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ABSTRACT

This paper provides evidence of how the beliefs of investors who step out of the market, or “non-marginal” investors, influence asset prices. Using more than two decades of respondent-level investor surveys, we construct wedge measures that quantify the distance between subjective investor beliefs and option-implied benchmarks. We use self-identified proxies for market participation to document that these wedges correspond with the beliefs of non-marginal investors. Non-marginal investors are generally more pessimistic in their market return forecasts and perceive greater crash risks than the pricing population. Subjective crash beliefs are a key determinant of participation, even when controlling for expected return beliefs. This heterogeneity, in part, explains the negative association between average expected returns estimated from surveys and future realized market returns. In the cross-section, stocks with greater sensitivity to non-marginal beliefs earn lower returns, particularly where disagreement is high. Taken together, the results provide evidence of a composition channel in which belief-driven exit concentrates risk among fewer investors.

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I. Introduction

Expectations play a central role in finance theory, but empirical evidence about investor expectations is difficult to come by. Greenwood and Shleifer (2014) use survey data and find that respondent expectations about stock market returns are negatively associated with future realized returns, inconsistent with rational models. Survey respondents assess the probability of a market crash far above, not below, the level implied by index option prices (Goetzmann et al., 2026). These findings present a puzzle. Why do investor beliefs from surveys diverge from those predicted by asset pricing theory and by empirical evidence on forecasting models?[1]

In this paper we compare survey respondents to the marginal investors who set prices in the stock market. The survey respondents are from a broader population of investors, some of whom are invested in the market and others who have stepped out of the market. The focus of the study is on the compositional differences that drive variation in the survey measures and cause them to decouple from beliefs implied by market prices. Specifically, we use time-series and respondent-level data from Robert Shiller's Investor Confidence Survey, which has collected survey data directly from investors since 1989. Using a sample that spans more than two decades, we extract beliefs embedded in market prices using benchmarks derived from S&P 500 option prices following Martin (2017).[2] Because the option benchmarks we examine are stated under the physical measure, they are represented on the same measure as the survey responses. We compute two spread measures to capture non-marginal investor beliefs. First, the expected market return spread (EMRS) is the survey average expected return minus the option-implied expected return. Second, the crash probability spread (CPS) is the survey average crash probability minus the option-implied crash probability. We exploit heterogeneity in stock market participation to confirm that the beliefs of those in the market track the option benchmarks more closely, while those who have stepped out of the market are driving variation in the spread.

We argue that beliefs about the stock market, particularly investor crash beliefs, influ-

[1] Similar expectation-price gaps appear in professional-forecaster surveys, retail-investor panels, and index-fund demand. See Egan et al. (2022), Adam et al. (2017), Jensen (2022), and Bianchi et al. (2022).

[2] The two benchmarks are the SVIX lower bound on the expected market return and a physical probability of a market crash recovered from the state prices of Breeden and Litzenberger (1978) under log utility. Because the expected-return benchmark is a bound rather than a point estimate, the expected-return spread we report understates its magnitude.

ence the participation decision. Market prices reflect only the beliefs of those who currently bear risk (Vissing-Jørgensen, 2002a; Attanasio and Vissing-Jorgensen, 2003). Option-implied crash probabilities in particular reflect the beliefs of the investors who bear disaster risk: when disaster beliefs are heterogeneous, the less pessimistic investors sell crash insurance to the more pessimistic and take on the risk, so crash premia weight their beliefs disproportionately (Chen et al., 2012). If the decision to stay invested depends on how likely investors think a crash is, then the survey population and the price-setting population will differ systematically. The survey overweights pessimists relative to the market, and the gap widens when pessimistic investors reduce their exposure. Under this interpretation the spread measures do not simply capture noise, but a compositional difference driven by belief-dependent participation.

This composition channel may provide an alternative explanation for a pattern that is difficult to reconcile with standard asset pricing models, namely the negative association between survey expected returns and future market returns. We start by establishing a striking fact from the survey data: investor beliefs based upon surveys are generally more pessimistic compared to option benchmarks. The spread between survey expected returns and option-implied expected returns is negative, on average. Goetzmann et al. (2026) establish that survey crash probabilities exceed option-implied crash probabilities in every month of the sample they consider. The negative EMRS and the positive CPS are consistent with belief-driven selection. They are concentrated among respondents at the margin of participation. We show that the negative predictability of survey expected returns is primarily driven by the component captured by EMRS. Moreover, the results are more pronounced during periods when more investors are stepping out of the market.

We argue that these results are consistent with a participation mechanism related to changes in risk-bearing capacity. In models of limited participation, only the investors who bear equity risk price returns, so the premium reflects their risk aversion rather than that of a representative agent (Basak and Cuoco, 1998). It rises when an adverse shock concentrates aggregate risk on the smaller pool of investors who actively choose their exposure (Chien et al., 2012). When pessimistic investors step out, the remaining investors must hold a larger share of the market and therefore require a higher premium, so a more negative spread precedes higher subsequent market returns. However, exit also leaves a more optimistic set of investors setting prices, which can work in the opposite direction. We evaluate which

force dominates, and find evidence favoring the former. This suggests that the survey and option-implied measures diverge because the set of investors bearing risk changes, rather than because the investors setting prices have erred. If this is the case, it follows that the beliefs of investors who have left the market, or "non-marginal" investors, are priced.

We next study participation propensities. The survey solicits whether investors advise being less invested in the market. Canonical models explain entry and exit in the stock market with variables such as wealth, fixed and information costs, awareness, and social interaction, together with the expected market return (Merton, 1987; Vissing-Jørgensen, 2002b; Gomes and Michaelides, 2005; Hong et al., 2004; Guiso and Jappelli, 2005). In these models, crash beliefs enter only through their effect on the expected return. That is, holding expected return fixed, an investor who has a low crash probability and one who has a much higher crash probability should be equally likely to participate. We test whether this is the case. Using the respondent-level data, we find strong evidence that investor crash beliefs are a significant factor in participation. The crash-probability spread has a strong positive association with the propensity to step out of the market, even after controlling for expected returns. A one-percentage-point increase in the spread is associated with a 0.34-percentage-point higher propensity to step out of the market.

To better understand the mechanisms through which the participation channel affects asset prices, we examine the sensitivities of individual stocks to investor beliefs, specifically their crash beliefs, and study whether these sensitivities explain cross-sectional variation in stock returns. We focus on the crash probabilities given that they are an important determinant of participation. For comparison, we also examine sensitivities to option-implied crash probabilities to distinguish the results from tail risk. Using portfolio sorts on the sensitivities, we show that the average excess returns decline nearly monotonically across deciles based upon CPS sensitivities. Stocks that earn positive returns when CPS increases earn lower future returns. The value-weighted hedge portfolio earns -0.57% in excess returns per month and the equal-weighted hedge portfolio -0.66%. The magnitudes are comparable after risk-adjustment. In contrast, sorting on the option-implied crash probability sensitivities produces a null result. The Fama–MacBeth regression results indicate that the findings still hold after controlling for individual stock characteristics.

Finally, we directly assess to what degree these results vary according to investor disagreement. Disagreement governs how much crash risk is transferred from the more pessimistic

investors to the less pessimistic, so the price of exposure to non-marginal beliefs should be more negative where opinions diverge. Alternatively, a price-pressure channel instead predicts that the effect should concentrate where short-sale constraints bind and keep pessimists out of the market. We interact the stock-level CPS sensitivity with five stock-level measures of disagreement and short sale constraints in the Fama–MacBeth regressions. We show that the results are stronger among stocks with greater analyst forecast dispersion. The interaction terms on proxies for limited arbitrage are, in contrast, insignificant. In all specifications, the uninteracted CPS sensitivities remain significant. The results imply that exposure to non-marginal investor beliefs is priced more strongly when investors disagree.

This paper makes four contributions. First, we construct direct measures of the distance between the beliefs of the surveyed investor population and the beliefs embedded in traded prices, at the respondent level and over two decades. Second, we show that subjective crash beliefs are a determinant of participation beyond expected return beliefs, a channel the participation literature has not isolated. Third, we show that the negative predictive relation between survey expectations and future market returns loads on the component of survey beliefs that prices do not reflect, or non-marginal investor beliefs, rather than on the component that they do. Fourth, we show that exposure to non-marginal investor beliefs is priced in the cross-section of stocks. Stock-level exposures to option-implied crash probabilities are not, suggesting that the effect is not compensation for tail risk.

The balance of the paper is organized as follows. Section II reviews the related literature, and Section III presents the hypothesis development. Section IV describes the survey, the option-implied benchmarks, and the construction of the two spreads, and documents their signs. Sections V and VI test the participation and predictability hypotheses. Section VII tests the pricing hypotheses while Section VIII examines interactions with disagreement measures. Section IX concludes.

II. Related Literature

The emerging consensus from empirical work on investor return expectations is that at least some major subset of investors holds extrapolative beliefs about the stock market. In addition to Greenwood and Shleifer (2014), Egan et al. (2022) document extrapolative beliefs recovered from index-fund demand. Adam et al. (2017) find that survey expectations

display excessive optimism at market peaks and excessive pessimism at market troughs, a pattern incompatible with rational expectations. Jensen (2022) finds that professional analyst forecasts contradict rational asset-pricing expectations, an effect potentially explained by optimism bias. Not all surveys of sophisticated forecasters find a relation to future returns: Söderlind (2010) finds little predictive power for the long-running Livingston Survey of professional economists, despite its correlation with standard forecasting instruments such as the dividend yield. The survey's forecasts of economic fundamentals show more predictive content, however. Campbell and Diebold (2009) find that the growth rate in expected real GDP negatively predicts aggregate stock returns, controlling for standard predictive variables, and Goetzmann et al. (2025) find that exposure to GDP-growth expectations also has explanatory power in the cross-section of returns. More recently, Bianchi et al. (2022) document systematically distorted beliefs in surveys of professional forecasters.[3] Because our data do not allow us to follow individual respondents over time, we cannot test whether a given respondent holds extrapolative beliefs, and we take no position on that interpretation. The distinction we draw is one of aggregation: when participation is belief-dependent, the broad-population survey average differs from the belief average of the investors who set prices. Adam and Nagel (2023) survey the evidence on expectations data in asset pricing and identify belief heterogeneity and the aggregation of measured beliefs as central open challenges, noting that participation constraints and inattention can render some investors effectively non-marginal.

While Greenwood and Shleifer (2014) document a common factor across different surveys, other empirical research examines heterogeneous beliefs about the stock market. Cassella and Gulen (2019), for example, construct a belief-based sentiment index from survey expectations of aggregate returns, weighting investor types by their market participation. They find that the index forecasts low future market returns in the time series, and pronounced effects on arbitrage-constrained stocks in the cross-section. Gandhi et al. (2023) combine option-implied and survey measures of return expectations and find that forward return expectations are excessively countercyclical, rising in bad times by more than investors' own subsequent short-term expectations justify. The demand-system asset pricing literature offers a generalization of the heterogeneity point: if the beliefs embedded in prices are a demand-weighted aggregate across investor types (Koijen and Yogo, 2019), then population

[3]Cocco et al. (2025) document a similar pattern in household surveys.

wedges such as the ones examined in this paper are exactly the kind of composition difference that heterogeneous demand predicts. Meeuwis et al. (2022) document the household-level heterogeneity in portfolios underlying such aggregation. Thesmar and Verner (2026) provide long-run evidence on the same heterogeneity from the belief side. They construct a subjective expected return series from an independent equity research firm's price targets and earnings forecasts over 1956 to 2024. They find that it is contrarian, that it is the only one of nine subjective measures that robustly predicts future market returns, and that it is weakly or negatively correlated with the expectations of individual investors. Martin and Papadimitriou (2022) make the aggregation point structurally. In their model investors differ in beliefs, wealth accumulates to those who proved correct, and the risk-neutral variance of the market reveals the expected excess return perceived by the wealth-weighted representative investor. The equal-weighted cross-sectional average expected excess return is a different object, and in equilibrium it can be negative even when the wealth-weighted average is positive. That distinction is the one our two spreads are built to measure, since the survey average is equal-weighted across respondents while the option-implied benchmark is not.

Our study contributes to this literature by measuring aggregation with granular, multivariate data. We observe the beliefs of a broad survey population together with option-implied benchmarks at matched horizons, and we show that the gap between them is concentrated among respondents who step away from the market and co-varies with the participation margin.

The analysis is also relevant to the stock market participation literature. Canonical models explain entry and exit through costs, wealth, awareness and social interaction, and where beliefs enter they do so through the expected return. Some studies in this literature do consider the role of beliefs in the participation decision. Guiso et al. (2008) make participation depend on the subjective probability of being cheated, which is specific to firm-level expropriation. Dimmock et al. (2016) link ambiguity aversion to participation, a measure that elicits a preference rather than a probability. A related empirical literature links subjective beliefs to portfolio behavior: Giglio et al. (2021) show that subjective return expectations map into portfolio allocations, and Choi and Robertson (2020) survey individual investors on the determinants of their equity allocations, among them beliefs about rare disasters.[4]

[4]An earlier literature observes participation directly rather than inferring it from prices; see Goetzmann

We demonstrate that subjective crash beliefs are an important determinant of participation propensity, beyond what can be explained by expected returns. A related strand asks whether stated survey beliefs are the beliefs that drive decisions. Adam et al. (2021) argue that reported return expectations are not risk-adjusted and should not be identified with the expectations required by standard asset-pricing theory. Liu and Palmer (2026) find that investment demand responds to beliefs beyond stated expectations, so stated beliefs understate the extrapolation in investors' actual decisions. Enke and Graeber (2023) show that cognitive uncertainty pulls stated beliefs toward uninformative priors, so stated beliefs can differ from decision-relevant beliefs even for attentive respondents. Our paper speaks to this question indirectly. It provides supportive evidence on the decision relevance of stated beliefs. In the cross-sectional tests, the negative association between returns and belief exposure grows stronger among stocks with greater analyst disagreement, which are likely to be correlated with uncertainty.

Ross (2015) proposed a method for recovering physical probability distributions from derivative prices. A separate line of work estimates the time series of the market-implied equity premium directly. A key contribution of Martin (2017) is a derivation and estimation of a tight bound on equity premium expectations, together with option-implied crash probabilities. Two further papers clarify the relationship between the equity premium and the full set of expected moments: Chabi-Yo and Loudis (2020) show that the influence of higher moments is itself time-varying, with skewness and kurtosis mattering more in turbulent periods, and Tetlock et al. (2024) derive a time series of equity premium point estimates that relies on the complete set of higher moments. In most of this work the recovered quantity is interpreted as the expectation of a marginal or representative investor. The present paper differs from that identification in one respect. We treat option-implied measures as summaries of beliefs embedded in traded prices, about whoever is setting prices regardless of their preferences, rather than as the subjective belief of any identified agent.[5]

Several papers find that asymmetry, in the form of skewness and jumps, plays an important role in conditional market expectations. Santa-Clara and Yan (2010) estimate the ex

and Massa (2003, 2005), who work from index fund investor accounts.

[5]Evidence from outside the options market is consistent with this view. Thesmar and Verner (2026) measure sophisticated investors' expectations directly from an equity research firm's own forecasts, with no preference assumption of any kind. They find evidence of the same contrarian and predictive behavior obtained using option-implied benchmarks.

ante equity premium implied by S&P 500 options, of which crash risk is a large component, and find that it predicts stock market returns. Bollerslev and Todorov (2011) derive an "investor fears" index from the compensation for jump tail risk, and Bollerslev et al. (2015) show that the jump tail component of the variance risk premium has significant predictive power for market returns. Andersen et al. (2015) and Andersen et al. (2020) model the S&P 500 option surface and find that a left-tail jump factor commands a time-varying risk premium and forecasts market returns, and that this tail-risk premium is priced across international option markets. Kozhan et al. (2013) find that the equity-index skew risk premium is tightly linked to the variance risk premium. Strategies isolating skewness from variance earn an insignificant premium. Schneider (2019) uses option portfolios to show that downside risk explains much of the forward market return. Beason and Schreindorfer (2022) document that a significant fraction of the equity premium is attributable to expected monthly returns in the negative 10% to 30% range. Kelly and Jiang (2014) show that tail risk forecasts aggregate market returns and that exposure to tail risk prices assets in the cross-section. This evidence connects to the rare-disaster models in which left-tail risks command first-order premia.[6] Our contribution to this literature is to separate the crash beliefs of the surveyed population from the crash risk priced in options. The spread between the two is not spanned by the option-implied crash probability, and exposure to it is priced in the cross-section while exposure to that benchmark is not.

III. Participation and Beliefs

A large literature measures investor beliefs directly from surveys (Greenwood and Shleifer, 2014; Giglio et al., 2021; Adam and Nagel, 2023). In much of this literature, the surveyed population is treated as a fixed pool, so that beliefs are averaged across all respondents regardless of their equity market exposure. In theoretical models of limited stock market participation, it is assumed that only the investors who bear equity risk price returns (Mankiw and Zeldes, 1991; Vissing-Jørgensen, 2002a; Brav et al., 2002; Attanasio and Vissing-Jorgensen, 2003), not investors who stepped away from the market. In equilibrium, restricting the population of who participates changes the risk borne by those who remain and the premium they require (Basak and Cuoco, 1998; Guvenen, 2009).

[6] See Rietz (1988); Barro (2006); Gabaix (2012); Wachter (2013).

A tension exists between these two literatures. Much of the beliefs literature treats the surveyed population as fixed over time, so that fluctuations in the beliefs of survey respondents are taken to correspond with the beliefs reflected in prices. The participation literature studies how the population changes, but has largely emphasized determinants other than beliefs. If beliefs drive participation, neither statement holds. Beliefs aggregated across the entire population need not correspond with the beliefs of the marginal investor, and may differ contingent on the participation decision. The beliefs of participants enter prices directly; the beliefs of those who step out can enter only indirectly, through their effect on who bears risk.

Canonical models of stock market participation focus on wealth, fixed and information costs, awareness, and social interaction, together with the expected market return (Merton, 1987; Vissing-Jørgensen, 2002b; Gomes and Michaelides, 2005; Hong et al., 2004; Guiso and Jappelli, 2005). In these models, crash beliefs enter only through their effect on the expected return. Holding a household's expected market return fixed, they do not distinguish between low and high subjective crash risk. Some empirical studies elicit gain and, in some cases, loss probabilities (Dominitz and Manski, 2007; Hurd et al., 2011; Hudomiet et al., 2011). Giglio et al. (2021) elicit subjective disaster probabilities directly and document a negative relation between them and expected returns. This work relates elicited beliefs to portfolio allocations and, in some cases, to stock ownership, but does not isolate the subjective probability of a catastrophic crash as a determinant of the participation decision, nor connect it to the beliefs embedded in prices.

The omission matters because, under standard risk-averse preferences, a crash is a state of high marginal utility, so the subjective probability of that state affects the decision to hold equity directly, not only through its effect on the mean. If beliefs affect participation in this way, whose beliefs matter for prices? There are two reasons the answer may extend beyond current participants. First, if the decision to participate depends on beliefs, investors who step out of the market may hold systematically lower expected returns and higher crash probabilities (Vissing-Jorgensen, 2003; Dominitz and Manski, 2007; Hurd et al., 2011; Giglio et al., 2021). As such, when aggregating across all respondents, survey-based measures place weight on pessimistic beliefs. Second, Greenwood and Shleifer (2014) show that survey-based expected returns negatively predict future realized returns. Changes in the participation margin influence who bears risk. If prices respond to these changes in composition, then the

beliefs of "non-marginal" investors should matter.

There are some studies that touch on this point, though incompletely. Evidence from surveys shows that beliefs influence whether individual investors choose to hold stocks (Vissing-Jorgensen, 2003; Malmendier and Nagel, 2011), but does not address how these beliefs may affect prices. Theoretical work shows that the composition of the investor base matters for risk premia (Gaudio, 2025), though in that model the participation decision does not directly depend on beliefs. Cao et al. (2005) show that uncertainty about returns keeps some investors out of the market, though they do not directly distinguish the role of beliefs. Building on these studies, we measure the beliefs of the investors who step out of the market and quantify the distortion that including them creates in survey-based expected returns.

With this motivation, this paper focuses on the wedge between the beliefs of the surveyed population of investors and those of investors who set prices. The distinction is one of weighting. A survey average weights each respondent equally, while prices weight beliefs by the capital behind them. Martin and Papadimitriou (2022) show that these are separate equilibrium objects, and that the equal-weighted average can take values the price-implied average cannot. We use rich survey data that spans more than two decades and allows us to directly observe a variety of beliefs about the stock market. To identify beliefs embedded in traded prices, we use option-implied objects as benchmarks.[7] We develop hypotheses from this wedge and test them in the sections that follow.

We distinguish the average belief of the full population the survey samples from the beliefs of the investors who bear market risk. Prices aggregate the latter, weighted by risk-bearing capacity (Jouini and Napp, 2007).[8] Aggregation is usually computed over a fixed set of investors. If beliefs drive participation, the set itself changes with beliefs, and beliefs reflected in the survey average and priced beliefs will differ. The survey measures this wider population, and option-implied measures benchmark the beliefs embedded in traded prices. Their difference is a composition wedge. Empirically, we capture two wedges. First, the expected market return spread (EMRS), the survey average expected market return minus its option-implied benchmark. Second, the crash probability spread (CPS), the survey average

[7] An alternative approach would be to directly calculate beliefs across different subpopulations. We do so in the analysis for validation purposes. Because survey responses within the subpopulations are sparse or absent in some periods, we cannot reliably produce time series based upon them.

[8] Chen et al. (2012) show how this operates for crash beliefs: less pessimistic investors sell disaster insurance to more pessimistic ones, and the price of that insurance falls as the sellers accumulate wealth.

crash probability minus the option-implied crash probability.[9]

In the analysis, participation is captured as a propensity rather than a binary state. The survey provides a number of questions that correspond with participation propensities. The main proxy is based upon the share advising to be less invested for the time being. In the empirical section, we evaluate each proxy's correspondence with aggregate participation for validation. The survey average can differ from the average among participating respondents through only two channels: how many respondents have left the market, which is a quantity of interest in the participation literature, and how different their beliefs are, which has been the focus of the beliefs literature.

We develop three hypotheses, which the empirical analysis that follows examines in turn.

H1: Participation and Wedge Dynamics. In the canonical models described above, entry and exit decisions are driven by a number of factors independent of beliefs. That is, households that participate and those that do not may hold the same beliefs, so that the wedge would be flat and contain no compositional content. If participation is driven at least in part by beliefs, households who step out of the market should have more pessimistic beliefs.

There are existing studies that link expected returns to the participation decision. Households with low experienced returns report less willingness to take financial risk, are less likely to hold equity, and are more pessimistic about future returns (Malmendier and Nagel, 2011), and subjective expected returns co-move with equity exposure (Hurd et al., 2011). Investors facing sufficient uncertainty optimally hold no equity over an interval of prices (Dow and Werlang, 1992) and the participation threshold moves with the uncertainty environment (Cao et al., 2005).

Crash beliefs may also be relevant to the participation decision. While surveys used in other studies elicit subjective probabilities of gains and losses (Hurd et al., 2011; Hudomiet et al., 2011; Giglio et al., 2021), they do not relate the probability of a catastrophic crash to the participation decision. However, there is a direct link to the ambiguity literature. Investors who are uncertain about the quality of their information react more strongly to bad news than to good. Epstein and Schneider (2008) show that this asymmetry generates a risk premium and induces negative skewness in returns. A higher subjective crash probability lowers the expected return; because it also raises the uncertainty the investor faces, it bears

[9]Prior work also compares survey and option-implied expected returns to test what surveys measure (Adam et al., 2021; Gandhi et al., 2023).

on the participation decision beyond its effect on the mean (Dow and Werlang, 1992; Cao et al., 2005). Consistent with this idea, ambiguity aversion is negatively related to stock market participation and to the share of financial assets held in equity (Dimmock et al., 2016). Conditional on ownership, ambiguity-averse respondents were also more likely to actively sell stocks during the financial crisis.

If non-participating households hold more pessimistic beliefs, the survey average should, in turn, be more pessimistic than the beliefs that prices reflect. That is, the spread between the survey-based and option-implied expected returns should be negative while that for crash probabilities should be positive on average.

H2: Aggregate Returns Predictability. Prominent explanations for the predictability of survey-based measures on market returns do not depend on the composition of respondents in the survey. For example, if investors extrapolate future returns, survey expectations may be higher after a run-up in prices and be associated with negative subsequent returns (Greenwood and Shleifer, 2014), irrespective of whether those survey-based measures account for respondents with equity exposure.[10] There are other explanations that work in a similar way, such as sticky volatility expectations (Lochstoer and Muir, 2022) and time-varying extrapolation (Cassella and Gulen, 2018). Under these explanations, the predictive content of survey-based measures should not depend on the participation margin.

In models of limited participation, the risk premia are proportional to the risk aversion of the investors who bear equity risk rather than that of a representative agent (Basak and Cuoco, 1998). When an adverse shock leaves aggregate risk concentrated among a smaller set of investors who actively choose their exposure, those investors must be induced to absorb it. As such, the equilibrium price of aggregate risk rises (Chien et al., 2012). Risk premia in such settings vary countercyclically as consumption and wealth shift between participants and non-participants (Guvenen, 2009). If participation itself responds to beliefs, however, exit by the more pessimistic contracts risk-bearing capacity and raises the required premium. It also leaves a less pessimistic set of investors pricing the market, which lowers it. These two forces work against each other, so which dominates is an empirical question.[11] Recent

[10] Barberis et al. (2015) formalize this mechanism in a consumption-based model in which extrapolators and rational traders both hold the market. They show that it reproduces the negative relation between survey expectations and subsequent returns.

[11] These models deliver comparative statics rather than dynamics for the participation margin, which in our data moves at monthly frequency. Chien et al. (2012) is the closest formalization of a time-varying

work recovers how much of the market the risk-bearing investor must hold to justify observed prices from index option prices (Tetlock et al., 2024). It shows that the share rose after 2008 and explains the higher post-crisis premium, and it moves with both pessimism measured from surveys and stock ownership, consistent with the composition channel.

We argue that the wedges index variation in the share of respondents who have stepped out of the market as well as the distance between their beliefs and the beliefs prices reflect. If a more negative spread corresponds with more limited risk capacity, it should be associated with higher subsequent market returns. Accordingly, the predictability of survey expected returns should strengthen in periods when a larger share of respondents has stepped out of the market. This prediction distinguishes the composition channel from extrapolation. We note that there are other theories of investor disagreement in which participation also has a central role but which operate differently (Miller, 1977; Harrison and Kreps, 1978; Hong and Stein, 2007). Pessimists may exit the market, leaving optimists to set prices. However, a key distinction concerning these accounts is that they predict lower subsequent returns due to short-sale constraints. A separate case is Martin and Papadimitriou (2022), where pessimists face no constraint and express their views by shorting. Even then the equal-weighted average belief differs from the belief prices reflect, because wealth accumulates to those who prove correct. The same holds in Barberis et al. (2015), where extrapolators and rational traders differ only in their beliefs and both hold the market at every date. Our setting adds the friction these models abstract from: when pessimists exit rather than short, their beliefs enter prices only through their effect on who bears risk.

H3: Cross-sectional Pricing. Standard asset pricing models do not predict any systematic differences in the returns of individual stocks that are more sensitive to changes in the beliefs of investors who step away from the market. This is because these investors do not trade in those stocks. However, there are other models that suggest that these investors may matter and provide distinguishable predictions. When investors hold different subjective crash probabilities, state prices depend on aggregate consumption and on how those beliefs are distributed across investors rather than on the belief of any one of them (Varian, 1985). A probability recovered from option prices is therefore an aggregate over that distribution,

effective participant set, and we do not attempt the dynamic version here. Cao et al. (2005) show that the premium falls with uncertainty dispersion under specific parametric assumptions. Our analysis approaches the question in a more generalized way.

weighing on the investors who hold the risk. Therefore, the crash probability spread measures the distance between the survey average and that aggregate. When disaster beliefs are heterogeneous, less pessimistic investors sell disaster insurance to the more pessimistic and thereby take on the disaster risk, so crash premia weight their beliefs disproportionately (Chen et al., 2012).[12]

A widening spread accompanies a state where crash risk has been transferred onto a narrower set of investors, whose marginal utility in a crash is correspondingly high (Basak and Cuoco, 1998; Guvenen, 2009). Stocks that pay off in those states may serve as a hedge such that the premium on the exposure will be negative. This is the opposite of what would be expected for tail risk compensation, which commands a positive premium (Kelly and Jiang, 2014). Exposure to the option-implied crash probability reflects risk already borne by the investors who set prices, so it should not be priced in the same way.

Investor disagreement is particularly relevant to the composition channel. Disagreement should be directly linked to how much of the risk is actually transferred. As such, the price of the exposure should be more negative when disagreement is high. This can be distinguished from other explanations related to disagreement. Disagreement that rises in bad times can generate return predictability concentrated in those periods without any compositional shifts (Cujean and Hasler, 2017). The effect should also appear in sensitivities to the option benchmark, which reflect tail risk already borne by the investors setting prices. In contrast, the composition channel predicts asymmetry in the direction, as discussed above. Disagreement could also accentuate the results due to short-sale constraints, which would be consistent with a price pressure mechanism (Miller, 1977). In contrast, the composition channel does not require a binding short-sale constraint. Even absent the constraint, investors may still choose not to participate due to significant crash beliefs, which may correspond with stronger expected uncertainty. Overpricing requires both dispersion and a binding constraint together (Boehme et al., 2006; Hong and Sraer, 2016), and so should be more concentrated in stocks facing binding short-sale constraints. Again, this need not be the case for the composition channel.

A natural concern for all three hypotheses is whether the wedges reflect time variation

[12]In Chen et al. (2012) greater disagreement improves risk sharing and lowers the disaster risk premium in the aggregate. The prediction here concerns the cross-sectional price of exposure to the transfer state rather than the aggregate premium, and the two need not move in the same direction.

in aggregate risk aversion rather than changes in beliefs. The concern is potentially relevant given that the option-implied crash benchmark is recovered under an assumed preference. As such, other channels affecting risk attitudes could be moving both legs of the spread. For example, imagining a crash may raise the demand to hedge against it, so that a respondent reports a crash probability that reflects the disutility of the state rather than its likelihood. A change in risk attitudes of that kind should also be reflected in the prices investors are willing to pay for insurance, and so should move the option-implied benchmark as well as the survey. Moreover, if risk aversion is a common factor that affects the survey measure and the option-implied crash probabilities alike, differencing them should remove it. That is a restriction rather than an identity, and it carries a testable implication: a factor that loads more heavily on one leg than on the other would leave the spread cyclical. In the data, we find that the spread does not co-move with the VIX (correlation $= -0.032$) although both of its legs do (correlations $= 0.407$ and 0.884).

IV. Data and Measure Construction

A. Investor Surveys

Robert Shiller's Stock Market Confidence Indices are based on survey data collected continuously since 1989, semi-annually for a decade and then monthly by the International Center for Finance at the Yale School of Management since July 2001. Shiller (2000) describes the indices constructed from these surveys, compares them to other sentiment indicators, and studies their dynamics in the aggregate.

In this paper, we use the disaggregated survey responses from which those indices are constructed. The sample period considered is from 1996 to 2025. About 300 questionnaires each month are mailed to individuals identified by a market survey firm as high-net-worth investors and institutional investors. Respondents may fill in the questionnaire when they wish, but they are asked to mark the date on which they complete it. It is not a longitudinal survey. Each month comprises a largely different sample of respondents, with a sampling goal of 20 to 50 responses for each of the two types, individual and institutional.

Several existing studies use data from the Shiller surveys.[13] Greenwood and Shleifer

[13]Other studies that use the disaggregated responses rather than the published indices include Bacchetta

(2014) find that the monthly investor confidence index constructed by aggregating the respondent-level Shiller survey is well correlated with several other investor surveys and with mutual fund flows. Barone-Adesi et al. (2015) estimate behavioral pricing kernels from market data and find that they correlate well with investor sentiment surveys, including indices constructed from the Shiller survey data used in this paper. Goetzmann et al. (2015) use the institutional investor responses from a telephone version of the survey about beliefs in market mispricing to study variation in investor mood. Schmidt-Engelbertz and Vasudevan (2025) use Shiller survey data to study the slope of the term structure of forecasts and to test for evidence of higher-order investor beliefs. Goetzmann et al. (2026) establish a positive spread between the crash probabilities reported in the Shiller survey data and option benchmarks, and provide evidence of non-fundamental factors influencing its time variation.

We use three of the survey's questions for the main analysis. First, the survey asks respondents for their expected market returns, specifically on the Dow Jones Industrial Average, over five horizons: one month, three months, six months, one year, and ten years. For the analysis we focus on the six-month horizon, to match the horizon of the crash-probability question, though we also report results for the other horizons, specifically those up through one year.

Second, the survey asks a question about participation propensity:

> "Although I expect a substantial rise in stock prices in the U.S. ultimately, I advise being less invested in stocks for the time being because I think that prices are likely to drop for a while."

Respondents choose "True," "False," or "No Opinion." We use this question as a self-reported proxy for participation. We construct the monthly step-out share as the fraction of respondents who answer "True."

Third, the survey solicits each respondent's subjective crash probability:

> "What do you think is the probability of a catastrophic stock market crash in the U.S., like that of October 28, 1929 or October 19, 1987, in the next six months, including the case that a crash occurred in the other countries and spreads to the U.S.? (An answer of 0% means that it cannot happen, an answer of 100% means it is sure to happen.)"

et al. (2009), Goetzmann et al. (2022), and Bastianello and Peng (2025).

The phrasing of this question has not been significantly altered during the sample period we examine. It therefore has the advantage of consistency across a period of more than two decades, during which the stock market, the macroeconomy, and the financial system have experienced variation.

We compare the survey data of interest with belief measures from other investor surveys and show that they are externally consistent. Internet Appendix Table IA.1 reports univariate regressions of the survey crash probability on relevant questions from the CFO Survey, AAII, Investors Intelligence, and Gallup. These surveys do not solicit crash probabilities, and so we focus on a broad set of questions that may at least be relevant. Internet Appendix Table IA.2 reports the corresponding regressions for the survey expected return, using the return forecasts of the CFO Survey and the Livingston Survey. Each explanatory variable is standardized, so the coefficients are comparable across surveys of different populations and formats. The survey crash probability is related to every variable with the predicted sign, and the relation is significant at the five percent level in 22 of 24 cases. The survey expected return is related to all five elicited return forecasts with the predicted sign, each significant at the ten percent level or better.

B. Options Data

For options market data, we use daily data on SPX (S&P 500 index) options from OptionMetrics from 1996 to 2025. The option-implied benchmarks are constructed following Martin (2017), which are physical rather than risk-neutral measures. For expected returns, the benchmark μ_t^{option} is the six-month SVIX lower bound, which uses the risk-neutral variance of the S&P 500 to bound the physical expected market return.[14] For crash probabilities, the benchmark q_t^{option} is the six-month physical probability of a market decline of 20% or more, recovered under log utility ($\gamma = 1$).[15]

[14] It is worthwhile to note that, because this benchmark is a lower bound, the expected-return spread will be underestimated.

[15] Recomputing the benchmark at coefficients of relative risk aversion of 0, 2 and 4 leaves the spread positive in every month at 2 and 4, and in 98% of months at 0, which is the risk-neutral case in which no preference is imposed. Higher risk aversion lowers the benchmark and widens the spread. The expected-return benchmark is computed from risk-neutral variance alone, so its value does not depend on this parameter, but its interpretation as an expected return does. Under power utility the implied equity premium is a roughly constant multiple of the SVIX bound rather than a fixed offset from it, and that multiple rises with risk aversion.

We match the option data to the survey responses by trading date, which lets us compare each survey response directly with the option-implied benchmark. The value used for each survey response is as of the close of the previous trading day. Specifically, we construct wedge measures based on the spread between the survey-based measure and the options market benchmark. The option market benchmarks are represented on the physical measure. Under log utility, the physical option-implied quantity is the belief that rationalizes option prices. Because state prices depend on how beliefs are distributed across investors rather than on the belief of any one of them (Varian, 1985), it is best read as an aggregate over that distribution, weighted toward the investors who bear equity risk. As such, it is represented on the same measure as the survey responses.

C. Market Data

For the aggregate market data, we use daily returns on the value-weighted index of the NYSE–AMEX–Nasdaq–Arca universe from the Center for Research in Security Prices (CRSP). Market volatility implied by the VIX is obtained from CBOE. Aggregate market turnover is constructed from CRSP as total daily share volume divided by total shares outstanding across the universe.

For the cross-sectional tests on individual stocks, we obtain data that features the universe of CRSP common stocks listed on the NYSE, AMEX, or Nasdaq. Returns are adjusted for delisting when applicable. At each monthly rebalance we require a lagged month-end price of at least \$5 in 2020 dollars. We obtain data on firm characteristics from four sources that are merged to the returns data. Accounting data are from the COMPUSTAT quarterly file, lagged using only the most recent values available based upon the report date. Analyst coverage and forecast dispersion are constructed from the IBES summary file. Institutional-ownership characteristics come from the Thomson Reuters 13F holdings data, using only the most recent values available based upon the report date. Fama–French five-factor and momentum return series are obtained from Kenneth French's data library.[16]

Aggregate equity mutual fund flows are constructed from the CRSP U.S. Mutual Fund database from 1999 to 2025.[17] We compute the monthly percent flow as the change in total

[16] `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

[17] Equity funds are defined as a Lipper asset code of EQ. The Lipper classification is populated in CRSP only from 1999.

net assets net of fund returns, aggregated across funds and scaled by lagged total net assets.[18]

D. Summary Statistics and Measure Description

Table 1 reports variable definitions and summary statistics, and Internet Appendix Table IA.3 reports univariate correlations. Three features of the summary statistics matter for what follows.

First, the average survey six-month expected return is 1.4%, compared with 4.2% for the option-implied benchmark. The EMRS is the difference between the survey and option-implied expected return. EMRS has a sample mean of −2.8 percentage points. This indicates that the survey respondents are on average more pessimistic than the option-implied benchmark. The EMRS is strongly correlated with the survey expected return (0.82) but negatively correlated with the option-implied benchmark (−0.51).

Second, the average survey crash probability is 19.0%, compared with 5.6% for the option-implied benchmark. The CPS is the difference between the survey and option-implied crash probabilities. Its sample average is +13.3 percentage points, more than twice the option-implied crash probability.

Third, the average participation propensity, measured by %StepOut, is 31.3%. It is negatively correlated with the EMRS (−0.43), so there are more respondents stepping out of the market when the spread is more negative. On the other hand, %StepOut is positively correlated with both the survey crash probability (0.27) and, more strongly, the option-implied crash probability (0.44). Its monthly correlation with the crash-probability spread is small in the aggregate (0.06).[19]

Figures 1 and 2 plot the survey and option-implied expected-return time series and the EMRS at the 1-month, 3-month, 6-month, and 1-year horizons. Survey expectations are more volatile and occasionally turn negative, while option-implied expected returns remain positive throughout the sample and spike during high-volatility episodes. The EMRS is negative in about three quarters of sample months, with especially large negative excursions around market-stress events (e.g., the Dot-com bust, the Great Financial Crisis, the 2020

[18] In month t, the equity fund flow is $100 \times \left[\sum_i \text{TNA}_{i,t} - \sum_i (1 + r_{i,t})\text{TNA}_{i,t-1}\right] / \sum_i \text{TNA}_{i,t-1}$, summed over equity funds i, where $r_{i,t}$ is the fund's monthly return.

[19] Later in the paper, we focus on the within month respondent-level relationship, which we find is significant.

COVID shock).

Figures 3 and 4 plot the survey and option-implied crash-probability series and the monthly CPS. The survey crash probability mean and the displayed quantiles (median and 90th percentile) lie consistently above the option-implied measure. The gap is positive in every month of the sample and widens over time, at 0.257 percentage points per year (t-value = 6.92). The widening comes from the survey leg (estimate = +0.206, t-value = 3.84) rather than the option leg (estimate = −0.051, t-value = −1.37). Like the EMRS, the crash probabilities appear to be correlated with market-stress events.

The two legs contribute unequally to the variation in the spread. Decomposing the variance of the spread into its survey and option-implied components, the survey leg accounts for 96.4 percent and the option-implied leg for 3.6 percent. Regressing the spread on each leg separately paints the same picture, with an R^2 of 0.76 for the survey leg and 0.00 for the option-implied leg. Together with the finding that the widening of the gap comes from the survey side, this indicates that the spread moves because survey beliefs move, and not because the option-implied benchmark is unusually low.

Figure 5 plots the monthly %StepOut series. The series is countercyclical: it rises through the Great Financial Crisis, reaching close to 80% at its peak, and is elevated again during the 2022 drawdown. The wide variation indicates that the mix of respondents advising to remain invested and to step out varies over the sample.

Together, the summary statistics confirm that the wedge measures are not flat. The signs correspond with the first hypothesis: the expected-return spread is negative on average while the crash-probability spread is positive. The patterns are consistent with a belief-driven participation mechanism. The magnitudes are economically large, with the average survey crash probability more than three times the option-implied benchmark.

V. Expected Returns and Non-Marginal Beliefs

A. Return Predictability and the Expected Return Spread

Greenwood and Shleifer (2014) establish that the survey average of expected returns forecasts future realized returns negatively. An interpretation of that result is that surveyed investors extrapolate returns. An alternative explanation is that the survey-based expected return is a

mixture of a price-relevant component and a "non-marginal" component, so that separating the two should strengthen the predictive relationship. The two explanations are not mutually exclusive. Individual respondents may still extrapolate but the survey average may also reflect who is and is not participating.

Table 2 presents the results. The specifications are estimated at the daily frequency. The dependent variable is the realized market return over the subsequent 180 days, to align with the horizon of the survey and option measures, and the explanatory variables are measured as of the observation date. Column (1) shows the specification for the survey expected market return, and Column (2) the option-implied expected market return. Columns (3) through (5) include EMRS, by itself and then in combination with each of the two underlying measures. All specifications include the past one-month and one-year market returns, VIX, and market turnover as controls, together with month-of-year and day-of-week fixed effects. Block bootstrapped standard errors, which correct for the serial correlation induced by the overlapping six-month forecast windows, are reported in parentheses.[20]

Consistent with Greenwood and Shleifer (2014), Column (1) shows that the survey expected return coefficient loads negatively and significantly (estimate = -0.260, t-value = -3.22). It indicates that high survey expectations predict low subsequent six-month realized returns. Column (2) shows the opposite sign for the option-implied expected return, whose coefficient loads positively and significantly (estimate = 4.103, t-value = 2.52), consistent with Martin (2017). Column (3) shows the EMRS coefficient on its own. As with the survey measure, it is negative and significant, and larger in absolute value (estimate = -0.342, t-value = -3.76). Column (4) shows that both the EMRS (estimate = -0.240, t-value = -2.96) and the option-implied measure (estimate = $+3.812$, t-value = 2.20) coefficients retain similar signs and significance. Column (5) shows that the survey coefficient flips to positive (estimate = $+3.812$, t-value = 2.12) while the EMRS coefficient remains negative (estimate = -4.052, t-value = -2.29). Both remain significant and much larger in absolute magnitude.[21]

[20]Because the predictors are persistent and correlated with return innovations, we also compute the finite-sample bias that this induces in the predictive slope. For the expected-return spread it is 0.67% of the point estimate and works against the reported result.

[21]The specification can be viewed as a reparameterization of the specification in Column (4). Because EMRS is the difference between the survey-based and option-implied measures, the survey coefficient in Column (5) equals the option coefficient in Column (4) while the EMRS coefficient equals the Column (4) EMRS coefficient minus the option coefficient.

The estimates are economically meaningful as well. A one-percentage point increase in the survey expected return is associated with a 0.26 percentage point lower six-month market return, while a one-percentage point increase in the EMRS is associated with a 0.34 percentage point lower return. A one-percentage-point increase in the option-implied expected return is associated with a 4.10-percentage-point higher return. The raw coefficients thus make the option-implied measure appear an order of magnitude more sensitive. However, it is possible that the differences are mostly due to the fact that the option-implied expected return varies less than the survey-based measures. Scaling each coefficient by the sample standard deviation shows a similar result. A one-standard-deviation increase in the survey expected return is associated with a decline of about 1.6 percentage points in the subsequent six-month return, roughly 11% of the overall variability of the market returns. The corresponding figure is 16% for the EMRS. As before, that for the option-implied measure is the largest of the three, at 66%.[22]

The results inform the second hypothesis, and provide some initial support for the compositional channel interpretation. We replicate the results from the existing literature: survey expected returns have a strong, negative coefficient. The option-implied measure explains the most variation in realized market returns. The spread, when interpreted as a measure of belief differentials, holds the opposite sign, even after controlling for option-implied expected returns. It explains a meaningful amount of variation in realized market returns, though not as much as the option-implied measure.

As a robustness check, we ask whether the results are specific to the six-month horizon used above for the dependent variable. Panel A of Internet Appendix Table IA.4 re-estimates the baseline regression with future returns measured over one month, three months, six months, and one year, holding the expected-market-return spread measure fixed at a six month horizon. The coefficient remains negative and significant at every horizon, though somewhat weaker at the one-month horizon. The absolute magnitudes increase with the horizon.

The results are also not specific to the horizon used to calculate the spread. Panel B of Internet Appendix Table IA.4 fixes the dependent variable horizon at six months but varies the horizon of the spread measure, both for the survey and option legs: one month, three months, six months, and one year. The spread predicts the six-month market return

[22]We note that this pattern could be driven in part by potential noise in the survey estimates.

negatively and significantly for each of the specifications. The predictability is strongest for the three- and six-month spreads and weakest for the twelve-month spread.

B. Non-Participation and the Expected-Return Spread

To more directly investigate the compositional channel explanation, we turn now to the survey questions that correspond with stock market participation.

Before turning to the main tests, we start by examining to what extent the participation questions actually correspond with aggregate participation. For this we construct tests based upon flows for equity mutual funds. To correspond with the baseline specifications, the dependent variable is the percentage equity fund flow from month t to $t+6$. The control variables include lagged VIX, the market return, aggregate turnover, equity fund flows, along with month-of-year fixed effects.

We consider three questions from the survey that are likely to correspond with participation. There is no question that offers a direct measure for participation, though the question wordings suggest that they should be related. As such, we empirically investigate how each measure corresponds with participation.[23] We form three measures based upon each of the questions: the fraction of investors advising to remain less invested in stocks (%StepOut), who believe that stocks are relatively overvalued (%Overvalued), and who are inclined to sell stocks (%Sell).

Internet Appendix Table IA.5 reports the results. All three measures have a negative coefficient, as expected. However, only %StepOut is statistically significant (estimate $= -2.495$, t-value $= -2.80$). When including all three measures in the same specification, %StepOut remains statistically significant (estimate $= -0.307$, t-value $= -2.74$) while the other measures are not. To assess the economic magnitudes, a one-standard-deviation increase in %StepOut

[23]The exact survey question wordings are as follows. For the %StepOut measure: "Although I expect a substantial rise in stock prices in the U. S. ultimately, I advise being less invested in stocks for the time being because I think that prices are likely to drop for a while," answered True, False, or No opinion. The measure corresponds with the proportion of investors during the month that answer "True." For the %Overvalued measure: "Stock prices in the United States, when compared with measures of true fundamental value or sensible investment value, are:" answered Too low, Too high, About right, or Do not know. The measure corresponds with the proportion of investors during the month that answer "Too high." For the %Sell measure: "Are you inclined now to buy stocks overall, or sell stocks overall, or hold steady and why?" answered Buy, Sell, or Hold. The measure corresponds with the proportion of investors during the month that answer "Sell."

is associated with a 0.31-percentage-point net outflow from equity funds over the following six months, which is relatively large compared to the 0.76 percentage point sample average of fund flows. As such, we use %StepOut as the primary proxy for participation propensities throughout the paper.

We next assess whether investors with more pessimistic beliefs about expected market returns correspond with participation propensities. If variation in EMRS is driven by compositional effects, it should be tied to the share of respondents who move away from the market. Alternatively, EMRS may simply reflect broad pessimism unrelated to participation. Under that interpretation, the fraction of respondents stepping out should be related to both legs of the wedge symmetrically, rather than loading disproportionately on the survey side.

To test this, we regress the survey expected returns, the option-implied expected returns, and the EMRS separately on the monthly %StepOut. Table 3 displays the results. These specifications use the same control variables as Table 2, but are estimated on the monthly panel and do not include fixed effects. %StepOut is strongly negatively related to the survey expected return (estimate $= -0.045$, t-value $= -3.46$) and to the EMRS (estimate $= -0.051$, t-value $= -3.40$) measures. In contrast, its relationship with the option-implied benchmark is economically negligible and statistically insignificant (estimate $= 0.001$, t-value $= 0.20$).

To provide sharper tests, we next use the disaggregated survey data to decompose the expected return spread based upon the participation proxies. If the EMRS reflects the composition of the pricing population, the differences should be concentrated among the respondents who are stepping away from the market and should be much smaller among those who remain in it.

We decompose the EMRS into investor groups defined by the participation proxies. For each proxy we form two groups according to whether the respondent is or is not likely to participate. We then report the survey expected return, the option-implied expected return, and the EMRS for each.[24] The results are displayed graphically in Figure 6. The tabular form is available in Table 4.

The non-participating group based upon the %StepOut measure has an average expected return of -1.2 percentage points, against $+3.3$ for the participating group. This is slightly

[24]For each pair the two groups are compared on the days on which both responded. We average each group's responses within the day and then across days, so both groups of a pair face the same option-implied benchmark.

below but closer to the option-implied benchmark of +4.3 in the matched sample. The EMRS is therefore −5.5 percentage points among StepOut respondents and −1.0 among StayIn respondents, and the difference is statistically significant. The two middle sets repeat the split on the valuation and trading questions, and the pattern holds: the non-participating group has an EMRS of −5.5 and −8.5 percentage points respectively, while the participating group is much smaller, or −0.7 and −1.9, respectively.

The far right set combines the three questions. Those that are flagged as non-participating on all three have an EMRS of −10.8 percentage points, twice the step-out spread. Those that are flagged as participating on all three have an EMRS of +0.5 percentage points, which is economically small in magnitude. The participating group holds beliefs that coincide with the price, while the non-participating group is furthest from it.

Overall, these results are consistent with the first hypothesis, namely that investors who have stepped out of the market are more pessimistic. Moreover, they provide affirmative evidence on our interpretation of the option-implied benchmarks as those reflecting the beliefs of investors in the pricing population. The decomposition also speaks to the source of the wedge. In Martin and Papadimitriou (2022), no friction keeps any investor out of the market, and the gap between the equal-weighted average belief and the belief that prices reflect arises entirely from the distribution of wealth across beliefs. Here the gap narrows sharply once respondents are sorted on whether they remain invested. This indicates that the participation margin distinguishes the survey average from priced beliefs.[25]

C. Composition and Return Predictability

The findings so far demonstrate that the participation proxies explain significant variation in the expected returns spread. If composition is also what makes the spread forecast returns, the predictability should depend on the fraction of non-participating investors. When participation is high, the survey average should be closer to that of the marginal investor so that the spread should contain little information about future returns. When participation is lower, the survey average tilts toward investors whose beliefs do not enter prices, and the spread should forecast returns more strongly.

[25]The relevant weight in Martin and Papadimitriou (2022) is investor wealth, which we cannot observe. As such, we cannot say to what extent wealth weighting contributes to this pattern.

We repeat the baseline returns predictability specifications on the monthly data but augment them with %StepOut and its interaction with EMRS. Table 5 reports the results.[26] Column (1) reports the spread on its own as a monthly baseline (estimate = −1.435, t-value = −3.14). Column (2) shows that %StepOut on its own does not predict returns (estimate = −0.007, t-value = −0.09). Column (3) adds the spread, which forecasts returns negatively and significantly and stays close to its baseline value (estimate = −1.550, t-value = −2.94). Column (4) adds the interaction, which is negative and significant (estimate = −4.017, t-value = −2.07). The spread forecasts returns more strongly the larger the share of respondents who have stepped out. The spread's own coefficient, which is the predictive slope when no respondents have stepped out, is small and insignificant. Evaluated at the average %StepOut, the implied slope is about −1.55, close to the column (3) estimate. A one-standard-deviation increase in %StepOut, about thirteen percentage points, is associated with a slope steeper by roughly one third. This is the amplification the composition channel predicts. Column (5) adds the option-implied expected return as a control, and the interaction remains negative and significant (estimate = −3.314, t-value = −1.99).

Overall, the results provide supportive evidence of the composition-based explanation of the expected-return puzzle. The spread predicts future market returns. A more negative spread precedes higher subsequent returns, which is the direction implied by the risk-bearing capacity channel. Exit by the more pessimistic concentrates the market's risk among fewer holders and raises the premium they require. The alternative that exit by pessimistic investors leaves a more optimistic set of investors setting prices does not appear to be a dominant factor.

VI. Crash Probabilities and Non-Marginal Beliefs

This section focuses on the role of investor beliefs in participation propensities.

[26] Because these specifications are estimated on monthly rather than daily observations, the spread's slope is not directly comparable to the daily estimate in Table 2.

A. Crash Beliefs and Participation

We start by examining the relationship between subjective crash beliefs and participation. For these tests, we use respondent-level data. As explained earlier, the survey is a repeated cross-section, so that the respondents cannot be tracked over time. As such, the variation we use is across respondents and over time, rather than within respondents. The dependent variable across all specifications is a dummy variable, StepOut, which corresponds with whether the respondent indicates that they advise remaining relatively less invested. The explanatory variables are as follows: the respondent's subjective crash probability estimate, the crash probability spread, and the option-implied crash probability as of the survey date. The control variables include the lagged one-month market return, the VIX, and aggregate turnover, and each specification includes month-of-year and day-of-week fixed effects. Because the observations are individual responses arriving on survey dates, robust standard errors are clustered on the date level and are reported in parentheses.

Table 6 displays the results. The survey crash probability and the CPS are both strongly positively related to the propensity to step out. The coefficient on the survey crash probability is positive and significant without (estimate = 0.505, t-value = 27.5) and with (estimate = 0.473, t-value = 25.6) the control variables. The coefficient on CPS is also positive and statistically significant (estimate = 0.464, t-value = 25.1). When the option-implied crash probability is included as a separate control, the CPS coefficient changes little in magnitude (from 0.464 to 0.470), while the option-implied benchmark enters positively on its own (estimate = 1.903, t-value = 7.0).[27] The spread is therefore associated with stepping out beyond the crash risk already reflected in option prices. Column (5) adds the option-implied expected return and the EMRS. The CPS coefficient attenuates but remains large and significant (estimate = 0.338, t-value = 15.0). This indicates that the crash-belief wedge is not merely a restatement of the expected-return wedge. That is, holding expected returns fixed, crash beliefs explain significant variation in participation propensity.

[27] Because the spread is the difference between the survey and option-implied crash probabilities, column (4) is unrestricted: the implied level coefficients are 0.470 and 1.433, both positive rather than equal and opposite, though the spread's own coefficient is unchanged when the option leg is freed.

B. Crash Probabilities and Expected Returns

We next examine the relationship between investor crash beliefs and expected returns. A substantial theoretical literature posits a positive association between crash risks and expected returns. An implication is that the crash probabilities and expected returns reflected in prices are determined by investors who participate in markets. What is unclear is what the relationship should be for investors who choose not to participate. Some investors may choose not to participate if they expect relatively lower returns due to higher crash risks relative to those that do. This would imply a negative relationship between crash probabilities and expected returns on the survey side.

Table 7 directly tests for the relationship between the expected return measures and subjective crash probabilities. The dependent variables are EMRS, the survey-based expected return, and the option-implied expected return. The key explanatory variables are the survey crash probabilities and CPS. The control variables and fixed effects included in each specification are identical to those of Table 6.

The subjective crash probabilities have a strong negative correspondence with the survey-based expected market return (estimate = -0.106, t-value = -28.0). We find similar results for the EMRS specification (estimate = -0.108, t-value = -27.7). In contrast, the coefficient for the option-implied expected return is positive and statistically significant (estimate = 0.002, t-value = 3.4). When focusing on CPS, the negative association with the survey-based dependent variables remains (estimate = -0.106, t-value = -27.9). However, the association with the option-implied expectation disappears and the coefficient is close to zero and is statistically insignificant.

The findings indicate that the survey crash probabilities are positively associated with option-implied expected returns, consistent with predictions of traditional asset pricing models. However, they are negatively associated with EMRS. The crash probability spread, which nets out the crash beliefs reflected in prices, has an insignificant association with the option-implied expected returns but retains a negative association with EMRS. These results suggest strong differences in the behavior of beliefs across investors in and out of the pricing population.

VII. Cross-Sectional Pricing Tests

This section presents the results from the cross-sectional tests on individual stock returns. The previous sections established the role of participation in the market return predictability tests and crash beliefs as a key determinant of participation propensities. When investors disagree about crash risk, less pessimistic investors take that risk on from the more pessimistic. As such, a widening spread signifies states in which crash risks are concentrated among a narrower set of investors. The tests that follow ask whether exposure to that state is priced.

To do so, we first estimate each stock's daily return sensitivity to CPS. For each stock i and month t, we estimate a rolling regression of the stock's daily excess return on the lead, contemporaneous, and lag CPS to account for asynchronicity potentially associated with daily returns. The estimation is over a window of the most recent 252 valid daily observations ending one trading day before the end of formation month t, requiring at least 126, so that the lead term uses no information dated after the formation date. Specifically, we use the following regression model:

$$r^e_{i,s} = \alpha_{i,t} + \beta^{\text{lag}}_{i,t} CPS_{s-1} + \beta^{0}_{i,t} CPS_s + \beta^{\text{lead}}_{i,t} CPS_{s+1} + \varepsilon_{i,s}, \tag{1}$$

where $r^e_{i,s}$ is stock i's total excess return and CPS_s is the aggregate daily crash-probability spread.

We define the CPS sensitivity as the sum of the CPS coefficients:

$$\beta^{\text{CPS}}_{i,t} = \beta^{\text{lag}}_{i,t} + \beta^{0}_{i,t} + \beta^{\text{lead}}_{i,t}, \tag{2}$$

For comparison, we construct analogous option-implied crash-probability sensitivities, $\beta^{q^{\text{option}}}_{i,t}$, using the same construction.

A. Portfolio Sorts

We start by forming portfolios based upon the CPS returns sensitivities. We form decile portfolios based on β^{CPS} at the end of each month using only information available up to

that point.[28] Based upon monthly returns, we estimate time-series regressions to calculate the performance of those portfolios for the following month. To evaluate performance, we use a Fama and French (2015) five-factor model with the momentum factor. All test statistics reported use Newey and West (1987) standard errors.

The results from the portfolio sorts are reported in Table 8. Equal-weighted portfolio excess returns decline across deciles, from 1.20% per month in the lowest β^{CPS} decile to 0.53% in the highest. The resulting hedge portfolio spread is −0.66% per month, significant at the 1% level. The alpha of the hedge portfolio is −0.50% per month, significant at the 5% level. The alphas associated with the individual decile portfolios generally decline. Results based upon value-weighted portfolios are similar. The hedge portfolio return is −0.57% per month, which is insignificant at the 5% level, though the alpha is −0.64% per month, which significant at the 5% level, and is of comparable magnitude. Together, the results suggest that stocks that earn lower returns when aggregate crash probability spread increases command higher average returns. In contrast, stocks that earn higher returns when aggregate crash probability spread increases command lower average returns.

For comparison, we examine the results when forming the portfolios based on $\beta_{i,t}^{q^{\text{option}}}$. Internet Appendix Table IA.6 displays the results. Across all specifications, the hedge portfolios are statistically insignificant, and neither the excess returns nor the alphas decline across the deciles. The β^{CPS} sorts produce a declining pattern in both excess returns and alphas, while the $\beta^{q^{\text{option}}}$ sorts are flatter. This again indicates that return sensitivity based upon CPS differs from that of the option-implied crash probabilities. If the cross-sectional effect were driven simply by exposure to market tail risk, sorts based upon the option-implied crash probabilities would produce a similar pattern, which is not the case.

We next present the factor loadings associated with the portfolios. Internet Appendix Table IA.7 reports the results. Across the deciles, market betas are close to one and do not show a monotonic pattern. The market beta of the hedge portfolio is indistinguishable from zero (t-value = −0.02). The hedge portfolio loads positively on momentum (estimate = 0.33, t-value = 2.32), consistent with survey crash beliefs responding to recent market performance. Its loadings on the remaining factors are statistically insignificant. For com-

[28] Decile breakpoints are computed from NYSE stocks only. Using breakpoints from the full cross-section instead yields a slightly larger spread for the equal-weight (estimate = −0.68, t-value = −2.75) and value-weighted (estimate = −0.64, t-value = −2.06) specifications, so the NYSE convention reported here is the more conservative of the two.

parison, Internet Appendix Table IA.8 displays the factor loadings for the $\beta^{q^{\text{option}}}$ portfolios. That hedge portfolio loads negatively on the market (estimate = −0.41, t-value = −3.62) and positively on CMA (estimate = 0.63, t-value = 2.16), and its remaining loadings are statistically insignificant. The contrast with the β^{CPS} portfolios provides a useful insight. Sorting on the option-implied crash probability produces a portfolio with pronounced market exposure and no abnormal return, whereas sorting on CPS produces a portfolio with no market exposure and a significant alpha. The two sensitivities therefore identify portfolios with different risk profiles rather than the same exposure in different degree.

B. Fama–MacBeth Regressions

The portfolio sorts establish a significant performance differential based upon stock-level CPS return sensitivities. We next turn to Fama–MacBeth regressions to better assess the predictability of β^{CPS} when conditioning on stock characteristics.

Table 9 presents the results. Column (1) includes $\beta^{\text{CPS}}_{i,t}$ alone, Column (2) includes $\beta^{q^{\text{option}}}_{i,t}$ alone, and Column (3) includes both. Columns (4) and (5) add a parsimonious set of firm characteristics: log market equity, book-to-market, leverage, the past twelve-month return, and the inverse of the share price. Column (5) additionally includes $\beta^{q^{\text{option}}}_{i,t}$.

Column (1) displays the results for β^{CPS} without the control variables. The coefficient is negative and significant (estimate = −5.84, t-value = −3.03). Consistent with the portfolio sorts, in Column (2), $\beta^{q^{\text{option}}}$ is statistically insignificant on its own (estimate = −0.39, t-value = −0.70). When both betas enter jointly in Column (3), β^{CPS} remains negative and significant (estimate = −5.50, t-value = −2.91), while $\beta^{q^{\text{option}}}$ stays insignificant. Adding the firm characteristics in Column (4) attenuates the β^{CPS} coefficient in absolute value but leaves it significant at the 1% level (estimate = −4.60, t-value = −2.90), and the full specification in Column (5) is similar (estimate = −4.29, t-value = −2.77). $\beta^{q^{\text{option}}}$ remains statistically insignificant throughout the specifications.

Taken together, the results are consistent with the risk-bearing capacity channel. They document a negative association between β^{CPS} and individual stock returns, which is robust to controlling for stock characteristics. The results suggest that a widening crash-probability spread accompanies a transfer of crash risk onto a narrower set of investors. As such, stocks that pay off in those states serve as hedges and earn lower average returns. The lack of

significance based on $\beta^{q^{\text{option}}}$ suggests that the results are not compensation for priced tail risk.

VIII. Disagreement and Pricing Tests

The previous section provides evidence that exposure to the aggregate crash probability spread is priced in the sample period for which we have data. This section tests how those pricing results relate to disagreement. Martin and Papadimitriou (2022) show that the premium investors require rises with the distance between the belief embedded in prices and the risk-neutral belief, so more widely dispersed beliefs command a higher premium even where no short-sale constraint binds. The composition channel makes a comparable prediction for crash-belief exposure. Where investors disagree more about a stock, more of its crash risk is transferred, so the price of exposure to the spread should be more negative among those stocks.

We examine stock-level measures of disagreement and limits to arbitrage. Specifically, we examine five measures. Analyst forecast dispersion is the standard measure of differences of opinion (Diether et al., 2002). Analyst coverage is a related proxy, which corresponds with a stock's information environment. Share turnover proxies for speculative disagreement in models where short-sale constraints bind (Scheinkman and Xiong, 2003). Institutional ownership captures the availability of shares to borrow. The change in ownership breadth is the Chen et al. (2002) measure of investor disagreement.

For the stock-level disagreement measures, we use Fama–MacBeth regressions to estimate the interaction term between $\beta_{i,t}^{\text{CPS}}$ and the stock-level measure $D_{i,t}$. $D_{i,t}$ is the level of each measure. The interaction terms use variables that are demeaned within the sample month before they are interacted. The regressions include the same set of control variables as in Table 9.

The results are reported in Table 10. The coefficient on $\beta_{i,t}^{\text{CPS}}$ is negative and significant across all five specifications. The analyst forecast dispersion interaction term coefficient is negative (estimate $= -4.501$, t-value $= -2.04$). This suggests that the pricing result is stronger among stocks with greater analyst disagreement. The change in ownership breadth interaction term is positive (estimate $= 10.085$, t-value $= 1.67$), suggesting that the pricing results are stronger among stocks whose ownership breadth is falling, though it is only

significant at the 10% level. The interaction terms for analyst coverage, turnover, and institutional ownership are not statistically significant. Institutional ownership proxies for the availability of shares to borrow, and its interaction is insignificant, which does not support binding short-sale constraints as the source of the result.

We next turn to the aggregate tests. If disagreement affects how much crash risk is transferred, the price of exposure to the spread should be more negative in periods when disagreement is high, and not only among stocks about which investors disagree. We estimate the monthly conditional γ_t, the Fama–MacBeth slope on $\beta_{i,t}^{\text{CPS}}$ from the specification of Column (4) in Table 9, and regress it on aggregate measures of disagreement and uncertainty. Analyst dispersion and the change in ownership breadth are the stock-level measures of Table 10 value-weighted across stocks each month. We also consider aggregate turnover and the VIX for comparison. Each measure is standardized, so the coefficient is the change in the price of crash-belief risk per one standard deviation.

Table 11 reports the results. Columns (1) to (4) enter one measure at a time and Column (5) enters all four jointly. The price of crash-belief risk is more negative in months of high aggregate analyst dispersion (estimate $= -6.474$, t-value $= -2.22$). The remaining three measures are statistically insignificant. In the joint specification the analyst dispersion coefficient is essentially unchanged (estimate $= -6.472$, t-value $= -2.22$), and the three other measures add no explanatory power, leaving the R^2 at the level of the analyst dispersion specification alone.

Overall, the results provide suggestive evidence for the third hypothesis. The stock-level tests provide evidence that the pricing results are stronger where disagreement is higher. The aggregate tests provide consistent evidence. Taken together, the limited arbitrage proxies do not have a significant interaction, while belief dispersion does.

IX. Conclusion

We study the role of beliefs of investors who have stepped out of the market and provide evidence on how these beliefs influence asset pricing. We identify their beliefs using rich survey data on two margins, each the spread between a survey-based measure and its option-implied benchmark: expected market returns and crash probabilities. We test the assumption that the option-implied benchmarks embed beliefs of the pricing population. In the time series, we

provide evidence that the negative association between subjective expected market returns and future realized market returns is strongly related to the spread. In turn, we show that this predictability strengthens when a larger share of respondents recommend stepping out of the market. Our evidence suggests that beliefs differ systematically with self-reported participation propensities. The findings suggest that crash beliefs, in particular, are an important determinant of participation propensities, even after controlling for expected returns.

To distinguish among channels behind these effects, we conduct tests on the cross-section of stock returns. Consistent with a risk-bearing channel, stocks that positively co-move with the crash-probability spread earn lower average returns. The results are significant even after accounting for factor and characteristic controls. In contrast, stocks that co-move with option-implied crash probability produce no significant return differential. Finally, we find suggestive evidence consistent with the hypothesis that the effects are stronger among stocks with high analyst disagreement. The proxies for limited arbitrage do not interact with the pricing result.

The results have a number of implications. For work on survey expectations, they imply that a survey average may not be a fixed-population object. Part of its variation and predictive content reflects who is answering rather than how beliefs change. It raises an interesting potential systematic source of variation that is generally unaccounted for in time-series and cross-sectional tests using survey data. For the participation literature, the results add subjective crash beliefs as a determinant of participation propensity, distinct from expected returns, a mechanism that reduced form models typically do not incorporate. With respect to research on option-implied expectations and tail risk, the results show that the crash beliefs of the surveyed population likely contain information that the option-implied crash probability does not span. Our results further suggest that exposure to this information may be priced while exposure to the option-implied crash probability may not be.

Several avenues remain open for future research. Existing models either fix the set of participating investors or let it respond to wealth and information costs, and those in which beliefs do drive participation turn on objects other than the probability of a catastrophic market crash. As our evidence shows, beliefs are an important determinant of participation. Martin and Papadimitriou (2022) develop a model that touches on this, in that prices there reflect the wealth-weighted average belief rather than the equal-weighted average, but their pessimists express their views by shorting rather than by exiting. Extending that structure

to the crash margin we study, where participation responds to tail beliefs specifically, would help formalize the mechanism we document. Finally, investor surveys are now available for a number of markets. Evidence that the spread is priced outside the United States would distinguish a general feature of belief aggregation from a feature of this particular survey.

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Figure 1. Survey and Option-Implied Expected Returns

This figure reports monthly survey and option-implied expected market returns at the 1-month, 3-month, 6-month, and 1-year horizons from January 1996 through December 2025. Panel A reports survey expected returns, and Panel B reports option-implied expected returns.

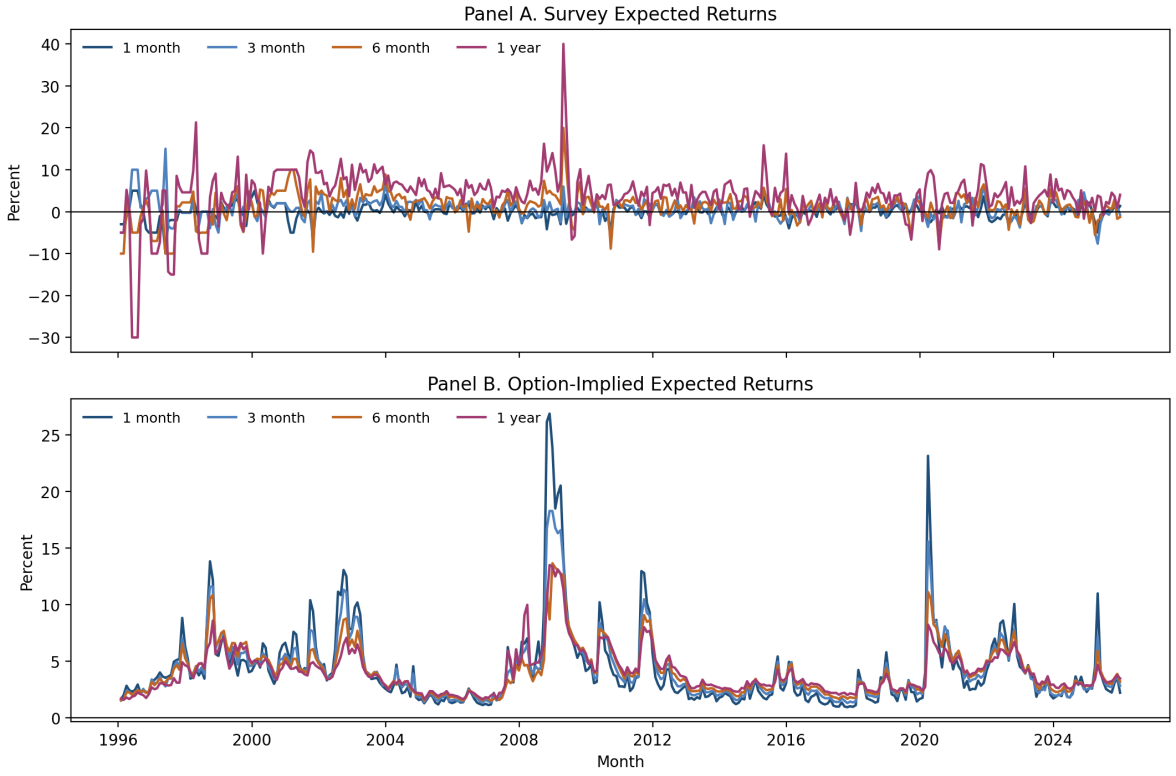


Figure 2. EMRS Time Series

This figure reports the monthly expected-market-return spread, computed as the difference between the survey and option-implied expected returns, at the 1-month, 3-month, 6-month, and 1-year horizons from January 1996 through December 2025. Panels A through D report the 1-month, 3-month, 6-month, and 1-year EMRS series, respectively.

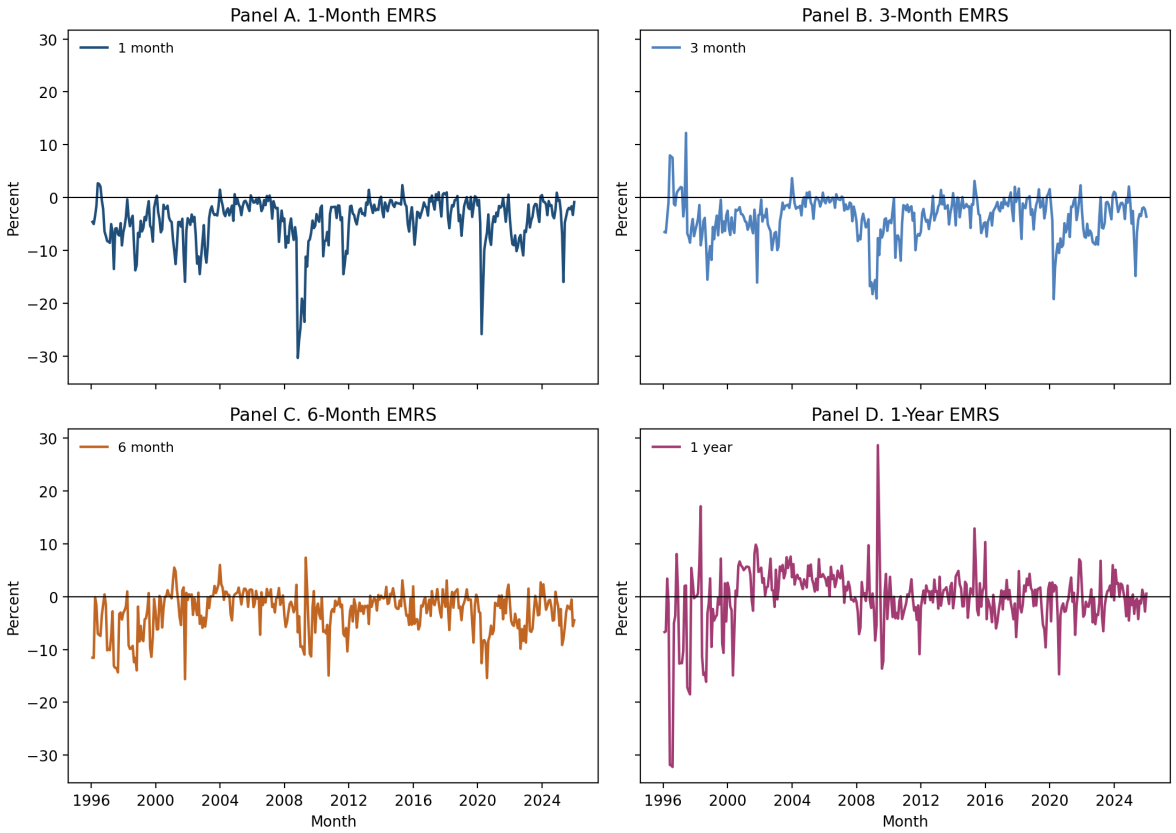


Figure 3. Survey and Option-Implied Crash Probabilities

This figure reports annual survey crash-probability moments from January 1996 through December 2025 and the annual mean option-implied crash probability from January 1996 through December 2025.

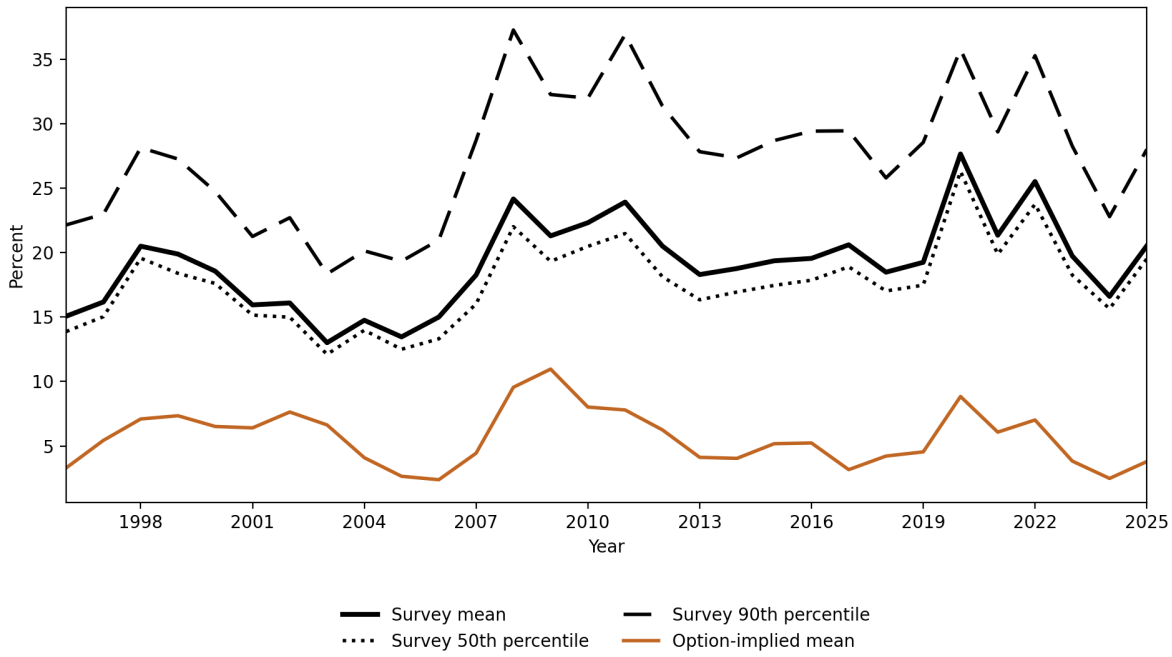


Figure 4. Monthly CPS

This figure reports the monthly mean crash-probability spread, defined as the difference between the survey and option-implied crash probability, from February 1996 through December 2025.

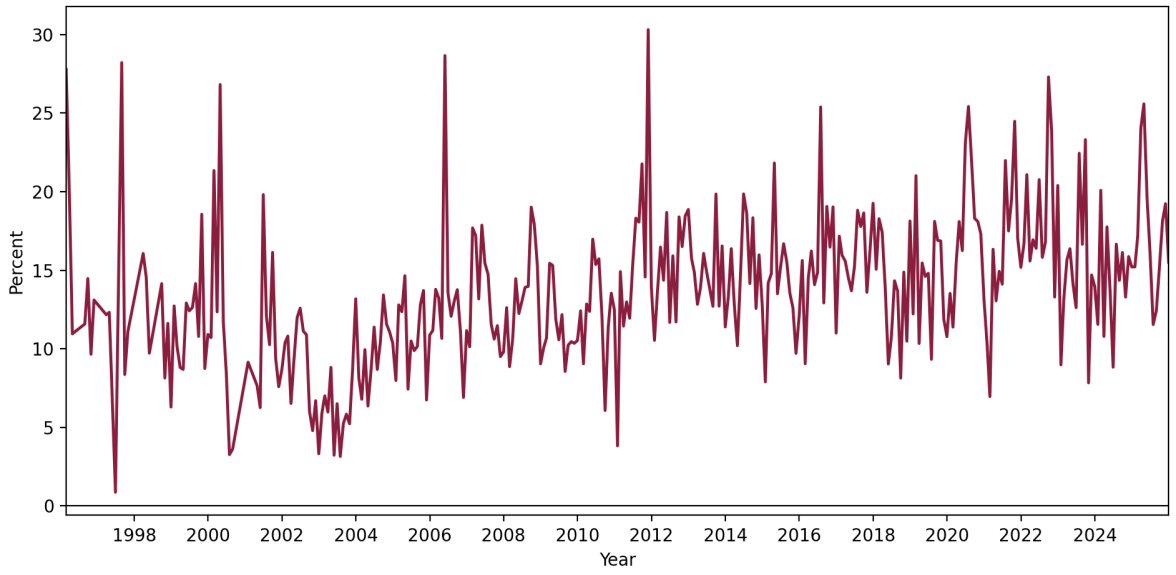


Figure 5. Monthly Step-Out Share
This figure reports the monthly %StepOut from March 1996 through December 2025.

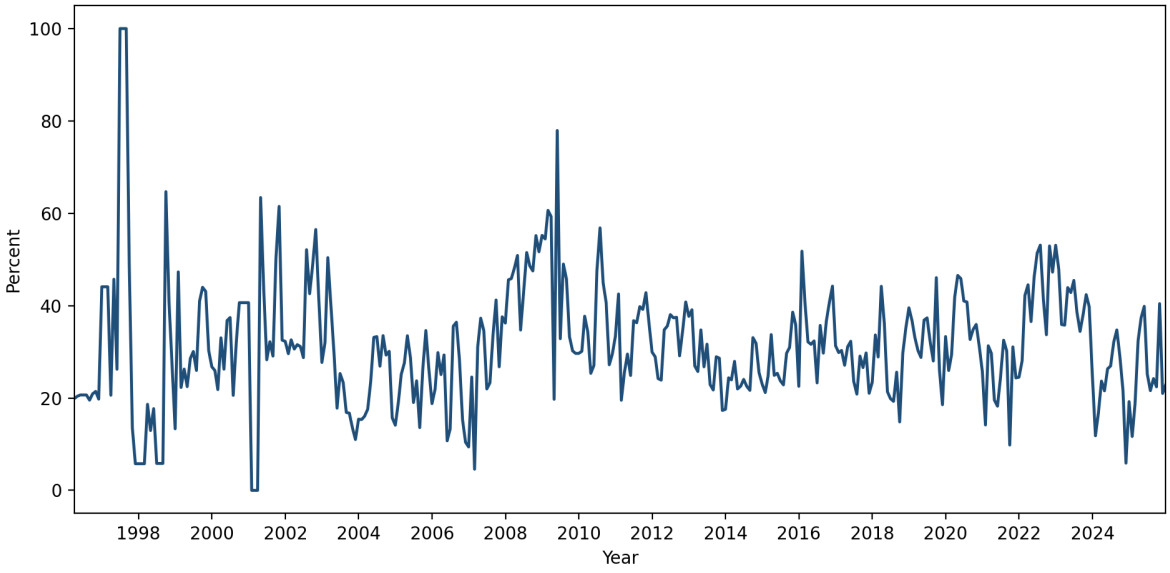


Figure 6. Subgroup Expected Returns by Participation Question

This figure reports six-month expected market returns for the participation subgroups of Table 4. Each cluster corresponds to one split: the step-out, valuation, and trading questions, and the composite of all three. Within a cluster, the three bars are the non-participating group's survey expected return, the participating group's survey expected return, and the option-implied expected return, which is common to the two groups. The gap between a survey bar and the option bar is that group's expected-market-return spread. Error bars are 95% confidence intervals from the estimates reported in Table 4.

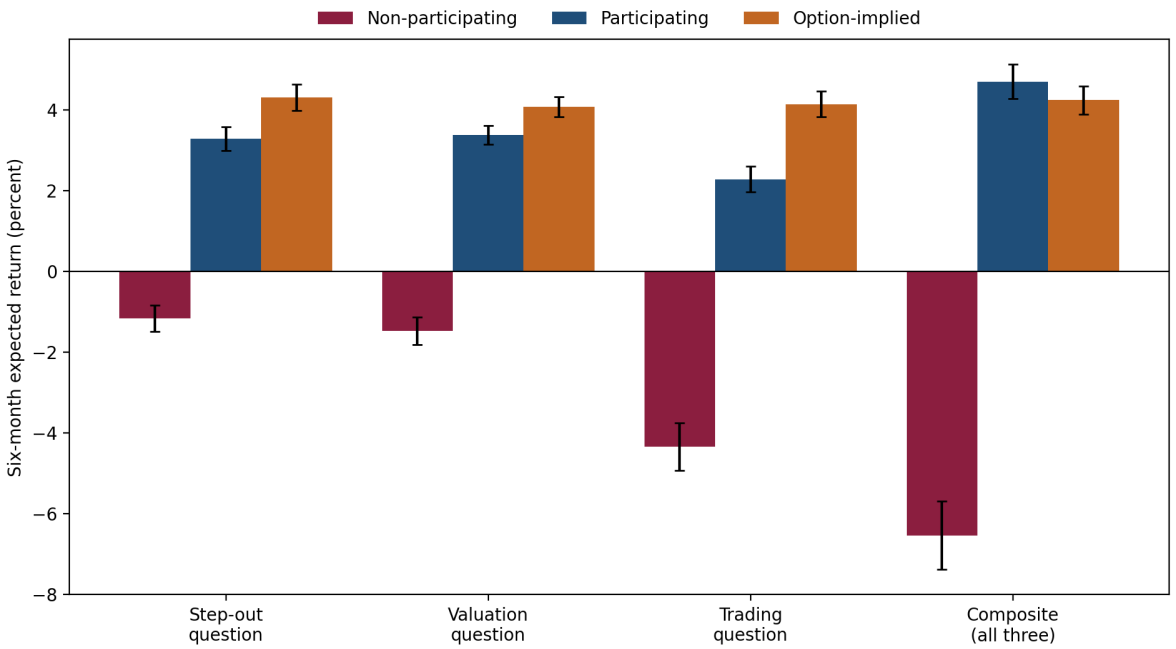


Table 1. Variable Definitions and Summary Statistics

This table provides variable definitions (Panel A) and monthly summary statistics (Panel B) over 1996–2025.

Panel A. Variable Definitions

Variable Name	Description
$E[R^M_{t,t+180}]^{Survey}$	Survey expected market return at the six-month horizon.
$E[R^M_{t,t+180}]^{Option}$	Option-implied expected market return at the six-month horizon, the Martin (2017) SVIX lower bound.
$EMRS^{180d}_t$	Expected-market-return spread, the survey minus the option-implied expected return.
π^{Survey}_t	Survey six-month subjective crash probability.
π^{Option}_t	Option-implied six-month physical crash probability of a 20% market decline.
CPS_t	Crash-probability spread, the survey minus the option-implied crash probability.
$\%StepOut_t$	Monthly share of respondents advising to be less invested in stocks, the step-out share s_t.
$R^M_{t-30,t-1}$	Cumulative market return over the 30 days ending the day before the survey month.
$R^M_{t-180,t-1}$	Cumulative market return over the 180 days ending the day before the survey month.
$R^M_{t,t+30}$	Cumulative market return over the 30 days following the survey month.
$R^M_{t,t+180}$	Cumulative market return over the 180 days following the survey month.
VIX_t	CBOE VIX index level.
$Turnover_t$	Aggregate market turnover.

Table 1 (continued). Variable Definitions and Summary Statistics

Panel B. Summary Statistics

Variable Name	N	Mean	Std Dev	25th Pctl	50th Pctl	75th Pctl
$E[R^M_{t,t+180}]^{Survey}$	358	0.014	0.035	-0.001	0.018	0.032
$E[R^M_{t,t+180}]^{Option}$	358	0.042	0.023	0.025	0.035	0.051
$EMRS^{180d}_t$	358	-0.028	0.041	-0.049	-0.019	-0.001
π^{Survey}_t	358	0.190	0.051	0.157	0.184	0.218
π^{Option}_t	358	0.056	0.025	0.037	0.053	0.071
CPS_t	358	0.133	0.046	0.104	0.130	0.160
$\%StepOut_t$	358	0.313	0.134	0.233	0.299	0.379
$R^M_{t-30,t-1}$	358	0.011	0.051	-0.009	0.018	0.042
$R^M_{t-180,t-1}$	358	0.067	0.140	0.017	0.097	0.151
$R^M_{t,t+30}$	357	0.011	0.051	-0.011	0.021	0.042
$R^M_{t,t+180}$	350	0.066	0.141	0.012	0.092	0.148
VIX_t	358	20.172	7.705	14.741	18.432	23.511
$Turnover_t$	358	9.627	3.524	7.138	9.174	11.533

Table 2. Returns Predictability

This table reports baseline regressions of subsequent 180-day market returns on survey expected returns, option-implied expected returns, and the expected-market-return spread. All specifications include lagged returns, VIX, turnover, day-of-week fixed effects, and month-of-year fixed effects. Block-bootstrapped standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable: $R^M_{t,t+180}$					
$E[R^M_{t,t+180d}]^{Survey}$	-0.260***				3.812**
	(0.081)				(1.799)
$EMRS^{180d}_t$			-0.342***	-0.240***	-4.052**
			(0.091)	(0.081)	(1.773)
$E[R^M_{t,t+180d}]^{Option}$		4.103**		3.812**	
		(1.630)		(1.735)	
Controls	Yes	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Observations	6860	6860	6860	6860	6860
R-squared	0.059	0.116	0.069	0.127	0.127

Table 3. Non-Participation and EMRS

This table reports monthly regressions of survey expected returns, option-implied expected returns, and the expected-market-return spread on non-participation. The dependent variables are the survey expected market return, the option-implied expected market return, and their difference, EMRS. The key explanatory variable is $\%StepOut$. The control variables and fixed effects are identical to Table 2. Block-bootstrapped standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	(1)	(2)	(3)
Dependent variable	$E[R^M_{t,t+180d}]^{Survey}$	$E[R^M_{t,t+180d}]^{Option}$	$EMRS^{180d}_t$
$\%StepOut_t$	-0.045***	0.001	-0.051***
	(0.013)	(0.005)	(0.015)
Controls	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	322	336	322
R-squared	0.152	0.871	0.535

Table 4. Expected Returns Decomposition

This table reports subgroup means of six-month survey expected returns, six-month option-implied expected returns, and EMRS on the respondent-level data. Columns (1) and (2) are associated with respondents advising to being less investored in stock for the time being and those that did not, respectively. Columns (3) and (4) are associated with respondents who report that stock prices are too high and those who did not, respectively. Columns (5) and (6) are associated with respondents indicating that they are inclined to sell and those that did not, respectively. Columns (7) and (8) represent a composite measure: respondents who are bearish on all three measures and those who are bearish on none of the three, respectively. Standard errors clustered on the date level are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Step Out	Stay In	Overvalued	Not Overvalued	Sell	No Sell	Composite Non-Part.	Composite Participate
$E[R^M_{t,t+180d}]^{Survey}$	-0.012	0.033	-0.015	0.034	-0.043	0.023	-0.065	0.047
$E[R^M_{t,t+180d}]^{Option}$	0.043	0.043	0.041	0.041	0.041	0.041	0.042	0.042
$EMRS_t^{180d}$	-0.055***	-0.010***	-0.055***	-0.007***	-0.085***	-0.019***	-0.108***	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.005)	(0.002)

Table 5. Realized Returns and Non-Participation

This table reports monthly regressions of the six-month-ahead realized market return on the expected-market-return spread, the step-out share, and their interaction. Block-bootstrapped standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: $R^{M}_{t,t+180}$				
$EMRS_t^{180d}$	-1.435***		-1.550***	-0.231	0.250
	(0.457)		(0.527)	(0.405)	(0.442)
$E[R^{M}_{t,t+180d}]^{Option}$					3.169***
					(0.861)
$\%StepOut_t$		-0.007	-0.087	-0.193	-0.154
		(0.086)	(0.107)	(0.140)	(0.128)
$EMRS_t^{180d} \times \%StepOut_t$				-4.017**	-3.314**
				(1.943)	(1.669)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	316	316	316	316	316
R-squared	0.089	0.027	0.095	0.116	0.147

Table 6. Investor Crash Beliefs and Participation

This table reports regressions of non-participation on subjective crash probabilities and the crash-probability spread using the respondent level data. The dependent variable is an indicator associated with whether the respondent recommends to be less invested, or *StepOut*. The key explanatory variables are the survey crash probability, CPS, and the option-implied crash probability. The control variables and fixed effects are identical to those in Table 2. Robust standard errors clustered on the date level are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable	$StepOut_{it}$	$StepOut_{it}$	$StepOut_{it}$	$StepOut_{it}$	$StepOut_{it}$
π_{it}^{Survey}	0.505***	0.473***			
	(0.018)	(0.018)			
CPS_{it}			0.464***	0.470***	0.338***
			(0.018)	(0.018)	(0.022)
π_t^{Option}				1.903***	2.011***
				(0.273)	(0.334)
$E[R_{t,t+180}^M]^{Option}$					-2.175***
					(0.377)
$EMRS_{it}^{180d}$					-1.699***
					(0.060)
Controls	No	Yes	Yes	Yes	Yes
Day-of-Week FEs	No	Yes	Yes	Yes	Yes
Month FEs	No	Yes	Yes	Yes	Yes
N	18409	18409	18409	18409	14030
R-squared	0.048	0.065	0.063	0.066	0.130

Table 7. Crash Probabilities and Expected Returns

This table presents the results from regression models where the dependent variables are $EMRS_{i,t}^{180d}$, $E[R_{t,t+180d}^{M}]_{i,t}^{Survey}$, and $E[R_{t,t+180d}^{M}]_{t}^{Option}$. Two-way fixed effects on the month and day-of-week levels are included where indicated, but not reported. Control variables from Table 2 are included where indicated, but not reported. Robust standard errors clustered on the date level are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	$EMRS_{i,t}^{180d}$	$E[R_{t,t+180d}^{M}]_{i,t}^{Survey}$	$E[R_{t,t+180d}^{M}]_{t}^{Option}$	$EMRS_{i,t}^{180d}$	$E[R_{t,t+180d}^{M}]_{i,t}^{Survey}$	$E[R_{t,t+180d}^{M}]_{t}^{Option}$
$\pi_{i,t}^{Survey}$	-0.108***	-0.106***	0.002***			
	(0.004)	(0.004)	(0.001)			
$CPS_{i,t}$				-0.106***	-0.106***	0.000
				(0.004)	(0.004)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	14030	14030	19142	14030	14030	19142
R2	0.158	0.094	0.783	0.155	0.094	0.783

Table 8. Stock-Level CPS Portfolios

This table reports monthly decile sorts on stock-level CPS sensitivities. The CPS sensitivities are calculated using lead-lag-sum betas estimated from daily returns and CPS over a 252-day backward-looking, rolling window. Each month, stocks are sorted based on $\beta_{i,t}^{CPS}$ into decile portfolios. Excess returns and risk-adjusted returns using a Fama and French (2015) five-factor model with the momentum factor are reported for both equal- and value-weighted portfolios. Newey-West standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

Portfolio	EW Excess Return	EW FF5+MOM Alpha	VW Excess Return	VW FF5+MOM Alpha
D1	1.195**	0.111	1.426***	0.369*
	(0.481)	(0.123)	(0.427)	(0.202)
D2	1.173***	0.177**	1.153***	0.115
	(0.393)	(0.083)	(0.333)	(0.124)
D3	1.207***	0.258***	1.155***	0.139
	(0.340)	(0.074)	(0.315)	(0.110)
D4	1.148***	0.236***	1.183***	0.241**
	(0.326)	(0.078)	(0.277)	(0.096)
D5	1.064***	0.170***	1.050***	0.057
	(0.304)	(0.063)	(0.274)	(0.099)
D6	0.983***	0.076	0.983***	-0.009
	(0.299)	(0.067)	(0.269)	(0.090)
D7	0.954***	0.027	0.979***	-0.062
	(0.294)	(0.057)	(0.245)	(0.079)
D8	0.886***	-0.043	1.039***	0.027
	(0.300)	(0.072)	(0.260)	(0.098)
D9	0.797**	-0.169**	0.784***	-0.270**
	(0.320)	(0.081)	(0.291)	(0.108)
D10	0.531	-0.387***	0.852**	-0.274**
	(0.393)	(0.134)	(0.343)	(0.138)
Hedge	-0.664***	-0.498**	-0.574*	-0.643**
	(0.249)	(0.220)	(0.311)	(0.283)

Table 9. Fama-Macbeth Regressions

The table reports results from the monthly Fama-MacBeth regressions. The key explanatory variables are $\beta_{i,t}^{CPS}$ and $\beta_{i,t}^{OptionProb}$. The control variables include the natural log of the market capitalization, book-to-market ratio, leverage ratio, past year returns, and the inverse of the share price. Newey-West standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: $r_{i,t+1}^{e}$				
$\beta_{i,t}^{CPS}$	-5.8390***		-5.4965***	-4.6023***	-4.2902***
	(1.9258)		(1.8900)	(1.5863)	(1.5461)
$\beta_{i,t}^{q^{\text{option}}}$		-0.3939	-0.6492		-0.5364
		(0.5608)	(0.6045)		(0.5036)
Log market equity				0.0007***	0.0006***
				(0.0002)	(0.0002)
Book-to-market				0.0031*	0.0030*
				(0.0017)	(0.0017)
Leverage				0.0000	-0.0002
				(0.0024)	(0.0024)
Past 12-month return				0.0009	0.0012
				(0.0019)	(0.0018)
Inverse price				-0.0215	-0.0209
				(0.0157)	(0.0150)
N Months	275	275	275	275	275
Avg N	3146	3146	3146	2994	2994
Avg R^2	0.0065	0.0079	0.0133	0.0391	0.0443

Table 10. Stock-level Disagreement and Limits to Arbitrage

This table reports the results of the monthly Fama-MacBeth regressions with interaction terms. The regressions include $\beta_{i,t}^{CPS}$, a stock-level measure $D_{i,t}$, and their interaction. $D_{i,t}$ includes: analyst forecast dispersion, analyst coverage, share turnover, institutional ownership, and the change in institutional ownership breadth. The control variables of Table 9 are included in all specifications. Newey-West standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	(1) Analyst disagreement	(2) Analyst coverage	(3) Turnover	(4) Institutional ownership	(5) Change in breadth
	Dependent variable: $r_{i,t+1}^{e}$				
$\beta_{i,t}^{CPS}$	-4.214**	-4.552***	-4.975***	-4.509***	-4.984***
	(1.792)	(1.547)	(1.547)	(1.557)	(1.642)
$\beta_{i,t}^{CPS} \times D_{i,t}$	-4.501**	-1.674	0.075	-3.635	10.085*
	(2.209)	(1.028)	(0.071)	(2.834)	(6.028)
$D_{i,t}$	-0.003***	0.003***	-0.000**	0.008***	0.007***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)
Control Variables	YES	YES	YES	YES	YES
N Months	275	275	275	275	275
Avg N	1992	2994	2994	2994	2529
SD of $D_{i,t}$	0.341	1.034	10.115	0.350	0.111

Table 11. Aggregate Disagreement and the Price of Crash-Belief Risk
This table reports time-series regressions of the monthly Fama–MacBeth γ estimates on aggregate measures of disagreement and uncertainty. In each month, next-month stock returns are regressed cross-sectionally on $\beta_{i,t}^{\text{CPS}}$ together with log market equity, book-to-market, leverage, the past twelve-month return, and the inverse of the share price. The slope on $\beta_{i,t}^{\text{CPS}}$ is retained as γ_t. All specifications include the lagged one-month and one-year market returns, the VIX, aggregate turnover, and month-of-year fixed effects. Newey–West standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: γ_t				
Analyst dispersion	-6.474**				-6.472**
	(2.922)				(2.919)
Change in breadth		0.327			0.051
		(2.279)			(2.065)
Aggregate turnover			0.563		2.540
			(1.939)		(1.725)
VIX				-3.866	-1.670
				(2.875)	(3.029)
Controls	Yes	Yes	Yes	Yes	Yes
Month-of-Year FE	Yes	Yes	Yes	Yes	Yes
N Months	275	275	275	275	275
R-squared	0.078	0.044	0.044	0.044	0.078

Internet Appendix

for

"Non-Marginal" Investor Beliefs

This Internet Appendix reports supplementary tables referenced in the main text.

Table IA.1. Cross-Survey Validation of the Survey Crash Probability

This table reports univariate regressions of the monthly survey crash probability on belief measures from other investor surveys. Each row is a separate regression. The dependent variable is the the survey crash probability, which is aggregated to the frequency of the other measure that it is compared against. Each explanatory variable is standardized, so the coefficient is the change in the dependent variable, in percentage points, associated with a one standard deviation change in the comparator. Newey–West standard errors are used to calculate the test statistics. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	Frequency	N	Sample	Expected	Coefficient	t-value
CFO Survey (US chief financial officers, quarterly)						
10th percentile, 1-year S&P return	Quarterly	83	2001Q4–2023Q2	-	-2.908***	-7.65
P(1-year S&P return < 0), skewed fit	Quarterly	81	2001Q4–2023Q2	+	2.993***	7.52
P(1-year S&P return < 0), Gaussian fit	Quarterly	83	2001Q4–2023Q2	+	2.863***	7.38
Implied subjective σ	Quarterly	83	2001Q4–2023Q2	+	1.834***	3.52
Subjective left-skew gap	Quarterly	83	2001Q4–2023Q2	-	-1.896***	-4.29
Optimism about the US economy	Quarterly	84	2002Q2–2023Q2	-	-2.449***	-5.53
Share less optimistic than last quarter	Quarterly	75	2001Q2–2020Q1	+	1.652***	3.26
Optimism diffusion (more minus less)	Quarterly	75	2001Q2–2020Q1	-	-1.762***	-3.69
P(negative real GDP growth)	Quarterly	13	2020Q2–2023Q2	+	2.259***	2.87
AAII (individual investors, weekly to monthly)						
Bearish share	Monthly	327	1996-03–2023-05	+	2.297***	5.33
Bull-bear spread	Monthly	327	1996-03–2023-05	-	-2.445***	-6.73
Bullish share	Monthly	327	1996-03–2023-05	-	-2.190***	-6.36
Investors Intelligence (newsletter writers, weekly to monthly)						
Bull share	Monthly	318	1996-03–2022-08	-	-1.598***	-3.26
Bull-bear spread	Monthly	318	1996-03–2022-08	-	-1.211**	-2.25
Bull ratio	Monthly	318	1996-03–2022-08	-	-1.061*	-1.95
Bear share	Monthly	318	1996-03–2022-08	+	0.636	1.10
Gallup Investor Optimism (investors with $\geq$\$10k investable, quarterly)						
M37 item (microdata)	Quarterly	37	2011Q2–2020Q2	-	-1.912***	-2.76
M40C pessimist share (microdata)	Quarterly	37	2011Q2–2020Q2	+	1.863***	3.07
M40C investor optimism (microdata)	Quarterly	37	2011Q2–2020Q2	-	-1.725**	-2.52
M40A item (microdata)	Quarterly	37	2011Q2–2020Q2	-	-1.740***	-2.65
M40D item (microdata)	Quarterly	37	2011Q2–2020Q2	-	-1.266**	-1.98
Investor Optimism Index (published)	Quarterly	94	1996Q4–2021Q4	-	-1.569***	-2.88
Index, economic subindex	Quarterly	93	1996Q4–2021Q2	-	-1.529***	-2.81
Index, personal subindex	Quarterly	93	1996Q4–2021Q2	-	-1.452**	-2.55

Table IA.2. Cross-Survey Validation of the Survey Expected Six-Month Market Return
This table reports univariate regressions of the monthly survey expected six-month market return on belief measures from other investor surveys. Each row is a separate regression. The dependent variable is aggregated to coincide with the other measure's frequency. Each explanatory variable is standardized, so the coefficient is the change in the dependent variable, in percentage points, associated with a one standard deviation change in the comparator. Newey–West standard errors are used to calculate the test statistics. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	Frequency	N	Sample	Expected	Coefficient	t-value
CFO Survey (US chief financial officers, quarterly)						
10th percentile, 1-year S&P return	Quarterly	83	2001Q4–2023Q2	+	0.538*	1.78
Mean expected 1-year S&P return	Quarterly	83	2001Q4–2023Q2	+	0.874***	3.70
90th percentile, 1-year S&P return	Quarterly	83	2001Q4–2023Q2	+	1.001***	4.49
Livingston Survey (professional forecasters, semiannual)						
6-month expected S&P return	Semiannual	57	1996Q2–2024Q2	+	0.717*	1.84
12-month expected S&P return	Semiannual	57	1996Q2–2024Q2	+	1.348***	4.14

Table IA.3. Correlations Matrix

This table reports pairwise Pearson correlations among the monthly aggregate variables.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1. $E[R^M_{t,t+180}]^{Survey}$	1.000												
2. $E[R^M_{t,t+180}]^{Option}$	0.070	1.000											
3. $EMRS^{180d}_t$	0.820	-0.514	1.000										
4. π^{Survey}_t	-0.100	0.437	-0.337	1.000									
5. π^{Option}_t	0.097	0.914	-0.442	0.433	1.000								
6. CPS_t	-0.164	-0.015	-0.132	0.871	-0.067	1.000							
7. $\%StepOut_t$	-0.227	0.413	-0.432	0.271	0.441	0.060	1.000						
8. $R^M_{t-30,t-1}$	-0.015	-0.326	0.174	-0.241	-0.314	-0.096	-0.244	1.000					
9. $R^M_{t-180,t-1}$	-0.188	-0.555	0.157	-0.239	-0.529	0.024	-0.421	0.433	1.000				
10. $R^M_{t,t+30}$	-0.135	0.089	-0.167	0.052	0.067	0.021	0.096	0.038	0.059	1.000			
11. $R^M_{t,t+180}$	-0.226	0.221	-0.322	0.121	0.068	0.097	0.072	0.054	0.026	0.427	1.000		
12. VIX_t	0.070	0.924	-0.470	0.407	0.884	-0.032	0.433	-0.509	-0.602	0.052	0.133	1.000	
13. $Turnover_t$	0.095	0.343	-0.115	0.474	0.319	0.350	0.205	-0.149	-0.204	0.001	0.054	0.318	1.000

Table IA.4. EMRS and Realized Returns Across Horizons

This table reports regressions of realized market returns on the expected-market-return spread, varying the horizon in two dimensions. Panel A reports the results where the spread is fixed at six months and the return horizon varies across the columns. Panel B reports the results where the return is fixed at six months and the horizon of the spread varies across the columns. Block-bootstrapped standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

Panel A. Fixed Six-Month Spread, Varying the Return Horizon

	(1)	(2)	(3)	(4)
Dependent variable	$R^M_{t,t+30}$	$R^M_{t,t+90}$	$R^M_{t,t+180}$	$R^M_{t,t+360}$
$EMRS^{180d}_t$	-0.076*	-0.206***	-0.342***	-0.531***
	(0.039)	(0.075)	(0.091)	(0.160)
Controls	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	7012	6950	6860	6677
R-squared	0.046	0.062	0.069	0.098

Panel B. Fixed Six-Month Return, Varying the Spread Horizon

	(1)	(2)	(3)	(4)
	Dependent variable: $R^M_{t,t+180}$			
$EMRS^{30d}_t$	-0.300**			
	(0.121)			
$EMRS^{90d}_t$		-0.326***		
		(0.083)		
$EMRS^{180d}_t$			-0.342***	
			(0.091)	
$EMRS^{360d}_t$				-0.107*
				(0.056)
Controls	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	6860	6860	6860	6860
R-squared	0.052	0.057	0.069	0.051

Table IA.5. Participation Questions and Equity Fund Flows

This table reports regressions of equity mutual fund flows on the share of survey respondents expressing each of three participation attitudes. %StepOut is the share who advise being less invested in stocks for the time being. %Overvalued is the share reporting that stock prices are too high relative to fundamental value, and %Sell is the share reporting that they are inclined to sell stocks overall. The dependent variable is the return-adjusted percent flow of equity mutual funds from month t through month $t+6$. Block-bootstrapped standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

	(1)	(2)	(3)	(4) Joint
Dependent variable: $\text{Flow}_{t,t+6}^{Equity}$				
%StepOut	-2.495***			-0.307***
	(0.892)			(0.112)
%Overvalued		-1.703		-0.253
		(1.162)		(0.162)
%Sell			-2.798	-0.055
			(2.331)	(0.103)
Controls	Yes	Yes	Yes	Yes
Lagged flow controls	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	307	308	308	307
R-squared	0.330	0.326	0.313	0.350

Table IA.6. Stock-Level Option-Probability Sorts

This table reports monthly decile sorts on stock-level option-implied crash probability sensitivities. The option-implied crash probability sensitivities are calculated using lead-lag-sum betas estimated from daily returns and option-implied crash probabilities over a 252-day backward-looking, rolling window. Each month, stocks are sorted based on $\beta_{i,t}^{option}$ into decile portfolios. Excess returns and risk-adjusted returns using a Fama and French (2015) five-factor model with the momentum factor are reported for both equal- and value-weighted portfolios. Newey-West standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

Portfolio	EW Excess Return	EW FF5+MOM Alpha	VW Excess Return	VW FF5+MOM Alpha
D1	0.944**	-0.194*	1.271**	-0.036
	(0.467)	(0.109)	(0.517)	(0.223)
D2	1.012***	-0.078	1.252***	0.126
	(0.393)	(0.089)	(0.386)	(0.137)
D3	1.040***	-0.009	1.151***	0.090
	(0.358)	(0.095)	(0.325)	(0.123)
D4	1.032***	0.033	0.884***	-0.194*
	(0.326)	(0.074)	(0.305)	(0.105)
D5	0.939***	-0.009	0.899***	-0.078
	(0.327)	(0.086)	(0.263)	(0.098)
D6	0.939***	0.005	1.026***	0.035
	(0.310)	(0.081)	(0.263)	(0.088)
D7	1.065***	0.188***	1.011***	0.018
	(0.285)	(0.061)	(0.231)	(0.082)
D8	1.002***	0.166***	0.996***	0.106
	(0.286)	(0.058)	(0.222)	(0.101)
D9	0.946***	0.139*	1.042***	0.137
	(0.306)	(0.075)	(0.241)	(0.109)
D10	0.773**	-0.070	0.860***	-0.052
	(0.380)	(0.117)	(0.326)	(0.148)
Hedge	-0.171	0.124	-0.411	-0.016
	(0.211)	(0.179)	(0.373)	(0.317)

Table IA.7. CPS Portfolio Factor Loadings

This table reports value-weighted FF5+MOM factor loadings for the monthly $\beta_{i,t}^{CPS}$ decile portfolios. Newey-West standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

Factor	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Hedge
MKTRF	1.123***	1.044***	0.989***	0.926***	0.970***	0.968***	0.986***	0.969***	1.010***	1.122***	-0.001
	(0.056)	(0.040)	(0.033)	(0.028)	(0.025)	(0.030)	(0.029)	(0.024)	(0.035)	(0.043)	(0.086)
SMB	0.328***	0.155**	0.119**	0.052	-0.049	0.009	0.055	-0.063	0.023	0.144**	-0.184
	(0.081)	(0.073)	(0.050)	(0.050)	(0.042)	(0.041)	(0.050)	(0.045)	(0.055)	(0.072)	(0.126)
HML	0.018	0.145*	0.135**	0.093	0.091**	0.115**	0.009	-0.050	-0.087	-0.125	-0.143
	(0.096)	(0.079)	(0.056)	(0.061)	(0.040)	(0.054)	(0.053)	(0.051)	(0.073)	(0.086)	(0.164)
RMW	-0.325***	-0.073	0.069	-0.019	0.031	0.022	0.140**	0.075	0.075	-0.130*	0.195
	(0.100)	(0.088)	(0.067)	(0.061)	(0.037)	(0.043)	(0.055)	(0.051)	(0.075)	(0.079)	(0.140)
CMA	0.149	-0.022	-0.016	0.035	0.029	-0.090	0.082	0.004	-0.047	-0.124	-0.274
	(0.192)	(0.119)	(0.101)	(0.075)	(0.070)	(0.081)	(0.074)	(0.085)	(0.113)	(0.116)	(0.250)
MOM	-0.197**	-0.085	-0.092*	-0.087**	-0.040	-0.024	0.008	0.030	0.039	0.129*	0.326**
	(0.080)	(0.053)	(0.054)	(0.040)	(0.029)	(0.032)	(0.030)	(0.034)	(0.044)	(0.077)	(0.141)

Table IA.8. Option-Probability Portfolio Factor Loadings

This table reports value-weighted FF5+MOM factor loadings for the monthly $\beta_{i,t}^{option}$ decile portfolios. Newey-West standard errors are reported in parentheses. Statistical significance is denoted for the 10%, 5%, and 1% levels as *, **, and ***, respectively.

Factor	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Hedge
MKTRF	1.353***	1.159***	1.045***	1.046***	0.946***	0.948***	0.925***	0.840***	0.861***	0.947***	-0.406***
	(0.087)	(0.047)	(0.046)	(0.028)	(0.029)	(0.020)	(0.033)	(0.034)	(0.037)	(0.049)	(0.112)
SMB	0.335***	0.129*	0.103*	0.063	-0.013	0.057	0.026	0.013	-0.014	0.114	-0.221
	(0.119)	(0.078)	(0.058)	(0.046)	(0.036)	(0.041)	(0.049)	(0.048)	(0.058)	(0.082)	(0.174)
HML	0.002	0.139	-0.025	0.089	0.019	0.056	0.126***	0.039	0.102*	-0.039	-0.041
	(0.176)	(0.092)	(0.087)	(0.060)	(0.064)	(0.051)	(0.043)	(0.052)	(0.062)	(0.085)	(0.188)
RMW	-0.086	-0.130	0.015	0.092	0.012	0.059	0.170**	0.048	0.026	-0.349***	-0.263
	(0.162)	(0.080)	(0.089)	(0.056)	(0.058)	(0.050)	(0.069)	(0.070)	(0.068)	(0.092)	(0.226)
CMA	-0.347	-0.449***	-0.157	-0.128	0.109	0.147*	0.209***	0.307***	0.159**	0.282**	0.629**
	(0.244)	(0.129)	(0.114)	(0.087)	(0.089)	(0.077)	(0.057)	(0.066)	(0.080)	(0.131)	(0.292)
MOM	-0.196**	-0.095*	-0.074*	-0.010	0.013	0.027	0.061**	0.002	0.039	0.013	0.209*
	(0.094)	(0.055)	(0.039)	(0.027)	(0.036)	(0.024)	(0.025)	(0.030)	(0.036)	(0.048)	(0.113)