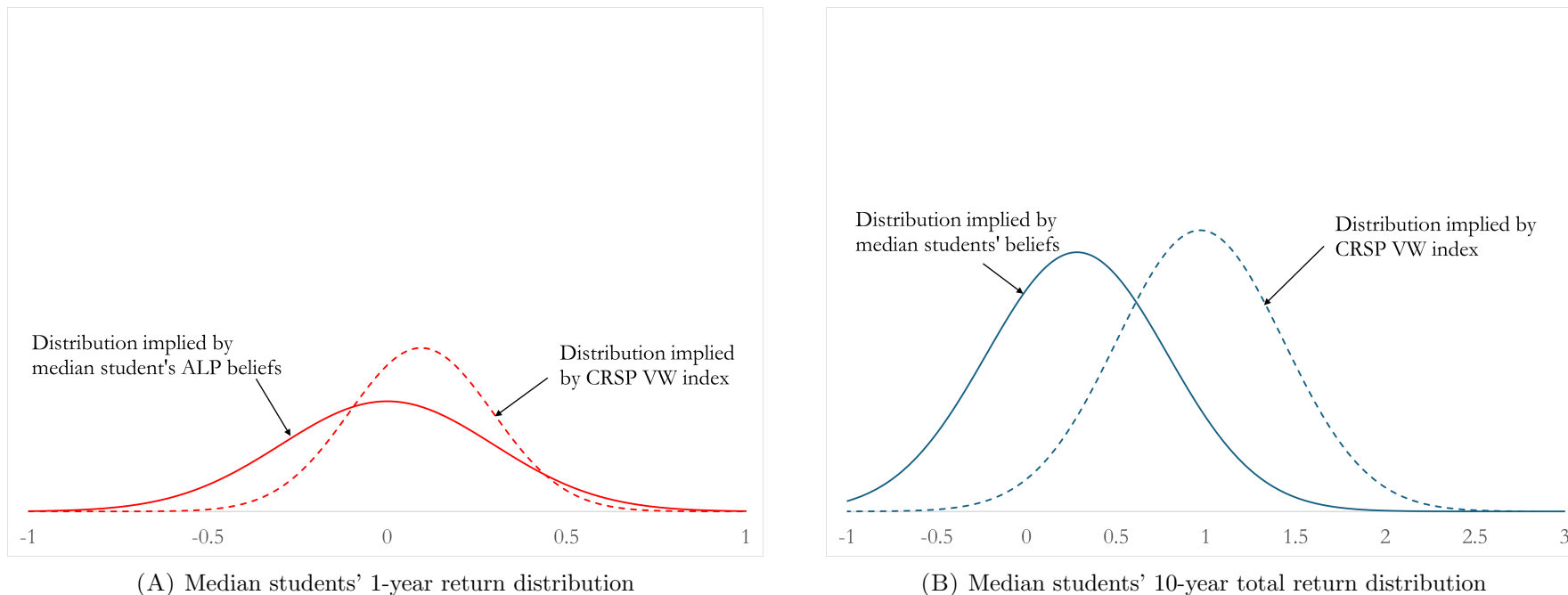
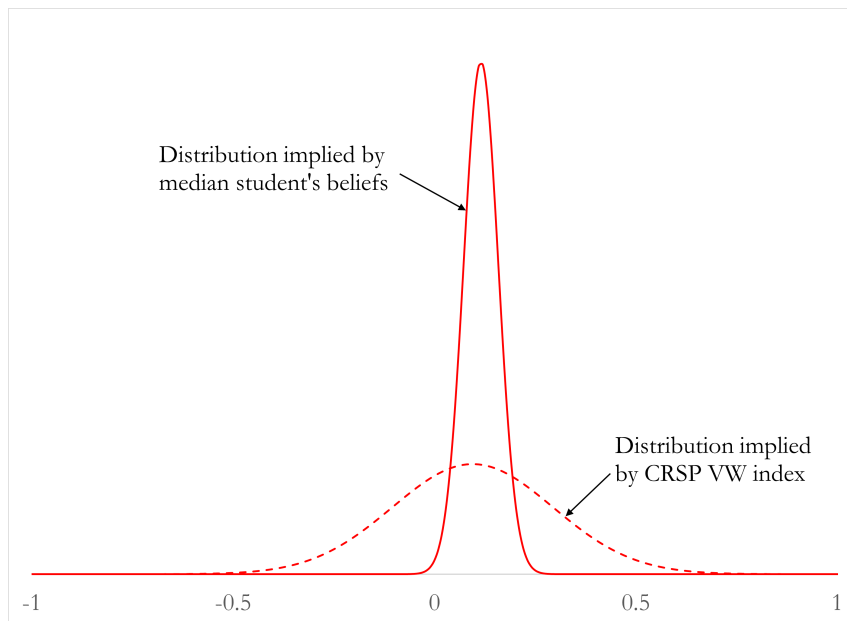
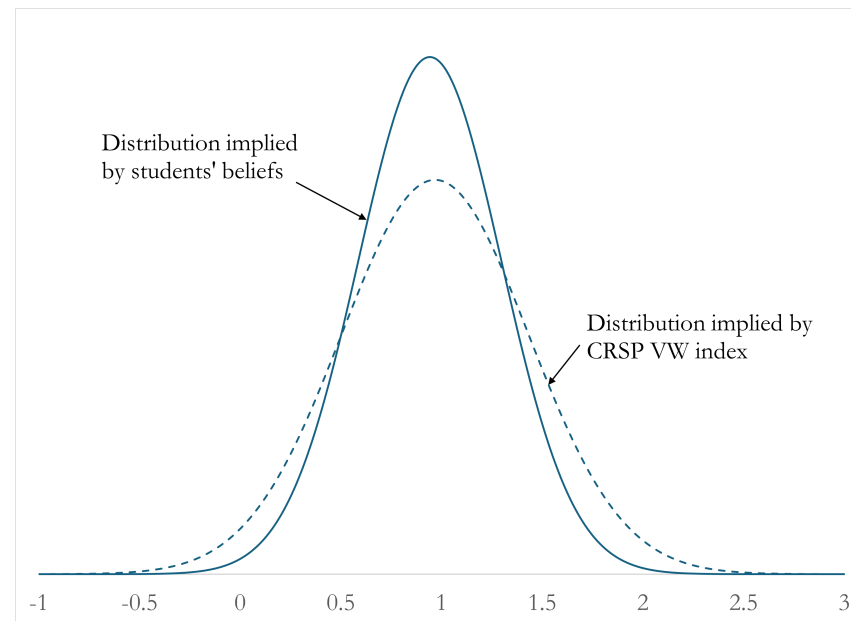


FIGURE IA-3 – HISTORICAL AND PERCEIVED RETURN DISTRIBUTIONS FOR STUDENTS BASED ON PROBABILITY ELICITATION TOTAL RETURN QUESTIONS. Panel A reports the distribution of 1-year returns implied by the first two moments of the CRSP value-weighted annual return over the 1926–2024 period (dashed red line) and the imputed 1-year distribution based on the median students' beliefs over spring–fall 2024 (solid red line). Panel B reports the distribution of 10-year total returns implied by the first two moments of the CRSP value-weighted index 10-year return over the 1926–2024 period (dashed blue line) and the implied 10-year total return distribution based on the median students' beliefs over spring–fall 2024 (solid blue line). The compression of near- and long-term uncertainty implied by these distributions is summarized in Panel A of Figure 3 of the main text.

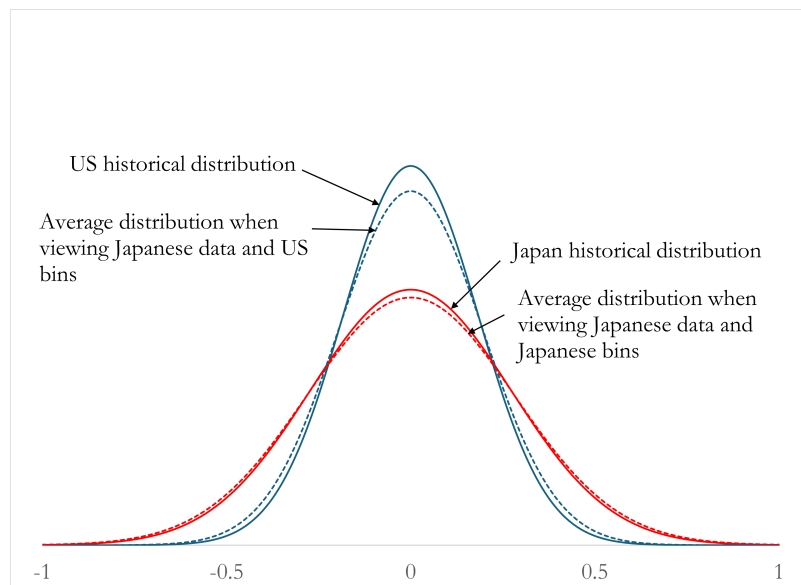


(A) Median student's 1-year return distribution based on quantile elicitation average annual return questions

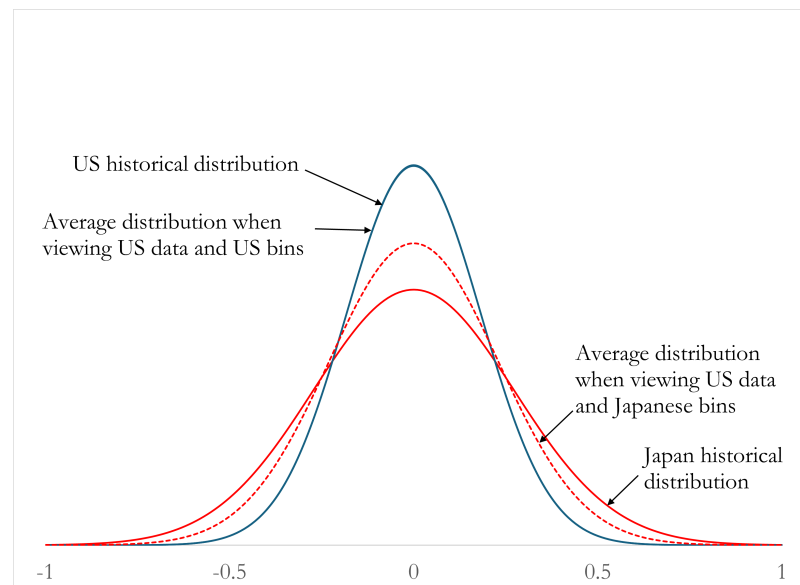


(B) Median student's 10-year total return distribution based on quantile elicitation average annual return questions

FIGURE IA-4 – HISTORICAL AND PERCEIVED RETURN DISTRIBUTIONS FOR STUDENTS BASED ON QUANTILE ELICITATION AVERAGE ANNUAL RETURN QUESTIONS. Panel A reports the distribution of 1-year returns implied by the first two moments of the CRSP value-weighted annual return over the 1926–2024 period (dashed red line) and the imputed 1-year distribution based on the median student's beliefs (solid red line). Panel B reports the distribution of 10-year total returns implied by the first two moments of the CRSP value-weighted index 10-year return over the 1926–2024 period (dashed blue line) and the imputed 10-year total return distribution based on the median student's beliefs (solid blue line). The compression of near- and long-term uncertainty implied by these distributions is summarized in Panel B of Figure 3 of the main text.



(A) Inferred return distributions for respondents who view Japanese historical returns, by bin definition



(B) Inferred return distributions for respondents who view US historical returns, by bin definition

FIGURE IA-5 – SENSITIVITY OF INFERRED STANDARD DEVIATION TO BIN DEFINITIONS. Respondents in Hartzmark and Sussman (2026) sequentially view 100 years of either historical US or Japanese returns in random order, then allocate balls across bins to reflect what they observed. Panel A reports results for respondents who view Japanese historical returns; Panel B reports results for respondents who view US historical returns. In each panel, the solid line reports the inferred distribution when bins are defined to match the historical data the respondent actually viewed, and the dashed line reports the inferred distribution when bins are instead defined to match the other country’s historical data. The red (blue) lines correspond to bins formed to match historical Japanese (US) data. For example, the Japanese bins are defined as $<-42\%$, -42 to -28% , $\dots$, $>62\%$, while the US bins are defined as $<-23\%$, -23 to -15% , $\dots$, $>39\%$. Historical standard deviations are as reported in Hartzmark and Sussman (2026) and mean inferred standard deviations are based on the authors’ Appendix A10.