Institutional Investors' Subjective Risk Premia: Time Variation and Disagreement

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Abstract

We study the role of subjective risk premia in explaining variation in investor subjective expected returns (both time variation and disagreement) using long-term Capital Market Assumptions of asset managers and investment consultants from 1987 to 2022. Market risk premia account for most of the countercyclicality and overall time variation in 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). Nonetheless, risk price explains about half of the transitory impact of risk premia on expected returns. Market risk premia also 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 must match to be consistent with institutional investors' beliefs.

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

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Introduction

Understanding the sources of variation in expected returns lies at the core of 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)).

Most studies proxy for expected returns using realized returns or their econometric forecasts, which capture objective expectations but not necessarily investors' beliefs. Individual investors' expected returns are extrapolative and negatively linked to risk, in stark contrast to objective expected returns (Greenwood and Shleifer (2014) and Jo, Lin, and You (2024)). By contrast, institutional investors' expected returns are countercyclical, positively related to risk, and closely aligned with objective expected returns (Dahlquist and Ibert (2024, 2025) and Couts, Gonçalves, and Loudis (2024)). Yet it remains unclear how much of the variation in institutional investors' return expectations reflects perceived risk versus mispricing.

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 cash and nine risky asset classes.

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

[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...".

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 not only by differences in perceived risk, but also by heterogeneity in risk aversion and views about mispricing.

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.

From each CMA, we extract long-term expected returns, volatilities, and correlations for cash and nine major asset classes. Using the aggregate allocations of US public pension funds, we construct a proxy for the wealth portfolio weights. Combining these weights with expected returns, volatilities, and correlations, we compute $\mathbb{E}[r]$ and Risk Quantity (covariance with the wealth portfolio) for each asset class. We then estimate the Risk Price as the slope coefficient from projecting $\mathbb{E}[r]$ onto Risk Quantity across asset classes, which implies Risk Premium = Risk Price $\times$ Risk Quantity and Alpha = $\mathbb{E}[r]$ - Risk Premium. This procedure yields 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 (for some asset classes even negatively linked to yields). These results show that, from the perspective of the institutions in our analysis, high yields indicate high risk

premia rather than undervaluation (which would translate into high alphas). 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 of US equities obtained from surveys of global fund managers. This external measure is not based on any particular risk model, and thus this finding suggests that our main results are not an artifact of treating the wealth portfolio as the only risk factor in our analysis.

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 is responsible for 100% of the risk premia effect on the wealth portfolio expected return time variation and around 90% of the risk premia effect when we consider all asset classes jointly. While these results suggest risk premia is the main driver of expected return time variation 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 58% for all asset classes jointly), alphas play a quantitatively important role in this case. Moreover, risk price and risk quantities are equally responsible for the risk premia effect: risk quantity explains 49% of the risk premia effect for the wealth portfolio and 57% of the risk premia effect when we consider all asset classes jointly. Moreover, the importance of alphas and risk aversion increase when we consider short-lived disagreement across institutions.

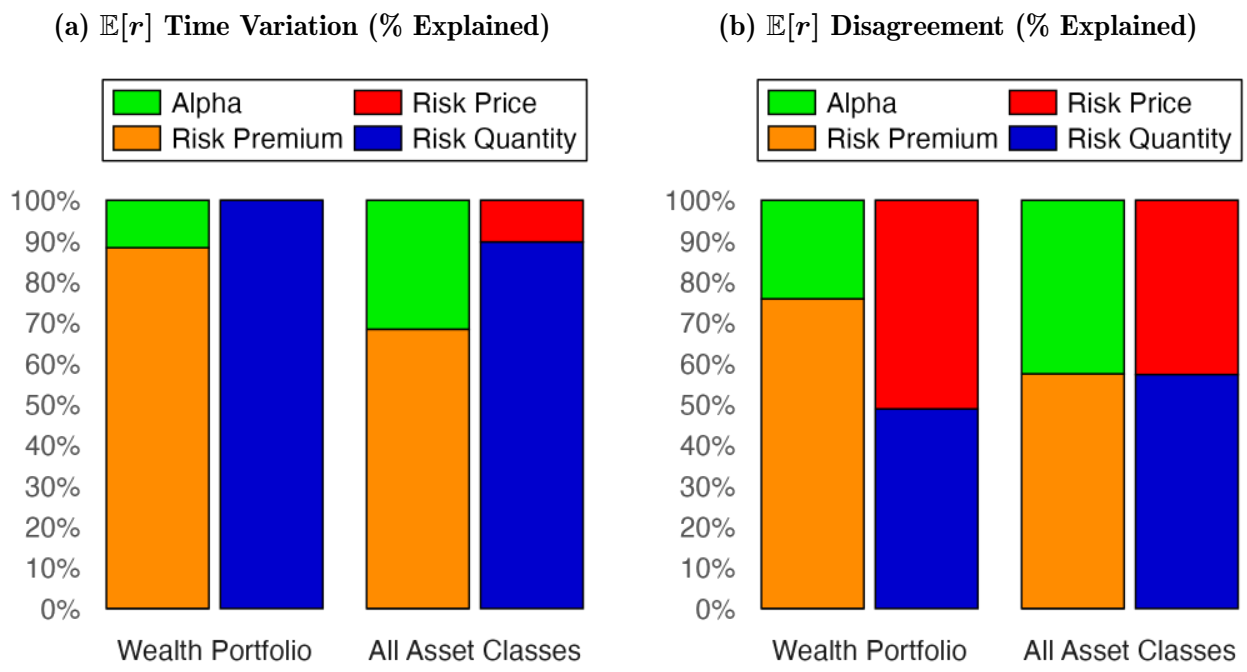


Figure 1
Decomposing Expected Return Time Variation and Disagreement

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 plot decompose expected return variation while the second and fourth bars of each plot 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' return expectations (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 US equities 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 slightly depending on the specification, 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 important 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, which no prior paper in the subjective beliefs literature has done.[3] We also focus on time variation and disagreement in risk premia (as opposed to variation across assets as in Jensen (2024) and Couts, Gonçalves, and Loudis (2024)). This later aspect allows us to

[2]The literature is too extensive to summarize here. However, some recent (including contemporaneous) papers are Greenwood and Shleifer (2014), Piazzesi, Salomao, and Schneider (2015), Adam, Marcet, and Beutel (2017), Cieslak (2018), Wu (2018), Bordalo et al. (2019), Adam, Matveev, and Nagel (2021), Delao and Myers (2021), Giglio et al. (2021), Nagel and Xu (2021, 2023), Wang (2021), Andonov and Rauh (2022), Liu et al. (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), Chaudhry (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), and Cui, Delao, and Myers (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 really 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, which equals the wealth portfolio expected excess return. 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.

connect directly to the part of the literature that studies time variation in subjective beliefs (e.g., Greenwood and Shleifer (2014), 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-based determinants of expected return time variation and disagreement. The key ingredient for evaluating these risk-based determinants 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 the link between expected returns and yields. 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

In this paper, our analysis focuses on and quantifies the sources of expected return variation in investors' beliefs (both over time and across institutions). In particular, we evaluate the significance of alphas and risk premia in driving expected return variation. 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 amount of expected return time variation and disagreement present in the 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 (i.e., we omit the term "excess") whenever convenient.

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 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).

Nevertheless, the interpretation of our μ decomposition relies on the CAPM as a benchmark risk-based model. For example, in a different risk-based model, α may entirely reflect a risk premium component (related to some risk factor other than r_w). So, to reinforce our interpretation of the μ decomposition, we later link our α variation to a measure of perceived undervaluation that does not require us to take a stand on a benchmark risk-based model

[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).

(see Subsection 3.3).

1.2 The Subjective Beliefs Data

Our beliefs dataset is based on the 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 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 funds have portfolio allocation reports that rely heavily on their consultants' CMAs, a feature we explore in our data collection process. In the case of asset managers (who often also have clients on 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.

[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. (2024) 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 shows that our main results are similar if we use only asset managers or only investment consultants.

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 quantitative 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 Dahlquist and Ibert (2024, 2025) and Couts, Gonçalves, and Loudis (2024) for evidence supporting this view).

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 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

[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 by showing that our main results are similar if we control for horizon heterogeneity in the belief aggregation process (for the time variation analysis) and in the cross-institution variance decomposition process (for the disagreement analysis).

[7]In Internet Appendix C, 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

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 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 as well as 9 risky asset classes, which are chosen to match the asset classes for which we have data on the wealth portfolio weights (discussed in the next paragraph). 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, Cash and Equity (US) are covered by all CMAs in our sample. Second, for each year (except 1987), we have at least one institution covering Cash, Fixed Income (US), Fixed Income (Ex US), Equity (US), Equity (Ex US), 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

(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).

[9] Years are defined based on the approximate timing of the institution's information set. For instance, if a CMA contains $\mathbb{E}_{2000}[R_{2000\to2010}]$, 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 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.

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 of the institutional investors, 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 displays the wealth portfolio weights used in our baseline analysis (we do not observe weights before 2001, and thus all weights for $t \leq 2001$ are set to match the 2001 weights).

There are two potential interpretations for the wealth portfolio weights we use. One is that we are measuring the market wealth portfolio without labor wealth (in the spirit of Stambaugh (1982) and Cederburg and O'Doherty (2019)), with the allocation of pension funds serving as a proxy for the allocation of all investors. The second is that we are measuring the wealth portfolio of institutional investors (in the spirit of Bretscher, Lewis, and Santosh (2024)), with the allocation of pension funds serving as a proxy for the allocation of all institutional investors. However, since many papers in the asset pricing literature use the equity market as a proxy for the wealth portfolio, Internet Appendix C also considers an alternative version of our analysis in which Equity (US) proxies for the investors' wealth portfolio. The results are qualitatively similar to the ones we report in the main text.

[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 (since they are the most commonly reported). 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 transformation of expected geometric returns into expected arithmetic returns, Internet Appendix C provides results (similar to our baseline 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). We also obtain similar (untabulated) results when we use expected geometric returns when available and expected arithmetic returns when expected geometric returns are not available

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 Equity (US) 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.

1.3 Aggregating Subjective Beliefs Across Institutions

The CMAs described in the prior subsection result in an unbalanced panel of institution-year observations (i.e., we do not observe CMAs for all institutions across all years, and a given institution-year CMA may not cover all asset classes we study). We use belief elements aggregated across 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 panel regression (with θ representing each μ and Σ element for our vector of asset classes):

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

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

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

where $\overline{\theta}^{fe}_n = \frac{1}{T} \cdot \sum_{t=1}^{T} \theta^{fe}_{n,t}$ 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.

Intuitively, $\theta^{fe}_{n,t}$ captures time variation in beliefs controlling for time variation in the composition of institutions (through the $\theta^{fe}_{n,j}$ fixed effects). However, the average $\theta^{fe}_{n,t}$ cannot be interpreted as the unconditional mean for the belief quantity. As such, our aggregation adjusts the $\theta^{fe}_{n,t}$ 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

[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, 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).

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 Equity (US) 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 Fixed Income (US) 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 Fixed Income (US).

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

[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.

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)).

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). This subsection explains 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 82.3%).[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 institution j at time t.[16,17] 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, 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 $\gamma_{j,t} = \mu_{j,w,t}/\nu_{j,w,t}$. The results 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.

[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.

[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.

[17] In Internet Appendix C, we consider two alternative $\gamma_{j,t}$ estimation methods (both provide similar results to the ones we report in the main text). One still uses linear projections of μ onto ν across asset classes for each institution-year observation, but weights different asset classes based on their respective wealth portfolio weights in the same period. The second uses the panel regression $\mu_{j,n,t} = \eta_j + \eta_t + \gamma_{j,t} \cdot \nu_{j,n,t} + \varepsilon_{j,n,t}$, which effectively gains power by imposing a restriction on the correlation structure between α and ν.

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 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 2.86 with a pooled average γ of 2.69, which are sensible risk aversion values.[18]

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

[18] Note that even though risk aversion does not vary across asset classes, the risk aversion average values in Table 3 do. The reason is that for each row in the table we use only the γ_t and $\gamma_{j,t}$ observations for which the given asset class is available. For example, Hedge Funds are available for 22 of the 36 sample years, and thus the reported time-series average risk aversion for hedge funds reflects the average γ_t over these 22 years.

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 observations 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 by 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 as per their own descriptions. 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 AQR CMA sets their expected nominal return on cash equivalents to equal $2/3 \cdot y_{b,t}^{(10y)} + 1/3 \cdot y_{b,t}^{(3m)}$ given their forecasting horizon is between five and ten years (which is in line with the expectations hypothesis).

Subtracting expected inflation on both sides of Equation 8 results in

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

where $y_{cash,t} = y_{b,t}^{(h)} - \pi_t^{(h)}$ 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. In Internet Appendix B, we provide some examples and also show that, under stylized assumptions, these valuation models imply $\mathbb{E}_t[R_n^{real}] = const + b_n \cdot y_{n,t}$, where $y_{n,t}$ is the real yield for asset class n at time t. Subtracting $\mathbb{E}_t[R_{cash}^{real}]$ from $\mathbb{E}_t[R_n^{real}]$, 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.The estimation accounts for the restriction that ω is the same across equations and focus on the six risky asset classes for which we can measure real yields.[19]

Our yield-based model provides a reasonable description of CMA formation. For $\mathbb{E}_t[R^{real}_{cash}]$, we have $R^2 = 70.3\%$, which is strikingly high for such a simple model. Moreover, across the μs of different asset classes, the R^2 values range from 35.4% (for Private Equity) to 61.0% (for Fixed Income (Ex US)). This result demonstrates that the link between CMA-based expected returns and yields extends far beyond equities (with Dahlquist and Ibert (2024, 2025) and Couts, Gonçalves, and Loudis (2024) documenting the results for equities and Dahlquist and Ibert (2025) also considering 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 or high alphas (arising from under-valuation). 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. The second and third columns in Table 4 shed light on this matter. They regress α and λ onto $(y_{n,t} - \omega/b_n \cdot y_{cash,t})$. Since $\mu = \alpha + \lambda$, the sum of the α and λ slope coefficients has to add to b_n, a restriction we account for in the estimation process. 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

[19] 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 Cleveland Fed (series EXPINF10YR from the FRED). We obtain $y_{n,t}$ for Fixed Income (US) and Fixed Income (Ex US) as the spread between the yield-to-worst for the Bloomberg Barclays US Aggregate Bond and Global Aggregate-Ex US indices (which are nominal yields) and $\pi^{(10)}$. For Equity (US) and Equity (Ex US), we obtain y_n as the inverse of the Shiller Cyclically Adjusted PE Ratio. We obtain $y_{n,t}$ for Private Equity from the aggregate EBITDA over Total Economic Value ratio of private equity buyout deals (extracted from Exhibit 1 of Nesbitt (2024)). We obtain $y_{n,t}$ 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).

the slope coefficient for λ tends to be relatively large and statistically significant. Moreover, the R^2 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 source of 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 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[20]

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

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 regress λ^{γ} and λ^{ν} onto $(y_{n,t} - \omega / b_n \cdot y_{cash,t})$ so 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 relative 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 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

[20] 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.

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 premia 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 Validating our Interpretation of α and λ

The previous subsection shows that the link between μ and yields is mainly driven by λ and not α. However, the economic interpretation that λ reflects a risk premium component and α reflects a subjective mispricing component rests on the use of r_w as a risk factor. On one hand, as shown in Couts, Gonçalves, and Loudis (2024), most of the CMAs that contain a methodology description discuss market risk exposures directly (e.g., by recognizing that market risk is a determinant of expected returns) or indirectly (e.g., by referring to the CAPM). On the other hand, if institutions also consider other risk factors, then α may partially capture a risk premium component. To address this issue, this subsection studies a direct measure of perceived mispricing for the Equity (US) asset class, which does not require using r_w as a risk factor. 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 results from regressions of 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).[21] 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 first three rows effectively show that the results obtained for the Equity (US) asset class in Table 4 are very similar over the 2001-2022 sample, which is the period over which we observe the perceived undervaluation variable. The next three rows show that α is positively and strongly linked to perceived undervaluation, with an R^2 of 83.1%, which validates our interpretation of α as reflecting subjective mispricing.[22] In contrast, perceived undervaluation is negatively linked to λ (through γ), the opposite of what we would expect if our risk premium measure was actually capturing subjective mispricing. The last five rows consider bivariate regressions of expected return elements onto the excess CAPE ratio and perceived undervaluation variables. While the excess CAPE ratio 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 underpricing has a non-trivial marginal (negative) effect on λ.[23] Overall, these results validate

[21] 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 Equity (US) asset class. As such, we simplify the analysis in Table 5 by using $\omega/b_n = 1$.

[22] Since the BofA survey participants are fund managers, the strong link between CMA α and BofA perceived underpricing 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 imply direct influence over portfolio allocation decisions (e.g., portfolio manager or chief investment officer).

[23] In Internet Appendix B.2, we provide an extended model of CMA formation for equities that highlights that the negative link between λ and perceived undervaluation is natural. The model also incorporates subjective growth, which we show helps explain expected return components beyond the excess CAPE ratio

our interpretation of λ as reflecting subjective risk premium and α as reflecting subjective mispricing.

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). 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 of the 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 (which we refer to as the 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 highlighting the differences when we focus on transitory time variation.

4.1 Components of μ Time Variation

To start, Figures 5(a) and 5(b) plot 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.

and perceived undervaluation.

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., Fixed Income (US), Equities (US), 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.[24] Most of the time variation in the expected returns of the wealth portfolio is explained by risk premia time variation since $\mathbb{V}(\lambda) = 88.4\%$ ($t_{stat} = 4.96$) and $\mathbb{V}(\alpha) = 11.6\%$ ($t_{stat} = 0.65$) is

[24] 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). 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 note that $\mathbb{V}(\alpha) = 1 - \mathbb{V}(\lambda)$ by construction.

statistically insignificant. When combining all asset classes, we have $\mathbb{V}(\lambda) = 68.4\%$ ($t_{stat} = 5.38$), 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 $\mathbb{V}(\alpha) = 31.6\%$ ($t_{stat} = 2.49$). Figure 8(a) provides a visual representation of the decomposition, which varies by asset class. For instance, α explains most of the μ time variation for Hedge Funds and Infrastructure.

We would like to 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

$$\mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \, , \, \lambda_{n,t} - \overline{\lambda}_n] \;=\; \mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \, , \, \lambda^{\gamma}_{n,t} - \overline{\lambda^{\gamma}_n}] \;+\; \mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \, , \, \lambda^{\nu}_{n,t} - \overline{\lambda^{\nu}_n}]$$

$$\Downarrow$$

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

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.[25] 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 $\mathbb{V}_\lambda(\nu) = 102.4\%$ ($t_{stat} = 4.28$) and $\mathbb{V}_\lambda(\gamma) = -2.4\%$ ($t_{stat} = -0.10$). Similarly, for all asset classes combines we have $\mathbb{V}_\lambda(\nu) = 89.8\%$ ($t_{stat} = 8.78$) and $\mathbb{V}_\lambda(\gamma) = 10.2\%$ ($t_{stat} = 1.00$).[26] Results vary by asset class, and Figure 8(c) provides a

[25] 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). 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 note that $\mathbb{V}_\lambda(\gamma) = 1 - \mathbb{V}_\lambda(\nu)$ by construction. Note also 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. So, our IV approach is not related to "endogeneity concerns", but rather reflects a simple way to obtain standard errors for $\mathbb{V}_\lambda(\nu)$ and $\mathbb{V}_\lambda(\gamma)$.

[26] Internet Appendix Table IA.6 provides our main results after splitting the sample into two halves (1987 to 2004 and 2005 to 2022). Most qualitative findings in the paper have been stable throughout our sample period. The only exception is the findings associated with the split between $\mathbb{V}_\lambda(\gamma)$ and $\mathbb{V}_\lambda(\nu)$. We find that risk aversion has been at least as important as risk quantity in explaining the expected return overall

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.

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 alternative 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 following a procedure analogous 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 $\mathbb{V}(\Delta\lambda) = 101.3\%$ ($t_{stat} = 9.14$) and $\mathbb{V}(\Delta\alpha) = -1.3\%$ ($t_{stat} = -0.12$). Moreover, for all asset classes combined λ drives the majority of the transitory time variation in μ since $\mathbb{V}(\Delta\lambda) = 61.7\%$ ($t_{stat} = 6.51$), but alpha also plays a quantitatively important role with $\mathbb{V}(\Delta\lambda) = 38.3\%$ ($t_{stat} = 4.04$). Results vary by asset class, and Figure 8(b) provides a visual

time variation in the second half of our sample period. So, risk aversion can be an important component of expected return time variation over extended periods, and thus should not be dismissed in favor of risk quantity as the only relevant risk-based component of time-varying expected returns. Of course, this result has to be taken with a grain of salt since each half of our sample period contains only 18 years of data.

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 $\mathbb{V}_\lambda(\Delta\gamma) = 59.9\%$ ($t_{stat} = 5.10$) and $\mathbb{V}_\lambda(\Delta\nu) = 40.1\%$ ($t_{stat} = 3.42$) when we focus on the wealth portfolio. Similarly, we have $\mathbb{V}_\lambda(\Delta\gamma) = 45.8\%$ ($t_{stat} = 3.89$) and $\mathbb{V}_\lambda(\Delta\nu) = 54.2\%$ ($t_{stat} = 4.61$) 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 increase 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 time variation.

5.1 Components of μ Disagreement

To start, Figures 9(a) and 9(b) plot 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. 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 μ overall time variation, which we show is dominated by ν time variation.

5.2 Decomposing μ Disagreement

We formalize the visual results from Figure 9 using 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 follows directly from Equation 7 with the linearization

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

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 reports (in the first four columns) 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.[27]

[27] 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 note that $\mathbb{D}(\alpha) = 1 - \mathbb{D}(\lambda)$ by construction.

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 $\mathbb{D}(\lambda) = 75.8\%$ ($t_{stat} = 9.49$) and $\mathbb{D}(\alpha) = 24.2\%$ ($t_{stat} = 3.02$). Moreover, for all asset classes combined we have $\mathbb{D}(\lambda) = 57.5\%$ ($t_{stat} = 4.49$) and $\mathbb{D}(\alpha) = 42.5\%$ ($t_{stat} = 3.33$). Results vary by asset class, and Figure 10(a) provides a visual representation of the decomposition. For instance, for Fixed Income (US and ex US) as well as Hedge Funds and Commodities, the alpha effect dominates.

Table 7 Panel B reports (in the first four columns) 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.[28] 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 $\mathbb{D}_\lambda(\gamma) = 51.1\%$ ($t_{stat} = 8.43$) and $\mathbb{D}_\lambda(\nu) = 48.9\%$ ($t_{stat} = 8.06$). Moreover, for all asset classes combined we have $\mathbb{D}_\lambda(\gamma) = 42.7\%$ ($t_{stat} = 4.66$) and $\mathbb{D}_\lambda(\nu) = 57.3\%$ ($t_{stat} = 6.25$). Results vary by asset class, and Figure 10(b) provides a visual representation of the decomposition.

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

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

[28] We estimate $\mathbb{D}_\lambda(\nu)$ 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 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 $\lambda^\nu_{n,t}$ 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 $\lambda^\gamma_{n,t}$ replacing $\lambda^\nu_{n,t}$, but note that $\mathbb{D}_\lambda(\gamma) = 1 - \mathbb{D}_\lambda(\nu)$ by construction.

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 that if it indicates an institution is optimistic in a given year, then it must imply the institution is also pessimistic 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 reports (in the last eight columns) 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 $\mathbb{D}(\alpha) = 39.0\%$ ($t_{stat} = 4.80$) and for the transitory disagreement with all asset classes combined we have $\mathbb{D}(\lambda) = 45.2\%$ ($t_{stat} = 3.51$) and $\mathbb{D}(\alpha) = 54.8\%$ ($t_{stat} = 4.25$). Figures 11(a) and 11(b) provide a visual representation of these decompositions, including results by asset class.

6 Conclusion

This paper quantifies the sources of variation in institutional investors' expected returns (both time variation and disagreement). The findings indicate that market risk premia account for most of the countercyclicality and overall time variation in expected returns, with the remainder attributed to alphas, which mainly captures subjective mispricing. The impact of risk premia is largely due to variation in risk quantities (i.e., subjective covariances

with the wealth portfolio) rather than variation in risk price (i.e., compensation per unit of risk). However, risk price does play a 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.

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 some investors undoubtedly have expected returns that reflect recent past returns (as in Greenwood and Shleifer (2014) and the subsequent literature that builds on their findings), we show that the CMAs from institutional investors report expected returns that better reflect risk perceptions. In addition, risk-based models that aim to capture the behavior of large institutional investors, who are likely marginal in financial markets, 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 largely linked to variation in perceived quantities of risk.

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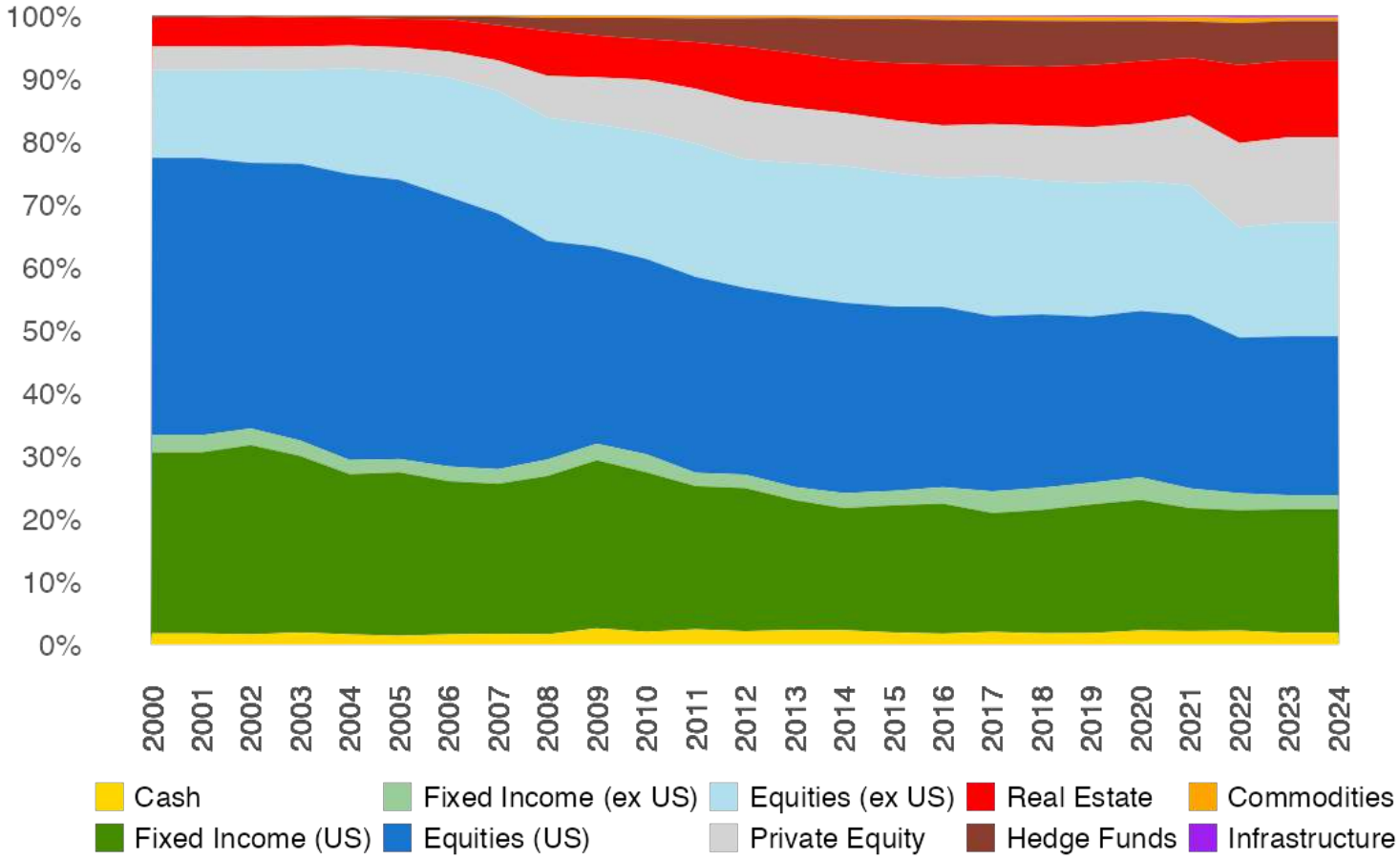


Figure 2
Wealth Portfolio Weights from US Public Pension Funds

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.

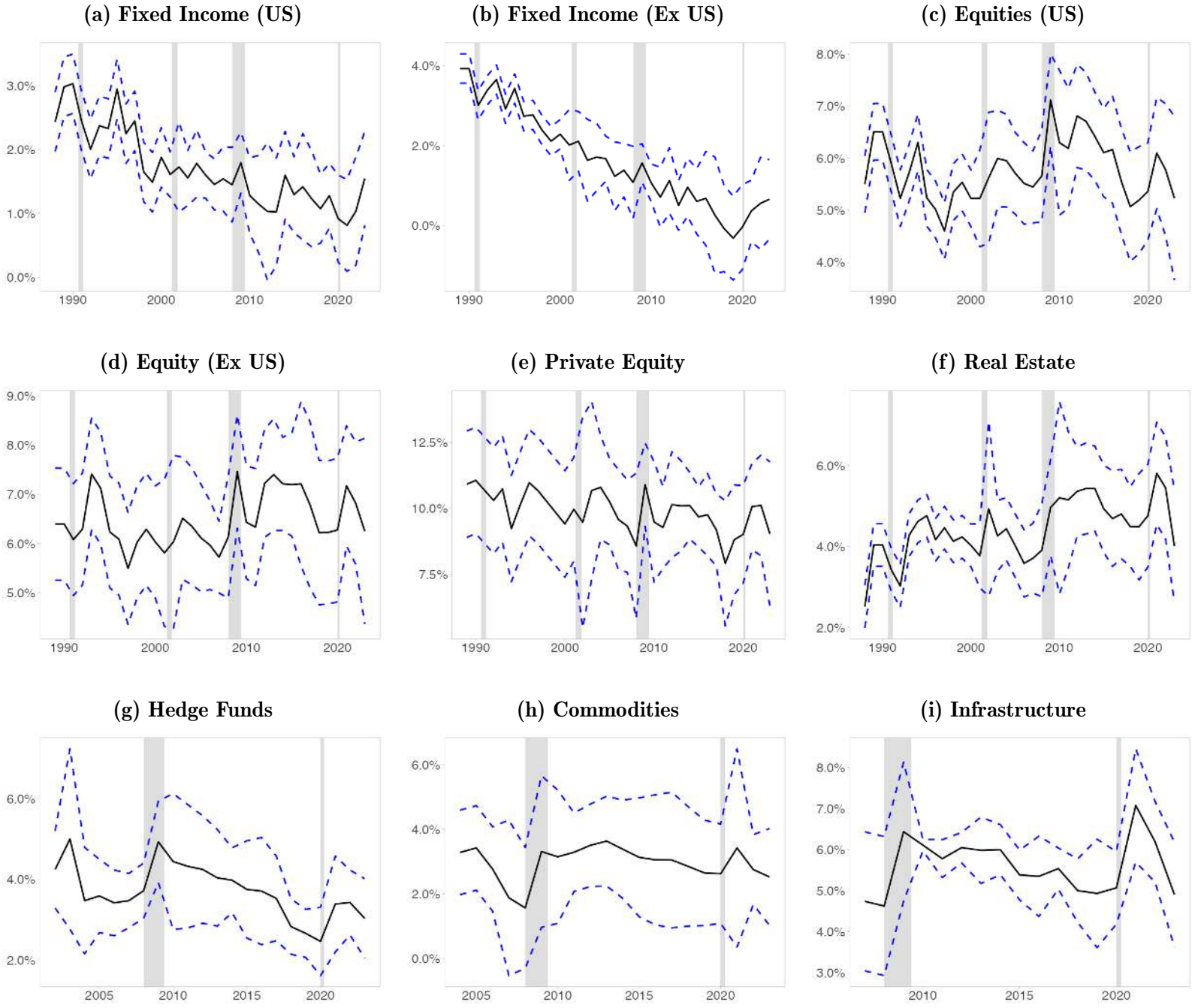


Figure 3

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.

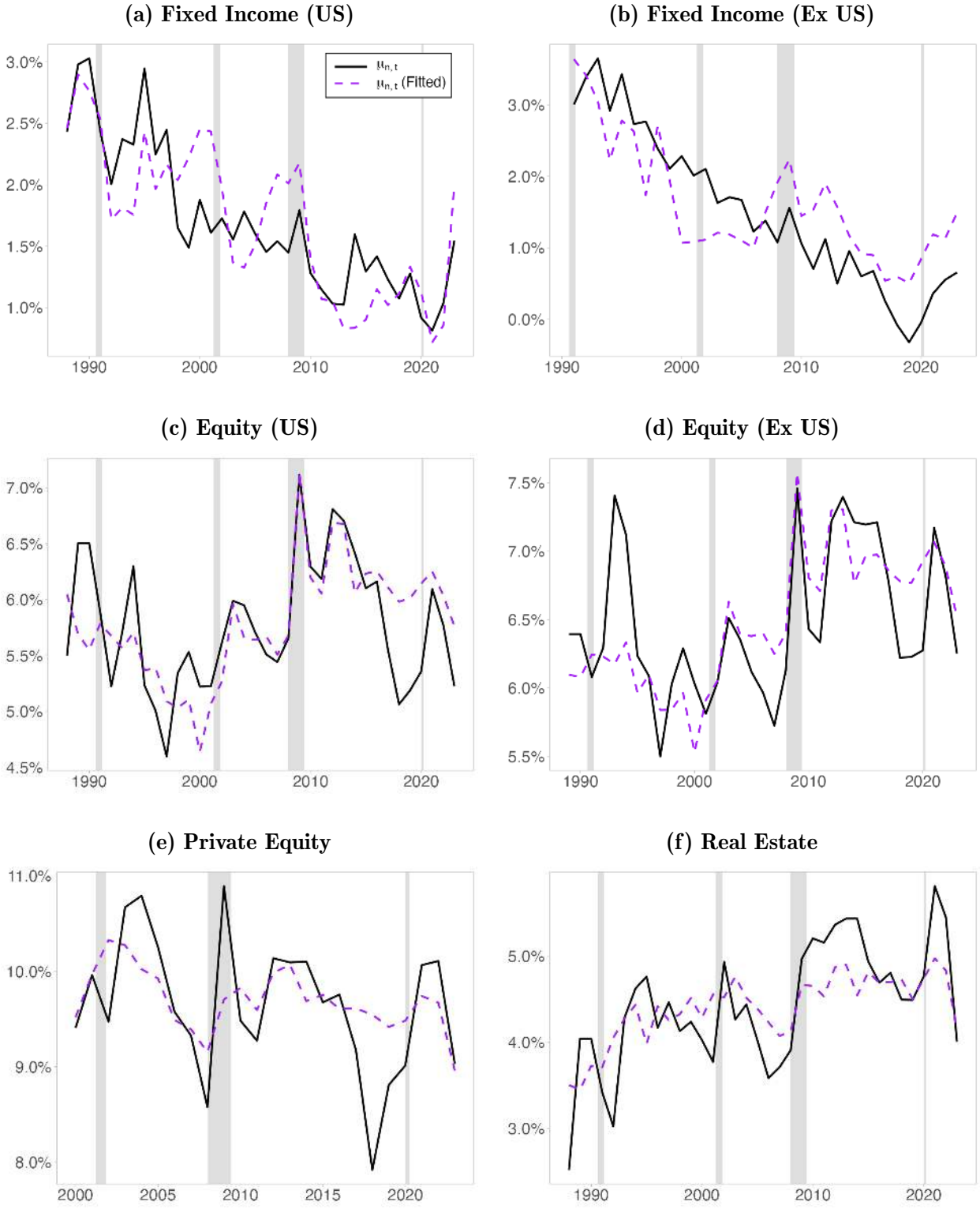


Figure 4
CMA μ vs Yield-Based μ

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 Footnote 19). Subsection 1.2 describes our beliefs data while Subsection 3.1 discusses the results from this figure.

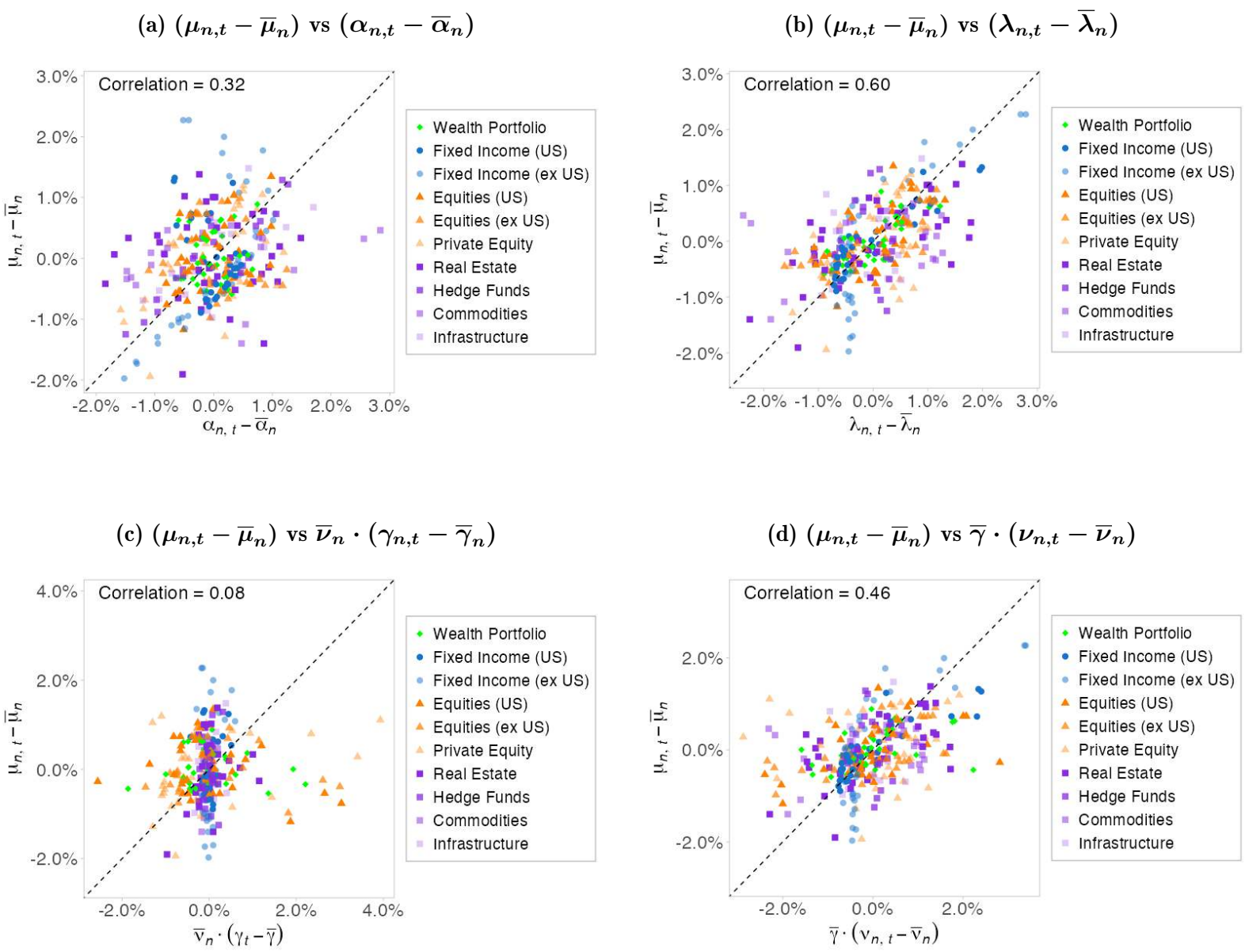


Figure 5
Components of Expected Return Time Variation

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.

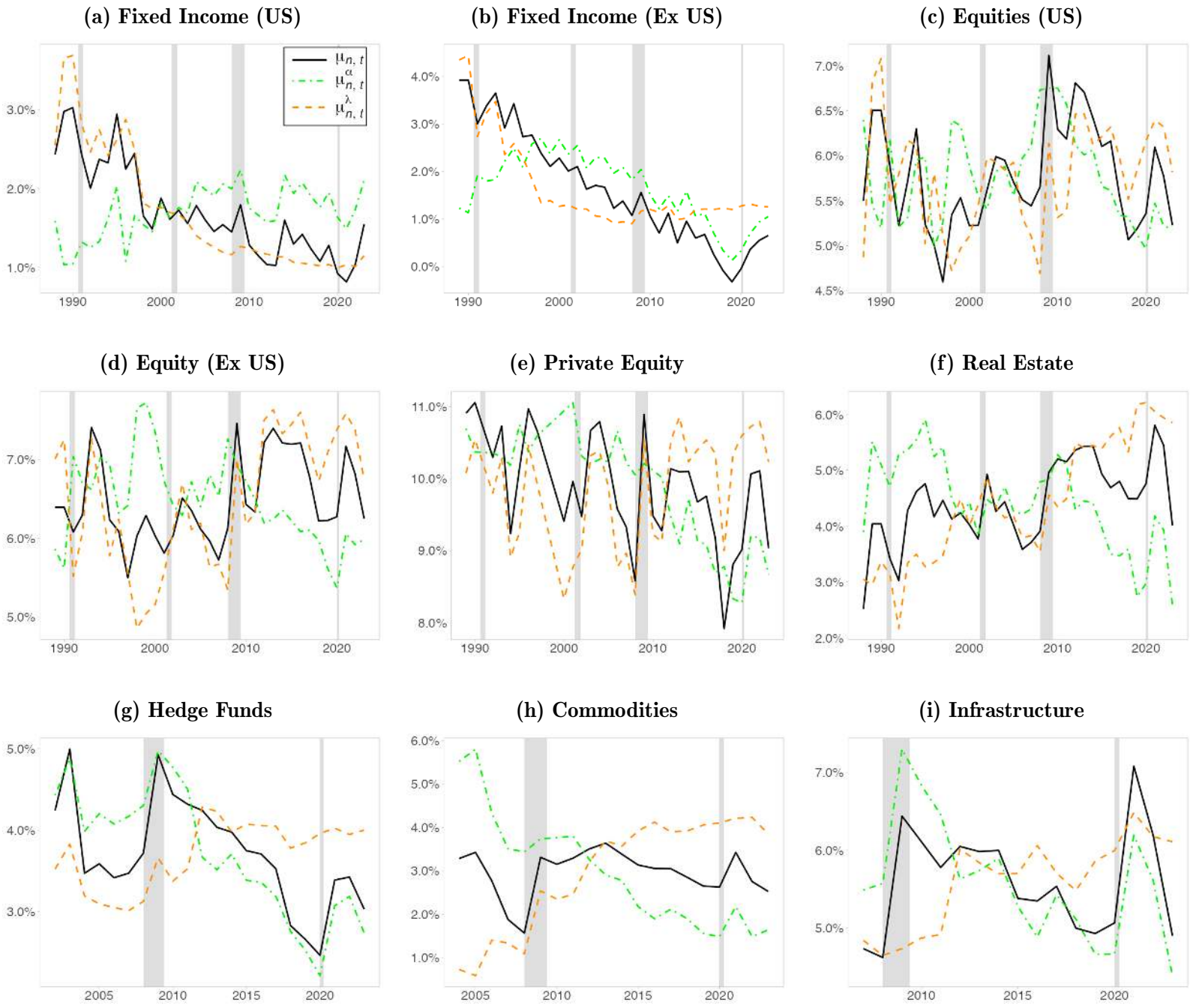


Figure 6
Time Series of Expected Return Components

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.

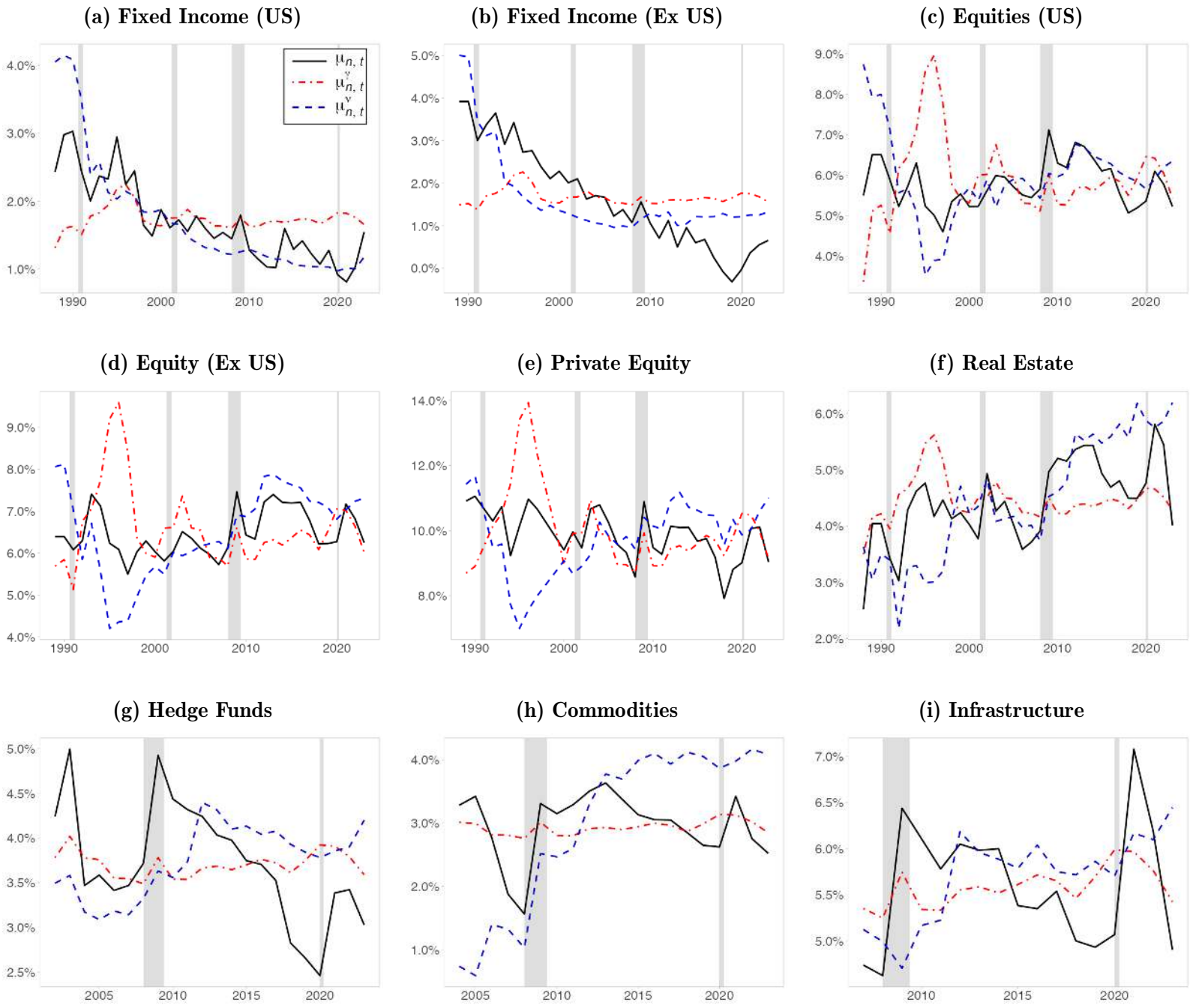


Figure 7
Time Series of Risk Premia Components

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.

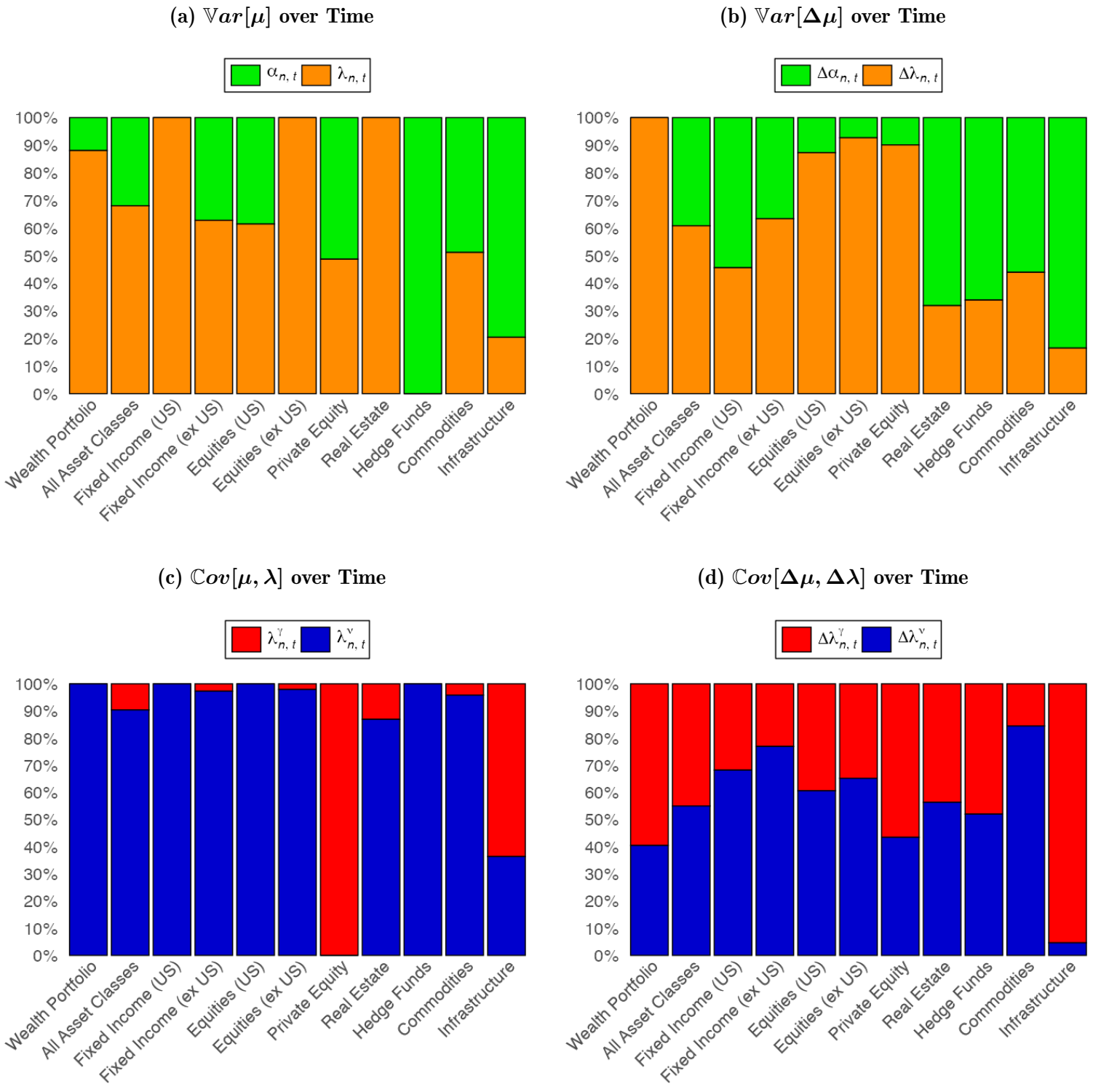


Figure 8
Decomposing Expected Return Time Variation

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.

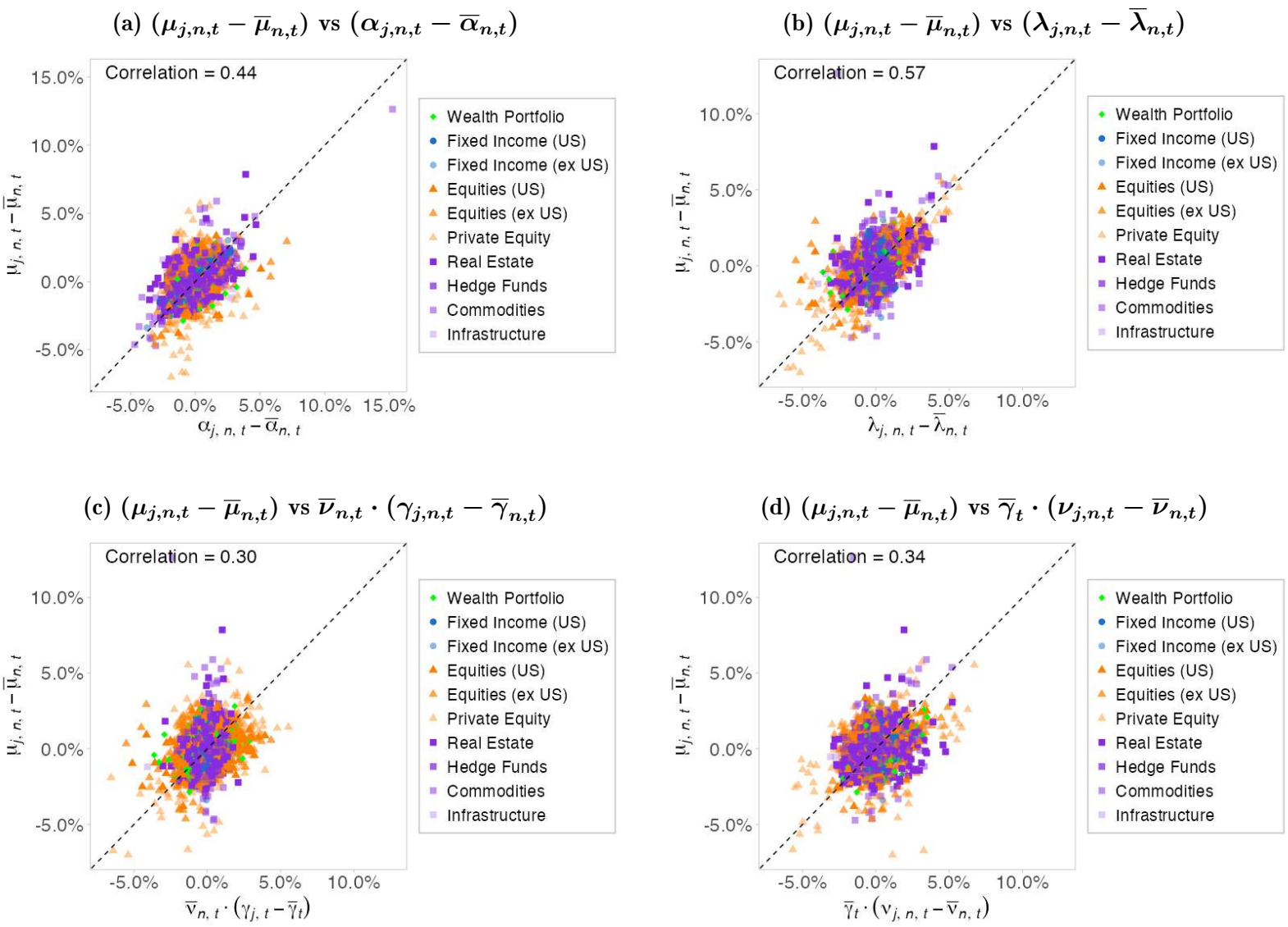
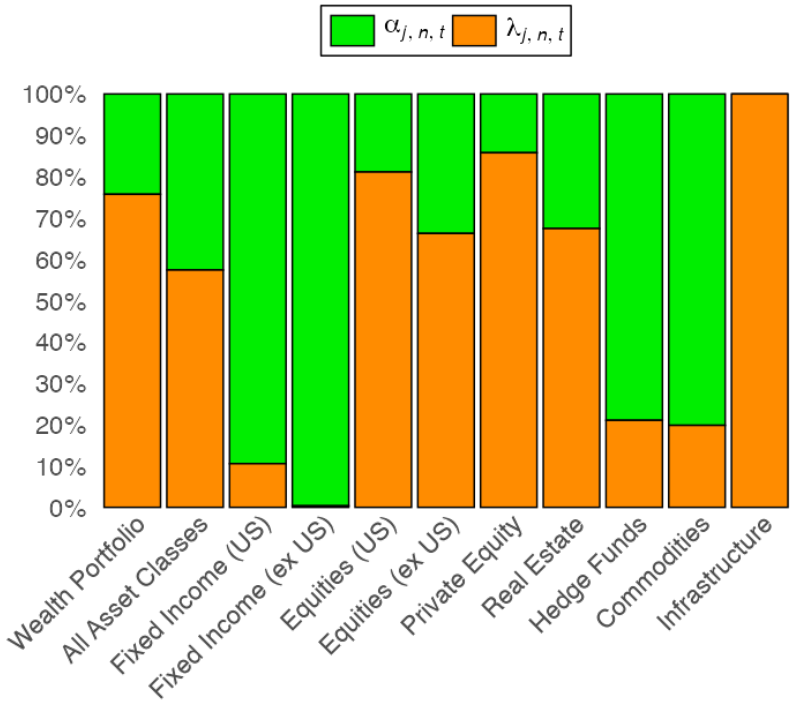


Figure 9
Components of Expected Return Disagreement

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



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

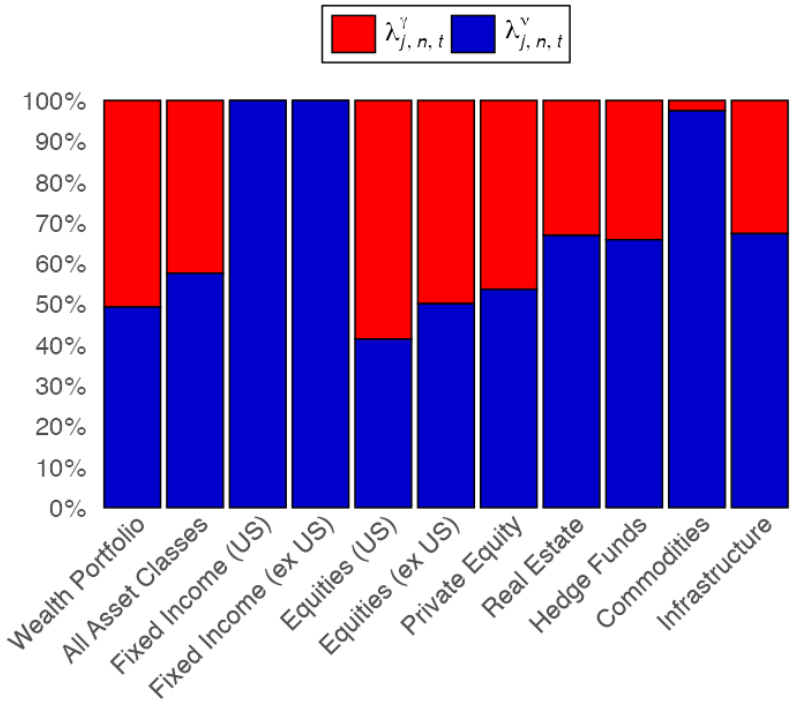


Figure 10
Decomposing Expected Return Disagreement

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.

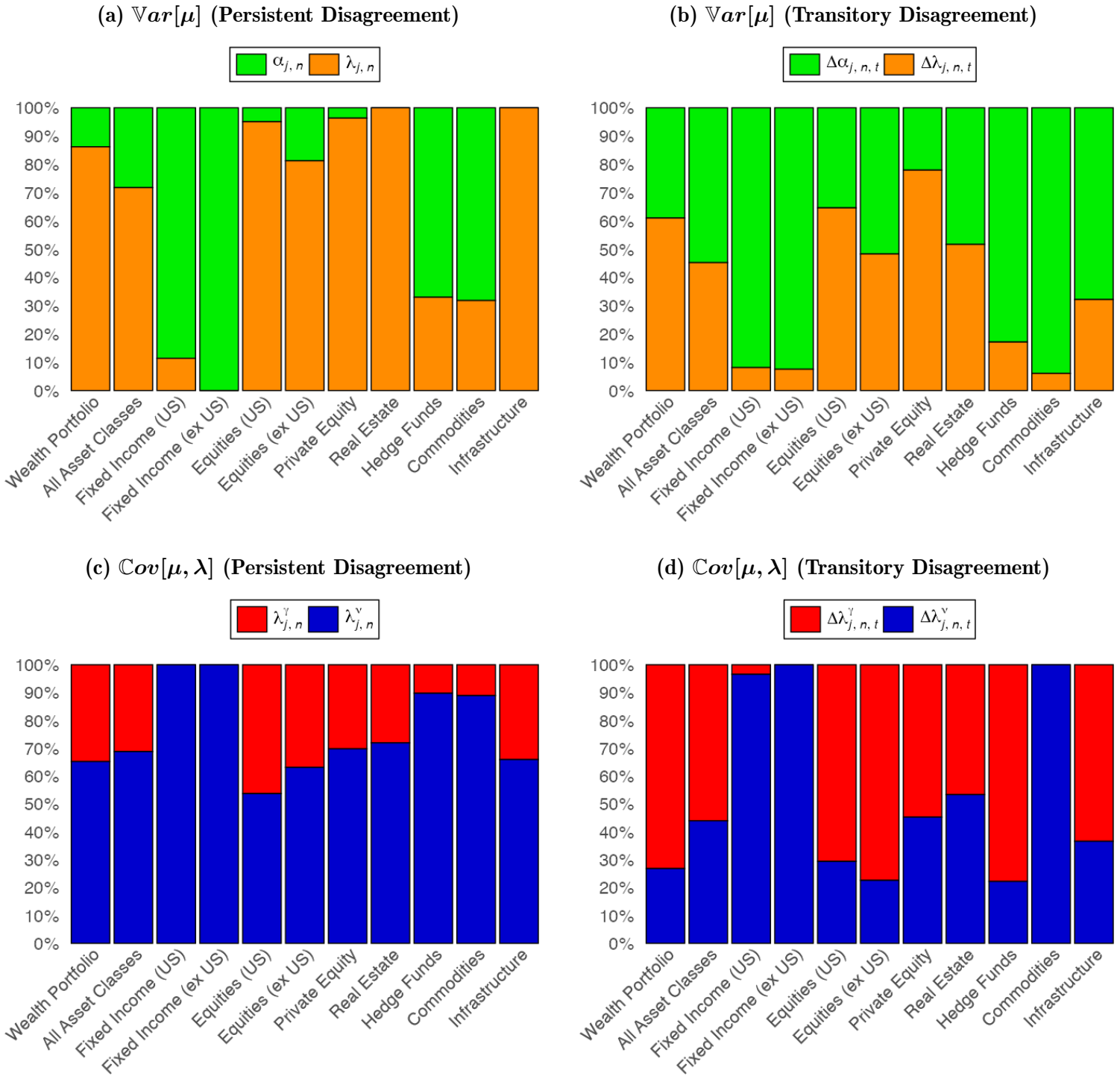


Figure 11

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**	≥ 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) Fixed Income (US); (2) Fixed Income (Ex US); (3) Equity (US); (4) Equity (Ex US);
(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	γ	ν	μ	σ	α	λ	γ	ν
Wealth Portfolio	45	36	361	4.7%	11.8%	0.8%	3.9%	2.86	1.4%	4.5%	11.7%	0.9%	3.6%	2.69	1.4%
Fixed Income (US)	42	36	352	1.7%	5.8%	0.8%	0.9%	2.86	0.3%	1.4%	5.2%	0.9%	0.5%	2.69	0.2%
Fixed Income (Ex US)	36	35	271	1.7%	9.9%	0.6%	1.1%	2.90	0.4%	0.9%	8.6%	0.2%	0.7%	2.76	0.3%
Equity (US)	45	36	361	5.8%	17.0%	0.4%	5.4%	2.86	1.9%	5.5%	17.0%	0.4%	5.0%	2.69	1.9%
Equity (Ex US)	44	35	351	6.5%	19.8%	0.9%	5.5%	2.90	2.0%	6.2%	19.2%	0.9%	5.3%	2.70	2.0%
Private Equity	34	34	309	9.9%	28.4%	2.3%	7.5%	2.94	2.6%	9.0%	25.8%	2.3%	6.7%	2.72	2.5%
Real Estate	42	36	357	4.4%	14.7%	2.4%	2.0%	2.86	0.7%	4.5%	14.0%	2.2%	2.4%	2.69	0.9%
Hedge Funds	33	22	230	3.7%	8.0%	2.0%	1.7%	2.79	0.6%	3.5%	7.9%	1.7%	1.8%	2.76	0.7%
Commodities	33	22	242	3.0%	18.3%	1.4%	1.5%	2.76	0.5%	3.0%	18.3%	1.1%	1.9%	2.71	0.7%
Infrastructure	17	17	88	5.6%	15.2%	2.7%	2.9%	2.76	1.1%	5.6%	15.3%	2.1%	3.4%	2.92	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	γ	ν	μ	σ	α	λ	γ	ν
Wealth Portfolio	45	36	361	0.4%	1.2%	0.3%	0.5%	0.53	0.3%	0.8%	1.3%	0.8%	1.0%	0.72	0.3%
Fixed Income (US)	42	36	352	0.6%	1.8%	0.3%	0.8%	0.53	0.3%	0.6%	1.3%	0.6%	0.3%	0.71	0.1%
Fixed Income (Ex US)	36	35	271	1.2%	2.1%	0.7%	0.9%	0.48	0.4%	0.8%	2.3%	0.9%	0.4%	0.72	0.1%
Equity (US)	45	36	361	0.6%	1.5%	0.5%	0.6%	0.53	0.4%	1.0%	1.4%	1.0%	1.3%	0.72	0.4%
Equity (Ex US)	44	35	351	0.5%	1.2%	0.6%	0.8%	0.48	0.4%	1.3%	1.9%	1.3%	1.4%	0.71	0.4%
Private Equity	34	34	309	0.8%	2.3%	0.8%	0.8%	0.48	0.4%	2.0%	5.3%	1.4%	2.2%	0.67	0.8%
Real Estate	42	36	357	0.7%	1.3%	0.8%	1.1%	0.53	0.4%	1.1%	3.5%	1.3%	1.5%	0.73	0.5%
Hedge Funds	33	22	230	0.7%	0.8%	0.8%	0.4%	0.23	0.1%	1.1%	2.4%	1.2%	0.8%	0.73	0.3%
Commodities	33	22	242	0.5%	0.8%	1.3%	1.3%	0.20	0.5%	1.8%	3.8%	1.8%	1.2%	0.69	0.4%
Infrastructure	17	17	88	0.7%	0.9%	0.8%	0.6%	0.21	0.2%	0.9%	3.6%	1.3%	1.6%	0.62	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	0.74	-0.04	0.44	-0.57	-0.75	0.24	0.66	0.34	0.43	-0.51	-0.33
Fixed Income (US)	42	36	352	-0.41	0.93	0.17	0.85	-0.72	-0.20	0.84	0.24	-0.09	0.31	-0.27	-0.24
Fixed Income (Ex US)	36	35	271	0.62	0.80	0.26	0.74	0.03	-0.10	0.87	0.13	-0.04	0.11	-0.29	-0.13
Equity (US)	45	36	361	0.42	0.60	-0.27	0.51	-0.48	-0.82	0.20	0.64	0.31	0.41	-0.57	-0.37
Equity (Ex US)	44	35	351	-0.19	0.76	-0.02	0.55	-0.78	-0.65	0.35	0.61	0.34	0.37	-0.47	-0.25
Private Equity	34	34	309	0.50	0.50	0.36	0.03	-0.50	-0.76	0.23	0.76	0.43	0.43	-0.39	-0.30
Real Estate	42	36	357	-0.03	0.68	0.31	0.61	-0.75	-0.22	0.13	0.60	0.44	0.41	-0.66	0.06
Hedge Funds	33	22	230	0.86	-0.03	0.06	-0.05	-0.54	0.05	0.71	0.21	0.04	0.14	-0.44	-0.14
Commodities	33	22	242	0.20	0.21	0.41	0.22	-0.91	0.32	0.76	0.27	-0.16	0.22	-0.35	0.03
Infrastructure	17	17	88	0.70	0.25	0.43	0.10	-0.52	0.31	0.11	0.37	0.46	0.22	-0.74	-0.05

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

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

where y values reflect real yields (with measurement described in Footnote 19). 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.

		μ	α	λ	λ^γ	λ^ν
Cash	ω	0.38	-	-	-	-
	(t_{stat})	(3.14)	-	-	-	-
	R^2_{adj}	70.3%	-	-	-	-
Fixed Income (US)	b	0.72	-0.14	0.87	-0.04	0.89
	(t_{stat})	(2.44)	(-1.75)	(5.58)	(-0.50)	(4.43)
	R^2_{adj}	56.7%	10.4%	49.9%	3.9%	54.4%
Fixed Income (Ex US)	b	0.67	0.25	0.42	0.02	0.40
	(t_{stat})	(2.86)	(1.65)	(3.85)	(0.49)	(3.32)
	R^2_{adj}	61.9%	21.6%	62.1%	3.0%	63.0%
Equity (US)	b	0.39	0.12	0.27	-0.15	0.42
	(t_{stat})	(5.39)	(1.42)	(4.60)	(-1.18)	(2.69)
	R^2_{adj}	41.0%	2.1%	22.9%	2.4%	16.6%
Equity (Ex US)	b	0.28	-0.13	0.41	-0.04	0.46
	(t_{stat})	(4.88)	(-1.82)	(6.02)	(-0.41)	(3.55)
	R^2_{adj}	45.4%	20.1%	54.7%	1.5%	40.3%
Private Equity	b	0.21	0.15	0.06	0.18	-0.12
	(t_{stat})	(3.31)	(1.35)	(0.47)	(2.66)	(-0.94)
	R^2_{adj}	35.4%	11.1%	3.2%	26.6%	3.0%
Real Estate	b	0.18	-0.18	0.36	0.04	0.33
	(t_{stat})	(2.32)	(-2.76)	(6.96)	(1.38)	(4.66)
	R^2_{adj}	52.2%	10.5%	56.2%	9.8%	41.4%

Table 5

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

This table reports results from regressions (for US Equities) of CMA-based aggregate μ and its components (α, λ, λ^{γ}, and λ^{ν}) onto the excess CAPE yield detailed in Footnote 19 (which is the $y_{n,t}$ measure for US Equities 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	0.14	0.26	0.07	0.18
	(t_{stat})	(6.67)	(1.35)	(3.99)	(0.86)	(2.16)
	R^2_{adj}	51.1%	1.8%	26.1%	-1.7%	20.5%
Perceived Undervaluation	**Coef**	0.25	0.50	-0.25	-0.21	-0.04
	(t_{stat})	(2.51)	(12.0)	(-3.06)	(-3.85)	(-0.37)
	R^2_{adj}	17.3%	83.1%	24.6%	22.3%	-3.9%
Excess CAPE Yield	**Coef**	0.38	0.11	0.28	0.09	0.19
	(t_{stat})	(9.99)	(3.57)	(5.01)	(1.15)	(2.14)
Perceived Undervaluation	**Coef**	0.22	0.50	-0.27	-0.22	-0.05
	(t_{stat})	(2.54)	(16.5)	(-3.16)	(-3.49)	(-0.42)
	R^2_{adj}	67.1%	86.3%	58.2%	23.3%	18.5%

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 24 and 25 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	11.6%	(0.65)	88.4%	(4.96)	-1.3%	(-0.12)	101.3%	(9.14)
All Asset Classes	31.6%	(2.49)	68.4%	(5.38)	38.3%	(4.04)	61.7%	(6.51)
Fixed Income (US)	-21.9%	(-1.77)	121.9%	(9.85)	54.4%	(3.59)	45.6%	(3.01)
Fixed Income (Ex US)	37.2%	(1.66)	62.8%	(2.81)	36.6%	(1.42)	63.4%	(2.46)
Equity (US)	38.0%	(1.97)	62.0%	(3.21)	12.2%	(1.03)	87.8%	(7.38)
Equity (Ex US)	-19.5%	(-1.46)	119.5%	(8.97)	7.0%	(0.57)	93.0%	(7.58)
Private Equity	50.2%	(2.75)	49.8%	(2.73)	8.5%	(1.73)	91.5%	(18.6)
Real Estate	-2.8%	(-0.17)	102.8%	(6.22)	65.9%	(5.24)	34.1%	(2.70)
Hedge Funds	101.9%	(4.42)	-1.9%	(-0.08)	65.9%	(10.0)	34.1%	(5.20)
Commodities	48.9%	(0.68)	51.1%	(0.71)	56.1%	(2.49)	43.9%	(1.95)
Infrastructure	78.9%	(5.31)	21.1%	(1.42)	82.6%	(13.2)	17.4%	(2.77)

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	-2.4%	(-0.10)	102.4%	(4.28)	59.9%	(5.10)	40.1%	(3.42)
All Asset Classes	10.2%	(1.00)	89.8%	(8.78)	45.8%	(3.89)	54.2%	(4.61)
Fixed Income (US)	-0.8%	(-0.07)	100.8%	(8.18)	31.4%	(1.69)	68.6%	(3.68)
Fixed Income (Ex US)	2.9%	(0.26)	97.1%	(8.54)	22.9%	(6.80)	77.1%	(22.9)
Equity (US)	-62.5%	(-0.99)	162.5%	(2.59)	40.4%	(1.54)	59.6%	(2.26)
Equity (Ex US)	2.4%	(0.10)	97.6%	(3.90)	36.1%	(1.67)	63.9%	(2.95)
Private Equity	104.1%	(1.29)	-4.1%	(-0.05)	56.8%	(6.47)	43.2%	(4.92)
Real Estate	13.1%	(2.18)	86.9%	(14.5)	43.2%	(1.51)	56.8%	(1.98)
Hedge Funds	-59.9%	(-0.08)	159.9%	(0.21)	48.6%	(7.09)	51.4%	(7.49)
Commodities	5.6%	(0.73)	94.4%	(12.3)	16.8%	(1.81)	83.2%	(8.99)
Infrastructure	65.6%	(1.39)	34.4%	(0.73)	98.4%	(1.42)	1.6%	(0.02)

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 27 and 28 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	24.2%	(3.02)	75.8%	(9.49)	13.8%	(3.34)	86.2%	(20.83)	39.0%	(4.80)	61.0%	(7.51)
All Asset Classes	42.5%	(3.33)	57.5%	(4.49)	28.2%	(1.76)	71.8%	(4.48)	54.8%	(4.25)	45.2%	(3.51)
Fixed Income (US)	89.4%	(15.4)	10.6%	(1.82)	88.6%	(23.8)	11.4%	(3.06)	91.9%	(22.8)	8.1%	(2.02)
Fixed Income (Ex US)	99.6%	(22.9)	0.4%	(0.09)	106.3%	(33.4)	-6.3%	(-1.99)	92.4%	(33.4)	7.6%	(2.72)
Equity (US)	18.7%	(2.61)	81.3%	(11.4)	4.9%	(1.36)	95.1%	(26.3)	35.4%	(4.43)	64.6%	(8.08)
Equity (Ex US)	33.4%	(5.89)	66.6%	(11.7)	18.7%	(3.25)	81.3%	(14.1)	51.7%	(4.60)	48.3%	(4.29)
Private Equity	14.4%	(3.54)	85.6%	(21.0)	3.7%	(0.66)	96.3%	(17.3)	22.1%	(3.74)	77.9%	(13.2)
Real Estate	32.5%	(6.06)	67.5%	(12.6)	-1.9%	(-0.37)	101.9%	(19.7)	48.3%	(10.2)	51.7%	(10.9)
Hedge Funds	79.0%	(7.89)	21.0%	(2.10)	67.0%	(10.9)	33.0%	(5.35)	82.9%	(16.2)	17.1%	(3.35)
Commodities	80.1%	(6.84)	19.9%	(1.70)	68.2%	(11.2)	31.8%	(5.23)	93.9%	(7.08)	6.1%	(0.46)
Infrastructure	-5.7%	(-0.38)	105.7%	(7.14)	-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	51.1%	(8.43)	48.9%	(8.06)	34.7%	(5.23)	65.3%	(9.82)	73.2%	(12.75)	26.8%	(4.68)
All Asset Classes	42.7%	(4.66)	57.3%	(6.25)	31.2%	(2.80)	68.8%	(6.19)	56.0%	(9.18)	44.0%	(7.21)
Fixed Income (US)	-21.6%	(-1.43)	121.6%	(8.06)	-57.1%	(-3.00)	157.1%	(8.25)	3.4%	(0.22)	96.6%	(6.08)
Fixed Income (Ex US)	-165.9%	(-0.09)	265.9%	(0.14)	-38.6%	(-0.89)	138.6%	(3.18)	-24.0%	(-1.26)	124.0%	(6.48)
Equity (US)	58.8%	(11.0)	41.2%	(7.72)	46.3%	(8.74)	53.7%	(10.2)	70.6%	(11.1)	29.4%	(4.63)
Equity (Ex US)	50.2%	(10.2)	49.8%	(10.1)	36.8%	(5.61)	63.2%	(9.62)	77.4%	(9.81)	22.6%	(2.87)
Private Equity	46.5%	(5.89)	53.5%	(6.78)	30.2%	(5.52)	69.8%	(12.8)	54.7%	(5.35)	45.3%	(4.43)
Real Estate	33.5%	(5.28)	66.5%	(10.5)	28.0%	(7.54)	72.0%	(19.4)	46.6%	(7.77)	53.4%	(8.89)
Hedge Funds	35.2%	(1.49)	64.8%	(2.73)	10.2%	(0.90)	89.8%	(7.93)	77.8%	(2.92)	22.2%	(0.83)
Commodities	3.4%	(0.20)	96.6%	(5.68)	11.1%	(1.55)	88.9%	(12.5)	-18.3%	(-0.17)	118.3%	(1.09)
Infrastructure	33.2%	(4.11)	66.8%	(8.28)	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

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A Data and Measurement Details

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

A.1 Subjective Beliefs Data and Measurement (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 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 nether (i) nor (ii) is available). Given this pecking order, 83.4% of the institution-year observations in our baseline sample is based on data collected from methods (i)+(ii), which we refer to as "direct CMAs".

As we explain in Section C, 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 of these type of institutions. 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 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).

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 (since they are the most commonly reported). 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] Internet Appendix C provides results (similar to our baseline results) that use expected arithmetic returns when available and expected geometric returns when expected arithmetic returns are not available (so that no transformation

[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.

is applied). We also obtain similar (untabulated) results when we use expected geometric returns when available and expected arithmetic returns when expected geometric returns are not available

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

For the analyses in Tables 5 and IA.5, 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 for 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.5) covers the period from April 2001 to February 2025 whereas the "Subjective $\mathbb{E}$[Growth]" variable (used in Table IA.5) 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.5.

A.3 Wealth Portfolio Weights Data and Measurement

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. **US Cash**: Cash + FICash
2. **Fixed Income (US)**: FIUS + ω_{FIUS}·FIOther
3. **Fixed Income (Ex US)**: FIExUS + $(1 - \omega_{\text{FIUS}})$·FIOther
4. **Equities (US)**: EQUS + ω_{EQUS}·EQOther
5. **Equities (ex US)**: 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 alloction 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 Equity (US) any weight from missing observations of Equity (Ex US) and Private Equity. Then, we assign to Fixed Income (US) any weight from missing Fixed Income (Ex US), 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.

B CMA Formation Through Valuation Models

B.1 A Simple Yield-Based Model of CMA Formation

B.2 A Building-Block Model of Equity CMA Formation

C Supplementary Empirical Results

This section describes additional results that supplement the main findings in the paper. Subsection C.2 provides results comparing simple models of yield-based CMA formation versus extrapolation-based CMA formation. Subsection C.1 compares our risk aversion estimates with CAPM-implied risk aversion values. 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 IA.3 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.3 start by focusing on expected nominal returns (as in Greenwood and Shleifer (2014)). Specifically, we consider the regressions

$$\mathbb{E}_t[R_n] \;= const \;+\; b_{n,yield} \cdot (y_{n,t} + \pi_t^{(h)}) \;+\; b_{n,return} \cdot R_{n,t} \;+\; u_{n,t} \tag{IA.3}$$

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.3] 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 Fixed Income (US) 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.3 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

$$\mathbb{E}_t[R_n^{real}] \;= const \;+\; b_{n,yield} \cdot y_{n,t} \;+\; b_{n,return} \cdot R_{n,t}^{real} \;+\; u_{n,t} \tag{IA.4}$$

[IA.3] We obtain $R_{n,t}$ for the Fixed Income (US) and Fixed Income (Ex US) 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 Equity (US) and Equity (Ex US), 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.4 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 Fixed Income (US) asset class, and even there the yield model dominates (e.g., the R^2 from a model with $b_{n,return} = 0$ is 90.5% and it only increases slightly to 92.7% when we allow for $b_{n,return} \neq 0$).

Finally, the last two columns in Table IA.3 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.3 estimate the regression

$$\mu_{n,t} \; = const \; + \; b_{n,yield} \cdot y^{\mu}_{n,t} \; + \; b_{n,return} \cdot (R_{n,t} - R_{f,t}) \; + \; u_{n,t} \tag{IA.5}$$

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.5 (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.4) 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

In this subsection, we consider alternative constructions of subjective beliefs.

C.5.1 $\mathbb{E}[R]$ Based on Original Expected Returns

In our baseline analysis, we ensure the conceptual definition underlying our expected return measure is the same for all CMAs. Specifically, we always use expected arithmetic returns (since they are the most commonly reported), and, to avoid losing observations, we use a log-Normal transformation to infer expected arithmetic returns from expected geometric returns (for the 22.2% of CMAs without an expected arithmetic return). However, one may worry that our results are driven by the 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 very similar to our baseline results. We also obtain similar (untabulated) results when we use expected geometric returns when available and expected arithmetic returns when expected geometric returns are not available.

C.5.2 Wealth Portfolio Based on US Equities

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 Equities (US) as the wealth portfolio. The results (in Figures IA.3 to IA.4) are very similar to our baseline results.

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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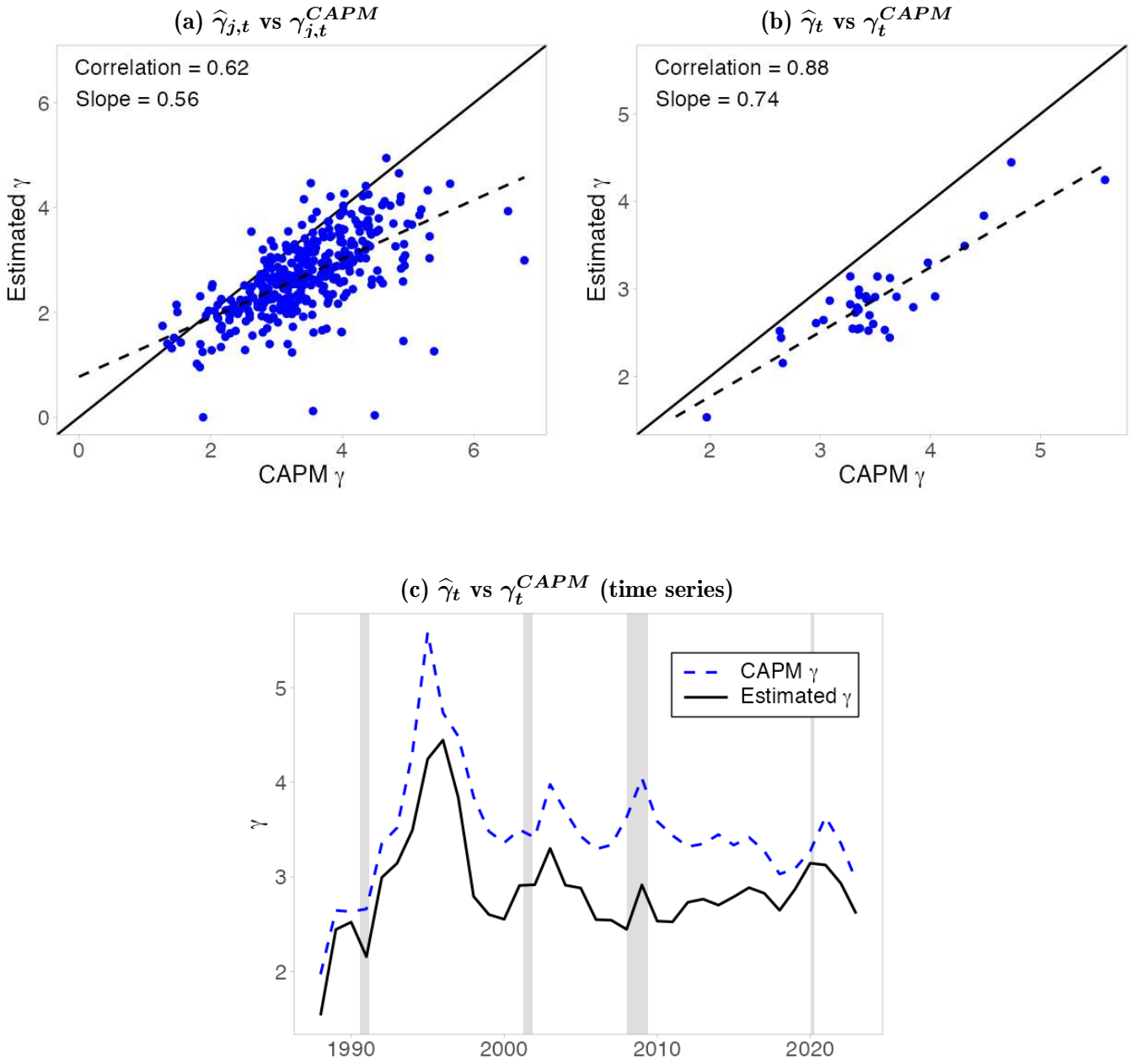
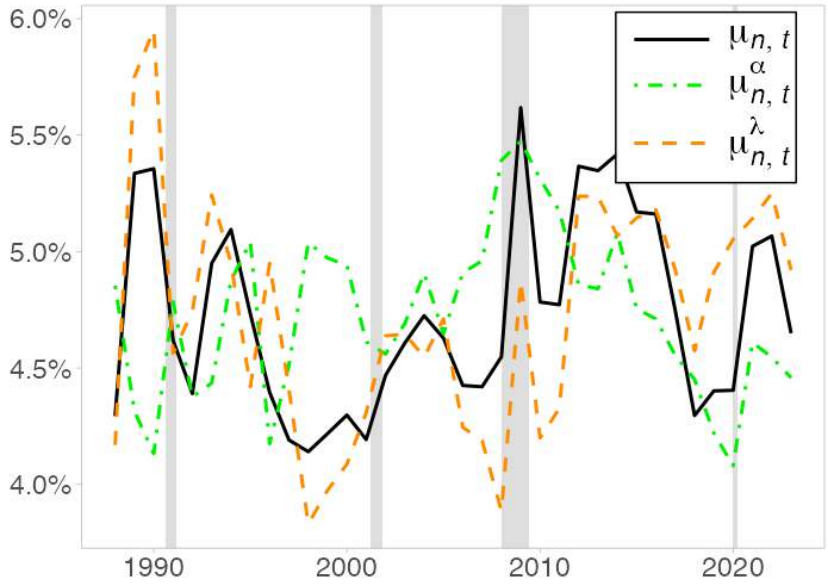


Figure IA.1
Estimated Risk Aversion vs CAPM Risk Aversion

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

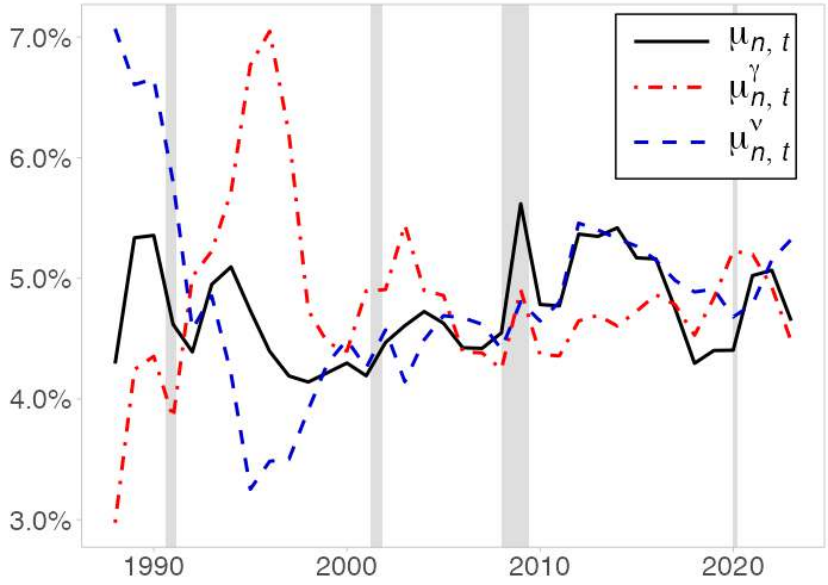


Figure IA.2
Time Series of Expected Return Components for the Wealth Portfolio

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.

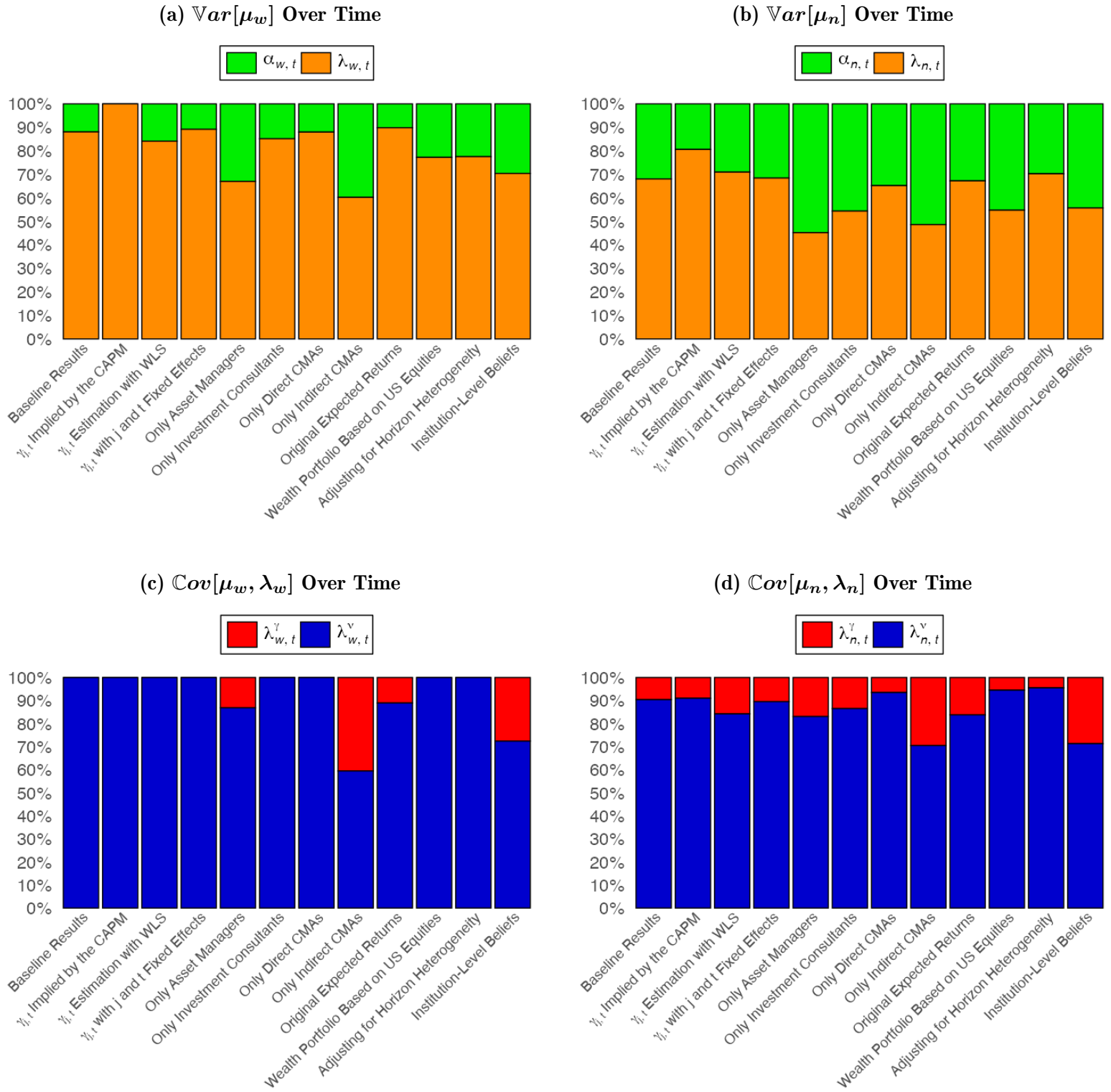


Figure IA.3
Decomposing Expected Return Time Variation: Alternative Specifications

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.

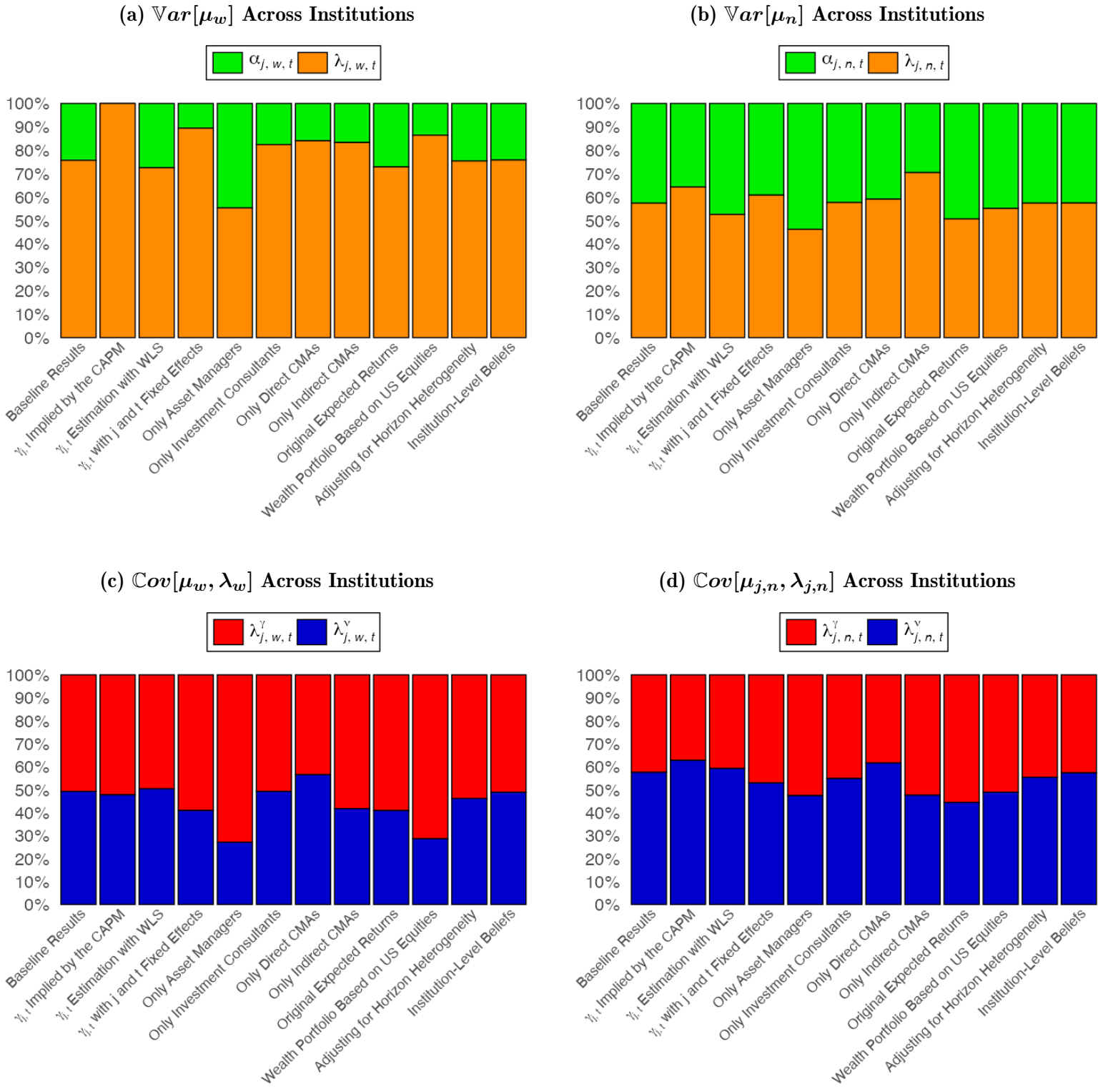


Figure IA.4
Decomposing Expected Return Disagreement: Alternative Specifications

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**
US Cash	US Cash (95%)	3-Month Libor (4.2%)	US Treasuries ST (0.3%)	US Inflation (0.3%)	
Fixed Income (US)	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%)
Fixed Income (Ex US)	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%)
Equity (US)	US Equities (65%)	US Equities Large Cap (35%)			
Equity (Ex US)	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**
US Cash					
Fixed Income (US)	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%)	
Fixed Income (Ex US)	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%)
Equity (US)					
Equity (Ex US)					
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 $\gamma^{CAPM}_{j,t} = \mu_{j,w,t}/\nu_{j,w,t}$ and $\gamma^{CAPM}_{t} = \mu_{w,t}/\nu_{w,t}$. 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.

	$\widehat{\gamma}_{j,t} = a + b \cdot \gamma^{CAPM}_{j,t} + \varepsilon_{j,t}$				$\widehat{\gamma}_{t} = a + b \cdot \gamma^{CAPM}_{t} + \varepsilon_{t}$
	[1]	[2]	[3]	[4]	[5]
a	0.76	-	-	-	0.29
$(t_{a=0})$	(5.99)	-	-	-	(1.39)
b	0.57	0.49	0.57	0.46	0.74
$(t_{b=0})$	(15.2)	(6.40)	(13.9)	(4.80)	(13.0)
$\{t_{b=1}\}$	{-11.6}	{-6.71}	{-10.6}	{-5.58}	{-4.61}
R^2_{total}	38.9%	63.1%	45.0%	69.1%	77.5%
R^2_{within}	-	27.4%	37.5%	22.8%	-
N_{obs}	361	361	361	361	36
Fixed Effects:					
Institution		×		×	
Year			×	×	

Table IA.3
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 Footnote 19. 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 =		$\mathbb{E}[R]$		$\mathbb{E}[R^{real}]$		μ	
	b_{yield}	0.98	0.95	0.95	0.93	0.88	0.88
	(t_{stat})	(14.2)	(18.1)	(9.71)	(11.0)	(7.07)	(6.75)
Fixed Income (US)	b_{return}		0.11		0.15		0.02
	(t_{stat})		(3.75)		(3.81)		(0.34)
	R^2_{adj}	95.8%	96.8%	90.5%	92.7%	76.3%	75.7%
	b_{yield}	0.95	0.95	0.91	0.90	0.90	0.90
	(t_{stat})	(14.6)	(14.6)	(7.99)	(10.2)	(10.5)	(11.8)
Fixed Income (Ex US)	b_{return}		0.00		0.03		-0.01
	(t_{stat})		(0.03)		(0.24)		(-0.07)
	R^2_{adj}	90.2%	89.8%	82.7%	82.2%	80.2%	79.5%
	b_{yield}	0.88	0.89	0.73	0.75	0.67	0.66
	(t_{stat})	(4.06)	(5.49)	(2.04)	(2.58)	(4.13)	(4.20)
Equity (US)	b_{return}		0.08		0.05		-0.03
	(t_{stat})		(1.14)		(0.51)		(-0.29)
	R^2_{adj}	76.3%	76.2%	52.5%	51.4%	43.1%	41.4%
	b_{yield}	0.87	0.87	0.72	0.71	0.72	0.72
	(t_{stat})	(4.20)	(4.41)	(1.72)	(1.81)	(5.85)	(5.66)
Equity (Ex US)	b_{return}		0.00		-0.08		-0.03
	(t_{stat})		(0.03)		(-2.04)		(-0.33)
	R^2_{adj}	74.8%	74.1%	50.9%	50.0%	50.5%	49.0%
	b_{yield}	0.86	0.88	0.76	0.76	0.54	0.58
	(t_{stat})	(8.20)	(8.63)	(5.32)	(4.51)	(3.13)	(3.18)
Private Equity	b_{return}		0.07		-0.00		0.07
	(t_{stat})		(0.69)		(-0.02)		(0.42)
	R^2_{adj}	72.2%	71.4%	55.9%	53.8%	26.1%	23.1%
	b_{yield}	0.88	0.88	0.61	0.60	0.51	0.50
	(t_{stat})	(5.28)	(5.48)	(3.99)	(4.04)	(3.81)	(3.94)
Real Estate	b_{return}		-0.02		-0.04		0.19
	(t_{stat})		(-0.30)		(-0.31)		(1.35)
	R^2_{adj}	77.5%	76.9%	35.0%	33.2%	24.1%	25.5%

Table IA.4

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.5 (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 Footnote 19. 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.

		μ	α	λ	λ^{γ}	λ^{ν}
	b	0.34	-0.08	0.42	-0.04	0.46
Fixed Income (US)	(t_{stat})	(7.07)	(-1.80)	(5.01)	(-1.05)	(5.11)
	R^2_{adj}	76.3%	14.8%	69.3%	2.1%	71.7%
	b	0.55	0.25	0.30	0.02	0.27
Fixed Income (Ex US)	(t_{stat})	(10.5)	(1.66)	(2.99)	(0.60)	(2.81)
	R^2_{adj}	80.2%	36.4%	62.1%	1.1%	61.5%
	b	0.29	0.07	0.22	-0.11	0.33
Equity (US)	(t_{stat})	(4.13)	(0.60)	(3.06)	(-0.51)	(1.62)
	R^2_{adj}	43.1%	0.3%	21.7%	-0.6%	14.3%
	b	0.29	-0.18	0.46	-0.09	0.55
Equity (Ex US)	(t_{stat})	(5.85)	(-1.76)	(4.46)	(-0.43)	(3.04)
	R^2_{adj}	50.5%	16.8%	54.8%	-1.0%	40.3%
	b	0.22	0.30	-0.08	0.10	-0.17
Private Equity	(t_{stat})	(3.13)	(2.97)	(-0.66)	(1.12)	(-1.64)
	R^2_{adj}	26.1%	38.1%	-2.0%	4.5%	16.4%
	b	0.37	0.14	0.22	0.15	0.07
Real Estate	(t_{stat})	(3.81)	(0.78)	(0.70)	(2.71)	(0.29)
	R^2_{adj}	24.1%	0.3%	1.5%	25.6%	-2.5%

Table IA.5

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

This table reports results from regressions (for US Equities) of CMA-based aggregate μ and its components (α, λ, λ^{γ}, and λ^{ν}) onto the excess CAPE yield detailed in Footnote 19 (which is the $y_{n,t}$ measure for US Equities 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	0.14	0.26	0.07	0.18
	(t_{stat})	(6.67)	(1.35)	(3.99)	(0.86)	(2.16)
	R^2_{adj}	51.1%	1.8%	26.1%	-1.7%	20.5%
Perceived Undervaluation	**Coef**	0.25	0.50	-0.25	-0.21	-0.04
	(t_{stat})	(2.51)	(12.0)	(-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**	0.38	0.11	0.28	0.09	0.19
	(t_{stat})	(9.99)	(3.57)	(5.01)	(1.15)	(2.14)
Perceived Undervaluation	**Coef**	0.22	0.50	-0.27	-0.22	-0.05
	(t_{stat})	(2.54)	(16.5)	(-3.16)	(-3.49)	(-0.42)
	R^2_{adj}	67.1%	86.3%	58.2%	23.3%	18.5%
Excess CAPE Yield	**Coef**	0.40	0.14	0.27	0.08	0.18
	(t_{stat})	(6.70)	(2.59)	(7.92)	(1.44)	(1.79)
Subjective $\mathbb{E}$[Growth]	**Coef**	0.11	-0.04	0.14	0.17	-0.03
	(t_{stat})	(2.20)	(-0.34)	(1.71)	(2.47)	(-0.28)
	R^2_{adj}	52.6%	-2.8%	32.2%	10.7%	16.8%
Excess CAPE Yield	**Coef**	0.39	0.11	0.28	0.10	(0.19)
	(t_{stat})	(13.0)	(3.84)	(5.68)	(1.51)	2.38
Perceived Undervaluation	**Coef**	0.25	0.50	-0.25	-0.20	(-0.06)
	(t_{stat})	(3.49)	(15.6)	(-3.47)	(-3.32)	-0.34
Subjective $\mathbb{E}$[Growth]	**Coef**	0.14	0.04	0.10	0.14	(-0.03)
	(t_{stat})	(4.58)	(1.55)	(2.32)	(1.55)	-0.54
	R^2_{adj}	73.3%	86.2%	61.1%	31.0%	14.9%

Table IA.6

Decomposing Expected Return Variation: Split Sample in 2 Halves

This table provides our main results on μ variance decomposition after splitting our sample period in two halves (1987 to 2004 and 2005 to 2022). Panel A provides results associated with Panel A of Tables 6 and 7, which focus on decomposing $\mathbb{V}ar[\mu]$ into the effects of alphas (α) and risk premia (λ). Panel B provides results associated with Panel B of Tables 6 and 7, which focus on decomposing $\mathbb{C}ov[\mu, \lambda]$ into the effects of risk price (γ) and risk quantity (ν). The results from this table are discussed in Footnote 26 of the main text.

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

	% from α				% from λ			
	1st Half	(t-stat)	2nd Half	(t-stat)	1st Half	(t-stat)	2nd Half	(t-stat)
Overall Time Variation:								
Wealth Portfolio	31.9%	(1.61)	36.5%	(8.04)	68.1%	(3.44)	63.5%	(14.0)
All Asset Classes	34.4%	(3.22)	53.4%	(4.60)	65.6%	(6.12)	46.6%	(4.01)
Disagreement:								
Wealth Portfolio	20.3%	(1.48)	24.6%	(2.94)	79.7%	(5.78)	75.4%	(9.02)
All Asset Classes	30.2%	(1.73)	44.0%	(3.55)	69.8%	(3.99)	56.0%	(4.52)

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

	% from γ				% from ν			
	1st Half	(t-stat)	2nd Half	(t-stat)	1st Half	(t-stat)	2nd Half	(t-stat)
Overall Time Variation:								
Wealth Portfolio	16.4%	(0.41)	61.4%	(6.26)	83.6%	(2.10)	38.6%	(3.94)
All Asset Classes	12.7%	(1.46)	49.1%	(5.35)	87.3%	(10.1)	50.9%	(5.56)
Disagreement:								
Wealth Portfolio	48.8%	(19.1)	51.4%	(6.97)	51.2%	(20.0)	48.6%	(6.59)
All Asset Classes	33.5%	(4.16)	44.0%	(4.26)	66.5%	(8.26)	56.0%	(5.41)