Subjective Alpha:
Beliefs and Portfolios of Financial Advisors

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Abstract

We survey financial advisors at wealth-management firms in six waves from 2022 to 2025 and link their responses to the client portfolios they manage. For each asset class, we elicit both the return an advisor *expects* and the return they *require*, splitting a return expectation into a required return, or risk compensation, and a residual we call subjective alpha, or perceived mispricing. The two components behave very differently. Required returns are risk-ordered across assets and nearly time-invariant, and they account for most of the variation in long-run expectations; short-run expectations instead move with subjective alpha. When forming beliefs, advisors respond to macroeconomic views and their own past returns, but through the alpha rather than the required return, and their portfolios do the same, trading on the alpha at the matching horizon, most sharply at the quarterly one. These patterns distinguish the structure of professional beliefs from retail investors' (Giglio et al., 2021), even as the strength of belief–portfolio pass-through is similar, and inform theories of how beliefs shape portfolios.

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1 Introduction

Financial advisors decide how a large and growing share of household wealth is invested. Standing between households and financial markets, they manage allocations across an increasingly broad menu of asset classes for their clients. At the scale on which they operate, these allocations can move prices, so advisors matter not only for household wealth but for asset markets. Yet we know little about how they form return beliefs across asset classes and horizons, or to what extent those beliefs are reflected in the portfolios they build. A growing literature links beliefs to portfolios, but largely for retail investors (Greenwood and Shleifer, 2014; Giglio et al., 2021).[1] Advisors, however, differ from retail investors in fundamental ways. They operate at far greater scale, have access to a much broader range of asset classes, and bring professional sophistication.

In this paper, we measure these beliefs directly and link them to the portfolios advisors build. We partner with Addepar, a technology and data platform that provides analytics and reporting to wealth managers, whose clients hold complex portfolios across the full spectrum of asset classes, including advisors ranging from single family offices to large multi advisor firms. The platform also maintains anonymized records of each individual investor's holdings as managed by the advisor, allowing us to merge survey responses with detailed portfolio data. Through this partnership, we designed and distributed a survey of return expectations and required returns to advisors on the platform across six waves between May 2022 and September 2025, yielding 453 responses from advisors at 250 firms.

The survey's most important feature is the joint elicitation of return expectations and required returns. For each asset class, alongside the expected total return, we ask each advisor for the minimum return they would require in order to invest, i.e., their hurdle rate. Throughout, a *return expectation* is the advisor's subjective expectation of the return to be realized over a stated horizon. Following Greenwood and Shleifer (2014), we distinguish it from the "expected return" of the asset-pricing literature, which in equilibrium coincides

[1] A separate literature studies the beliefs of large institutions such as pension funds and asset managers, and in a few cases links them to portfolios (Andonov and Rauh, 2022; Dahlquist and Ibert, 2024; Couts et al., 2024; Gao et al., 2026). There, however, beliefs are measured as house-level capital-market assumptions rather than the subjective views of the individuals who make the allocation decisions.

with the discount rate. Eliciting both lets us decompose a return expectation into two components: a required return and a residual, which we call *subjective alpha*. These are the two objects around which asset pricing is organized. The required return is a subjective discount rate: the compensation the advisor demands for bearing an asset's risk, and the basis on which assets are valued. The subjective alpha is a perceived mispricing: the return the advisor believes an asset offers beyond risk compensation, and a measure of the advisor's belief that markets are inefficient and can be beaten.

The survey has three further features that make it well suited to studying advisors' beliefs. It covers up to fourteen asset classes, spanning public and private markets, so we observe how a given advisor's views differ across the asset classes they cover. It elicits beliefs at both one-year and ten-year horizons, separating short- and long-run views on the same asset. And, it is fielded as a repeated cross-section over three and a half years, a window that spans a rate-hiking cycle, the spring-2023 banking stress, and the post-2023 AI rally, giving us variation across advisors, asset classes, horizons, and time.

In reading the elicited minimum as a required return, we follow Greenwood and Shleifer (2014), who interpret the Gallup survey's "minimum acceptable rate of return" in the same way, and later work that adopts this reading (Gnan and Schleritzko, 2023). A natural concern is that advisors read the question differently in practice. Their responses, however, display the properties of a required rate of return. They are almost never negative, they exceed advisors' own risk-free rates, they increase with asset risk under conventional rankings, and, within advisor and across the asset classes they cover, they are higher for the asset classes an advisor expects to decline most in a severe recession. In requiring higher returns on the assets they view as riskier, advisors exhibit a positive risk–return relationship, unlike the flat or inverted one often found among retail investors.

We then use the survey to answer two questions: what drives the structure of and variation in advisors' return expectations, and how do these expectations affect portfolio decisions. We document three main findings.

First, advisors' return expectations are organized by horizon. Long-run expectations are anchored to the required return. A variance decomposition attributes 73 percent of the variation in ten-year expectations to variation in required returns. Short-run expectations,

by contrast, decouple from it. At the one-year horizon the required return accounts for only 34 percent of the variation in expectations, and the subjective alpha for the remaining 66 percent. The two components behave very differently over time. The required return is highly persistent. Within the same respondent it changes little across waves surveyed years apart, and stays within a 1.3-percentage-point band while the federal funds rate rises by four and a half percentage points and partly reverses. The subjective alpha moves with market conditions. Its standard deviation is 5.3 percentage points at the one-year horizon against 3.5 at ten years, and on core asset classes its average moved from -6.8 percentage points in the dislocated markets of 2022 to 0.1 by 2025. Advisors, in effect, believe that markets are efficient in the long run but can experience large deviations from efficiency in the short run.

Second, we ask what moves these beliefs. Two determinants stand out: the asset class's recent returns and the advisor's macroeconomic views. Each determinant acts on the return expectation rather than the required return, so its effect accumulates in the subjective alpha. The clearest case is extrapolation. A one-percentage-point higher return on an asset class over the past quarter raises the advisor's short-run alpha on that asset class by 0.174 percentage points, and the effect loads on the most recent quarter more than on the trailing year. Extrapolation is strongest in real estate, and reverses in Treasuries.

Macroeconomic views move beliefs the same way. Optimism about growth raises return expectations and alpha, subjective recession probability lowers them, and higher expected inflation raises nominal expected returns but leaves the nominal required return unchanged, so there is no Fisher pass-through into the hurdle. Perceptions of tail risk point the same way, though with less precision. Self-reported advisor observable characteristics, such as seniority and decision authority, explain essentially none of the heterogeneity in beliefs. Overall, the required return is not only stable over time but also unresponsive to the forces that move return expectations.

Third, beliefs predict portfolio decisions, through the subjective alpha rather than the required return. In advisors' stated plans to change portfolio allocations, which we elicit in the survey, subjective alpha predicts planned increases over and above the level of the return expectation itself. In executed trades, which we measure as active rebalancing net

of the mechanical drift in portfolio shares induced by price movements, short-run alpha predicts the rebalancing of an asset class over the next quarter and long-run alpha predicts it over the next year. When short- and long-horizon beliefs enter together, the matching horizon dominates at each trade horizon. The required return is uninformative for trading behavior. Advisors act, in other words, on the component of their beliefs that measures perceived mispricing, and they do so at the horizon to which the belief applies.

Three features sharpen this result. First, the effect is concentrated in public equity, one asset class where an advisor can act on a view within a quarter. Second, it appears in the flow of trading rather than in the stock of holdings. Third, stated intentions bind on the extensive margin, in building asset classes outside the advisor's active book, rather than in fine-tuning existing positions. The magnitude is modest. A one standard deviation increase in short-run alpha moves about 1.0 percentage point of an asset class's share of firm assets over the following quarter, an elasticity of roughly 0.17. For self-directed retail investors, beliefs are reflected in the *level* of equity holdings, but changes in beliefs do not predict *when* they trade (Giglio et al., 2021). Advisors differ: subjective alpha predicts their trading at the horizon that matches the belief, while the level of holdings moves little. Beliefs thus shape professional portfolios through the flow, where in retail portfolios they largely rest in the stock.

Our setting is not without caveats. First, although our surveys span three and a half years, each wave draws only between 34 and 112 respondents, so we are limited in our ability to run high-frequency panel analyses on individual advisors' beliefs. Second, our respondents are wealth managers, while observed portfolio decisions reflect the joint influence of advisors and end-clients. To the extent end-clients hold beliefs that differ from their advisors', the estimated belief–portfolio sensitivity is subject to attenuation bias. That we nonetheless find economically meaningful sensitivities is consistent with the substantial influence advisors have on advised portfolios documented elsewhere (Foerster et al., 2017; Linnainmaa et al., 2021). Third, our respondents are advisors on a single technology platform. While Addepar's user base is diverse, results may not generalize to all wealth-management contexts.

Our paper contributes to three literatures. The first is the literature on subjective return

expectations. Survey-based measures of beliefs have become central to asset pricing (Adam and Nagel, 2023), with evidence drawn from retail investors (Greenwood and Shleifer, 2014; Giglio et al., 2021; Choi and Robertson, 2020), wealthy households (Bender et al., 2022), and, more recently, institutions: public pension funds (Andonov and Rauh, 2022), large asset managers (Dahlquist and Ibert, 2024), institutional allocators (Couts et al., 2024), and mutual funds (Gao et al., 2026). In this literature, professional beliefs are typically measured from house-level capital-market assumptions, and return expectations are elicited separately. We provide, to our knowledge, the first joint elicitation of return expectations *and* required returns at the asset class level from the professionals who make allocation decisions. The joint design yields a decomposition of expectations into a subjective discount rate and a subjective alpha that requires no asset-pricing model. Couts et al. (2024) obtain a related split by imposing the CAPM on institutional capital-market assumptions. The decomposition speaks to debates on the cyclicality of subjective risk premia (Nagel and Xu, 2023) and on sticky discount rates (Gormsen and Huber, 2025). In our data, the subjective price of risk is stable and risk-ordered while perceived mispricing carries the cycle, giving the corporate finance evidence on sticky discount rates a buy-side counterpart.

The second is the literature linking beliefs to portfolios. Among retail investors, measured expectations predict portfolio shares with economically modest sensitivity (Giglio et al., 2021). In equilibrium demand systems, beliefs are the latent shifters of institutional demand (Koijen and Yogo, 2019). A separate body of work shows that financial advisors matter for what their clients hold. Advised portfolios reflect the advisor's own characteristics and beliefs more than the client's (Foerster et al., 2017; Linnainmaa et al., 2021). We connect these strands by observing both the advisor's beliefs and the portfolios they manage, on a platform whose holdings data have been used to study the portfolios of the wealthy (Balloch and Richers, 2023; Gabaix et al., 2024). Doing so separates the belief-holder from the portfolio-holder. Pass-through in our setting runs through the subjective alpha at horizons that correspond to beliefs. Unlike self-directed households, low estimated elasticities are likely driven by delegated management, rather than investor sophistication.

The third is the literature on horizon-dependent expectations. Return expectations differ systematically across horizons (Bastianello and Peng, 2025), short-horizon views embed beliefs about the beliefs of others (Schmidt-Engelbertz and Vasudevan, 2025), and theories of belief formation generate horizon structure from the way investors extrapolate from recent data (Rabin and Vayanos, 2010; Jin and Peng, 2024). Our contribution is to show that the horizon organizes not only the level of expectations but their composition. Long-run expectations are anchored to the required return, short-run expectations embed perceived mispricing, and each component predicts trading at its own horizon. Theories of belief formation therefore have a sharper target. The object that moves at short horizons is not the price of risk but the perceived alpha.

The remainder of the paper is organized as follows. Section 2 describes the survey design, sample, and portfolio data. Section 3 validates the required return measure and establishes its stability. Section 4 documents the term structure of expectations and its state dependence. Section 5 traces where beliefs come from. Section 6 links beliefs to stated plans and executed trades. Section 7 draws out the implications for theories, and Section 8 concludes.

2 Data and survey design

Our data come from Addepar, a financial technology company whose platform wealth and asset management firms use to aggregate, reconcile, and report their clients' investments. A firm that adopts the platform links its clients' accounts, and the platform assembles positions, transactions, and valuations from custodial and other data feeds. Advisors rely on the platform for client-facing performance reporting, so coverage is comprehensive by construction. The data span equities, fixed income, private equity, real estate, and collectibles, for a client base that ranges from single-family offices to large wealth-management firms. Addepar data have previously been used to study the investment performance of the ultra-rich (Balloch and Richers, 2023) and the asset demand of U.S. households (Gabaix et al., 2024). We describe the portfolio panel in Section 2.3.

2.1 Survey design

To analyze the subjective beliefs of financial advisors, we partner with Addepar to design a survey distributed through their platform. The survey comprises three main parts: screening, current and planned investments, and subjective beliefs.

The first part of the survey screens respondents. It asks for the respondent's role at the firm, how often they make portfolio allocation decisions for clients, and the percent of allocation decisions driven by their advice. Roles are chosen from a list that includes investment professionals, financial advisors, executives, investors, advisor associates, operations staff, and software developers, of which respondents can select more than one. Our goal is to reach professionals senior enough to influence clients' portfolio allocations. Most respondents indeed identify as investment professionals, financial advisors, executives, or investors.

The second set of questions asks in which asset classes the advisor is actively investing, and whether they plan to increase, decrease, or leave unchanged their allocation to each of a specific list of asset classes over the next year. The selected asset classes determine the questions posed in remainder of the survey: the belief questions in the third part are asked only for the asset classes the advisor selects as actively invested or with plans to increase allocations, and response rates are essentially complete for selected asset classes. The menu originally comprised nine asset classes: U.S. Treasuries and agency debt, U.S. corporate bonds, U.S. equities, international equities (labeled global equities in the exhibits), equity-strategy hedge funds, multi-strategy hedge funds, private equity buyout, venture capital, and real estate funds. Starting with the fourth wave, the menu was expanded to add cash and money market funds, municipal bonds, and private debt, and to split international equities into developed-market ex-U.S. and emerging-market equities.[2] Our analysis of trading restricts to the nine asset classes of the original menu, which we refer to as the *core* asset classes. Eight of the nine are covered in every wave, and international equities in the first three, so each asset class is observed across repeated waves and asset class effects can

[2]Ahead of the fourth wave, in February 2024, the survey instrument was redesigned: the visual format was updated, the asset class menu was expanded, and an explicit "don't know" option was added to the planned-allocation question. Appendix A9 reproduces both versions in full.

be separated from wave effects. The asset classes added in the expansion appear only in the later waves, most of which cannot yet be linked to portfolio data, and therefore enter the belief analyses only.

The third part elicits subjective beliefs. For each asset class in which an advisor indicates existing or planned investments, we ask two sets of return questions. First, we ask advisors to "enter the expected total return (nominal capital appreciation plus payouts) over the next year and the average expected total return over the next ten years (annualized)." These return expectations at the one-year and ten-year horizons are denoted by $\mathbb{E}[r^{1Y}]$ and $\mathbb{E}[r^{10Y}]$, respectively.

This question design aligns with approaches used in earlier literature (Greenwood and Shleifer, 2014; Hartzmark and Sussman, 2024), with two differences. First, since the question covers asset classes beyond equities and bonds, such as venture capital and private equity, we explicitly remind advisors to account for payouts. Given that the survey participants are professional investors, we consider the use of jargon appropriate and find additional explanation unnecessary. Second, we ask advisors to report return expectations for two horizons: one year, representing the short run, and ten years, representing the long run. As we demonstrate, this design captures distinct factors in the belief-formation process.

The second belief question asks "what is the minimum rate of return you would require to make an investment in each of the below asset classes over one year? (In other words, what would be the lowest rate of return at which you would be willing to make a new investment in each asset class over one year?)" The question is modeled on the Gallup survey, which asked individual investors for "the minimum acceptable rate of return" on their portfolio over the next twelve months, and we follow Greenwood and Shleifer (2014) and Gnan and Schleritzko (2023) in reading responses as the advisor's required rate of return, denoted $\mathbb{R}[r^{1Y}]$. The two questions are designed to measure different objects. The return expectation is a forecast of the return the advisor believes an asset class will deliver over the horizon. The required return is a threshold: the compensation the advisor demands for holding the asset class over one year. For an advisor who views an asset class as fairly priced, the two coincide. For an advisor who perceives mispricing,

the return they expect deviates from the return they require, and the gap measures the abnormal return they believe the asset class offers. Section 3 presents evidence supporting the interpretation of $\mathbb{R}[r^{1Y}]$ as a required return, and Section 4 analyzes the differences between responses to the first and second questions.

When answering questions in this part of the survey, advisors move a slider that ranges between -5 and 10 percent for bonds, and between -15 and 30 percent for other assets. If a respondent clicks through a question without moving the slider, the survey records the slider minimum (-5 or -15). We discard such responses.

The survey also elicits a set of auxiliary beliefs that enter our analysis. Advisors are asked to report expected GDP growth and inflation at the one-year and ten-year horizons, along with the probability of a recession over the next year. These macroeconomic views are the belief determinants studied in Section 5. For each asset class they cover, advisors also report the return they would expect in a severe recession. This crash return belief serves as a subjective measure of the asset class's riskiness and is used to validate the required return measure in Section 3. From the third wave onward, we also ask respondents to provide a subjective risk-free rate, elicited directly in the third wave and proxied thereafter by the return expectation for cash. This is the advisor-specific benchmark against which we show that required returns exceed the advisor's own risk-free rate. The last three waves additionally elicit expectations of the federal funds rate at one- and ten-year horizons. The full survey is reproduced in Appendix A9.

Because of the screening questions, the estimation sample consists of the asset classes advisors themselves selected. This selection captures active management rather than mechanical holdings. Of the selected asset class–wave observations, 83 percent match a portfolio position in the survey quarter, while the holdings advisors do *not* select appear to represent passive or legacy positions that are not under active management. By value, the selected classes account for about 54 percent of the assets in these firms' portfolios, and the fourteen asset classes the survey covers for about 74 percent; the remainder consists of unselected positions and of holdings the survey does not itemize, such as directly held real estate and private companies. We therefore refer to the selected asset classes as the advisor's *active book*. Our results speak to advisors' active decisions rather than to passive

holdings. Appendix A2 reports the full analysis of match rates and unselected holdings.

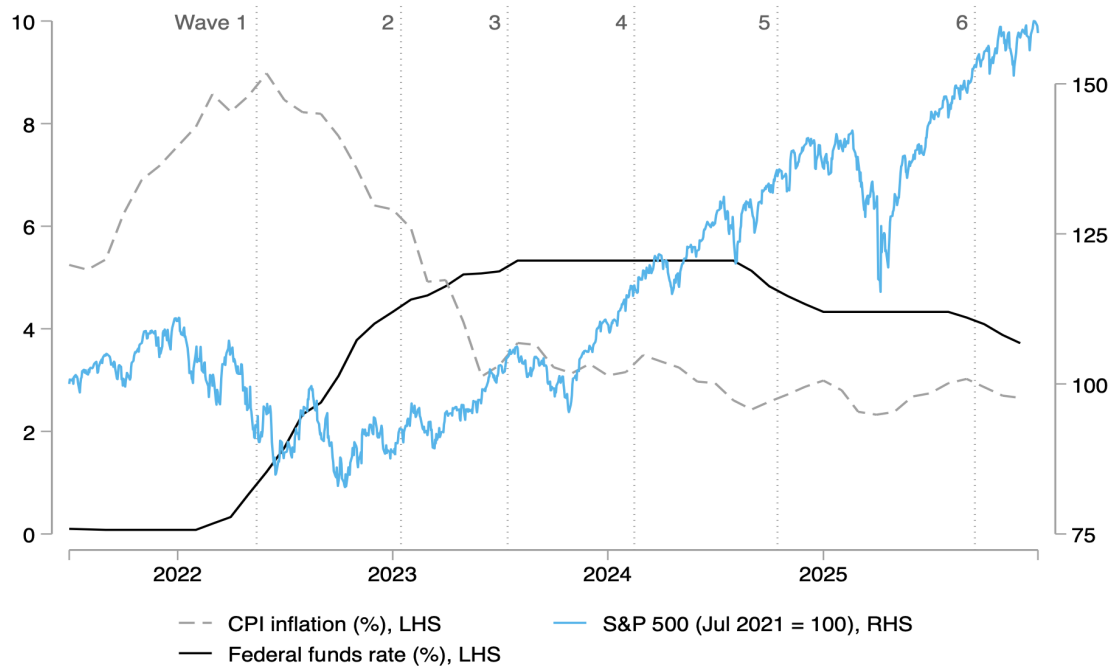
2.2 Survey implementation

The survey is distributed to wealth advisors at firms using the Addepar platform, targeting individuals responsible for providing investment advice, such as CIOs and wealth managers. The screening questions ensure that respondents hold relevant advisory roles, are regularly involved in portfolio allocation decisions for clients, and for whom a substantial share of allocation decisions is driven by their advice. Where a firm contributes several responses in a wave, one is designated the firm's *main respondent*, and all analyses use main respondents.

To encourage advisors to complete our survey, we provide respondents with an anonymized summary of return expectation data across asset classes and macroeconomic fundamentals. This information is valuable to advisors, as it is typically not publicly available and offers additional insights for asset management. While many sources of capital market assumptions exist, it is rare to find subjective return expectations at the asset class level for both the short and long term. Moreover, portfolio management for individual investors differs from institutional approaches, making the perspectives of peer advisors particularly relevant. Misreporting expectations in the survey offers no strategic advantage, as it would only skew the summary statistics in the final report. We also leverage the long-standing goodwill between the Addepar platform and its clients to encourage advisors to provide honest responses.

The survey has six waves: May 2022, January 2023, July 2023, February 2024, October 2024, and September 2025. Figure 1 places the waves in their macroeconomic context. The first wave was fielded near the peak of the inflation surge, with the federal funds rate just beginning to rise and equities falling. The second and third waves span the rapid tightening of 2022–23. The second sits close to the equity market trough, and the third coincides with the end of the hiking cycle. The fourth and fifth waves were fielded with the policy rate at its peak and then just past the first cuts, with inflation largely normalized and equities rallying. The sixth wave follows further easing, with equities at

Figure 1: Timing of the six survey waves



Notes: Vertical lines mark the six survey waves: May 2022, January 2023, July 2023, February 2024, October 2024, and September 2025. The left axis shows the effective federal funds rate and twelve-month CPI inflation, in percent. The right axis shows the S&P 500 index, normalized to 100 in July 2021. Source: FRED.

record highs after the sharp but short-lived selloff triggered by tariff policy in the spring of 2025. The waves thus sample beliefs in a dislocated market, through a full tightening cycle, and in a strong recovery. Across the six waves we obtain 453 responses at 250 firms (278 unique respondents outside the February 2024 wave, whose identifiers cannot be linked across waves). 1,787 asset class level observations carry the full belief triple ($\mathbb{E}[r^{1Y}]$, $\mathbb{E}[r^{10Y}]$, $\mathbb{R}[r^{1Y}]$). Some respondents answer in multiple waves, enough to compute within-respondent stability measures (Section 3.2), but the panel dimension is thin, so the study is best interpreted as a repeated cross-section.

Participation is voluntary, and we cannot characterize the advisors who chose not to respond. Our data do not include the set of advisors invited in each wave or their characteristics, so we cannot compare respondents with non-respondents. Selection into the survey therefore qualifies the interpretation of belief levels. If, for example, advisors

with stronger views or a greater interest in capital-market assumptions are more likely to respond, average beliefs may not represent the advisor population. Most of our results, however, are within-respondent comparisons, across asset classes, horizons, and waves, and these are less exposed to selection into the survey.

2.3 Portfolio data and the survey–portfolio merge

The portfolio data cover every asset class position in every client portfolio of the firms on the platform, at a quarterly frequency through 2025Q4. The data are reported on the platform daily and are closely scrutinized, because firms use them for client-facing performance reporting and for tax preparation. We use an external, anonymized version of the data that is reported monthly, which we aggregate into a quarterly panel for analysis. We verify the accounting identity that a position's ending value equals its starting value plus net flows plus returns, which holds exactly for 99 percent of rows, and we drop implausible observations. Roughly 5.1 million portfolio-asset class-quarter observations remain. Appendix A3 details the filters and diagnostics.

We merge survey responses to portfolios on firm, asset class, and quarter. One limitation is mechanical. The fourth wave, fielded in February 2024, cannot be linked, because its raw responses lack platform identifiers. Portfolio-linked analyses therefore use the four linkable waves, the first three plus October 2024. The September 2025 wave will become linkable for forward outcomes once portfolio data beyond 2025Q4 arrive. Belief analyses use all six waves.

2.4 Summary statistics

Appendix Figure A1 shows the distribution of advisor characteristics collected in the screening part of the survey. Respondents span a range of roles, the most common being investment professionals, and most report frequent involvement in portfolio allocation decisions for their clients. On average, advisors report decision-making power of 66%, and 21% report full decision-making authority. Appendix A1 contains additional details.

Panels A and B of Table 1 present summary statistics for the survey responses across all

six waves. Panel A reports the return beliefs at the respondent–asset class–wave level, and Panel B the macroeconomic beliefs at the respondent–wave level. Three patterns preview the paper's results. First, long-run return expectations exceed short-run ones on average. Second, required returns sit close to long-run expectations. Third, as a consequence, the long-run subjective alpha, α^{10Y}, is centered near zero with modest dispersion (S.D. 3.5 pp), while the short-run subjective alpha, α^{1Y}, is substantially more dispersed (S.D. 5.3 pp). Sections 3 and 4 analyze this structure.

Panels C and D of Table 1 turn to the firms and the client portfolios they manage. As of each firm's latest panel quarter, the 194 survey-linked firms have median assets under management of 335 million USD, spread across a median of 36 client portfolios and 9 of the fourteen surveyed asset classes. On average, 47 percent of firm assets are in equities, 24 percent in cash and fixed income, and 28 percent in alternatives, including hedge funds, private equity, venture capital, and real estate. Client portfolios average 3.6 million USD and hold 5 asset classes on average. Panel E summarizes the firm–asset class–quarter panel used in the trading analysis: quarterly asset class returns average about one percent, and quarterly net flows are centered near zero with meaningful dispersion; Section 6.2 defines the trade variables.

3 Measuring the required rate of return

The decomposition of a return expectation into a required return and a subjective alpha hinges on reading the minimum-rate-of-return responses as required returns. Model-based alternatives infer required returns by imposing an asset-pricing model, most commonly the CAPM (Couts et al., 2024), and therefore confront a version of the joint-hypothesis problem (Fama, 1970). A survey measure imposes no model, but it must establish instead that respondents interpret the question as intended. This section presents the evidence in two steps. Section 3.1 shows that the cross-section of responses has the properties a required return should have; Section 3.2 shows that the responses are stable over time, through a full monetary-policy cycle and within the same respondent re-surveyed years apart.

Table 1: Summary statistics

	Mean	p25	p50	p75	S.D.	N
Panel A: Return beliefs (respondent × asset class × wave)						
1Y return expectation, $\mathbb{E}[r^{1Y}]$	6.4	4.0	6.0	9.0	4.9	2,063
10Y return expectation, $\mathbb{E}[r^{10Y}]$	7.8	5.0	7.0	10.0	4.4	2,147
1Y required rate of return, $\mathbb{R}[r^{1Y}]$	7.2	4.0	7.0	10.0	4.6	2,066
1Y subjective alpha, α^{1Y}	-0.6	-1.0	0.0	2.0	5.3	1,872
10Y subjective alpha, α^{10Y}	0.8	0.0	1.0	2.0	3.5	1,900
Crash return in a severe recession	-9.8	-20.0	-10.0	3.0	18.3	1,913
Panel B: Macroeconomic beliefs (respondent × wave)						
Expected GDP growth, 1Y	2.0	1.0	2.0	3.0	2.0	280
Expected GDP growth, 10Y	3.0	2.0	3.0	4.0	1.5	287
Expected inflation, 1Y	3.8	3.0	4.0	5.0	1.8	291
Expected inflation, 10Y	2.9	2.0	3.0	3.0	1.2	291
Recession probability, 1Y	46.4	30.0	50.0	62.0	22.8	296
Panel C: Firm level						
Firm AUM (USD millions)	1,269	126	335	1,043	2,738	194
Client portfolios managed	355	9	36	182	1,495	194
Asset classes held (of 14)	9.3	8.0	9.0	12.0	2.8	194
Equity share (% of AUM)	47.3	29.9	46.8	65.1	24.0	194
Cash and fixed income share (%)	24.4	7.7	21.0	35.3	20.0	194
Alternatives share (%)	28.4	6.3	24.3	40.8	24.4	194
Panel D: Client portfolio level						
Client AUM (USD millions)	3.6	0.1	0.6	2.3	29.7	68,929
Asset classes held	4.9	3.0	5.0	6.0	2.7	68,929
Panel E: Firm × asset class × quarter panel						
Quarterly asset class return (%)	1.1	-0.7	0.8	2.8	5.4	2,541
Quarterly net flow (% of asset class value)	-0.1	-0.3	-0.0	0.1	1.4	2,541

Notes: Panels A and B cover the survey responses over six waves (May 2022–September 2025), main respondents, slider-floor (minimum) responses excluded. Panel A pools all asset classes at the respondent–asset class–wave level. The crash return is the return expected for an asset class in a severe recession. Panel B is at the respondent–wave level, in percent (recession probability from 0 to 100). Panels C and D are measured at each firm's latest panel quarter (2025Q4 for most firms), for the survey-linked firms in the analytical sample; AUM is the sum of starting-of-quarter asset class values, and composition shares group the fourteen surveyed asset classes into equities, cash and fixed income, and alternatives (hedge funds, private equity, venture capital, and real estate). Panel E pools the firm–asset class–quarter panel over 2022Q1–2025Q4; the trade variables are defined in Section 6.2.

3.1 Cross sectional evidence

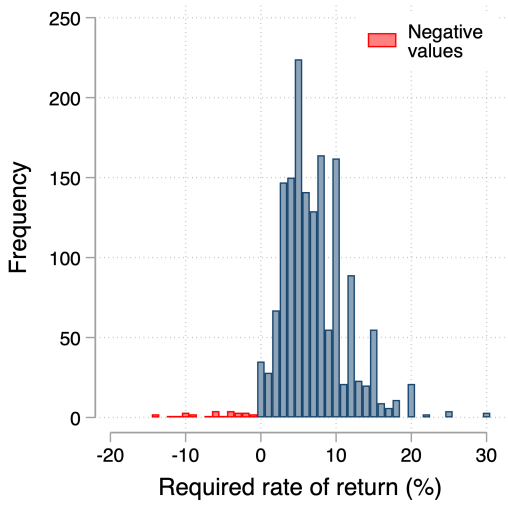
First, required returns should rarely be negative. A hurdle reflects compensation for risk or institutional constraints and therefore sits above a risk-free rate that is itself rarely negative. Panels (a) and (b) of Figure 2 show histograms of the required return responses and, for comparison, the one-year return expectations. Only 1.6 percent of required return responses are negative, while a substantially larger share of return expectations fall below zero. Both shares are computed among engaged responses, since slider-floor responses, which record the scale minimum, are discarded throughout. Advisors are thus not avoiding negative answers in general. They avoid them precisely where a negative answer would contradict the concept being elicited.

Second, required returns should exceed the advisor's own risk-free rate. Panel (c) of Figure 2 plots the distribution of the difference between the required return and the subjective risk-free rate. The difference is positive for the large majority of responses. This also addresses the concern that advisors read the minimum-return question as asking for a risk-free rate. The two responses differ, and they differ in the direction a risk premium implies.

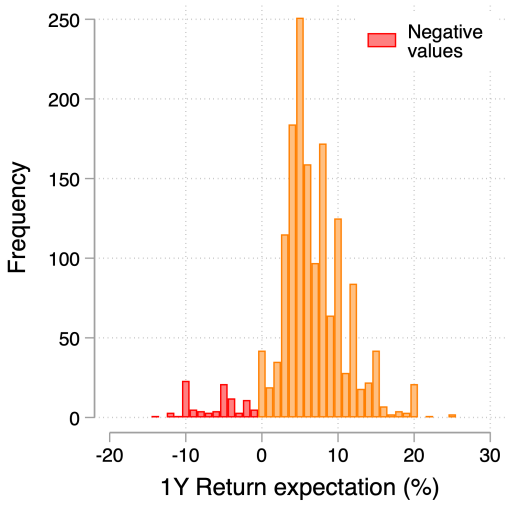
Third, required returns are ordered by conventional risk. Panels (e) and (f) of Figure 2 plot the distribution of required returns for the six asset classes whose risk is straightforward to rank: Treasury and corporate bonds, U.S. and global equities, and private equity buyout and venture capital. Venture capital and private equity buyout command the highest hurdles, U.S. and global equities intermediate ones, and corporate and Treasury bonds the lowest, in line with conventional perceptions of risk. We exclude asset classes whose ex-ante risk is harder to rank, such as real estate and hedge fund strategies.[3] Panel (f) repeats the exercise for one-year return expectations, and the ordering breaks down. Short-run expectations deviate substantially from required returns, a first sign of the wedge the rest of the paper studies.

[3]The exclusion is disclosive rather than cosmetic. The excluded asset classes' median required returns do not fit a clean conventional ordering (multi-strategy hedge funds sit below U.S. equities, while equity-strategy hedge funds and real estate funds tie with global equities), which is why we treat their conventional risk ranks as ambiguous. For such asset classes, the fourth fact carries the evidence. It requires no ranking assumption and covers all asset classes.

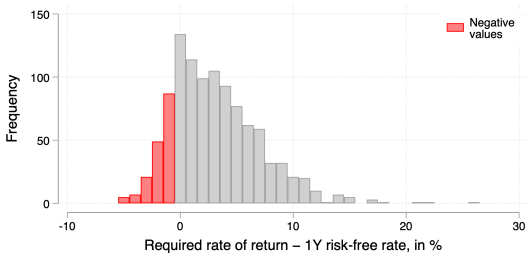
Figure 2: Validation of the required rate of return



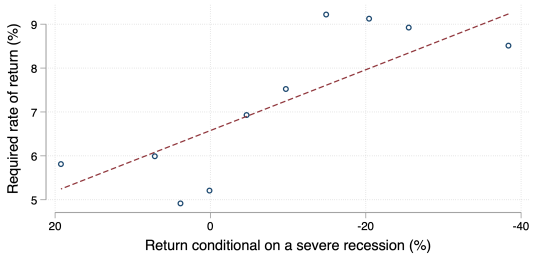
(a) Required rate of return



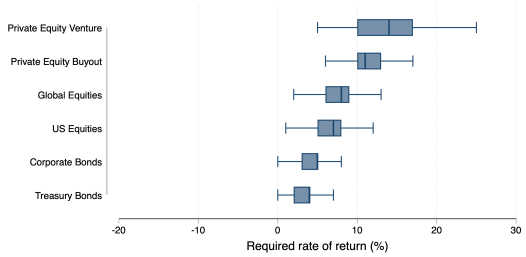
(b) One-year return expectation



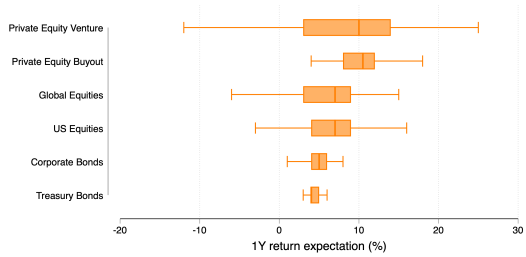
(c) Difference from the subjective risk-free rate



(d) Required returns and perceived risk



(e) Required rate of return by asset class



(f) One-year return expectation by asset class

Notes: Panels (a) and (b) show histograms of required return and one-year expectation responses across all asset classes and waves. Only 1.6 percent of required return responses are negative. Panel (c) shows the difference between the required rate of return and the subjective risk-free rate, which is elicited directly in the third wave and proxied by the return expectation for cash in the fourth through sixth waves. The first two waves elicited neither and are excluded. Panel (d) presents a binned scatter plot of required rates of return against the crash return belief, with the x-axis reversed so that asset classes perceived as riskier lie further to the right. Panels (e) and (f) show the median, interquartile range, and whiskers of required rates of return and one-year return expectations for the six asset classes whose risk is straightforward to rank. Whiskers span 1.5 times the interquartile range to the nearest quartile with available responses, and outliers are excluded.

Fourth, required returns are ordered by the advisor's own perception of risk. The survey asks for the return each asset class would deliver in a severe recession. Panel (d) of Figure 2 plots required returns against this crash return belief in a binned scatter, with the x-axis reversed so that asset classes perceived as riskier lie further to the right. Hurdles rise with perceived crash exposure. The relationship also holds within advisor and across the full menu of asset classes. With respondent fixed effects, so that identification is across asset classes, the coefficient on the crash return belief is -0.075, roughly three-quarters of a percentage point of additional required return for every ten points of additional expected drawdown, and the rank correlation between the asset class medians of required returns and of crash beliefs is -0.66. The cross-section of hurdles is priced by advisors' own subjective risk ranking rather than by any ranking we impose.

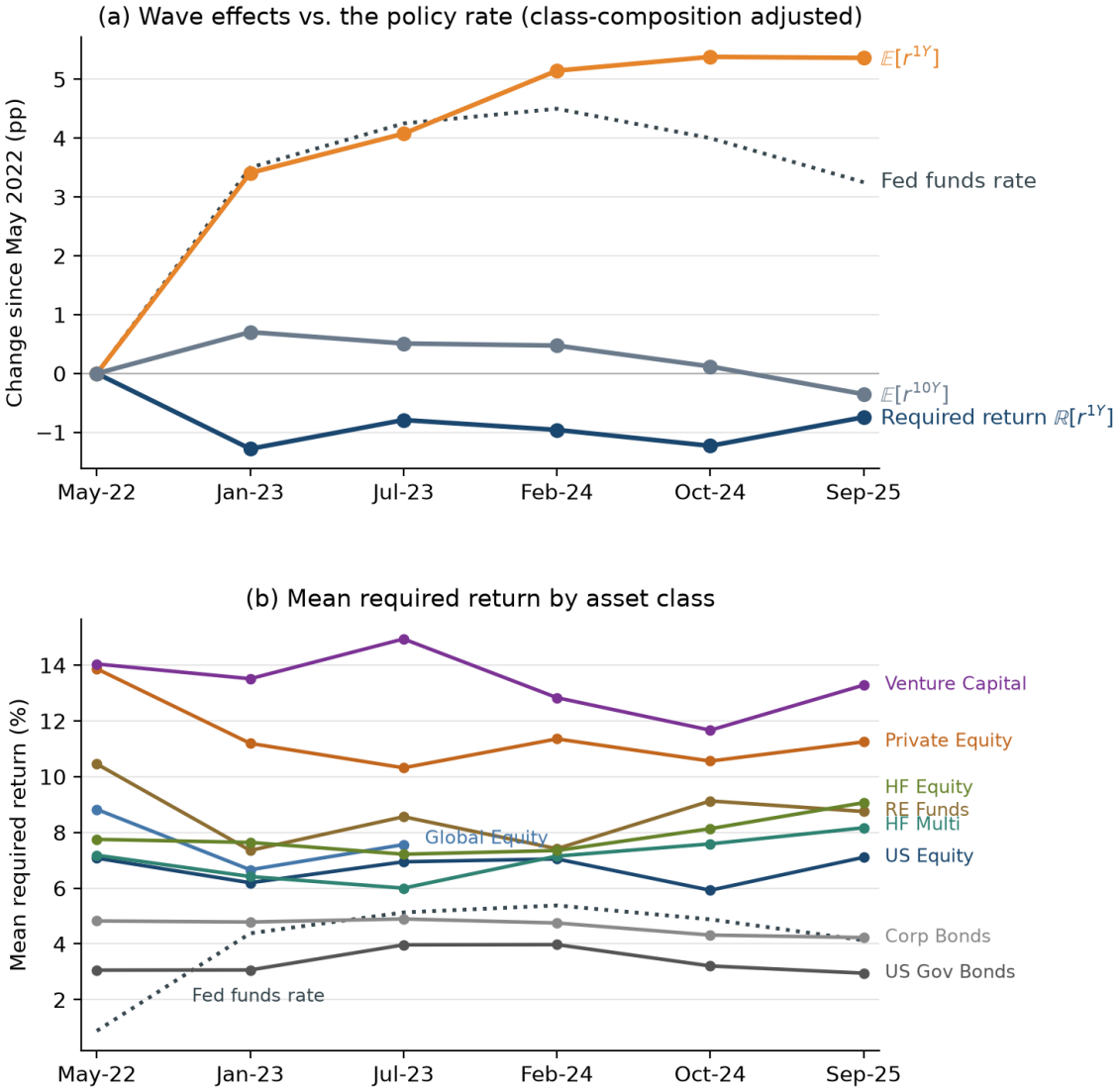
3.2 Time series evidence

The validation facts concern the cross-section of responses. A second, independent test asks how required returns behave over time, and the sample period supplies a demanding testing ground. Between the first wave (May 2022) and the last (September 2025), the federal funds rate rose from below one percent to above five percent and then fell by more than a percentage point, equity markets completed a bear market and a recovery, and advisors' own one-year return expectations swung accordingly. If the minimum rate of return question were picking up transient sentiment, or if respondents answered it with the prevailing level of rates in mind, responses would track these conditions.

We find that they do not. Panel (a) of Figure 3 plots wave effects for each belief: the change in its composition-adjusted mean since the first wave, estimated with asset class fixed effects. The one-year expectation absorbs the tightening nearly one-for-one through 2023 and remains elevated as rates decline, for a range of 5.4 percentage points. The required return moves within a 1.3-percentage-point band over the entire period, uncorrelated with the policy rate, and the ten-year expectation stays within 1.1 points. A four-and-a-half-point rise and partial reversal in the risk-free rate leaves advisors' hurdles essentially unchanged. Panel (b) shows that the aggregate stability is not an artifact of

pooling. Asset class by asset class, mean required returns are essentially flat across the six waves, preserving the risk ordering of the third fact, even as the funds rate sweeps beneath them.

Figure 3: Required returns across the 2022–2025 rate cycle



Notes: Panel (a) shows wave effects for each labeled belief: coefficients on survey-wave dummies from a regression on the nine core asset classes with asset class fixed effects, standard errors clustered at the respondent level, expressed as changes since the May 2022 wave; the dotted line is the federal funds target-range midpoint in the survey month, likewise expressed as a change since May 2022. Panel (b) shows the mean required return by asset class in each wave, in levels, with the federal funds midpoint in levels; global equities is covered only in the first three waves. The July 2023 wave may straddle the July 26, 2023 hike; using the post-hike range would raise that point by 0.25.

The same stability appears at the level of the individual respondent. For advisors who answer in multiple waves, the required return reported for a given asset class has a correlation of 0.56 across wave pairs, and of 0.63 for pairs more than two years apart; the corresponding correlation for the one-year expectation is 0.39 (Appendix Table A8). The required return behaves like a stable personal trait. The short-run expectation behaves like a state variable. Stability across waves also addresses measurement concerns directly. If the minimum-return responses were slider noise or casual guesses, they would not remain stable in the time series. And if the strong association between required returns and ten-year expectations documented in Section 4 reflected common-method variance, with adjacent sliders answered from a common anchor, the anchoring would have to be implausibly selective: the same instrument, the same page, and the same slider format produce a strong association with the ten-year expectation and essentially none with the one-year expectation.

In sum, the minimum-rate-of-return responses behave the way a required return should. They are risk ordered in the cross-section and anchored over time. Because the required return is stable, changes in return expectations cannot reflect changes in risk compensation. Whatever moves must appear in the subjective alpha. The next section traces that variation across horizons.

4 Return expectations in the short run and long run

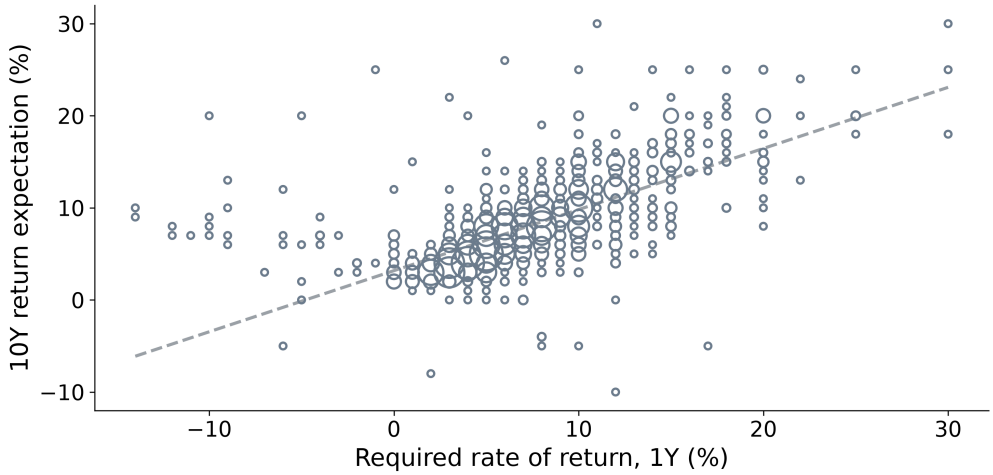
In this section, we examine the structure of return expectations at short and long horizons. Specifically, we decompose a return expectation into two components: the required rate of return and a residual component that captures the idea of subjective alpha, or perceived mispricing.

4.1 Long-run return expectations

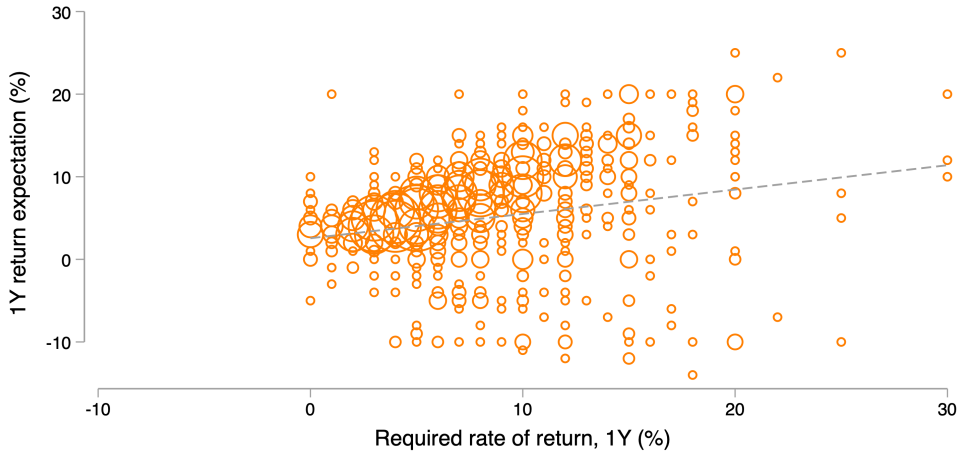
We begin with advisors' long-run return expectations, represented by their ten-year return expectations. Figure 4, Panel (a), presents a scatter plot where the x-axis represents $\mathbb{R}[r^{1Y}]$, the required rate of return, and the y-axis represents $\mathbb{E}[r^{10Y}]$, the ten-year return

expectation. Each circle corresponds to a unique pair of values for these variables, with the size of the circle indicating the number of observations for that pair. The dashed line shows a fitted linear relationship between the two variables. As illustrated in the figure, there is a strong, positive correlation between the ten-year return expectation and the required rate of return, with a steeply positive fitted line.

Figure 4: Return expectations and required returns



(a) Long-run return expectations



(b) Short-run return expectations

Notes: Panel (a) illustrates the correlation between long-run return expectations ($\mathbb{E}[r^{10Y}]$) and required rates of return ($\mathbb{R}[r^{1Y}]$). Panel (b) depicts the correlation between short-run return expectations ($\mathbb{E}[r^{1Y}]$) and required rates of return ($\mathbb{R}[r^{1Y}]$). In both Panels, each circle represents a unique pair of values for these variables, with the size of the circle reflecting the number of observations for that pair.

We formalize this intuition by regressing the ten-year return expectation on the required rate of return. In Panel A of Table 2, column (1) shows that, in an OLS regression without any fixed effects, a 1 percentage point increase in required rates of return is associated with an average increase of 0.69 percentage points in ten-year return expectations. Adding fixed effects for each respondent in each wave, which controls for individual optimism or pessimism across asset classes within a given wave, increases the coefficient to 0.81, as shown in column (2).

To examine this relationship within narrower asset classes, column (3) restricts the sample to risky assets only (excluding bonds, cash, municipal bonds, and real estate funds), while column (4) focuses on equities and equity-like assets, including U.S. Equities, Global Equities, Hedge Fund Equity Strategies, Private Equity Buyout, and Venture Capital. Across all specifications, the estimated association between required rates of return and long-run return expectations remains large, highly statistically significant, and close to one. Within asset class, where the cross-asset class risk ordering is absorbed, the loading is smaller (Appendix A6). This indicates that whenever the required rate of return changes, the ten-year return expectation adjusts nearly one-for-one, though slightly less. These results suggest that advisors perceive a strong relationship between these two variables and incorporate this belief into their reported expectations. Appendix A6 reports the full fixed-effect ladder, together with additional belief results.

4.2 Short-run return expectations

We next examine advisors' short-run return expectations, represented by their one-year return expectations. Figure 4, Panel (b), presents a scatter plot where the y-axis now represents the one-year return expectation. Compared to Panel (a), the positive correlation between return expectations and required rates of return is substantially weaker, even though the two variables are elicited based on the same horizon of one year. The fitted line remains positive but has a much flatter slope.

To quantify the weakened relationship more formally, we repeat the same set of regression exercises by replacing the ten-year return expectation with the one-year return

Table 2: Regressions of return expectations on required rates of return

	Full sample (1)	Full sample (2)	Risky assets (3)	Equities only (4)
Panel A. Dependent variable: $\mathbb{E}[r^{10Y}]$				
$\mathbb{R}[r^{1Y}]$	0.69***	0.81***	0.76***	0.82***
	(0.04)	(0.04)	(0.06)	(0.05)
Respondent×wave FE	N	Y	Y	Y
Observations	1,787	1,768	1,052	696
R-squared	0.51	0.72	0.71	0.77
Panel B. Dependent variable: $\mathbb{E}[r^{1Y}]$				
$\mathbb{R}[r^{1Y}]$	0.38***	0.49***	0.41***	0.40***
	(0.05)	(0.05)	(0.08)	(0.08)
Respondent×wave FE	N	Y	Y	Y
Observations	1,787	1,768	1,052	696
R-squared	0.13	0.49	0.57	0.62

Notes: Six survey waves (May 2022–September 2025), main respondents, minimum (slider-floor) responses excluded; observations with all three of $\mathbb{E}[r^{1Y}]$, $\mathbb{E}[r^{10Y}]$, $\mathbb{R}[r^{1Y}]$ non-missing. "Risky assets" excludes bonds, cash, munis, and real estate funds; "Equities only" is US and Global Equities, Hedge Fund Equity, Private Equity Buyout, and Venture Capital. SEs clustered at the respondent level; $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

expectation as the dependent variable. These results are shown in Panel B of Table 2. Across the six waves pooled, a 1 percentage point increase in required rates of return is associated with an increase of 0.38 percentage points in short-run return expectations without fixed effects (column 1) and 0.49 within respondent-wave (column 2)—roughly half the corresponding ten-year coefficients, at both the full-sample and subsample level. The pooled coefficient, moreover, conceals sharp variation over time. As Section 4.5 shows, the short-run association is far weaker in the 2022–23 waves, when markets were dislocated, and strengthens substantially thereafter. Short-run return expectations can decouple from required rates of return. When and how much they decouple turns out to be a finding in itself.

4.3 Subjective alpha

To quantify the extent to which advisors' return expectations deviate from required returns, we define the difference as "subjective alpha," which represents the gap between

the subjective return expectation and the subjective required rate of return. The ten-year subjective alpha is calculated as the difference between the ten-year return expectation and the required rate of return:

$$\alpha^{10Y} = \mathbb{E}[r^{10Y}] - \mathbb{R}[r^{1Y}], \tag{1}$$

while the one-year subjective alpha is similarly defined as:

$$\alpha^{1Y} = \mathbb{E}[r^{1Y}] - \mathbb{R}[r^{1Y}]. \tag{2}$$

Both alphas are measured against the one-year hurdle, since the survey elicits the required return at the one-year horizon only. The ten-year alpha therefore compares a ten-year expectation with a one-year required return.

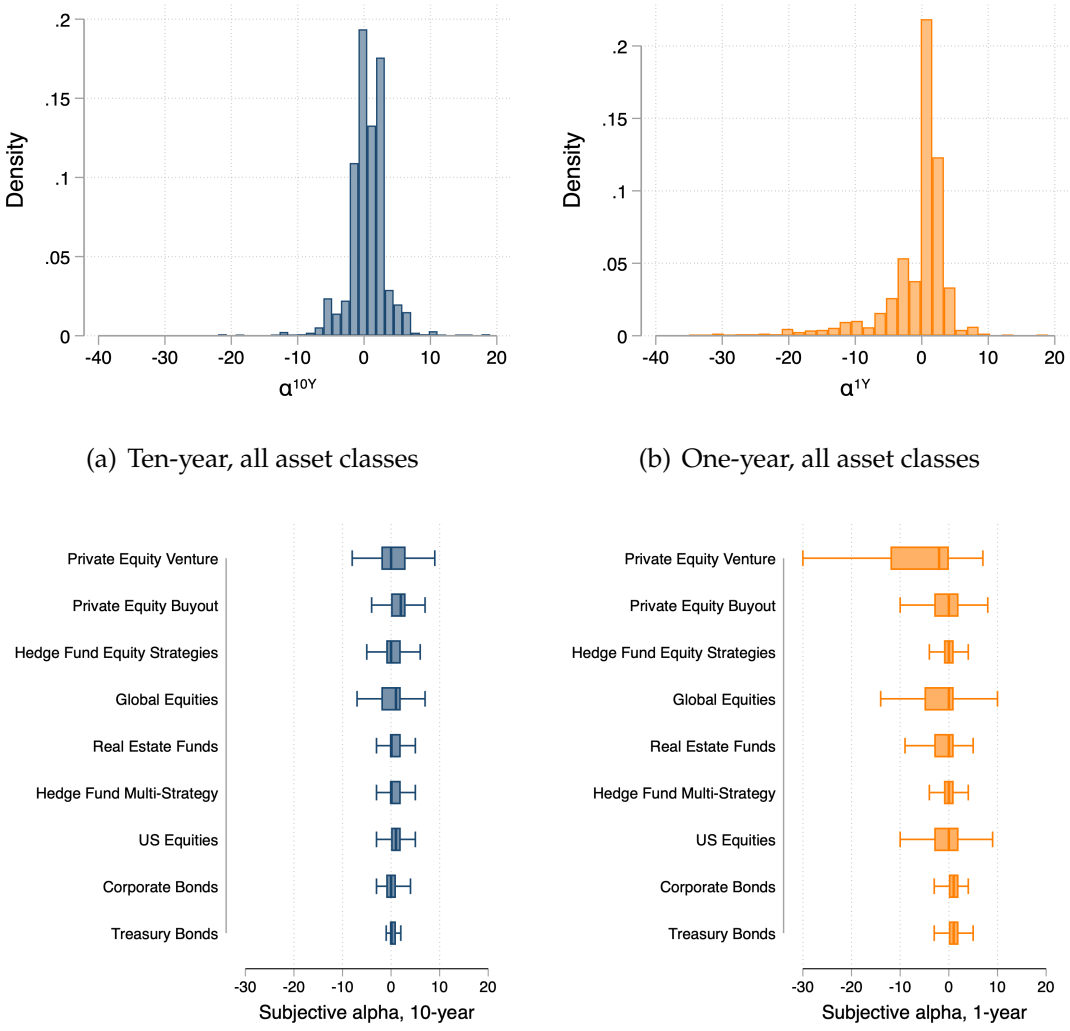
Panels (a) and (b) of Figure 5 present histograms of these two measures of subjective alpha. Panel (a) shows the distribution of ten-year subjective alpha, which clusters strongly around zero, with few observations exceeding 10% in absolute magnitude. In contrast, Panel (b) depicts the distribution of one-year subjective alpha, which, while also clustered around zero, displays much greater dispersion.

This pattern—greater variance in short-run subjective alpha compared to long-run subjective alpha—is consistent across all asset classes in our analysis. Panels (c) and (d) of Figure 5 provide summary statistics for subjective alpha by asset class. Panel (a) demonstrates that long-run subjective alpha remains close to zero for all asset classes. In contrast, Panel (b) reveals substantially more variation in short-run subjective alpha across nearly all asset classes.

4.4 Variance decomposition

To investigate the drivers of variation in long-run and short-run return expectations, we perform a variance decomposition. Taking the variance of both sides of the relationship

Figure 5: Subjective alphas



(a) Ten-year, all asset classes

(b) One-year, all asset classes

(c) Ten-year, by asset class

(d) One-year, by asset class

Notes: Panels (a) and (b) show histograms of ten-year and one-year subjective alpha, the difference between the return expectation at each horizon and the required rate of return, across all asset classes and waves. Panels (c) and (d) show the distributions of the two measures by asset class.

Table 3: Variance decomposition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
% of $\mathbb{E}[r^{10Y}]$ variation										
from $\mathbb{R}[r^{1Y}]$	73	73	72	50	72	72	51	50	40	27
from α^{10Y}	27	27	28	50	28	28	49	50	60	73
% of $\mathbb{E}[r^{1Y}]$ variation										
from $\mathbb{R}[r^{1Y}]$	34	40	37	13	39	39	18	19	12	5
from α^{1Y}	66	60	63	87	61	61	82	81	88	95
Wave FE		Y			Y		Y			
Advisor FE			Y		Y				Y	
Asset class FE				Y			Y		Y	
Wave×Advisor FE						Y				
Wave×Class FE								Y		
Advisor×Class FE										Y

Notes: Share of variance in return expectations attributable to the required return (slope of a regression of $\mathbb{R}[r^{1Y}]$ on $\mathbb{E}[r]$) vs. subjective alpha (the complement). Six waves; sample as in Table 2.

$\mathbb{E}[r] = \mathbb{R}[r] + \alpha$ yields:

$$\text{Var}\left[\mathbb{E}[r]\right] = \text{Cov}\left[\mathbb{E}[r], \mathbb{R}[r]\right] + \text{Cov}\left[\mathbb{E}[r], \alpha\right]. \tag{3}$$

Rearranging this equation allows us to decompose the variance in $\mathbb{E}[r]$ into two components:

$$1 = \frac{\text{Cov}\left[\mathbb{E}[r], \mathbb{R}[r]\right]}{\text{Var}\left[\mathbb{E}[r]\right]} + \frac{\text{Cov}\left[\mathbb{E}[r], \alpha\right]}{\text{Var}\left[\mathbb{E}[r]\right]}, \tag{4}$$

where the first term represents the proportion of variance attributable to the required rate of return, and the second term represents the proportion attributable to subjective alpha. The first term can be obtained from a regression of $\mathbb{R}[r]$ on $\mathbb{E}[r]$, while the second term corresponds to the coefficient from a regression of α on $\mathbb{E}[r]$. This approach has the advantage of allowing us to control for variation explained by specific advisors, survey waves, and other factors through fixed effects. We estimate these coefficients for both ten-year and one-year return expectations.

The results of the variance decomposition are presented in Table 3. Focusing first on

ten-year return expectations, column (1) shows the unconditional variance decomposition results, i.e., without fixed effects: 73 percent of the variation in ten-year return expectations is attributable to the required rate of return, while only 27 percent is explained by subjective alpha. Controlling for variation across waves or advisors has little effect on these estimates, as shown in columns (2) and (3). Therefore, across asset classes, most variation in long-run return expectations is driven by the required rate of return. Column (4) shows that controlling for asset class fixed effects results in variation being equally attributed to the required rate of return and subjective alpha. This suggests that variation across asset classes is primarily captured by the required rate of return.

Columns (5) through (10) further consider specific sources of variation in return expectations through the inclusion of various fixed effects. Column (5) includes both wave and advisor fixed effects, while column (6) includes wave×advisor fixed effects, allowing us to focus on asset-specific variation in return expectations. Consistent with previous findings, nearly three-quarters of the variation in the ten-year return expectation across assets is driven by the required rate of return.

In column (7), we include both wave and asset class fixed effects, and in column (8), we include wave×asset class fixed effects. This allows us to focus on the different views held by advisors about the same asset class during the same survey wave. In these two columns, we find that the required rate of return and subjective alpha each account for about half of the variation. In columns (9) and (10), which isolate variation over time, the required rate of return's share falls further, to 40 and 27 percent—variation over time is mostly subjective alpha. It is worth noting, however, that in column (10), the regression specification requires an advisor to have taken the survey multiple times, which is relatively rare in our setting.

While our measure of required returns is elicited directly from survey responses, the results of the variance decomposition for ten-year return expectations are strikingly similar to those in Couts et al. (2024), where the required rate of return is inferred by assuming the CAPM holds.[4] By contrast, our measure of required returns is "model-free," as we

[4]More specifically, in their approach, risk premia (which are equivalent to the required returns in our setting) are calculated as the product of institutions' return expectations and βs derived from covariance matrices under the CAPM framework.

do not assume a specific asset-pricing model to impute the required rate of return but instead rely on survey respondents to directly provide their perceived values. Despite this methodological difference, both studies find that a significant portion of the variation in long-run return expectations is driven by risk premia, with this identification largely explained by variation across asset classes.

Turning to one-year return expectations, which represent the short-run expectations and are not included in Couts et al. (2024), we find a markedly different result. The unconditional variance decomposition of short-run return expectations is driven 66 percent by subjective alpha and only 34 percent by the required rate of return, as shown in column (1). Adding fixed effects in any combination leaves subjective alpha the majority component, and within wave–asset class or advisor–asset class cells its share rises above 80 percent. Overall, the results in this section show that long-run return expectations are primarily driven by the required rate of return, while short-run return expectations are primarily driven by subjective alpha.

4.5 Discussion

The pooled estimates above average over a sample period that begins in a bear market and ends in a recovery, and the short-run decoupling turns out to be concentrated in the former. Estimating the Panel-B regression of Table 2 wave by wave (with respondent fixed effects within each wave), the coefficient of the one-year expectation on the required return is 0.24 pooled across the first three waves (May 2022–July 2023) and 0.75 across the last three (February 2024–September 2025)—in the later waves, short-run expectations track the hurdle nearly as tightly as long-run expectations do (0.80 and 0.82 for the ten-year expectation in the same subperiods). The composition of the sample plays no role. Restricting to the nine core asset classes leaves both subperiod estimates unchanged (Appendix Table A11, Panel C).

In mid-2022, with markets dislocated, the average short-run subjective alpha on the nine core asset classes stood at −6.8 percentage points—advisors expected returns far below what they required—and one-year expectations bore little relation to hurdles. As

markets normalized, expectations converged back toward required returns. By the final wave the average short-run alpha was 0.1 percentage points, and the cross-sectional link between expectations and hurdles re-tightened. Perceived short-run mispricing is not a permanent feature of advisors' beliefs. It opens in stressed markets and closes in calm ones.[5]

The results of this section admit a simple reading. Over the long run, advisors expect asset returns to converge to the levels their required returns dictate. The required return accounts for most of the variation in ten-year expectations, and the two are close in level, so the long-run alpha is centered near zero. Over the short run, expectations decouple from required returns, and the gap is state dependent. Perceived mispricing opened widest in the dislocated markets of 2022 and had mostly closed by 2025 (Section 4.5). Advisors do not, however, see mispricing only in their favor. Negative short-run alphas are common (Figure 5), which is difficult to square with pure overconfidence in asset selection and points instead to constraints. Advisors may hold asset classes they view pessimistically because of client preferences or diversification needs.

The horizon dependence of rationality connects our evidence to the literature. Survey expectations for the aggregate market appear strongly extrapolative at short horizons (Greenwood and Shleifer, 2014), the long-term forecasts of large asset managers sit closer to rational benchmarks (Dahlquist and Ibert, 2024), and Bastianello and Peng (2025) document that short-term expectations are procyclical while long-term expectations are countercyclical. Our evidence extends the pattern to financial advisors and to a broad menu of asset classes. As for why horizons differ, we outline two possibilities. Different horizons may engage different considerations, with higher-order beliefs mattering at short horizons (Schmidt-Engelbertz and Vasudevan, 2025) and valuations at long ones (Bastianello and Peng, 2025). Alternatively, investors may expect alpha itself to mean-revert, so that short-run mispricing washes out over a decade (Rabin and Vayanos, 2010; Jin and Peng, 2024).

[5]One alternative reading deserves note. The strengthening coincides with the February 2024 questionnaire redesign, which expanded the asset class menu. Two observations argue against a pure instrument effect. The subperiod estimates are unchanged when computed on the eight asset classes present in every wave under identical question wording, and the convergence of the *level* of expectations toward hurdles (Figure 3) already begins between the 2022 and 2023 waves, before any redesign.

5 Where beliefs come from

The previous section establishes an important structure inside return expectations. The required return is a stable, risk-ordered anchor, and the short-run expectation moves around it. This section asks what does the moving. We examine the standard suspects from the expectations literature—macroeconomic views, tail-risk beliefs, and past returns—and ask, for each, which *component* of the return expectation it acts on. The answer is uniform. Every determinant that moves beliefs moves the return expectation and hence the subjective alpha, and essentially none moves the required return. The required return is not merely stable over time (Section 3.2), it is also insensitive to forces that drive expectations.

5.1 Determinants of return expectations

Table 4 reports regressions of the one-year return expectation, the required return, and the short-run subjective alpha on past returns, macroeconomic views, and tail-risk beliefs. The strongest determinant of return expectations is respondents' expectations about the probability of a recession. On average, respondents who believe a recession is certain in the coming year expect a 9.7 percentage point lower return on their investments, in column (1). Expectations about recession probability explains 14 percent of the variation in return expectations. The estimated coefficient is only slightly smaller when controlling for asset class and date fixed effects, which explain more variation in return expectations, but not the estimated relationship between recession probability and required returns. Importantly, the R-squared of a regression of the required return on expectations of recession has an R-squared of essentially zero (0.04 percent). It follows that return expectations change because the subjective alpha moves in response to differences in expectations of recession, while the required return is firmly anchored.

This is mirrored in the regressions of return expectations on expected GDP growth. Although expected GDP growth explains less variation in return expectations than recession probability, it explains more variation in subjective alpha than in one-year return expectations, and less than one percent of the variation in required return. The rela-

Table 4: Determinants of beliefs: return expectations move, the hurdle does not

Dependent variable	$\mathbb{E}[r^{1Y}]$		$\mathbb{R}[r^{1Y}]$		α^{1Y}	
	(1)	(2)	(3)	(4)	(5)	(6)
Recession probability	-0.097***	-0.082***	0.003	-0.007	-0.111***	-0.083***
	(0.019)	(0.024)	(0.012)	(0.011)	(0.024)	(0.026)
Asset class FE		Y		Y		Y
Date FE		Y		Y		Y
Observations	1,076	1,076	1,070	1,070	980	980
R-squared	0.14	0.33	0.0004	0.65	0.15	0.42
Expected GDP growth	0.407	0.426**	-0.151	-0.124	0.549	0.559***
	(0.370)	(0.179)	(0.147)	(0.083)	(0.435)	(0.167)
Asset class FE		Y		Y		Y
Date FE		Y		Y		Y
Observations	1,028	1,028	995	995	936	936
R-squared	0.03	0.32	0.009	0.65	0.05	0.42
Crash return	0.021	0.086**	-0.023	0.006	0.051	0.079
	(0.027)	(0.041)	(0.020)	(0.015)	(0.040)	(0.055)
Respondent FE		Y		Y		Y
Asset class FE		Y		Y		Y
Observations	909	898	894	885	834	824
R-squared	0.004	0.57	0.009	0.87	0.014	0.65
Expected inflation	-0.046	0.412***	0.134	-0.044	-0.212	0.441**
	(0.306)	(0.141)	(0.225)	(0.152)	(0.450)	(0.187)
Asset class FE		Y		Y		Y
Date FE		Y		Y		Y
Observations	1,060	1,060	1,034	1,034	964	964
R-squared	0.0003	0.30	0.006	0.65	0.006	0.39

Notes: Sample: the four portfolio-linkable waves. Weighted by starting position, SEs clustered at the respondent level. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

tionship between expected GDP growth and return expectations is statistically significant when predicting one-year return expectation and short-run subjective alpha, but not for the required return. In this case, the estimates are statistically significance only when controlling for asset class and date fixed effects, which are more important drivers of expectations, as reflected in the larger R-squared of columns (2), (4), and (6), relative to specifications without fixed effects.

On its own, return expectations conditional on a severe recession ("crash return") explain very little of the variation in return expectations. In the cross section of respondents and within asset class, higher crash returns are not associated with higher required returns. The crash return row, in turn, is not at odds with the pricing result across asset classes of Section 3.1. There, crash beliefs price the hurdle *across* asset classes (respondent fixed effects only); here, asset class fixed effects absorb that ranking, and *within*-asset class variation in crash beliefs leaves the hurdle unmoved—risk compensation is cross-sectional, once again.

Expected inflation explains even less variation in return expectations, and in the four waves that are linked to portfolios, are associated with higher one-year return expectations and short-run subjective alpha, but has no statistically significant on the required return.[6] Recession probability, expected GDP growth, and expected inflation all move the one-year expectation and the alpha. None has a detectable effect on the required return.[7]

5.2 Extrapolation

The strong anchoring of required returns relative to expectations of recession, GDP growth, crash returns, and inflation carries over to respondent-level past returns, with one marginal exception, as shown in panel A of Table 5. A firm's own recent returns

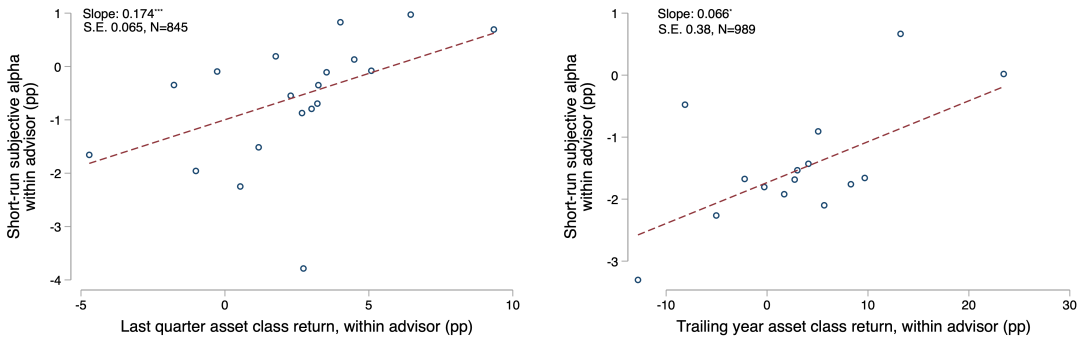
[6]The absence of inflation pass-through is notable in its own right. Advisors raise their *nominal* return expectations when they expect inflation, but do not raise the nominal return they require. The inflation result is the one determinant sensitive to sample. In the six-wave unweighted survey sample of Appendix Table A6, its coefficient is small and insignificant, while the growth and recession results carry over.

[7]Respondent characteristics, such as decision-making power and professional role, explain neither expectations nor hurdles (Appendix Table A6). Belief heterogeneity among these professionals is idiosyncratic, echoing the persistent unexplained heterogeneity documented for retail investors by Giglio et al. (2021). Appendix A6 reports the macro views' effects on all five belief outcomes and the full lag structure of past returns.

move expectations but the required return declines slightly after a strong quarter, as if recent gains make advisors less demanding, so part of the alpha response to the latest quarter reflects the hurdle dipping rather than the expectation rising. When regressing return expectations on a firm's trailing twelve month returns, we recover the pattern in Table 4: own recent returns move expectations, the required return is unchanged by past returns, and the alpha response is statistically significant. As before, past returns explain more variation in short-run subjective alpha than in either return expectations or required returns.

Three features stand out. First, extrapolation varies by horizon in a way that mirrors the paper's central decomposition. The one-year return expectation extrapolates the trailing year. The required return, if anything, *falls* after a good recent quarter. The two effects compound, so the short-run alpha loads hardest on the most recent quarter (0.174 per percentage point of last-quarter return); Figure 6 displays the two slopes as binned scatter plots. Advisors do not merely expect recent performance to continue—they read it as mispricing.

Figure 6: Within-advisor extrapolation of short-run alpha



(a) Last quarter (t-1)

(b) Trailing year (t-4,t-1)

Notes: Binned scatter plots of the respondent-demeaned short-run subjective alpha against the respondent-demeaned past return of the asset class, weighted by starting position; slopes are the Panel-A coefficients of Table 5. Left panel: last completed quarter. Right panel: trailing year.

Second, the effect of the most recent quarter's return on short-run subjective alpha is largely driven by equities, while the effect of trailing twelve month returns is driven by alternatives. In Table 5 panel B, the first two columns include all public equity asset

Table 5: Extrapolation: beliefs on past realized returns, by lag horizon

Panel A: Beliefs and past realized returns						
Dependent variable	$\mathbb{E}[r^{1Y}]$		$\mathbb{R}[r^{1Y}]$		α^{1Y}	
	(1)	(2)	(3)	(4)	(5)	(6)
Own return, last quarter	0.161*	0.105	-0.142**	-0.108*	0.311***	0.174***
	(0.089)	(0.066)	(0.063)	(0.061)	(0.098)	(0.065)
Respondent FE		Y		Y		Y
Observations	949	934	922	911	859	845
R-squared	0.02	0.56	0.03	0.51	0.07	0.52
Own return, trailing year	0.035	0.059***	-0.032	-0.016	0.088*	0.066*
	(0.035)	(0.021)	(0.024)	(0.025)	(0.046)	(0.038)
Respondent FE		Y		Y		Y
Observations	1,106	1,088	1,098	1,083	1,006	989
R-squared	0.01	0.51	0.01	0.51	0.02	0.55
Panel B: α^{1Y}, by asset class group						
Dependent variable: α^{1Y}	Equities		Fixed Income		Alternatives	
	(1)	(2)	(3)	(4)	(5)	(6)
Own return, last quarter	0.315***	0.059	-0.097*	-0.071	0.225	0.183
	(0.099)	(0.088)	(0.052)	(0.146)	(0.179)	(0.201)
Respondent FE		Y		Y		Y
Observations	245	228	255	227	359	349
R-squared	0.121	0.869	0.018	0.392	0.011	0.476
Own return, trailing year	0.053	0.102	-0.031	-0.020	0.281***	0.180***
	(0.050)	(0.062)	(0.038)	(0.040)	(0.085)	(0.053)
Respondent FE		Y		Y		Y
Observations	281	259	291	254	434	422
R-squared	0.02	0.92	0.004	0.41	0.05	0.45
Panel C: α^{1Y}, by asset class group with asset class x wave fixed effects						
Own return, last quarter	0.241		-0.213**		0.130	
	(0.228)		(0.106)		(0.189)	
Own return, trailing year		0.040		-0.131*		0.027
		(0.054)		(0.075)		(0.075)
Asset class x wave FE	Y	Y	Y	Y	Y	Y
Observations	245	281	255	291	359	434
R-squared	0.14	0.34	0.14	0.21	0.32	0.45

Notes: Weighted by starting position, with SEs clustered at the respondent level. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

classes. The first regression specification shows that last quarter returns explain 12 percent of the variation in the short-run subjective alpha for equities, compared with less than 2 percent in fixed income or alternatives. The estimated coefficients for equities are positive, significant only without respondent fixed effects. By contract, the short-run subjective alpha in fixed income is always negatively related to past realized returns, in columns (3) and (4). Columns (5) and (6) show that while recent quarter returns do not explain much variation in alternatives return expectations, respondents extrapolate trailing twelve month returns more in alternatives than in equities or fixed income. This is possibly because in alternatives appraisal-based returns may be smoothed and autocorrelated, making the recent quarter return a less informative predictor than the trailing twelve month return. Extrapolation among professionals is not a uniform reflex but an asset class specific habit.

Third, the pattern reflects belief formation, not private information. The last set of regressions in panel C include asset class by wave fixed effects, which implicitly control for the common component of returns within each asset class in each survey wave. This explains a substantial additional share of variation in short-run subjective alpha, and weakens the estimated relationship between own returns and return expectations for both equities and alternatives. By contrast, in fixed income, asset class by wave fixed effects strengthen the negative relationship between past realized returns and short-run subjective alpha. Asset class performance is an important driver of short-run subjective alpha.

6 Beliefs and portfolios

The final question is whether the beliefs documented so far matter for the portfolios advisors manage. This section answers in five steps. Stated plans respond to subjective alpha (Section 6.1). Executed rebalancing responds to alpha as well, and does so at matching horizons. Short-run alpha predicts the next quarter's rebalancing, long-run alpha the next year's (Section 6.3). The effect is concentrated in equity, the most liquid and widely held asset class (Section 6.4). It lives in the flow of trading, not the stock of

Table 6: Beliefs and stated plans to change allocations

	(1)	(2)	(3)	(4)
$\mathbb{E}[r^{1Y}]$	0.039***			
	(0.005)			
$\mathbb{E}[r^{10Y}]$			0.039***	
			(0.008)	
$\mathbb{R}[r^{1Y}]$		0.025***		0.026**
		(0.009)		(0.010)
α^{1Y}		0.039***		
		(0.005)		
α^{10Y}				0.048***
				(0.009)
Asset class FE	Y	Y	Y	Y
Advisor FE	Y	Y	Y	Y
Observations	2,048	1,858	2,137	1,889
R-squared	0.28	0.28	0.25	0.26

Notes: The dependent variable is Increase−Decrease, built from dummies for a stated plan to increase or decrease the allocation to the class over the next year (from the fourth wave the question offers an explicit don't-know option, treated as neither). Six waves; SEs clustered at the respondent level. $^{*}p < .10, ^{**}p < .05, ^{***}p < .01$.

holdings, whose cross-section reflects firm style (Section 6.5). And stated intentions bind on the extensive margin—entering an asset class outside the active book—rather than in fine-tuning existing positions (Section 6.6).

6.1 Stated plans respond to alpha

We first examine how beliefs influence stated plans to change allocations, using responses to the survey question: "Do you plan to change your allocation to the following assets over the next year? If so, how?" The possible responses are qualitative: "Increase," "Decrease," "No change," or "Don't know." We convert them into the difference of two dummies, Increase−Decrease, and regress it on beliefs, with asset class and advisor fixed effects, so that the identification comes from which of their own asset classes an advisor plans to favor. The results are in Table 6.

Higher one-year return expectations predict a stated intention to increase the allocation (column 1), and so does the long-run expectation (column 3). Decomposing the

expectations (columns 2 and 4) shows that subjective alpha plays the dominant role. At both horizons its coefficient exceeds that of the required return. The hurdle component is not repellent in the pooled sample—its coefficient is positive—but the pooled estimate conceals the now-familiar time pattern. In the first three waves the hurdle component is null while alpha is strong, and it turns positive only in the later waves (Appendix Table A11, Panel E), when expectations re-coupled to hurdles (Section 4.5) and level and mispricing variation became difficult to separate. Plans lean toward perceived mispricing. The sharper separation between alpha and hurdle appears in executed trades below, where the required return never predicts rebalancing.

6.2 Measuring executed rebalancing

We link the survey to the portfolio panel at the firm × asset class × quarter level, using the four linkable waves (Section 2.3). Our headline trade measure is *active rebalancing*: for each client portfolio, we compute the counterfactual end-of-quarter asset class share that would have obtained absent any flows—using the accounting identity, this is the position value under price drift alone—and measure the deviation of the actual share from it. The measure thus isolates deliberate allocation shifts, purged of valuation effects. Two companion families serve as robustness: the raw change in the asset class's portfolio share (in percentage points), and the net dollar flow into the asset class as a share of portfolio value. Each measure is computed at three horizons—the survey quarter (t), one quarter forward (t+1), and one year forward (t+1 through t+4). Measures are aggregated to the firm level, weighting client portfolios by position size, and winsorized (share-based measures at 2.5 percent, flows and returns at 1 percent); Appendix A4 gives formal definitions. The forward horizons are strictly post-survey, so beliefs are measured before the trades they predict.

The estimation sample restricts to the nine core asset classes, and identification mirrors the belief design: with respondent and asset class fixed effects, the question is whether the asset class an advisor rates above their own average—and above the market's average rating of that asset class—is the asset class they subsequently rebalance toward. This

within-advisor, variation across asset classes is substantial: over half of the variance in one-year expectations lies within respondent-wave. For cuts by asset class group, where respondent fixed effects are too demanding, we use asset class and wave fixed effects instead and report both.

6.3 The term structure of trading

Table 7 contains the paper's central portfolio result. Each cell regresses active rebalancing—current, one quarter forward, or one year forward—on one belief variable: the short-run expectation or alpha, and the long-run expectation or alpha.

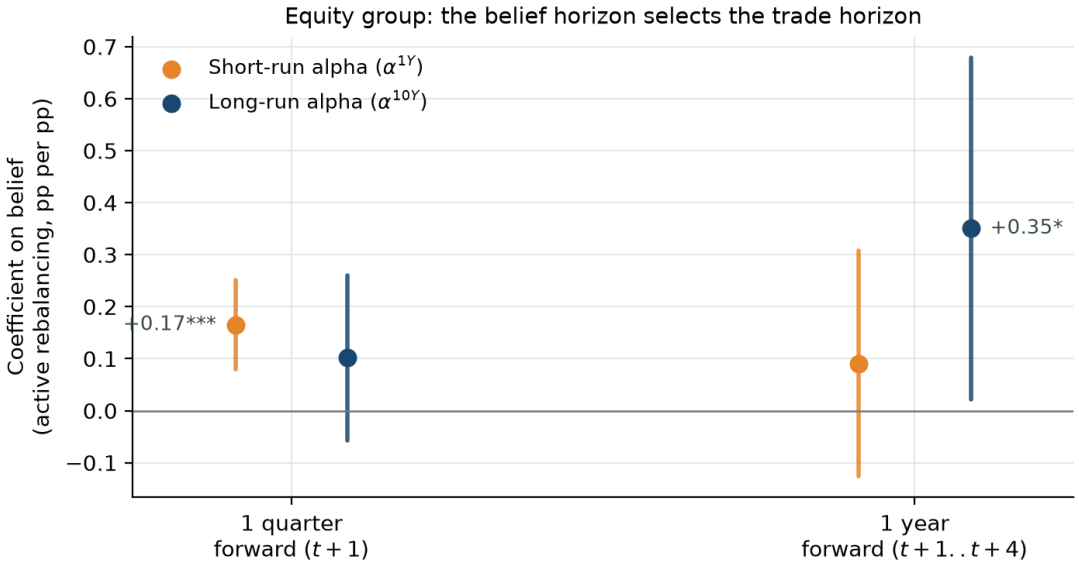
Read down the diagonal of Panel A. Short-run beliefs predict rebalancing one quarter ahead—a one-point increase in short-run alpha raises next-quarter active rebalancing of the asset class by 0.165 percentage points (s.e. 0.052)—and have no effect at the one-year horizon. Long-run beliefs are the mirror image: no quarterly effect, but the ten-year expectation and the long-run alpha predict rebalancing over the following year. In a joint horse race of the two expectations, the short-run coefficient dominates at the quarterly horizon (+0.168, significant at the 1 percent level, against +0.079 for the ten-year expectation), and the ranking flips exactly at the annual horizon (+0.071 against +0.500, the latter significant at the 10 percent level). In other words, the horizon of the belief selects the horizon of the trade. The long-run leg, we note, is estimated less precisely and is significant at the 10 percent level ($p = 0.08$); dropping the single most influential observation moves it outside conventional significance ($p = 0.21$; Appendix Table A11, Panel F), so we report it as suggestive, while the short-run leg is significant in every specification of Appendix Table A4 except the imprecisely estimated within-firm variant. Figure 7 displays the equity block graphically.

Table 7: Belief–rebalancing coefficients by belief horizon and trade horizon

Panel A: Pooled nine asset classes						
Dependent variable	1Q forward			1Y forward		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}[r^{1Y}]$	0.100***			0.069		
	(0.037)			(0.125)		
α^{1Y}		0.104***	0.094**		0.047	0.284
		(0.032)	(0.044)		(0.149)	(0.333)
Asset class FE	Y	Y	Y	Y	Y	Y
Wave FE	Y	Y		Y	Y	
Respondent FE			Y			Y
Observations	911	834	817	930	853	836
R-squared	0.05	0.06	0.24	0.16	0.16	0.39
$\mathbb{E}[r^{10Y}]$	0.006			0.257		
	(0.081)			(0.387)		
α^{10Y}		0.061	0.145		0.302	0.631*
		(0.066)	(0.110)		(0.189)	(0.352)
Asset class FE	Y	Y	Y	Y	Y	Y
Wave FE	Y	Y		Y	Y	
Respondent FE			Y			Y
Observations	993	858	842	1,012	877	862
R-squared	0.07	0.05	0.24	0.14	0.15	0.38
Panel B: Equity group only						
$\mathbb{E}[r^{1Y}]$	0.167***					
	(0.063)					
α^{1Y}		0.165***	0.183			
		(0.052)	(0.183)			
$\mathbb{E}[r^{10Y}]$				0.533**		
				(0.260)		
α^{10Y}					0.351*	0.129
					(0.200)	(0.441)
Asset class FE	Y	Y	Y	Y	Y	Y
Wave FE	Y	Y		Y	Y	
Respondent FE			Y			Y
Observations	237	213	165	268	233	181
R-squared	0.04	0.05	0.53	0.14	0.19	0.67

Notes: Weighted by starting position, SEs (in parentheses) clustered at the respondent level. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$. Trading outcomes use the four linkable waves (May 2022, January 2023, July 2023, and October 2024).

Figure 7: The belief horizon selects the trade horizon



Notes: Coefficients from the equity block of Table 7: active rebalancing at each horizon regressed on short-run alpha (orange) and long-run alpha (navy); whiskers are 90 percent confidence intervals, clustered at the respondent level.

Three features sharpen the interpretation. First, it is the alpha, not the hurdle. The required return on its own never predicts rebalancing at any horizon, and controlling for it leaves the alpha coefficient intact (Appendix Table A11, Panel A). In executed trades, unlike in stated plans, the separation between the two components is unambiguous. Second, it is not momentum: controlling for the asset class's trailing and contemporaneous returns leaves the coefficients essentially unchanged, so advisors are not simply buying what recently rose; extrapolation operates upstream, at belief formation (Section 5), not at the trading stage. Third, the timing is informative: current-quarter estimates are small and insignificant (untabulated), the response appears at t+1, and consecutive-quarter rebalancing is essentially uncorrelated. Advisors trade in lumps, and beliefs precede the trades they predict.

The magnitudes are moderate and disciplined. A one-standard-deviation increase in short-run alpha moves about 1.0 percentage point of the asset class's share of firm assets over the following quarter, an elasticity of roughly 0.17, at least an order of magnitude below the frictionless benchmark (Merton, 1969, 1971). The comparison with retail investors

is qualitative rather than one of magnitudes. Giglio et al. (2021) find that retail beliefs are reflected in the *level* of equity holdings but that belief changes do not predict *when* investors trade. In our setting the pattern is reversed: subjective alpha predicts advisors' trading at the matching horizon, while the level of holdings responds little. Beliefs move professional portfolios through the flow of trading, where in retail portfolios they are visible mainly in the stock.

6.4 An equity phenomenon

Panel C of Table 7 splits the nine asset classes into five groups. At the quarterly horizon, equity is the only group with a significant belief–trade relationship. Bonds are noisy—a few very large Treasury positions destabilize the value-weighted estimates—and the remaining groups show no quarterly response, consistent with capital-call and liquidity frictions that break the link between a current view and a current trade. At the annual horizon, two non-equity cells attain significance (at the 10 and 5 percent levels, respectively)—positive for private equity and venture capital, as delayed execution of a view would predict, and negative for hedge funds—but both estimates flip sign across fixed-effect structures and belief variables, and we treat them as noise rather than evidence. Equity is the only group whose response is robust. The concentration makes economic sense. Equity is the most liquid and most widely held asset class, the one where an advisor can act on a view within a quarter. It also disciplines our claims—we do not assert a general belief–trade elasticity across asset classes, only a robust one where trading is feasible.

6.5 The flow encodes beliefs; the stock encodes style

A natural companion regression replaces rebalancing with the *level* of the asset class share—the analogue of the cross-sectional relationship in Giglio et al. (2021), where more optimistic investors hold higher equity shares. In our setting the levels regression delivers the opposite sign. Across firms, a one-point higher one-year expectation is associated with a 0.66-point *lower* current share of the asset class (Table 8).

Table 8: The flow of trading encodes beliefs; the stock of holdings encodes style

	Level (asset class share)		Flow (1Q rebalancing)	
	(1)	(2)	(3)	(4)
Panel A: Equities group only				
$\mathbb{E}[r^{1Y}]$	-0.610**	-0.080	0.167***	0.151
	(0.300)	(0.236)	(0.063)	(0.157)
Asset class FE	Y	Y	Y	Y
Wave FE	Y		Y	
Firm FE		Y		Y
Observations	240	192	237	190
R-squared	0.40	0.95	0.04	0.43
$\mathbb{R}[r^{1Y}]$	-1.397*	0.841	0.033	0.230
	(0.736)	(0.691)	(0.149)	(0.363)
Asset class FE	Y	Y	Y	Y
Wave FE	Y		Y	
Firm FE		Y		Y
Observations	245	201	242	199
R-squared	0.44	0.95	0.02	0.48
α^{1Y}	-0.327	-0.177	0.165***	0.179
	(0.266)	(0.378)	(0.052)	(0.210)
Asset class FE	Y	Y	Y	Y
Wave FE	Y		Y	
Firm FE		Y		Y
Observations	216	171	213	169
R-squared	0.39	0.95	0.05	0.47
Panel B: Pooled nine asset classes				
$\mathbb{E}[r^{1Y}]$	-0.349**	-0.436***	0.100***	0.096**
	(0.149)	(0.161)	(0.037)	(0.045)
Asset class FE	Y	Y	Y	Y
Wave FE	Y		Y	
Firm FE		Y		Y
Observations	930	914	911	896
R-squared	0.49	0.77	0.05	0.20

Notes: VW, weighted by starting position, SEs clustered at respondent. The negative belief–level relationship is a cross-firm style effect; the flow relationship survives within firm. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

The resolution is that the level and the flow answer different questions. The negative levels coefficient becomes smaller and statistically insignificant within-firm. It is a cross-firm *style* effect, as reflected in the R-squared of 95 percent. Firms specialize enormously—equity allocations span nearly the full unit interval across firms—and specialists are not systematically bullish on their specialty, while non-specialists may hold little of an asset class yet can rate its prospects highly. Comparing a firm to itself, the negative association is significantly muted, while the flow relationship's point estimate is very similar, though less precisely estimated. Firms rebalance toward the asset classes they currently consider mispriced. The stock of holdings is dominated by style and portfolio construction, while advisors express their beliefs through the flow of trading. This is why our evidence is built on rebalancing, and why the levels comparison to Giglio et al. (2021) does not transport to multi-asset delegated portfolios while the flow comparison does.

6.6 Stated intentions and the extensive margin

Section 6.1 showed that stated plans respond to alpha. Do advisors follow through on these plans? On the *intensive* margin—adjusting asset classes already in the active book—the answer is no. Regressing forward rebalancing on the stated-action dummies yields a uniform null across trade families. But the plan-to-change question is asked more broadly than the belief questions—it covers asset classes the advisor is *not* actively investing in—and there the answer reverses (Table 9).

When an advisor reports a plan to increase an asset class outside their active book—in effect, a plan to enter or build a position—the plan predicts execution: 1.98 percentage points of forward net inflow and 1.06 percentage points of forward share gain in the following quarter, with raw means monotonic in the stated action. Intentions bind when starting something new, not when fine-tuning the existing book—exactly the pattern that fixed adjustment costs predict, where discrete decisions (entering an asset class) clear the threshold that marginal adjustments do not.

Table 9: Stated intentions bind on the extensive margin

Dependent variable:	Reported existing investments		Reported no investments	
	Δ Share (pp)	Net flow (% AUM)	Δ Share (pp)	Net flow (% AUM)
	(1)	(2)	(3)	(4)
Panel A: Regressions of stated plans				
Plans to increase	0.02	-0.38	1.07**	2.10**
	(0.11)	(0.29)	(0.49)	(1.02)
Plans to decrease	-0.03	-0.77*	-0.64*	0.19
	(0.19)	(0.43)	(0.36)	(0.47)
Don't know	0.10	-0.67	0.33*	0.38
	(0.12)	(0.52)	(0.19)	(0.37)
Asset class FE	Y	Y	Y	Y
Wave FE	Y	Y	Y	Y
Observations	1,324	1,324	477	477
R-squared	0.17	0.17	0.27	0.26
Panel B: Raw means				
Increase	-0.38	-0.13	0.44	1.26
No change	-0.61	0.40	-0.24	-0.29
Decrease	-0.58	-0.53	-0.85	-0.22
I Don't Know	-0.57	-0.09	-0.13	-0.04

Notes: Action sample over nine pooled asset classes, linkable waves; asset class + wave FE; reference category "No change"; SEs clustered at respondent. Panel B reports mean forward net flow and share change (both in pp) by stated action. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

6.7 Robustness

The quarterly equity result is stable to winsorization from 1 to 10 percent (all estimates significant at the 1 percent level). It retains its sign and significance across all three families of trade measures and both weightings (at the 10 percent level for the share-change family); within firm the point estimate is similar, though imprecisely estimated. It also survives relaxing the belief sample filter. Re-estimating on all observations with a one-year expectation (rather than requiring a valid required return) yields a similar, slightly attenuated coefficient on a larger sample. The annual long-run leg is stable to winsorization but is estimated less precisely, and we flag it as suggestive throughout. Macroeconomic views also predict equity trading directly, in parallel with the belief about the asset class itself (Appendix A7). Appendix A5 collects the full battery.

7 Discussion: implications for theories

Our results speak to three ongoing debates, in each of which the object we elicit—the subjective required return—has been the missing measurement.

The first concerns the nature of subjective risk premia. A long-standing tension in the expectations literature is that subjective return expectations appear procyclical—high after good times—while leading rational models require compensation for risk to be countercyclical (Greenwood and Shleifer, 2014). Inference in that debate has proceeded by subtracting an observed risk-free rate from an elicited expectation, or by imposing an asset-pricing model (Nagel and Xu, 2023; Couts et al., 2024). Eliciting the required return directly, we can locate the cyclicality. In our advisors' minds, risk compensation is a *cross-sectional* object—coherent, risk-ordered, priced off their own crash beliefs—that scarcely moves over time, while all cyclical variation in expectations is perceived mispricing, opening in the 2022 dislocation and closing by 2025. As a description of practitioners' subjective models, the evidence favors belief-based accounts of time-varying expected returns over preference-based ones. The stability of the hurdle across a full policy-rate cycle also gives the corporate-finance evidence on sticky discount rates (Gormsen and Huber, 2025) a buy-side counterpart. The professionals allocating household wealth anchor their hurdles

much as CFOs do.

The second debate concerns why portfolios respond so weakly to beliefs. Giglio et al. (2021) document a belief–portfolio sensitivity an order of magnitude below frictionless benchmarks for retail investors and attribute the gap to frictions, showing that sensitivity rises with attention and sophistication. Our advisors are professionally attentive and trade client wealth at negligible marginal cost, yet their portfolios, too, adjust only partially to beliefs. In their case the friction is unlikely to be cognitive; it appears institutional, taking the form of mandates, review calendars, and client consent. The adjustment signatures we document—lumpy trades, effects arriving one quarter after the belief, intentions that bind on entry but not on fine-tuning—are those of fixed adjustment costs, migrated from the household's mind to the advisory relationship. Modeling delegated portfolio adjustment with such frictions strikes us as a productive next step.

The third debate concerns inference from holdings. The flow–stock dichotomy carries a lesson for the growing literature that infers beliefs or demand from holdings. In demand-system approaches (Koijen and Yogo, 2019), persistent institutional "latent demand" absorbs much of the cross-section of holdings. Our evidence gives that residual an interpretation and a warning. The level of a delegated multi-asset portfolio encodes style and specialization, not beliefs—the belief–level correlation is, if anything, negative—while beliefs surface in flows. Survey-measured beliefs and holdings-inferred demand are complements, but they should be linked through trades, not levels.

8 Conclusion

We elicit, from the professionals who allocate wealth on behalf of high-net-worth households, both halves of a return expectation: what they expect an asset class to earn, and what they require of it. The gap between the two—subjective alpha—turns out to be the organizing object of both beliefs and behavior. Required returns are well-behaved and risk-ordered in the cross-section yet anchored to ten-year views and immobile through a full monetary-policy cycle. The determinants of beliefs we measure—extrapolation of past returns, macroeconomic views, tail risk—act on return expectations and therefore

land in the alpha; and it is the alpha, not the hurdle, that advisors act on, in stated plans and in executed trades, at the horizon the belief refers to.

Taken together, the evidence describes professionals who believe that markets are efficient in the long run but episodically inefficient in the short run. They form their short-run views in part by extrapolating publicly observable asset class returns, most strongly where price signals are stalest. And they express those views in portfolios cautiously—through lumpy quarterly rebalancing of liquid asset classes and through decisive entries into new ones. They act on their beliefs through trading, at the horizons to which those beliefs apply.

Several extensions are within reach of the design. A further wave of portfolio data will make the 2025 survey wave linkable to trades and sharpen the long-horizon leg of the trading term structure. Belief updating by the advisors who answer repeatedly can be studied directly; and the state-dependence of perceived mispricing—alpha that opens in dislocations and closes in calm markets—invites a longer sample spanning more than one cycle. More broadly, the two-object elicitation is portable. Any survey that asks what investors expect could also ask what they require. We suspect that much of what is measured as disagreement about return expectations reflects disagreement about perceived mispricing.

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Online Appendix for

Subjective Alpha:

Beliefs and Portfolios of Financial Advisors

A1 Additional details on the screening questions

Table A1 tabulates self-reported decision-making power and platform assets under management by the extent of involvement in portfolio allocation decisions, across the main respondents of all six waves.

Table A1: Self-reported decision power and assets under management, by frequency of involvement in allocation decisions

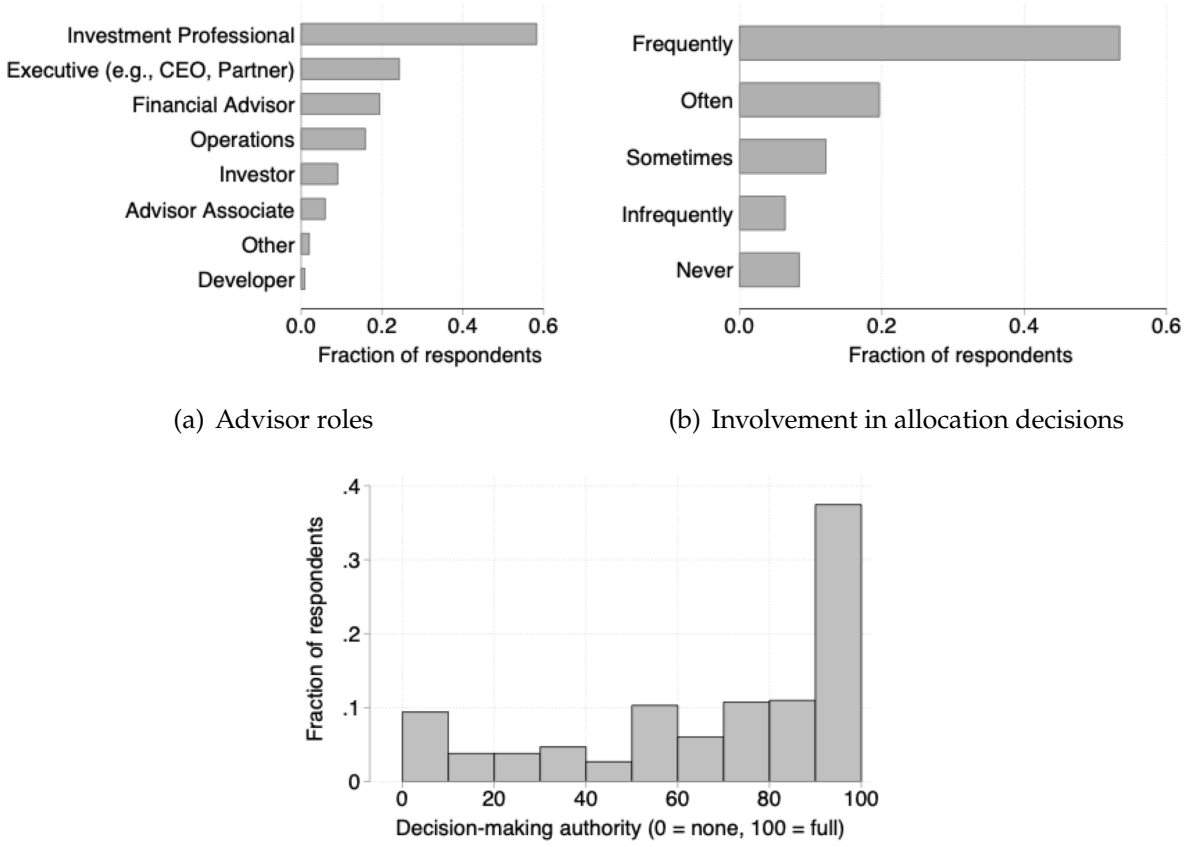
Frequency of	Decision power (%)		Firm AUM (USD millions)		
involvement	Mean	Median	Mean	Median	N
Frequently	85	90	973	366	242
Often	66	70	1,377	364	89
Sometimes	44	44	579	183	55
Infrequently	19	10	690	339	29
Never	8	0	2,724	696	38
Total	66	75	1,103	332	453

Notes: Main survey respondents across all six waves, grouped by their answer to the screening question "To what extent do you make decisions on portfolio allocation for clients?" Decision power is the self-reported share of allocation decisions driven by the respondent's advice (0–100 slider). Firm AUM is the platform assets under management of the respondent's firm as of 2025Q4; the AUM columns cover the linkable-firm subset (the February 2024 wave cannot be linked), so their effective N is smaller than the count column.

A2 The active book: match rates and false negatives

The screener defines the estimation sample (Section 2.1). This appendix documents how the selected asset classes relate to actual holdings. Among screener-selected asset class–wave observations outside the unlinkable fourth wave, 83 percent match a portfolio position in the survey quarter and 91 percent correspond to an asset class the firm has

Figure A1: Distribution of advisor characteristics



(a) Advisor roles

(b) Involvement in allocation decisions

(c) Decision power

Notes: Distributions of self-reported advisor roles (multiple selections allowed), extent of involvement in portfolio allocation decisions, and decision-making power over portfolio allocations, across the main respondents of all six waves.

held at some point; most asset classes match at 80–89 percent, with equity-strategy hedge funds the outlier (69 percent), reflecting positions accessed through external managers off the platform.

The reverse case—asset classes the firm holds but the advisor did not select—is informative about what the screener measures. Table A2 repeats the match-rate calculation for *unselected* asset class–wave observations. Selection raises the probability of a same-quarter position by roughly 16 percentage points on average, and the gap is concentrated exactly where it should be. Core exposures—developed-market equity, cash, corporate bonds—are held at nearly the selected rate even when unselected, while discretionary asset classes such as equity-strategy hedge funds collapse to a 38 percent match.

Table A2: Match rates for unselected asset class–wave observations

Asset class	Unselected N	% quarter match	% firm ever held
Developed Mkt Equity	225	85%	95%
Cash	216	84%	94%
EM Equity	40	82%	85%
Corporate Bonds	115	81%	92%
U.S. Equity	19	74%	84%
Hedge Funds Multi	185	73%	84%
Private Equity	106	73%	86%
Private Debt	236	68%	79%
Muni Bonds	257	57%	72%
Venture Capital	103	55%	70%
Global Equity	38	55%	71%
Real Estate Funds	115	55%	71%
U.S. Gov Bonds	93	47%	72%
Hedge Funds Equity	181	38%	43%
All asset classes	1,929	67%	79%

Notes: Class–wave observations with a populated screener in which the asset class was *not* selected, outside the fourth wave. "% quarter match": a portfolio position in the asset class exists in the survey quarter; "% firm ever held": the firm holds the asset class at some point in the panel.

What are the unselected-yet-held positions? Table A3 compares them with selected-and-held positions. Unrecorded positions are smaller and less broadly held. Splitting by breadth—the share of the firm's clients holding the position—identifies two categories: roughly 40 percent are firm-wide core exposures held by a majority of clients (cash sweeps, bond ladders, index equity), and roughly 20 percent are legacy positions concentrated in fewer than a tenth of clients. Both sit outside the advisor's active deliberation, which

is why they are absent from the screener despite being held. The estimation sample is advisors' active decisions, and 92 percent of it falls in the selected-and-held cell.

Table A3: Anatomy of the false negatives

Median	Unrecorded (screener NO)	Recorded (screener YES)
Position size (USD m)	15	36
Share of firm AUM (%)	1.3	3.2
Breadth (% of firm's clients holding)	35	50
Number of client portfolios	7	11

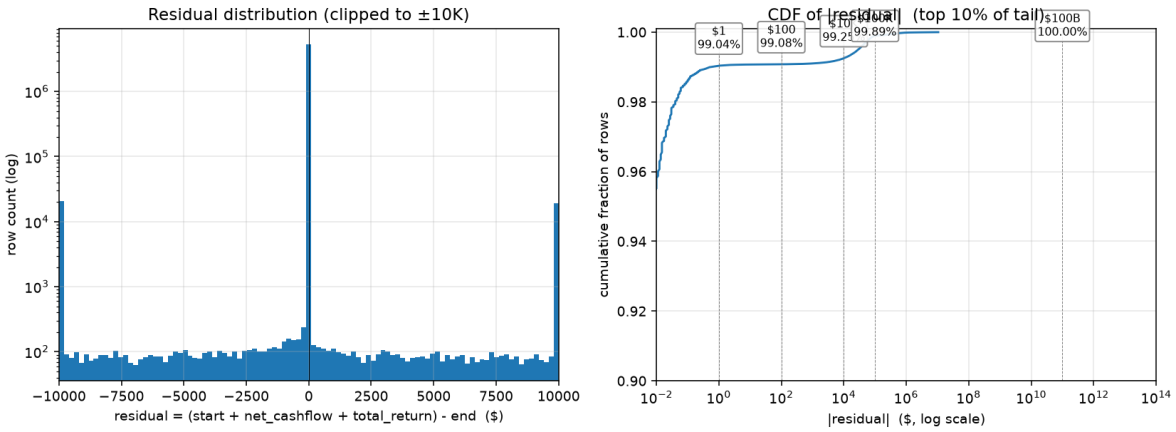
Notes: Medians across asset class–wave observations with a position in the survey quarter, split by whether the advisor selected the asset class in the screener.

A3 Merge and data quality

The portfolio panel is validated in three steps before use. First, the accounting identity: for each portfolio × asset class × quarter row, the ending value must equal the starting value plus net flows plus returns. The identity holds to the dollar for 99 percent of rows. We drop the small remainder where it fails by more than one dollar, as well as three extreme rows in which the platform forced the identity by dumping an unaccounted residual into the flow field. Figure A2 shows the residual distribution. Second, implausibility filters: for positions above one thousand dollars we drop rows with quarterly returns beyond ±100 percent, flows exceeding ten times the position, ten-fold within-quarter growth, or an ending value below a tenth of the starting value—about 2 percent of the sample, but rows that would otherwise dominate the value-weighted regressions. Third, asset class identifiers are mapped to a fixed taxonomy, with an assertion that catches any new asset class string in a future refresh.

On the survey side, the fourth wave's raw responses lack platform identifiers and receive pseudo-identifiers so that respondent fixed effects remain valid. The wave is excluded from all portfolio-linked analyses. The merge is many-to-one on firm, asset class, and quarter. The full build pipeline is implemented twice—in the original Stata code and in an independent Python port—and the two agree on the headline trade measure with a correlation of 0.9997. The replication package documents both.

Figure A2: Accounting-identity residuals in the portfolio panel



Notes: Distribution of the residual of the accounting identity (ending value minus starting value, net flows, and returns) across portfolio × asset class × quarter rows. Ninety-nine percent of rows satisfy the identity exactly; rows failing it by more than one dollar are dropped.

A4 Measurement of the trade variables

For each client portfolio p, asset class c, and quarter t, the *active rebalancing* measure starts from the counterfactual position value absent flows, $\text{end}_{pct} - \text{flow}_{pct}$, which by the accounting identity equals the value under price drift alone. Dividing by the portfolio-level counterfactual total gives the counterfactual asset class share, and the measure is the percentage deviation of the actual end-of-quarter share from it. A difference form (actual minus counterfactual share, in percentage points) behaves nearly identically and serves as a check. The *share change* family is the change in the asset class's portfolio share in percentage points. A legacy ratio form (percent change in the share) is retained in the data but not used, because near-zero starting shares give it extreme tails at the annual horizon. The *net flow* family is the asset class's net dollar flow over portfolio value.

Each measure is computed at the survey quarter, one quarter forward, and cumulatively over the four following quarters, with lead validity enforced on the quarter index. Portfolio-level measures are aggregated to the firm by value-weighting with the starting position (equal-weighted versions serve as robustness). Value-weighting the portfolio-level measures is not equivalent to aggregating dollars first, which washes out within-firm

heterogeneity. Share-based measures are winsorized at 2.5 percent at the firm level and flows and returns at 1 percent, after removing infinities generated by division by tiny starting positions.

A5 Additional robustness

Table A4 collects the robustness battery for the trading term structure: the winsorization ladder, the families of trade measures and weightings, within-firm identification, and the relaxed belief sample filter. Two further checks are described in the text: the long-run leg's sensitivity to the single most influential observation (Section 6.3), and the near-zero autocorrelation of consecutive-quarter rebalancing, which supports the event-driven reading of the timing.

Table A4: Robustness of the trading term structure

	$\alpha^{1Y} \to$ 1Q forward	$\alpha^{10Y} \to$ 1Y forward
Panel A: winsorization ladder (equity, class + wave FE)		
1% cut	0.164^{***} (0.052)	0.351^{*} (0.200)
2.5% cut	0.161^{***} (0.052)	0.346^{*} (0.200)
5% cut	0.146^{***} (0.045)	0.336^{*} (0.192)
10% cut	0.107^{***} (0.037)	0.286^{*} (0.169)
Panel B: trade-measure families and weightings (equity)		
Active rebalancing, VW	0.165^{***} (0.052)	0.351^{*} (0.200)
Active rebalancing, EW	0.226^{**} (0.090)	0.798^{***} (0.299)
Share change (pp), VW	0.030^{*} (0.017)	0.005 (0.067)
Net flow (% AUM), VW	0.051^{**} (0.025)	−0.055 (0.099)
Panel C: identification and sample variants (1Q horizon)		
Within firm (firm + asset class FE)	0.179 (0.210)	
Pooled nine asset classes (respondent + asset class FE)	0.094^{**} (0.044)	
Relaxed filter: all $\mathbb{E}[r^{1Y}]$ responses, on $\mathbb{E}[r^{1Y}]$	0.163^{***} (0.061)	
Panel D: momentum controls (equity)		
No return controls	0.165^{***} (0.052)	0.351^{*} (0.200)
+ contemporaneous return	0.149^{***} (0.052)	0.358^{*} (0.199)
+ contemporaneous and trailing-year returns	0.149^{***} (0.052)	0.342^{*} (0.195)

Notes: Each cell is a separate regression; SEs (in parentheses) clustered at the respondent level. Panel A re-winsorizes the active-rebalancing measure at progressively harsher cuts. Panel B varies the trade measure and weighting. Panel C varies identification and, in its last row, relaxes the belief-sample filter to all observations with a one-year expectation; Panel D adds return controls. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

A6 Additional results on beliefs

This appendix collects additional belief-side results referenced in the main text. Table A5 reports the regression of return expectations on required returns under ten fixed-effect specifications, extending Table 2: the ten-year loading is large wherever variation across asset classes remains and smaller once asset class fixed effects absorb the between-asset class ordering, while the one-year loading is smaller than the ten-year loading in every specification. Table A6 reports the effect of each macroeconomic view on all five belief outcomes, complementing the determinants table in the main text: growth and recession views move one-year expectations and alphas, expected inflation and the ten-year outcomes are largely insignificant in that sample, and no view moves the required return. Table A7 enters eight quarterly lags of the firm's own asset class return jointly; the coefficients are mixed in sign and display no stable pattern, consistent with the interpretation that the extrapolation documented in the main text operates through recent, publicly observable asset class level performance rather than through any particular lag of the firm's own history. Table A8 reports the test–retest correlations underlying Section 3.2.

Table A5: Return expectations on required returns: the fixed-effect ladder

Fixed effects	$\mathbb{E}[r^{10Y}]$	$\mathbb{E}[r^{1Y}]$
None	0.69^{***} (0.04)	0.38^{***} (0.05)
Wave	0.70^{***} (0.04)	0.44^{***} (0.05)
Advisor	0.77^{***} (0.05)	0.46^{***} (0.06)
Asset class	0.36^{***} (0.04)	0.23^{***} (0.05)
Wave + Advisor	0.76^{***} (0.05)	0.47^{***} (0.05)
Wave × Advisor	0.81^{***} (0.04)	0.49^{***} (0.05)
Wave + Asset class	0.37^{***} (0.05)	0.28^{***} (0.05)
Wave × Asset class	0.36^{***} (0.05)	0.29^{***} (0.05)
Advisor + Asset class	0.32^{***} (0.06)	0.26^{***} (0.07)
Advisor × Asset class	0.15 (0.09)	0.06 (0.09)

Notes: Coefficient of the column return expectation on $\mathbb{R}[r^{1Y}]$ under each fixed-effect specification; belief triple sample, SEs clustered at the respondent level. The ten-year loading is large wherever cross-class variation remains (0.69–0.81) and smaller once class fixed effects absorb the between-class ordering; the one-year loading is smaller than the ten-year loading in every specification. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

Table A6: Macroeconomic views, respondent characteristics, and the five belief outcomes

	$\mathbb{E}[r^{1Y}]$	$\mathbb{E}[r^{10Y}]$	$\mathbb{R}[r^{1Y}]$	α^{1Y}	α^{10Y}
Expected GDP growth (1Y)	0.357^{***}	0.020	-0.024	0.430^{***}	0.102
	(0.111)	(0.061)	(0.088)	(0.128)	(0.085)
Recession probability (1Y)	-0.034^{***}	-0.003	0.004	-0.043^{***}	-0.014^{*}
	(0.009)	(0.007)	(0.009)	(0.011)	(0.008)
Expected inflation (1Y)	0.075	0.028	0.127	-0.059	-0.125
	(0.099)	(0.089)	(0.113)	(0.149)	(0.112)
Decision power	-0.011^{**}	-0.009^{**}	-0.002	-0.008	-0.008
	(0.005)	(0.004)	(0.005)	(0.006)	(0.005)
Role: investment professional	-0.594^{*}	-0.378	-0.090	-0.264	-0.204
	(0.326)	(0.251)	(0.369)	(0.383)	(0.317)

Notes: Each cell is a separate regression of the column belief on the row determinant (macroeconomic views and respondent characteristics), with asset class and wave fixed effects, on the six-wave survey sample (unweighted), SEs clustered at the respondent level. Growth and recession views move one-year expectations and alphas; expected inflation is insignificant, and the ten-year outcomes are insignificant apart from a marginal recession-probability effect; no view moves the required returns. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

Table A7: Beliefs on the full lag structure of past returns

	$\mathbb{E}[r^{1Y}]$	$\mathbb{R}[r^{1Y}]$	α^{1Y}
$L1$ own return	0.074	−0.163	0.164
	(0.131)	(0.107)	(0.114)
$L2$ own return	0.085	−0.034	0.114*
	(0.065)	(0.054)	(0.059)
$L3$ own return	−0.300***	0.122*	−0.347***
	(0.099)	(0.070)	(0.087)
$L4$ own return	0.133	−0.146	0.173**
	(0.099)	(0.108)	(0.083)
$L5$ own return	0.178	−0.153	0.247*
	(0.150)	(0.104)	(0.145)
$L6$ own return	−0.118	0.016	−0.033
	(0.180)	(0.118)	(0.139)
$L7$ own return	0.242**	0.033	0.178*
	(0.113)	(0.052)	(0.102)
$L8$ own return	0.141	−0.011	0.088
	(0.093)	(0.065)	(0.095)
Observations	265	289	265

Notes: Each column regresses the belief on eight quarterly lags of the firm's own value-weighted class return jointly, with respondent and class fixed effects, weighted by starting position, SEs clustered at the respondent level. The coefficients are mixed in sign and display no stable pattern across lags; the scattered significant coefficients alternate in sign, consistent with multicollinearity among overlapping lagged returns rather than a robust lag structure. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

Table A8: Test–retest stability of beliefs within respondent × class

	N pairs	Corr. (all pairs)	Corr. (≥2 years apart)	Mean change (pp)
$\mathbb{R}[r^{1Y}]$	309	0.56	0.63	−0.45
$\mathbb{E}[r^{1Y}]$	260	0.39	0.35	+1.89

Notes: Pairs of responses by the same respondent for the same asset class in different waves (nine core asset classes). Correlations are between the earlier and later response; the mean change is later minus earlier.

A7 Additional results on trading

Advisors' macroeconomic views predict their equity trading directly. Table A10, Panel A, regresses one-quarter-forward active rebalancing on each macro view: higher expected GDP growth and lower recession probability predict more rebalancing into equity, in the theoretically expected directions, while the fixed-income responses are noisier. Panel B horse-races each macro view against the asset class specific one-year expectation: the belief about the asset class itself remains the tighter predictor, and the macro views are largely absorbed, with expected GDP growth retaining marginal independent explanatory power. The macro channel thus operates in parallel with, and more weakly than, the belief about the asset class itself studied in the main text.

Table A10: Macroeconomic views and executed trading

Macro view	Sample	Coefficient	N
Panel A: one macro view at a time (respondent + asset class FE)			
Expected GDP growth	Equity	0.485^{**} (0.218)	173
Recession probability	Equity	-0.028^{*} (0.016)	191
Expected inflation	Fixed income	0.246 (0.187)	177
Expected GDP growth	Fixed income	-0.239 (0.990)	167
Panel B: horse race with the class-specific expectation (respondent + class + wave FE)			
$\mathbb{E}[r^{1Y}]$ + Recession probability	Pooled	0.100^{**} (0.046) | 0.002 (0.023)	944
$\mathbb{E}[r^{1Y}]$ + Expected inflation	Pooled	0.115^{**} (0.045) | -0.129 (0.128)	928
$\mathbb{E}[r^{1Y}]$ + Expected GDP growth	Pooled	0.087 (0.053) | 0.531^{*} (0.306)	904

Notes: Dependent variable: one-quarter-forward active rebalancing. Panel B reports the class-expectation coefficient followed by the macro coefficient. Weighted by starting position; SEs clustered at the respondent level. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

Table A9: Belief–rebalancing, fixed income and alternatives

Panel A: Fixed income						
Dependent variable	1Q forward			1Y forward		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}[r^{1Y}]$	0.019					
	(0.352)					
α^{1Y}		-0.012	0.007			
		(0.239)	(0.294)			
$\mathbb{E}[r^{10Y}]$				-1.499		
				(0.962)		
α^{10Y}					-1.008	-0.144
					(0.790)	(0.723)
Asset class FE	Y	Y	Y	Y	Y	Y
Wave FE	Y	Y		Y	Y	
Respondent FE			Y			Y
Observations	244	231	189	247	226	181
R-squared	0.07	0.07	0.34	0.07	0.06	0.59
Panel B: Alternatives						
$\mathbb{E}[r^{1Y}]$	0.022					
	(0.032)					
α^{1Y}		0.040	0.045			
		(0.030)	(0.044)			
$\mathbb{E}[r^{10Y}]$				0.182		
				(0.657)		
α^{10Y}					0.542	1.055
					(0.396)	(0.643)
Asset class FE	Y	Y	Y	Y	Y	Y
Wave FE	Y	Y		Y	Y	
Respondent FE			Y			Y
Observations	430	390	377	497	418	408
R-squared	0.06	0.06	0.29	0.17	0.19	0.50

Notes: Weighted by starting position, SEs (in parentheses) clustered at the respondent level. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$. Trading outcomes use the four linkable waves (May 2022, January 2023, July 2023, and October 2024).

A8 Tabulations of results referenced in the text

Table A11 collects point estimates that are quoted in the main text without a table of their own: the required-return trading regressions (Panel A), the horse races between short- and long-horizon beliefs (Panel B), the subperiod slopes of expectations on required returns (Panel C), the platform-wide versus firm-own return comparison (Panel D), the stated-plans subperiod split (Panel E), and the leave-one-out check on the long-run trading leg (Panel F).

Table A11: Tabulations of results referenced in the text

	(1)	(2)
Panel A: required return and trading (equity; 1Q forward, 1Y forward)		
$\mathbb{R}[r^{1Y}]$ alone	0.033 (0.149)	−0.139 (0.250)
α^{1Y}, controlling for $\mathbb{R}[r^{1Y}]$	0.202*** (0.059)	
$\mathbb{R}[r^{1Y}]$, same regression	0.253* (0.145)	
α^{10Y}, controlling for $\mathbb{R}[r^{1Y}]$		0.535** (0.236)
$\mathbb{R}[r^{1Y}]$, same regression		0.412 (0.318)
Panel B: horse races (equity; 1Q forward, 1Y forward)		
$\mathbb{E}[r^{1Y}]$, jointly with $\mathbb{E}[r^{10Y}]$	0.168*** (0.060)	0.071 (0.126)
$\mathbb{E}[r^{10Y}]$, same regressions	0.079 (0.129)	0.500* (0.254)
α^{1Y}, jointly with α^{10Y}	0.151*** (0.057)	0.036 (0.131)
α^{10Y}, same regressions	−0.014 (0.102)	0.336 (0.207)
Panel C: $\mathbb{E}$-on-$\mathbb{R}$ slopes by subperiod (waves 1–3, waves 4–6)		
$\mathbb{E}[r^{1Y}]$	0.24*** (0.07)	0.75*** (0.07)
$\mathbb{E}[r^{10Y}]$	0.80*** (0.05)	0.82*** (0.07)
Panel D: α^{1Y} on last-quarter returns (alone, joint)		
Platform-wide class return	0.234*** (0.082)	0.173 (0.129)
Firm's own class return	0.174*** (0.065)	0.061 (0.088)
Panel E: stated plans, Increase−Decrease (waves 1–3, waves 4–6)		
$\mathbb{R}[r^{1Y}]$	−0.002 (0.011)	0.063*** (0.014)
α^{1Y}	0.035*** (0.006)	0.072*** (0.009)
Panel F: $\alpha^{10Y} \rightarrow$1Y-forward rebalancing, leave-one-out (baseline, worst case)		
Coefficient	0.351* (0.200)	0.246 (0.193)
p-value	0.08	0.21

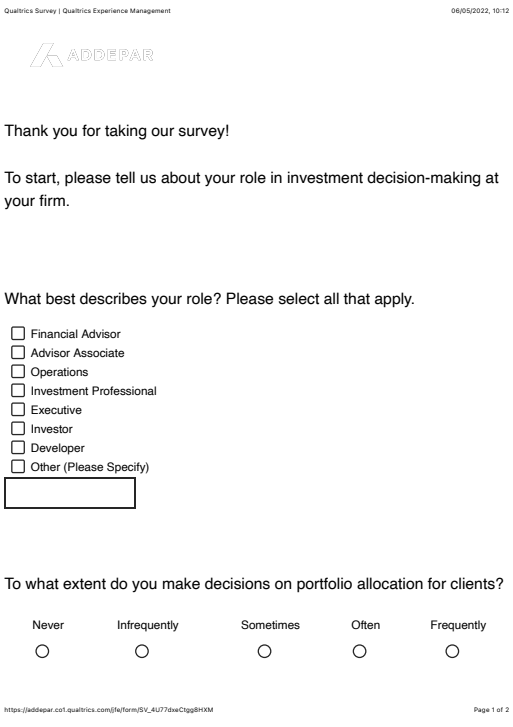
Notes: Tabulations of results quoted in the text without a table of their own. Panels A, B, and F: equity group, class + wave FE, weighted by starting position, four linkable waves; columns are 1Q-forward and 1Y-forward active rebalancing (Panel F columns are the baseline and the leave-one-out worst case). Panel C: slope of the row expectation on $\mathbb{R}[r^{1Y}]$ with respondent×wave FE, unweighted, by subperiod. Panel D: last-quarter platform-wide vs. firm-own class return, respondent FE, four linkable waves; column (2) enters both jointly. Panel E: the specification of column (2) of Table 6, by subperiod. SEs in parentheses, clustered at the respondent level. $^{*}p < .10$, $^{**}p < .05$, $^{***}p < .01$.

A9 Survey instrument

This appendix reproduces the survey instrument. The first set of pages shows the May 2022 export of the original instrument, used with minor variations in the first three waves. Three differences between this export and the fielded surveys deserve note. The recession

question shown here, which asks for the maximum drawdown expected in a recession, was fielded as a question about the market movement expected in a severe recession on a scale from −100 to 100, the phrasing shown in the redesigned instrument below. The question asking whether other advisors or specialist managers also make investment decisions for the respondent's clients was removed before fielding. And from the third wave the survey added a direct question about the respondent's subjective risk-free rate. The second set of pages shows the redesigned instrument introduced in February 2024 and used in the fourth through sixth waves. The redesign updated the visual format, expanded the asset class menu as described in Section 2.1, added an explicit "don't know" option to the planned-allocation question, and added questions about the future path of the federal funds rate.

Original instrument (waves 1–3)



Qualtrics Survey | Qualtrics Experience Management 06/05/2022, 10:12

ADDEPAR

Thank you for taking our survey!

To start, please tell us about your role in investment decision-making at your firm.

What best describes your role? Please select all that apply.

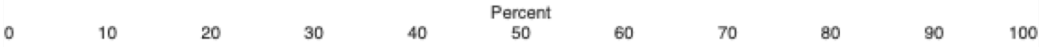
- ☐ Financial Advisor
- ☐ Advisor Associate
- ☐ Operations
- ☐ Investment Professional
- ☐ Executive
- ☐ Investor
- ☐ Developer
- ☐ Other (Please Specify)

To what extent do you make decisions on portfolio allocation for clients?

Never	Infrequently	Sometimes	Often	Frequently
○	○	○	○	○

https://addepar.co1.qualtrics.com/jfe/form/SV_4U77dxeCtggBHXM Page 1 of 2

What portion of portfolio allocation decisions are driven by your advice?



Please move the slider to indicate your choice

ADDEPAR

Now, we'd like to understand the current and future asset classes in which you invest.

In which of the following asset classes are you actively investing?

- ☐ US Treasuries and Agency Debt
- ☐ US Corporate Bonds (e.g., Barclays AGG)
- ☐ US Equities (e.g., S&P 500)
- ☐ International Equities (e.g. MSCI World, non-US equities)
- ☐ Hedge Funds Equity Strategies
- ☐ Hedge Funds Multi-Strategy
- ☐ Private Equity Buyout
- ☐ Private Equity Venture
- ☐ Real Estate Funds

Do you plan to change your allocation to the following assets over the next year? If so, how?

	Increase	Decrease	No Change
US Treasuries and Agency Debt	○	○	○
US Corporate Bonds (e.g., Barclays AGG)	○	○	○
US Equities (e.g., S&P 500)	○	○	○

ADDEPAR

In this next section, we'd like to ask you specific questions about the asset classes in which you are involved. In paired questions, please note that the scale is the same for both. . . .

Powered by Qualtrics

ADDEPAR

For invested assets of **US Treasuries and Agency Debt,** please enter the expected total return (nominal capital appreciation plus payouts) over the next year, and average return over the next ten years (annualized).

Percent Total Return

-5 -4 -2 -1 1 3 4 6 7 9 10

1 Year Return

10 Year Return

For **US Treasuries and Agency Debt**, what is the minimum rate of return you would require to make an investment for one year / 10 years?

Percent Total Return

-5 -4 -2 -1 1 3 4 6 7 9 10

1 Year Return ☐ I don't know

ADDEPAR

In this section, we would like to know what you anticipate in terms of GDP growth and inflation.

What do you expect the average annual growth rate of US nominal GDP to be over the next year / 10 years?

Percent

-5 -4 -2 -1 1 3 4 6 7 9 10

1 Year ☐ I don't know

10 Years ☐ I don't know

What do you expect the annual US inflation rate (e.g., CPI) to be over the next year / 10 years?

-5 -4 -2 -1 1 3 4 6 7 9 10

1 Year ☐ I don't know

ADDEPAR

What is the probability of a recession in the next year? (An answer of 0% means that it cannot happen; an answer of 100% means it is sure to happen.)

Percent

0 10 20 30 40 50 60 70 80 90 100

Probability

What is the maximum drawdown (e.g., decline) you expect in a recession, in the following asset classes? An answer of 0% means no loss; an answer of 100% means complete loss.

Percent

0 10 20 30 40 50 60 70 80 90 100

US Treasuries and Agency Debt ☐ I don't know

US Corporate Bonds (e.g. Barclays AGG) ☐ I don't know

ADDEPAR

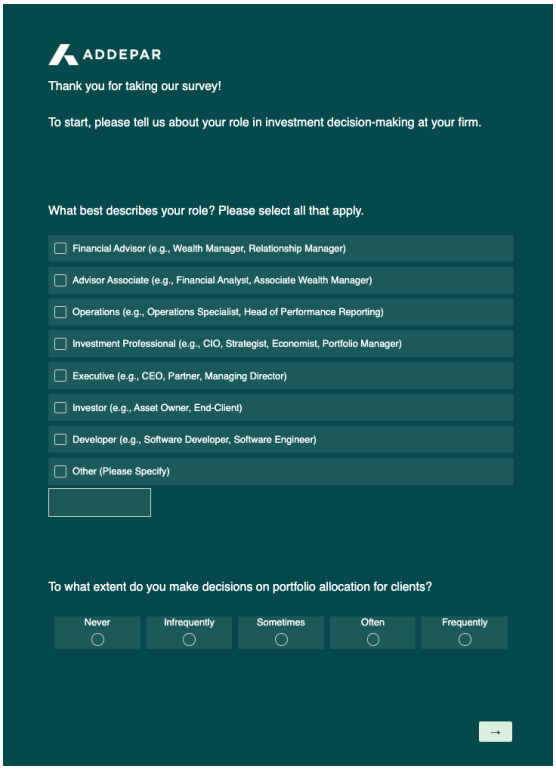
Two final questions before you go!

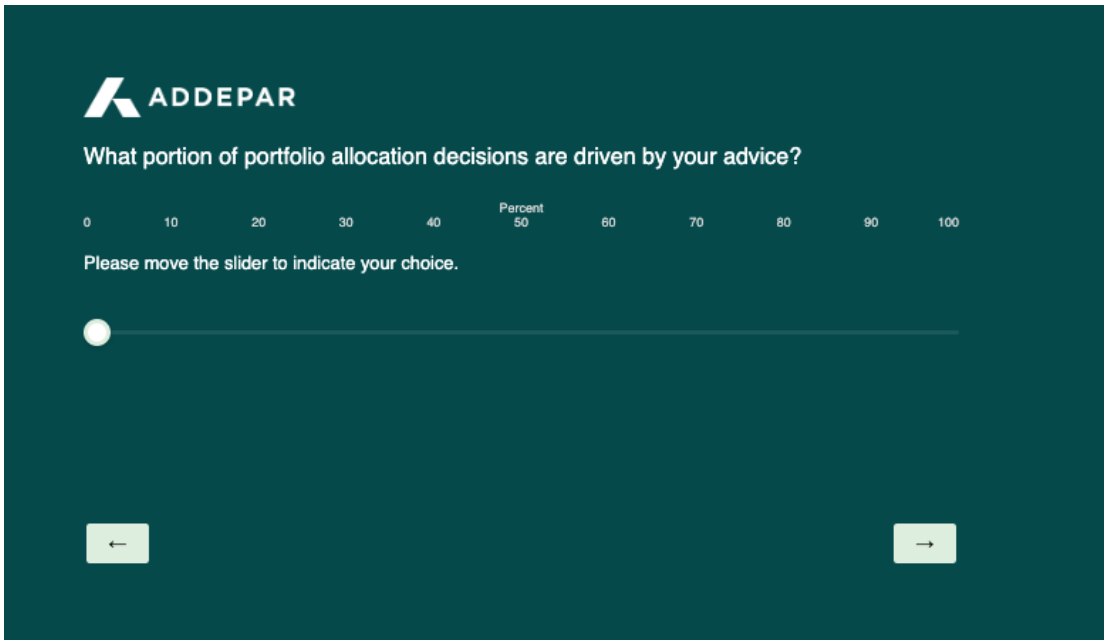
What are your current sources of CMA information?

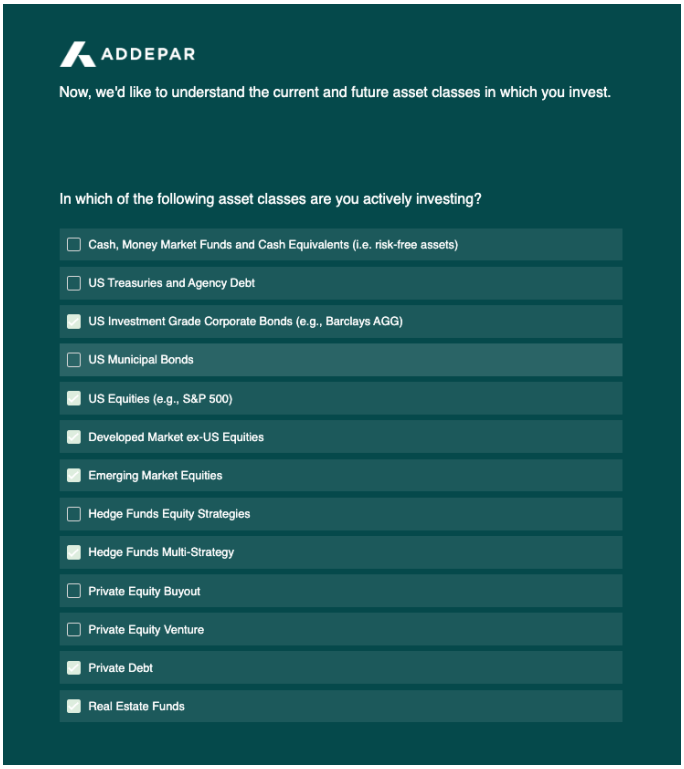
Do you have any other feedback for Addepar / Addepar Research?

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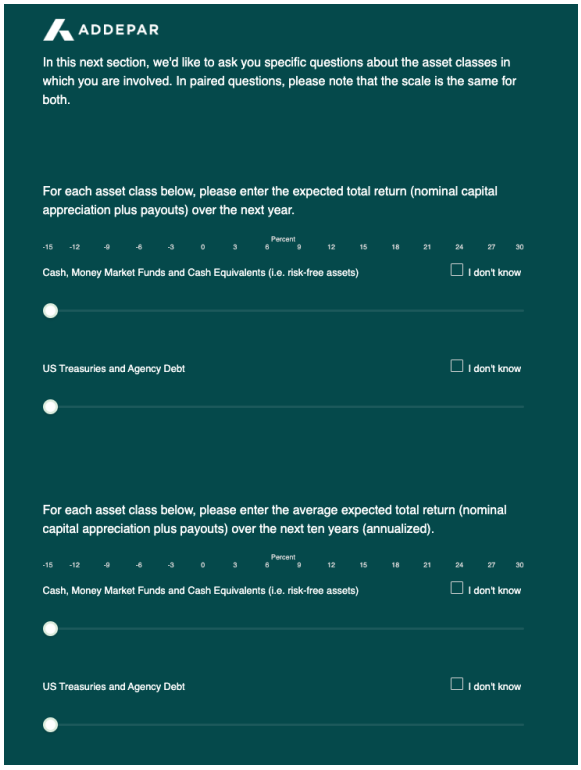
Redesigned instrument (waves 4–6)

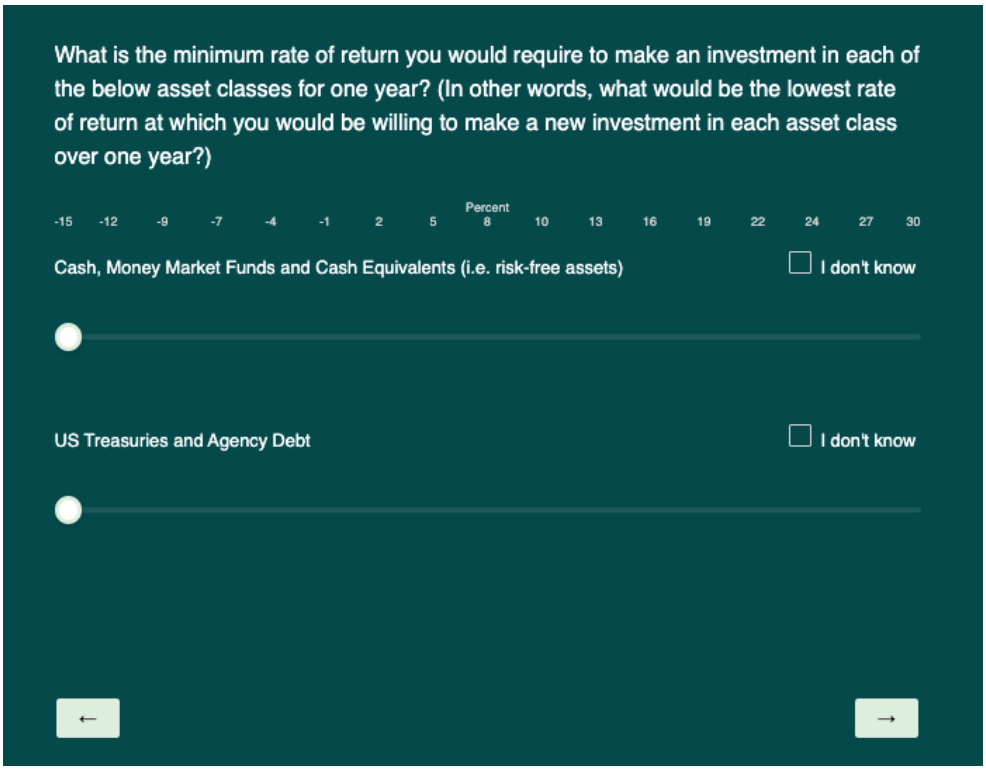


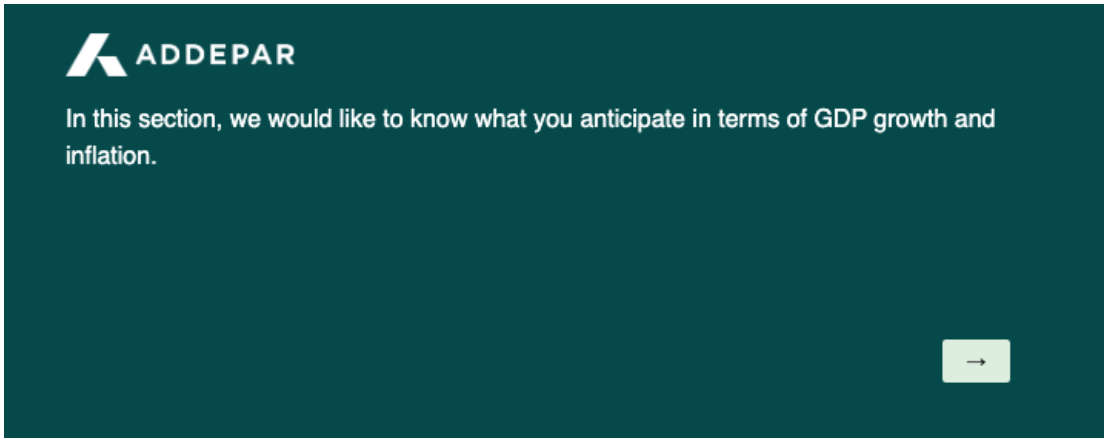

ADDEPAR
What portion of portfolio allocation decisions are driven by your advice?
Percent
0 10 20 30 40 50 60 70 80 90 100
Please move the slider to indicate your choice.
←
→

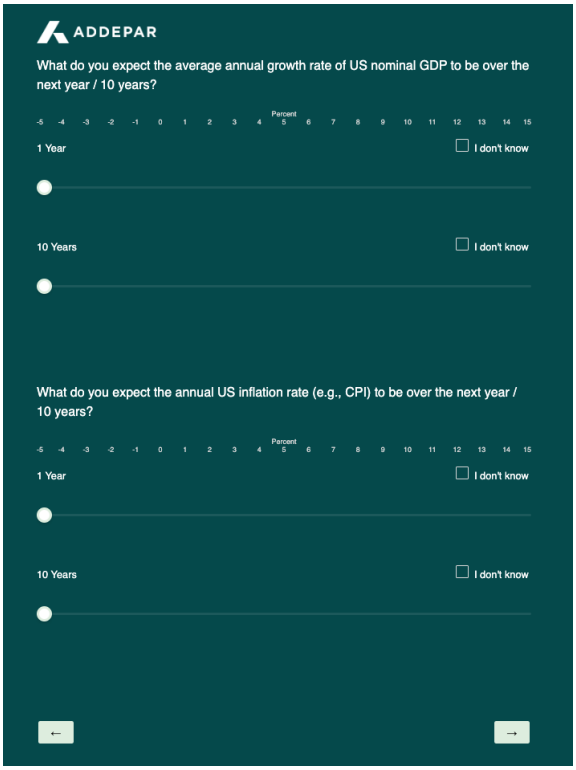

ADDEPAR
Now, we'd like to understand the current and future asset classes in which you invest.
In which of the following asset classes are you actively investing?
Cash, Money Market Funds and Cash Equivalents (i.e. risk-free assets)
US Treasuries and Agency Debt
US Investment Grade Corporate Bonds (e.g., Barclays AGG)
US Municipal Bonds
US Equities (e.g., S&P 500)
Developed Market ex-US Equities
Emerging Market Equities
Hedge Funds Equity Strategies
Hedge Funds Multi-Strategy
Private Equity Buyout
Private Equity Venture
Private Debt
Real Estate Funds

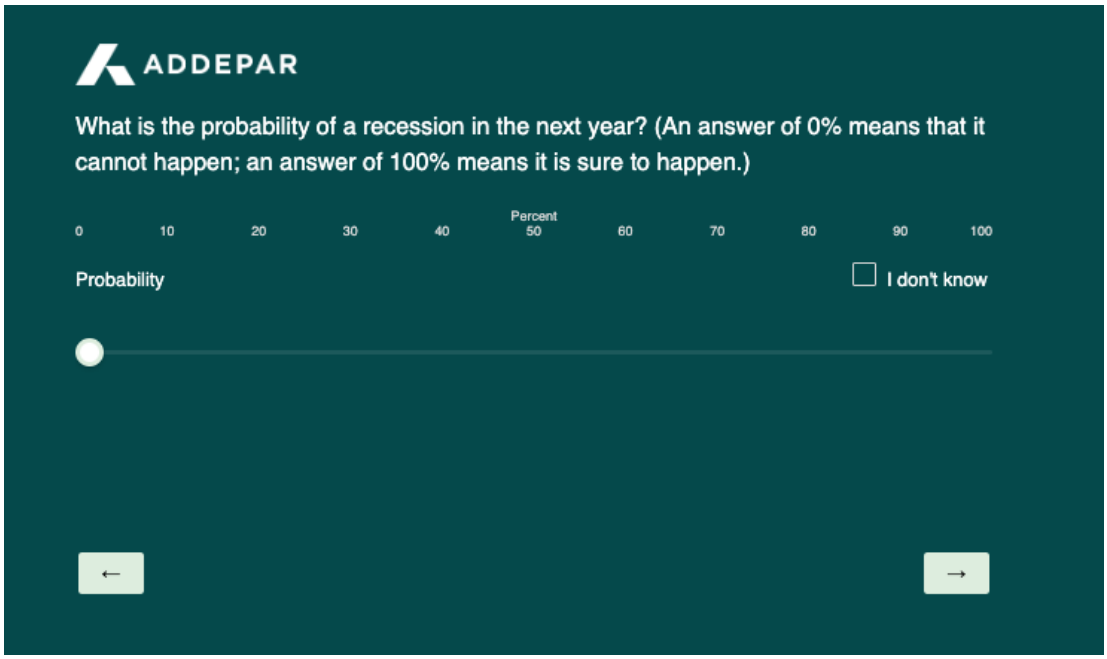

Do you plan to change your allocation to the following assets over the next year? If so, how?
Increase
Decrease
No Change
I Don't Know
Cash, Money Market Funds and Cash Equivalents (i.e. risk-free assets)
US Treasuries and Agency Debt
US Investment Grade Corporate Bonds (e.g., Barclays AGG)
US Municipal Bonds
US Equities (e.g., S&P 500)
Developed Market ex-US Equities
Emerging Market Equities
Hedge Funds Equity Strategies
Hedge Funds Multi-Strategy
Private Equity Buyout
Private Equity Venture
Private Debt
Real Estate Funds

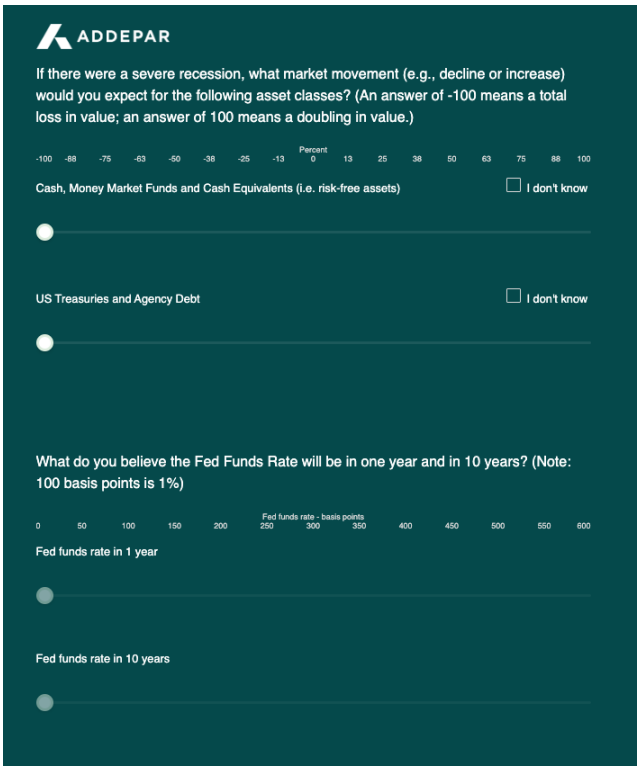

ADDEPAR
In this next section, we'd like to ask you specific questions about the asset classes in which you are involved. In paired questions, please note that the scale is the same for both.
For each asset class below, please enter the expected total return (nominal capital appreciation plus payouts) over the next year.
Percent
-15 -12 -9 -6 -3 0 3 6 9 12 15 18 21 24 27 30
Cash, Money Market Funds and Cash Equivalents (i.e. risk-free assets)
I don't know
US Treasuries and Agency Debt
I don't know
For each asset class below, please enter the average expected total return (nominal capital appreciation plus payouts) over the next ten years (annualized).
Percent
-15 -12 -9 -6 -3 0 3 6 9 12 15 18 21 24 27 30
Cash, Money Market Funds and Cash Equivalents (i.e. risk-free assets)
I don't know
US Treasuries and Agency Debt
I don't know

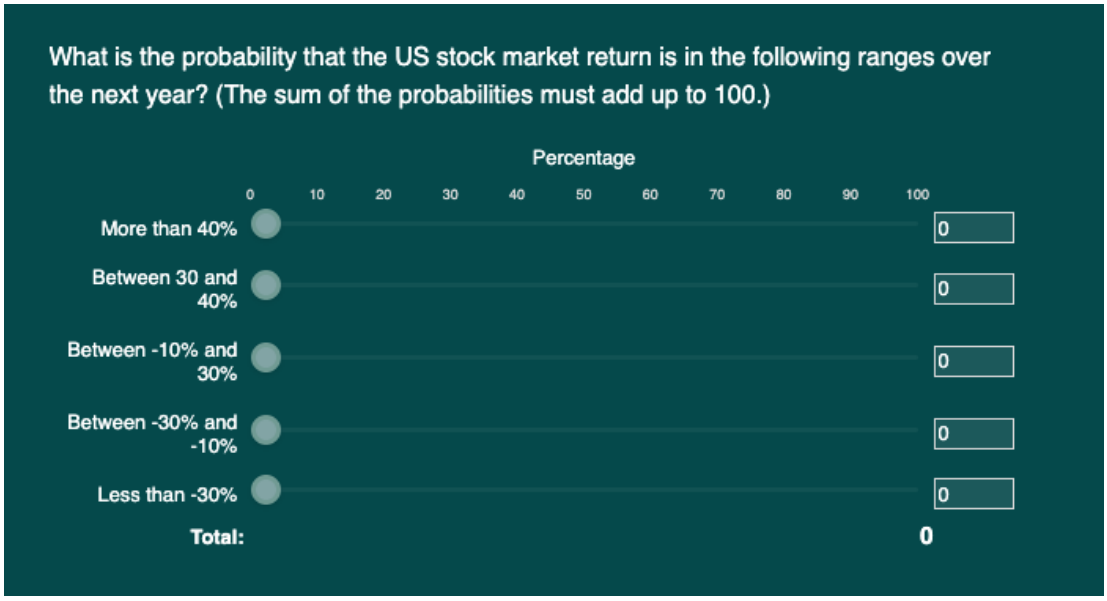

What is the minimum rate of return you would require to make an investment in each of the below asset classes for one year? (In other words, what would be the lowest rate of return at which you would be willing to make a new investment in each asset class over one year?)
Percent
-15 -12 -9 -7 -4 -1 2 5 8 10 13 16 19 22 24 27 30
Cash, Money Market Funds and Cash Equivalents (i.e. risk-free assets)
I don't know
US Treasuries and Agency Debt
I don't know
←
→


ADDEPAR
In this section, we would like to know what you anticipate in terms of GDP growth and inflation.
→


ADDEPAR
What do you expect the average annual growth rate of US nominal GDP to be over the next year / 10 years?
Percent
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
1 Year
I don't know
10 Years
I don't know
What do you expect the annual US inflation rate (e.g., CPI) to be over the next year / 10 years?
Percent
-5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
1 Year
I don't know
10 Years
I don't know
←
→


ADDEPAR
What is the probability of a recession in the next year? (An answer of 0% means that it cannot happen; an answer of 100% means it is sure to happen.)
Percent
0 10 20 30 40 50 60 70 80 90 100
Probability
I don't know
←
→


ADDEPAR
If there were a severe recession, what market movement (e.g., decline or increase) would you expect for the following asset classes? (An answer of -100 means a total loss in value; an answer of 100 means a doubling in value.)
Percent
-100 -88 -75 -63 -50 -38 -25 -13 0 13 25 38 50 63 75 88 100
Cash, Money Market Funds and Cash Equivalents (i.e. risk-free assets)
I don't know
US Treasuries and Agency Debt
I don't know
What do you believe the Fed Funds Rate will be in one year and in 10 years? (Note: 100 basis points is 1%)
Fed funds rate - basis points
0 50 100 150 200 250 300 350 400 450 500 550 600
Fed funds rate in 1 year
Fed funds rate in 10 years


What is the probability that the US stock market return is in the following ranges over the next year? (The sum of the probabilities must add up to 100.)
Percentage
0 10 20 30 40 50 60 70 80 90 100
More than 40%
0
Between 30 and 40%
0
Between -10% and 30%
0
Between -30% and -10%
0
Less than -30%
0
Total:
0