Long-Term Expectations

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ABSTRACT

Perceived long-term (ten-year horizon) return distributions are remarkably bearish and most individuals believe that uncertainty is only marginally greater in the long term than the near term (one-year horizon), resulting in inferred variance ratios that require unprecedented levels of mean reversion. Although respondents' near-term beliefs are extrapolative, long-term beliefs are counter-cyclical. Long-term beliefs are more important than near-term beliefs in explaining equity market participation. Respondents agree more about long-term than near-term returns and respondents' characteristics better explain long-term, versus near-term, belief heterogeneity. These patterns have important implications for understanding household finance and both behavioral and traditional asset pricing.

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Long-Term Expectations

Time-series and cross-sectional variation in individuals' beliefs regarding the distribution of returns play a central role in household finance, rational asset pricing models, and behavioral asset pricing models. Extant evidence reveals that individuals' return beliefs exhibit substantial heterogeneity, tend to be bearish relative to historical values, are extrapolative (i.e., positively related to lag returns), are inversely related to traditional economic measures of expected returns (such as the dividend to price ratio), play an important role in the equity market participation decision, and are associated with respondent characteristics. As pointed out by Nagel (p. 2128, Brunnermeier et al., 2021), although asset prices should be a function of expectations over long horizons, empirical work examining beliefs almost universally focuses on respondents' views of equity markets in the near-term (typically the following year).

Using 3,859 individuals' perceptions of return distribution probabilities (i.e., their perceived likelihood markets rise, rise 20%, or fall 20%) for an 87-month sample period, we examine and compare both time-series and cross-sectional variation in individuals' beliefs about the distribution of long-term equity market returns (over the next decade) versus their beliefs regarding the distribution of near-term returns (over the next year). We begin by investigating how long-term beliefs compare to historical values and near-term beliefs as well as the associated implications for serial correlation in equity returns. Next, we consider how time-series variation in lag market returns, market valuation levels, and market risk impact time-series variation in individuals' near- and long-term beliefs and the associated implications for both behavioral and traditional asset pricing theory. Our last set of tests focus on cross-sectional variation in beliefs to (1) examine the relative importance of near- and long-term beliefs in driving stock market participation, (2) investigate the role of signals in driving belief heterogeneity by exploiting the differences in near- and long-term beliefs, and (3) better understand why long-term beliefs differ so dramatically from historical values.

Consistent with previous work, our initial tests reveal the typical individual perceives an expected one-year return that is lower than the historical average and one-year uncertainty that is slightly greater than the historical average. Long-term views for the vast majority of respondents, however, are orders of magnitude different than historical values. Individuals severely underestimate (relative to historical values) both long-term expected returns and long-term return uncertainty. As a result, the typical individual's perceived distribution of long-term equity returns imply that, relative to historical averages, they are effectively *certain* that U.S. equity markets will underperform over the next decade. Moreover, the relative certainty of the perceived distribution of long-term returns means that the variance ratio implied by the typical respondent's beliefs is only possible if markets exhibit unprecedented levels of mean reversion.

Our second set of tests focuses on time-series variation in long-term expectations and the implications for how households form beliefs and for both traditional and behavioral asset pricing models. Previous work (e.g., Vissing-Jorgensen, 2003; Greenwood and Shleifer, 2014; Amromin and Sharpe, 2014; Adam, Matveev, and Nagel, 2020) finds that time-series variation in the typical individuals' perception of near-term expected returns is positively related to both lag market returns (i.e., most individuals extrapolate returns) and market valuation levels (i.e., most individuals are more bullish when markets are richly valued). As Barberis, Greenwood, Jin, and Shleifer (2015) point out, these findings are consistent with behavioral models of return extrapolation, but inconsistent with both (1) traditional models of rational time-varying expected returns based on habit, long-run risk, or rare disasters, and (2) behavioral models of extrapolation of fundamentals, prospect theory, ambiguity aversion, and noise trader risk. We find very different results, however, when examining time-series variation in the perceived distribution of long-term returns. In contrast to pro-cyclical near-term beliefs, long-term return beliefs are counter-cyclical—the typical individual's expectations regarding long-term returns are higher following poor market performance, when market valuations are low, and when market risk is high.

Our data also allows us to investigate how time-series variation in the typical respondent's perceived uncertainty varies with market conditions. Consistent with economic theory, the typical individual's perception of near-term return uncertainty tends to be inversely related to lag returns and market valuation levels, but positively related to expected market volatility (i.e., VIX). The relation for long-term uncertainty, however, is asymmetric—when markets are cheap (or lag returns are low), respondents perceive a higher likelihood of a strong long-term return (i.e., increased right-tail likelihood), but a slightly lower likelihood of an extremely poor (i.e., decreased left-tail likelihood) long-term return.

The time-series tests provide a startling new dimension to the evidence relating individuals' beliefs to lag returns, market valuation levels, and market risk. For example, the results are consistent with the explanation that although respondents perceive both a decline in near-term returns and an increase in near-term volatility when valuation levels and lag returns are low, they also recognize the long-term risk premium is high because near-term risk is high and markets are cheap. Interestingly, the pattern (although not the magnitude) in respondents' perceptions largely match the empirical evidence, i.e., market returns are associated with near-term momentum and long-term reversals (e.g., Lo and

MacKinlay, 1988; Poterba and Summers, 1988; Moskowitz, Ooi, and Pedersen, 2012). Regardless, the conflicting near- and long-term belief patterns imply that the relations between lag returns, valuation levels, and investors' beliefs are more complex than previously recognized or modeled.

We begin our cross-sectional tests by evaluating the relation between stock market participation and both near- and long-term beliefs. Theoretically, it is not clear whether equity participation decisions should be more strongly related to near- or long-term beliefs. Nagel (see Brunnermeier et al., 2021) points out that perceived valuations (that should directly impact the decision to invest in equities, e.g., see Dominitz and Manski, 2007) depend on long-horizon beliefs (i.e., the present value of all future cash flows). In contrast, individuals can adjust positions at any point in time based on their near-term expectations. For example, if an individual is bullish about the next 12 months but bearish thereafter, the individual could hold equities now, but liquidate in one year. In such a case, long-term expectations may be unimportant once controlling for near-term expectations. Consistent with previous work, near-term expected returns are strongly positively related to equity market participation. Consistent with Nagel's intuition, however, equity market participation is much more strongly related to long-term return beliefs than near-term return beliefs. For example, in a regression of equity market participation on standardized (to allow direct comparison of coefficients) one- and ten-year respondent expected returns, the coefficient associated with expected returns over the next decade is nearly five times the magnitude of the coefficient associated with expected returns over the next year. Similarly, the fraction of assets allocated to equity (when including all respondents or when limited to those who participate in equity markets) is strongly related to long-term expected returns but does not exhibit a meaningful relation with near-term expected returns. In short, the participation decision is much more strongly related to long-term return beliefs than near-term return beliefs.

A number of behavioral models (e.g., Hong and Stein, 1999; Hirshleifer and Teoh, 2003; Basak, 2005; Scheinkman and Xiong, 2013; Atmaz and Basak, 2018; Martin and Papadimitriou, 2019) assume differences in signals play an important role in driving belief heterogeneity. The near- and long-term beliefs' data provide a unique opportunity to better understand the role of signals versus priors in belief formation.[1] Specifically, at a fundamental level, heterogeneity in expectations reflects differences

[1] We do not assume survey respondents have material private information regarding equity markets—rather, as Hong and Stein (2007) point out, heterogeneity in signals can arise from gradual information flow, limited attention, variation in access to information, and differential interpretation of the same information. The term "heterogeneous priors" is subject to a difference in semantics in the literature. To be clear, we follow Patton and Timmermann (2010) who suggest that "heterogeneous priors" imply that absent any signal, "…each forecaster comes with prior beliefs…" regarding the distribution of returns. Thus, heterogeneity in the interpretation of any information, even if shared across individuals, is a

in prior beliefs or differences in signals.[2] As pointed out by Patton and Timmermann (2010), the latter will have a greater impact on dispersion in near-horizon beliefs than dispersion in long-horizon beliefs as signals are, by their nature, temporary. Thus, if respondents have diverse, but constant, expected returns (i.e., signals play no role in belief dispersion), the cross-sectional standard deviation of 10-year expected returns is mechanically ten times the cross-sectional standard deviation of one-year expected returns. In contrast, if signals play a meaningful role in belief dispersion, then respondents will agree more about long-term expected returns than near-term expected returns. Our test suggests signals play an important role in belief heterogeneity as the cross-sectional dispersion in ten-year expected returns is approximately one-quarter the expected value under the null that signals play no role in belief dispersion (and therefore dispersion is proportional to horizon).

Our last set of tests examine how respondent characteristics relate to heterogeneity in near- and long-term beliefs with the goals of (1) providing an additional test of the hypothesis that signals play an important role in driving belief heterogeneity and (2) better understanding why variance ratios inferred from near- and long-term beliefs differ so substantially from historical values. Because signals are, by definition, mean zero (over time), signals should be independent of respondent characteristics. For example, assume better educated respondents pay more attention to financial news—better educated respondents will be more bullish than others when their signal is positive and more bearish than others when their signal is negative. Thus, on average, better educated respondents receiving more (or stronger) signals cannot explain a relation between education levels and beliefs.[3] Better educated respondents' superior knowledge of the historical stock market record, however, can explain a systematic relation between education and beliefs, i.e., better educated respondents may hold higher priors due to their better understanding of the stock market. In short, if signals play a meaningful role in explaining belief dispersion, respondent characteristics will be more strongly related to long-term beliefs (where signals play a smaller role and priors play a larger role) than near-term beliefs. Our empirical tests provide strong support for this hypothesis. For example, a year of additional education is associated with a 5.4% standard deviation higher long-term expected return versus a 3.1% standard

form of "differences in signals" in our study, and theirs. In contrast, for example, Hong and Stein (2007) denote different interpretations of the same information as "heterogeneous priors."

[2] By prior beliefs we mean the portion of the variation in expected returns across individuals that is stable over time, and in particular, does not vary with the current economic state. For example, individuals who grow up in a period with poor equity returns may hold more bearish views than individuals who grow up in a period with strong equity returns (e.g., Malmendier and Nagel, 2011).

[3] In this scenario, signals are sometimes positively cross-sectionally associated with education and sometimes negatively cross-sectionally associated with education and, on average (over time), independent of education.

deviation higher expected near-term expected return (and the difference is statistically significant at the 1% level).

Last, we further exploit the relation between respondent characteristics and beliefs to better understand why most individuals' perceptions generate variance ratios that differ so substantially from historical values. Specifically, there are at least three reasons a respondent's variance ratio will differ from unity. First, Pástor and Stambaugh (2012) demonstrate parameter uncertainty (e.g., unknown true expected annual future returns) implies an investor should be more uncertain about long-run returns, i.e., an individual's variance ratio computed from their perceived near- and long-term return distributions *should* be greater than the variance ratio based on the historical return data. Second, respondents may believe long-term returns are mean-reverting as historical long-term variance ratios are less than one (e.g., Siegel, 2014). Third, individuals may not understand the relation between time and uncertainty (e.g., variance is directly proportional to time in a serially uncorrelated world). Inconsistent with the hypothesis that parameter uncertainty has a meaningful impact on most individuals' long-term expected return uncertainty, more than four out of five respondents perceive return distributions that imply variance ratios less than historical values. In contrast, we find substantial support for the hypothesis that the failure to understand the relation between time and uncertainty contributes to the small variance ratios as respondents who are more likely to understand markets—those with higher income, higher numeracy, and those who own equities—exhibit meaningfully larger variance ratios than their lower income, lower numeracy, and non-equity-market-participating contemporaries. Further consistent with the hypothesis that numeracy impacts perceived return beliefs, respondents with smaller variance ratios tend to underestimate the likelihood they will experience a car accident in the next five years relative to the implied likelihood computed from their perceived likelihood of a crash in the next year. Nonetheless, the low implied variance ratio patterns persist even when the sample is constrained to high income respondents, high numeracy respondents, and respondents who hold equities. For example, when we limit the sample to the 36% of respondents who report annual income in excess of $75,000, 87% report beliefs that imply variance ratios less than unity and 78% report beliefs that imply variance ratios less than the historical market variance ratio. In sum, the results suggest that both (1) the failure to understand the relation between time and uncertainty and (2) beliefs that markets are mean-reverting contribute to the low inferred variance ratios.

Our work contributes to the household finance, behavioral finance, and traditional asset pricing literatures. Although there is extensive evidence that time-series variation in individuals' near-term return beliefs is positively related to lag returns and market valuation levels (properties we observe in our data as well), individuals appear to recognize that the market risk premium is higher following poor market performance, when market valuation levels are low, and when VIX is high. These results have implications for both behavioral and traditional finance theory. For example, investors extrapolating returns underlie many of the classic behavioral models (De Long, Shleifer, Summers, and Waldmann, 1990; Cutler, Poterba, and Summers, 1990; Barberis, Shliefer, and Vishny, 1998; Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999) as well as more recent models of investor behavior (e.g., Barberis, Greenwood, Jin, and Shleifer, 2018, or Jin and Sui, 2021) and bubble formation (e.g., Abreu and Brunnermeier, 2003) and, as noted above, there is substantial empirical evidence that the typical individual extrapolates (near-term) returns.[4] Consistent with our evidence, several recent behavioral theories (e.g., Kyle, Obizhaeva, and Wang, 2020; Daniel, Hirshleifer, and Sun, 2020; Bordalo, Gennaioli, La Porta, and Shleifer, 2020) emphasize that near- and long-term perceptions may differ. As far as we are aware, however, no model contains retail investors who simultaneously view low lag returns or low valuation levels as a negative signal for near-term returns but a positive signal for long-term returns. Our results, for example, are consistent with a model where individuals suffer from a "now is not the time" bias—recognizing that although the expected long-term market premium is high, near-term uncertainty is also high and prices may drop even further in the near term.

Our results also have implications for more traditional asset pricing, as models based on habit (e.g., Campbell and Cochrane, 1999), long-run risk (e.g., Bansal, Kiku, and Yaron, 2012) or rare disasters (e.g., Wachter, 2013) are inconsistent with the extant evidence that individuals' return expectations are lower after prices fall and when market valuation levels are low. This inconsistency, however, is limited to near-term beliefs—time-series variation in long-term beliefs is counter-cyclical as these models suggest. Moreover, one limitation of traditional tests of these models is the reliance on the view that realized returns, on average, reflect expected returns. That is, as Pástor and Stambaugh (2012) point out, "expected return is notoriously hard to estimate." Employing long-term expectations as the dependent variable overcomes this issue providing, arguably, a more powerful test and, at a minimum, a robustness test. Regardless, our results suggest that time-series variation in individuals' beliefs is more complicated than previously recognized or modeled and that individuals are more

[4] Although these models are often used to explain cross-sectional return patterns, Moskowitz, Ooi, and Pedersen (2012) point out these models can also explain the time-series patterns of near-term momentum and long-term reversals in market returns.

aware of the relation between lag returns, market valuation levels, and equilibrium returns than the near-term pro-cyclical extrapolation evidence suggests.

Our results also have implications for understanding household finance. The vast majority of individuals' perceptions of the distribution of long-term returns are far too bearish and unreasonably narrow implying variance ratios that are only possible if long-term market returns exhibit unprecedented levels of mean reversion.[5] Bearish long-term views may help explain the equity premium puzzle (e.g., Basak and Cuoco, 1998), as despite the bearishness, long-term beliefs are much more important than near-term expectations in explaining equity market participation. The examination of respondent characteristics and variance ratios reveals no evidence that parameter or conditional expected return uncertainty implies that, even when limiting the sample to high income, high numeracy, equity holders, most respondents perceive long-run returns as proportionally more volatile than near-term returns.

Our study also contributes to a large theoretical and empirical literature that demonstrates dispersion in beliefs has important implications for market efficiency and trading volume (e.g., see Atmaz and Basak's (2018) review of this literature). Consistent with signals playing an important role in belief heterogeneity (1) respondents agree much more about long-term beliefs than near term beliefs, and (2) respondent characteristics tend to be more strongly related to long-term beliefs than near-term beliefs. In short, comparing near- and long-term beliefs provides new evidence that dispersion in beliefs has both a fixed and transitory component with the latter having a greater impact on near-term belief dispersion.

The balance of our study is organized as follows. The following section provides a brief review of the closely related literature and discusses the data. Section II presents our initial tests comparing respondent perceptions of near- and long-term return distributions. Section III presents our examination of time-series relations and Section IV presents our investigation of cross-sectional relations. Section V provides discussion and robustness tests. Section VI concludes.

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[5] Respondents' overly narrow distribution (relative to historical norms) of perceived long-term returns is consistent with Ben-David, Graham, and Harvey's (2013) evidence that CFOs are much too confident in their long-term equity forecasts (what they call "miscalibration").

I. Background and Data

A. Investor Beliefs

Classic economic theory holds that rational individuals, using the same data and expected return model, form identical expectations (e.g., see discussions in Vissing-Jorgensen, 2003; Malmendier and Nagel, 2011; Brunnermeier et al., 2021). Inconsistent with this view, a broad literature reveals that individuals' beliefs are heterogeneous and this variation influences stock market participation (e.g., Vissing-Jorgensen, 2003; Dominitz and Manski, 2007; Hudomiet, Kezdi, and Willis, 2011; Hurd, Van Rooij, and Winter, 2011; Amromin and Sharpe, 2014; Lee, Rosenthal, Veld, and Veld-Merkoulova, 2015; Dimmock, Kouwenberg, Mitchel, and Peijnenburg, 2016). Moreover, individuals' near-term expected returns tend to be higher when lag market returns are high (i.e., extrapolative) and when markets are richly priced (e.g., De Bondt, 1993; Vissing-Jorgensen, 2003; Hurd, 2009; Hurd, Van Rooij, and Winter, 2011; Amromin and Sharpe, 2014; Greenwood and Shleifer, 2014; Giglio, Maggiori, Stroebel, and Utkus, 2020). Previous work also reveals that heterogeneity in beliefs is related to investor characteristics. White, more educated, and wealthier respondents, for instance, hold more optimistic views (e.g., Kezdi and Willis, 2008; Dominitz and Manski, 2005, 2007; Das, Kuhnen, and Nagel, 2020).

With a few notable exceptions, the vast majority of work studying beliefs focuses on the next year. Although primarily focusing on expected returns over the next 12 months, Vissing-Jorgensen (2003) also examines investors' ten-year expected returns between 1998-2002 (UBS/Gallup survey data) and finds that (1) the cross-sectional average ten-year expected return has lower time-series variation than the cross-sectional average one-year expected return, and (2) respondent age is inversely related to expected returns for both the near- and long-terms. Amromin and Sharpe (2014) consider longer-term expected returns for a sample of approximately 150 individuals per wave of the Michigan Surveys of Consumer Attitudes and Behavior between 2000-2005. This survey asks respondents for expected annual return for a "broadly diversified portfolio of U.S. stocks" over the next three years, followed by would they, "expect the average returns over the next 10 to 20 years to be much different?" If respondents answer yes, they are asked how much different? Greenwood and Shleifer (2014) also use the Michigan three-year expectations data (between 2000 and 2005) as one of six measures of investors' expected returns.[6] Although primarily focused on near-term expected returns, Giglio,

[6] Adam, Matveev, and Nagel (2020; Table 3) examine the relation between the price/dividend ratio and 28 surveys including four long-term horizon surveys. Although they conclude that "almost all" of the surveys and horizons exhibit "procyclical" expectations, the point estimates for the four long-term horizon surveys (Shiller's mean and median individual investor surveys and Shiller's mean and median professional investor surveys) are negative, albeit only one of

Maggiori, Stroebel, and Utkus (2021) incorporate some analysis of long-term expected returns based on a survey of Vanguard investors. Similarly, Dahlquist and Ibert (2022) also find evidence of counter-cyclical long-term beliefs amongst a small survey of large asset managers. In addition, John Graham and Campbell Harvey's well-known surveys ask CFOs to predict annual stock returns over both the next year and decade as well as the 80% confidence interval for those estimates. Ben-David, Graham, and Harvey (2013) find that CFOs are overconfident as both their one- and ten-year confidence intervals tend to be more narrow than historical values. The authors find little evidence that CFOs' near- or long-term expected returns are related to lag market returns. De La O and Myers (2021) also find evidence that one- and two-year I/B/E/S (aggregated) forecasts better explain time-series variation in the market's price-dividend and price-earnings ratios than one- and ten-year horizon CFO expected return expectations from the Graham and Harvey Global Business Outlook Survey.[7]

B. Data

Our primary dataset comes from the RAND American Life Panel (ALP), an ongoing nationally representative longitudinal panel that started in 2003. The initial (2003) sample of approximately 2,000 individuals has grown to more than 6,000 individuals over time (see Pollard and Baird (2017) for additional details regarding the ALP). Because respondents are compensated, completion rates—typically around 70%—are much higher than most surveys.[8] During the financial crisis in late 2008, ALP began surveying participants regarding the "Effects of the Financial Crisis." The first "wave" of data collection began in November 2008 and the final wave ends in 2016. ALP executed this survey for a total of 61 waves (i.e., there are 61 data collection points) in either long-form (29 waves) or short-form (32 waves) formats. The long-form wave questionnaires include six questions regarding both near- and long-term perceived stock market return distributions. Specifically, respondents are asked three questions about near-term beliefs:

> *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*

the four coefficients (professional investors' median) is statistically meaningful at the 5% level or better. These Shiller surveys are based on relatively small samples (e.g., 75 individual investors) and, contrary to the other surveys in their study (as well as the authors' overall conclusion), also exhibit counter-cyclical near-term expectations.

[7] Da, Huang, and Jin (2021) focus on the extrapolative patterns in even shorter-term individual stock return beliefs using crowd-source stock ranking data. They find extensive extrapolation evidence, especially among non-professionals.

[8] See https://www.rand.org/research/data/alp/panel/completion-rates.html.

-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?

Respondents are asked three analogous questions regarding returns over the next decade:

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 short-form wave questionnaires ask the three return probability questions for near-term returns, but only the first question (the likelihood equity markets are worth more in 10 years) for long-term returns.[9]

The surveys also collect data regarding respondents' gender, race, marital status, employment status, age, education, income, and equity ownership (including equity held directly and equity in pension/retirement accounts). In six of the surveys (executed in January 2011, 2012, 2013, 2014, 2015, and 2016), ALP also collected information regarding respondents' assets allowing us to compute the fraction of financial assets held in equites for this subsample. In addition, in six ALP (non-financial crisis) surveys between 2008 and 2018, ALP asked respondents to rate their numeracy (e.g., how strongly they agree with the statement, "I am good at mathematics"). We use each individual's average value from these six surveys as a measure of their numeracy. Appendix A provides details regarding construction of the respondent characteristic variables.

Table I reports descriptive statistics of respondent characteristics for our pooled cross-sectional time-series of 89,993 observations (from 3,859 individuals; the average respondent participates in more than 23 survey waves) that include any individual-survey wave observation where the respondent answers at least one of the six stock market expectations questions. Our sample is almost 59% female, nearly two thirds are married, approximately half are working, and the average respondent is 51 years old with 15 years of education. Income levels average slightly more than $68,000 (with an intraquartile range from $32,500 to 87,500) and 43% of respondents hold some equity.

[Insert Table I about here]

[9] Wave 44 of the survey was split into two portions (44.1 and 44.2). Only respondents to 44.1 were asked the likelihood that stock returns over the next decade would exceed 20% or fall by more than 20%.

II. The Perceived Distribution of Expected Long-Term Returns

The first three rows of Panel A in Table II report the number of waves, pooled cross-sectional time-series number of observations, mean, 25th percentile, median, 75th percentile, and standard deviation of respondents' answers to the likelihood of the market rising, rising more than 20%, and falling more than 20% over the next year. The penultimate column reports historical values based on the CRSP value-weighted index between 1926 and 2020. The final column reports the fraction of respondents who report perceived likelihoods lower than the associated historical value.[10]

[Insert Table II about here]

Consistent with previous work (e.g., Hurd, 2009; Das, Kuhnen, and Nagel, 2020; Hurd, van Rooij, and Winter, 2011; Kuhnen and Miu, 2017), individuals' near-term beliefs tend to be more bearish than historical values—the typical (median) respondent believes markets are as likely to fall as rise in the next year compared to a historical likelihood of 75%. Moreover, as shown in the final column, 83% of respondents' perception of the likelihood markets rise in the next year is lower than this historical average. As shown in the second and third rows (second to last column), markets have increased by more than 20% approximately once every three years and fallen by more than 20% only once every 16 years—historically, markets are 425% more likely to rise by 20% than fall by 20% (i.e., 0.330/0.063-1=4.25). The typical respondent, however, underestimates (relative to the historical values) the upside likelihood and overestimates the downside likelihood such that the median respondent perceives the likelihood of a 20% loss is the same as the likelihood of a 20% gain.

Following previous work (e.g., Ben-David, Graham and Harvey, 2013), we assume perceived returns are normally distributed and infer each respondent's perceived expected return distribution from their two outside probability estimates.[11] Specifically, we estimate the perceived distribution of continuously compounded expected returns from the respondent's estimates of the likelihoods of a

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[10] We report historical values based on total returns. As detailed in the Internet Appendix, we find nearly identical results when examining returns excluding dividends.

[11] Ben-David, Graham, and Harvey (2013) estimate CFOs' standard deviation of perceived expected return distributions based on two questions regarding S&P 500 returns: "There is a 1-in-10 chance the actual return will be less than __%" and "There is a 1-in-10 chance the actual return will be greater than __%." Thus, different from the ALP data we use that gives a return and asks for a likelihood (e.g., chance market earns more than 20%), the CFO survey gives a likelihood and asks for a return (e.g., 1-in-10 chance return will be greater than __%). Inferring perceived expected return distributions from either uses the same process, i.e., there is a unique normal distribution that fits any pair of return probability beliefs. See Cook (2010) for details. Note also that Ben-David, Graham, and Harvey assume discrete returns are normally distributed.

gain greater than 20% or a loss greater than 20% at both the one- and ten-year horizons.[12,13] The mapping of probability estimates into return distribution moments requires, of course, that a respondent's perceived likelihoods satisfy basic probability laws, e.g., the sum of probabilities cannot exceed 100%.[14] Approximately 75% of the near-term forecasts and 69% of the long-term forecasts are consistent with probability laws and allow us to estimate the mean and variance of the perceived distribution of near-term returns and long-term returns for each respondent at each point in time.[15] Because estimation of distributional parameters can generates extreme values, we winsorize (at the 5th and 95th percentiles) the estimates of respondents' implied perceptions of the mean and standard deviation of the distribution for near- and long-term returns.

Consistent with the first three rows, the bottom two rows of Panel A reveal that individuals' return likelihood perceptions translate into perceived expected returns and standard deviations that are more bearish than historical distributions. For instance, 86% of respondents report probabilities that imply their expected return belief in the next year is below the historical average continuously compounded one-year return. In addition, the results suggest that the typical individual perceives the distribution of expected one-year returns has slightly greater volatility than the historical one-year return distribution, e.g., 56% (1-0.44) of respondents' inferred distributions yield a standard deviation that is greater than the historical standard deviation of one-year returns. The left panel in Figure 1 summarizes these results. Using the mean and standard deviation of the CRSP value-weighted index, the blue line reports the implied historical distribution for continuously compounded one-year U.S. equity returns. The red line is computed from the median estimated perceived expected return and standard deviation. In

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12 We assume continuous returns are normally distributed (i.e., discrete returns are log-normally distributed) because (1) we are interested in variance ratios, (2) the central limit theorem implies continuously compounded returns will be normally distributed at long horizons (e.g., Fama and French, 2018), and (3) realized long-term discrete returns more closely resemble log-normal distribution than a normal distribution.

13 Because we focus on continuously compounded returns, we convert respondents' estimates of the likelihood of discrete returns to continuously compounded returns when estimating the respondent's perceived distribution of near- or long-term expected returns. Specifically, a respondent's likelihood of a 20% or greater gain in (discrete) prices is equivalent to the respondent's likelihood of a continuously compounded return of 18.2% (i.e., ln(1.2)) and the reported likelihood of a 20% or greater fall in prices is equivalent to the respondent's likelihood of a -22.3% (i.e., ln(0.8)) or worse continuously compounded return.

14 Specifically, there are two (non-mutually exclusive) scenarios that are inconsistent with probability laws: (1) the sum of the probabilities is greater than or equal to 100% or (2) the perceived likelihood of a 20% gain or a 20% loss is zero.

15 As noted above, we follow Ben-David, Graham, and Harvey (2013) and use the two outside return likelihoods to estimate the perceived distribution of expected returns. It is also possible to estimate the perceived distribution using all three likelihood estimates by minimizing the sum of squared errors (see, e.g., Dominitz and Manski, 1997). The limitation of the three-point estimate is that a greater number of individuals are excluded from the analysis due to violation of basic probability laws (e.g., the respondent reports a 70% chance the market rises and a 30% chance the market falls by more than 20%). Given our desire to capture the views of the greatest number of individuals, we focus on two-point estimates. As detailed in the Internet Appendix, the two- and three-point estimates are similar. For example, the correlation between the two- and three-point estimates of expected returns and standard deviations range from 0.84 to 0.92.

short, the median respondent's perceived expected return is more bearish than the historical distribution. More than 69% of the area under the red curve lies to the left of the mean of the blue curve implying that the typical respondent believes there is a less than one in three chance returns in the next year will be at least as high as the market's historical average.[16]

[Insert Figure 1 about here]

Panel B in Table II reports analogous statistics for respondents' perceptions of the distribution of expected equity returns over the next decade. The results reveal that, relative to historical values, the typical individual severely underestimates both long-term expected returns and long-term return volatility. For example, the median respondent perceives only a 50/50 chance that the market increases more than 20% in the next decade versus a 93% historical likelihood (second to last column).

The bottom two rows of Panel B reveal that the median respondent's perception of the ten-year expected return distribution has an expected value of 3.2% (i.e., 0.32% annually) and standard deviation of only 29.1%—both values are substantially smaller than the historical ten-year average continuously compounded return of 96.2% and standard deviation of 47.4%. The right panel in Figure 1 summarizes the results in Panel B—the red line reports the ten-year continuously-compounded perceived distribution based on median beliefs about the mean and variance and the blue line reports the distribution based on historical ten-year mean and variance of the CRSP value-weighted index. The median respondent's beliefs regarding returns over the next decade suggest they are effectively certain returns in the next decade will underperform historical averages, i.e., more than 99.9% of the area under the red curve lies to the left of the mean of the blue curve. Although the perceived long-term return distribution for the median respondent has only a small amount of overlap with the left tail of the empirical long-term return distribution, the perceived near-term return distribution exhibits substantial overlap with the empirical near-term return distribution. Nonetheless, long-term expected returns are more optimistic than near-term expected returns. That is, given returns are continuous, ten times the one-year median respondent expected return (i.e., -20% = -2% × 10 years) is substantially smaller than the perceived 10-year expected return (3.2%) and both are orders of magnitude smaller than the historical average 10-year continuous return (96.2%).

[16] Sias, Starks, and Turtle (2022) investigate the role of the negativity bias in helping to explain this bearishness.

Because ALP captures perceived probabilities for both near- and long-term return distributions, we can estimate the ten-year variance ratio ($\sigma_{i,t}^2(\mathrm{r}_{10\text{ year}})/10)/\sigma_{i,t}^2(\mathrm{r}_{1\text{ year}})$) for *each* respondent.[17] Consistent with previous work (e.g., Poterba and Summers, 1988; Pástor and Stambaugh, 2012), the second to last column in Panel C reports long-term market returns exhibit substantial mean reversion—as the ten-year variance ratio for the continuously-compounded CRSP value-weighted index is 55.9% (versus 100% if returns were serially independent).[18] As shown in Panel C, however, the median respondent's perceived distributions imply a variance ratio of 14.6%—a value only possible if equity markets exhibit unprecedented levels of mean reversion.[19] Moreover, nearly nine out of ten (89%) of respondents report beliefs that imply variance ratios less than unity (bottom row) and more than four out of five (82%) respondents report beliefs that imply variance ratios less than the CRSP historical value (last column of top row in Panel C).

III. Time-Series Variation in Expectations

Previous work demonstrates that time-series variation in investors' near-term return beliefs is positively related to lag returns and inversely related to traditional expected return metrics such as the dividend-price ratio. As Barberis, Greenwood, Jin, and Shleifer (2015) point out (see their Table 1 and associated discussion), these results have important implications for asset pricing theory as the patterns are consistent with behavioral models of extrapolative returns, but inconsistent with behavioral models of extrapolation of fundamentals, prospect theory, ambiguity aversion, and noise trader risk as well as traditional asset pricing models based on habit, long-run risk, or rare disaster to explain time-varying required returns.

We begin to examine the time-series variation in near- and long-term beliefs by evaluating how they relate to lag returns—that is, does our sample exhibit return extrapolation in near-term beliefs

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[17] We denote respondent *i*'s period *t* belief about the expected one- and ten-year market returns as, $E_{i,t}(\mathrm{r}_{1\text{ year}})$ and $E_{i,t}(\mathrm{r}_{10\text{ year}})$, respectively. Analogously, we define beliefs about the variance of one- and ten-year market returns as, $\sigma_{i,t}^2(\mathrm{r}_{1\text{ year}})$ and $\sigma_{i,t}^2(\mathrm{r}_{10\text{ year}})$, respectively.

[18] Following previous work, we estimate the ten-year variance ratio for U.S. equities based on overlapping data at a monthly frequency. As pointed out by others, the long-term variance ratio estimate for U.S. equities is based on a small sample of independent observations and therefore is likely a noisy estimate of the true value. Our point, however, remains regardless of the limitations of the historical estimates—most respondents' perceived distributions are only possible if the market exhibits unprecedented levels of mean reversion.

[19] Consider a simple example of two subsequent 10-year periods. Returns in the first ten years consist of five years of 25.3% and five years of -19.3% generating a ten-year return of 30%. Returns in the second ten years consist of five years of 19.48% and five years of -25.12% generating a ten-year return of -28.2%. In this example, matching the median figures in Table II, annual returns exhibit a standard deviation of 22.5%, ten-year returns exhibit a standard deviation of 29.1%, and the initial ten-year gain is almost completely reversed over the subsequent 10 years (+30% followed by -28.2%).

consistent with previous work, and are long-term beliefs equally extrapolative? We also expand on this work by examining how time-series variation in respondents' perceptions of risk vary with lag returns. Our initial tests focus on beliefs about return probabilities as this sample (1) more closely matches the survey expectations used by Greenwood and Shleifer (2014), (2) includes all respondents (including those whose beliefs violate probability laws), and (3) includes the likelihood markets rise in the next year or decade in all 61 waves (versus the 29 waves where we can estimate long-term expected returns).[20] The sample period includes 66 different months over the 87-month period between November 2008 and January 2016.[21]

Table III reports estimates from univariate panel regressions of the perceived likelihoods of the market rising, rising more than 20%, and falling more than 20% over the next year or decade. To ensure we capture time-series (rather than cross-sectional) variation in beliefs, we "include" respondent fixed effects by de-meaning the time-series of each regressor for each respondent.[22,23] In addition, to allow direct of comparison across variables, we rescale each (previously demeaned by respondent) regressor to unit variance over all observations (which, of course, does not impact the associated *t*-statistic) such that the associated coefficient is the change in the dependent variable given a one standard deviation change in the independent variable. Standard errors are clustered by respondent.

[Insert Table III about here]

The first column of Panel A in Table III reveals, consistent with previous evidence, but inconsistent with traditional asset pricing theory and many behavioral models, that respondents hold more bullish near-term views following strong market performance. Specifically, a one-standard deviation higher lag six-month (12-month) return is associated with a 1.01% (0.52%) increase in the perceived likelihood markets rise over the next year (both are statistically significant at the 1% level). Consistent with traditional economic theory, however, the second and third column of the second

[20] For example, Greenwood and Shleifer (2014) compute expectations for the Gallup poll as the percentage of respondents who report being optimistic/very optimistic less the percentage reporting being pessimistic/very pessimistic.

[21] The first two ALP financial crisis surveys included November 2008 through March 2009. At that point, the surveys become monthly until April 2013 when they become quarterly.

[22] It is possible, for example, that some individuals are more likely respond to surveys when they are bullish. As a result, the cross-sectional average or median response may be related to lag return because of changing samples. Because the ALP data identifies respondents, we add respondent fixed effects to preclude this possibility. Nonetheless, as detailed in the Internet Appendix, we find similar results when using the cross-sectional median beliefs.

[23] Demeaning the regressors by respondent is identical to adding respondent fixed effects (see, for example, http://pages.stern.nyu.edu/~adesouza/sasfinphd/index/node60.html). Note also that because these respondent fixed effects limit the sample to those who respond in at least two surveys, the samples sizes in Tables III and IV (ranging from 25,030 to 89,409) are slightly smaller than the sample sizes in Table II (ranging from 25,560 to 89,633).

row reveals that lower returns over the previous year are associated with an increase in perceived uncertainty, i.e., higher lag returns are associated with a lower perceived likelihood of markets falling or rising more than 20% over the next year.[24]

The fourth column in Panel A repeats the analysis for the likelihood markets rise in the next decade and reveals a surprising result. Contrary to the relation documented for near-term returns (in both our data and previous work), time-series variation in the likelihood markets rise in the next decade is strongly inversely related to lag returns. For example, a one standard deviation higher lag six-month (12-month) return is associated with a 0.40% (1.57%) lower perceived likelihood markets rise in the next decade.[25] Further consistent with respondents recognizing that high lag returns are associated with lower expected returns, high lag returns are negatively related to the perceived likelihood of a 20% rise in prices in the next decade, but largely independent of the perceived likelihood of a 20% fall in prices in the next decade.

As detailed above, a number of studies report that individuals' near-term expected returns move inversely to market valuation measures (e.g., dividend to price ratio) inconsistent with rational asset pricing models of time-varying expected returns as well as many behavioral models. That is, individuals' perceived near-term expected returns are low when traditional measures suggest expected returns (and risk) are high.[26] Thus, we next investigate seven such measures—dividend yield, net payout yield, Lettau and Ludvigson's (2001) consumption-aggregate wealth (*cay*) ratio, Shiller's CAPE ratio, surplus consumption ratio computed from consumption data, surplus consumption ratio computed from options data, and VIX. All variables are measured at the end of the month prior to the survey and we multiply CAPE and both surplus consumption ratio variables by -1 such that a higher value for any of the valuation metrics implies higher expected returns/lower current valuation level. The CAPE data is from Robert Shiller's website, the *cay* data is from Martin Lettau's website, and Alex Kontoghiorghes generously provided both surplus consumption measures.[27] We follow Boudoukh, Michaely, Richardson, and Roberts (2007) to compute the market's monthly dividend yield

[24] Similarly, the results reveal that higher lag returns over the previous six months are associated with a decrease in the perceived likelihood of a 20% loss. There is also some evidence that high returns in the previous six months are associated with an increase in the perceived likelihood of a 20% gain (marginally significant at the 10% level).
[25] As detailed in the Internet Appendix, respondents exhibit consistency across their views, e.g., the correlation between the perceived likelihood that markets rise in the next year and the perceived likelihood markets rise in the next decade is 0.7.
[26] In rational asset pricing framework, these measures capture expected returns either because they capture time-series variation in risk aversion or time-series variation in risk.
[27] Kontoghiorghes (2019) finds that the surplus consumption ratio estimated from options data overcomes issues with consumption data and better captures the consumption-based asset pricing factor.

(dividends over the past 12 months/end of period market capitalization) and net payout yield (dividends plus repurchases less issuances over past 12 months/end of period market capitalization) and exclude financials. Further following these authors, we use the natural logarithm of both ratios.[28] The authors propose the net payout yield better captures valuation levels as firms have increasingly substituted share repurchases for dividends.

The univariate panel regression results in the first column of Panel B in Table III are fully consistent with the results of (almost all) previous studies and reveal that respondents hold more bullish near-term views when markets are richly valued and market risk is low. Specifically, the perceived likelihood of a positive market return in the following year exhibits a material (statistically significant at the 5% level or better) negative relation with all seven market valuation/risk measures. Once again, however, the relation changes dramatically when examining the likelihood markets rise in the next decade as the coefficients in the fourth column are all positive (and statistically significant at the 1% level). For example, a one standard deviation higher dividend to price ratio is associated with 0.42% lower likelihood markets rise in the next year, but a 1.94% higher likelihood markets rise in the next decade. The results in columns (2), (3), (5), and (6) also suggest that respondents perceive that low market valuations and high VIX are associated with increased near-term risk, but higher long-term expected returns. For example, a one standard deviation higher dividend to price ratio is associated with a 1.26% higher perceived likelihood markets rise by 20% in the next year and a 0.76% higher perceived likelihood markets fall by at least 20% in the next year. In contrast, a one-standard deviation higher dividend to price ratio is strongly positively related to the perceived likelihood of a 20% gain in prices over the next decade, but independent of the perceived likelihood of a 20% fall in prices in the next decade. In sum, the results in Panels A and B suggest that the typical respondent associates low valuation levels and low lag returns with lower perceived near-term returns, higher perceived near-term volatility, and higher perceived long-term returns.

Because the ALP is a nationally representative panel, fewer than half of the respondents hold any equities (see Table I). As a result, it is possible that ALP respondents' beliefs may have little relation to the beliefs of market participants. To examine this possibility, we follow Greenwood and Shleifer (2014) and compute the relation between respondent expectations and mutual fund flows. Specifically,

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[28] Specifically, we follow the method detailed in Michael Roberts' spreadsheet ("Updated Month TS" tab available at http://finance.wharton.upenn.edu/~mrrobert/styled-9/styled-13/index.html) to compute both monthly aggregate dividend yield and monthly aggregate net payout yield for non-financial ordinary firms (share codes 10 and 11). Following these authors, the natural logarithm of net payout ratio is given by ln(0.1+dy-ney) where dy is the dividend yield, and ney measures net equity issuance, both measured over the prior 11 months relative to current month market capitalization (see the referenced spreadsheet for greater detail).

we use Investment Company Institute data to compute monthly flows to equity mutual funds as total flows scaled by total net assets.[29] We also compute net exchanges from bond and money market funds to equity funds (scaled by total assets) as Ben-Rephael, Kandel, and Wohl (2012) propose that net exchanges—reflecting active decisions made by investors—better capture investors' views than net flows that also capture passive decisions (e.g., automated pension fund contributions). Consistent with Greenwood and Shleifer (2014), the first column of Panel C reveals a strong positive relation between the perceived likelihood markets rise in the next year and mutual fund flows or net exchanges (statistically significant at the 1% level). Once again, however, the results reverse when we consider the likelihood markets rise in the next decade. Specifically, although we find no evidence of a meaningful relation between fund flows and the perceived likelihood that markets rise in the next decade, a higher perceived likelihood of markets rising over the next decade (column 4) is associated with money moving from equity funds to bond funds.[30]

The relations between the likelihood of a 20% gain or loss in the next year (columns (2) and (3)) or decade (columns (5) and (6)) are largely consistent with the results in Panels A and B. Specifically, money flows from bond funds to equity funds when perceived near term risk is low (i.e., the likelihood of a 20% gain or loss in the next year is lower) and, as discussed above, respondents perceive the likelihood of a 20% gain in long-term returns is also low. In sum, the results in Panel C are largely consistent with the hypothesis that investors shift from equities to safer alternatives when they perceive greater uncertainty even though perceived long-term expected returns are higher. Mutual fund flows exhibit an identical pattern with the exception that flows are positively correlated with the perceived likelihood of a 20% rise in near-term returns.

Table IV repeats the univariate panel regression analysis replacing probability beliefs with inferred expected returns and standard deviations for the return distribution. This sample is limited to respondents who report probabilities that do not violate probability laws (i.e., those observations for which we can estimate the first two moments of the return distribution). Although the results in the first two columns are based on all 61 survey waves, the results in the last two columns are based on

[29] We follow Baker and Wurgler (2007) and define the following mutual fund types as equity: aggressive growth, growth, balanced, growth and income, sector, income equity, income mixed, and asset allocation.

[30] Our panel regression framework regresses individuals' beliefs regarding returns over the next year or the next decade on mutual fund (or net exchanges). In the Internet Appendix we regress flows (or exchanges) on the *average* perceived likelihood markets rise in the next year and next decade simultaneously, i.e., a time-series regression rather than the Table III panel that controls for respondent-specific effects. The results of the time-series regression reveal that net exchanges (and flows) are positively related to the average perceived likelihood markets rise in the next year but inversely related to the average perceived likelihood markets rise in the next decade.

the 29 long-form surveys in 35 unique months starting November 2008 and ending in January 2016 (i.e., over the same 87-month period as both the first and last surveys are long form).

[Insert Table IV about here]

Despite the sample differences, the long-term expected return results in Table IV are consistent with those in Table III. Inferred long-term expected returns rise with lower lag returns (Panel A) and cheaper valuations (Panel B). The results in the fourth column reveals a negative relation between lag return and the perceived standard deviation of long-term returns; but as shown in Table III, this is driven by the negative relation between lag returns and the likelihood of a 20% gain rather than increased perceived risk (i.e., the likelihood of a 20% fall in prices in the next decade). The results for near-term inferred expected returns are less consistent—inferred expected returns over the next year are positively related to returns over the previous six months but negatively related to returns over the previous year. Similarly, the first column in Panel B finds some evidence that low valuation/high risk is associated with higher near-term expected returns as the coefficients with dividend to price ratio, CAPE, and one of the surplus consumption ratios are positive and meaningfully different from zero. The coefficient on *cay*, however, is negative (and significant at the 1% level). Once again, the results appear to be related to the fact that most of the valuation metrics tend to be more strongly related to the perceived likelihood markets rise by 20% in the next year than fall by 20% in the next year.[31,32]

In sum, the results in the first column of Tables III and IV are inconsistent with traditional asset pricing models and many behavioral models but largely consistent with previous work demonstrating individuals tend to hold more bullish near-term beliefs when lag returns or market valuation levels are high. Surprisingly, however, these relations reverse when considering long-horizon beliefs. Moreover, perceived near-term risk tends to rise when lag returns, or valuations levels, are low. Thus, although time-series variation in near-term beliefs is inconsistent with traditional models of time-varying expected returns, time-series variation in both long-term expected returns and near-term uncertainty perceptions are largely consistent with such models. Similarly, although the near-term results are consistent with behavioral models where investors extrapolate returns, the long-term results are inconsistent with such models. Although a number of models incorporate both extrapolating and contrarian investors (e.g., Barberis, Greenwood, Jin, and Shleifer, 2018; Egan, MacKay, and Yang,

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[31] As an additional robustness test of the possibility that ALP respondents may not reflect investors' beliefs, we repeat these tests limiting the sample to ALP respondents who hold equity. The results, detailed in the Internet Appendix, are nearly identical.

[32] One potential reason that the results in column 1 of Tables III and IV differ is that the most numeracy-challenged respondents have been removed in Table IV due to our filter requiring that beliefs must satisfy basic probability laws.

2020) or investors that sometime extrapolate and sometimes act as contrarians (e.g., Barberis, Shleifer, and Vishny, 1998), we are unaware of any model that suggests the same investor views recent poor returns as bearish for the near term but bullish for the long term. Our results are consistent with world in which individuals suffer from a "now is not the time" bias. For example, in a financial crisis (e.g., when one recently experienced low lag returns), one may perceive a higher likelihood of a continued decline in near-term prices, while simultaneously recognizing that long-term expected returns are high precisely because it is a risky time to invest. As a result, net exchanges out of equity funds (to bond funds) at time of low near-term expected returns and high long-term expected returns may reflect individuals' reluctance to add assets to a market they perceive as unusually risky regardless of the higher long-term expected return. In short, the results suggest a more nuanced view of the relation between expectations, lag returns, and market valuation levels—despite their pro-cyclical near-term views, respondents appear to recognize that low lag returns, low valuation levels, and high market risk are associated with greater near-term uncertainty and a larger long-term risk premium.

IV. Cross-Sectional Belief Heterogeneity

The results in the previous sections demonstrate that most individuals' perceptions of the distribution of long-term expected returns (1) differ dramatically from historical values, and (2) exhibit counter-cyclical time-series properties (in contrast to the pro-cyclicality of near-term beliefs). One cannot, however, infer cross-sectional variation from these patterns as the time-series and cross-sectional patterns are unique dimensions. For instance, it is straightforward to generate examples where respondents agree more about near-term returns than long-term returns and all respondents believe markets exhibit long-term mean-reversion or all respondents believe markets exhibit long-term momentum. In this section we focus on variation across respondents to better understand the importance of long-term expectations in stock market participation, the role of signals in driving belief heterogeneity, and why most respondents hold views of long-term uncertainty that differ so dramatically from historical values.

A. Long-Term Expectations and Stock Market Participation

Although valuations should be a function of long-term expectations, it is possible that long-term perceptions are unimportant as individuals can always adjust positions based on their near-term perceptions. A respondent who holds bullish near-term views, for example, may hold equities even if their long-term view is bearish as the respondent can always liquidate their position (for example, bubble riding strategies). Previous work (see Section I.A) reveals a strong positive relation between variation in near-term expected returns and stock market participation. In this section, we add perceived long-term expected returns, near-term risk, and long-term risk as explanatory variables to the analysis. Specifically, following the literature (e.g., Hong, Kubik, and Stein, 2004; Puri and Robinson, 2007; Giannetti and Wang, 2016; Barth, Papageorge, and Thom, 2020), we estimate a linear probability model of stock market participation on near- and long-term beliefs.[33] To allow direct comparison between coefficients, we standardize (i.e., rescale to zero mean and unit variance) expected returns and standard deviations.

The first column in Table V reports the coefficient from a regression of stock market participation (as shown in Table I, 43% of ALP respondents hold equities) on wave fixed effects and near-term expected returns. The *t*-statistics in Table V (reported parenthetically) are based on standard errors clustered at the respondent level. To ensure results do not arise from differences in samples, we limit the analysis to respondent-wave observations where we can measure both near- and long-term expected returns and uncertainty. Consistent with previous work, respondents with more bullish near-term beliefs are more likely to invest in equities. Specifically, a one standard deviation higher near-term expected return is associated with a 5.5% increase in the likelihood of holding equities (statistically significant at the 1% level).

The results in the second column suggest that the relation between near-term beliefs and market participation largely arises from the correlation between near- and long-term beliefs. That is, once including the long-term expected return, the coefficient associated with the near-term expected return falls from 5.5% to 2.2%. Moreover, because both variables are standardized, we can directly compare the estimates—the coefficients suggest that perceived long-term expected returns are nearly five times (0.108/0.022=4.88) as important as perceived near-term expected returns in explaining equity market participation. The penultimate row reveals that the difference in coefficients is statistically significant at the 1% level. The third column adds the standard deviations of the perceived one- and ten-year returns.[34] Consistent with traditional theory, both near- and long-term uncertainty are associated with

[33] As detailed in the Internet Appendix, limited dependent variable models generate identical conclusions.

[34] Most extant work assumes variation in expected returns drives variation in participation (e.g., Dominitz and Manski, 2007). It is possible, of course, that those who choose to participate in equity markets, for whatever reason, learn more about historical equity returns, i.e., causation runs the other way (see discussion in Dimmock, Kouwenberg, Mitchell, and Peijnenburg, 2016). The relations between participation, near-term expectation, and long-term expectations, however, appear harder to reconcile with the explanation that a better understanding of historical equity returns primarily drives the relation between expected returns and participation as it would require that participation "causes" a better understanding of long-term returns than near-term returns and, at the same time, the vast majority of individuals—including those participating in equity markets—grossly underestimate long-term equity returns.

a lower likelihood of participating in equity markets and we cannot reject the hypothesis that near- and long-term uncertainty are equally important. The difference in coefficients associated with expected returns remains large and statistically significant (at the 1% level).

The final column adds respondent characteristics to test if these variables fully account for the relation between long-term beliefs and equity market participation.[35] The results reveal that although respondent characteristics reduce the magnitude of the coefficient associated with long-term expected returns, the relation between stock market participation and both near- and long-term expected returns remains statistically significant (at the 1% level) and the effect size for long-term expected returns remains meaningfully larger (at the 1% level) than near-term expected returns. The effects associated with both near- and long-term uncertainty, however, are largely absorbed by other respondent characteristics.[36] In sum, we reject the hypothesis that long-term beliefs are unimportant as equity market participation is much more strongly related to long-term beliefs than near-term beliefs.

The first column of Table VI reports results of a regression of the fraction of financial assets held in equities on near- and long-term expected returns and standard deviations. The second column reports results when including respondent characteristics (gender, race, marital status, working, retired, age, years of education, income, and numeracy) as regressors. As above, expected returns and standard deviations are standardized to allow direct comparison. The bottom two rows report *p*-values from tests of coefficient equality for near- and long-term expected returns and standard deviations, respectively. As discussed in the data section, this sample is limited to six waves of the ALP Financial Crisis Surveys (Januarys for 2011-2016) that ask respondents to report their asset values (see Appendix A for details). The final two columns report analogous results when limited to respondents who report participating in equity markets (i.e., the fraction of assets held in equities is greater than zero).

[Insert Table VI about here]

The relation between long-term expected returns and the fraction of assets held in equity is statistically significant (at the 1% level) and economically meaningful in all four regressions. For example, when including respondent characteristics, a one standard deviation higher long-term

[35] Several studies (e.g., Hansen and Sargent, 2001) suggest ambiguity aversion may result in bearish expectations. As detailed in the Internet Appendix (for the subsample with ambiguity aversion data), the results are effectively identical when controlling for the Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016) ambiguity aversion measure.

[36] As detailed in the Internet Appendix, we reach similar conclusions when we repeat these tests replacing expected returns and uncertainty with probability beliefs (e.g., the likelihood markets rise in the next year or decade). The only substantial change is that both near- and long-term downside risk (i.e., the likelihood of a 20% fall in prices in the next year or decade) remain meaningfully negatively related to stock market participation even when controlling for respondent characteristics.

expected return is associated with a 5.5% larger allocation to equities for the broader sample reported column (2) and a 3.2% larger allocation to equities for the sample limited to stock market participants reported in column (4). In contrast, the coefficient associated with near-term expected returns is only marginally significant (at the 10% level) in one of the four regressions. The difference between the coefficients associated with near- and long-term expected returns is statistically meaningful (at the 1% level) in all four cases.

B. Dispersion in Long-Term Beliefs

The relation between horizon and dispersion in beliefs can be used to test if signals play a meaningful role in driving belief dispersion. To examine these relations, we consider a simplified version of the Patton and Timmermann (2010) model where individuals have both heterogeneity in priors (i.e., heterogeneity in beliefs absent signals) and heterogeneity in signals.[37] Specifically, we begin by assuming that, absent any signals, each individual i has a prior belief, μ_i, regarding the continuously compounded annual return. Each individual i also receives a (mean-zero) signal for year t denoted $\eta_{i,t,1}$, that is independent of heterogeneity in priors (i.e., $\text{cov}(\mu_i,\eta_{i,t,1})=0$).[38] The individual's expected return over the next year is the sum of their prior and signal:[39]

$$E_{i,t}(r_1) = \mu_i + \eta_{i,t,1}. \tag{1}$$

Similarly, the individual's expected return for the next decade is given by:

$$E_{i,t}(r_{10}) = 10\mu_i + \eta_{i,t,1} + \eta_{i,t,2} + \ldots + \eta_{i,t,10}. \tag{2}$$

Patton and Timmermann (2010) point out that because signals are, by their nature, temporary deviations, signals will have a larger relative impact on dispersion in near-term beliefs than dispersion in long-term beliefs. Specifically, using ψ to denote cross-sectional standard deviation (to differentiate it from the standard deviation of an individual's perceived distribution of expected returns, σ), the

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[37] In the Patton and Timmermann (2010) model, forecasters receive both common and unique signals (η_t and $\nu_{i,t}$, respectively, in their model). In our simplified version, we collapse these signals into a single signal (for each year t) and allow signals to be correlated to capture the two (common and unique) components.

[38] Note that other than independence from priors, we do not assume anything else about the signals, e.g., the signals may exhibit time-series correlation (e.g., $\text{cov}(\eta_{i,1},\eta_{i,2})\neq 0$) or cross-sectional correlation (e.g., $\text{cov}(\eta_{i,1},\eta_{j,1})\neq 0$)).

[39] As noted in the introduction, differences in signals does not imply some set of ALP respondents have non-public "private" information. Rather as Hong and Stein (2007) point out, differences in "signals" for non-professionals can arise from gradual information flow, limited attention, variation in access to information, and differential interpretation of the same information.

ratio of the cross-sectional variance of long-term (Equation (2)) to near-term (Equation (1)) expected returns is given by:

$$\begin{aligned}\frac{\psi^2\left(E_t\left(r_{10}\right)\right)}{\psi^2\left(E_t\left(r_1\right)\right)} &= \frac{\psi^2\left(10\mu\right)+\psi^2\left(\eta_{t,1}+\eta_{t,2}+...+\eta_{t,10}\right)+2\operatorname{cov}\left(10\mu,\eta_{t,1}+\eta_{t,2}+...+\eta_{t,10}\right)}{\psi^2\left(\mu\right)+\psi^2\left(\eta_{t,1}\right)+2\operatorname{cov}\left(\mu,\eta_{t,1}\right)} \\ &= \frac{\psi^2\left(10\mu\right)+\psi^2\left(\eta_{t,1}+\eta_{t,2}+...+\eta_{t,10}\right)}{\psi^2\left(\mu\right)+\psi^2\left(\eta_{t,1}\right)}\end{aligned} \tag{3}$$

where the covariance terms in Equation (3) are zero because signals are independent of priors.

If signals play no role in belief heterogeneity (i.e., all the η terms are zero), then the cross-sectional variance of ten-year expected returns is simply 100 times the cross-sectional variance of one-year expected returns, or, equivalently, the cross-sectional standard deviation of long-term expected returns will be 10 times the cross-sectional standard deviation of one-year expected returns:

$$\frac{\psi\left(E_t\left(r_{10}\right)\right)}{\psi\left(E_t\left(r_1\right)\right)}=\frac{\psi\left(10\mu\right)}{\psi\left(\mu\right)}=10. \tag{4}$$

In contrast, if signals play a meaningful role in belief dispersion, then respondents will disagree more about near-term expected returns than long-term expected returns and Equation (4) will be less than ten. The intuition is straightforward—consider a simple example where only near-term signals are non-zero (i.e., $\eta_{t,2}=\eta_{t,3}=...=\eta_{t,10}=0$)—the relative importance of near-term signals ($\eta_{t,1}$) in explaining dispersion in the left-hand side of Equation (1) is much greater than its relative importance in explaining dispersion in the left-hand side of Equation (2).

Columns 2-4 in Table VII report the cross-sectional standard deviation of expected returns over the next year or decade as well as the ratio of the standard deviation of ten-year expected returns to the standard deviation of one-year expected returns for each of the 29 long-form waves. Column 1 reports the respondent sample size for each wave. Panel B reports the time-series averages as well as the time-series minimum and maximum of these values. The results reveal that dispersion in long-term expected returns is much less than expected relative to dispersion in near-term forecasts if heterogeneity in signals played no role in explaining cross-sectional heterogeneity in expected returns. The average reported in Panel B of column 4 reveals that cross-sectional variation in ten-year expected returns is only 2.72 times the dispersion in one-year expected returns (ranging from 2.48 times to 3.16 times) versus an expected value of 10 if heterogeneity in investors' expectations were fully explained by priors (i.e., Equation (4)). A Morgan-Pitman test of equality of variance for paired data based on one-tenth the ten-year expected returns versus one-year expected returns is rejected at the 1% level in every wave.

[Insert Table VII about here]

In short, the results in Table VII suggest that signals play an important role in explaining belief dispersion and that the importance of signals declines with belief horizon. The results provide empirical support for models that rely on divergent signals (e.g., Hong and Stein, 1999; Hirshleifer and Teoh, 2003; Basak, 2005; Scheinkman and Xiong, 2013; Atmaz and Basak, 2018; Martin and Papadimitriou, 2019).

C. Respondent Characteristics, Horizon, and Belief Dispersion

Variation in signals will also impact the relation between respondent characteristics and beliefs measured at different horizons. Specifically, because signals are as likely to be positive as negative, heterogeneity in signals should not explain a *systematic* relation between respondent characteristics and beliefs. As noted in the introduction, for example, assuming more educated respondents have more informative signals than less educated respondents, implies that education would sometimes be associated with greater optimism and other times greater pessimism. These two conditions—characteristics are related to dispersion in beliefs because they are related to dispersion in priors and priors are relatively more important at long-horizons (see previous subsection)—suggest that if both signals and priors play a meaningful role in belief dispersion, respondent characteristics will be more strongly related to long-horizon belief dispersion than near-horizon belief dispersion.[40]

We investigate this hypothesis by regressing one- and ten-year expected returns and standard deviations on survey wave fixed effects and respondent characteristics. Because cross-sectional variation in long-term expected returns and risk (standard deviations) are larger than their near-term counterparts (see Table II), we standardize each dependent variable so that the resulting coefficient associated with a characteristic reflects the impact of a one-unit change in the explanatory variable on a standard deviation change in expected returns or uncertainty. Standard errors are clustered at the respondent level.

The first three columns in Table VIII report the results of regressions of expected returns in the next year, expected returns in the next decade, and their difference on respondent characteristics. Providing further support for the hypothesis that signal dispersion meaningfully impacts belief

[40] The Internet Appendix provides a formal proof within our model framework.

dispersion, respondent characteristics are more strongly related to cross-sectional heterogeneity in long-term expected returns than near-term expected returns. For instance, for the seven characteristics where the difference is statistically meaningful (column (3)), the (absolute) value of the coefficient associated with the ten-year expected returns is larger than the corresponding coefficient associated with one-year expected returns. For example, one year of additional education is associated with a 3.1% standard deviation higher one-year expected return, but a 5.4% standard deviation higher ten-year expected return.[41]

[Insert Table VIII about here]

Columns (4)-(6) repeat the analysis for the standard deviation of perceived near- and long-term returns. Of the seven significant differences reported in column (6), the absolute value of the coefficient associated with perceived long-term uncertainty is greater than the coefficient associated with near-term uncertainty in five cases. In short, consistent with the hypothesis that both signals and priors play an important role in explaining belief heterogeneity, the results in the first six columns of Table VIII reveal that respondent characteristics tend to be more strongly related to cross-sectional heterogeneity in long-term beliefs than near-term beliefs. As detailed in the Internet Appendix, we find the same patterns when examining perceptions of near- and long-term return probabilities (e.g., the perceived likelihood markets rise in the next year or decade).

C. Respondent Characteristics and Variance Ratios

As discussed in the introduction, there are at least three reasons why respondents' variance ratios may differ from unity: (1) parameter uncertainty implies variance ratios computed from perceived expected return distributions should exceed the historical market variance ratio and may rationally exceed unity (Pástor and Stambaugh, 2012), (2) individuals may believe long-term returns are mean-reverting (as Siegel (2014) suggests), and (3) respondents may simply not understand that variance is proportional to time in a serially independent world.[42] The results in Panel C of Table II are inconsistent with the hypothesis that ALP respondents' perceptions of long-term market uncertainty are greater than historical values as a result of parameter and conditional expected return uncertainty

[41] One interesting result is that females have larger one-year expected returns. As detailed in the Internet Appendix, this occurs because, controlling for other characteristics, females report a slightly lower likelihood markets fall by 20% in the next year and a slightly greater likelihood markets rise by 20% in the next year. Females, however, hold much more bearish long-term beliefs—believing it is more likely markets fall by at least 20% over the next decade and less likely markets rise by at least 20% over the next decade (see Internet Appendix for details).

[42] The final "bad at math" explanation includes the possibility that respondents do understand that variance is proportional to time but still systematically err in their estimate of long-term return likelihoods.

(this result is in contrast to Pástor and Stambaugh's evidence that CFOs hold views that imply variance ratios larger than unity).[43]

To further investigate why most respondents hold views that are possible only if markets exhibit unprecedented levels of mean reversion, we regress standardized variance ratios on respondent characteristics (and wave fixed effects). Because variance ratios are larger when the difference between ten-year and one-year standard deviations are larger, the results of the variance ratio regression (reported in the last column of Table VIII) are nearly identical to the results of the difference in standard deviations regression (reported in column (6) of Table VIII). The results in either column suggest that failing to understand the relation between time and uncertainty helps explain the low variance ratio implied by most respondents' beliefs as greater education, income, and numeracy are all associated with variance ratios that more closely approximate historical values. Moreover, consistent with the joint hypothesis that white males have a greater opportunity to learn about markets than others and failing to fully understand the relation between time and uncertainty contributes to the low variance ratios, females and non-whites exhibit lower variance ratios. The results also reveal evidence those currently working exhibit lower variance ratios.

Given these relations, one possibility is that although most respondents exhibit variance ratios that differ greatly from historical values and unity, a substantial subset of respondents do understand the relation between time and uncertainty but also recognize that, historically, U.S. markets are mean-reverting. To investigate this possibility, we partition respondents by income, numeracy, and equity ownership. We hypothesize that if the failure to understand the relation between time and uncertainty plays little role in long-term return perceptions for respondents who are more likely to play a larger role in equity markets, then high income, high numeracy, and respondents who hold equities should report variance ratios near, or above (if parameter uncertainty contributes to their beliefs), historical values. When limited to observations where we can estimate variance ratios, 36% of observations are high-income (>$75,000) respondents, 77% are high-numeracy respondents, 59% hold equity, and 24% are high-income, high-numeracy, equity holders.[44]

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[43] The results suggest that most individuals (ALP respondents) hold views that differ from CFOs—perhaps because CFOs better understand the impact of parameter uncertainty than most individuals. Specifically, Pástor and Stambaugh (2013) point out that predictive variance is a function of five components (1) i.i.d. uncertainty, (2) mean reversion, (3) uncertainty about future expected returns, (4) uncertainty about current expected returns, and (5) estimation risk. Although mean reversion contributes negatively to the variance ratio, the last three components contribute positively. Using the Graham and Harvey CFO data, Pástor and Stambaugh conclude the final three components are more important than mean reversion in CFO near- and long-term beliefs.

[44] The fraction who hold equity differs from the values reported in Table I because this sample is limited to long-form surveys and respondents who report values that are consistent with probability laws. As detailed in Appendix A, high

The first six columns in Table IX report the pooled cross-sectional time-series mean of the perceived standard deviation of the one- and ten-year expected return distributions for groups sorted on income, numeracy, and equity ownership. The final two columns report values for high-income, high-numeracy, equity owners versus all others. The third row reports the average variance ratio for each group. The fourth row reports the fraction of variance ratios less than unity and the *p*-value from a sign test that the median variance ratio does not differ from unity. The fifth row analogously reports the fraction of variance ratios less than the historical market average of 0.558 along with the associated *p*-value that the median variance ratio does not differ from 0.558. The last row reports a *z*-statistic associated from a Wilcoxon rank sum test of equality across the partitions.

[Insert Table IX about here]

The analysis in Table IX generates two important results. First, consistent with the hypothesis that a failure to fully understand the relation between time and uncertainty contributes to the implausibly low variance ratios, lower income, lower numeracy, and non-equity holding respondents tend to report meaningfully smaller variance ratios than their higher income, higher numeracy, and equity-holding counterparts.[45] Moreover, the difference in variance ratios primarily results from differences in the variance of perceived long-term distributions. Second, although the differences between the groups have the expected sign, the vast majority of individuals in the "more sophisticated" group report values that generate variance ratios much too small relative to historical norms. For example, even when limiting the sample to respondents with annual income in excess of $75,000, who believe they have strong math skills and own equity, 87% of respondents report variance ratios less than unity and more than three in four report variance ratios less than the historical value of 0.558. In sum, the results suggest that a combination of a belief equity markets are mean-reverting and a failure to fully understand the relation between uncertainty and time primarily drives the low variance ratios.

As a final test of the importance of numeracy, we compare variance ratios to a measure, that absent a numeracy link, should be independent of stock market expectations—the extent to which respondents mis-calibrate their long-term auto accident likelihood. Specifically, in a survey fielded

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numeracy respondents are those that (on average) report their self-assessed math ability on the top half of the scale (e.g., on surveys using a seven-point scale where 1=strongly disagree, 4=neither agree or disagree, and 7=strongly agree, those who answer 5, 6, or 7).

[45] Because our data is a panel, individuals appear multiple times in Table IX (and can switch categories in the case of income or equity ownership). As a robustness test, we repeat the analysis first computing the time-series median variance ratio for each individual and then computing a Wilcoxon test of these values (i.e., one observation per respondent). As detailed in the Internet Appendix, the same pattern remains, and the results are statistically significant at the 1% level in every case.

between August 2006 and November 2007, ALP asked respondents "*What is the percent chance that you will get into a car accident while driving during the next year?*" and "*What is the percent chance that you will get into a car accident while driving during the next 5 years?*" Although some respondents may have rational reasons to assume non-independence (e.g., the respondent expects to move and increase their commute in the coming year), the true risk for most respondents should be relatively independent over time implying that, given their one-year risk, their 5-year risk should be $1\text{-}(1\text{-perceived probability}_{1\text{ year}})^5$. If individuals tendency to underestimate long-term uncertainty arises, in part, from a systematic bias that tends to underestimate long-term risk, we expect (1) most individuals will underestimate their 5-year auto accident risk, i.e., $(1\text{-}(1\text{-perceived probability}_{1\text{ year}})^5)$ - perceived $\text{probabilty}_{5\text{-year}}>0$, and (2) the miscalibration of 5-year auto accident risk $(1\text{-}(1\text{-perceived probability}_{1\text{ year}})^5$ - (perceived $\text{probabilty}_{5\text{-year}}$)) will be negatively cross-sectionally correlated with both self-accessed numeracy and variance ratios. That is, individuals who suffer most from innumeracy will tend to underestimate their 5-year auto accident risk (relative to their perceived 1-year risk), underestimate long-term equity market uncertainty (relative to their perceived near-term equity market uncertainty), and recognize they are weaker at math.

Of the 3,859 individuals in our sample, 870 have adequate data for auto accident miscalibration metric, self-accessed numeracy, and variance ratios (we use each individual's mean variance ratio from all waves with sufficient data). Consistent with the hypothesis that most individuals underestimate long-term uncertainty, 92% of the 870 individuals underestimate their 5-year auto accident risk relative to their 1-year auto accident risk, i.e., $1\text{-}(1\text{-perceived probability}_{1\text{ year}})^5 >$ perceived $\text{probabilty}_{5\text{-year}}$. Moreover, the Spearman correlations between auto accident miscalibration and self-assessed math ability and variance ratios are -12% and -9%, respectively (both are statistically significant at the 1% level).

III. Discussion and Robustness

Surveys can be sensitive to language and interpretation. For example, there are at least three approaches to estimating respondents' perceived distribution of expected returns: (1) ask for distributional parameters (e.g., what is the variance of returns over the next decade?), (2) provide respondents a likelihood as a prompt to elicit a return (e.g., there is a 1 in 10 chance returns will be less than ___ in the next decade), and (3) provide respondents a return and ask for a likelihood (e.g., what are the chances that markets will be lower ten years from today?). A growing body of research suggests, however, that asking respondents about probabilistic expectations has considerable value (e.g., see reviews by Manski, 2004, 2018).

In addition, the ALP questions are, arguably, the simplest approach to mental calculations—presumably, nearly everyone can understand the question of whether one expects the stock market to be higher or lower ten years from today. Few (including most economists), however, would be able to easily infer the likelihood of a 20% gain in ten years given a one-year expected return and standard deviation. Nonetheless, the ALP questions are so straightforward, they arguably are the best method to capture respondents' actual views (which explains why this structure has become popular in surveys eliciting beliefs).[46] The results reveal that the long-term expected stock return distribution perceived by most respondents differs dramatically from historical values. We also take comfort in the fact that, at least for long-horizon returns, ALP respondents exhibit the same miscalibration pattern as CFOs (i.e., too narrow ten-year variances relative to historical values) despite the fact that CFOs represent the right-tail of financial experience and knowledge, and the ALP and Graham and Harvey questionnaires take different approaches to measuring distribution return distributions (the ALP asks for likelihoods given return values, whereas CFO surveys ask for returns given likelihoods). Nonetheless, our tests do reveal that miscalibration tends to be worse for those with lower income, numeracy, and for non-equity holders, consistent with the hypothesis that some of the miscalibration results from failing to understand the relation between time and uncertainty. Regardless, the overall pattern is ubiquitous—even high income, high numeracy, equity holders tend to greatly underestimate long-term uncertainty.

Nonetheless, some remain skeptical of survey results. Cochrane (2011, 2017) posits, for example, that respondents' reported views may reflect risk neutral probabilities rather than true subjective probabilities. Recent work (e.g., Adam, Matveev, and Nagel, 2020), however, finds strong evidence inconsistent with this hypothesis using multiple related tests. Lamont (2004) views survey data, "…just one rung above anecdotes in the quality ladder." Yet evidence suggests surveys do reflect respondents' beliefs and actions (e.g., Greenwood and Shleifer, 2014; Giglio, Maggiori, Stroebel, and Utkus, 2021). Greenwood and Shleifer (2014) propose that the overall evidence suggests, "…it is more plausible to conclude that investors understand the questions, and to take their answers at face value."

[46] As Manski (2004, 2018) points outs, eliciting probabilistic expectations overcomes many of the limitations of alternative approaches and, as such, the use of probabilistic expectations has become ubiquitous in the past few decades including the Health and Retirement Study, the Survey of Economic Expectations, the National Longitudinal Survey of Youth, the Survey of Consumer Expectations, and the Bank of Italy Survey of Household Income and Wealth.

Another concern is that when individuals have no idea regarding a probability, they respond 50%. Thus, our results could be impacted by individuals who actually have "no opinion" regarding the distribution of equity returns (de Bruin, Fischhoff, Halpern-Felscher, and Millstein, 2000). ALP data allows us to examine this possibility. Specifically, for respondents who report a 50% chance markets rise in the next year, ALP asks "Do you think it is equally likely the shares will be worth more in a year as it is they will be worth less or are you just unsure about the chances?" ALP asks an analogous question about returns over the next decade (in all but the first ALP financial crisis survey) for respondents who report a 50/50 chance markets will rise in the next decade. To examine this issue, we eliminate all respondents who report their 50/50 perceived probability indicates they are just unsure about the chances. As detail in the Internet Appendix, the results are nearly identical after eliminating these observations.

Additional limitations include the facts that that survey answers can be "glib" (Amromin and Sharpe, 2014), our data cover a period of 87 months (e.g., compared to lengthier calendar samples, such as Greenwood and Shleifer's (2014) 192 months of Gallup/UBS data), and more than half of the respondents do not hold equities. Nonetheless, the ALP data also has unique advantages. For example, we can track each individual's responses through time, and can estimate both near- and long-term perceived expected returns and uncertainty. Moreover, our analysis of both time-series and cross-sectional patterns in near-term expected returns is largely consistent with the literature. Further, study of a dataset that includes beliefs, and characteristics for at least some respondents that choose not to participate in equity markets may mitigate concerns with selection biases among declared investment professionals and other market participants. Finally, the fact that distributions of near- and long-term expected returns and uncertainty are strongly associated with lag returns, market valuation levels, stock market participation, and respondent characteristics suggest that the data do capture systematic variation in investors' beliefs, inconsistent with the notion that the data are just noise.

IV. Conclusions

Most individuals hold remarkably bearish views about the distribution of long-term expected returns—dramatically underestimating both long-term expected returns and long-term return uncertainty. In fact, the typical individual's perception of the distribution of ten-year expected returns implies that they are effectively certain performance in the future will be worse than performance in the past. The narrow variance of perceived long-term returns is only possible if markets exhibit unprecedented levels of mean reversion. The effect is ubiquitous—more than four out of five respondents' beliefs imply variance ratios less than the historical value. The result is also inconsistent with the Pástor and Stambaugh (2012) hypothesis that because uncertainty regarding expected return beliefs increases with horizon, individuals rationally perceive long-term expected return uncertainty as greater than historical market variance.

The time-series properties of long-term expected returns differ sharply from short-term expected returns. Consistent with previous work, time-series variation in near-term expected returns is positively related to lag market returns and market valuation levels. Surprisingly, however, these relations reverse when examining long-term expected returns. For instance, although most individuals extrapolate returns in forming near-term expected returns, long-term expected returns are higher following low market returns (consistent with the near-term momentum/long-term reversals pattern in market returns, e.g., Moskowitz, Ooi, and Pedersen, 2012). Similarly, although a high dividend to price ratio or VIX is associated with a lower perceived likelihood markets rise in the next year, these variables are also associated with an increased perceived likelihood markets rise in the next decade. Consistent with the view that individuals recognize that low lag returns or high dividend to price ratios are indicative of market stress, we also find that low lag returns and cheap valuation levels are associated with greater near-term uncertainty. Moreover, these time-series patterns are consistent with the low variance ratios reported by most respondents as both imply a belief in mean-reversion. In short, time-series variation in long-term expected returns tend to match traditional asset pricing theories and some behavioral theories but is inconsistent with behavioral theories that rely on return extrapolation. In contrast, variation in near-term expected returns tends to match behavioral theories that rely on return extrapolation but not with traditional asset pricing theories or behavioral theories of extrapolation of fundamentals, prospect theory, ambiguity aversion, and noise trader risk.

Our tests also reveal that despite the disconnect between perceived and historical long-term return distributions, long-term beliefs are much more important than near-term beliefs in explaining stock market participation. Consistent with the hypothesis that signals play an important role in belief dispersion, respondents agree much more about long-term expected returns than near-term expected returns and respondent characteristics are more strongly related to cross-sectional variation in long-term expected returns than near-term expected returns. In addition, consistent with the hypothesis that misunderstanding the relation between time and uncertainty plays a substantial role in explaining the small variance ratios, variance ratios are larger for higher-income, higher-numeracy, and equity-holding respondents. In addition, miscalibration in long-term stock market risk is correlated with miscalibration in long-term auto accident risk. Nonetheless, even when limited to high-income, high-numeracy, equity owners, the median variance ratio is still more than 60% lower than the historical value.

Our tests have important implications for household finance, behavioral finance, and traditional asset pricing. In short, the patterns in long-term beliefs, time-series variation in long-term beliefs, and cross-sectional variation in long-term beliefs are more complicated than previously recognized. For instance, no current traditional or behavioral model would appear to be able to explain the time-series patterns in both respondents' near-term and respondents' long-term beliefs.

REFERENCES

Abreu, Dilip and Markus K. Brunnermeier, 2003, Bubbles and Crashes, *Econometrica* 71, 173-204.

Adam, Klaus, Dmitry Matveev, and Stefan Nagel, 2020, Do Survey Expectations of Stock Returns Reflect Risk Adjustments?, *Journal of Monetary Economics*, forthcoming.

Amromin, Gene, and Steven A. Sharpe, 2014, From the Horse's Mouth: Economic Conditions and Investor Expectations of Risk and Return, *Management Science* 60, 845-866.

Atmaz, Adem and Suleyman Basak, 2018, Belief Dispersion in the Stock Market, *Journal of Finance* 73, 1225–1279.

Baker, Malcolm, Jeffrey Wurgler, 2007, Investor Sentiment in the Stock Market, *Journal of Economic Perspectives* 21, 129–151.

Bansal, Ravi, Dana Kiku, and Amir Yaron, 2012, An Empirical Evaluation of the Long-run Risks Model for Asset Prices, *Critical Finance Review* 1, 183-221.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-343.

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer, 2015, X-CAPM: An Extrapolative Capital Asset Pricing Model. *Journal of Financial Economics* 115, 1-24.

Barth, Daniel, Nicholas W. Papageorge, and Kevin Thom, 2020, Genetic Endowments and Wealth Inequality, *Journal of Political Economy* 128, 1474-1522.

Basak, Suleyman, and Domenico Cuoco, 1998, An Equilibrium Model with Restricted Stock Market Participation, *Review of Financial Studies* 11, 309-341.

Basak, Suleyman, 2005, Asset Pricing with Heterogeneous Beliefs, *Journal of Banking and Finance* 29, 2849-2881.

Ben-David, Itzhak, John R. Graham, and Campbell R. Harvey, 2013, Managerial Miscalibration, *Quarterly Journal of Economics* 128, 1547–1584.

Ben-Rephael, Azi, Shmuel Kandel, and Avi Wohl, 2012, Measuring Investor Sentiment with Mutual Fund Flows, *Journal of Financial Economics* 104, 363-382.

Boudoukh, Jacob, Roni Michaely, Matthew Richardson, and Michael R. Roberts, 2007, On the Importance of Measuring Payout Yield: Implications for Empirical Asset Pricing, *Journal of Finance* 62, 877–915.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer, 2020, Expectations of Fundamentals and Stock Market Puzzles, Working paper, Oxford Said Business School, Università Bocconi, Brown University, and Harvard University.

Brunnermeier, Markus, Emmanuel Farhi, Ralph S.J. Koijen, Arvind Krishnamurthy, Sydney C. Ludvigson, Hanno Lustig, Stefan Nagel and Monika Piazzesi, 2021, Review Article: Perspectives on the Future of Asset Pricing, *Review of Financial Studies*, 34, 2126-2160.

Campbell, John Y., and John H. Cochrane, 1999, By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior, *Journal of Political Economy* 107, 205-251.

Cook, John D., 2010, Determining Distribution Parameters from Quantiles, Department of Biostatistics, University of Texas M. D. Anderson Cancer Center, Houston, TX.

Cochrane, John, 2011, Presidential Address: Discount Rates, *Journal of Finance* 66, 1048-1108.

Cochrane, John, 2017, Macro-Finance, *Review of Finance* 21, 945-985.

Presidential Address: Discount Rates, *Journal of Finance* 66, 1048-1108.

Cutler, David M., James M. Poterba, and Lawrence H. Summers, 1990, Speculative Dynamics and the Role of Feedback Traders, *American Economic Review* 80, 63-68.

Da, Zhi, Xing Huang, and Lawrence J. Jin, 2021, Extrapolative Beliefs in the Cross-Section: What can we Learn from the Crowds? *Journal of Financial Economics* 140, 175-196.

Dahlquist, Magnus, and Markus Ibert, 2022, Equity Return Expectations and Portfolios: Evidence from Large Asset Managers, Working Paper, Stockholm School of Economics, CEPR, and the Board of Governors of the Federal Reserve System.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions, *Journal of Finance* 53, 1839–1885.

Daniel, Kent, David Hirshleifer, and Lin Sun, 2020, Short- and Long-Horizon Behavioral Factors, *Review of Financial Studies* 33, 1673-1736.

Das, Sreyoshi, Camelia M. Kuhnen, and Stefan Nagel, 2020, Socioeconomic Status and Macroeconomic Expectations, *Review of Financial Studies* 33, 395-432.

De Bondt, Werner P. M., 1993, Betting on Trends: Intuitive Forecasts of Financial Risk and Return, *International Journal of Forecasting* 9, 355-371.

De La O, Ricardo and Sean Myers, 2021, Subjective Cash Flows and Discount Rate Expectations, *Journal of Finance* 76, 1339-1387.

de Bruin, Wandi Bruine, Baruch Fischhoff, Susan G. Millstein, and Bonnie L. Halpern-Felsher, 2000, Verbal and Numerical Expressions of Probability: "It's a Fifty-Fifty Chance", *Organizational Behavior and Human Decision Processes* 81, 115–131.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert Waldmann, 1990, Positive Feedback Investment Strategies and Destabilizing Rational Speculation, *Journal of Finance* 45, 379-395.

Dimmock, Stephen G., Roy Kouwenberg, Olivia S. Mitchell, and Kim Peijnenburg, 2016, Ambiguity Aversion and Household Portfolio Choice Puzzles: Empirical Evidence, *Journal of Financial Economics* 119, 559–577.

Dominitz J, Manski Charles F., 1997, Using Expectations Data to Study Subjective Income Expectations, *Journal of the American Statistical Association* 92, 855–867.

Dominitz, Jeff, and Charles F. Manski, 2007, Expected Equity Returns and Portfolio Choice: Evidence from the Health and Retirement Study, *Journal of the European Economic Association* 5, 369–379.

Fama, Eugene, and Kenneth French, 2018, Long-Horizon Returns, *The Review of Asset Pricing Studies* 8, 232-252.

Giannetti, Mariassunta, and Tracy Yue Wang, 2016, Corporate Scandals and Household Stock Market Participation, *Journal of Finance* 71, 2591–2636.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Stephan Utkus, 2021, Five Facts About Beliefs and Portfolios, *American Economic Review* 111, 1481-1522.

Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of Returns and Expected Returns, *Review of Financial Studies* 27, 714-746.

Hansen, Lars Peter, and Thomas J. Sargent, 2001, Robust Control and Model Uncertainty, *American Economic Review (Papers and Proceedings)* 91, 60-66.

Hirshleifer, David and Siew Hong Teoh, 2003, Limited Attention, Information Disclosure, and Financial Reporting, *Journal of Accounting and Economics* 36, 327-386.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2004, Social Interaction and Stock-Market Participation, *Journal of Finance* 59, 137-163.

Hong, Harrison, and Jeremy C. Stein, 1999, A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets, *Journal of Finance* 54, 2143–2184.

Hong, Harrison, and Jeremy C. Stein, 2007, Disagreement and the Stock Market, *Journal of Economic Perspectives* 21, 109–128.

Hudomiet, Peter, Gabor Kezdi, and Robert J. Willis, 2011, Stock Market Crash and Expectations of American Households, *Journal of Applied Econometrics* 26, 393–415.

Hurd, Michael D., 2009, Subjective Probabilities in Household Surveys, *Annual Review of Economics* 1, 543–562.

Hurd, Michael, Maarten Van Rooij, and Joachim Winter, 2011, Stock Market Expectations of Dutch Households, *Journal of Applied Econometrics* 26, 416–436.

Jin, Lawrence J., and Pengfei Sui, 2021, Asset Pricing with Return Extrapolation, *Journal of Financial Economics (forthcoming).*

Kontoghiorghes, Alexander P., 2019, Option-Implied Price of Risk, Working paper, Queen Mary University of London.

Kuhnen, Camelia, M. and Andrei C. Miu, 2017, Socioeconomic Status and Learning from Financial Information *Journal of Financial Economics* 124, 349-372.

Kyle, Albert S., Anna A. Obizhaeva, and Yajun Wang, 2020, Beliefs Aggregation and Return Predictability, Working Paper University of Maryland, New Economic School, and Baruch College.

Lamont, Owen A., 2004. Comment on Vissing-Jorgensen, A., 2004. Perspectives on behavioral finance: Does "Irrationality" disappear with wealth? Evidence from expectations and actions towards an explanation of household portfolio choice heterogeneity. In: Gertler M., Rogoff, K. (Eds.), NBER Macroeconomics Annual 2003, 18. MIT Press, Cambridge, MA.

Lee, Boram, Leonard Rosenthal, Chris Veld, and Yulia Veld-Merkoulova, 2015, Stock Market Expectations and Risk Aversion of Individual Investors, *International Review of Financial Analysis* 40, 122–131.

Lo, Andrew W., and A. Craig MacKinlay, 1988, Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test, *Review of Financial Studies* 1, 41–66.

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression Babies: Do Macroeconomic Experiences Affect Risk Taking? *Quarterly Journal of Economics*, 126, 373–416.

Manski, Charles F., 2004, Measuring Expectations, *Econometrica* 72, 1329–1376.

Manski, Charles F., 2018, Survey Measurement of Probabilistic Macroeconomic Expectations: Progress and Promise, *NBER Macroeconomics Annual* 32, 411–471.

Merton, Robert C., 1969, Lifetime Portfolio Selection Under Uncertainty: The Continuous-Time Case, *Review of Economics and Statistics* 51, 247–257.

Moskowitz, Tobias, Yao Hua Ooi, and Lasse Heje Pedersen, 2012, Time Series Momentum, *Journal of Financial Economics* 104, 228–250.

Pollard, Michael and Matthew Baird, 2017, The RAND American Life Panel: Technical Description, Working paper, RAND Labor and Population division, Santa Monica, CA.

Pástor, Lubos, and Robert Stambaugh, 2012, Are Stocks Really Less Volatile in the Long Run?, *Journal of Finance* 67, 431–477.

Patton, Andrew, J. and Allan Timmermann, 2010, Why do Forecasters Disagree? Lessons from the Term Structure of Cross-Sectional Disperson, *Journal of Monetary Economics* 57, 803-820.

Poterba, James M. and Lawrence H. Summers, 1998, Mean Reversion in Stock Prices: Evidence and Implications, *Journal of Financial Economics* 22, 27-59.

Puri, Manju and David T. Robinson, 2007, Optimism and Economic Choice, *Journal of Financial Economics* 86, 71–99.

Scheinkman, Jose A., and Wei Xiong, 2003, Overconfidence and Speculative Bubbles, *Journal of Political Economy* 111, 1183-1220.

Sias, Richard, Laura Starks, and Harry Turtle, 2022, The Negativity Bias in Perceived Expected Return Distributions: Evidence from a Pandemic, Working Paper, University of Arizona, University of Texas at Austin, and Colorado State University.

Siegel, Jeremy, 2014, Stocks for the Long Run: The Definitive Guide to Financial Market Returns and Long-Term Investment Strategies, 5th ed., New York: McGraw-Hill.

Vissing-Jorgensen, Annette, 2003, Perspectives on Behavioral Finance: Does 'Irrationality' Disappear with Wealth? Evidence from Expectations and Actions," NBER Macroeconomic Annuals, Gertler M, and Rogoff K (eds). MIT Press: Cambridge, MA, 139-208.

Wachter, Jessica A., 2013, Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility? *Journal of Finance* 68, 987-1035.

Appendix A – Variable Detail and Construction

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.
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.
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: inc.<$5k, $5k≤inc<$7.499k, $7.5k≤inc<$9.999k, $10k≤inc<$12.499k, $12.5k≤inc<$14.999k, $15k≤inc<$19.999k, $20k≤inc<$24.999k, $25k≤inc<$29.999k, $30k≤inc<$34.999k, $35k≤inc<$39.999k, $40k≤inc<$49.999k, $50k≤inc<$59.999k, $60k≤inc<$74.999k, $75k≤inc. The family income part 2 groupings are: $75k≤inc<$99.999k, $100k≤inc<$124.999k, $125k≤inc<$199.999k, $200k≤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.
Numeracy	In six ALP (non-effects of the financial crisis) surveys (between 7/2008 and 9/2018) respondents are asked about their math ability. Specifically, in two surveys, respondents are asked "How strongly do you agree or disagree with the following statement? – I am good at mathematics." In four surveys, respondents indicate the extent that they agree or disagree with the statement, "I am pretty good at math." Potential answers vary across the surveys—including five possible values (strongly disagree, disagree, neither agree nor disagree, agree, strongly agree), six possible values (strongly agree, agree, slightly agree, slightly disagree, disagree, strongly disagree), or seven possible values (a 7-point scale ranging from strongly disagree to strongly agree). We recode where necessary so higher values always indicate higher self-assessed math ability and then rescale each question such that all values like between 0 and 1. For example with the 6-point scale above, strongly agree=1, agree=0.8, slightly agree=0.6, slightly disagree=0.4,

	disagree=0.2, strongly disagree disagree=0). We compute the average value for each respondent as their self-assessed numeracy. We define those with average values greater than 0.5 as high numeracy.
Holds equities	In the first two waves of the financial crisis surveys, respondents 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." In subsequent waves, respondents are asked, "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?" Respondents are then asked about equity holdings in retirement accounts, "Are any of these retirement accounts invested in stocks or stock mutual funds, either fully or partially?" We classify respondents who hold report owning stocks (either directly or in retirement account) as equity holders.
%Stock	In Effects of the Financial Crisis waves 23 (January 2011), 35 (January 2012), 47 (January 2013), 53 (January 2014), 57 (January 2015), and 61 (January 2016), respondents were asked about the value of their assets. We define the %Stock as the value of stocks held directly and in retirement accounts divided by the value of financial assets. Financial assets include the sum of (1) real estate holdings (excluding primary home, secondary home, business real estate, and/or farm real estate), (2) bonds (corporate, municipal, government, or foreign bonds, or bond funds, excluding retirement accounts), (3) CDs, government savings bonds, and T-bills, (4) other savings or assets, (5) assets held in trust not reported elsewhere, (6) checking, savings, and money market funds, (7) stocks held directly, (8) stocks held in retirement accounts, and (9) retirement assets excluding stock, less (10) other debt (excluding debt on mortgages and transportation) and (11) credit card debt. Respondents report the total value of their retirement accounts and the fraction of retirement assets held in equities. Items (8) and (9) are computed from these values. %Stock is the sum of stocks held directly (item (7)) and stocks held in retirement accounts (item (8)) divided by total assets. Approximately 2% of observations reveal %Stock greater than one (due to debt). To minimize the effect of outliers, we set values greater than 1 to 1.

Table I
ALP Respondents

This table reports pooled cross-sectional time-series descriptive statistics of respondents in our sample. See Appendix A for variable construction details. Except for %Stock and numeracy, the sample period is November 2008 through January 2016 and includes 61 waves of the "Effects of the Financial Crisis" surveys. The sample for %Stock includes six waves of the Effects of the Financial Crisis surveys (23, 35, 47, 53, 57, 61). The numeracy measure is based on six ALP surveys.

	N	Mean	25th percentile	Median	75th percentile	Standard deviation
Female	89,993	0.587	0	1	1	0.492
White race	89,958	0.874	1	1	1	0.332
Married	89,992	0.646	0	1	1	0.478
Working	89,979	0.478	0	0	1	0.500
Retired	89,979	0.170	0	0	0	0.376
Age	89,993	51.253	40	53	62	14.999
Years Education	89,987	14.752	13	14	16	2.606
Income	89,720	68,059	32,500	55,000	87,500	50,720
Numeracy	88,691	0.672	0.517	0.750	0.833	0.237
Holds equities	89,773	0.434	0	0	1	0.496
%Stock	5,514	0.360	0	0.288	0.667	0.355

Table II
Beliefs Regarding Near- and Long-Term Stock Returns

This table reports descriptive statistics for the pooled cross-sectional time-series of American Life Panel Survey data between 2008 and 2016. The first three rows in Panel A report summary statistics for investor perceptions over the next 12 months regarding the likelihood the market rises, rises more than 20%, and falls by more than 20%. The next two rows report summary statistics for the implied expected return and standard deviation estimated from respondent probabilities from the likelihood of a 20% or greater gain and a 20% or greater loss over the next year. The second to last column reports the historical average (computed from the CRSP value-weighted index between 1926 and 2020). The final column reports the fraction of observations below the historical average. Panel B reports analogous statistics for the likelihood equity markets rise, rise by more than 20%, and fall by more than 20% over the next decade. The first row in Panel C reports summary statistics for the variance ratio implied by investors' ten- and one-year beliefs. The final row reports the proportion of variance ratios that are less than one.

	N (waves)	*N* (obs.)	Mean	25^{th}	Median	75th	Std. Dev.	Historical	%<Hist.
Panel A: Stock market expectations over next year									
P(market>0)	61	89,633	0.434	0.200	0.500	0.600	0.270	0.747	0.828
P(market>20%)	61	84,727	0.264	0.100	0.200	0.500	0.213	0.330	0.661
P(market<-20%)	61	87,100	0.243	0.100	0.200	0.400	0.198	0.063	0.218
$E_{i,t}(r_{1\ year})$	61	61,848	-0.010	-0.051	-0.020	0.038	0.103	0.093	0.861
$\sigma_{i,t}(r_{1\ year})$	61	61,848	0.299	0.158	0.225	0.338	0.213	0.201	0.443
Panel B: Stock market expectations over next decade									
P(market>0)	61	89,479	0.563	0.310	0.510	0.800	0.299	0.958	0.906
P(market>20%)	29	39,852	0.427	0.200	0.500	0.600	0.269	0.929	0.958
P(market<-20%)	29	38,674	0.235	0.100	0.200	0.400	0.195	0.014	0.085
$E_{i,t}(r_{10\ years})$	29	25,560	0.129	-0.020	0.032	0.182	0.254	0.962	1.000
$\sigma_{i,t}(r_{10\ years})$	29	25,560	0.421	0.176	0.291	0.507	0.361	0.474	0.714
Panel C: Implied variance ratio $((\sigma_{i,t}^2(r_{10yr})/10)/(\sigma_{i,t}^2(r_{1yr}))$									
Variance ratio	29	22,499	0.390	0.099	0.146	0.373	0.585	0.559	0.822
%Variance ratio<1	29	22,499	0.892						

Table III
Extraplation, Valuation, and Near- and Long-Term Perceived Stock Return Probabilities

This table reports coefficients from panel regressions of perceived respondent probabilities for the distribution of stock returns (in percent) over the next year and decade on lag market returns (Panel A), market valuation metrics (Panel B), and mutual fund flows or net exchanges from bond/money market funds to equity funds (Panel C). Each coefficient represents the results of a univariate panel regression. Each regressor is demeaned by each respondent and then rescaled to unit variance to facilitate interpretation across variables. Sample sizes range from 84,463 to 89,409 observations in the first four columns and from 38,293 to 39,504 observations in the final two columns and the sample period is November 2008 and January 2016. Standard errors are clustered at the respondent level and *t*-statistics are reported parenthetically. Statistical significance at the one, five and ten percent levels are indicated by ***, **, and *, respectively.

	$P(R_{m,1\ year}>0)$	$P(R_{m,1\ year}>0.2)$	$P(R_{m,1\ year}<-0.2)$	$P(R_{m,10\ years}>0)$	$P(R_{m,10\ years}>0.2)$	$P(R_{m,10\ years}<-0.2)$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Perceived probability coefficient estimates on lagged market returns						
$R_{m,-1\ to\ -6}$	1.011***	0.137*	-0.605***	-0.400***	-2.217***	0.046
	(13.26)	(1.93)	(-9.89)	(-5.60)	(-19.88)	(0.55)
$R_{m,-1\ to\ -12}$	0.521***	-1.011***	-0.607***	-1.566***	-2.782***	0.056
	(5.44)	(-11.96)	(-8.17)	(-17.69)	(-23.21)	(0.62)
Panel B: Perceived probability coefficient estimates on market valuations						
$\ln(D/P)_{-1}$	-0.420***	1.256***	0.758***	1.942***	2.808***	0.020
	(-4.14)	(13.90)	(9.37)	(20.27)	(22.57)	(0.22)
$\ln(\text{net payout}/P)_{-1}$	-0.248**	0.647***	0.652***	1.211***	2.647***	0.096
	(-2.43)	(7.20)	(8.35)	(12.65)	(22.44)	(1.07)
Cay_{-1}	-0.314***	0.495***	0.693***	1.337***	2.469***	-0.086
	(-3.86)	(6.68)	(10.55)	(16.69)	(20.30)	(-0.92)
-1*$CAPE_{-1}$	-0.476***	1.134***	0.649***	2.165***	2.859***	-0.209*
	(-4.10)	(10.76)	(7.04)	(19.01)	(18.82)	(-1.81)
-1*Surplus $cons._{-1}$	-0.331**	1.116***	0.408***	2.018***	2.581***	-0.281**
	(-2.54)	(9.46)	(3.96)	(15.62)	(16.31)	(-2.34)
-1*Surplus $cons._{-1}^{OPT}$	-0.619***	0.884***	0.684***	1.643***	2.694***	-0.167
	(-5.77)	(9.01)	(8.05)	(15.72)	(19.72)	(-1.61)
VIX_{-1}	-0.897***	0.921***	0.672***	1.428***	3.100***	-0.216**
	(-8.74)	(9.65)	(8.39)	(14.63)	(23.23)	(-2.09)
Panel C: Perceived probability coefficient estimates on mutual fund flows, and net exchanges						
Mutual fund flows	0.496***	0.264***	-0.424***	-0.072	-1.599***	0.005
	(7.59)	(4.40)	(-7.70)	(-1.18)	(-14.91)	(0.06)
Net exchanges	0.552***	-0.149**	-0.469***	-0.571***	-2.249***	0.021
	(8.21)	(-2.35)	(-8.14)	(-8.95)	(-19.77)	(0.24)

Table IV
Extrapolation, Valuation, and the Perceived Distribution of Near- and Long-Term Stock Returns

This table reports coefficients from panel regressions of respondents' inferred mean and standard deviation for the perceived distribution of stock returns (in percent) over the next year and decade on lag market returns, (Panel A), market valuation metrics (Panel B), and mutual fund flows or net exchanges from bond/money market funds to equity funds (Panel C). Each coefficient represents the results of a univariate panel regression. Expected returns and standard deviations are inferred from respondents' reported likelihood the market rises or falls more than 20% over the next year or decade. Each regressor is demeaned by each respondent and then rescaled to unit variance to facilitate interpretation across variables. Sample sizes are 61,481 observations for the first two columns (all waves) and 25,030 observations for the last two columns (long-form waves) between November 2008 and January 2016. Standard errors are clustered at the respondent level and *t*-statistics are reported parenthetically. Statistical significance at the one, five and ten percent levels are indicated by ***, **, and *, respectively.

	$E_{i,t}(r_{1\ year})$	$\sigma_{i,t}(r_{1\ year})$	$E_{i,t}(r_{10\ years})$	$\sigma_{i,t}(r_{10\ years})$
Panel A: Perceived distributions and lag market returns				
$R_{m,-1\ to\ -6}$	0.389***	-0.279***	-1.071***	-1.037***
	(9.40)	(-3.58)	(-7.66)	(-5.08)
$R_{m,-1\ to\ -12}$	-0.139***	-0.837***	-1.622***	-1.423***
	(-2.97)	(-9.44)	(-11.52)	(-6.86)
Panel B: Perceived distributions and market valuations				
$\ln(D/P)_{-1}$	0.191***	1.100***	1.656***	1.627***
	(3.81)	(11.66)	(11.63)	(7.68)
$\ln(\text{net payout}/P)_{-1}$	-0.067	0.642***	1.516***	1.596***
	(-1.37)	(6.50)	(10.46)	(7.17)
Cay_{-1}	-0.136***	0.708***	1.487***	1.280***
	(-3.20)	(8.67)	(10.57)	(5.91)
-1^*CAPE_{-1}	0.191***	1.000***	1.794***	1.315***
	(3.34)	(9.14)	(11.08)	(5.46)
$-1^*\text{Surplus cons.}_{-1}$	0.331***	0.826***	1.699***	1.091***
	(5.26)	(6.60)	(10.23)	(4.39)
$-1^*\text{Surplus cons.}_{-1}^{OPT}$	0.061	0.920***	1.632***	1.351***
	(1.13)	(8.91)	(10.85)	(5.93)
VIX_{-1}	0.065	0.908***	1.943***	1.645***
	(1.25)	(9.36)	(12.43)	(7.29)
Panel C: Perceived distributions, mutual fund flows, and net exchanges				
Mutual fund flows	0.328***	-0.123*	-0.729***	-0.621***
	(9.00)	(-1.69)	(-5.66)	(-3.08)
Net exchanges	0.148***	-0.354***	-1.207***	-1.035***
	(4.00)	(-4.79)	(-9.03)	(-5.03)

Table V
Near- and Long-Term Beliefs and Stock Market Participation

This table reports regressions of stock market participation on near- and long-term measures of expected return, standard deviation, and investor characteristics. Column 1 reports results for the regression of stock market participation on the inferred expected return in the next year. Column 2 adds expected return for the next decade. Column 3 adds the standard deviation of the one- and ten-year expected return distributions. Column 4 adds respondent characteristics. Expected returns and standard deviations in the next year or decade are standardized. Standard errors are clustered at the respondent level. The penultimate row reports *p*-values from a test of the hypothesis that the coefficient associated with the one-year expected return does not differ from the coefficient associated with the ten-year expected return. The bottom row reports *p*-values from an analogous test for the near- and long-term standard deviation. We report *t*-statistics in parentheses and significance at the one, five and ten percent levels are indicated by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)
$E_{i,t}$ ($r_{1\ year}$)	0.055***	0.022***	0.022***	0.023***
	(8.97)	(3.86)	(3.89)	(4.58)
$E_{i,t}$ ($r_{10\ years}$)		0.108***	0.125***	0.061***
		(18.26)	(17.04)	(8.49)
$\sigma_{i,t}$ ($r_{1\ year}$)			-0.018***	-0.009
			(-3.14)	(-1.64)
$\sigma_{i,t}$ ($r_{10\ years}$)			-0.024***	-0.008
			(-3.62)	(-1.34)
Female				-0.029
				(-1.62)
Race white				0.164***
				(6.74)
Married				0.068***
				(3.48)
Working				0.093***
				(5.54)
Retired				0.029
				(0.90)
Age				0.005***
				(7.55)
Years Education				0.030***
				(8.51)
Income/100k				0.232***
				(12.92)
Numeracy				0.051
				(1.40)
Wave fixed effects	Yes	Yes	Yes	Yes
N	22,457	22,457	22,457	22,131
R^2	0.025	0.067	0.071	0.262
p-value:				
$E_{i,t}$ ($r_{1\ year}$)=$E_{i,t}$ ($r_{10\ year}$)		0.01***	0.01***	0.01***
p-value:				
$\sigma_{i,t}$ ($r_{1\ year}$)=$\sigma_{i,t}$ ($r_{10\ year}$)			0.54	0.96

Table VI
Near- and Long-Term Beliefs and Fraction of Financial Assets in Equity

Columns (1) and (3) reports regressions of the fraction in financial assets held in equity on near- and long-term measures of expected return and standard deviation. Columns (2) and (4) add respondent characteristics (gender, race, marital status, working, retired, age, years of education, income, and numeracy) to the regression. The first two column report results for the regression of fraction of financial assets held in equity as the dependent variable. The final two columns repeat the analysis for the sample limited to those who participate in equity markets. Expected returns and standard deviations in the next year or decade are standardized. Standard errors are clustered at the respondent level. The penultimate row reports the *p*-values from a test of the hypothesis that the coefficient associated with the one-year expected return does not differ from the coefficient associated with the ten-year expected return. The bottom row reports *p*-values from an analogous test for the near- and long-term standard deviation. The fraction of financial assets held in equities is limited to ALP's Effects of the Financial Crisis waves 23 (January 2011), 35 (January 2012), 47 (January 2013), 53 (January 2014), 57 (January 2015), and 61 (January 2016). We report *t*-statistics in parentheses and significance at the one, five and ten percent levels are indicated by ***, **, and *, respectively.

	%Stock (All respondents)		%Stock (Stock market participants only)	
	(1)	(2)	(3)	(4)
$E_{i,t}$ ($r_{1\ year}$)	0.009	0.014*	-0.010	-0.009
	(1.05)	(1.68)	(-1.11)	(-0.95)
$E_{i,t}$ ($r_{10\ years}$)	0.082***	0.055***	0.034***	0.032***
	(8.65)	(5.92)	(3.27)	(3.06)
$\sigma_{i,t}$ ($r_{1\ year}$)	-0.009	-0.009	0.008	0.005
	(-0.97)	(-1.05)	(0.87)	(0.53)
$\sigma_{i,t}$ ($r_{10\ years}$)	-0.022	-0.014	-0.014	-0.013
	(-2.16)**	(-1.47)	(-1.29)	(-1.24)
Respondent characteristics	No	Yes	No	Yes
Wave fixed effects	Yes	Yes	Yes	Yes
N	3,252	3,230	2,254	2,244
R^2	0.049	0.133	0.011	0.034
p-value: $E_{i,t}$ ($r_{1\ year}$)=$E_{i,t}$ ($r_{10\ year}$)	0.01***	0.01***	0.01***	0.01***
p-value: $\sigma_{i,t}$ ($r_{1\ year}$)=$\sigma_{i,t}$ ($r_{10\ year}$)	0.40	0.72	0.18	0.27

Table VII
Forecast Horizon and Belief Heterogeneity

This table reports descriptive statistics for each of the 29 long-form surveys providing data on perceptions for both near- and long-term expected returns. Panel A provides data for each survey wave with accompanying summary statistics across all surveys in Panel B. The first three columns report the number of respondents and the cross-sectional standard deviation of the perceived one- and ten-year expected returns. Column (4) reports the ratio of the ten-year cross-sectional standard deviation to the one-year standard deviation. ψ denotes cross-sectional standard deviation.

	N	$\psi(E_{i,t}(r_1))$	$\psi(E_{i,t}(r_{10}))$	$\frac{\psi(E_{i,t}(r_{10}))}{\psi(E_{i,t}(r_1))}$
	(1)	(2)	(3)	(4)
Panel A. Cross-sectional dispersion by survey				
200811	776	0.123	0.316	2.568
200902	773	0.108	0.302	2.793
200907	1,109	0.097	0.262	2.697
200910	988	0.095	0.264	2.791
201001	1,083	0.091	0.272	2.983
201004	1,072	0.092	0.246	2.668
201007	979	0.090	0.247	2.735
201010	1,072	0.087	0.248	2.844
201101	1,064	0.082	0.259	3.162
201104	538	0.087	0.241	2.770
201107	605	0.089	0.252	2.827
201110	542	0.094	0.256	2.714
201201	624	0.086	0.233	2.715
201204	632	0.088	0.266	3.027
201207	588	0.085	0.251	2.935
201210	557	0.087	0.239	2.739
201301	645	0.091	0.243	2.663
201304	846	0.094	0.238	2.543
201307	841	0.092	0.230	2.507
201310	806	0.092	0.233	2.545
201401	584	0.095	0.237	2.501
201404	773	0.094	0.233	2.484
201407	765	0.091	0.232	2.540
201410	731	0.088	0.245	2.786
201501	756	0.088	0.229	2.603
201503	733	0.086	0.242	2.818
201507	694	0.084	0.238	2.822
201510	661	0.085	0.225	2.654
201601	662	0.090	0.224	2.494
Panel B. Time-series summary measures				
Average	776	0.091	0.248	2.722
Min.	538	0.082	0.224	2.484
Max.	1,109	0.123	0.316	3.162

Table VIII
Near- and Long-Term Beliefs and Respondent Characteristics

We examine the relation between respondent characteristics and standardized dependent variables over near- and long-term horizons. Columns 1-3 report regression results of the perceived expected return in the next year (column 1), decade (column 2), or their difference (10-year less 1-year; column 3). Columns 4-6 report analogous results for the perceived standard deviation in market returns for the next year (column 4), decade (column 5), and their difference (column 6). Respondent characteristics include age, years of education, annual income, numeracy, and indicators for gender, ethnicity, married, working, and retired. All dependent variables are standardized to mean zero and unit variance to allow direct comparison across columns. Standard errors are clustered at the respondent level. Significance at the one, five, and ten percent levels are indicated by ***, **, and *, respectively.

	$E_{i,t}$ (r$_i$)			$\sigma_{i,t}$ ($r_{i,}$)			Variance ratio
	1 year	10 year	Difference	1 year	10 year	Difference	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Female	0.064**	-0.247***	-0.283***	-0.035	-0.152***	-0.147***	-0.147***
White race	-0.024	0.111***	0.125***	-0.019	0.055	0.072**	0.062**
Married	-0.033	-0.085**	-0.077**	0.018	-0.015	-0.027	-0.038
Working	-0.003	-0.124***	-0.128***	-0.054*	-0.091***	-0.068***	-0.080***
Retired	0.053	0.043	0.025	-0.086*	-0.039	0.009	0.029
Age	0.001	0.001	0.001	-0.005***	-0.002	0.001*	0.001
Years Education	0.031***	0.054***	0.045***	0.011*	0.026***	0.022***	0.025***
Income	0.031	0.233***	0.233***	-0.058**	0.070**	0.112***	0.125***
Numeracy	0.176***	0.416***	0.369***	-0.103	0.070	0.139***	0.174***
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22,171	22,171	22,171	22,171	22,171	22,171	22,171
R^2	0.017	0.119	0.112	0.015	0.024	0.027	0.031

Table IX
Variance Ratios, Income, Numeracy, and Equity Ownership

The first six columns in this table reports the average inferred standard deviation of one-year expected return distributions, ten-year expected return distributions, and associated variance ratio for individuals with high (>$75k) and low income, high and low numeracy, those who hold equities versus those who do not hold equities. The last two columns compare high-income, high-numeracy, equity-owning respondents with the remaining respondents. The fourth and fifth rows report the fraction of variance ratios less than unity, or less than the historical market variance ratio of 0.558, respectively, along with an associated *p*-value from a sign test that the median does not differ from unity, or 0.558, respectively. The bottom row reports *z*-statistics from a Wilcoxon rank sum test of variance ratio equality across the groups. Statistical significance at the 1% level is indicated by ***.

	Income		Numeracy		Holds Equities		High Income, High Numeracy, Holds Equities	
	High (n=8,096)	Low (n=14,326)	High (n=17,069)	Low (n=5,187)	Yes (n=13,222)	No (n=9,235)	Yes (5,402)	No (16,737)
$\sigma_{i,t}$ ($r_{1\ year}$)	0.272	0.275	0.271	0.282	0.271	0.278	0.269	0.275
$\sigma_{i,t}$ ($r_{10\ year}$)	0.444	0.397	0.420	0.393	0.442	0.374	0.465	0.398
Variance ratio	0.453	0.355	0.408	0.329	0.451	0.302	0.497	0.356
%(VR)<1	0.868***	0.905***	0.885***	0.916***	0.869***	0.925***	0.852***	0.905***
(*p*-value)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
%(VR)<0.558	0.780***	0.845***	0.811***	0.857***	0.782***	0.878***	0.753***	0.844***
(*p*-value)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Z-statistic	16.67***		10.81***		24.36***		20.40***	

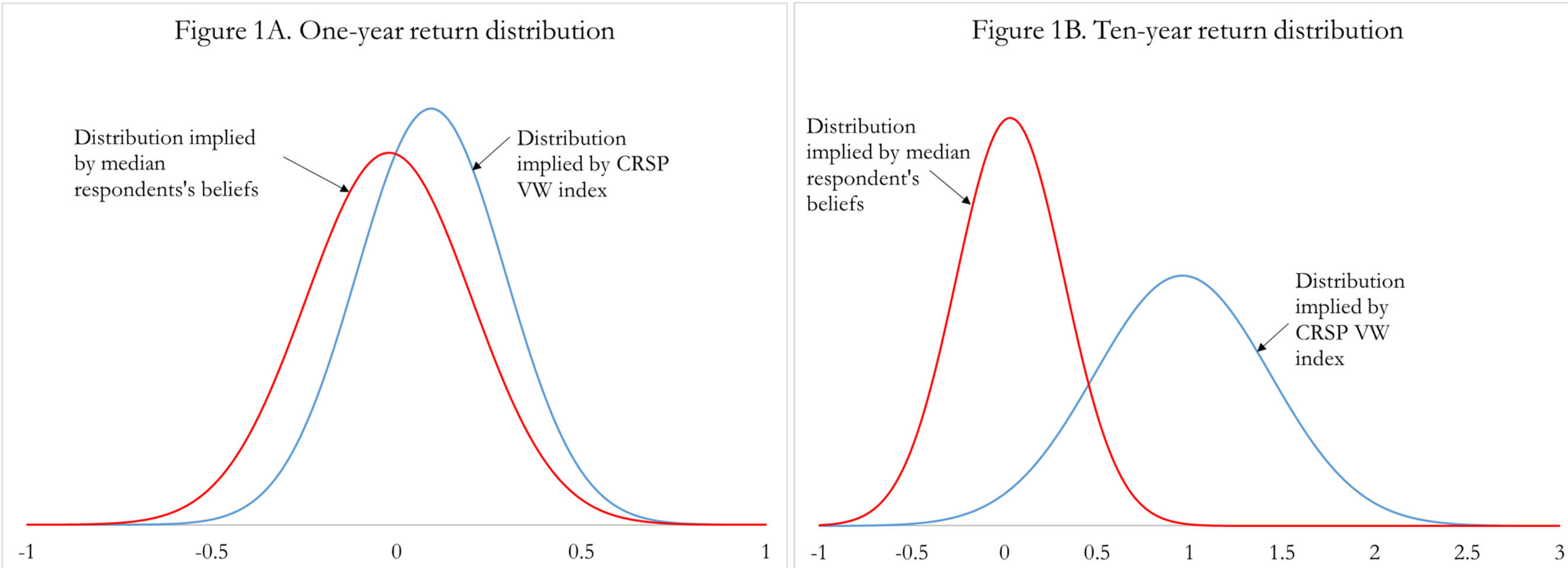

Figure 1. Historical and survey based return beliefs for equity returns. The left panel reports the empirical distribution of historical one-year returns for the CRSP value-weighted index over the 1926-2020 period in blue, and the imputed distribution of survey based returns from the American Life Panel surveys over 2008-2016 based on the median respondent's beliefs in red. The right panel reports the empirical distribution of historical ten-year returns for the CRSP value-weighted index over the 1926-2020 period in blue, and the imputed ten-year return distribution based on the median investor's belief in red.