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Spencer Couts,
University of Southern California

Andrei S. Goncalves,
The Ohio State University

Yicheng Liu,
The Ohio State University

Johnathan Loudis,
University of Notre Dame

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Institutional Investors' Subjective Risk Premia: Time Variation and Disagreement

Spencer Couts* Andrei S. Gonçalves† Yicheng Liu‡ Johnathan Loudis§

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Abstract

We study the role of institutional investors' subjective risk premia in explaining variation in their subjective expected returns (both over time and across investors). Our analysis uses long-term Capital Market Assumptions from asset managers and investment consultants from 1987 to 2022. Perceived market risk premia account for most of the countercyclicality and overall time variation in subjective expected returns, with the remainder driven by alphas (perceived mispricing). The risk premia effect stems almost entirely from time variation in perceived risk quantities rather than risk price (risk aversion). Additionally, market risk premia explain most of the expected return disagreement, but here alphas play a significant role, and risk price and risk quantities contribute roughly equally to the risk premia effect. These results provide benchmark moments that asset pricing models should match to be consistent with institutional investors' beliefs.

JEL Classification: G10, G11, G12, G23, G40

Keywords: Institutional Investors, Subjective Beliefs, Subjective Risk Premia

*Price School of Public Policy, University of Southern California. E-mail: couts@usc.edu.

†Fisher College of Business, The Ohio State University. E-mail: goncalves.11@osu.edu.

‡Fisher College of Business, The Ohio State University. E-mail: liu.9716@buckeyemail.osu.edu.

§Mendoza College of Business, University of Notre Dame. E-mail: jloudis@nd.edu.

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Introduction

Understanding the sources of variation in expected returns is central to asset pricing. Risk-based theories link this variation to changes in risk premia, reflecting both the price of risk (risk aversion) and the quantity of risk (variances and covariances).[1] In contrast, behavioral theories emphasize mispricing. Accordingly, the asset pricing literature has centered on identifying the economic forces that drive expected return variation (see Cochrane (2011)).

Previous research studies the drivers of variation in *objective expected returns* using realized returns or their econometric forecasts. Analogous to Delao and Myers (2021), we instead quantify the sources of variation in *investors' subjective expected returns*. Additionally, we focus on institutional investors, departing from the emphasis on individual investors in the subjective beliefs literature (Adam and Nagel (2023)). From the few papers on institutional investors' beliefs, we know their expected returns are countercyclical, heterogeneous, and linked to portfolio allocations (Dahlquist and Ibert (2024, 2025)). We also know they display a positive risk-return tradeoff and forecast future returns (Couts, Gonçalves, and Loudis (2024)). However, it remains unknown how much of the variation in institutional investors' expected returns reflects perceived mispricing versus subjective risk quantity and risk price.

In this paper, we fill this gap in the literature by quantifying the importance of subjective mispricing and risk premia (through both risk price and risk quantity) in explaining subjective expected return variation over time and across institutions (i.e., disagreement). We do so using the long-term Capital Market Assumptions (CMAs) of major asset managers and investment consultants from 1987 to 2022, covering their expectations about future returns, volatilities, and correlations for the primary asset classes held by institutional investors.

We find that market risk premia explain the vast majority of the time variation in expected returns, including their countercyclicality. The rest is explained by alphas (perceived mispricing). Additionally, the risk premia effect is driven almost entirely by time variation in

[1] For instance, Fama (2016) states that "My view is that risk aversion moves dramatically through time. In particular, it's very high during bad periods and it's lower during good periods, and that affects the pricing of assets and then [their] expected returns...".

risk quantities (subjective covariances with the wealth portfolio) rather than risk price (risk aversion). For disagreement, risk premia again explain most of the variation, but here alphas play a quantitatively important role. Also, in this case, risk price and risk quantity contribute about equally to the risk premia effect. Overall, time variation in expected returns primarily reflects shifts in perceived risk. In contrast, disagreement across institutions is shaped by both differences in perceived risk and heterogeneity in risk aversion and mispricing views.

Unpacking our Analysis

Our empirical strategy is based on the following decomposition for expected excess returns:

$$\mathbb{E}[r] = \text{Alpha} + \underbrace{\text{Risk Price} \times \text{Risk Quantity}}_{\text{Risk Premium}} \tag{1}$$

which is economically motivated by the Capital Asset Pricing Model (CAPM), but works as an identity in our empirical analysis since we do not impose zero alphas.

We proxy for the wealth portfolio weights using the aggregate allocations of US public pension funds. Then, for each CMA, we extract long-term beliefs: expected returns, volatilities, and correlations for cash and nine major asset classes. Combining these beliefs with the wealth portfolio weights, we compute $\mathbb{E}[r]$ and Risk Quantity (covariance with the wealth portfolio) for each asset class. In turn, we estimate Risk Price as the slope coefficient from projecting $\mathbb{E}[r]$ onto Risk Quantity across asset classes and calculate the corresponding Alphas. This process produces all components of Equation 1 for each CMA, allowing us to analyze their relative contributions to the time variation and disagreement in expected returns.

We start from the countercyclicality of institutional investors' expected returns, which arises from the relation between expected returns and yields (first documented for equities by Dahlquist and Ibert (2024)). We show that the link between expected returns and yields extends to US and Ex US fixed income asset classes as well as to private equity and real estate. Then, we demonstrate that this relation is driven by a positive link between risk premia and yields, mainly through the risk quantity channel. In contrast, alphas tend to be weakly linked to yields (even negatively for some asset classes). These results show that, from the perspective of the institutions in our sample, high yields indicate high risk premia rather than undervaluation (which would translate into high alphas in the long-run). Importantly, we also show that, in the context of US equities, 83.1% of the time variation in our alphas is explained by an external measure of perceived undervaluation (based on surveys of global fund managers). This finding suggests subjective mispricing is likely the primary driver of our alphas because this undervaluation measure is not based on any particular risk model. That said, our alphas may also reflect risk premia from non-market risk factors.

Next, we explore the total time variation in expected returns through a variance decomposition applied to Equation 1 with expected return components varying over time. As Figure 1(a) shows, we find that risk premia time variation explains almost 90% of the expected return time variation in the wealth portfolio and almost 70% when we consider all asset classes jointly. Moreover, risk quantity explains 100% of the risk premia effect for the wealth portfolio and around 90% of the risk premia effect when we consider all asset classes jointly. While these results suggest expected return time variation is mainly driven by risk premia due to shifts in perceived risk quantity, they do not imply time variation in risk aversion is irrelevant. For instance, when considering short-lived expected return movements (through annual differences in expected returns), we find that risk premia continue to drive most of the variation in expected returns. However, in this case, risk quantity and risk price are roughly equally responsible for the risk premia effect.

Finally, we also explore expected return disagreement through a variance decomposition applied to Equation 1, but in this case considering variation in expected return components across institutions rather than over time. As Figure 1(b) shows, while risk premia also drive most of the expected return disagreement (76% for the wealth portfolio and 57% for all asset classes jointly), alphas play a quantitatively important role in this case. Moreover, risk price and risk quantity are equally responsible for the risk premia effect: risk quantity explains 49% of the risk premia effect for the wealth portfolio and 58% of the risk premia effect when we consider all asset classes jointly. In addition, the importance of alphas and risk aversion increases when we consider short-lived disagreement across institutions.

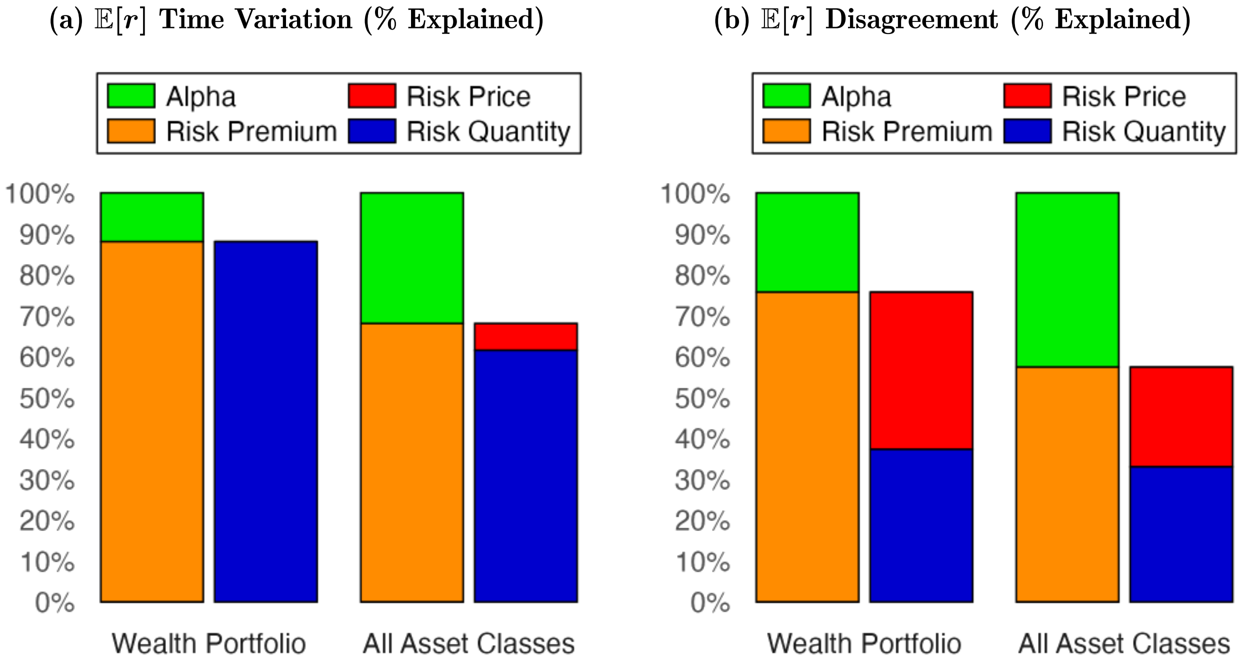

Figure 1

Decomposing Expected Return Time Variation and Disagreement

This figure shows the results from our expected excess return decomposition. Both panels provide results for the wealth portfolio as well as for all nine asset classes jointly (see Table 2 for the asset classes). Panel (a) focuses on decomposing expected return variation over time, with details provided in Section 4. Panel (b) focuses on decomposing expected return variation across institutions (i.e., disagreement), with details provided in Section 5. The first and third bars of each panel decompose expected return variation while the second and fourth bars of each panel decompose the risk premia effect on expected return variation.

Overall, our results indicate subjective risk premia (especially through perceived risk quantity) play a major role in explaining variation in institutional investors' expected returns (both time variation and disagreement). We explore several modifications to our baseline empirical procedure, including alternative methods to estimate risk aversion (e.g., risk aversion implied from CAPM restrictions), different subsets of CMAs (e.g., only asset managers), alternative ways to construct beliefs (e.g., using the US Equity asset class as the wealth portfolio), and alternative variance decomposition procedures (e.g., controlling for heterogeneity in forecasting horizons). While the specific quantitative results from these tests differ somewhat across specifications, our core findings are overall consistent regardless of the specification used.

Contribution to the Literature

Our paper primarily contributes to the subjective beliefs literature in asset pricing.[2] Adam and Nagel (2023) summarize this literature and highlight two key issues for subsequent research: (i) to explore the link between subjective expectations of risk and return and (ii) to explore the beliefs of agents not typically covered in the literature. For instance, Adam and Nagel (2023) state that "We need more work exploring how investors...risk perceptions are linked to the subjective risk premia that they demand to hold risky assets" and also ask "...do investor groups that are excluded from individual investor surveys have systematically different expectations?"

Our work makes progress on both of these dimensions. We tackle issue (i) by directly studying the link between subjective expected returns and subjective risk premia. We add to the literature by separately identifying the effect of subjective risk quantity and subjective risk price.[3] We also focus on how expected return disagreement and time variation (including its countercyclicality) is linked to risk premia instead of emphasizing the risk-return tradeoff as in Jensen (2024) and Couts, Gonçalves, and Loudis (2024). This latter aspect allows us to connect directly to the part of the literature that studies time variation in subjective beliefs

[2]Some recent (including contemporaneous) papers are Cieslak (2018), Wu (2018), Adam, Matveev, and Nagel (2021), Delao and Myers (2021), Giglio et al. (2021), Nagel and Xu (2021, 2023), Wang (2021), Andonov and Rauh (2022), Lochstoer and Muir (2022), Beutel and Weber (2023), Gnan and Schleritzko (2023), Boons, Ottonello, and Valkanov (2023), Gandhi, Gormsen, and Lazarus (2023), Bastianello (2024), Bastianello and Peng (2024), Bordalo et al. (2024), Dahlquist, Ibert, and Wilke (2024), Dahlquist and Ibert (2024, 2025), Décaire and Graham (2024), Décaire and Guenzel (2024), Décaire, Sosyura, and Wittry (2024), Delao, Han, and Myers (2024), Delao and Myers (2024), Egan, MacKay, and Yang (2024), Fukui, Gormsen, and Huber (2024), Gormsen and Huber (2024a,b), Gormsen, Huber, and Oh (2024), Jensen (2024), Jo, Lin, and You (2024), Kremens, Martin, and Varela (2024), Loudis (2024), Bastianello, Décaire, and Guenzel (2025), Bastianello and Peng (2025), Begenau, Liang, and Siriwardane (2025), Cui, Delao, and Myers (2025), and Ghosh, Korteweg, and Xu (2025).

[3]To be precise, what we mean by risk price is the loading of the Stochastic Discount Factor onto the risk factor of interest. This is different from the "β price of risk" studied in Couts, Gonçalves, and Loudis (2024), which reflects the risk premium on the risk factor of interest. For instance, in the CAPM, the risk price is the aggregate risk aversion of investors whereas the "β price of risk" is the market risk premium (the expected excess return on the wealth portfolio). Since the market risk premium is given by risk aversion multiplied by market variance, it contains both a risk price and a risk quantity. This aspect is important because different macro-finance models (reviewed by Cochrane (2017)) have different implications for what drives the market risk premium (risk price or risk quantity) and the "β price of risk" alone cannot shed light on this matter.

(e.g., Greenwood and Shleifer (2014), Adam, Marcet, and Beutel (2017), Wang (2021), Delao and Myers (2021, 2024), Nagel and Xu (2023), and Dahlquist and Ibert (2024, 2025)).

In terms of issue (ii), we study the beliefs of asset managers and investment consultants, which have received little attention in the prior literature. In this sense, the three closest papers to ours are Couts, Gonçalves, and Loudis (2024) and Dahlquist and Ibert (2024, 2025). As discussed above, our contribution relative to Couts, Gonçalves, and Loudis (2024) is the focus on risk premia countercyclicality, time variation, and disagreement, and the separation of the effects of risk price and risk quantity. Dahlquist and Ibert (2024) study time variation in expected equity returns and the pass through of beliefs to portfolio allocations (which relates to disagreement). Dahlquist and Ibert (2025) also study expected return time variation and disagreement, but for multiple asset classes and multiple financial professionals (including the type of asset managers and investment consultants we study). In particular, they show that subjective expected returns move one-to-one with measures of objective expected returns and also highlight the importance of mean-reversion in valuation ratios as a driver of disagreement. Our work is complementary to theirs as we focus on quantifying the importance of risk premia components in explaining expected return time variation and disagreement. The key ingredient to explore risk premia components is our use of the subjective covariance matrices of institutional investors, which they do not explore.

The rest of this paper is organized as follows. Section 1 discusses the framework and CMAs dataset used for decomposing subjective expected returns into alpha and risk premia components. Section 2 explains how we estimate risk aversion and summarizes the expected return components we extract from the CMAs. Section 3 highlights the importance of risk premia (through risk quantity) for expected return countercyclicality. In turn, Sections 4 and 5 formally decompose expected return variation over time and across institutions into the effects of alpha, risk price, and risk quantity. Section 6 concludes by summarizing our findings and their broader implications. The Internet Appendix provides details about the data we use and presents results that supplement the findings in the main text.

1 Decomposing Subjective Expected Returns: Setup & Beliefs Data

Our analysis focuses on the sources of variation in institutional investors' subjective expected returns (both over time and across institutions). In particular, we quantify the fraction of expected return variation attributed to variation in alphas and risk premia. Moreover, we also measure the relative importance of risk quantity and risk price in driving the risk premia effect on expected return variation. Subsection 1.1 explains the baseline framework for our expected return decomposition. Then, Subsection 1.2 describes the beliefs data we use to implement the decomposition and Subsection 1.3 explains how we aggregate belief elements across institutions for the time variation part of our analysis. Finally, Subsection 1.4 illustrates the degree of expected return time variation and disagreement present in the subjective beliefs data.

Throughout this paper, t indexes time (i.e., year), n indexes asset (i.e., asset class), and j indexes investor (i.e., institution). Moreover, R_{cash} reflects the gross nominal return on a cash-like asset and R reflects the vector of gross nominal returns on the other assets in our analysis. So, $r = R - R_{cash}$ is the vector of returns in excess of cash returns. Also, we suppress time indexes inside moments to simplify notation when convenient (e.g., $\mathbb{E}_{j,t}[r_n] \equiv \mathbb{E}_{j,t}[r_{n,t+h_j}]$).

1.1 The Expected Return Decomposition Framework

Letting r_w reflect the excess return on the wealth portfolio, we use the following decomposition for investor j's subjective expected excess return on asset n at time t:

$$\underbrace{\mu_{j,n,t}}_{\text{Expected Excess Return}} = \underbrace{\alpha_{j,n,t}}_{\text{Alpha}} + \underbrace{\lambda_{j,n,t}}_{\text{Risk Premium}} \tag{2}$$

with

$$\underbrace{\lambda_{j,n,t}}_{\text{Risk Premium}} = \underbrace{\gamma_{j,t}}_{\text{Risk Price (Risk Aversion)}} \cdot \underbrace{\nu_{j,n,t}}_{\text{Risk Quantity (Covariance)}} \tag{3}$$

where $\mu_{j,n,t} = \mathbb{E}_{j,t}[r_n]$, $\nu_{j,n,t} = \mathbb{C}ov_{j,t}[r_n, r_w]$, and $\alpha_{j,n,t} = \mu_{j,n,t} - \gamma_{j,t} \cdot \nu_{j,n,t}$.

In words, $\mu = \alpha + \lambda$ is the expected excess return, which has a subjective mispricing or alpha component (α) and a subjective risk premium component (λ). Moreover, $\lambda = \gamma \cdot \nu$ depends on the investor's risk aversion (γ) and the exposure of the asset to the wealth portfolio as perceived by the investor (ν). So, γ captures "risk price," whereas ν captures "risk quantity" from the perspective of the investor.

In our empirical analysis, we use Equation 2 to decompose μ variation over time and across investors into the effect of alphas (α) and risk premia (λ). We then use Equation 3 to understand the role of risk prices (γ) and risk quantities (ν) in the risk premia effect.[4] To simplify exposition, hereafter we refer to μ as reflecting expected returns whenever convenient (i.e., we omit the term "excess").

Note that Equations 2 and 3 (and thus our μ decomposition) hold as identities since we do not impose restrictions on α. Under the Capital Asset Pricing Model (CAPM), we would have $\alpha = 0$ (if beliefs and wealth portfolio weights were perfectly measured). However, we allow for subjective mispricing and risk premia from non-market risk factors (as well as data measurement issues) by allowing for $\alpha \neq 0$. This flexibility is needed since Couts, Gonçalves, and Loudis (2024) formally reject the CAPM as a full description of the subjective beliefs we study (despite confirming the positive CAPM risk-return tradeoff).

The fact that α reflects both subjective mispricing and subjective risk premia from non-market risk factors implies that the fraction of μ variation attributed to α is an upper bound on the fraction of μ variation due to subjective mispricing. Fortunately, this aspect does not limit the qualitative interpretation of our results since we find that most of the μ variation

[4] Couts, Gonçalves, and Loudis (2024) explore Equation 2 using the same beliefs dataset we rely on. However, they focus on the risk-return tradeoff across asset classes rather than the dynamics of investors' return expectations (time variation and disagreement), offering only limited results on the latter. Even more importantly, they do not identify the role of risk prices and risk quantities in the risk premia effect (i.e., they do not study Equation 3), which is a major focus of our analysis. Specifically, they measure $\lambda_{j,n,t}$ but do not separately identify $\gamma_{j,t}$ and $\nu_{j,n,t}$. The reason is that variation in $\lambda_{j,n,t}$ across asset classes is entirely driven by $\nu_{j,n,t}$ (since $\gamma_{j,t}$ does not vary across assets), and thus there is no benefit in separately identifying $\gamma_{j,t}$ and $\nu_{j,n,t}$ when studying the risk-return tradeoff across asset classes. Note that Couts, Gonçalves, and Loudis (2024) use the definition $\lambda_{j,n,t} = \lambda_{j,w,t} \cdot \beta_{j,n,t}$, with $\lambda_{j,w,t} = \gamma_{j,t} \cdot \nu_{j,w,t}$ and $\beta_{j,n,t} = \nu_{j,n,t}/\nu_{j,w,t}$. Our $\lambda_{j,n,t}$ definition is equivalent to theirs but provides a direct way to separately identify the effect of risk price (γ) and risk quantity (ν) whereas theirs does not since $\lambda_{j,w,t} = \gamma_{j,t} \cdot \nu_{j,w,t}$ contains both a risk price effect (γ) and risk quantity effect (ν_w).

is due to λ and not α. Nevertheless, we later show that more than 80% of the α variation for the US Equity asset class is explained by a measure of perceived undervaluation of US equities that is model-agnostic (see Subsection 3.3). This results implies that α variation mostly captures variation in subjective mispricing (at least for equities). For this reason, hereafter we mainly refer to α and subjective mispricing interchangeably. We return to this issue when discussing the results from some alternative asset classes (e.g., Hedge Funds), in which case a non-trivial portion of the α variation is likely due to non-market risk factors.

1.2 The Subjective Beliefs Data

Our beliefs dataset is based on the long-term Capital Market Assumptions (CMAs) of asset managers (or "managers" for short) and investment consultants (or "consultants" for short), with all data collection details provided in Internet Appendix A.[5] This subsection provides a brief description of our CMAs dataset and how we use it to obtain the belief elements necessary to implement the decompositions in Equations 2 and 3, including information on how we define the wealth portfolio. Our description borrows heavily from Couts, Gonçalves, and Loudis (2024) since we use the same data collection process.

Envestnet PMC provides a succinct description of what CMAs are in their 2023 CMA Methodology report: "Capital markets assumptions are the expected returns, standard deviations, and correlation estimates that represent the long-term risk/return forecasts for various asset classes. We use these values to score portfolio risk, assist advisors in portfolio construction, construct our own asset allocation models and create Monte Carlo simulation inputs for portfolio wealth forecasts."

As is clear from this description, CMAs are an important component of the underlying

[5] Our ultimate goal is to better understand the beliefs of institutional investors. As such, the inclusion of asset managers is important. We also include investment consultants as we argue that their views provide an indirect way to learn about the beliefs of institutional investors. Andonov et al. (2025) provide empirical evidence in support of this argument, which indicates that (i) the beliefs of institutional investors and investment consultants are simultaneously based on common signals and/or (ii) the beliefs of investment consultants have a causal impact on the beliefs of institutional investors. While we do not attempt to separate these two channels in our paper, Internet Appendix C.4 shows that our main results are similar if we use only asset managers or only investment consultants.

business of investment firms. In the case of investment consultants, the CMAs are mainly used to advise their clients on portfolio allocation decisions. For instance, pension fund portfolio allocations are linked to the CMAs of their consultants (see Begenau, Liang, and Siriwardane (2025) and Andonov et al. (2025)). In the case of asset managers (who often also have clients in their wealth management division), the CMAs are used both to advise clients and to guide the overall portfolio allocation of multi asset class funds within the institution. For instance, the equity share of mutual funds that invest in both equities and fixed income is connected to the expected equity returns from the CMAs of their overall asset management companies (see Dahlquist and Ibert (2024)).

In contrast to the typical surveys about expected returns used in the literature, CMAs are not responses to questions designed by a third party research team. Instead, CMAs are fully developed documents produced organically by institutions. Moreover, CMAs tend to rely heavily on valuation models and statistical analysis. As a consequence, it is plausible to view CMAs as reflecting more sophisticated beliefs than the typical beliefs derived from surveys of individual investors or from surveys or reports of some classes of financial professionals less focused on portfolio allocation (see Ilmanen (2025)). For instance, Couts, Gonçalves, and Loudis (2024) show that expected returns from CMAs forecast future returns across asset classes and over time with a slope coefficient close to one. Relatedly, Dahlquist and Ibert (2025) show that the subjective expected returns from CMAs move one-to-one with ex-ante measures of objective expected returns.

We collect the long-term CMAs of 45 institutions in total (22 managers and 23 consultants). The forecasting horizons vary from 4 years to 30 years, with the median and modal horizon being 10 years (which comprises 45.2% of the institution-year observations for which we observe horizon).[6] The bulk of the data (83.4% of the institution-year observations) comes

[6] Our expected return decomposition framework from Subsection 1.1 holds for any given horizon. So, our baseline analysis includes data from all institution-year observations regardless of forecasting horizon (and selects the 10 year horizon for institution-year observations with multiple horizons). However, part of the disagreement in expected returns we study may come from horizon heterogeneity (which is embedded in both risk premia and alphas). We address this issue in Internet Appendix C.6 by showing that our main results are similar if we control for horizon heterogeneity in the belief aggregation process (for the time variation

directly from the CMAs of the institutions we cover through direct data requests and/or online searches for their CMAs. However, we supplement the direct CMAs of these institutions with indirect CMAs obtained from pension funds through their internal reports.[7]

Table 1 shows the list of managers and consultants that have at least one CMA in our sample.[8] As it is clear from the table, our sample covers many of the major asset managers and investment consultants. For instance, our managers have total Assets Under Management (AUM) above \$37 Trillion at the end of 2021, which is equivalent to more than 42.7% of the total AUM of all the top 50 asset managers in the world (by AUM). Similarly, in a typical year from 2001 to 2021, our consultants include the primary consultant of more than 50% of the US public pension funds, covering more than 70% of the AUM in this class of funds.

The first two columns in Table 2 provide the number of CMAs in our sample by year as well as the number of "direct CMAs" (i.e., CMAs obtained directly from documents of the underlying institution).[9] From 1987 to 1996, our dataset covers a single institution. However, in 1997 two new institutions enter the dataset, which then grows over time, reaching 30 institutions by the end of our sample in 2022.[10] For completeness, the third and fourth

analysis) and in the cross-institution variance decomposition process (for the disagreement analysis).

[7]In Internet Appendix C.4, we show that our results are similar whether we rely only on the direct CMAs of these institutions or only on the indirect CMAs we obtain from pension funds, alleviating potential concerns with either data collection approach.

[8]Two comments are in order. First, our definition of "investment consultants" is broad enough to encompass (i) institutions that focus on consulting for institutional investors (e.g., Callan), (ii) institutions that provide broad investment advising services that reach asset managers, institutional investors, and retail investors (e.g., Research Affiliates), and (iii) institutions (often called "wealth advisers") that tend to focus more on investment advising for wealthy individuals (e.g., CWO). Second, many institutions (e.g., BNY Mellon, Cliffwater, and Envestnet) have both an asset management business as well as a consulting or wealth advising business. The classification in Table 1 is based on our (somewhat subjective) assessment of whether the asset management side of a given institution is large enough to justify classifying it as an asset manager (e.g., by analysing their AUM and website self-descriptions). However, our classification has no impact on our main analysis since all results presented in the main text are based on a sample that combines asset managers and investment consultants. Our classification only plays a role when we provide results separately for asset managers and investment consultants, which are each consistent with our main results (see Internet Appendix C.4).

[9]Years are defined based on the approximate timing of the institution's information set. For instance, if a CMA contains $\mathbb{E}_{2000}[R_{2000\rightarrow 2010}]$, then our year variable is 2000.

[10]Note that the maximum number of institutions in any given year is 30 even though we have 45 unique institutions in our dataset. The reason is that the data for some institution-years come from CMAs we obtain online or from pension fund reports, neither of which ensures continuous coverage of a given institution over

columns in Table 2 also provide the breakdown of institutions into managers and consultants.

Each institution-year CMA covers a range of asset classes. We map these asset classes into Cash and 9 risky asset classes. The risky asset classes are chosen to match the asset classes for which we have data on the wealth portfolio weights (discussed below). The right panel columns in Table 2 provide the number of CMAs covering each asset class in our sample by year. There are two important observations. First, the Cash and US Equity asset classes are covered by all CMAs in our sample. Second, for each year (except 1987), we have at least one institution covering Cash, US Fixed Income, Ex US Fixed Income, US Equity, Ex US Equity, and Real Estate, which are the asset classes that dominate the wealth portfolio weights.

For each CMA (i.e., each institution-year observation), we have expected returns and expected volatilities for each asset class as well as the expected correlation matrix across asset classes.[11] As in Couts, Gonçalves, and Loudis (2024), we use these quantities to obtain institution j subjective expected excess returns ($\mu_{j,t}$) and the subjective covariance matrix of excess returns ($\Sigma_{j,t}$). We then combine these $\mu_{j,t}$ and $\Sigma_{j,t}$ values with wealth portfolio weights to obtain all μ and ν quantities in Equations 2 and 3 for each institution-year observation.

Since we do not observe the wealth portfolio weights for each institutional investor, we proxy for them by using the aggregated weights of US public pension funds obtained from the Center for Retirement Research at Boston College (see Internet Appendix A.3 for details). Figure 2 plots these wealth portfolio weights (we do not observe weights before 2001, and

time. For all data sent to us directly by the underlying institutions, our coverage is continuous (i.e., annual). See Internet Appendix A for further details on our CMA data collection process.

[11] We observe expected arithmetic returns in 77.8% of our CMAs and expected geometric returns in 58.5% of our CMAs (with 36.3% of our CMAs providing both). To ensure the conceptual definition underlying our μ measure is the same for all our institution-year observations, we always use expected arithmetic returns in our baseline analysis. This approach is consistent with the μ definition from the analogue of Equation 2 in typical asset pricing models and also with the fact that our CMAs report expected arithmetic returns more frequently than expected geometric returns. For the 22.2% of CMAs that do not report expected arithmetic returns, we obtain them from the reported beliefs under the properties of a log-Normal distribution (see Internet Appendix A.1 for details). However, to ensure our results are not due to this log-Normal transformation, Internet Appendix C.5 provides results that use expected arithmetic returns when available and expected geometric returns when expected arithmetic returns are not available (so that no transformation is applied). It also reports results based on expected geometric returns, with the log-Normal transformation used for the 41.5% of CMAs that only report expected arithmetic returns.

thus all weights for $t \leq 2001$ are set to match the 2001 weights). There are two potential interpretations for these weights. The first is that they reflect the market wealth portfolio excluding labor wealth (in the spirit of Stambaugh (1982) and Cederburg and O'Doherty (2019)). In this case, the allocation of pension funds serves as a proxy for the allocation of all investors. The second is that they reflect the wealth portfolio of institutional investors (in the spirit of Bretscher, Lewis, and Santosh (2024)). In this case, the allocation of pension funds serves as a proxy for the allocation of all institutional investors.

Internet Appendix C.5 considers an alternative version of our analysis in which the US Equity asset class proxies for the investors' wealth portfolio (in line with many papers in the asset pricing literature). The results are qualitatively similar to the ones we report in the main text. One might be tempted to further consider the maximum Sharpe ratio portfolio implied from the CMAs as an alternative definition for the market portfolio. Internet Appendix C.5 also explains why that is not a viable alternative. In a nutshell, the maximum Sharpe ratio portfolio always prices its underlying assets (Roll (1977)) and one cannot separately identify risk quantity and risk price using the maximum Sharpe portfolio.

1.3 Aggregating Subjective Beliefs Across Institutions

The CMAs described in the prior subsection result in an unbalanced panel (i.e., we do not observe CMAs for all institution-years, and a given institution-year CMA may not cover all asset classes we study). So, for each asset class, we use belief elements aggregated across available institutions (at each t) in all analyses that study time variation in expected returns and its components.[12] To account for the fact that sample composition changes over time (i.e., at each t we have different institutions in our sample), we start by running the following

[12]Using belief elements aggregated across institutions ensures each year receives the same weight in our analysis so that the results properly reflect a decomposition of expected return time variation throughout our sample period. Using aggregated beliefs is also useful to produce a long time-series of each belief element (for plotting purpose). However, in Internet Appendix C.6, we provide similar results to the ones reported in the main text for our analyses of expected return time variation while using our unbalanced panel of institution-year observations. In our panel regressions, we add institution by asset class fixed effects and weight observations so that each year receives the same weight in our analysis (these adjustments ensure a focus on expected return time variation throughout our sample period).

panel regression (with θ representing each μ and Σ element for our vector of asset classes):

$$\theta_{j,n,t} \ = \theta_{n,t}^{fe} \ + \ \theta_{n,j}^{fe} \ + \ \epsilon_{j,n,t} \tag{4}$$

where $\theta_{n,t}^{fe}$ is a time fixed effect (for asset class n) and $\theta_{n,j}^{fe}$ is an institution fixed effect (for asset class n). We then measure our aggregate time series for $\theta_{j,n,t}$ as

$$\theta_{n,t} \ = \theta_{n,t}^{fe} \ + \ (\overline{\theta}_n - \overline{\theta}_n^{fe}) \tag{5}$$

where $\overline{\theta}_n^{fe} = \frac{1}{T} \cdot \sum_{t=1}^{T} \theta_{n,t}^{fe}$ and $\overline{\theta}_n = \frac{1}{T} \cdot \sum_{t=1}^{T} \overline{\theta}_{n,t}$, with $\overline{\theta}_{n,t} = \frac{1}{J_t} \sum_{j=1}^{J_t} \theta_{j,n,t}$. Finally, we obtain $\mu_{w,t}$, $\nu_{w,t}$, and $\nu_{n,t}$ by combining these aggregate μ and Σ elements with the wealth portfolio weights described in the prior subsection.

The aggregation method follows Couts, Gonçalves, and Loudis (2024). Intuitively, $\theta_{n,t}^{fe}$ captures time variation in beliefs controlling for time variation in the composition of institutions (through the $\theta_{n,j}^{fe}$ fixed effects). However, the average $\theta_{n,t}^{fe}$ cannot be interpreted as the unconditional mean for the belief quantity. As such, our aggregation adjusts the $\theta_{n,t}^{fe}$ values by adding a constant that ensures that the average $\theta_{n,t}$ matches the average $\overline{\theta}_{n,t}$ (which reflects the cross-sectional average for asset class n at time t).

While the $\theta_{n,t}$ and $\overline{\theta}_{n,t}$ time-series have the same average, our aggregation method underlying $\theta_{n,t}$ is designed to produce time variation that accounts for sample composition whereas $\overline{\theta}_{n,t}$ is not. The reason is that aggregating without accounting for sample composition would induce time variation in beliefs that is purely due to variation in the set of institutions providing the given belief quantity (e.g., it would exist even if beliefs were constant over time within each institution).

1.4 Time Variation and Disagreement in Expected Returns

Our analysis focuses on decomposing the variation in institutional investors' expected returns (time variation and disagreement). Figure 3 graphically illustrates the level of time-series variation and disagreement in expected returns present in the data. Specifically, each graph in Figure 3 plots, for a given asset class, $\mu_{n,t} \pm \sigma_{\mu,n,t}$, where $\sigma_{\mu,n,t} = \sqrt{\mathbb{V}ar_t[\mu_{j,n,t} - \overline{\mu}_{n,t}]}$.[13,14] Clearly, for all asset classes, we have substantial time series variation as well as disagreement in expected returns considering that μ reflects annualized long-term expected returns.

To put the forecasting horizon effect in context, if we assume that μ reflects a 10-year horizon (the typical horizon in the data) and follows a first-order autoregressive process with persistence ϕ, then a 1% movement in μ implies a $10 \cdot (1-\phi)/(1-\phi^{10}) \cdot 100\%$ movement in the 1-year expected excess return ($\mu^{(1y)}$). For example, for US Equity we have that a 1% movement in μ translates to a 4.4% movement in $\mu^{(1y)}$, which highlights that the expected return variation in Figure 3(c) is sizable. For asset classes with more persistence, the horizon effect is weaker. For instance, for US Fixed Income we have that a 1% movement in μ translates to a 2.1% movement in $\mu^{(1y)}$. Nevertheless, applying this calibration to Figure 3(a) also suggests non-trivial variation in the expected returns of US Fixed Income.

While we do not study the connection between expected returns and subsequent realized returns in this paper, Couts, Gonçalves, and Loudis (2024) show that $\mu_{n,t}^{(1y)}$ values constructed from CMAs forecast next year realized excess returns across asset classes and over time with a slope coefficient close to one (economically and statistically). Moreover, Dahlquist and Ibert (2024) show that long-term equity expected excess returns from institutions similar to ours vary one-to-one with a measure of objective long-term equity expected excess returns, with Couts, Gonçalves, and Loudis (2024) extending this finding over time and Dahlquist and Ibert (2025) extending it to multiple asset classes and other financial professionals.

So, overall, $\mu_{n,t}$ has substantial variation over time and across institutions. Moreover, the variation over time is deeply linked to variation in objective expected returns as opposed to mostly reflecting extrapolative expectations as is the case for individual investors (see Greenwood and Shleifer (2014)).

[13] For $t < 1999$ (i.e., years with less than 5 institutions in the sample), we replace $\sigma_{\mu,n,t}$ with $\sigma_{\mu,n,1999}$.

[14] It may seem surprising that expected excess returns on fixed income have declined over our sample period. However, this is in line with realized excess returns since Couts, Gonçalves, and Loudis (2024) show that fixed income $\mu_{n,t}$ predicts subsequent fixed income realized excess returns. Moreover, Dahlquist and Ibert (2025) provide a plot of the objective risk premium in the bond market that features a similar decline.

2 The Subjective Expected Return Components

This section provides an initial analysis of subjective expected returns (μ) and their components in Equations 2 and 3 (α, λ, γ, and ν). Subsection 2.1 explains how we estimate γ that is time-varying and heterogeneous and Subsection 2.2 takes our γ estimates as given to summarize μ and its components. The main result is that there is substantial variation in the expected return components, with μ being strongly correlated with λ (mainly through ν) over time and across institutions.

2.1 Estimating Time Varying and Heterogeneous Risk Aversion

Combining Equations 2 and 3, we have that aggregate expected returns are given by

$$\mu_{n,t} \;=\; \alpha_{n,t} \;+\; \lambda_{n,t} \;=\; \alpha_{n,t} \;+\; \gamma_t \cdot \nu_{n,t} \tag{6}$$

and that institution-level expected returns satisfy

$$\mu_{j,n,t} \;=\; \alpha_{j,n,t} \;+\; \lambda_{j,n,t} \;=\; \alpha_{j,n,t} \;+\; \gamma_{j,t} \cdot \nu_{j,n,t} \tag{7}$$

Our paper quantifies the effect of each subjective expected return component (α, λ, γ, and ν) on μ time variation (through Equation 6) and on μ disagreement (through Equation 7). The prior section explains how we measure μ and ν directly from the CMAs of the institutions in our sample, but performing the full decompositions in Equations 6 and 7 requires us to also estimate risk aversion (γ). We now explain how we estimate risk aversion that is allowed to vary over time (t) and across institutions (j).

Our estimation approach is simple. For each institution-year observation, we estimate $\gamma_{j,t}$ from the slope coefficient of a linear projection of μ onto ν across asset classes (the median R^2 from these projections is above 80%).[15] That is, we estimate $\gamma_{j,t}$ by comparing the subjective expected returns of asset classes with different subjective risk quantities as perceived by

[15]Note that a linear projection of μ onto ν across institutions for each year-asset class observation would recover $\gamma_{n,t}$, which is not consistent with Equation 7 (i.e., risk aversion should not vary across asset classes). Similarly, a linear projection of μ onto ν across time periods for each institution-asset class would recover $\gamma_{j,n}$, which is also not consistent with Equation 7.

institution j at time t.[16] To obtain the aggregate estimated risk aversion, we aggregate the estimated $\gamma_{j,t}$ across institutions each year following the procedure described in Subsection 1.3 (with $\theta_{j,n,t} = \gamma_{j,t}$).

An alternative approach would be to assume that the CAPM holds exactly for the wealth portfolio (i.e., $\alpha_{j,w,t} = 0$). From Equations 6 and 7, this alternative approach would imply the aggregate CAPM risk aversion $\gamma_t = \mu_{w,t}/\nu_{w,t}$ at time t and the CAPM risk aversion $\gamma_{j,t} = \mu_{j,w,t}/\nu_{j,w,t}$ for institution j at time t. Our projections across asset classes avoid assuming that the CAPM fully explains the wealth portfolio expected return. In fact, with our estimation approach, we could find that $\gamma_{j,t} = 0$ for all institution-year observations, which would lead to the conclusion that all variation in μ is driven by α. If we instead relied on the CAPM risk aversion, we would remove this possibility by construction.

Nevertheless, Internet Appendix C.1 provides a comparison of our risk aversion estimates with the ones implied by the CAPM. In addition, Internet Appendix C.3 replicates our main results using the CAPM risk aversion that imposes $\gamma_t = \mu_{w,t}/\nu_{w,t}$ and $\gamma_{j,t} = \mu_{j,w,t}/\nu_{j,w,t}$. Internet Appendix C.3 also considers two alternative γ estimation methods designed to reduce potential noise in our baseline estimation (by either putting restrictions on $\gamma_{j,t}$ or assigning higher weight to asset classes that are more important in the wealth portfolio). In all cases, the results are qualitatively similar to the ones we provide in the main text.

2.2 Summarizing the Subjective Expected Return Components

The CMA data described in Subsection 1.2 contain expected returns (μ) and risk quantities (ν) for all asset classes whereas the prior subsection gives us risk aversion (γ). In turn, we recover, for each asset class, annual aggregate alphas from $\alpha_{n,t} = \mu_{n,t} - \gamma_t \cdot \nu_{n,t}$ (i.e., Equation 6) and institution-year alphas from $\alpha_{j,n,t} = \mu_{j,n,t} - \gamma_{j,t} \cdot \nu_{j,n,t}$ (i.e., Equation 7). As such, we

[16] Our risk aversion estimation approach is analogous to how traditional asset pricing tests estimate risk price from cross-sectional regressions of realized returns on estimated risk exposures. Specifically, under rational expectations, we have $\nu_{j,n,t} = \nu_{n,t}$ and $\mu_{j,n,t} = \mu_{n,t}$ with $r_{n,t+1} = \mu_{n,t} + u_{n,t+1}$, where $u_{n,t+1}$ is the unexpected return (uncorrelated with any time t variable by construction). So, the slope coefficient of a projection of $r_{n,t+1}$ onto $\nu_{n,t}$ across test assets recovers the same quantity (in population) as the slope coefficient of a projection of $\mu_{n,t}$ onto $\nu_{n,t}$ across test assets.

have all the subjective expected return components of Equations 6 and 7. This subsection provides summary statistics on these expected return components as well as on subjective volatilities, σ, which are used to construct ν.

Table 3 Panel A provides average values for each expected return component. In the columns under "Time-Series Averages", each value reflects the time-series average of the respective aggregate expected return component (e.g., $\frac{1}{T_n} \cdot \sum_{t=1}^{T} \mu_{n,t}$). In the columns under "Pooled Averages", each value reflects the pooled average across all institution-year observations for the given expected return component (e.g., $\frac{1}{\#(j,t)} \cdot \sum_{(j,t)} \mu_{j,n,t}$). The average values are overall reasonable. For instance, the wealth portfolio time-series average μ is 4.7%, with 0.8% corresponding to alpha (α) and 3.9% to risk premium (λ). Moreover, the time-series average γ is 2.87 with a pooled average γ of 2.70, which are sensible risk aversion values.

Table 3 Panel B provides information about the variation in each expected return component. In the columns under "Time-Series Variation", each value reflects the time-series standard deviation of the respective aggregate expected return component (e.g., $\sqrt{\mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n]}$). In the columns under "Cross-Institution Variation", each value reflects the time series average of the cross-institution standard deviation of the respective expected return components (e.g., $\frac{1}{T_n} \cdot \sum_{t=1}^{T} \sqrt{\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]}$). The reported values indicate that beliefs have substantial variation both over time and across institutions, with the latter reflecting disagreement. For instance, the wealth portfolio μ has a time-series standard deviation of 0.4% and a cross-institution standard deviation of 0.8%, with both of these numbers being non-trivial in comparison to the time-series average for the wealth portfolio μ, which is 4.7%. Moreover, the wealth portfolio λ has a similar variability as its μ, with a time-series standard deviation of 0.5% and a cross-institution standard deviation of 1.0%.

Table 3 Panel C provides correlations of expected return components over time and across institutions. In the columns under "Time-Series Correlations", each value reflects the time-series correlation between the respective aggregate expected return components (e.g., $\mathbb{C}or[\mu_{n,t}, \lambda_{n,t}]$). In the columns under "Cross-Institution Correlations", each value reflects the time-series average of the cross-institution correlation between the respective expected return components (e.g., $\frac{1}{T_n} \cdot \sum_{t=1}^{T} \mathbb{C}or[\mu_{j,n,t}, \lambda_{j,n,t}]$). The most interesting observation from Panel C is that λ and ν have higher time-series and cross-institution correlations with μ than either α or γ do for the wealth portfolio and most asset classes. This result highlights the tight connection between expected returns (μ) and risk premia (λ) through risk quantity (ν).

3 Decomposing the Link Between Expected Returns and Yields

An important property of CMA-based expected equity returns is that they are countercyclical (Dahlquist and Ibert (2024, 2025) and Couts, Gonçalves, and Loudis (2024)). This countercyclicality arises from the connection between equity expected returns and the respective earnings yields. In this section, we show that this link between μ and yields holds beyond equities. Moreover, we show that it arises mainly from the risk premium (λ) component of μ (through risk quantity, ν) rather than the alpha (α) component. Subsection 3.1 provides a simple yield-based model of CMA formation to guide our analysis. Subsection 3.2 then studies the empirical link between yields and μ components and Subsection 3.3 builds on this analysis to provide an external validation of our interpretation of λ as subjective risk premium and α as subjective mispricing.

3.1 A Simple Yield-Based Model of CMA Formation

We start from a simple yield-based model of CMA formation. In this model, a representative institution has a forecasting horizon of h years and obtains its expected nominal return on cash from

$$\mathbb{E}_t[R_{cash}] = \omega \cdot (const + y_{b,t}^{(h)}) + (1-\omega) \cdot (const + \pi_t^{(h)}) \tag{8}$$

where $y_{b,t}^{(h)}$ is the h-year nominal bond yield and $\pi_t^{(h)}$ is the h-year inflation expectation.

In words, the institution assigns some weight (ω) to the expectations hypothesis (that the h-year expected return on cash moves one-to-one with the h-year yield) and some weight $(1-\omega)$ to the Fisher hypothesis (that nominal interest rates move one-to-one with expected inflation). While simplistic, the model in Equation 8 captures the essence of how cash expectations are formed in CMAs. For instance, the 2022 Cliffwater CMA explicitly sets their expected nominal return on cash equivalents to be slightly above their inflation forecast (which is in line with the Fisher hypothesis) whereas the 2022 Sellwood CMA sets their expected nominal return on cash equivalents to equal the current long-term yield minus the average historical term premium (which is in line with the expectations hypothesis).

Subtracting expected inflation on both sides of Equation 8 results in

$$\mathbb{E}_t[R^{real}_{cash}] \; = const \; + \; \omega \cdot y_{cash,t} \tag{9}$$

where $y_{cash,t} = y^{(h)}_{b,t} - \pi^{(h)}_t$ reflects the real yield on cash under the perspective of CMAs.

For other asset classes, we assume the institution uses valuation models. This is also consistent with how institutions form their CMAs (see Ilmanen and Maloney (2025a,b)). In Internet Appendix B, we show that, under stylized assumptions, these valuation models imply $\mathbb{E}_t[R^{real}_n] = const + b_n \cdot y_{n,t}$, where $y_{n,t}$ is the real yield for asset class n at time t. Subtracting $\mathbb{E}_t[R^{real}_{cash}]$ from $\mathbb{E}_t[R^{real}_n]$, we then have

$$\mu_{n,t} \; = const \; + \; \underbrace{b_n \cdot y_{n,t} \; - \; \omega \cdot y_{cash,t}}_{b_n \cdot (y_{n,t} \, - \, \omega / b_n \cdot y_{cash,t})} \tag{10}$$

which (together with Equation 9) summarizes our yield-based model of CMA formation.

3.2 Decomposing the Link Between μ and Yields

The first column in Table 4 provides the results from estimating the system in Equations 9 and 10 while accounting for the restriction that ω is the same across equations. This analysis considers only the six risky asset classes for which we can measure real yields (Internet Appendix A.4 provides measurement details for yields and expected inflation).

Our yield-based model provides a reasonable description of CMA formation. For $\mathbb{E}_t[R^{real}_{cash}]$, we have $R^2_{adj} = 70.4\%$, which is strikingly high for such a simple model. Moreover, across the μs of different asset classes, the R^2_{adj} values range from 31.2% (for US Equity) to 71.2% (for Ex US Fixed Income). Figure 4 provides a visualization of these results by plotting μ against the fitted values from the yield-based model, showing that much of the variation in μ

is explained by yields. These results demonstrate that the link between CMA-based expected returns and yields extends far beyond equities (Dahlquist and Ibert (2024, 2025) and Couts, Gonçalves, and Loudis (2024) document the results for equities while Dahlquist and Ibert (2025) also consider junk bonds).

However, the link between μ and yields does not tell us whether, from the perspective of these institutions, high yields indicate high risk premia (perceived compensation for market risk) or high alphas (perceived undervaluation). The former is the hallmark of risk-based models whereas the latter is a common feature of behavioral models in which prices are driven by sentiment. To shed light on this matter, the second and third columns in Table 4 provide the results from regressions of α and λ onto $(y_{n,t} - \omega/b_n \cdot y_{cash,t})$ such that the slope coefficients add to b_n (since $\mu = \alpha + \lambda$). The results show that variation in yields is more indicative of variation in risk premia than in alphas for all asset classes (with the exception of Private Equity, which we discuss below). In particular, the slope coefficient for α tends to be relatively small and statistically insignificant (even negative in three asset classes) whereas the slope coefficient for λ tends to be relatively large and statistically significant. Moreover, the R^2_{adj} values tend to be substantially higher for λ than for α.

The fact that high yields tend to indicate high risk premia from the perspective of CMAs is informative about the nature of the cyclicality in CMA-based expected returns. To explore this issue further, we decompose risk premia into risk price and risk quantity effects. To facilitate the interpretation of the slope coefficients, we transform the $\lambda_{n,t} = \gamma_t \cdot \nu_{n,t}$ equation into an additive relation using a method analogous to the one in Chen, Da, and Zhao (2013). Specifically, we define the function $\lambda(\gamma, \nu) = \gamma \cdot \nu$, which satisfies $\lambda(\gamma_t, \nu_{n,t}) = \lambda_{n,t}$. Then, we rewrite the λ equation as[17]

$$\lambda_{n,t} \; = \lambda(\overline{\gamma}, \overline{\nu}_n) \; + \; \lambda^{\gamma}_{n,t} \; + \; \lambda^{\nu}_{n,t} \tag{11}$$

[17]Note that if $\gamma_t = \overline{\gamma}$ (so that risk price does not vary over time), then we have $\lambda^{\gamma}_{n,t} = 0$ and $\lambda^{\nu}_{n,t} = \lambda(\overline{\gamma}, \nu_{n,t}) - \lambda(\overline{\gamma}, \overline{\nu}_n)$. Similarly, if $\nu_{n,t} = \overline{\nu}_n$ (so that risk quantity does not vary over time), then we have $\lambda^{\gamma}_{n,t} = \lambda(\gamma_t, \overline{\nu}_n) - \lambda(\overline{\gamma}, \overline{\nu}_n)$ and $\lambda^{\nu}_{n,t} = 0$. So, we have that $\lambda^{\gamma}_{n,t}$ captures the effect of time-varying risk price whereas $\lambda^{\nu}_{n,t}$ captures the effect of time-varying risk quantity.

where

$$\lambda^{\gamma}_{n,t} \equiv 0.5 \cdot \{[\,\lambda(\gamma_t, \nu_{n,t}) - \lambda(\overline{\gamma}, \nu_{n,t})\,] \;+\; [\,\lambda(\gamma_t, \overline{\nu}_n) - \lambda(\overline{\gamma}, \overline{\nu}_n)\,]\} \tag{12}$$

$$\lambda^{\nu}_{n,t} \equiv 0.5 \cdot \{[\,\lambda(\gamma_t, \nu_{n,t}) - \lambda(\gamma_t, \overline{\nu}_n)\,] \;+\; [\,\lambda(\overline{\gamma}, \nu_{n,t}) - \lambda(\overline{\gamma}, \overline{\nu}_n)\,]\} \tag{13}$$

so that λ^{γ} and λ^{ν} reflect, respectively, the effects of γ and ν variation on λ variation.

The fourth and fifth columns in Table 4 provide the results from regressions of λ^{γ} and λ^{ν} onto $(y_{n,t} - \omega/b_n \cdot y_{cash,t})$ such that the slope coefficients add to the λ slope coefficient. The results show that variation in yields is more indicative of variation in perceived risk quantity than risk price. In particular, the slope coefficient for λ^{γ} tends to be relatively small and statistically insignificant (even negative in three asset classes) whereas the slope coefficient for λ^{ν} tends to be relatively large and statistically significant. Moreover, the R^2_{adj} values tend to be substantially higher for λ^{ν} than for λ^{γ}.

One exception to the above results is Private Equity, where λ^{γ} is the only component of expected returns that is significantly connected to yields. There are at least two likely reasons for this result, and they are not mutually exclusive. The first is that institutions view private equity valuations as less reflective of risk quantity given the frictions of investing in this market (see, e.g., Brown, Gonçalves, and Hu (2023)). The second is that measuring risk exposure of private equity is hard given the interaction between illiquid assets and closed-end fund structures (see, e.g., Brown, Ghysels, and Gredil (2023)). As a consequence, the risk quantity has little variation over time in the case of private equity, which even mutes the total risk premium effect.

Internet Appendix C.2 provides a reduced-form analysis of the relation between expected returns and yields, which does not depend on the yield-based model of CMA formation proposed in the prior subsection (i.e., the system in Equations 9 and 10). The results are similar to the ones described above (albeit the yield-based model of CMA formation remains useful in the economic interpretation of the results). Using that reduced form implementation, we also show that a yield-based CMA formation better describes the expected returns from institutional investors in comparison to an extrapolation-based CMA formation in the spirit of what Greenwood and Shleifer (2014) propose for individual investors.

3.3 Solidifying the Interpretation of α and λ

The previous subsection shows that the link between μ and yields is mainly driven by λ rather than α. However, the economic interpretation that λ captures nearly all of the risk premium component of subjective expected returns (so that α reflects mainly subjective mispricing) rests on the assumption that r_w is the dominant risk factor for the institutions in our sample. If they were instead primarily concerned with other sources of risk, our λ would capture only part of the true risk premium component so that α would largely reflect risk premia from risk factors beyond r_w. On one hand, as shown in Couts, Gonçalves, and Loudis (2024), CMAs often discuss market risk exposures directly and indirectly. On the other hand, other risk factors are also discussed in the CMAs (albeit often in the context of alternative asset classes).

To address this issue, this subsection studies a direct measure of perceived mispricing for the US Equity asset class, which is agnostic about the risk factors relevant to investors. Specifically, we measure the (negative of the) net fraction of fund managers who answer "yes" to the question of whether US equities are overvalued in the Bank of America (BofA) survey of global fund managers (see Internet Appendix A.2 for measurement details). This is a measure of undervaluation of US equities as perceived by global fund managers (and independent of CMAs), with undervaluation theoretically implying high alphas.

Table 5 provides the results from regressing the expected return elements onto $y_{n,t} - y_{cash,t}$ ("Excess CAPE Yield" in the table) and the BofA measure of undervaluation for US equities ("Perceived Undervaluation" in the table).[18] We normalize the predictive variables to z-scores (and multiply slope coefficients by 100) since the units of the excess CAPE yield and the perceived undervaluation variables are not comparable. The sample period is from 2001 to 2022, which is the period over which we observe the perceived undervaluation variable. The

[18] Note that, according to the CMA formation model of Subsection 3.1, the relevant yield variable is $y_{n,t} - \omega/b_n \cdot y_{cash,t}$ and not $y_{n,t} - y_{cash,t}$. However, Table 4 shows that $\omega \approx b_n$ for the US Equity asset class. As such, we simplify the analysis in Table 5 by using $\omega/b_n = 1$.

first three rows of Table 5 show that the results over this shorter sample closely mirror those for the US Equity asset class over the full sample in Table 4. The next three rows show that α is positively and strongly linked to perceived undervaluation, with an R^2 of 83.1%. This provides strong evidence that alpha is mainly capturing subjective mispricing.[19] In contrast, perceived undervaluation is negatively linked to λ (through γ), the opposite of what we would expect if our risk premium measure was somehow capturing subjective mispricing. The last five rows consider bivariate regressions of expected return elements onto the excess CAPE yield and perceived undervaluation variables. While the excess CAPE yield is the main driver of μ, perceived undervaluation has a significant marginal effect on μ, which arises from its strong link to α. Moreover, perceived undervaluation has a non-trivial marginal (negative) effect on λ.

In Internet Appendix B.2, we provide an extended model of CMA formation for equities. The model also incorporates subjective growth, which we show helps explain expected return components beyond the excess CAPE yield and perceived undervaluation. Yet, the result that α is mostly driven by perceived undervaluation remains valid even after controlling for expected growth.

Overall, these results solidify the interpretation that λ captures most of the risk premium component of subjective expected returns so that α mainly reflects subjective mispricing. Nevertheless, due to data limitations, this validation analysis focuses on the US Equity asset class (which is also the focus of most of the subjective beliefs literature). For other asset classes, it is possible that our λ captures only part of the risk premium component of expected returns so that α reflects a combination of subjective mispricing and non-market risk premia. As such, for other asset classes, the fraction of μ variation attributed to α is an

[19]Since the BofA survey participants are fund managers, the strong link between CMA α and BofA perceived undervaluation also shows that CMAs are informative about the views of fund managers even though they are produced at the level of the institution (e.g., we have the Invesco CMA instead of the CMA of a given fund within Invesco). This aspect is perhaps not surprising since, as reported in Couts, Gonçalves, and Loudis (2024), most of the CMAs that report their authors have at least one coauthor who holds a job title that likely implies direct influence over portfolio allocation decisions (e.g., portfolio manager or chief investment officer). Moreover, the portfolio allocations of mutual funds and pension funds are linked to CMAs (see Dahlquist and Ibert (2024), Begenau, Liang, and Siriwardane (2025), and Andonov et al. (2025)).

upper bound on the fraction of μ variation due to subjective mispricing. We return to this issue when discussing the variance decomposition results from some alternative asset classes (e.g., Hedge Funds).

4 Decomposing Time Variation in Expected Returns

The prior section shows that the link between μ and yields over time is largely driven by λ (through ν), which speaks to the nature of the μ countercyclicality. This section goes one step further to quantify the importance of different expected return components in explaining all expected return time variation (not only the portion linked to yields). Similar to the prior section, we find that most time variation in μ is driven by λ (through ν). However, we also show that γ plays a non-trivial role in explaining short-lived movements in μ (i.e., expected return transitory time variation). Subsection 4.1 provides some intuitive visualizations of these results, with Subsection 4.2 presenting a formal variance decomposition for μ time variation and Subsection 4.3 extending it to transitory time variation.

4.1 Components of μ Time Variation

To start, Figures 5(a) and 5(b) provide scatterplots of μ against α and λ (with each belief element time-series demeaned by asset class). There is a strong link between time variation in μ and λ (e.g., a correlation of 0.60) and a much weaker link between time variation in μ and α (e.g., a correlation of 0.32). Since $\lambda_{n,t} = \gamma_t \cdot \nu_{n,t}$ has a risk price (γ) and a risk quantity (ν) component, we also provide Figures 5(c) and 5(d), which show that the link between time variation in μ and ν is much stronger than the link between time variation in μ and γ.

To better inspect the time-series link between μ and its components, we create counterfactual expected return time series where only one expected return component is allowed to vary over time, with other quantities set to their respective time-series averages. We label these counterfactual expected returns μ^{α}, μ^{λ}, μ^{γ}, and μ^{ν}, with the superscript on μ indicating the component that varies over time.

Figure 6 plots, for each asset class, the time series of μ, μ^{α}, and μ^{λ}. The results show that, for most asset classes (e.g., US Fixed Income, US Equity, and Real Estate), the time variation in μ^{λ} closely tracks the time variation in μ, whereas the time variation in μ^{α} has a relatively weak connection to the time variation in μ. However, the figure also shows that for some asset classes (e.g., Hedge Funds and Infrastructure) μ^{α} tracks μ better than μ^{λ} does.

Since λ has a γ and a ν component, Figure 7 plots, for each asset class, the time series of μ, μ^{γ}, and μ^{ν}. For asset classes with μ^{λ} time variation closely tracking μ time variation (e.g., Real Estate), we also tend to find that μ^{ν} time variation closely tracks μ time variation, whereas the same is not true for μ^{γ}. However, short-term movements in μ^{γ} do tend to track short-term movements in μ (see, e.g., Real Estate in the early 1990s).

4.2 Decomposing $\mathbb{V}ar[\mu]$ over Time

Next, we formally decompose expected return time variation into its components. We show that, in line with Figures 5 to 7, overall expected return time variation is dominated by risk premia (λ), mainly through time variation in risk quantity (ν).

Note that Equation 6 implies the following decomposition for μ time variation:

$$\begin{aligned} \mathbb{V}ar[\mu_{n,t}-\overline{\mu}_n] &= \mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\,,\,\alpha_{n,t}-\overline{\alpha}_n] + \mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\,,\,\lambda_{n,t}-\overline{\lambda}_n] \\ &\Downarrow \\ 1 &= \underbrace{\frac{\mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\,,\,\alpha_{n,t}-\overline{\alpha}_n]}{\mathbb{V}ar[\mu_{n,t}-\overline{\mu}_n]}}_{\mathbb{V}(\alpha)} + \underbrace{\frac{\mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\,,\,\lambda_{n,t}-\overline{\lambda}_n]}{\mathbb{V}ar[\mu_{n,t}-\overline{\mu}_n]}}_{\mathbb{V}(\lambda)} \end{aligned} \tag{14}$$

Table 6 Panel A reports (in the first four columns) estimates and t-statistics for $\mathbb{V}(\alpha)$ and $\mathbb{V}(\lambda)$ for the wealth portfolio, all asset classes combined, and each individual asset class.[20] Similarly, Figure 8(a) displays $\mathbb{V}(\alpha)$ and $\mathbb{V}(\lambda)$ graphically. Most of the time variation in the expected returns of the wealth portfolio is explained by risk premia time variation

[20] In line with Equation 14, we estimate $\mathbb{V}(\lambda)$ for asset class n as the slope coefficient from an OLS regression of $\lambda_{n,t}$ onto $\mu_{n,t}$ (and use Newey and West (1987, 1994) for standard errors). Similarly, we estimate $\mathbb{V}(\lambda)$ for all asset classes combined as the slope coefficient from an OLS regression of $\lambda_{n,t}$ onto $\mu_{n,t}$ with asset class fixed effects (and use Driscoll and Kraay (1998) with Newey and West (1994) lag selection for standard errors). $\mathbb{V}(\alpha)$ is estimated analogously with $\alpha_{n,t}$ replacing $\lambda_{n,t}$, but $\mathbb{V}(\alpha) = 1 - \mathbb{V}(\lambda)$ by construction.

since $\mathbb{V}(\lambda) = 88.1\%$ ($t_{stat} = 4.89$) and $\mathbb{V}(\alpha) = 11.9\%$ ($t_{stat} = 0.66$). When combining all asset classes, we have $\mathbb{V}(\lambda) = 68.1\%$ ($t_{stat} = 5.33$), which indicates that risk premia also drive the overall time variation in μ. However, in this case alphas also play a quantitatively important role, with $\mathbb{V}(\alpha) = 31.9\%$ ($t_{stat} = 2.50$). The reason is that α has a stronger effect for some alternative asset classes than for traditional ones, with the wealth portfolio weights concentrating in traditional asset classes like equities and fixed income. For instance, α explains effectively all μ time variation for Hedge Funds. This result is consistent with anecdotal evidence from the text in CMAs, which often indicate that pure alpha and risk factors beyond market risk matter for hedge funds.

For instance, the 2019 Northern Trust CMA states that "The primary benefit of hedge fund strategies is the ability to provide nontraditional and uncorrelated return premiums to the traditional portfolio, by producing alpha – returns not explained by risk exposures. Our 3.7% hedge fund return forecast represents the combination of expected alpha (0.5%) and expected returns from risk exposures (3.2%). Our forecast is based on our risk factor model, which includes the following risk factors: market, term, credit, size, value, momentum, emerging market, commodity and currency."

So, in the context of Hedge Funds, our αs likely capture both subjective mispricing (which hedge funds are expected to translate into alpha) and non-market risk premia. This aspect clarifies why αs play a large role in explaining expected return variation for Hedge Funds. Note that the natural implication is that the fraction of expected return variability we attribute to α is an upper bound for the total variability due to subjective mispricing. For traditional asset classes, this upper bound is likely close to the true effect of subjective mispricing (because non-market risk factors matter less). However, for Hedge Funds, this upper bound is likely much higher than the true effect of mispricing, with α largely reflecting non-market risk premia.

We next further decompose the risk premia (λ) effect on expected return time variation into the effect of risk price (γ) and risk quantity (ν). We do so using the λ linearization in

Equation 11, which implies the decomposition

$$\begin{aligned}
\mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\ ,\ \lambda_{n,t}-\overline{\lambda}_n] &= \mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\ ,\ \lambda^{\gamma}_{n,t}-\overline{\lambda}^{\gamma}_n] + \mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\ ,\ \lambda^{\nu}_{n,t}-\overline{\lambda}^{\nu}_n] \\
&\Downarrow \\
1 &= \underbrace{\frac{\mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\ ,\ \lambda^{\gamma}_{n,t}-\overline{\lambda}^{\gamma}_n]}{\mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\ ,\ \lambda_{n,t}-\overline{\lambda}_n]}}_{\mathbb{V}_{\lambda}(\gamma)} + \underbrace{\frac{\mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\ ,\ \lambda^{\nu}_{n,t}-\overline{\lambda}^{\nu}_n]}{\mathbb{C}ov[\mu_{n,t}-\overline{\mu}_n\ ,\ \lambda_{n,t}-\overline{\lambda}_n]}}_{\mathbb{V}_{\lambda}(\nu)} \qquad (15)
\end{aligned}$$

Table 6 Panel B reports (in the first four columns) estimates and t-statistics for $\mathbb{V}_{\lambda}(\gamma)$ and $\mathbb{V}_{\lambda}(\nu)$ for the wealth portfolio, all asset classes combined, and each individual asset class.[21] For the wealth portfolio and also for all asset classes combined, almost the entire effect of risk premia on expected return time variation is driven by risk quantity. In particular, for the wealth portfolio we have $\mathbb{V}_{\lambda}(\nu) = 102.3\%$ ($t_{stat} = 4.25$) and $\mathbb{V}_{\lambda}(\gamma) = -2.3\%$ ($t_{stat} = -0.09$). Similarly, for all asset classes combines we have $\mathbb{V}_{\lambda}(\nu) = 90.4\%$ ($t_{stat} = 8.91$) and $\mathbb{V}_{\lambda}(\gamma) = 9.6\%$ ($t_{stat} = 0.95$).

Results vary by asset class, and Figure 8(c) provides a visual representation of the decomposition. For each asset class except for Private Equity and Infrastructure, almost the entire effect of risk premia on expected return time variation is driven by risk quantity. This result is consistent with our finding in Subsection 3.2 that risk price matters more than risk quantity in explaining the cyclicality of Private Equity expected returns.

4.3 Decomposing $\mathbb{V}ar[\Delta\mu]$ over Time

The decompositions in Equations 14 and 15 capture the overall time variation in μ, which tends to be driven by persistent movements in beliefs. To explore more transitory belief movements, we take annual differences in Equation 6, resulting in the following alternative

[21] In line with Equation 15, we estimate $\mathbb{V}_{\lambda}(\nu)$ for asset class n as the slope coefficient from an IV regression of $\lambda^{\nu}_{n,t}$ onto $\lambda_{n,t}$ with $\mu_{n,t}$ as the instrument (and use Newey and West (1987, 1994) for standard errors). Similarly, we estimate $\mathbb{V}_{\lambda}(\nu)$ for all asset classes combined as the slope coefficient from an IV regression of $\lambda^{\nu}_{n,t}$ onto $\lambda_{n,t}$ with $\mu_{n,t}$ as the instrument and asset class fixed effects (and use Driscoll and Kraay (1998) with Newey and West (1994) lag selection for standard errors). $\mathbb{V}_{\lambda}(\gamma)$ is estimated analogously with $\lambda^{\gamma}_{n,t}$ replacing $\lambda^{\nu}_{n,t}$, but $\mathbb{V}_{\lambda}(\gamma) = 1 - \mathbb{V}_{\lambda}(\nu)$ by construction. Note that the $\mathbb{V}_{\lambda}(\nu)$ and $\mathbb{V}_{\lambda}(\gamma)$ terms reflect ratios of covariances, which are consistently estimated with the IV regressions we use.

variance decompositions:

$$1 = \underbrace{\frac{\mathbb{C}ov[\Delta\mu_{n,t} - \overline{\Delta\mu}_n \,,\, \Delta\alpha_{n,t} - \overline{\Delta\alpha}_n]}{\mathbb{V}ar[\Delta\mu_{n,t} - \overline{\Delta\mu}_n]}}_{\mathbb{V}(\Delta\alpha)} + \underbrace{\frac{\mathbb{C}ov[\Delta\mu_{n,t} - \overline{\Delta\mu}_n \,,\, \Delta\lambda_{n,t} - \overline{\Delta\lambda}_n]}{\mathbb{V}ar[\Delta\mu_{n,t} - \overline{\Delta\mu}_n]}}_{\mathbb{V}(\Delta\lambda)} \tag{16}$$

and

$$1 = \underbrace{\frac{\mathbb{C}ov[\Delta\mu_{n,t} - \overline{\Delta\mu}_n \,,\, \Delta\lambda^{\gamma}_{n,t} - \overline{\Delta\lambda}^{\gamma}_n]}{\mathbb{C}ov[\Delta\mu_{n,t} - \overline{\Delta\mu}_n \,,\, \Delta\lambda_{n,t} - \overline{\Delta\lambda}_n]}}_{\mathbb{V}_{\lambda}(\Delta\gamma)} + \underbrace{\frac{\mathbb{C}ov[\Delta\mu_{n,t} - \overline{\Delta\mu}_n \,,\, \Delta\lambda^{\nu}_{n,t} - \overline{\Delta\lambda}^{\nu}_n]}{\mathbb{C}ov[\Delta\mu_{n,t} - \overline{\Delta\mu}_n \,,\, \Delta\lambda_{n,t} - \overline{\Delta\lambda}_n]}}_{\mathbb{V}_{\lambda}(\Delta\nu)} \tag{17}$$

which we estimate analogously to the decompositions in Equations 14 and 15.

Table 6 Panel A reports (in the last four columns) estimates and t-statistics for $\mathbb{V}(\Delta\alpha)$ and $\mathbb{V}(\Delta\lambda)$ for the wealth portfolio, all asset classes combined, and each individual asset class. The results are qualitatively similar to the ones for $\mathbb{V}(\alpha)$ and $\mathbb{V}(\lambda)$. In particular, for the wealth portfolio the transitory time variation in μ is completely driven by λ, with $\mathbb{V}(\Delta\lambda) = 100.9\%$ ($t_{stat} = 8.96$) and $\mathbb{V}(\Delta\alpha) = -0.9\%$ ($t_{stat} = -0.08$). Moreover, for all asset classes combined, λ still drives the majority of the transitory time variation in μ since $\mathbb{V}(\Delta\lambda) = 60.8\%$ ($t_{stat} = 6.15$), but in this case alpha also plays a quantitatively important role with $\mathbb{V}(\Delta\lambda) = 39.2\%$ ($t_{stat} = 3.96$). As before, results vary by asset class, and Figure 8(b) provides a visual representation of the decomposition.

Table 6 Panel B reports (in the last four columns) estimates and t-statistics for $\mathbb{V}_{\lambda}(\Delta\gamma)$ and $\mathbb{V}_{\lambda}(\Delta\nu)$ for the wealth portfolio, all asset classes combined, and each individual asset class. In this case, results are qualitatively different from the ones we obtain for $\mathbb{V}_{\lambda}(\gamma)$ and $\mathbb{V}_{\lambda}(\nu)$. In particular, risk aversion is as important as risk quantity in driving the effect of risk premia on expected return transitory time variation. For instance, we have $\mathbb{V}_{\lambda}(\Delta\gamma) = 59.5\%$ ($t_{stat} = 5.07$) and $\mathbb{V}_{\lambda}(\Delta\nu) = 40.5\%$ ($t_{stat} = 3.45$) when we focus on the wealth portfolio. Similarly, we have $\mathbb{V}_{\lambda}(\Delta\gamma) = 45.0\%$ ($t_{stat} = 3.83$) and $\mathbb{V}_{\lambda}(\Delta\nu) = 55.0\%$ ($t_{stat} = 4.69$) when we consider all asset classes jointly. Figure 8(d) provides a visual representation of the decomposition. Contrasting Figures 8(c) and 8(d) clearly highlights the difference: the importance of risk aversion in driving the risk premia effect is much higher when we focus on transitory time variation in μ as opposed to the overall time variation in μ.

5 Decomposing Disagreement in Expected Returns

While the prior sections focus on μ time variation, this section explores μ disagreement (i.e., μ variation across institutions). We find that μ disagreement is mostly driven by λ (similar to μ time variation), but in this case α plays a quantitatively non-trivial role. Moreover,γ and ν are (roughly) equally important in driving the λ effect. Also, the importance of α and γ increases when we focus on short-lived disagreement (which we refer to as transitory disagreement). Subsection 5.1 provides some intuitive visualizations of these results, with Subsection 5.2 presenting a formal variance decomposition for μ disagreement and Subsection 5.3 highlighting the differences when we focus on transitory disagreement.

5.1 Components of μ Disagreement

To start, Figures 9(a) and 9(b) provide scatterplots of μ against α and λ (with each belief element cross-institution demeaned each year). μ disagreement is linked to both α disagreement and λ disagreement, but the link is somewhat stronger with the latter. In particular, the correlation between λ and μ is 0.57, which is higher than the 0.44 correlation between α and μ. However, the difference in correlations here is lower than the analogous difference for μ time variation (presented in Figure 5).

Since $\lambda_{j,n,t} = \gamma_{j,t} \cdot \nu_{j,n,t}$ has a risk price (γ) and a risk quantity (ν) component, we also provide Figures 9(c) and 9(d), which show that the link between μ disagreement and γ heterogeneity is comparable to the link between μ disagreement and ν disagreement. This result is in stark contrast to the findings associated with μ overall time variation. In particular, as shown in Figure 5, μ time variation has a substantially stronger link to ν time variation than it does to γ times variation.

5.2 Decomposing μ Disagreement

We formalize the visual results from Figure 9 through the following decompositions for μ disagreement:

$$1 \;=\; \underbrace{\frac{\mathbb{C}ov[\mu_{j,n,t}-\overline{\mu}_{n,t}\;,\;\alpha_{j,n,t}-\overline{\alpha}_{n,t}]}{\mathbb{V}ar[\mu_{j,n,t}-\overline{\mu}_{n,t}]}}_{\mathbb{D}(\alpha)} \;+\; \underbrace{\frac{\mathbb{C}ov[\mu_{j,n,t}-\overline{\mu}_{n,t}\;,\;\lambda_{j,n,t}-\overline{\lambda}_{n,t}]}{\mathbb{V}ar[\mu_{j,n,t}-\overline{\mu}_{n,t}]}}_{\mathbb{D}(\lambda)}. \tag{18}$$

and

$$1 \;=\; \underbrace{\frac{\mathbb{C}ov[\mu_{j,n,t}-\overline{\mu}_{n,t}\;,\;\lambda^{\gamma}_{j,n,t}-\overline{\lambda}^{\gamma}_{n,t}]}{\mathbb{C}ov[\mu_{j,n,t}-\overline{\mu}_{n,t}\;,\;\lambda_{j,n,t}-\overline{\lambda}_{n,t}]}}_{\mathbb{D}_{\lambda}(\gamma)} \;+\; \underbrace{\frac{\mathbb{C}ov[\mu_{j,n,t}-\overline{\mu}_{n,t}\;,\;\lambda^{\nu}_{j,n,t}-\overline{\lambda}^{\nu}_{n,t}]}{\mathbb{C}ov[\mu_{j,n,t}-\overline{\mu}_{n,t}\;,\;\lambda_{j,n,t}-\overline{\lambda}_{n,t}]}}_{\mathbb{D}_{\lambda}(\nu)} \tag{19}$$

which follow directly from Equation 7 with the linearization (analogous to Equation 11)

$$\lambda_{j,n,t} \;=\lambda(\overline{\gamma}_t,\overline{\nu}_{n,t}) \;+\; \lambda^{\gamma}_{j,n,t} \;+\; \lambda^{\nu}_{j,n,t} \tag{20}$$

where

$$\lambda^{\gamma}_{j,n,t} \;\equiv 0.5\cdot\{[\,\lambda(\gamma_{j,t},\nu_{j,n,t})-\lambda(\overline{\gamma}_t,\nu_{j,n,t})\,] \;+\; [\,\lambda(\gamma_{j,t},\overline{\nu}_{n,t})-\lambda(\overline{\gamma}_t,\overline{\nu}_{n,t})\,]\} \tag{21}$$

$$\lambda^{\nu}_{j,n,t} \;\equiv 0.5\cdot\{[\,\lambda(\gamma_{j,t},\nu_{j,n,t})-\lambda(\gamma_{j,t},\overline{\nu}_{n,t})\,] \;+\; [\,\lambda(\overline{\gamma},\nu_{j,n,t})-\lambda(\overline{\gamma},\overline{\nu}_{n,t})\,]\} \tag{22}$$

so that λ^{γ} and λ^{ν} reflect, respectively, the effects of γ and ν disagreement on λ disagreement.

Table 7 Panel A (first four columns) and Figure 10(a) provide estimates and t-statistics for $\mathbb{D}(\alpha)$ and $\mathbb{D}(\lambda)$ for the wealth portfolio, all asset classes combined, and each individual asset class.[22] Risk premia disagreement drives most of the variation in expected return disagreement, but alpha disagreement also plays a quantitatively relevant role. For instance, for the wealth portfolio we have $\mathbb{D}(\lambda) = 75.7\%$ ($t_{stat} = 9.47$) and $\mathbb{D}(\alpha) = 24.3\%$ ($t_{stat} = 3.03$). Moreover, for all asset classes combined we have $\mathbb{D}(\lambda) = 57.4\%$ ($t_{stat} = 4.48$) and $\mathbb{D}(\alpha) = 42.6\%$

[22]In line with Equation 18, we estimate $\mathbb{D}(\lambda)$ for asset class n as the slope coefficient from an OLS regression of $\lambda_{j,n,t}$ onto $\mu_{j,n,t}$ with time fixed effects (and use Driscoll and Kraay (1998) with Newey and West (1994) lag selection for standard errors). We estimate $\mathbb{D}(\lambda)$ for all asset classes combined as the slope coefficient from an OLS regression of $\lambda_{j,n,t}$ onto $\mu_{j,n,t}$ with asset class by year fixed effects (and use standard errors clustered by year, asset class, and institution). $\mathbb{D}(\alpha)$ is estimated analogously with $\alpha_{j,n,t}$ replacing $\lambda_{j,n,t}$, but $\mathbb{D}(\alpha) = 1 - \mathbb{D}(\lambda)$ by construction.

($t_{stat} = 3.32$). Results vary by asset class, with the alpha effect dominating for US and Ex US Fixed Income as well as Hedge Funds and Commodities.

Similarly, Table 7 Panel B (first four columns) and Figure 10(b) provide estimates and t-statistics for $\mathbb{D}_\lambda(\gamma)$ and $\mathbb{D}_\lambda(\nu)$ for the wealth portfolio, all asset classes combined, and each individual asset class.[23] In contrast to the λ effect on μ overall time variation, the λ effect on μ disagreement is driven roughly equally by risk price (γ) and risk quantity (ν). For instance, for the wealth portfolio we have $\mathbb{D}_\lambda(\gamma) = 50.7\%$ ($t_{stat} = 8.28$) and $\mathbb{D}_\lambda(\nu) = 49.3\%$ ($t_{stat} = 8.04$). Moreover, for all asset classes combined we have $\mathbb{D}_\lambda(\gamma) = 42.5\%$ ($t_{stat} = 4.59$) and $\mathbb{D}_\lambda(\nu) = 57.6\%$ ($t_{stat} = 6.22$). While risk quantity drives all the risk premia effect for commodities and the two fixed income asset classes, the risk premia effect is small for these asset classes in the first place.

5.3 Decomposing μ Disagreement (Persistent vs Transitory)

As in the μ time variation analysis, we can separate persistent and transitory disagreement. To do that, we estimate a fixed effects model analogous to Equation 4 for each expected return component (using institutions with at least two years in our dataset). For instance, for μ we estimate

$$\mu_{j,n,t} = \mu_{n,t}^{fe} + \mu_{n,j}^{fe} + \epsilon_{j,n,t} \tag{23}$$

and treat $\mu_{n,j} \equiv \mu_{n,j}^{fe}$ as the persistent disagreement and $\Delta\mu_{j,n,t} \equiv \epsilon_{j,n,t}$ as the transitory disagreement. Intuitively, $\mu_{n,j}$ reflects disagreement that never vanishes (since it does not have a time index) so that an institution can be generally optimistic or pessimistic. In contrast, $\Delta\mu_{j,n,t}$ reflects short-lived disagreement since it moves over time and averages to zero within each institution (for each asset class). So, if $\Delta\mu$ indicates an institution is optimistic about

[23] In line with Equation 19, we estimate $\mathbb{D}_\lambda(\nu)$ for asset class n as the slope coefficient from an IV regression of $\lambda_{n,t}^{\nu}$ onto $\lambda_{n,t}$ with $\mu_{n,t}$ as the instrument and time fixed effects (and use Driscoll and Kraay (1998) with Newey and West (1994) lag selection for standard errors). We estimate $\mathbb{D}_\lambda(\nu)$ for all asset classes combined as the slope coefficient from an IV regression of $\lambda_{n,t}^{\nu}$ onto $\lambda_{n,t}$ with $\mu_{n,t}$ as the instrument and asset class by year fixed effects (and use standard errors clustered by year, asset class, and institution). $\mathbb{D}_\lambda(\gamma)$ is estimated analogously with $\lambda_{n,t}^{\gamma}$ replacing $\lambda_{n,t}^{\nu}$, but $\mathbb{D}_\lambda(\gamma) = 1 - \mathbb{D}_\lambda(\nu)$ by construction.

an asset class in a given year, then it must also imply the institution is pessimistic about the same asset class in other years (on average).

As Table 7 shows, most of the variation in disagreement reflects persistent disagreement. In particular, 70% of the total μ disagreement is driven by persistent disagreement and 79% of the total λ disagreement reflects persistent disagreement. This result indicates that the overall disagreement decomposition in the previous subsection is more reflective of persistent disagreement.

Table 7 Panel A (last eight columns) and Figures 11(a) and 11(b) provide estimates and t-statistics for $\mathbb{D}(\alpha)$ and $\mathbb{D}(\lambda)$ using only persistent disagreement or only transitory disagreement. The key finding is that λ plays an even stronger role for persistent disagreement, but a weaker role in transitory disagreement. In fact, for transitory disagreement, λ and α have similar quantitative effects. For instance, for the wealth portfolio transitory disagreement, we have $\mathbb{D}(\lambda) = 61.0\%$ ($t_{stat} = 7.51$) and $\mathbb{D}(\alpha) = 39.0\%$ ($t_{stat} = 4.80$).

The difference is even more striking when we consider the role of risk quantity and risk price in the risk premia effect, which is covered in Table 7 Panel B (last eight columns) and Figures 11(c) and 11(d). The risk premia effect on persistent disagreement is mainly driven by risk quantity disagreement whereas the risk premia effect on transitory disagreement is mostly driven by risk price heterogeneity.

6 Conclusion

In this paper, we use the long-term Capital Market Assumptions (CMAs) of major investment institutions from 1987 to 2022 to quantify the sources of their expected return variation (both time variation and disagreement). Our findings indicate that perceived market risk premia account for most of the countercyclicality and overall time variation in subjective expected returns, with the remainder attributed to alphas. The impact of risk premia is mainly due to variation in risk quantities (i.e., subjective covariances with the wealth portfolio) rather than variation in risk price (i.e., risk aversion). However, risk price plays an important role, explaining about half of the short-lived effect of risk premia on expected returns. In terms of disagreement, market risk premia are again the primary factor, but alphas have a significant influence. Moreover, both risk price and risk quantity contribute (roughly) equally to the effect of risk premia on expected return disagreement.

We obtain the aforementioned results using a decomposition in which risk premia arise entirely from market risk. If, in reality, investors are also concerned about other risks, then the role of alpha in explaining expected return variation in our analysis can be viewed as an upper bound on the effect of subjective mispricing (as alphas also reflect non-market risk premia). Since our main finding is that risk premia play the major part in explaining variation in expected returns, this upper bound interpretation does not impose any limit on the qualitative interpretation of our results. Nevertheless, for US equities, we show that alpha variation is almost entirely explained by variation in subjective mispricing from surveys that are agnostic about the relevant risk factors (so, the upper bound is tight). This result is important because the US Equity asset class dominates the wealth portfolio and much of the subjective beliefs literature. Of course, for some other asset classes, non-market risk premia may drive alpha variation, as suggested by how CMAs discuss the risk premia of hedge funds.

Importantly, given the nature of CMAs, our results speak to variation in subjective long-term expected returns. It is entirely possible that perceived mispricing explains a large fraction of variation in subjective short-term expected returns. Long-term expectations are more important when thinking about the overall variation and cyclicality in asset prices (Gonçalves (2023) and Cho and Polk (2024)) as well as capital allocation in the economy (Binsbergen and Opp (2019)). They are also key when studying the allocations of long-term institutional investors such as pension funds (Andonov et al. (2025)). However, short-term expectations are important in many contexts (e.g., when considering investors' market timing behavior). Future research should explore the different behavior of short and long-term return expectations (see, e.g., the subsequent work by Bastianello and Peng (2025)).

Overall, our results have important asset pricing implications. For instance, asset pricing models with subjective beliefs should recognize that variation in subjective expected returns over time and across investors is largely due to variation in risk perceptions (at least for institutional investors). This aspect highlights the importance of investor heterogeneity in models of subjective beliefs via heterogeneity in beliefs about risk. While the return expectations of some investors mirror recent past returns with little connection to risk (Greenwood and Shleifer (2014)), we show that the CMAs from institutional investors imply expected returns that better reflect risk perceptions. In addition, risk-based models that aim to capture the behavior of large institutional investors, who are important participants in most asset classes, should be consistent with the belief behavior we document herein. In particular, while risk aversion variation plays a role in expected return disagreement and short-lived expected return movements, the overall time variation in expected returns is mainly linked to time variation in perceived quantities of risk.

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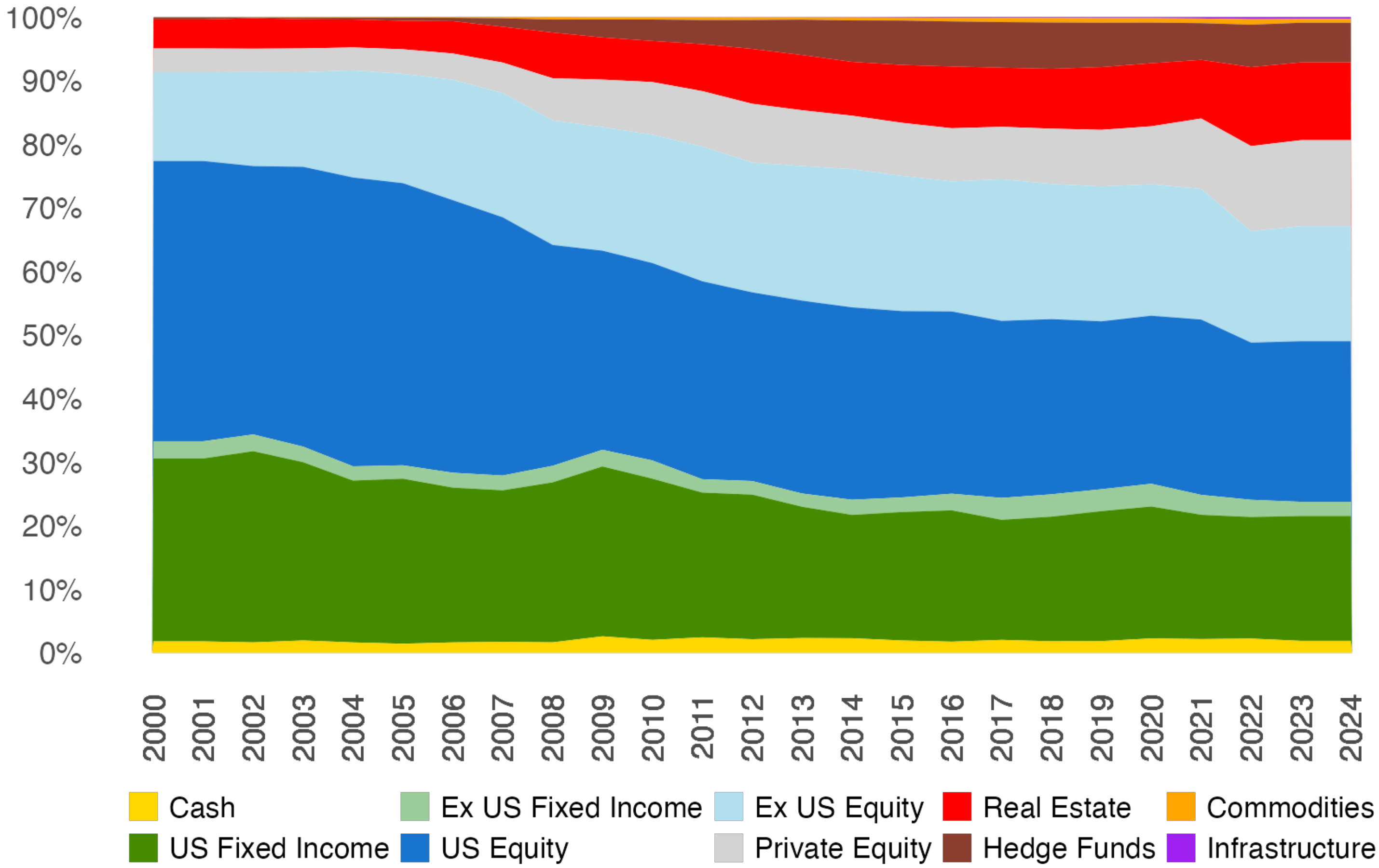


Figure 2
Wealth Portfolio Weights from US Public Pension Funds

This figure depicts the wealth portfolio weights used in our empirical analysis. We proxy for the wealth portfolio weights using the aggregated portfolio weights of US public pension funds obtained from the Center for Retirement Research at Boston College (see Internet Appendix A.3 for details). Since we do not observe weights before 2001, all weights for $t \leq 2001$ are set to match the 2001 weights.

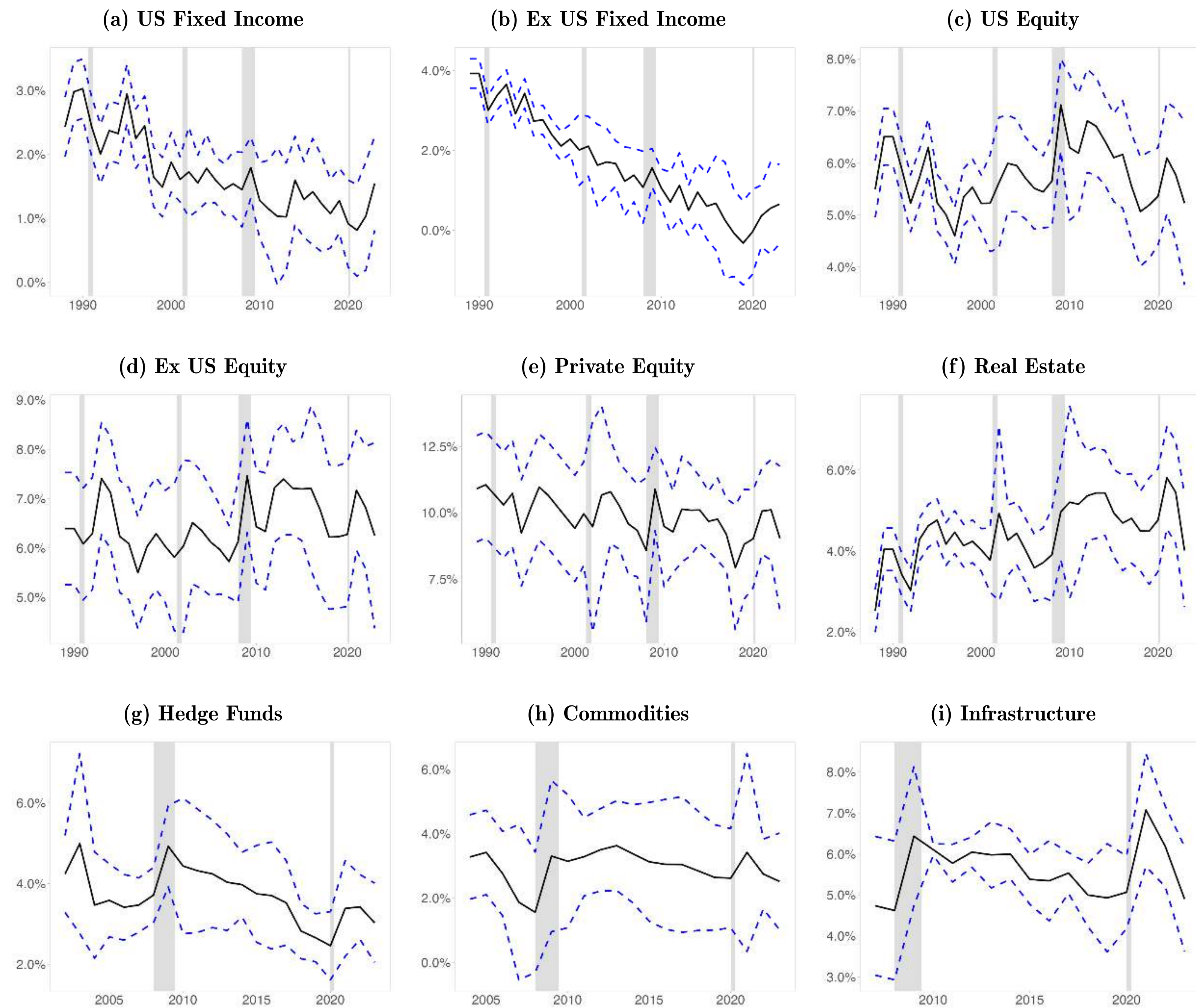


Figure 3

Expected Return Time Variation and Disagreement: $\mu \pm \sigma_\mu$

This figure depicts (in the black solid line) the time series of subjective expected excess returns aggregated across institutions ($\mu_{n,t}$ from Equation 5) for each asset class in our analysis. It also shows (in the blue dashed lines) the $\mu_{n,t} \pm \sigma_{\mu,n,t}$, where $\sigma_{\mu,n,t} = \sqrt{\mathbb{V}ar_t[\mu_{j,n,t} - \overline{\mu}_{n,t}]}$ reflects the level of disagreement across institutions (js) for asset class n in year t. For $t < 1999$ (i.e., years when we have less than 5 institutions in the sample), we replace $\sigma_{\mu,n,t}$ with $\sigma_{\mu,n,1999}$. Subsection 1.2 describes our beliefs data and Subsection 1.4 provides an analysis of this figure.

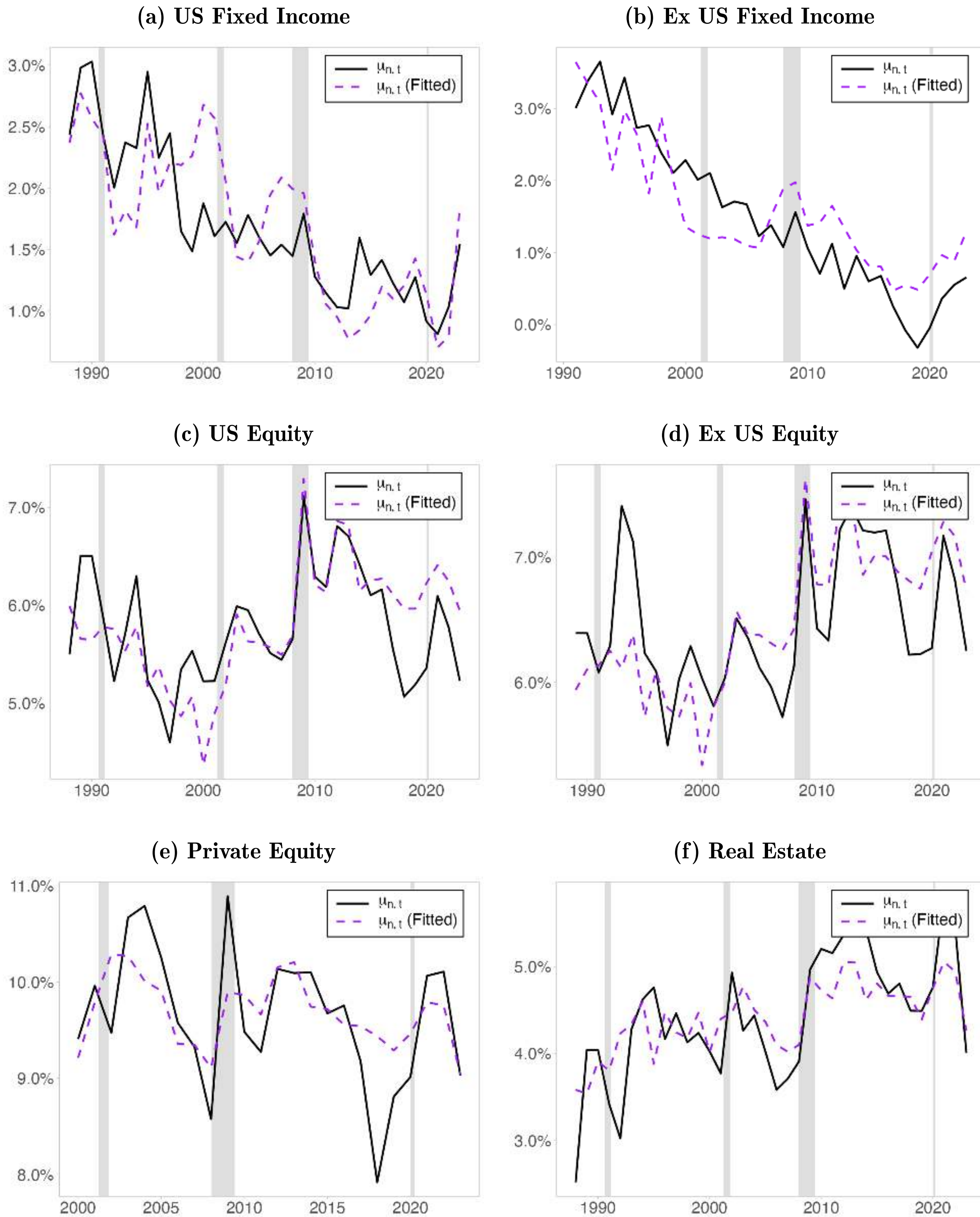


Figure 4

CMA μ vs Yield-Based μ

This figure depicts time series plots of aggregate expected excess returns from CMAs ($\mu_{n,t}$) in solid black lines against their fitted values from the simple yield-based model of CMA formation we propose in Subsection 3.1 in dashed purple lines (estimated in the first column of Table 4). The model implies

$$\mathbb{E}_t[R^{real}_{cash}] = const + \omega \cdot y_{cash,t} + \varepsilon_{cash,t} \qquad \text{and} \qquad \mu_{n,t} = const + b_n \cdot y_{n,t} - \omega \cdot y_{cash,t} + \varepsilon_{n,t}$$

where y values reflect real yields (with measurement described in Internet Appendix A.4). Subsection 1.2 describes our beliefs data while Subsection 3.1 discusses the results from this figure.

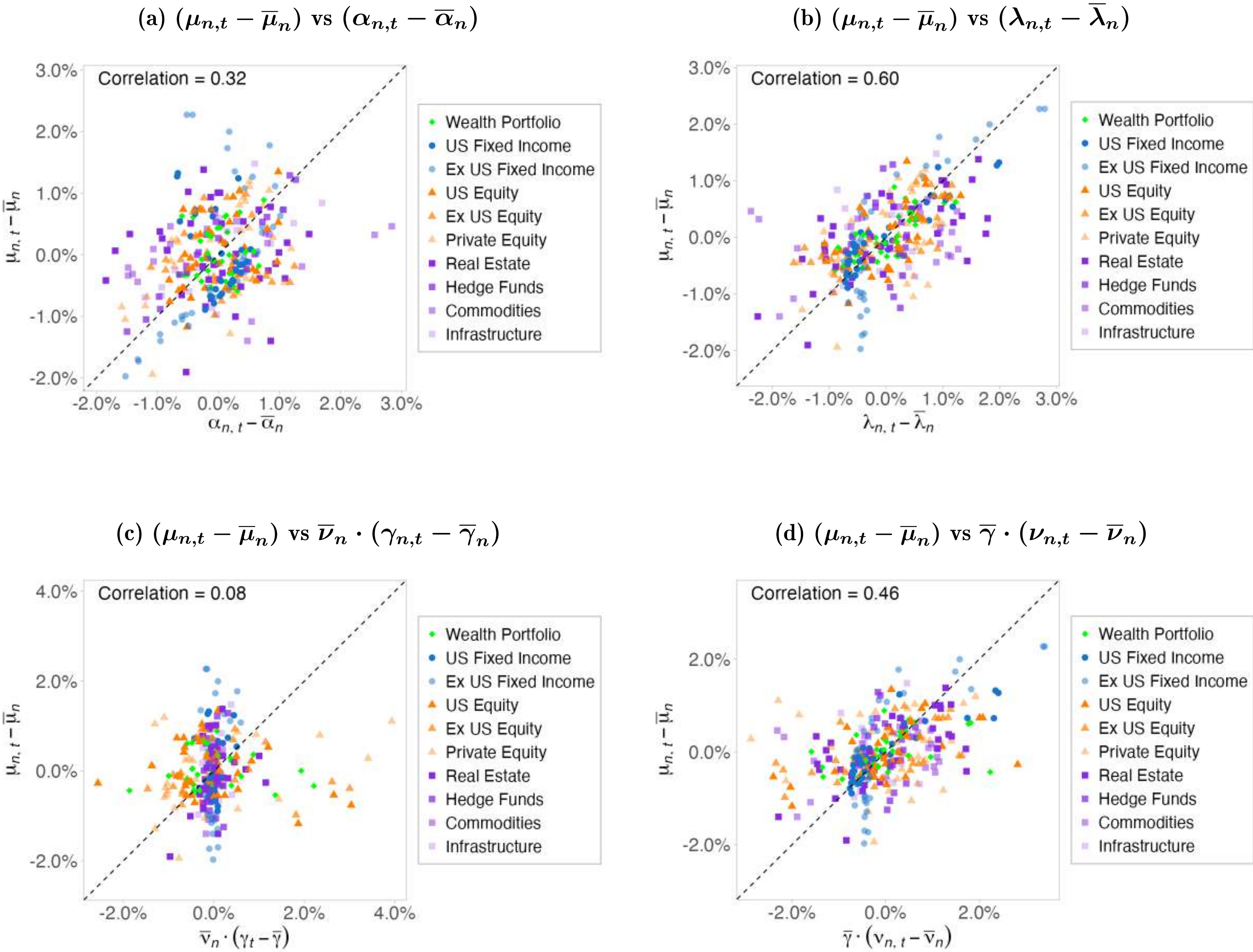


Figure 5

Components of Expected Return Time Variation

This figure depicts scatterplots of aggregate demeaned expected returns $(\mu_{n,t} - \overline{\mu}_n)$ against their components for the wealth portfolio and each asset class in our analysis. All panels focus on aggregate expected return time variation. In Panels (a) and (b), the expected return components are due to time variation in alphas $(\alpha_{n,t} - \overline{\alpha}_n)$ and risk premia $(\lambda_{n,t} - \overline{\lambda}_n)$. In Panels (c) and (d), the expected return components are due to time variation in risk aversion, $\overline{\nu}_n \cdot (\gamma_t - \overline{\gamma})$, and risk quantity, $\overline{\gamma} \cdot (\nu_{n,t} - \overline{\nu}_n)$. Subsection 1.2 describes our beliefs data while Subsection 4.1 discusses the results from this figure.

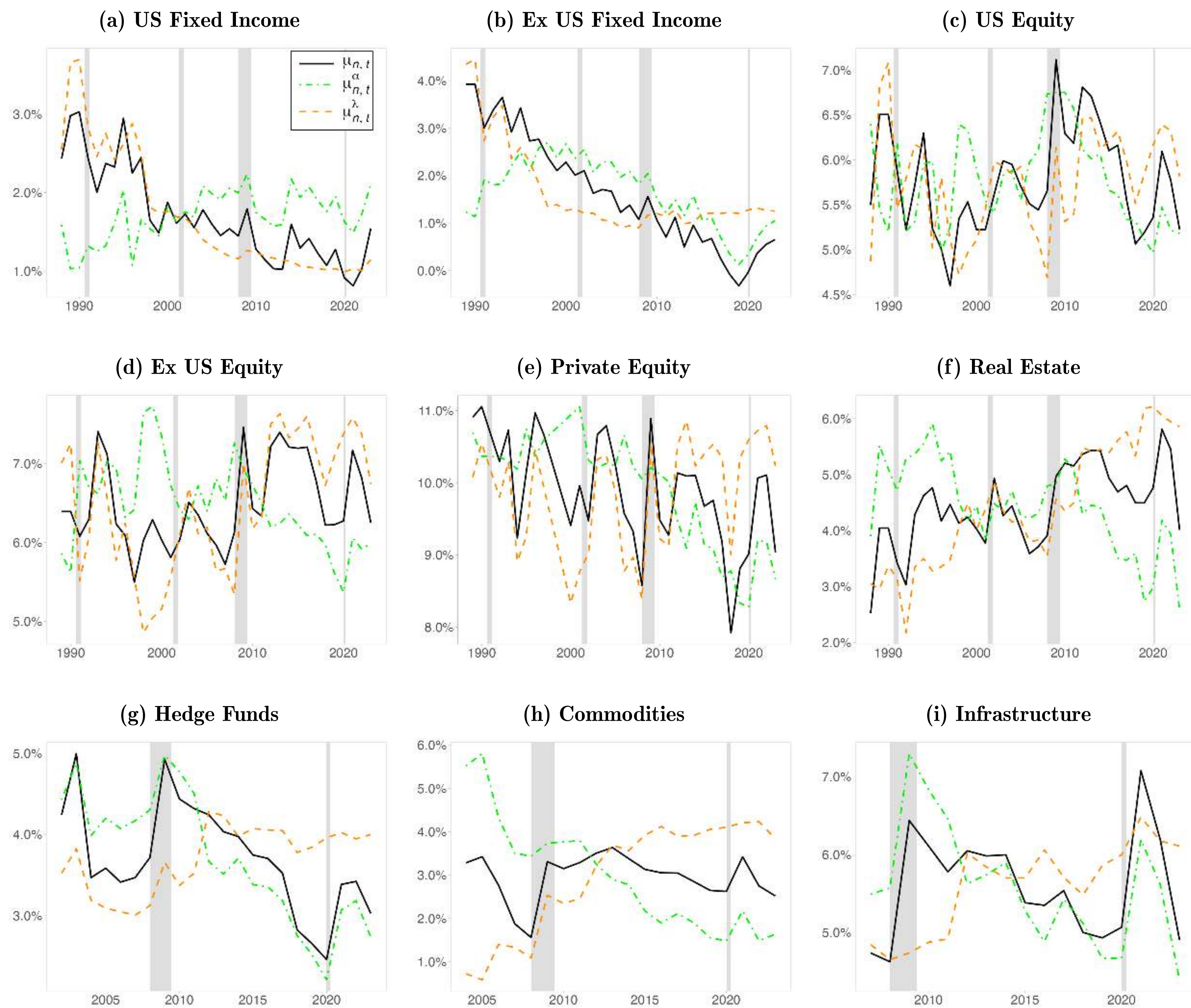


Figure 6
Time Series of Expected Return Components

This figure depicts time series plots of aggregate expected returns ($\mu_{n,t}$) in solid black lines against counterfactual aggregate expected returns that would prevail if (i) only alphas varied over time ($\mu^{\alpha}_{n,t} = \alpha_{n,t} + \overline{\lambda}_n$) in dashed-dotted green lines or (ii) only risk premia varied over time ($\mu^{\lambda}_{n,t} = \overline{\alpha}_n + \lambda_{n,t}$) in dashed orange lines. Subsection 1.2 describes our beliefs data while Subsection 4.1 discusses the results from this figure.

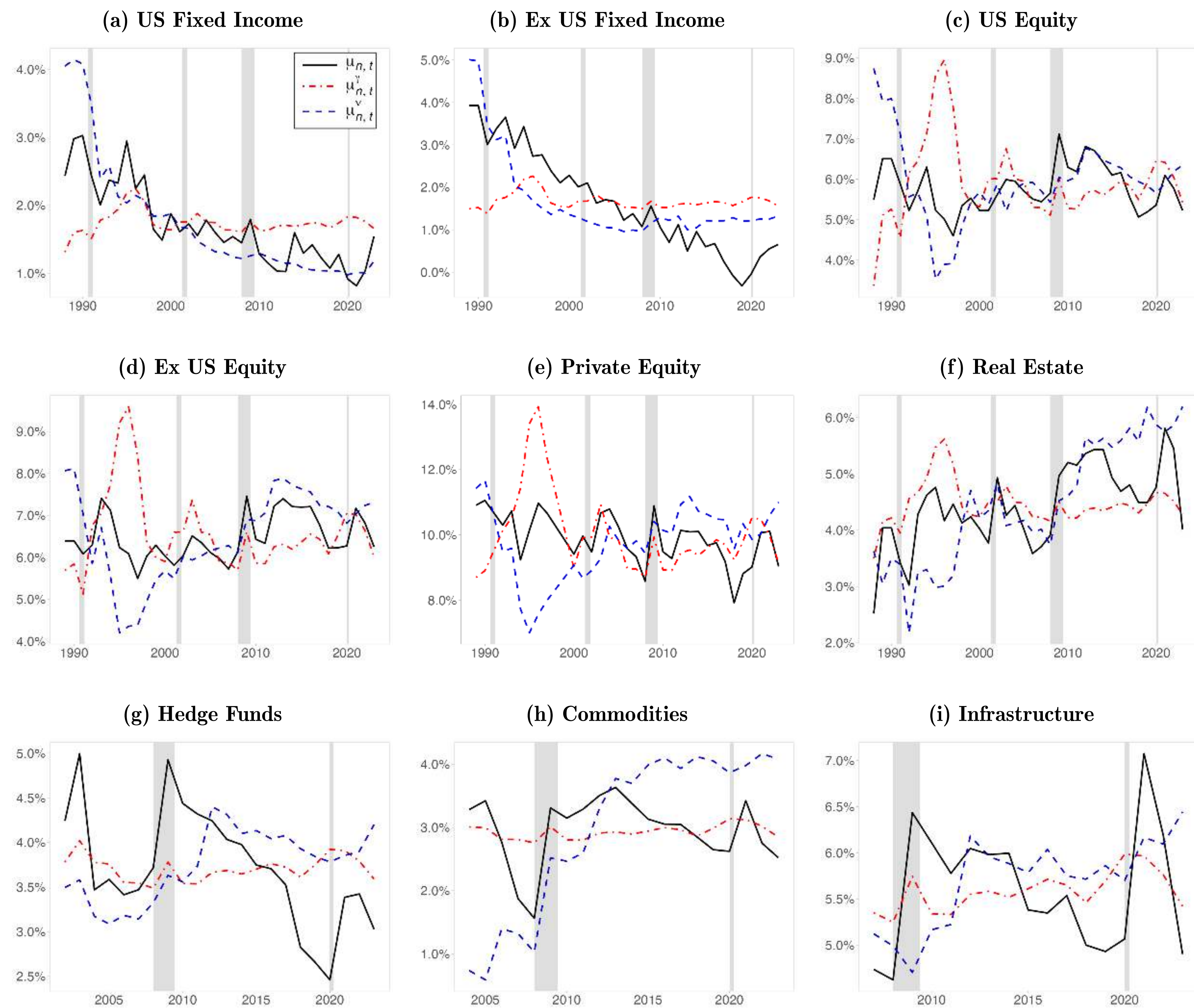


Figure 7
Time Series of Risk Premia Components

This figure depicts time series plots of aggregate expected returns ($\mu_{n,t}$) in solid black lines against counterfactual aggregate expected returns that would prevail if (i) only risk aversion varied over time ($\mu^{\gamma}_{n,t} = \overline{\alpha}_n + \gamma_t \cdot \overline{\nu}_n$) in dashed-dotted red lines or (ii) only risk quantity varied over time ($\mu^{\nu}_{n,t} = \overline{\alpha}_n + \overline{\gamma} \cdot \nu_{n,t}$) in dashed blue lines. Subsection 1.2 describes our beliefs data while Subsection 4.1 discusses the results from this figure.

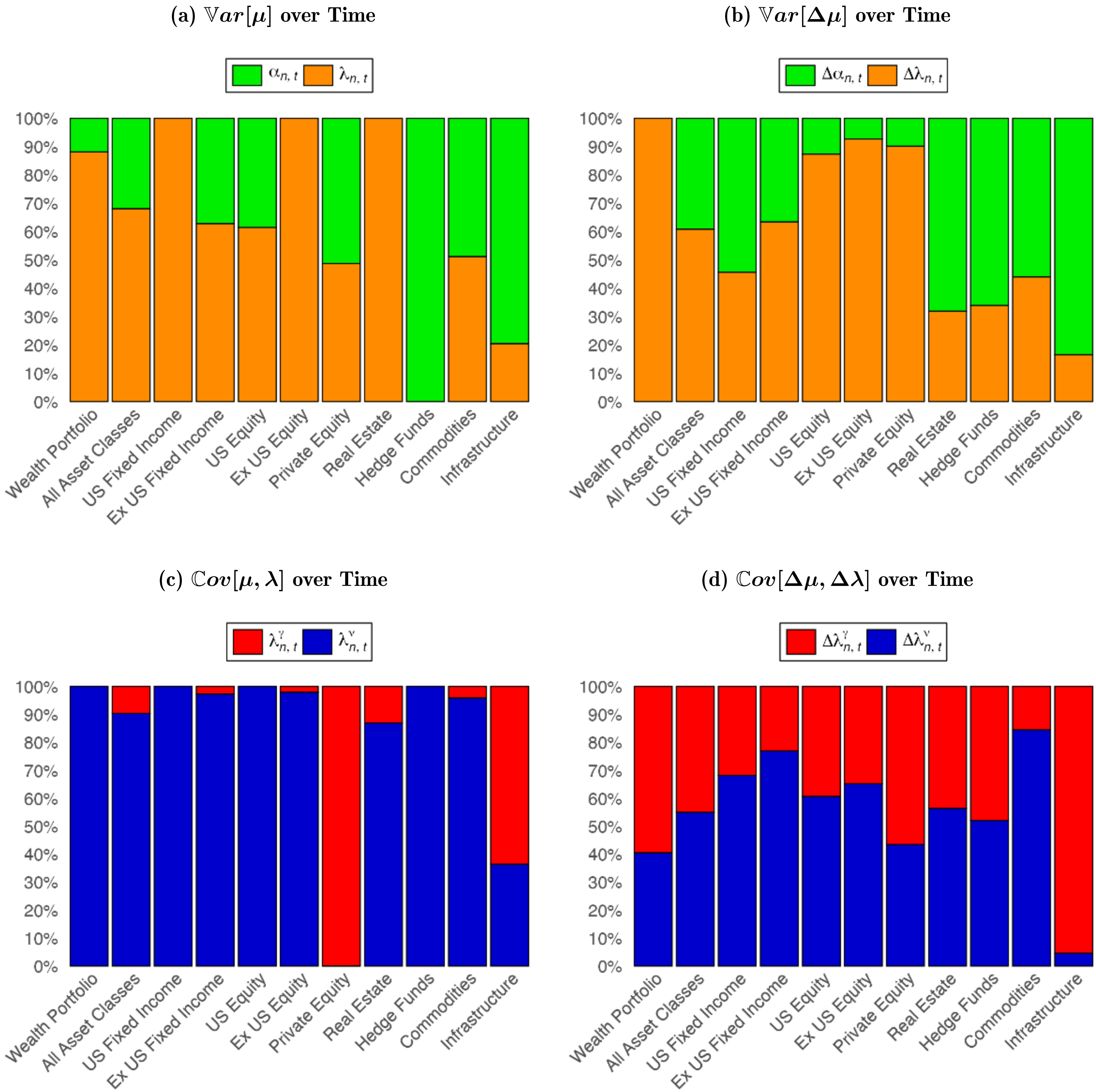


Figure 8

Decomposing Expected Return Time Variation

This figure provides a visualization of the results reported in Table 6. Panel (a) depicts decompositions of aggregate expected return time variation, $\mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n]$, based on Equation 14. Panel (c) depicts decompositions of the risk premium effect on aggregate expected return overall time variation, $\mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n, \lambda_{n,t} - \overline{\lambda}_n]$, based on Equation 15. Panels (b) and (d) are analogous to Panels (a) and (c), respectively, but replace μ with $\Delta\mu$ (same for μ components) to focus on transitory time variation, which is a relatively small portion of the total time variation. Subsection 1.2 describes our beliefs data while Subsections 4.2 and 4.3 discuss the results from this figure.

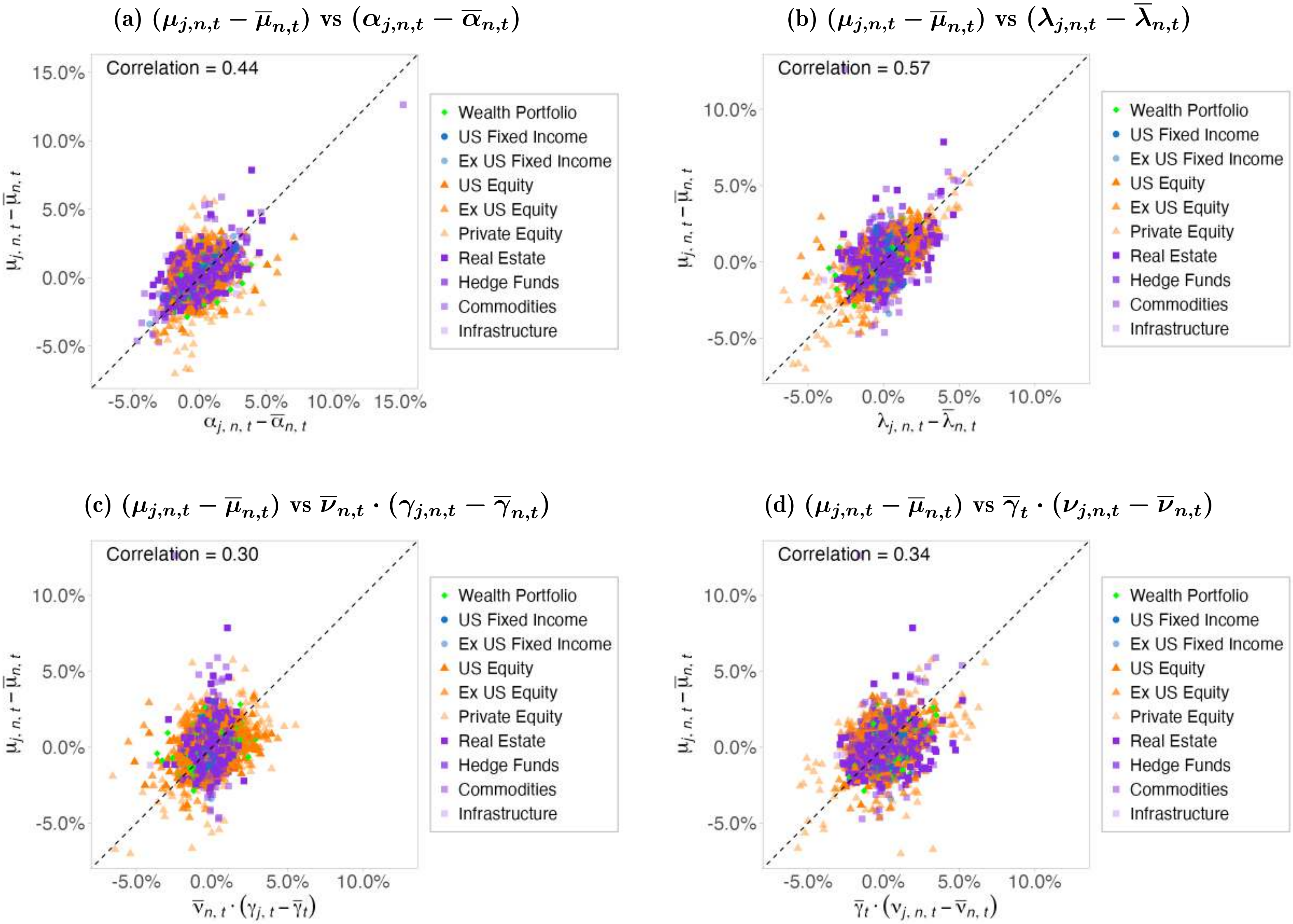
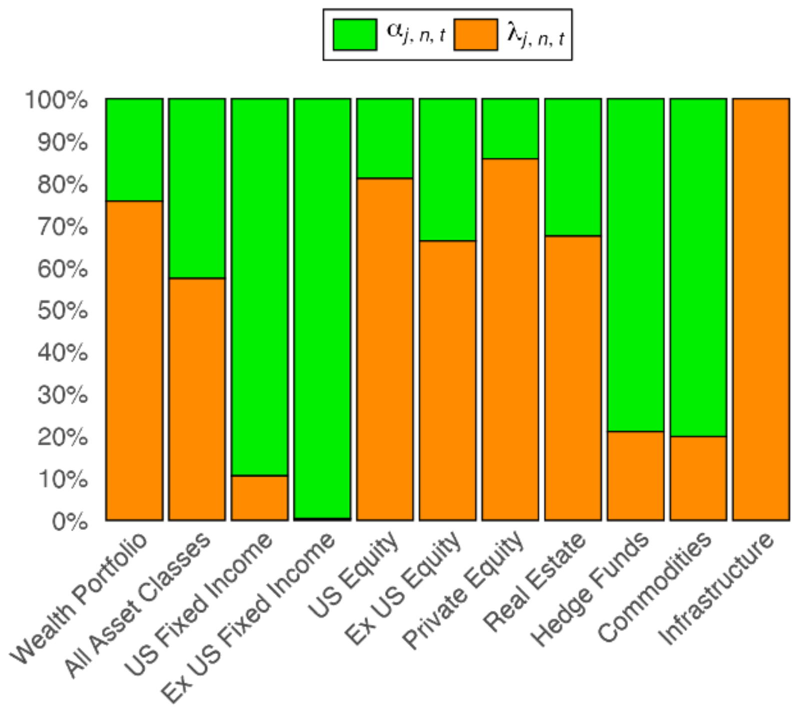


Figure 9

Components of Expected Return Disagreement

This figure depicts scatterplots of institution-level demeaned expected returns $(\mu_{j,n,t} - \overline{\mu}_{n,t})$ against their components for the wealth portfolio and each asset class in our analysis. All panels focus on expected return disagreement across institutions. In Panels (a) and (b), the expected return components are due to disagreement in alphas $(\alpha_{j,n,t} - \overline{\alpha}_{n,t})$ and risk premia $(\lambda_{j,n,t} - \overline{\lambda}_{n,t})$. In Panels (c) and (d), the expected return components are due to disagreement in risk aversion, $\overline{\nu}_{n,t} \cdot (\gamma_{j,t} - \overline{\gamma}_t)$, and risk quantity, $\overline{\gamma}_t \cdot (\nu_{j,n,t} - \overline{\nu}_{n,t})$. Subsection 1.2 describes our beliefs data while Subsection 5.1 discusses the results from this figure.

(a) $\mathbb{V}ar[\boldsymbol{\mu}]$ Across Institutions



(b) $\mathbb{C}ov[\boldsymbol{\mu}, \boldsymbol{\lambda}]$ Across Institutions

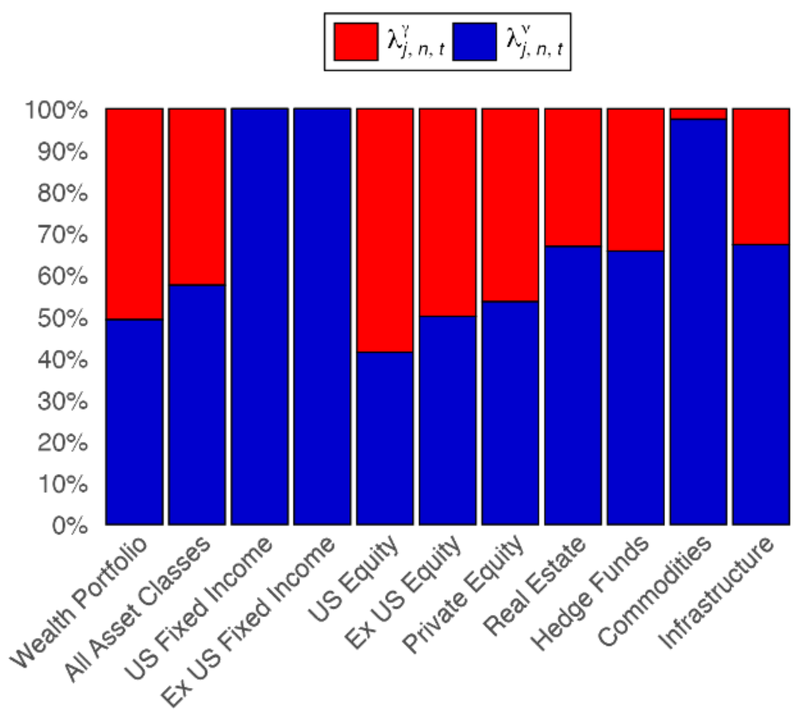


Figure 10

Decomposing Expected Return Disagreement

This figure provides a visualization of the results reported in Table 7 ("total disagreement" block of each panel). Panel (a) depicts decompositions of expected return disagreement across institutions, $\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]$, based on Equation 18. Panel (b) depicts decompositions of the risk premium effect on expected return disagreement across institutions, $\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}, \lambda_{j,n,t} - \overline{\lambda}_{n,t}]$, based on Equation 19. Subsection 1.2 describes our beliefs data while Subsection 5.2 discusses the results from this figure.

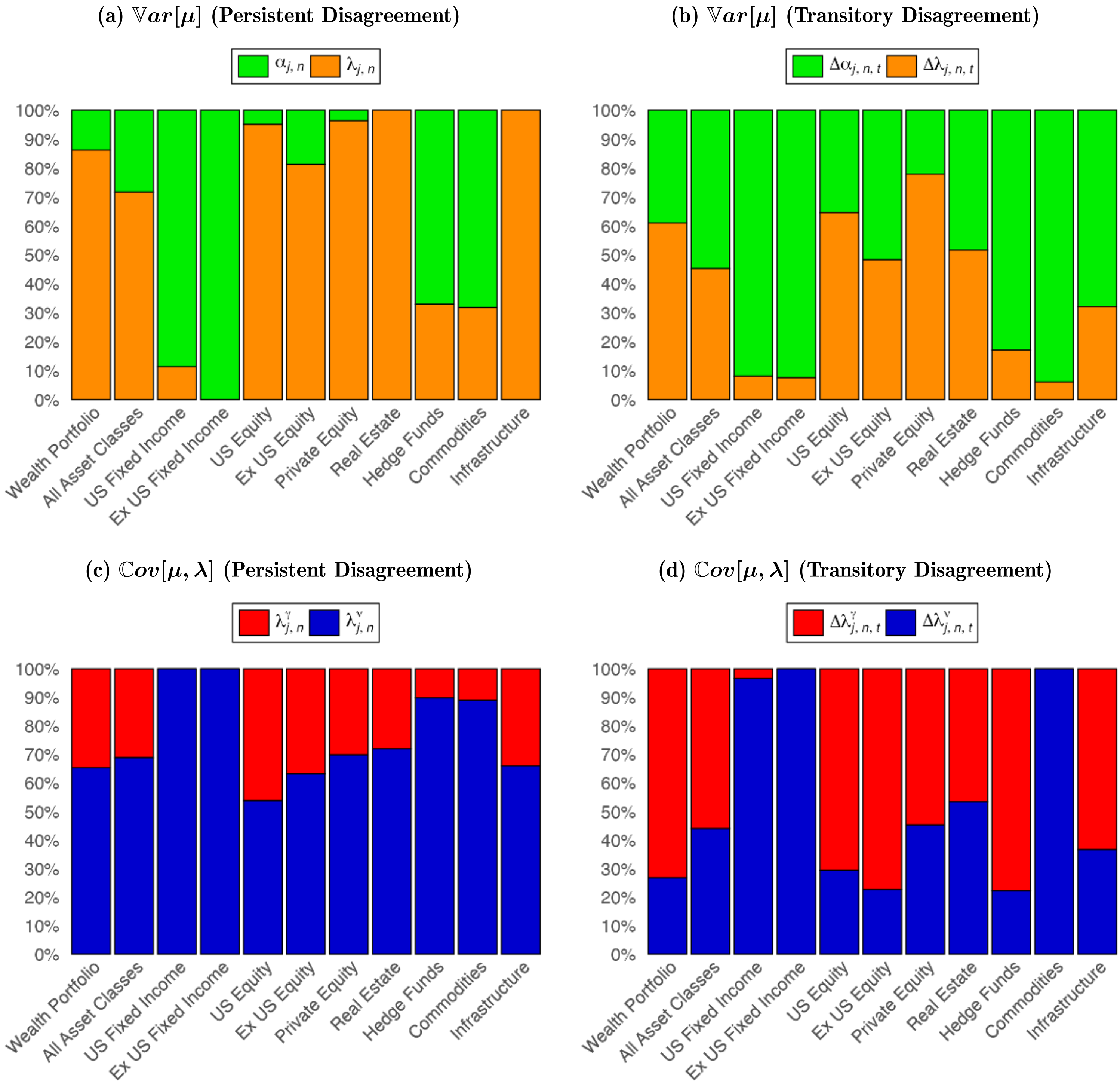


Figure 11

Decomposing Expected Return Disagreement (Persistent vs Transitory)

This figure provides a visualization of the results reported in Table 7 ("persistent disagreement" and "transitory disagreement" blocks of each panel). Panel (a) and (b) depict decompositions of expected return disagreement across institutions, $\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]$, based on equations analogous to Equation 18, but using only the persistent component (Panel (a)) or only the transitory components (Panel (b)). Panels (c) and (d) depict decompositions of the risk premium effect on expected return disagreement across institutions, $\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}, \lambda_{j,n,t} - \overline{\lambda}_{n,t}]$, based on equations analogous to Equation 19, but using only the persistent component (Panel (c)) or only the transitory components (Panel (d)). The persistent ($\mu_{j,n} \equiv \mu^{fe}_{j,n}$) and transitory ($\Delta\mu_{j,n,t} \equiv \epsilon_{j,n,t}$) disagreement parts of μ are obtained from Equation 23 (using institutions with at least two years in our dataset), with analogous equations applied to μ components (α, λ, λ^{γ}, and λ^{ν}). Subsection 1.2 describes our beliefs data while Subsection 5.3 discusses the results from this figure.

Table 1
Asset Managers and Investment Consultants in our Sample

The table reports information on the list of institutions that have at least one CMA in our sample. Panel A details the asset managers (or simply "managers"), with information on their Assets Under Manager (AUM) ranking, dollar value (in trillion of dollars), and fraction relative to the total AUM of the top 50 AUM managers in the world. The data is from the October 2022 report on the world's largest 500 asset managers by the Thinking Ahead Institute and the Pensions & Investments company (TAI-P&I). Three of the managers in our dataset were not covered in the TAI-P&I reports, and thus we obtained their AUM from alternative sources and provided the rank they would have if present in the 2022 TAI-P&I report (this is why Merrill Lynch and Morgan Stanley both are ranked #18). BGI (or Barclays Global Investors) was acquired by Blackrock in 2009, and thus we do not report BGI AUM information. One institution has not provided us authorization to release their name, and thus we refer to it as "Manager #22" (and do not report their AUM information). Panel B details the investment consultants (or simply "consultants"), with information on their role as primary consultants for US public pension funds (note that each US public pension fund has at most one primary consultant). Specifically, each row in Panel B reports information about the pension funds for which the given consultant is the primary consultant of on average from 2001 to 2021. The data is from the Center for Retirement Research at Boston College. Section 1.2 provides more details about our subjective beliefs data.

PANEL A - Asset Managers				PANEL B - Investment Consultants			
	AUM Information				US Pension Fund Consultant		
Manager Name	Rank	$ AUM	% Top 50	Consultant Name	# Funds	% Funds	% AUM
BGI	-	-	-	**Angeles**	1	0.3%	0.4%
BNY Mellon	9	$2.43 T	2.8%	**Aon**	19	8.8%	14.8
Capital Group	7	$2.72 T	3.1%	**Buckingham**	-	-	-
Envestnet	77	$0.36 T	0.4%	**Callan**	24	11.2%	11.9%
Franklin Templeton	17	$1.58 T	1.8%	**CAPTRUST**	-	-	-
Goldman Sachs	8	$2.47 T	2.9%	**Cliffwater**	1	0.5%	0.6%
Invesco	15	$1.61 T	1.9%	**CSG**	-	-	-
JP Morgan	5	$3.11 T	3.6%	**CWO**	-	-	-
Merrill Lynch	18	$1.57 T	1.8%	**Inspire**	-	-	-
Morgan Stanley	18	$1.49 T	1.7%	**MacroAnalytics**	-	-	-
Northern Trust	16	$1.61 T	1.9%	**Meketa**	6	2.6%	2.4%
Nuveen	22	$1.26 T	1.5%	**Mercer**	6	2.6%	2.5%
PFM	156	$0.13 T	0.2%	**Milliman**	1	0.7%	0.2%
PGIM	13	$1.74 T	2.0%	**NEPC**	19	8.7%	4.5%
PIMCO	12	$2.00 T	2.3%	**PCA**	9	4.0%	7.4%
Russell Inv	81	$0.34 T	0.4%	**ResearchAffiliates**	-	-	-
SEI	85	$0.31 T	0.4%	**RVK**	8	3.8%	6.2%
T. Rowe Price	14	$1.69 T	2.0%	**Segal**	2	0.7%	0.1%
Vanguard	2	$8.47 T	9.8%	**Sellwood**	-	-	-
Voya	71	$0.41 T	0.5%	**Strategic Inv Sol**	8	3.5%	6.5%
Wells Fargo	16	$1.61 T	1.9%	**Verus**	4	1.7%	1.2%
Manager #22	-	-	-	**Wilshire**	11	5.3	13.1
				WTW	2	0.7%	0.5%
Total	-	> $37 T	> 42.7%	**Total**	$\geq$ 121	$\geq$ 55.1%	$\geq$ 72.3%

Table 2

Sample Coverage of CMAs (by Year)

This table reports information on our sample of Capital Market Assumptions (CMAs) over time. The left panel details, for each year, the total number of CMAs in our sample, the number of direct CMAs from the underlying institutions, the number of CMAs from asset managers (or simply "managers"), and the number of CMAs from investment consultants (or simply "consultants"). The right panel reports, for each year, the number of CMAs covering each of the asset classes in our sample. Section 1.2 provides more details about our subjective beliefs data.

	# of CMAs in Dataset				# of CMAs Covering the Given Asset Class									
	All CMAs	Direct CMAs	Managers	Consultants	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1987	1	0	0	1	1	1	0	1	0	0	1	0	0	0
1988	1	1	0	1	1	1	1	1	1	1	1	0	0	0
1989	1	1	0	1	1	1	1	1	1	1	1	0	0	0
1990	1	1	0	1	1	1	1	1	1	0	1	0	0	0
1991	1	1	0	1	1	1	1	1	1	1	1	0	0	0
1992	1	1	0	1	1	1	1	1	1	1	1	0	0	0
1993	1	1	0	1	1	1	1	1	1	1	1	0	0	0
1994	1	1	0	1	1	1	1	1	1	1	1	0	0	0
1995	1	1	0	1	1	1	1	1	1	1	1	0	0	0
1996	1	1	0	1	1	1	1	1	1	1	1	0	0	0
1997	3	3	1	2	3	3	3	3	3	1	3	0	1	0
1998	4	4	1	3	4	4	4	4	4	1	4	0	1	0
1999	5	4	1	4	5	5	4	5	5	3	5	0	0	0
2000	5	5	1	4	5	5	4	5	5	3	5	0	0	0
2001	9	5	2	7	9	8	5	9	9	7	8	2	0	0
2002	8	5	1	7	8	8	4	8	8	6	7	3	0	0
2003	8	6	1	7	8	8	5	8	8	7	8	3	1	0
2004	8	6	1	7	8	8	5	8	8	8	8	4	1	0
2005	9	7	2	7	9	9	7	9	9	9	9	6	6	0
2006	10	8	1	9	10	10	7	10	10	10	10	7	6	1
2007	13	9	3	10	13	13	10	13	13	13	13	9	9	1
2008	12	9	4	8	12	12	9	12	11	10	12	7	8	2
2009	15	11	5	10	15	14	10	15	13	13	15	9	11	2
2010	15	11	5	10	15	14	11	15	13	13	15	10	11	2
2011	15	11	4	11	15	14	11	15	15	14	15	11	12	3
2012	18	13	6	12	18	18	14	18	17	17	18	13	14	5
2013	14	11	3	11	14	14	11	14	14	14	14	11	12	5
2014	15	13	5	10	15	15	12	15	15	14	15	11	12	5
2015	15	13	6	9	15	15	13	15	15	13	15	11	13	5
2016	15	14	6	9	15	15	12	15	15	13	15	11	13	4
2017	16	15	7	9	16	16	13	16	16	13	16	13	14	5
2018	23	19	12	11	23	22	15	23	22	19	23	16	18	7
2019	20	19	10	10	20	20	14	20	20	17	20	16	17	7
2020	25	22	11	14	25	23	18	25	25	20	25	20	21	12
2021	21	21	11	10	21	20	16	21	20	19	21	16	17	10
2022	30	28	18	12	30	29	25	30	29	24	28	21	24	12
Total	361	301	128	233	361	352	271	361	351	309	357	230	242	88

(0) Cash; (1) US Fixed Income; (2) Ex US Fixed Income; (3) US Equity; (4) Ex US Equity;
(5) Private Equity; (6) Real Estate; (7) Hedge Funds; (8) Commodities; (9) Infrastructure

Table 3
Summary of Expected Return Components

Panel A provides average values for each expected return component (from Equations 2 and 3). We provide both the time-series averages and the pooled averages. Panel B provides information about the variation in each expected return component. We provide both the time-series variation and the cross-institution variation (i.e., disagreement). Panel C provides correlations of expected return components. We provide both the time-series correlations and the cross-institution correlations. Subsection 1.2 describes our beliefs data while Subsection 2.2 discusses the results from this table.

PANEL A - Average Values of Expected Return Components

	Number of			Time-Series Averages						Pooled Averages					
Asset Class	Inst.	Years	Obs.	μ	σ	α	λ	ν	γ	μ	σ	α	λ	ν	γ
Wealth Portfolio	45	36	361	4.7%	11.8%	0.8%	3.9%	1.4%	2.87	4.5%	11.6%	0.9%	3.6%	1.4%	2.70
US Fixed Income	42	36	352	1.7%	5.8%	0.8%	0.9%	0.3%	-	1.4%	5.2%	0.9%	0.5%	0.2%	-
Ex US Fixed Income	36	35	271	1.7%	9.9%	0.5%	1.1%	0.4%	-	0.9%	8.6%	0.2%	0.7%	0.3%	-
US Equity	45	36	361	5.8%	17.0%	0.4%	5.4%	1.9%	-	5.5%	17.0%	0.4%	5.0%	1.9%	-
Ex US Equity	44	35	351	6.5%	19.8%	0.9%	5.5%	1.9%	-	6.2%	19.2%	0.9%	5.3%	2.0%	-
Private Equity	34	34	309	9.9%	28.4%	2.3%	7.6%	2.6%	-	9.0%	25.8%	2.3%	6.7%	2.5%	-
Real Estate	42	36	357	4.4%	14.7%	2.4%	2.0%	0.7%	-	4.5%	14.0%	2.1%	2.4%	0.9%	-
Hedge Funds	33	22	230	3.7%	8.0%	2.0%	1.7%	0.6%	-	3.5%	7.9%	1.7%	1.8%	0.7%	-
Commodities	33	22	242	3.0%	18.3%	1.4%	1.5%	0.5%	-	3.0%	18.3%	1.1%	1.9%	0.7%	-
Infrastructure	17	17	88	5.6%	15.2%	2.7%	2.9%	1.1%	-	5.6%	15.3%	2.1%	3.4%	1.2%	-

PANEL B - Variation in Expected Return Components

	Number of			Time-Series Variation						Cross-Institution Variation					
Asset Class	Inst.	Years	Obs.	μ	σ	α	λ	ν	γ	μ	σ	α	λ	ν	γ
Wealth Portfolio	45	36	361	0.4%	1.2%	0.3%	0.5%	0.3%	0.53	0.8%	1.3%	0.8%	1.0%	0.3%	0.72
US Fixed Income	42	36	352	0.6%	1.8%	0.3%	0.8%	0.3%	-	0.6%	1.3%	0.6%	0.3%	0.1%	-
Ex US Fixed Income	36	35	271	1.2%	2.1%	0.7%	0.9%	0.4%	-	0.8%	2.3%	0.9%	0.4%	0.1%	-
US Equity	45	36	361	0.6%	1.5%	0.5%	0.6%	0.4%	-	1.0%	1.4%	1.0%	1.3%	0.4%	-
Ex US Equity	44	35	351	0.5%	1.2%	0.6%	0.8%	0.4%	-	1.3%	1.9%	1.3%	1.4%	0.4%	-
Private Equity	34	34	309	0.8%	2.3%	0.8%	0.8%	0.4%	-	2.0%	5.3%	1.4%	2.2%	0.8%	-
Real Estate	42	36	357	0.7%	1.3%	0.8%	1.1%	0.4%	-	1.1%	3.5%	1.3%	1.6%	0.5%	-
Hedge Funds	33	22	230	0.7%	0.8%	0.8%	0.4%	0.1%	-	1.1%	2.4%	1.2%	0.8%	0.3%	-
Commodities	33	22	242	0.5%	0.8%	1.3%	1.3%	0.5%	-	1.8%	3.8%	1.8%	1.2%	0.4%	-
Infrastructure	17	17	88	0.7%	0.9%	0.8%	0.6%	0.2%	-	0.9%	3.6%	1.3%	1.6%	0.5%	-

PANEL C - Correlations Between Expected Return Components

	Number of			Time-Series Correlations						Cross-Institution Correlations					
Asset Class	Inst.	Years	Obs.	(μ, α)	(μ, λ)	(μ, γ)	(μ, ν)	(α, λ)	(γ, ν)	(μ, α)	(μ, λ)	(μ, γ)	(μ, ν)	(α, λ)	(γ, ν)
Wealth Portfolio	45	36	361	0.14	0.73	-0.04	0.44	-0.57	-0.74	0.24	0.66	0.33	0.42	-0.51	-0.33
US Fixed Income	42	36	352	-0.41	0.93	0.17	0.85	-0.72	-0.21	0.84	0.24	-0.09	0.31	-0.27	-0.24
Ex US Fixed Income	36	35	271	0.62	0.80	0.25	0.74	0.03	-0.10	0.87	0.13	-0.04	0.11	-0.29	-0.13
US Equity	45	36	361	0.42	0.59	-0.27	0.51	-0.48	-0.82	0.20	0.64	0.31	0.41	-0.57	-0.38
Ex US Equity	44	35	351	-0.19	0.76	-0.02	0.56	-0.78	-0.64	0.35	0.61	0.34	0.37	-0.47	-0.25
Private Equity	34	34	309	0.51	0.49	0.35	0.03	-0.51	-0.75	0.23	0.76	0.43	0.43	-0.39	-0.30
Real Estate	42	36	357	-0.02	0.68	0.31	0.61	-0.75	-0.21	0.13	0.60	0.44	0.41	-0.66	0.06
Hedge Funds	33	22	230	0.86	-0.03	0.04	-0.04	-0.55	0.08	0.71	0.21	0.03	0.14	-0.44	-0.14
Commodities	33	22	242	0.20	0.21	0.39	0.23	-0.91	0.36	0.76	0.27	-0.16	0.22	-0.35	0.03
Infrastructure	17	17	88	0.70	0.24	0.42	0.11	-0.53	0.38	0.11	0.37	0.45	0.22	-0.74	-0.06

Table 4
Decomposing Link Between Expected Returns and Yields

This table reports results from regressions of CMA-based aggregate expected returns on yields for different asset classes guided by the simple yield-based model of CMA formation from Section 3.1, which implies

$$\begin{aligned}\mathbb{E}_t[R^{real}_{cash}] &= const \; + \; \omega \cdot y_{cash,t} \; + \; \varepsilon_{cash,t} \\ \mu_{n,t} &= const \; + \; b_n \cdot y_{n,t} \; - \; \omega \cdot y_{cash,t} \; + \; \varepsilon_{n,t}\end{aligned}$$

where y values reflect real yields (with measurement described in Internet Appendix A.4). The first column estimates this system of equations. The second and third columns decompose μ into α and λ so that the respective b coefficients add to the b coefficient for μ. The fourth and fifth columns decompose λ into λ^{γ} and λ^{ν} so that the respective b coefficients add to the b coefficient for λ. Standard errors are based on Newey and West (1987, 1994). Subsection 1.2 describes our beliefs data while Subsection 3.1 discusses the results from this table.

		$\boldsymbol{\mu}$	$\boldsymbol{\alpha}$	$\boldsymbol{\lambda}$	$\boldsymbol{\lambda^{\gamma}}$	$\boldsymbol{\lambda^{\nu}}$
	$\boldsymbol{\omega}$	0.36	-	-	-	-
Cash	$(\boldsymbol{t_{stat}})$	(2.94)	-	-	-	-
	$\boldsymbol{R^2_{adj}}$	70.4%	-	-	-	-
	$\boldsymbol{b}$	0.67	-0.12	0.79	-0.03	0.81
US Fixed Income	$(\boldsymbol{t_{stat}})$	(2.22)	(-1.73)	(4.61)	(-0.46)	(3.83)
	$\boldsymbol{R^2_{adj}}$	49.4%	5.1%	41.6%	-0.1%	44.5%
	$\boldsymbol{b}$	0.68	0.27	0.41	0.02	0.39
Ex US Fixed Income	$(\boldsymbol{t_{stat}})$	(3.75)	(1.87)	(3.77)	(0.45)	(3.26)
	$\boldsymbol{R^2_{adj}}$	71.2%	27.8%	61.9%	0.8%	61.8%
	$\boldsymbol{b}$	0.36	0.11	0.25	-0.13	0.37
US Equity	$(\boldsymbol{t_{stat}})$	(3.67)	(1.57)	(5.15)	(-1.25)	(2.81)
	$\boldsymbol{R^2_{adj}}$	31.2%	-5.2%	23.4%	-1.1%	14.1%
	$\boldsymbol{b}$	0.21	-0.08	0.29	-0.02	0.30
Ex US Equity	$(\boldsymbol{t_{stat}})$	(2.55)	(-1.76)	(7.06)	(-0.30)	(3.73)
	$\boldsymbol{R^2_{adj}}$	33.9%	19.2%	53.7%	-1.5%	39.2%
	$\boldsymbol{b}$	0.23	0.07	0.16	0.17	0.00
Private Equity	$(\boldsymbol{t_{stat}})$	(3.12)	(0.59)	(1.45)	(2.18)	(-0.03)
	$\boldsymbol{R^2_{adj}}$	42.6%	1.4%	11.1%	23.2%	-2.9%
	$\boldsymbol{b}$	0.21	-0.16	0.37	0.04	0.34
Real Estate	$(\boldsymbol{t_{stat}})$	(2.70)	(-2.53)	(7.36)	(1.11)	(5.96)
	$\boldsymbol{R^2_{adj}}$	55.4%	2.9%	48.5%	5.8%	35.3%

Table 5

Linking μ Components to Yields and Perceived Undervaluation (US Equity)

This table reports results from regressions (for US Equity asset class) of CMA-based aggregate μ and its components (α, λ, λ^{γ}, and λ^{ν}) onto the excess CAPE yield (which is the $y_{n,t}$ measure for US Equity in Table 4) as well as onto a variable from the Bank of America (BofA) survey of global fund managers. The variable is the "Perceived Undervaluation", which reflects the (negative of the) net fraction of fund managers who answer "yes" to the question of whether US equities are overvalued. The sample for this table is restricted to the 2001 to 2022 period (due to the availability of the BofA Perceived Undervaluation variable). We provide further details about the BofA surveys and measurement in Internet Appendix A.2. The slope coefficients are normalized to be interpreted as the effect of a one standard deviation movement in the independent variable on the dependent variable (in % units). Standard errors are based on Newey and West (1987) with three annual lags given the relatively short sample (t-statistics in this table tend to be even larger with Newey and West (1994) automatic lag selection procedure). Subsection 1.2 describes our beliefs data while Subsection 3.3 discusses the results from this table.

		μ	α	λ	λ^{γ}	λ^{ν}
Excess CAPE Yield	**Coef**	0.40	0.13	0.27	0.07	0.20
	(t_{stat})	(6.80)	(1.15)	(3.96)	(0.67)	(2.29)
	R^2_{adj}	51.1%	1.1%	28.1%	-2.3%	25.0%
Perceived Undervaluation	**Coef**	0.25	0.50	-0.25	-0.21	-0.04
	(t_{stat})	(2.51)	(12.00)	(-3.06)	(-3.85)	(-0.37)
	R^2_{adj}	17.3%	83.1%	24.6%	22.3%	-3.9%
Excess CAPE Yield	**Coef**	0.39	0.11	0.28	0.08	0.20
	(t_{stat})	(9.48)	(3.33)	(5.15)	(0.85)	(2.36)
Perceived Undervaluation	**Coef**	0.23	0.50	-0.27	-0.22	-0.05
	(t_{stat})	(2.83)	(17.90)	(-3.12)	(-3.13)	(-0.41)
	R^2_{adj}	68.5%	86.5%	58.7%	22.0%	22.9%

Table 6
Decomposing Expected Return Time Variation

Panel A reports values associated with decompositions of aggregate expected return time variation, $\mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n]$, based on Equation 14. Panel B reports values associated with decompositions of the risk premium effect on aggregate expected return overall time variation, $\mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n, \lambda_{n,t} - \overline{\lambda}_n]$, based on Equation 15. Each panel also reports results from analogous decompositions after replacing μ with $\Delta\mu$ (same for μ components) to focus on transitory time variation, which is a relatively small portion of the total time variation in expected returns. Footnotes 20 and 21 provide details about estimation and standard errors for Panels A and B, respectively. Subsection 1.2 describes our beliefs data while Subsections 4.2 and 4.3 discuss the results from this table.

PANEL A - Decomposing $\mathbb{V}ar[\mu]$ Over Time

	$\mathbb{V}ar[\mu]$				$\mathbb{V}ar[\Delta\mu]$			
	% from α		% from λ		% from α		% from λ	
	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})
Wealth Portfolio	11.9%	(0.66)	88.1%	(4.89)	-0.9%	(-0.08)	100.9%	(8.96)
All Asset Classes	31.9%	(2.50)	68.1%	(5.33)	39.2%	(3.96)	60.8%	(6.15)
US Fixed Income	-21.9%	(-1.77)	121.9%	(9.87)	54.4%	(3.59)	45.6%	(3.01)
Ex US Fixed Income	37.2%	(1.66)	62.8%	(2.81)	36.6%	(1.42)	63.4%	(2.46)
US Equity	38.6%	(2.00)	61.5%	(3.18)	12.7%	(1.07)	87.3%	(7.35)
Ex US Equity	-19.5%	(-1.46)	119.5%	(8.94)	7.3%	(0.60)	92.7%	(7.56)
Private Equity	51.3%	(2.81)	48.7%	(2.67)	9.9%	(1.46)	90.1%	(13.3)
Real Estate	-2.5%	(-0.15)	102.5%	(6.14)	68.1%	(5.07)	31.9%	(2.37)
Hedge Funds	102.1%	(4.37)	-2.1%	(-0.09)	66.1%	(9.96)	33.9%	(5.11)
Commodities	48.9%	(0.67)	51.2%	(0.71)	56.0%	(2.50)	44.0%	(1.96)
Infrastructure	79.6%	(4.74)	20.4%	(1.22)	83.5%	(13.7)	16.5%	(2.70)

PANEL B - Decomposing $\mathbb{C}ov[\mu, \lambda]$ Over Time

	$\mathbb{C}ov[\mu, \lambda]$				$\mathbb{C}ov[\Delta\mu, \Delta\lambda]$			
	% from γ		% from ν		% from γ		% from ν	
	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})
Wealth Portfolio	-2.3%	(-0.09)	102.3%	(4.25)	59.5%	(5.07)	40.5%	(3.45)
All Asset Classes	9.6%	(0.95)	90.4%	(8.91)	45.0%	(3.83)	55.0%	(4.69)
US Fixed Income	-1.0%	(-0.08)	101.0%	(8.17)	31.8%	(1.71)	68.2%	(3.67)
Ex US Fixed Income	2.7%	(0.24)	97.3%	(8.61)	23.1%	(7.01)	76.9%	(23.4)
US Equity	-64.8%	(-1.04)	164.8%	(2.64)	39.4%	(1.60)	60.6%	(2.47)
Ex US Equity	2.1%	(0.09)	97.9%	(4.01)	34.8%	(1.62)	65.2%	(3.04)
Private Equity	104.0%	(1.26)	-4.0%	(-0.05)	56.5%	(6.40)	43.5%	(4.93)
Real Estate	13.1%	(2.12)	86.9%	(14.1)	43.6%	(1.40)	56.4%	(1.80)
Hedge Funds	-25.6%	(-0.06)	125.6%	(0.28)	48.0%	(8.26)	52.0%	(8.95)
Commodities	4.2%	(0.68)	95.8%	(15.7)	15.5%	(1.93)	84.5%	(10.5)
Infrastructure	63.6%	(1.39)	36.4%	(0.79)	95.4%	(1.31)	4.6%	(0.06)

Table 7
Decomposing Expected Return Disagreement

Panel A reports values associated with decompositions of expected return disagreement across institutions, $\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]$, based on Equation 18. Panel B reports values associated with decompositions of the risk premium effect on expected return disagreement across institutions, $\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}, \lambda_{j,n,t} - \overline{\lambda}_{n,t}]$, based on Equation 19. Each panel also reports results from analogous decompositions after replacing μ and its components (α, λ, λ^{γ}, and λ^{ν}) with their respective persistent ($\mu_{j,n} \equiv \mu^{fe}_{j,n}$) and transitory ($\Delta\mu_{j,n,t} \equiv \epsilon_{j,n,t}$) disagreement parts constructed based on equations analogous to Equation 23 (and subsetting to institutions with at least two years in the sample to ensure $\Delta\mu$ is not zero). The headers of the "persistent disagreement" and "transitory disagreement" blocks of the table show the fraction of μ disagreement (in Panel A) and λ disagreement (in Panel B) driven by persistent versus transitory disagreement. Footnotes 22 and 23 provide details about estimation and standard errors for Panels A and B, respectively. Subsection 1.2 describes our beliefs data while Subsections 5.2 and 5.3 discuss the results from this table.

PANEL A - Decomposing $\mathbb{V}ar[\mu]$ Across Institutions

	Total Disagreement				Persistent Disagreement (70%)				Transitory Disagreement (30%)			
	% from α		% from λ		% from α		% from λ		% from α		% from λ	
	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})
Wealth Portfolio	24.3%	(3.03)	75.7%	(9.47)	13.8%	(3.34)	86.2%	(20.8)	39.0%	(4.80)	61.0%	(7.51)
All Asset Classes	42.6%	(3.32)	57.4%	(4.48)	28.2%	(1.76)	71.8%	(4.48)	54.8%	(4.25)	45.2%	(3.51)
US Fixed Income	89.4%	(15.4)	10.6%	(1.82)	88.6%	(23.8)	11.4%	(3.06)	91.9%	(22.8)	8.1%	(2.02)
Ex US Fixed Income	99.6%	(22.8)	0.4%	(0.08)	106.4%	(33.4)	-6.4%	(-1.99)	92.5%	(33.4)	7.6%	(2.72)
US Equity	18.9%	(2.68)	81.1%	(11.5)	4.9%	(1.36)	95.1%	(26.3)	35.4%	(4.43)	64.6%	(8.08)
Ex US Equity	33.7%	(6.02)	66.3%	(11.8)	18.8%	(3.25)	81.3%	(14.1)	51.7%	(4.60)	48.3%	(4.29)
Private Equity	14.2%	(3.44)	85.8%	(20.7)	3.7%	(0.66)	96.3%	(17.3)	22.1%	(3.74)	77.9%	(13.2)
Real Estate	32.6%	(6.08)	67.4%	(12.6)	-1.9%	(-0.37)	101.9%	(19.7)	48.3%	(10.2)	51.7%	(10.9)
Hedge Funds	79.0%	(7.88)	21.1%	(2.10)	67.0%	(10.9)	33.0%	(5.35)	82.9%	(16.2)	17.2%	(3.35)
Commodities	80.2%	(6.86)	19.8%	(1.70)	68.2%	(11.2)	31.8%	(5.23)	93.9%	(7.08)	6.1%	(0.46)
Infrastructure	-5.0%	(-0.33)	105.0%	(7.00)	-48.8%	(-3.60)	148.8%	(11.0)	67.8%	(5.70)	32.2%	(2.70)

PANEL B - Decomposing $\mathbb{C}ov[\mu, \lambda]$ Across Institutions

	Total Disagreement				Persistent Disagreement (79%)				Transitory Disagreement (21%)			
	% from γ		% from ν		% from γ		% from ν		% from γ		% from ν	
	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})	Coef	(t_{stat})
Wealth Portfolio	50.7%	(8.28)	49.3%	(8.04)	34.7%	(5.23)	65.3%	(9.82)	73.2%	(12.8)	26.8%	(4.68)
All Asset Classes	42.5%	(4.59)	57.6%	(6.22)	31.2%	(2.80)	68.8%	(6.19)	56.0%	(9.18)	44.0%	(7.21)
US Fixed Income	-21.9%	(-1.44)	121.9%	(7.99)	-57.1%	(-3.00)	157.1%	(8.25)	3.4%	(0.22)	96.6%	(6.08)
Ex US Fixed Income	-182.0%	(-0.08)	282.0%	(0.13)	-38.6%	(-0.89)	138.6%	(3.18)	-24.0%	(-1.26)	124.0%	(6.48)
US Equity	58.6%	(10.9)	41.4%	(7.74)	46.3%	(8.74)	53.7%	(10.2)	70.6%	(11.1)	29.4%	(4.63)
Ex US Equity	49.9%	(9.93)	50.1%	(9.96)	36.8%	(5.61)	63.2%	(9.62)	77.4%	(9.81)	22.6%	(2.87)
Private Equity	46.4%	(5.92)	53.6%	(6.84)	30.2%	(5.52)	69.8%	(12.8)	54.7%	(5.35)	45.3%	(4.43)
Real Estate	33.2%	(5.05)	66.9%	(10.2)	28.0%	(7.54)	72.0%	(19.4)	46.6%	(7.77)	53.4%	(8.89)
Hedge Funds	34.2%	(1.43)	65.8%	(2.76)	10.2%	(0.90)	89.8%	(7.93)	77.8%	(2.92)	22.2%	(0.83)
Commodities	2.5%	(0.14)	97.5%	(5.52)	11.1%	(1.55)	88.9%	(12.4)	-18.3%	(-0.17)	118.3%	(1.09)
Infrastructure	32.7%	(3.89)	67.3%	(8.00)	34.0%	(5.39)	66.0%	(10.4)	63.4%	(2.77)	36.6%	(1.60)

Internet Appendix

“Institutional Investors’ Subjective Risk Premia: Time Variation and Disagreement”

By Spencer J. Couts, Andrei S. Gonçalves, Yicheng Liu, and Johnathan A. Loudis

Contents

A Data and Measurement Details **IA.1**

A.1 Data and Measurement: Subjective Beliefs (from CMAs) IA.1

A.2 Data and Measurement: Subjective Beliefs (from BofA Surveys) IA.5

A.3 Data and Measurement: Wealth Portfolio Weights IA.6

A.4 Data and Measurement: Yields and Expected Inflation IA.8

B CMA Formation Through Valuation Models **IA.10**

B.1 Deriving the Simple Yield-Based Model of CMA Formation IA.10

B.2 Results from the Full Building-Block Model of Equity CMA Formation . . . IA.13

C Supplementary Empirical Results **IA.14**

C.1 Comparing Risk Aversion Estimates with CAPM Risk Aversion IA.14

C.2 Understanding CMA Formation: Yield-Based versus Extrapolation-Based . . IA.16

C.3 Alternative Risk Aversion Estimation Methods IA.18

C.4 Alternative Subsets of the Data IA.19

C.5 Alternative Constructions of Subjective Beliefs and Market Portfolio Weights IA.20

C.6 Alternative Variance Decomposition Estimation Methods IA.22

A Data and Measurement Details

This section describes the beliefs (and wealth portfolio) data we use in our analyses.

A.1 Data and Measurement: Subjective Beliefs (from CMAs)

This subsection details our CMAs data collection process and our measurement of belief quantities. We follow Couts, Gonçalves, and Loudis (2024), with few exceptions (which we note in the text and provide the underlying rationale).

A.1.1 Data Collection Process

We collected the long-term CMAs of 45 institutions in total: 22 asset managers and 23 investment consultants. We relied on three complementary data collection approaches:

(i) The bulk of the data comes directly from the institutions covered in our CMAs. We identify individuals within each institution that are connected to the production of CMAs and contact them directly to request access to their data. In all successful cases, the institution sent us continuous (at least annual) data covering from some initial year until their most recent CMA, and thus these data are free of issues related to attrition rates.

(ii) To complement the data sent directly by institutions, we also obtain data from online sources. As in Dahlquist and Ibert (2024), our approach is simple: we obtain the most recent CMA of each institution directly from their website and complement these CMAs with prior CMAs obtained through google searches and `archive.org`.

(iii) The third data collection approach is based on indirect data obtained from pension funds. Specifically, we contacted various pension funds to request the CMAs they rely on when deciding their portfolio allocations. In the successful cases, the pension funds sent us their portfolio allocation reports and/or their CMA reports. In turn, these reports include the numbers (expected returns, volatilities, and correlations) associated with the CMAs of third party institutions that the pension fund rely on (including consultants and sometimes asset managers).

Whenever an institution-year observation is available through more than one of the three methods above, we rely on a pecking order for data selection (we use (i) when available, (ii) when (i) is not available, and (iii) when neither (i) nor (ii) is available). Given this pecking order, 83.4% of the institution-year observations in our baseline sample are based on data collected from methods (i)+(ii), which we refer to as "direct CMAs".

As we explain in Section C.4, while the results we report in the main text combine consultants with managers and rely on this pecking order, we explore different subsets of the data in our robustness checks to demonstrate that our results are not due to particular biases that may be present in different data collection processes. For example, we show that our results are qualitatively similar if we rely only on consultants or only on managers, indicating that our results are not due to any particular incentive that is specific to either type of institution. Analogously, we show that our results are qualitatively similar if we rely only on data collection process (i)+(ii) or only on data collection process (iii), indicating that our results are not due to potential biases that may arise from collecting data directly from the institution or collecting data indirectly through pension funds.

Our final sample contains a cash asset class as well as 9 risky asset classes. We select these 9 risky asset classes because we are able to measure their wealth portfolio weights (see Subsection A.3). Choosing only these 9 broad asset classes makes it manageable to provide results by asset class. This aspect differs from Couts, Gonçalves, and Loudis (2024), who study cash plus 19 other asset classes as they do not provide results by asset class (since they focus on variation across asset classes).

It is important to note that each institution-year CMA covers a range of asset classes with names that do not necessarily match the exact names of the 10 asset classes we study (which we refer to as the "broad asset classes"). Moreover, the asset classes covered in the CMAs vary across institutions and over time. So, we develop a detailed procedure to match the asset classes covered in the CMAs to our broad asset classes. First, we identify the asset classes in each CMA based on the asset class name used in the CMA report and/or the actual portfolio index stated in the CMA report. Second, we manually map each asset class in each institution-year CMA to an institution-specific asset class name (fixed over time) that reflects the underlying asset class well. Third, we map each institution-specific asset class name to a slightly more general asset class name (which we refer to as the master asset class) that reflects the institution-specific asset class name reasonably well while allowing for small mismatches to accommodate asset classes from different institutions under the same master asset class. Fourth, for each CMA, we match each of our broad asset classes to the most closely related master asset class available (with the possibility of no match).

Table IA.1 provides the results from our asset class matching procedure. The first column shows the broad asset classes we cover in the paper. The other columns provide the list of master asset classes that we match to these broad asset classes. They also provide the fraction of institution-year CMAs that have the respective match (within the institution-year CMAs that have some match for the given broad asset class). For most broad asset classes, the option #1 master asset class is responsible for at least 50% of the matches. However, for Private Equity and Real Estate the option #1 master asset class is responsible for a small fraction of the matches. The reason is that we keep Global Private Equity and Global Real Estate as the option #1 master asset classes (given their generality) while the most commonly available master asset classes for these two broad asset classes are US Private Equity and US Core Real Estate, respectively.

A.1.2 Extracting Beliefs from the CMAs

As JP Morgan details in their 2015 report, their expected returns (μ), expected volatilities (σ), and expected correlations (ρ) are all obtained based on their views on log returns through a log-Normal transformation.[IA.1] Specifically, they first form their beliefs in log return space and then translate to raw return space using the assumption that log returns are normally

[IA.1] The use of μ and σ in this section embeds a slight abuse of notation since μ and σ reflect expected excess return and excess return volatility in the main text while they reflect expected return and return volatility in this section (so, they are not in excess of cash returns here).

distributed. In mathematical terms, they report (for each asset class n)

$$\begin{pmatrix} \mu_n \\ \sigma_n^2 \\ \rho_{n,k} \end{pmatrix} = \begin{pmatrix} e^{\widetilde{\mu}_n + \frac{1}{2}\cdot\widetilde{\sigma}_n^2} - 1 \\ e^{2\cdot(\widetilde{\mu}_n + \frac{1}{2}\cdot\widetilde{\sigma}_n^2)} \cdot (e^{\widetilde{\sigma}_n^2} - 1) \\ \left(e^{\widetilde{\rho}_{n,k}\cdot\widetilde{\sigma}_n\cdot\widetilde{\sigma}_k} - 1\right) / \sqrt{(e^{\widetilde{\sigma}_n^2} - 1)\cdot(e^{\widetilde{\sigma}_k^2} - 1)} \end{pmatrix} \tag{IA.1}$$

which imply

$$\begin{pmatrix} \widetilde{\sigma}_n^2 \\ \widetilde{\mu}_n \\ \widetilde{\rho}_{n,k} \end{pmatrix} = \begin{pmatrix} log\left(1 + \sigma_n^2/(\mu_n + 1)^2\right) \\ log(\mu_n + 1) - \frac{1}{2}\cdot\widetilde{\sigma}_n^2 \\ log\left(1 + \rho_{n,k}\cdot\sqrt{(e^{\widetilde{\sigma}_n^2} - 1)\cdot(e^{\widetilde{\sigma}_k^2} - 1)}\right) / (\widetilde{\sigma}_n \cdot \widetilde{\sigma}_k) \end{pmatrix} \tag{IA.2}$$

where $\widetilde{\mu}$, $\widetilde{\sigma}$, and $\widetilde{\rho}$ are the expected log returns, expected log volatilities, and expected log correlations. The JP Morgan 2015 report also provides $e^{\widetilde{\mu}_n} - 1$ as the "expected compound return" or "expected geometric return".

All institution-year CMAs in our sample contain σ_n and $\rho_{n,k}$. However, they vary on whether they contain only expected arithmetic returns (which is μ in our notation), only expected geometric returns (which is $e^{\widetilde{\mu}_n} - 1$ in our notation), or both. In particular, 41.5% of our CMAs report only expected arithmetic returns, 22.2% of our CMAs report only expected geometric returns, and 36.3% of our CMAs report both. To ensure the conceptual definition underlying our expected return measure is the same for all our institution-year observations, we always use expected arithmetic returns in our baseline analysis. This approach is consistent with the expected return definition from the analogue of Equation 2 in typical asset pricing models and also with the fact that our CMAs report expected arithmetic returns more frequently than expected geometric returns. To avoid losing observations, we use the transformation $\mu_n = e^{\widetilde{\mu}_n + \frac{1}{2}\cdot\widetilde{\sigma}_n^2}$ for the 22.2% of CMAs without μ_n.[IA.2] Section C.5 provides

[IA.2] Specifically, we observe σ_n and $\widetilde{\mu}_n$ and solve the system of equations

$$\begin{pmatrix} \mu_n \\ \widetilde{\sigma}_n^2 \end{pmatrix} = \begin{pmatrix} e^{\widetilde{\mu}_n + \frac{1}{2}\cdot\widetilde{\sigma}_n^2} - 1 \\ log\left(1 + \sigma_n^2/(\mu_n + 1)^2\right) \end{pmatrix}$$

for μ_n and $\widetilde{\sigma}_n^2$ numerically using a root-solving algorithm.

results that use expected arithmetic returns when available and expected geometric returns when expected arithmetic returns are not available (so that no transformation is applied). It also reports results focused on expected geometric returns, with the log-Normal transformation, $\widetilde{\mu}_n = log(\mu_n + 1) - \frac{1}{2} \cdot \widetilde{\sigma}_n^2$, used for the 41.5% of CMAs that only report expected arithmetic returns.

A.2 Data and Measurement: Subjective Beliefs (from BofA Surveys)

For the analyses in Tables 5 and IA.3, we also use data from the Bank of America (BofA) survey of global fund managers. The survey is conducted monthly and BofA distributes files with the results to a pool of clients and survey participants. The results are reported in graphical format, often containing time-series plots for results associated with questions that are asked consistently over time. As shown in Bastianello and Peng (2024), the majority of the survey participants are directly involved in managing investment portfolios (see Bastianello and Peng (2024) for further details about these BofA surveys).

We use two variables from the BofA surveys of fund managers. The first, which we refer to as "Perceived Undervaluation", reflects the (negative of the) net fraction of fund managers who answer "yes" to the question of whether US equities are overvalued. The second, which we refer to as "Subjective $\mathbb{E}$[Growth]", reflects the net fraction of fund managers who answer "yes" to the question of whether global profits will improve over the next twelve months. Following the data collection process in Bastianello and Peng (2024), we obtain the graphs for these two variables from online plots based on the BofA survey conducted in February of 2025. We then extract the relevant numerical data using the software WebPlotDigitizer. The "Perceived Undervaluation" variable (used in Tables 5 and IA.3) covers the period from April 2001 to February 2025 whereas the "Subjective $\mathbb{E}$[Growth]" variable (used in Table IA.3) covers the period from November 1997 to February 2025. We align the December values (from 2001 to 2022) with our annual data from CMAs in order to perform the analyses in Tables 5 and IA.3.

A.3 Data and Measurement: Wealth Portfolio Weights

We proxy for the wealth portfolio weights using the aggregated portfolio weights of US public pension funds obtained from the Center for Retirement Research (CRR) at Boston College. Specifically, we collect information on the dollar allocations across asset classes for each pension fund (from the "Detailed Investment Data" dataset). Then, we aggregate allocations across pension funds each year.

CRR provides information on allocations for a range of asset classes, many of which have zero weights for most pension funds. To create the aggregate allocations on our broad asset classes, we sum the allocations on their underlying asset classes as follows (with asset class names as recorded in the CRR dataset):

1. **Cash**: Cash + FICash
2. **US Fixed Income**: FIUS + ω_{FIUS}·FIOther
3. **Ex US Fixed Income**: FIExUS + $(1 - \omega_{\text{FIUS}})$·FIOther
4. **US Equity**: EQUS + ω_{EQUS}·EQOther
5. **Ex US Equity**: EQExUS + $(1 - \omega_{\text{EQUS}})$·EQOther
6. **Private Equity**: EQPrivate + PrivatePlacement + MLP
7. **Real Estate**: RECore + REMisc + RENonCore + PrivRealEstate + REIT + RealAssets + RETriple
8. **Hedge Funds**: AbsRtrn + RelativeRtrn + RiskParity + CoveredCall + CreditOpp + DistrssedDebt + DistrssedLend + HedgeEQ + AltInflation + Hedge + MultiClass + OppDebt + OppEQ + Opp + GTAA
9. **Commodities**: Commod+Farm+NatResources+Timber
10. **Infrastructure**: Infrast

FIUS and EQUS reflect asset classes that are based on US investments, FIExUS and EQExUS reflect asset classes that are based on international investments, and FIOther and EQOther reflect asset classes that can potentially combine US and Ex US investments. We construct these six asset classes as follows:

1. **FIUS**: FIDomestic + FITIPS + FITreasury
2. **EQUS**: EQDomesticLarge + EQDomesticMisc + EQDomesticMid + EQDomesticSmall
3. **FIExUS**: FIEmerg + FIGlobal + FIIntl
4. **EQExUS**: EQIntlActv + EQIntlDev + EQGlobal + EQIntlMisc + EQIntlPass + EQIntlEmerg + EQGlobalGrowth
5. **FIOther**: FICore + FINonCore + FICorpBonds + FIValue + FIConv + FIAlt + FIFundsFunds + FIMisc + FIETI + FINominal + FIInvestGrd + FIBelowInvestGrd + FIHighYield + FILoans + PrivateDebt + FIMortgage + FIGIPS + FIOpp + FIStructured + ω_{FI}·MiscEQFI
6. **EQOther**: EQCore+EQLarge+EQMisc+EQMicro+EQSmall+EQOpportunistic+EQSocialResp + $(1-\omega_{\text{FI}})$·MiscEQFI

The ω_{FIUS}, ω_{EQUS}, and ω_{FI} weights are constructed as follows:

1. ω_{FI} equals the allocation on FIUS+FIExUS+FIOther* divided by the allocation on FIUS+FIExUS+FIOther*+EQUS+EQExUS+EQOther*, where FIOther* and EQOther* are the FIOther and EQOther asset classes with MiscEQFI set to zero (so that we do not need ω_{FI} to compute them).
2. ω_{FIUS} is the allocation on FIUS divided by the allocation on FIUS+FIExUS
3. ω_{EQUS} is the allocation on EQUS divided by the allocation on EQUS+EQExUS

Given the allocations on the broad asset classes, we construct wealth portfolio weights by dividing each broad asset class allocation by the sum of allocations to the broad asset classes in the given year.

When measuring the wealth portfolio at the institution-year level, if a CMA does not have belief data for a given asset class, then we set the respective wealth portfolio weight to zero and adjust the other weights to add to one. Specifically, we start by assigning to US Equity any weight from missing observations of Ex US Equity and Private Equity. Then, we assign to US Fixed Income any weight from missing Ex US Fixed Income, and vice versa. Finally, we assign to all available asset classes (in proportion to their weights) any weight from other missing asset classes. This process ensures the wealth portfolio weights always add to one. We perform an analogous procedure when constructing aggregate beliefs that require the wealth portfolio weights, except that this process is applied to each year aggregated beliefs (described in Subsection 1.3) as opposed to each institution-year beliefs.

A.4 Data and Measurement: Yields and Expected Inflation

Section 3 studies the link between CMA-based expected return components (μ, α, λ, ν, γ) and real yields (y_n). Below, we describe the data and measurement for yields and expected inflation.

We obtain $y_{cash} = y_b^{(10)} - \pi^{(10)}$, with $y_b^{(10)}$ as the 10-year US Treasury bond yield (series GS10 from the FRED) and $\pi^{(10)}$ as the 10-year expected inflation from the Federal Reserve survey of professional forecasters (since 1990) and Blue Chip (from 1987 to 1989), both available from the website of the Federal Reserve bank of Philadelphia.[IA.3] We obtain y_n for US Fixed Income as the spread between the yield-to-worst for the Bloomberg Barclays US Aggregate Bond index (which is a nominal yield) and $\pi^{(10)}$. Similarly, we obtain y_n for Ex US Fixed Income as the spread between the yield-to-worst for the Global Aggregate-Ex US index and $\pi^{(10)}$. For US Equity and Ex US Equity (both reflecting returns from the perspective

[IA.3] https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/inflation-forecasts of US investors), we obtain y_n as the inverse of the Shiller Cyclically Adjusted Price-to-Earnings (CAPE) ratio. We obtain y_n for Private Equity from the aggregate EBITDA over Total Enterprise Value ratio of private equity buyout deals (extracted from Exhibit 1 of Nesbitt (2024)). Finally, we obtain y_n for Real Estate from the (annual average of quarterly) aggregate transaction-based cap rate (i.e., net operating income over total market value) of real estate properties from the National Council of Real Estate Investment Fiduciaries (NCREIF).

B CMA Formation Through Valuation Models

This section considers CMA formation through valuation models.

B.1 Deriving the Simple Yield-Based Model of CMA Formation

In the main text, we use $\mathbb{E}_t[R_n^{real}] = const + b_n \cdot y_{n,t}$ (where $y_{n,t}$ is the real yield for asset class n) as a simple yield-based model of CMA formation (see Subsection 3.1). This subsection explains the underlying assumptions for the model's validity. However, note that Subsection C.2 takes a more reduced-form approach to studying the relation between expected returns and yields, reaching similar conclusions to the ones we provide in the main text using the yield-based model of CMA formation described here (albeit even in that case the model is useful in justifying the independent variables used in the regressions for the different asset classes).

B.1.1 Fixed Income Asset Classes

Consider an idealized portfolio (indexed by n) of default-free zero-coupon bonds with duration of H_n years (for zero-coupon bonds, duration and maturity are equivalent). Suppose the expectation is that the portfolio will be managed so as to keep H_n fixed from t to $t+h$. In this case, the expected real return on this portfolio from t to $t+h$ can be obtained using the following building-block model:

$$\mathbb{E}_t[R_n^{real}] = \mathbb{E}_t[\text{Average Yield}] + \mathbb{E}_t[\text{Roll Down Return}] + \mathbb{E}_\text{t}[\text{Valuation Change Return}] - \mathbb{E}_\text{t}[\text{Inflation}] \tag{IA.3}$$

where

$$\mathbb{E}_t[\text{Average Yield}] \; = \overline{y}_t^{(H_n)} \; = \; 0.5 \cdot (y_t^{(H_n)} + \mathbb{E}_t[y_{t+h}^{(H_n)}]) \tag{IA.4}$$

is the expected average nominal yield from t to $t+h$,

$$\mathbb{E}_\text{t}[\text{Roll Down Return}] \; = \; - H_n \cdot \left(\overline{y}_t^{(H_n - 1)} - \overline{y}_t^{(H_n)} \right) \tag{IA.5}$$

reflects the expected return from rebalancing the portfolio each year to keep H_n constant,

$$\mathbb{E}_t[\text{Valuation Change Return}] \;=\; -\,H_n \cdot \left(\frac{\mathbb{E}_t[y_{t+h}^{(H_n)}] - y_t^{(H_n)}}{h} \right) \tag{IA.6}$$

reflects the expected return from the average change in the valuation of the bonds in the portfolio, and $\mathbb{E}_t[\text{Inflation}] = \pi_t^{(h)}$.

Our simple yield-based model of CMA formation assumes the yield curve is not expected to change from t to $t+h$, and also that it is driven by a level factor such that $\overline{y}_t^{(H_n)} = a_{H_n} + y_t^{(level)}$. In this case, we have $\mathbb{E}_t[\text{Average Yield}] = y_t^{(H_n)}$ and $\mathbb{E}_t[\text{Valuation Change Return}] = 0$, with $\mathbb{E}_t[\text{Roll Down Return}]$ varying by H_n but not over time. Consequently, the expected real return simplifies to

$$\mathbb{E}_t[R_n^{real}] \;= const + \,(y_t^{(H_n)} - \pi_t^{(h)}) \tag{IA.7}$$

CMAs typically use some variant of the building-block model in Equation IA.3. For fixed income asset classes that contain bonds that pay coupons and can potentially default (which is our case), institutions often use yield-to-maturity ($ytm_{n,t}$) instead of the zero-coupon yield ($y_t^{(H_n)}$) and subtract expected losses (which we approximate as $\mathbb{E}_t[loss] = const + \vartheta_n \cdot Real\,Yield$). Incorporating these, Equation IA.7 becomes

$$\mathbb{E}_t[R_n^{real}] \;= const + \,b_n \cdot y_{n,t} \tag{IA.8}$$

where $y_{n,t} = ytm_{n,t} - \pi_t^{(h)}$ is the real yield on the given bond portfolio and $b_n = 1 - \vartheta_n$. Equation IA.8 is directly used in the main text for fixed income asset classes under our yied-based model of CMA formation.

B.1.2 Other Asset Classes

Other asset classes have variable income. For these asset classes, the expected real return from t to $t+h$ can be obtained using the following building-block model (see Ilmanen and

Maloney (2025a,b)):[IA.4]

$$\begin{aligned}\mathbb{E}_t[R_n^{real}] &= \mathbb{E}_t[\text{Payout Yield}] + \mathbb{E}_t[\text{Fundamental Growth}] + \mathbb{E}_t[\text{Valuation Multiple Growth}] \\ &= pr \cdot E_t/P_t \; + \; \mathbb{E}_t[E_{t+h}/E_t] \; + \; \mathbb{E}_t[PE_{t+h}/PE_t] \end{aligned} \tag{IA.9}$$

where E_t is earnings per share, P_t is price per share, PE_t is the price-to-earnings ratio, and pr is the payout-to-earnings ratio (assumed constant).

The first line of Equation IA.9 provides the general building-block model commonly used in CMAs whereas the second line specializes it to use E_t as the core fundamental (also common in CMAs). Our yield-based model of CMA formation then follows from assuming a constant expected fundamental growth and a mean-reverting PE_t ratio such that $PE_{t+h}/PE_t = const - \kappa_{PE} \cdot PE_t$, where $\kappa_{PE} > 0$. In this case, Equation IA.9 becomes

$$\mathbb{E}_t[R_n^{real}] \; = const \; + \; b_n \cdot y_{n,t} \tag{IA.10}$$

where $b_n = pr - \kappa_{PE}$ and $y_{n,t} = E_t/P_t$ is the real yield.

In our empirical analysis (see Section A.4), we measure $y_{n,t}$ as the inverse of the Shiller Cyclically Adjusted Price-to-Earnings (CAPE) ratio for public equity asset classes (so that earnings is net income). For the Real Estate asset class, we instead measure $y_{n,t}$ as the inverse of the cap rate (so that earnings is net operating income and the price reflects total property value), in line with the fact that CMAs typically consider unlevered real estate projections. Finally, for the Private Equity asset class, we measure $y_{n,t}$ as EBITDA over Total Enterprise Value of buyout deals (for measurement reasons) even though private equity returns in CMAs typically reflect levered returns. This approach further requires assuming that the leverage and cost of debt of buyout deals are constant over time so that Equity E_t/P_t = Firm E_t/P_t + Debt/Equity $\cdot$ (Firm E_t/P_t − Cost of Debt), which implies we can use Equation IA.10 for Private Equity with $y_{n,t}$ = Firm E_t/P_t (and have $b_n = (1 + \text{Debt/Equity}) \cdot (pr - \kappa_{PE})$).

[IA.4] This building-block model is referred to as the sum-of-the-parts method in the academic literature (see, e.g., Ferreira and Santa-Clara (2011)).

B.2 Results from the Full Building-Block Model of Equity CMA Formation

While our main analysis focuses on the simple yield-based model of CMA formation described in the prior subsection, the general Equation IA.9 implies earnings growth and PE growth should also affect expected returns in CMAs. To check their importance, Table IA.3 provides results (analogous to Table 5) in which the $\mu_{n,t}$ of the US Equity asset class is regressed on $y_{n,t}$ (the Excess CAPE yield) as well as signals for $\mathbb{E}_t[E_{t+h}/E_t]$ and $\mathbb{E}_t[PE_{t+h}/PE_t]$ coming from the Bank of American (BofA) survey of global fund managers (with measurement details provided in Subsection A.2). The $\mathbb{E}_t[E_{t+h}/E_t]$ signal is the "Subjective $\mathbb{E}$[Growth]" variable, which reflects the net fraction of fund managers who answer "yes" to the question of whether global profits will improve over the next twelve months. The $\mathbb{E}_t[PE_{t+h}/PE_t]$ signal is the "Perceived Undervaluation" variable, which reflects the (negative of the) net fraction of fund managers who answer "yes" to the question of whether US equities are overvalued.

The first column in Table IA.3 indicates that both Subjective $\mathbb{E}$[Growth] and Perceived Undervaluation help explain variation in $\mu_{n,t}$ beyond the Excess CAPE yield. In particular, the regression R^2 increases from 51.1% when only the Excess CAPE yield is used to 76.4% when all three variables are used. The other columns show the results for each expected return component in the $\mu_{n,t} = \alpha_{n,t} + \lambda_{n,t} = \alpha_{n,t} + \lambda^{\gamma}_{n,t} + \lambda^{\nu}_{n,t}$ decomposition. The most important result from these other columns is that α continues to be mostly driven by perceived undervaluation even after controlling for expected growth.

C Supplementary Empirical Results

This section describes additional results that supplement the main findings in the paper. Subsection C.1 compares our risk aversion estimates with CAPM-implied risk aversion values. Subsection C.2 provides results comparing simple models of yield-based CMA formation versus extrapolation-based CMA formation. The remaining subsections provide results applying different changes to our empirical procedure (as robustness checks). We replicate our main results (from Figures 8 and 10) under these different empirical procedures and provide all results in Figures IA.3 to IA.4. In a nutshell, we find that while the quantitative results from our variance decompositions somewhat differ across specifications, our qualitative findings using these alternative empirical decisions are similar to the ones we obtain in our baseline analysis.

C.1 Comparing Risk Aversion Estimates with CAPM Risk Aversion

As explained in Subsection 2.1, our approach to estimate risk aversion is simple (see Subsection C.3 for results under alternative risk aversion estimation procedures). For each institution-year observation, we estimate $\gamma_{j,t}$ from the slope coefficient of a linear projection of μ onto ν across asset classes, which is analogous to how traditional asset pricing tests estimate risk price from cross-sectional regressions of realized returns on estimated risk exposures. Then, to obtain the aggregate estimated risk aversion, we aggregate the estimated $\gamma_{j,t}$ across institutions each year following the procedure described in Subsection 1.3 (with $\theta_{j,n,t} = \gamma_{j,t}$).

An alternative approach would be to assume that the CAPM holds exactly for the wealth portfolio (i.e., $\alpha_{j,w,t} = 0$). From Equations 6 and 7, this alternative approach would imply the aggregate CAPM risk aversion $\gamma_t = \mu_{w,t}/\nu_{w,t}$ at time t and the CAPM risk aversion $\gamma_{j,t} = \mu_{j,w,t}/\nu_{j,w,t}$ for institution j at time t. Our projections across asset classes avoid assuming that the CAPM fully explains the wealth portfolio expected return. In fact, with our estimation approach, we could in principle find that $\gamma_{j,t} = 0$ for all institution-year observations, which would lead to the conclusion that all variation in μ is driven by α. If we instead relied on the CAPM risk aversion, we would remove this possibility by construction.

Nevertheless, it is useful to compare our estimated risk aversion (which we refer to as $\widehat{\gamma}$ for the rest of this subsection) to the CAPM risk aversion (which we refer to as γ^{CAPM} for the rest of this subsection) to understand how close our risk price estimates are from the CAPM ideal. Figure IA.1 provides a visual analysis of the link between $\widehat{\gamma}$ and γ^{CAPM}. From Figure IA.1(a), we see that there is a strong link between $\widehat{\gamma}$ and γ^{CAPM}, but that the two are far from perfectly correlated, with $\mathbb{C}or[\widehat{\gamma}, \gamma^{CAPM}] = 0.62$. As Figure IA.1(b) shows, aggregating across institutions each year leads to a much higher correlation of $\mathbb{C}or[\widehat{\gamma}, \gamma^{CAPM}] = 0.88$. Yet, even at the aggregate, we are far from the $\widehat{\gamma} = \gamma^{CAPM}$ prediction. In particular, Figure IA.1(c) shows that while the time variation in $\widehat{\gamma}$ tracks the time variation in γ^{CAPM}, we generally have $\widehat{\gamma}_t < \gamma_t^{CAPM}$.

Table IA.2 formalizes the visual observations of the prior paragraph through regressions of $\widehat{\gamma}$ onto γ^{CAPM}. Columns [1] to [4] provide regressions using institution-year observations with different types of fixed effects to explore alternative forms of variation in the data. We have slope coefficients around 0.5 and we can always reject the hypothesis that the slope coefficient is zero, indicating a statistically significant relation between $\widehat{\gamma}$ and γ^{CAPM}. However, we can also always reject the hypothesis that the slope coefficient is one, indicating the beliefs data are not perfectly consistent with the CAPM (in line with the results in Couts, Gonçalves, and Loudis (2024)). Column [5] provides regression results using aggregate risk aversion. In this case, the slope coefficient increases to 0.74 and it remains highly statistically significant. However, we continue to reject the hypothesis that the slope coefficient is one, solidifying the idea that the beliefs data are not perfectly consistent with the CAPM. These results highlight the importance of incorporating alphas in our analysis, which accommodate deviations from the relation between expected returns and risk quantities implied by the CAPM.

C.2 Understanding CMA Formation: Yield-Based versus Extrapolation-Based

In Section 3, we study the relation between expected returns and yields using a simple yield-based model of CMA formation. In this subsection, we contrast yield-based CMA formation with extrapolation-based CMA formation (as explored in Greenwood and Shleifer (2014) for individual investors). The results are provided in Table IA.4 with both the dependent and independent variables normalized to z-score units to facilitate the comparison between the effect of yields with the effect of realized returns.

The first two columns in Table IA.4 start by focusing on expected nominal returns (as in Greenwood and Shleifer (2014)). Specifically, we consider the regressions

$$\mathbb{E}_t[R_n] \ = const \ + \ b_{n,yield} \cdot (y_{n,t} + \pi_t^{(h)}) \ + \ b_{n,return} \cdot R_{n,t} \ + \ u_{n,t} \tag{IA.11}$$

where $y_{n,t} + \pi_t^{(h)}$ is the nominal yield for asset class n at the end of year t and $R_{n,t}$ is the nominal return for asset class n in year t.[IA.5] The results indicate that yield-based CMA formation better describes expected returns from CMAs. Specifically, the only positive and statistically significant $b_{n,return}$ (as implied by extrapolation) is for the US Fixed Income asset class, and even there the yield model dominates (e.g., the R^2 from a model with $b_{n,return} = 0$ is 95.8% and it only increases slightly to 96.8% when we allow for $b_{n,return} \neq 0$).

While Greenwood and Shleifer (2014) focus on nominal returns, institutional investors consider inflation, so the next two columns in Table IA.4 consider expected returns minus expected inflation, $\mathbb{E}_t[R_n^{real}] \equiv \mathbb{E}_t[R_n] - \pi_t^{(h)}$. In this case, we use the regressions

$$\mathbb{E}_t[R_n^{real}] \ = const \ + \ b_{n,yield} \cdot y_{n,t} \ + \ b_{n,return} \cdot R_{n,t}^{real} \ + \ u_{n,t} \tag{IA.12}$$

[IA.5] We obtain $R_{n,t}$ for the US and Ex US Fixed Income asset classes using the nominal annual returns to the Bloomberg Barclays US Aggregate Bond and Global Aggregate-Ex US indices, respectively (both available on Bloomberg). For US and Ex US Equity, we obtain $R_{n,t}$ using annual nominal returns to the S&P 500 and MSCI World ex US Indices, respectively (both available on Bloomberg). For the Private Equity asset class, we proxy for $R_{n,t}$ using the realized 1-year IRR for aggregate US buyout funds from the MSCI Private Capital Intel. Finally, for the Real Estate asset class, we obtain $R_{n,t}$ using annual nominal returns on the NTBI index from NCREIF until 2019 and on the RCA CPPI Index from MSCI thereafter (since the NTBI index was discontinued in Q1/2020), both of which are transaction-based indices. The realized inflation used to calculate $R_{n,t}^{real}$ in Equation IA.12 is obtained from Robert Shiller's data library (and reflects the realized annual growth in the US CPI index).

which (under $b_{n,return} = 0$) are internally consistent with the simple yield-based model of CMA formation discussed in Subsection 3.1. The results continue to indicate that yield-based CMA formation better describes expected returns from CMAs. Specifically, we still have that the only positive and statistically significant $b_{n,return}$ (as implied by extrapolation) is for the US Fixed Income asset class, and even there the yield model dominates (e.g., the R^2 from a model with $b_{n,return} = 0$ is 92.9% and it only increases slightly to 94.7% when we allow for $b_{n,return} \neq 0$).

Finally, the last two columns in Table IA.4 consider expected excess returns ($\mu_{n,t}$) as we focus on these in our main analysis. To be fully consistent with the yield-based model of CMA formation in Subsection 3.1, the regressions would need two yield variables ($y_{n,t}$ and $y_{cash,t}$) with different parameters (and we would also need to impose cross-equation restrictions). To avoid this complication, we simplify the yield based model of CMA formation of Subsection 3.1. For fixed income asset classes, $y_{n,t}$ is highly correlated with $y_{cash,t}$ so that we treat $y_{n,t} \approx y_{cash,t}$, which allows us to use $y^{\mu}_{n,t} = y_{n,t}$ as the only yield variable. For the other asset classes, the results in Table 4 suggest that $b_n \approx \omega$ is a reasonable approximation so that we can use $y^{\mu}_{n,t} = y_{n,t} - y_{cash,t}$ as the only yield variable. So, the last two columns in Table IA.4 estimate the regression

$$\mu_{n,t} \; = const \; + \; b_{n,yield} \cdot y^{\mu}_{n,t} \; + \; b_{n,return} \cdot (R_{n,t} - R_{f,t}) \; + \; u_{n,t} \tag{IA.13}$$

where $R_{f,t}$ is the annual return for the 1-month Treasury bill obtained from Kenneth French's data library. In this case, the evidence for extrapolation is even weaker since $b_{n,return}$ is not statistically significant for any asset class (and the point estimate is even negative for three out of the six asset classes).

The overall results in this subsection indicate that a yield-based CMA formation better describes the expected returns from institutional investors in comparison to an extrapolation-based CMA formation in the spirit of what Greenwood and Shleifer (2014) propose for individual investors.

For completeness, we also replicate Table 4 using Equation IA.13 (with $b_{n,return} = 0$), which represents a more reduced-form analysis of the relation between expected returns and yields in comparison to the yield-based model of CMA formation discussed in Subsection 3.1. The results (provided in Table IA.5) are very similar to what we report in the main text (note that we do not use z-score units in this case to be consistent with Table 4). Specifically, for most asset classes, the relation between expected returns and yields is driven by risk premia (mainly through risk quantity) rather than alphas. The exceptions are Private Equity (as in the results reported in the main text) and Real Estate. For Real Estate, both α and λ seem relevant in this case (and the λ effect arises mainly through risk aversion). The difference in the Real Estate results between the structural and reduced-form analyses likely steams from the fact that Real Estate is the asset class for which the $\omega = b_n$ requirement for the validity of the reduced-form analysis is most violated (as per the results in Table 4).

C.3 Alternative Risk Aversion Estimation Methods

In the main text, we estimate $\gamma_{j,t}$ from the slope coefficient of a linear projection of μ onto ν across asset classes. In this subsection, we consider different ways to estimate $\gamma_{j,t}$.

C.3.1 $\gamma_{j,t}$ Implied by the CAPM

As discussed in Subsection C.1, the CAPM implies $\gamma_{j,t} = \mu_{j,w,t}/\nu_{j,w,t}$ and $\gamma_t = \mu_{w,t}/\nu_{w,t}$. So, we replicate our main results using this alternative approach. The results (in Figures IA.3 to IA.4) are qualitatively similar to the ones we provide in the main text. Quantitatively, they suggest an even stronger effect of λ (through ν) on μ, and thus strengthen our main findings.

C.3.2 $\gamma_{j,t}$ Estimation with Weighted Least Squares

Our baseline linear projection of μ onto ν across asset classes treats each asset class equally. However, some asset classes are more important than others, as highlighted by their different wealth portfolio weights in Figure 2. So, we replicate our main results using a Weighted Least Squares (WLS) projection where the WLS weights are based on the wealth portfolio weights. The results (in Figures IA.3 to IA.4) are very similar to our baseline results.

C.3.3 $\gamma_{j,t}$ Estimation with j and t Fixed Effects

One limitation of our main analysis is that our $\gamma_{j,t}$ estimation is based on only nine asset classes (so, nine data points for each linear projection). We address this issue by imposing a restriction on the correlation structure between α and ν. Specifically, our main estimation can be written as the panel regression $\mu_{j,n,t} = \eta_{j,t} + \gamma_{j,t} \cdot \nu_{j,n,t} + \varepsilon_{j,n,t}$ and here we consider the panel regression $\mu_{j,n,t} = \eta_j + \eta_t + \gamma_{j,t} \cdot \nu_{j,n,t} + \varepsilon_{j,n,t}$. That is, we gain power by assuming $\eta_{j,t} = \eta_j + \eta_t$, which effectively imposes a restriction on the correlation structure between α and ν. The results (in Figures IA.3 to IA.4) are very similar to our baseline results.

C.4 Alternative Subsets of the Data

In the main text, we provide results using all CMAs in our dataset. In this subsection, we consider alternative subsets of CMAs.

C.4.1 Only Managers or Only Consultants

Managers and consultants may have different approaches to their CMAs (and also face different incentives). So, we provide results separately for each group of institutions (with 128 institution-year observations for managers and 233 for consultants). The results (in Figures IA.3 to IA.4) are qualitatively similar to our baseline results. Quantitatively, the biggest difference is that the importance of alpha time variation in explaining expected return time variation increases. This pattern is true in both cases (i.e., when we use only asset managers and when we use only investment consultants). The reason is that risk aversion is estimated for each (j, t). When we include more CMAs in a given year (as is the case in our baseline analysis), estimation noise is diluted in the aggregation process so that we better estimate the fraction of expected return variation attributed to each source.

C.4.2 Only Direct CMAs or Only Indirect CMAs

One may worry that pension fund reports do not reflect the true CMAs of the institutions we are trying to capture, which would affect the reliability of the indirect CMAs in our dataset.

Relatedly, one may worry that institutions have incentives to send us (or release online) a selected set of CMAs that make them "look good", which would affect the reliability of the direct CMAs in our dataset. So, we provide results separately for the direct and indirect CMAs in our dataset (with 301 direct CMAs and 123 indirect CMAs). The results (in Figures IA.3 to IA.4) are qualitatively similar to our baseline results. Quantitatively, the biggest difference is that the importance of alpha time variation in explaining expected return time variation increases when we use only indirect CMAs. This result is similar to what we find when using only managers or only consultants, and it has the same root cause: there is a large decline in the number of institution-year observations when we use only indirect CMAs.

C.5 Alternative Constructions of Subjective Beliefs and Market Portfolio Weights

In this subsection, we consider alternative constructions of subjective beliefs and market portfolio weights.

C.5.1 $\mathbb{E}[\boldsymbol{R}]$ without Transformation

As explained in Subsection A.1.2, our CMAs vary on whether they contain only expected arithmetic returns, only expected geometric returns, or both. In particular, 41.5% of our CMAs report only expected arithmetic returns, 22.2% of our CMAs report only expected geometric returns, and 36.3% of our CMAs report both. To ensure the conceptual definition underlying our expected return measure is the same for all our institution-year observations, we always use expected arithmetic returns in our baseline analysis. This approach is consistent with the expected return definition from the analogue of Equation 2 in typical asset pricing models and also with the fact that our CMAs report expected arithmetic returns more frequently than expected geometric returns. To avoid losing observations, we use the log-Normal transformation discussed in Subsection A.1.2 for the 22.2% of CMAs without expected arithmetic returns. However, one may worry that our results are driven by this transformation. To address this issue, we explore a specification that uses expected arithmetic returns when available and expected geometric returns when expected arithmetic returns are not available (so that no transformation is applied). The results (in Figures IA.3 to IA.4) are quantitatively similar to our baseline results.

C.5.2 $\mathbb{E}[\boldsymbol{R}]$ Transformed to Geometric

The above subsection shows that defining μ using the expected returns directly reported in CMAs leads to results that are quantitatively similar to the ones we report in the main text. However, the choice between expected arithmetic returns and expected geometric returns should have some quantitative effect since the expected return Equation 2 can be approximately written as

$$\mathbb{E}_{j,t}[log(R_n) - log(R_{Cash})] \approx \underbrace{\alpha_{j,n,t} - 0.5 \cdot (\mathbb{V}ar_{j,t}[log(R_n)] - \mathbb{V}ar_{j,t}[log(R_{Cash})])}_{\alpha \text{ under expected geometric returns}} + \lambda_{j,n,t} \tag{IA.14}$$

so that defining μ based on expected geometric returns should lead to a measured alpha that captures not only the true alpha but also the Jensen's inequality term. To explore this aspect, we also consider a specification that defines μ based on expected geometric returns, with the log-Normal transformation $\mathbb{E}_{j,t}[log(R_n)] = log(\mathbb{E}_{j,t}[R_n]) - \frac{1}{2} \cdot \mathbb{V}ar_{j,t}[log(R_n)]$ (from Subsection A.1.2) used for the 41.5% of CMAs that only report expected arithmetic returns. While the results (in Figures IA.3 to IA.4) are qualitatively similar to our main findings, there is a non-trivial quantitative effect from changing from expected arithmetic returns to expected geometric returns. In particular, the explanatory power of alpha increases relative to the explanatory power of risk quantity, as expected given Equation IA.14 and the definition of expected geometric returns.

C.5.3 Wealth Portfolio Based on US Equity Asset Class

In our baseline analysis, we use the allocation of US public pension funds to obtain wealth portfolio weights. However, it is common in the asset pricing literature to use equities as the wealth portfolio. So, we replicate our main results using the US Equity asset class as the wealth portfolio. The results (in Figures IA.3 to IA.4) are very similar to our baseline results.

C.5.4 Wealth Portfolio Based on Maximum Sharpe Ratio Portfolio

One might be tempted to use the maximum Sharpe ratio portfolio implied from the CMAs as the unique risk factor in a single factor model (instead of directly measuring wealth portfolio weights as we do). We do not follow this approach for three reasons. First, the maximum Sharpe ratio portfolio always prices its underlying assets (Roll (1977)), and thus we would have that all alphas are zero by construction so that 100% of the variation in expected excess returns would be driven by risk premia. Of course, in this case the expression "risk premia" is simply a synonym for "expected excess returns", thereby losing its economic content. Second (and related to the first), the alphas we identify for the US Equity asset class under our model are strongly correlated with perceived mispricing that does not impose any model (see Subsection 3.3). And third, one cannot separately identify risk quantity and risk price when using the maximum Sharpe ratio portfolio as the risk factor. The reason is that the Sharpe ratios of r_p and $\phi \cdot r_p$ are the same for any positive ϕ so that we have an infinite number of maximum Sharpe ratio portfolios. So, the separation between risk quantity and risk price in this case would boil down to a normalization on the sum of the weights for the maximum Sharpe ratio portfolio (with any positive sum of weights being valid since the remaining weight would reflect a cash position). The economic intuition for this result is that data on beliefs about asset returns cannot separately identify risk quantity and risk price (i.e., risk aversion). For that, we need to take a stand on what is the relevant risk factor to investors (which implicitly reflects investors' preference structure). The use of the maximum Sharpe Ratio portfolio as a single risk factor imposes no preference structure (i.e., it holds for any preference structure), and thus cannot separately identify risk quantity and risk price.

C.6 Alternative Variance Decomposition Estimation Methods

In this subsection, we consider alternative variance decomposition estimation methods.

C.6.1 Decomposing μ Variation Adjusting for Horizon Heterogeneity

The forecasting horizons in our CMAs vary from 4 years to 30 years, with the median and modal horizon being 10 years. Conceptually, this is not an issue since expected return decomposition framework from Subsection 1.1 holds for any given horizon. However, part of the disagreement in expected returns we study may come from horizon heterogeneity (which is embedded in both risk premia and alphas). To address this empirical issue, we consider an alternative approach that controls for horizon heterogeneity in the belief aggregation process (for the time series analysis) and in the variance decomposition process (for the disagreement analysis). Specifically, in the case of our time-series analysis, we add horizon by asset class fixed effects in Equation 4 so that our aggregated beliefs control for horizon heterogeneity (that could otherwise induce time variation in the horizon underlying aggregated beliefs). In the case of our disagreement analysis, we add horizon by asset class fixed effects directly in the panel regressions used to estimate $\mathbb{D}(\alpha)$, $\mathbb{D}(\lambda)$, $\mathbb{D}_\lambda(\gamma)$, and $\mathbb{D}_\lambda(\nu)$. We observe the forecasting horizon for 61% of our institution-year observations and allow the other observations to have a separate fixed effect in our panel regressions. The results (in Figures IA.3 to IA.4) are very similar to our baseline results.

C.6.2 Decomposing μ Time Variation using Institution-Level Beliefs

In our main analysis, we decompose expected return time variation using aggregated beliefs. Using belief elements aggregated across institutions ensures each year receives the same weight in our analysis so that the results properly reflect a decomposition of expected return time variation throughout our sample period. However, we also explore a specification in which the decomposition of expected return time variation is done at the institution level. Specifically, we use our unbalanced panel of institution-year observations. We add institution by asset class fixed effects and weight observations so that each year receives the same weight in our analysis (these adjustments ensure a focus on expected return time variation throughout our sample period). The results (in Figures IA.3 to IA.4) are very similar to our baseline results.

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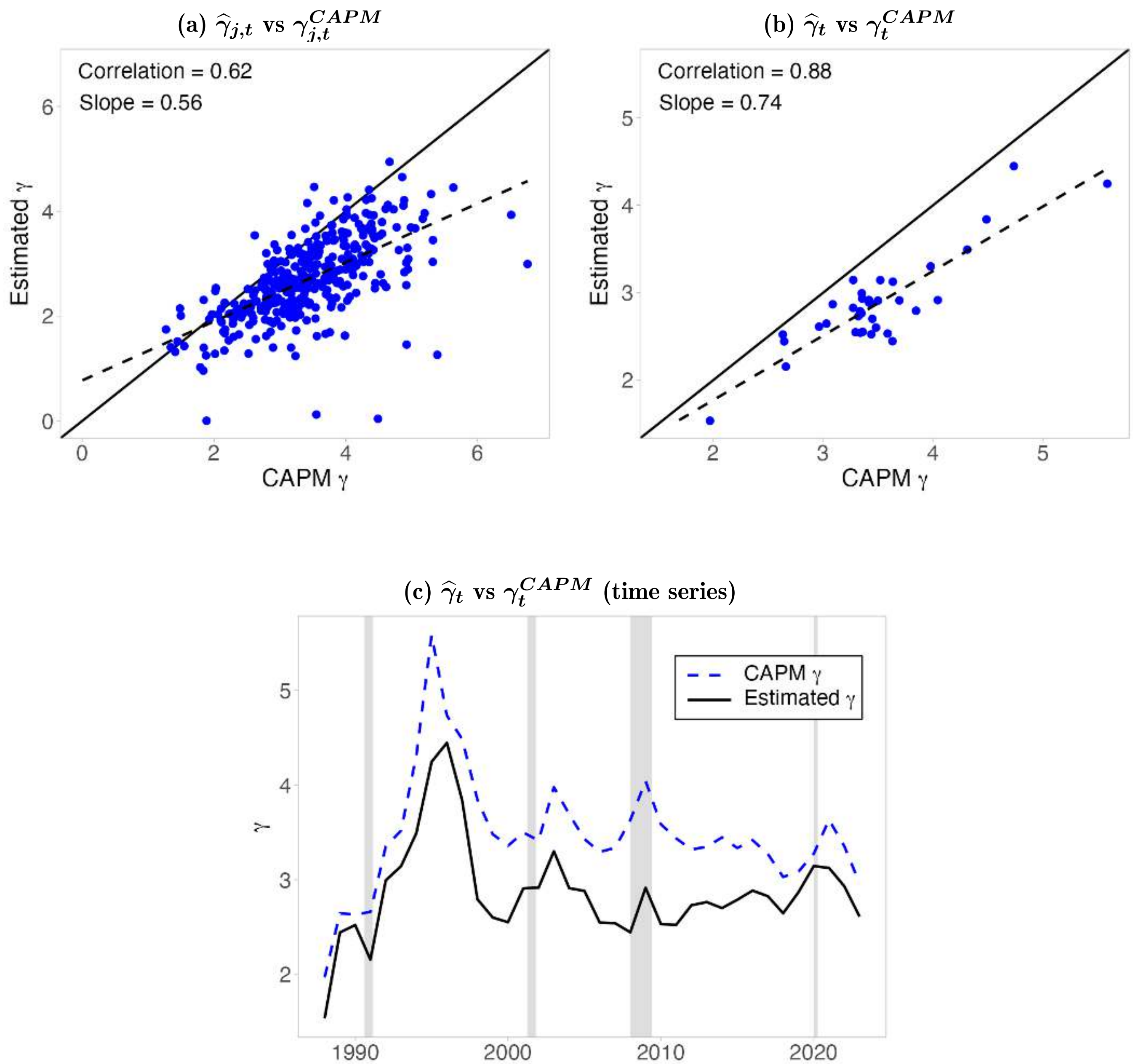
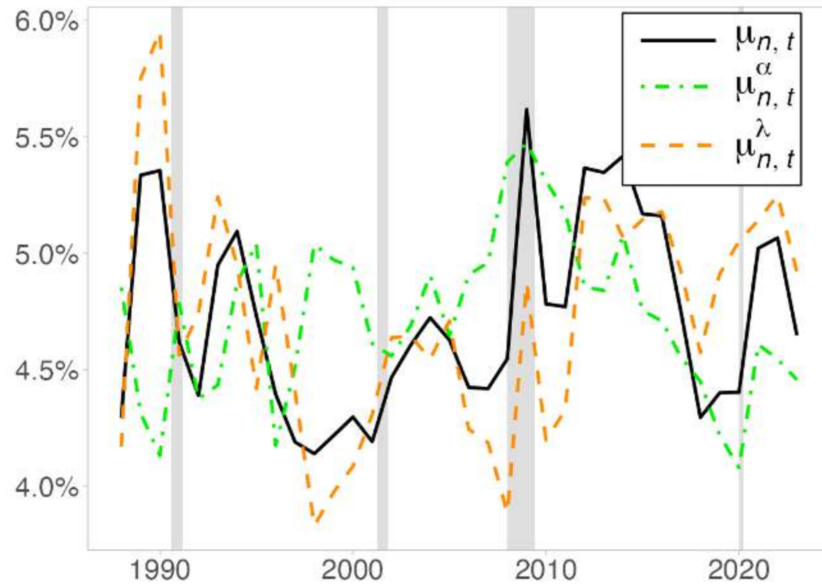


Figure IA.1

Estimated Risk Aversion vs CAPM Risk Aversion

This figure depicts our estimated risk aversion ($\widehat{\gamma}$) against the CAPM-implied risk aversion (γ^{CAPM}). For each institution-year observation, we obtain $\widehat{\gamma}_{j,t}$ from the slope coefficient of a linear projection of μ onto ν across asset classes (and use the aggregation method in Subsection 1.3 to obtain $\widehat{\gamma}_t$). In contrast, we obtain $\gamma_{j,t}^{CAPM} = \mu_{j,w,t}/\nu_{j,w,t}$ and $\gamma_t^{CAPM} = \mu_{w,t}/\nu_{w,t}$. Panel (a) provides a scatterplot for the institution-level risk aversion for all institution-year observations while Panels (b) and (c) provide a scatterplot and a time series plot for the aggregate risk aversion for all years. Subsection 1.2 describes our beliefs data while Subsection C.1 explains our risk aversion estimation procedure and discusses the results in this figure.

(a) Expected Return Components



(b) Risk Premium Components

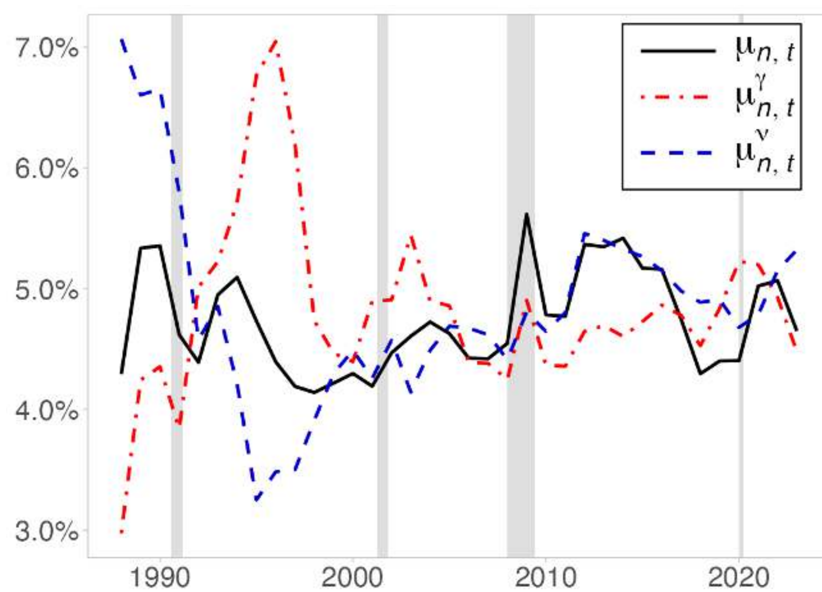


Figure IA.2

Time Series of Expected Return Components for the Wealth Portfolio

This figure replicates Figure 6(a) and Figure 7(b), but for the wealth portfolio (instead of single asset classes). Panel (a) depicts a time series plot of aggregate expected returns for the wealth portfolio ($\mu_{w,t}$) in a solid black line against counterfactual aggregate expected returns that would prevail if (i) only alphas varied over time ($\mu^{\alpha}_{w,t} = \alpha_{w,t} + \overline{\lambda}_w$) in dashed-dotted green lines or (ii) only risk premia varied over time ($\mu^{\lambda}_{w,t} = \overline{\alpha}_w + \lambda_{w,t}$) in dashed orange lines. Panel (b) depicts the same $\mu_{w,t}$ in a solid black line against counterfactual aggregate expected returns that would prevail if (i) only risk aversion varied over time ($\mu^{\gamma}_{w,t} = \overline{\alpha}_w + \gamma_t \cdot \overline{\nu}_w$) in dashed-dotted red lines or (ii) only risk quantity varied over time ($\mu^{\nu}_{w,t} = \overline{\alpha}_w + \overline{\gamma} \cdot \nu_{w,t}$) in dashed blue lines. Subsection 1.2 describes our beliefs data while Subsection 4.1 discusses the results from this figure.

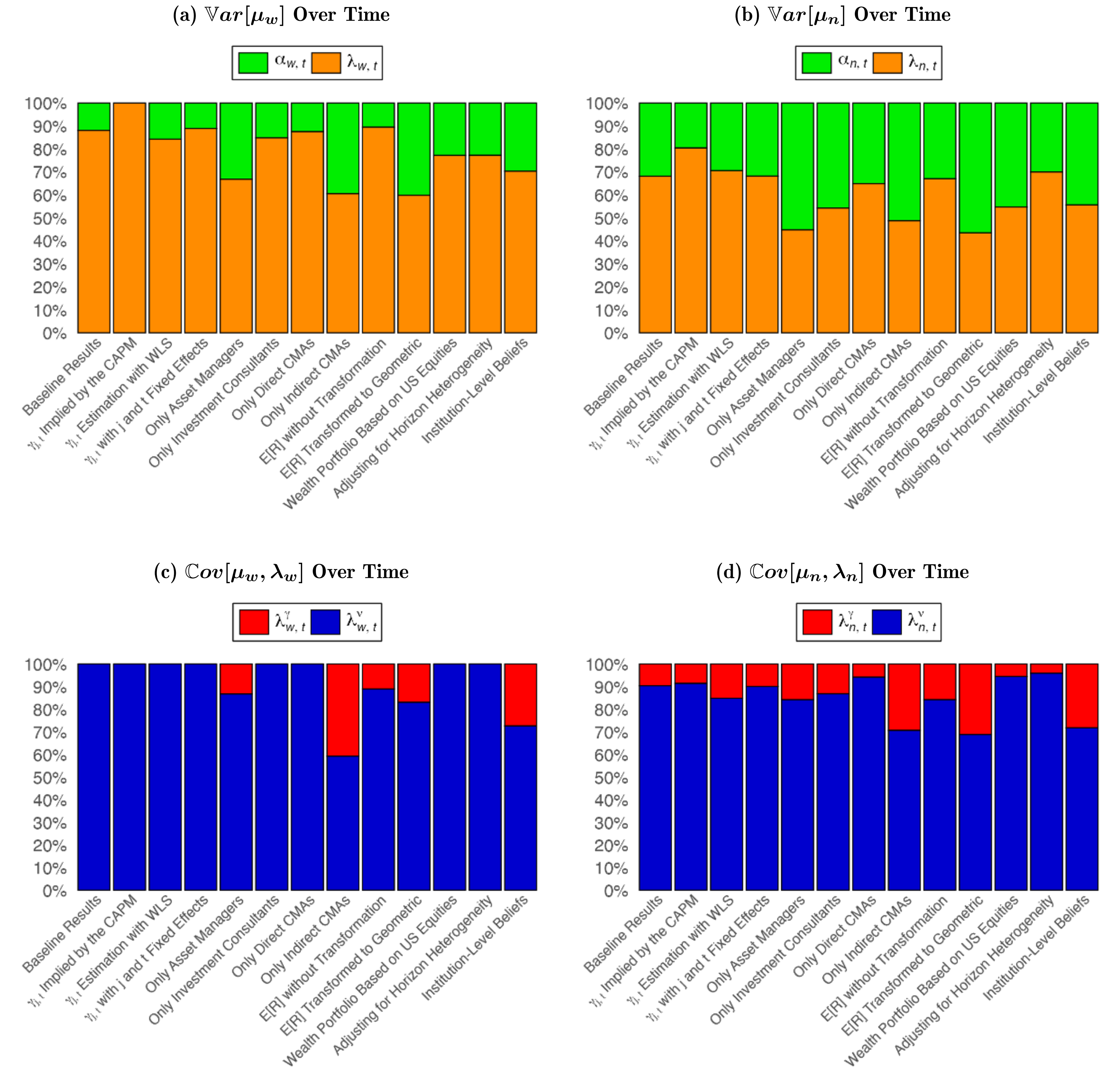


Figure IA.3
Decomposing Expected Return Time Variation: Alternative Specifications

This figure reproduces the key results from Figures 8(a) and 8(c) in the main text using alternative empirical specifications. Panel (a) reproduces the decomposition of $\mathbb{V}ar[\mu_w]$, Panel (b) reproduces the decomposition of $\mathbb{V}ar[\mu_n]$ with all asset classes, Panel (c) reproduces the decomposition of $\mathbb{C}ov[\mu_w, \lambda_w]$, and Panel (d) reproduces the decomposition of $\mathbb{C}ov[\mu_n, \lambda_n]$ with all asset classes. Section C provides details on the alternative empirical specifications and discusses the results from this figure.

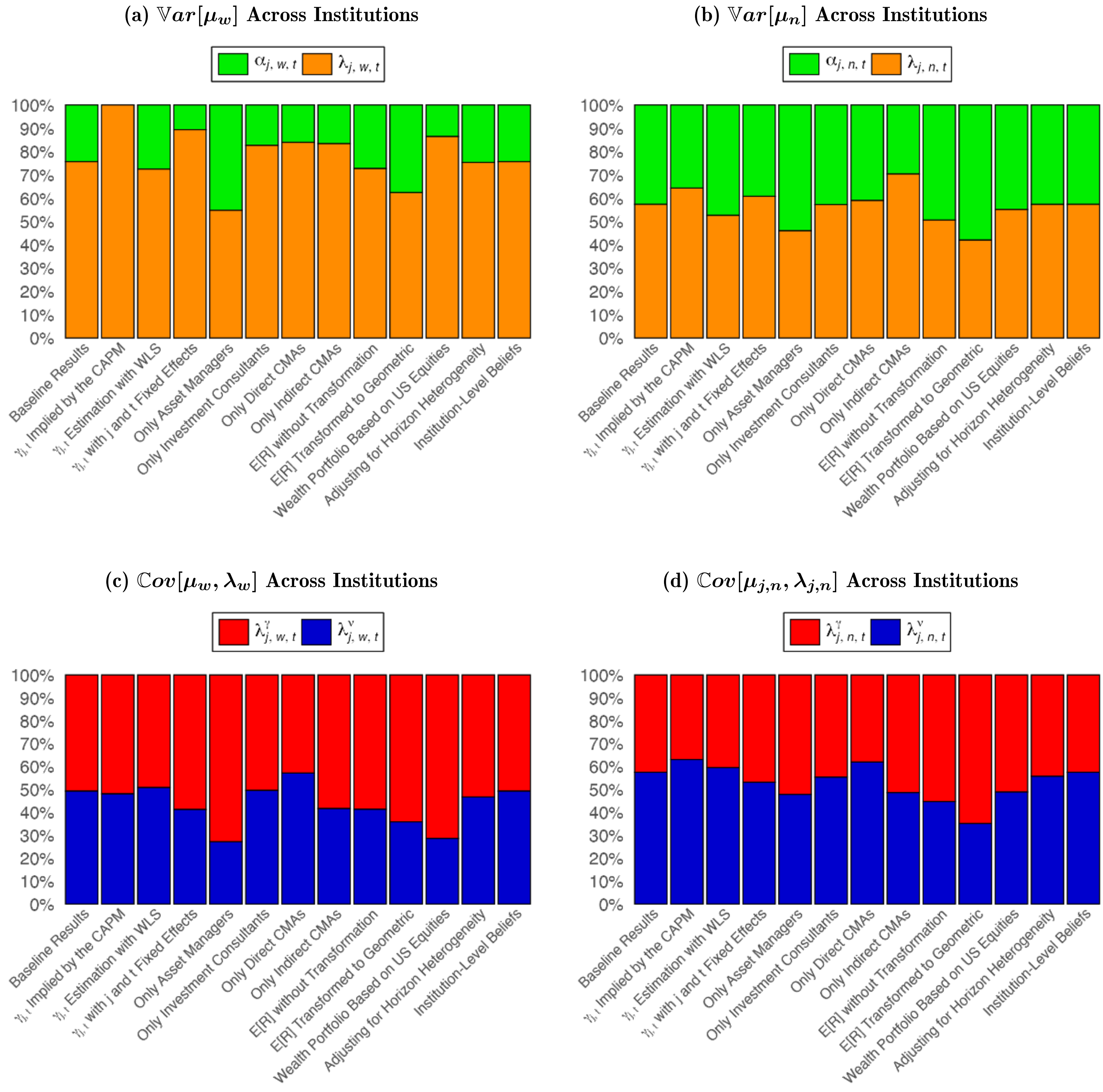


Figure IA.4
Decomposing Expected Return Disagreement: Alternative Specifications

This figure reproduces the key results from Figure 10 in the main text, which focuses on cross-institution variation (i.e., disagreement), using alternative empirical specifications. Panel (a) reproduces the decomposition of $\mathbb{V}ar[\mu_w]$, Panel (b) reproduces the decomposition of $\mathbb{V}ar[\mu_n]$ with all asset classes, Panel (c) reproduces the decomposition of $\mathbb{C}ov[\mu_w, \lambda_w]$, and Panel (d) reproduces the decomposition of $\mathbb{C}ov[\mu_n, \lambda_n]$ with all asset classes. Section C provides details on the alternative empirical specifications and discusses the results from this figure.

Table IA.1
Constructing our Asset Classes

This table provides the results from our procedure to match the broad asset classes covered in the paper to the asset classes covered in the CMAs. The procedure is as follows. First, we identify the asset classes in each CMA based on the asset class names used in the CMA report and/or the actual portfolio index stated in the CMA report. Second, we manually map each asset class in each institution-year CMA to an institution-specific asset class name (fixed over time) that reflects the underlying asset class well. Third, we map each institution-specific asset class name to a slightly more general asset class name (which we refer to as the master asset class) that reflects the institution-specific asset class name reasonably well while allowing for small mismatches to accommodate asset classes from different institution under the same master asset class. Fourth, for each CMA, we match each of our broad asset classes to the most closely related master asset class available (with the possibility of no match). The first column shows the broad asset classes we cover in the paper. The other columns provide the list of master asset classes that we match to these broad asset classes. They also provide the fraction of institution-year CMAs that have the respective match (within the institution-year CMAs that have some match for the given broad asset class). Subsections 1.2 and A.1 provide more details about our subjective beliefs data.

	Master Asset Classes Used (in order)				
Broad Asset Class	**Option #1**	**Option #2**	**Option #3**	**Option #4**	**Option #5**
Cash	US Cash (95%)	3-Month Libor (4.2%)	US Treasuries ST (0.3%)	US Inflation (0.3%)	
US Fixed Income	US Bonds (76%)	US Bonds Credit (1.4%)	US Fixed Income Core+ (7.7%)	US Fixed Income Core (8.5%)	US Corporate Fixed Income (1.7%)
Ex US Fixed Income	Global Ex US Bonds (50%)	Global Dev. Ex US Fixed Income (5.5%)	Global Ex US Corp. Bonds (1.8%)	Global Ex US Inv. Grade Bonds (0.7%)	Global Ex US Govt. Bonds (20%)
US Equity	US Equities (65%)	US Equities Large Cap (35%)			
Ex US Equity	Global Dev. Ex US Equities (52%)	Global Ex US Equities (35%)	EAFE Index (9.7%)	Global Equities (3.1%)	
Private Equity	Global Private Equity (0.6%)	Private Equity+Venture Capital (1.3%)	Private Equity Fund of Funds (3.9%)	US Private Equity (85%)	Private Investments (3.6%)
Real Estate	Global Real Estate (4.5%)	Real Estate Public+Private (5.6%)	Private Real Estate (14%)	US Core Real Estate (61%)	Global REITs (3.4%)
Hedge Funds	Hedge Funds (76%)	Equal-Weighted Average of Different Hedge Fund Strategies* (24.3%)			
Commodities	Commodities (97%)	Commodity Futures (2.9%)			
Infrastructure	Global Infrastructure (75%)	Private Infrastructure (15%)	Public Infrastructure (10%)		
	Master Asset Classes Used (in order)				
Broad Asset Class	**Option #6**	**Option #7**	**Option #8**	**Option #9**	**Option #10**
Cash					
US Fixed Income	US Corp. Bonds Inv. Grade (1.4%)	Midterm Corp. Bonds Inv. Grade (0.3%)	Midterm US Bonds (0.6%)	Midterm US Govt. Credit (2.8%)	
Ex US Fixed Income	Global Bonds/Credit (6.3%)	Global Corp. Bonds (0.4%)	Global Govt. Bonds (13%)	Global Ex US Govt. Bonds Hedged (0.7%)	Global Bonds Hedged (2.6%)
US Equity					
Ex US Equity					
Private Equity	Buyouts (5.2%)				
Real Estate	REITs (9.5%)	Real Assets (0.3%)	Global Real Estate Hedged (1.4%)		
Hedge Funds					
Commodities					
Infrastructure					

* For Hedge Funds, we take the average of all available hedge fund strategies when the primary and substitute 1 categories are missing.
The hedge fund strategies are (they vary by institution-year observation) "Funds of Funds", "Multi Strategy", "Discretionary", "Open Mandate", "Directional", "Non-Directional", "Event Driven", "Market Neutral", "Relative Value", "Long-Short", "Long Bias", "Macro", "CTA", "Equity Style", "Credit Style Bonds Hedged", "Asymmetric Style", "Equity Hedged", "Convertible", "Moderate Aggregate Risk", "Absolute Returns", "Managed Futures"

Table IA.2
Relation Between Estimated Risk Aversion and CAPM Risk Aversion

This tables provides results from projections of our estimated risk aversion ($\widehat{\gamma}$) against the CAPM-implied risk aversion (γ^{CAPM}). For each institution-year observation, we obtain $\widehat{\gamma}_{j,t}$ from the slope coefficient of a linear projection of μ onto ν across asset classes (and use the aggregation method in Subsection 1.3 to obtain $\widehat{\gamma}_t$). In contrast, we obtain $\gamma_{j,t}^{CAPM} = \mu_{j,w,t}/\nu_{j,w,t}$ and $\gamma_t^{CAPM} = \mu_{w,t}/\nu_{w,t}$. The first four columns use institution-level risk aversion for all institution-year observations while the last column uses aggregate risk aversion for all years. Standard errors are based on Driscoll and Kraay (1998) with Newey and West (1994) lag selection for the first four columns and on Newey and West (1987, 1994) for the last column. Subsection 1.2 describes our beliefs data while Subsection C.1 explains our risk aversion estimation procedure and discusses the results from this table.

	$\widehat{\gamma}_{j,t} = a + b \cdot \gamma_{j,t}^{CAPM} + \varepsilon_{j,t}$				$\widehat{\gamma}_t = a + b \cdot \gamma_t^{CAPM} + \varepsilon_t$
	[1]	**[2]**	**[3]**	**[4]**	**[5]**
a	0.77	-	-	-	0.30
$(t_{a=0})$	(6.11)	-	-	-	(1.38)
b	0.56	0.48	0.57	0.46	0.74
$(t_{b=0})$	(15.37)	(6.07)	(14.08)	(4.68)	(12.92)
$\{t_{b=1}\}$	{-12.0}	{-6.6}	{-10.8}	{-5.59}	{-4.58}
R^2_{total}	38.9%	63.1%	44.9%	69.1%	77.2%
R^2_{within}		26.6%	37.9%	22.5%	
N_{obs}	361	361	361	361	36
Fixed Effects:					
Institution		×		×	
Year			×	×	

Table IA.3

Linking μ Components to Yields, Perceived Undervaluation, and $\mathbb{E}$[Growth] (US Equities)

This table reports results from regressions (for the US Equity asset class) of CMA-based aggregate μ and its components (α, λ, λ^γ, and λ^ν) onto the excess CAPE yield (which is the $y_{n,t}$ measure for US Equity in Table 4) as well as onto two variables from the Bank of America (BofA) survey of global fund managers. The first BofA variable is the "Perceived Undervaluation", which reflects the (negative of the) net fraction of fund managers who answer "yes" to the question of whether US equities are overvalued. The second BofA variable is the "Subjective $\mathbb{E}$[Growth]", which reflects the net fraction of fund managers who answer "yes" to the question of whether global profits will improve over the next twelve months. The sample for this table is restricted to the 2001 to 2022 period (due to the availability of the BofA Perceived Undervaluation variable). We provide further details about the BofA surveys and measurement in Internet Appendix A.2. The slope coefficients are normalized to be interpreted as the effect of a one standard deviation movement in the independent variable on the dependent variable (in % units). Standard errors are based on Newey and West (1987) with three annual lags given the relatively short sample (t-statistics in this table tend to be even larger with Newey and West (1994) automatic lag selection procedure). Subsection 1.2 describes our beliefs data while Subsection 3.3 discusses the results from this table.

		μ	α	λ	λ^γ	λ^ν
Excess CAPE Yield	**Coef**	0.40	0.13	0.27	0.07	0.20
	(t_{stat})	(6.80)	(1.15)	(3.96)	(0.67)	(2.29)
	R^2_{adj}	51.1%	1.1%	28.1%	-2.3%	25.0%
Perceived Undervaluation	**Coef**	0.25	0.50	-0.25	-0.21	-0.04
	(t_{stat})	(2.51)	(12.00)	(-3.06)	(-3.85)	(-0.37)
	R^2_{adj}	17.3%	83.1%	24.6%	22.3%	-3.9%
Subjective $\mathbb{E}$[Growth]	**Coef**	0.08	-0.04	0.13	0.16	-0.04
	(t_{stat})	(1.01)	(-0.26)	(1.02)	(1.75)	(-0.35)
	R^2_{adj}	-2.6%	-4.3%	2.6%	10.9%	-4.1%
Excess CAPE Yield	**Coef**	0.39	0.11	0.28	0.08	0.20
	(t_{stat})	(9.48)	(3.33)	(5.15)	(0.85)	(2.36)
Perceived Undervaluation	**Coef**	0.23	0.50	-0.27	-0.22	-0.05
	(t_{stat})	(2.83)	(17.90)	(-3.12)	(-3.13)	(-0.41)
	R^2_{adj}	68.5%	86.5%	58.7%	22.0%	22.9%
Excess CAPE Yield	**Coef**	0.41	0.13	0.28	0.08	0.20
	(t_{stat})	(6.91)	(1.84)	(8.76)	(1.29)	(2.09)
Subjective $\mathbb{E}$[Growth]	**Coef**	0.12	-0.03	0.15	0.17	-0.02
	(t_{stat})	(2.12)	(-0.32)	(2.05)	(2.50)	(-0.23)
	R^2_{adj}	53.7%	-3.7%	35.6%	10.4%	21.3%
Excess CAPE Yield	**Coef**	0.40	0.11	0.29	0.09	0.20
	(t_{stat})	(13.99)	(3.64)	(6.11)	(1.32)	(2.43)
Perceived Undervaluation	**Coef**	0.26	0.51	-0.25	-0.19	-0.05
	(t_{stat})	(4.58)	(17.04)	(-3.65)	(-3.07)	(-0.37)
Subjective $\mathbb{E}$[Growth]	**Coef**	0.16	0.05	0.11	0.14	-0.03
	(t_{stat})	(5.35)	(1.77)	(2.65)	(1.57)	(-0.45)
	R^2_{adj}	76.4%	86.6%	62.8%	30.1%	19.2%

Table IA.4

Understanding CMA Formation: Yield-Based versus Extrapolation-Based

This table reports results from regressions of CMA-based aggregate expected returns on yields and realized annual returns for different asset classes. The first column block uses nominal expected returns, nominal yields, and nominal realized returns. The second column block uses expected returns minus expected inflation rate, real yields, and realized returns minus realized inflation. The third column block uses expected returns minus cash expected returns (μ), real yields in excess of the cash real yield (except for fixed income asset classes, which use just real yields), and realized returns in excess of annual realized 1-month Treasury bill returns. The measures of expected inflation and real yields (for all asset classes) are described in Subsection A.4. Nominal yields are equal to real yields plus the expected inflation rate. The slope coefficients are normalized to interpret both dependent and independent variables as z-scores (i.e., in standard deviation units). Standard errors are based on Newey and West (1987, 1994). Subsection 1.2 describes our beliefs data while Subsection C.2 discusses the results from this table.

	Dependent Variables =	$\mathbb{E}[\boldsymbol{R}]$		$\mathbb{E}[\boldsymbol{R}^{real}]$		$\boldsymbol{\mu}$	
US Fixed Income	$\boldsymbol{b_{yield}}$	0.98	0.95	0.96	0.95	0.84	0.84
	$(\boldsymbol{t_{stat}})$	(14.2)	(18.1)	(10.4)	(12.9)	(4.37)	(4.15)
	$\boldsymbol{b_{return}}$		0.11		0.14		0.03
	$(\boldsymbol{t_{stat}})$		(3.75)		(4.26)		(0.38)
	$\boldsymbol{R^2_{adj}}$	95.8%	96.8%	92.9%	94.7%	69.1%	68.3%
Ex US Fixed Income	$\boldsymbol{b_{yield}}$	0.95	0.95	0.93	0.92	0.93	0.92
	$(\boldsymbol{t_{stat}})$	(14.6)	(14.6)	(10.9)	(11.3)	(13.7)	(13.9)
	$\boldsymbol{b_{return}}$		0.00		0.01		0.03
	$(\boldsymbol{t_{stat}})$		(0.03)		(0.08)		(0.54)
	$\boldsymbol{R^2_{adj}}$	90.2%	89.8%	85.5%	85.0%	85.2%	84.8%
US Equity	$\boldsymbol{b_{yield}}$	0.82	0.83	0.59	0.60	0.68	0.67
	$(\boldsymbol{t_{stat}})$	(1.84)	(2.67)	(0.85)	(1.45)	(4.58)	(4.39)
	$\boldsymbol{b_{return}}$		0.07		0.04		-0.04
	$(\boldsymbol{t_{stat}})$		(0.86)		(0.35)		(-0.49)
	$\boldsymbol{R^2_{adj}}$	65.5%	65.0%	32.9%	31.0%	44.4%	43.0%
Ex US Equity	$\boldsymbol{b_{yield}}$	0.78	0.79	0.51	0.50	0.72	0.72
	$(\boldsymbol{t_{stat}})$	(1.96)	(2.32)	(0.90)	(0.88)	(6.00)	(5.89)
	$\boldsymbol{b_{return}}$		0.01		-0.04		-0.03
	$(\boldsymbol{t_{stat}})$		(0.29)		(-0.47)		(-0.39)
	$\boldsymbol{R^2_{adj}}$	60.3%	59.1%	23.3%	21.0%	51.1%	49.6%
Private Equity	$\boldsymbol{b_{yield}}$	0.86	0.90	0.86	0.90	0.63	0.71
	$(\boldsymbol{t_{stat}})$	(8.79)	(10.2)	(9.69)	(10.7)	(3.54)	(4.37)
	$\boldsymbol{b_{return}}$		0.11		0.10		0.15
	$(\boldsymbol{t_{stat}})$		(1.10)		(0.89)		(1.02)
	$\boldsymbol{R^2_{adj}}$	73.2%	73.2%	73.1%	72.7%	37.4%	36.2%
Real Estate	$\boldsymbol{b_{yield}}$	0.91	0.91	0.80	0.81	0.65	0.64
	$(\boldsymbol{t_{stat}})$	(5.65)	(6.22)	(5.14)	(6.60)	(5.79)	(5.99)
	$\boldsymbol{b_{return}}$		0.03		0.11		0.21
	$(\boldsymbol{t_{stat}})$		(0.38)		(0.85)		(1.60)
	$\boldsymbol{R^2_{adj}}$	81.6%	81.2%	63.2%	63.5%	40.6%	43.3%

Table IA.5

Decomposing Link Between Expected Returns and Yields (Reduced-Form Implementation)

This table reports results from regressions of CMA-based aggregate expected returns on yields for different asset classes based on Equation IA.13 (with $b_{n,return} = 0$), which represents a more reduced-form analysis of the relation between expected returns and yields in comparison to the yield-based model of CMA formation discussed in Subsection 3.1 (with estimation results provided in Table 4). Measurement details for real yields are provided in Subsection A.4. The first column estimates the equations separately for each asset class with μ as the dependent variable. The second and third columns decompose μ into α and λ so that the respective b coefficients add to the b coefficient for μ. The fourth and fifth columns decompose λ into λ^γ and λ^ν so that the respective b coefficients add to the b coefficient for λ. Standard errors are based on Newey and West (1987, 1994). Subsection 1.2 describes our beliefs data while Subsection C.2 discusses the results from this table.

		$\boldsymbol{\mu}$	$\boldsymbol{\alpha}$	$\boldsymbol{\lambda}$	$\boldsymbol{\lambda^\gamma}$	$\boldsymbol{\lambda^\nu}$
	$\boldsymbol{b}$	0.28	-0.07	0.35	-0.02	0.37
US Fixed Income	$(\boldsymbol{t_{stat}})$	(4.37)	(-1.60)	(3.60)	(-0.81)	(3.99)
	$\boldsymbol{R^2_{adj}}$	69.1%	10.7%	60.6%	0.1%	61.0%
	$\boldsymbol{b}$	0.53	0.26	0.27	0.02	0.24
Ex US Fixed Income	$(\boldsymbol{t_{stat}})$	(13.71)	(2.55)	(3.04)	(0.65)	(3.31)
	$\boldsymbol{R^2_{adj}}$	85.2%	46.2%	56.4%	1.8%	54.6%
	$\boldsymbol{b}$	0.24	0.05	0.19	-0.09	0.28
US Equity	$(\boldsymbol{t_{stat}})$	(4.58)	(0.49)	(3.62)	(-0.57)	(1.76)
	$\boldsymbol{R^2_{adj}}$	44.4%	-0.8%	25.9%	-0.8%	15.8%
	$\boldsymbol{b}$	0.23	-0.15	0.38	-0.07	0.46
Ex US Equity	$(\boldsymbol{t_{stat}})$	(6.00)	(-1.98)	(4.99)	(-0.46)	(3.21)
	$\boldsymbol{R^2_{adj}}$	51.1%	18.7%	57.2%	-0.8%	42.2%
	$\boldsymbol{b}$	0.28	0.28	0.00	0.12	-0.12
Private Equity	$(\boldsymbol{t_{stat}})$	(3.54)	(2.73)	(0.03)	(1.37)	(-0.83)
	$\boldsymbol{R^2_{adj}}$	37.4%	27.3%	-4.5%	7.8%	4.1%
	$\boldsymbol{b}$	0.46	0.10	0.35	0.14	0.22
Real Estate	$(\boldsymbol{t_{stat}})$	(5.79)	(0.80)	(2.42)	(2.84)	(1.36)
	$\boldsymbol{R^2_{adj}}$	40.6%	-1.1%	8.4%	20.5%	1.1%