Institutional Investors' Subjective Risk Premia: Time Variation and Disagreement

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Abstract

In this paper, we study the role of subjective risk premia in explaining subjective expected return time variation and disagreement using the long-term Capital Market Assumptions of major asset managers and investment consultants from 1987 to 2022. We find that market risk premia explain most of the expected return time variation, with the rest explained by alphas. The risk premia effect is almost entirely driven by time variation in risk quantities as opposed to risk price. Nevertheless, risk price explains about half of the transitory effect of risk premia on expected returns. Market risk premia also explain most of the expected return disagreement, but in this case alphas have a quantitatively significant effect, and risk price and risk quantities are roughly equally responsible for the risk premia effect. Our results provide benchmark moments that asset pricing models should match to be consistent with institutional investors' beliefs.

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

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Introduction

Understanding what drives variation in expected returns is at the heart of asset pricing. Risk-based theories imply expected return variation is determined by risk premia variation, with a role for both risk price (through risk aversion) and risk quantity (through variances and covariances).[1] At the same time, behavioral theories put the spotlight on other factors that go beyond risk premia effects. As such, the asset pricing literature has focused on understanding what drives variation in expected returns (see Cochrane (2011)).

Most studies proxy for expected returns using econometric forecasts of future returns. While informative about objective expected returns, this approach does not necessarily uncover the determinants of investors' expected returns. In fact, the recent literature highlights the importance of studying subjective expected returns (see Adam and Nagel (2023)). For instance, Dahlquist and Ibert (2024a,b) show the expected returns of institutional investors are countercyclical (increase in bad times) and heterogeneous (embed substantial disagreement). Yet, we know little about how these expected returns are linked to perceived risk.

In this paper, we study the role of subjective risk premia in explaining subjective expected return time variation and disagreement using the long-term Capital Market Assumptions (CMAs) of major asset managers and investment consultants from 1987 to 2022. We find that market risk premia explain most of the expected return time variation, with the rest explained by alphas (i.e., factors beyond market risk premia). The risk premia effect is almost entirely driven by time variation in risk quantities (i.e., subjective covariances with the wealth portfolio) as opposed to risk price (i.e., subjective compensation per unit of risk). Nevertheless, risk price explains about half of the transitory effect of risk premia on expected returns. In terms of disagreement, market risk premia also explain most of the expected return disagreement, but in this case alphas have a quantitatively significant effect, and risk price and risk quantities are roughly equally responsible for the risk premia effect.

[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...".

To understand our empirical strategy, consider the following decomposition for expected excess returns (μ):

$$\mu \ = \text{Alpha } (\alpha) \ + \ \underbrace{\text{Risk Aversion} \cdot \text{Risk Quantity}}_{\text{Risk Premium } (\lambda)} \ (\gamma \cdot \nu) \tag{1}$$

This decomposition works as an identity in our empirical analysis, but is economically motivated by the Capital Asset Pricing Model (CAPM), which implies Equation 1 with $\alpha = 0$ when ν is a covariance with the wealth portfolio.

We extract from the CMAs in our dataset (long-term) expected returns, volatilities, and correlations for 9 asset classes plus US Cash, which we treat as a proxy for the risk-free asset. In turn, we measure the aggregate allocation of US public pension funds, using it to construct a proxy for the wealth portfolio weights. Then, we combine the wealth portfolio weights with expected returns, volatilities, and correlations to calculate μ and ν for each asset class in each CMA (i.e., institution-year observation) in our sample. Finally, for each CMA, we estimate γ from the slope coefficient of a linear projection of μ onto ν across asset classes, which in turn yields $\lambda = \gamma \cdot \nu$ and $\alpha = \mu - \lambda$. So, we have all elements of Equation 1 for each CMA and perform several analyses to understand the importance of each of these expected return components (α, λ, γ, ν) in driving expected return time variation and disagreement.

Figure 1 graphically demonstrates our main results, with a focus on the wealth portfolio. Figure 1(a) plots the time series of wealth portfolio expected excess returns aggregated across institutions ($\mu_{w,t}$) together with the counterfactual $\mu_{w,t}$ that would prevail if (i) only the wealth portfolio risk premium varied over time ($\mu^{\lambda}_{w,t}$) or (ii) only the wealth portfolio variance varied over time ($\mu^{\nu}_{w,t}$). As it is clear from the figure, $\mu_{w,t}$ and $\mu^{\lambda}_{w,t}$ move together over time, with most of this risk premium connection to expected returns due to risk quantity given the strong time series link between $\mu_{w,t}$ and $\mu^{\nu}_{w,t}$. These results can also be seen from time series correlations if we define μ^{α}_{w} and μ^{γ}_{w} analogously to μ^{λ}_{w} and μ^{ν}_{w} (so that they reflect time variation in α and γ, respectively). Notably, we observe a strong $\mathbb{C}or[\mu_{w,t}, \mu^{\lambda}_{w,t}] = 0.74$, in contrast to the much weaker $\mathbb{C}or[\mu_{w,t}, \mu^{\alpha}_{w,t}] = 0.14$. Similarly, the strong $\mathbb{C}or[\mu_{w,t}, \mu^{\nu}_{w,t}] = 0.44$ stands in contrast to the nearly negligible $\mathbb{C}or[\mu_{w,t}, \mu^{\gamma}_{w,t}] = -0.04$.

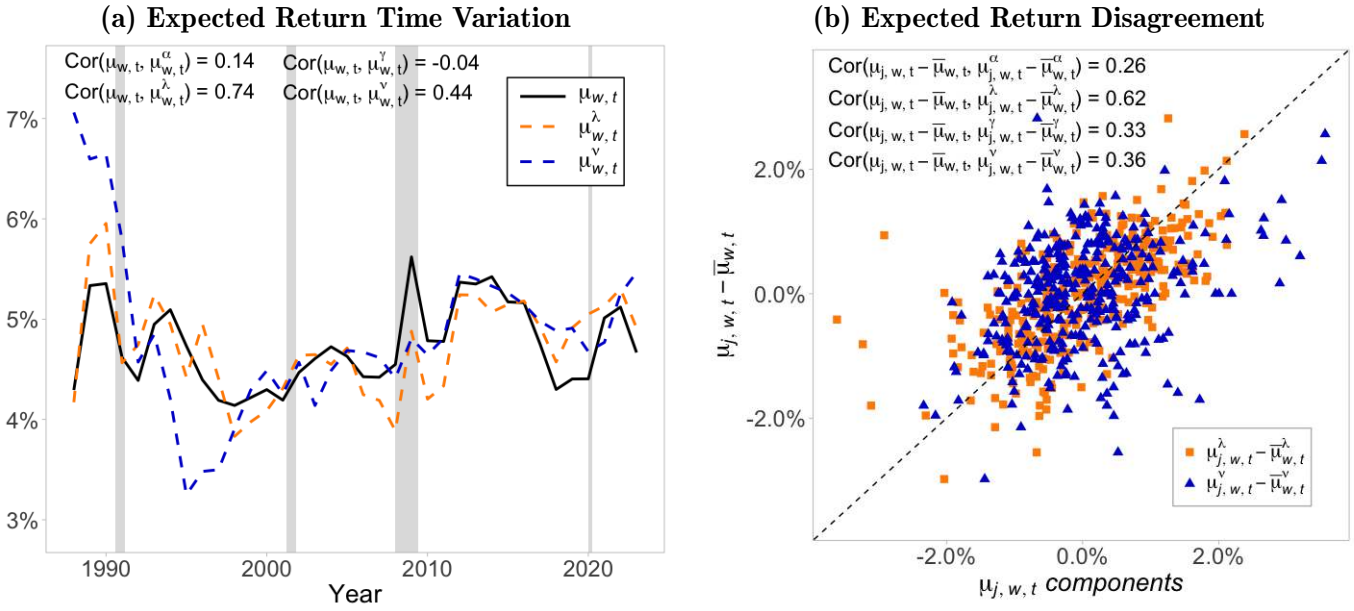


Figure 1
Expected Return Time Variation and Disagreement (Wealth Portfolio)

This figure highlights the main results from the paper with a focus on the wealth portfolio (t index time and j index institution). Panel (a) provides a time series plot for the subjective expected excess return on the wealth portfolio aggregated across institutions ($\mu_{w,t}$) as well as the counterfactual $\mu_{w,t}$ that would prevail if (i) only the wealth portfolio risk premium varied over time ($\mu^{\lambda}_{w,t}$) or (ii) only the wealth portfolio variance varied over time ($\mu^{\nu}_{w,t}$). Panel (b) provides a scatterplot of the demeaned subjective expected excess return on the wealth portfolio for each j at each t ($\mu_{j,w,t} - \overline{\mu}_{w,t}$) as well as analogous quantities for the counterfactual demeaned $\mu_{j,w,t}$ that would prevail if (i) only the wealth portfolio risk premium varied across institutions ($\mu^{\lambda}_{j,w,t} - \overline{\mu}^{\lambda}_{w,t}$) or (ii) only the wealth portfolio variance varied across institutions ($\mu^{\nu}_{j,w,t} - \overline{\mu}^{\nu}_{w,t}$). Measurement details are provided in Sections 1 and 2.

Figure 1(b) provides a scatterplot of $\mu_{j,w,t}$ against $\mu^{\lambda}_{j,w,t}$ and $\mu^{\nu}_{j,w,t}$ for all institution-year observations (j,t). All quantities are demeaned by their respective cross-institution averages to reflect disagreement. Analogous to the time series plot, there is a clear link between disagreement in μ_w and μ^{λ}_w, with a correlation of 0.62, which is much higher than the 0.26 correlation between disagreement in μ_w and μ^{α}_w. Similarly, there is a clear link between disagreement in μ_w and μ^{ν}_w, with a correlation of 0.36, but in this case we have a comparable correlation (of 0.33) between disagreement in μ_w and μ^{γ}_w. So, expected return disagreement is also more connected to risk premium than alpha, but in this case risk price disagreement (i.e., risk aversion heterogeneity) is as important as risk quantity disagreement.

We formalize the visual observations from Figure 1(a) through decompositions of expected return variation over time. 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. Since expected returns are persistent, we also explore annual differences in expected returns, which capture transitory expected return movements. Risk premia continue to drive most of the variation in expected returns (100% for the wealth portfolio and 62% for all asset classes jointly), but in this case risk quantity and risk price are roughly equally responsible for the risk premia effect. In particular, for the wealth portfolio risk quantity captures 40% of the risk premia effect whereas it captures 54% of the risk premia effect for all asset classes jointly.

We also formalize the visual observations from Figure 1(b), but in this case through decompositions of expected return variation across institutions, which reflects disagreement. 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.

Overall, our results indicate risk premia (especially through risk quantity) play a major role in explaining expected return variation over time and across institutions. We explore several modifications to our baseline empirical procedure, including alternative methods to estimate risk aversion (e.g., γ 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 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.

Contribution to the Literature

Our most direct contribution is to the subjective beliefs literature in asset pricing.[2] Adam and Nagel (2023) summarize this literature and highlight two key challenges for subsequent work: (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 speaks to both of these challenges. We address challenge (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 extensive, so we cannot properly summarize it here. However, some recent (including contemporaneous) papers are Greenwood and Shleifer (2014), Piazzesi, Salomao, and Schneider (2015), Adam, Marcet, and Bautel (2017), Cieslak (2018), Wu (2018), Bordalo et al. (2019), Adam, Matveev, and Nagel (2021), De La O 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), Balloch and Peng (2024), Bordalo et al. (2024), Chaudhry (2024), Dahlquist, Ibert, and Wilke (2024), Dahlquist and Ibert (2024a,b), Décaire and Graham (2024), Décaire and Guenzel (2024), Décaire, Sosyura, and Wittry (2024), De La O, Han, and Myers (2024), De La O 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), and Loudis (2024).

[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", 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), De La O and Myers (2021, 2024), Nagel and Xu (2023), and Dahlquist and Ibert (2024a,b)).

In terms of challenge (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 (2024a,b). As discussed above, our contribution relative to Couts, Gonçalves, and Loudis (2024) is the focus on risk premia time variation and disagreement, and the separation of the effects of risk price and risk quantity. Dahlquist and Ibert (2024a) study time variation in expected equity returns and the pass through of beliefs to portfolio allocations (which relates to disagreement). Dahlquist and Ibert (2024b) 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 highlight the importance of expectations about long-term valuations. Our work is complementary to theirs as we focus on understanding the risk-based determinants of expected return time variation and disagreement. The key ingredient for that 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 for decomposing subjective expected returns into alpha and risk premia components. It also details the CMAs dataset we use to empirically construct our measures of subjective risk and return expectations. Section 2 explains how we estimate risk aversion and summarizes the expected return components we extract from the CMAs. Section 3 provides results for our decompositions of expected return variation under the assumption that risk aversion is constant and homogeneous, which allows us to highlight the role of risk quantity in a simple setting. Section 4 extends our decompositions of expected return variation to allow for time variation and heterogeneity in risk aversion. Section 5 concludes by summarizing our findings and their broad implications. The Internet Appendix provides details about the data we use and presents empirical results that supplement the empirical findings in the main text.

1 Decomposing Subjective Expected Returns: Setup & Beliefs Data

In this paper, our analysis focuses on decomposing the drivers of expected excess return time variation and disagreement. In particular, we evaluate the significance of alphas and risk premia in driving this variation. We also evaluate the extent to which variation in risk quantities and risk price drive the risk premia effect on expected returns. Subsection 1.1 explains the baseline framework for our expected return decomposition. In turn, Subsection 1.2 describes the beliefs data we use to implement the decomposition empirically and Subsection 1.3 explains how we aggregate beliefs across institutions in the time-series portion of our analysis. Finally, Subsection 1.4 illustrates the level 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 reflects gross returns while $r = R - R_f$ reflects excess returns relative to the risk-free asset, which we assume exists (and proxy for by using the US Cash asset class). Finally, to simplify notation, we suppress time indexes inside moments 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 return on the wealth portfolio in excess of the risk-free asset, we use the following decomposition for investor's j 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 $\alpha_{j,n,t} = \mu_{j,n,t} - \gamma_{j,t} \cdot \nu_{j,n,t}$.

Equations 2 and 3 hold as identities in our analysis since we do not impose restrictions on

alpha. However, the economic interpretation of each μ component comes from the conditional Capital Asset Pricing Model (CAPM), which implies Equations 2 and 3 with $\alpha_{j,n,t} = 0$.[4] In particular, $\lambda_{j,n,t}$ is investor's j subjective risk premium on asset n at time t, which depends on the investor's risk aversion ($\gamma_{j,t}$) and the exposure of asset n to the wealth portfolio as perceived by the investor ($\nu_{j,n,t}$). So, γ captures "risk price" whereas ν captures "risk quantity" from the perspective of investor j.

In our empirical analysis, we use Equation 2 to perform our decomposition of variation in subjective expected excess returns (μ) into the effect of alphas (α) and market 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.[5]

It is common in the literature to refer to μ as risk premium. We instead refer to μ as expected excess return (or expected return as a shorthand) to clarify that μ has both a risk premium (λ) component as well as an alpha (α) component.[6] Note that, if the CAPM truly holds (and beliefs and wealth portfolio weights are perfectly measured), then $\alpha_{j,n,t} = 0$. However, we allow for model mispecification (or data measurement issues) by allowing for

[4]Note that while the CAPM was originally derived under homogeneous beliefs (Sharpe (1964) and Lintner (1965)), it continues to hold with many forms of belief heterogeneity (see Levy, Levy, and Benita (2006) and the references cited therein). Moreover, in some models of belief heterogeneity, the CAPM holds under the subjective beliefs of investors even though it fails in realized returns (see Andrei, Cujean, and Wilson (2023)). That said, we do not assume the CAPM holds in realized returns or under the subjective beliefs of investors (i.e., we allow for $\alpha_{j,n,t} \neq 0$). Instead, we rely on the CAPM for the interpretation of the three components in Equation 3, which remains valid even if the CAPM does not hold.

[5]Couts, Gonçalves, and Loudis (2024) explored Equation 2 using the same beliefs dataset we rely on. However, they focus on the risk-return tradeoff across asset classes instead of the time variation and disagreement in expected returns (albeit they provide some limited results on these). 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 do 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).

[6]To be even more precise, λ is the risk premium due to market risk exposure. So, our alpha component can include a risk premium component, but from risk factors beyond the wealth portfolio.

$\alpha_{j,n,t} \neq 0$. If we imposed $\alpha_{j,n,t} = 0$, then Equation 3 (and its respective decomposition) would remain the same, but Equation 2 would imply $\mu_{j,n,t} = \lambda_{j,n,t}$ so that 100% of the variation in subjective expected excess returns would be driven by subjective risk premia variation.

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 (of "consultants" for short), with all data collection details provided in Internet Appendix A.[7] This subsection provides a brief description of our CMAs dataset and how we use it to obtain the belief quantities 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.

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

[7] 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. This argument is valid if (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 explore these two channels in our paper, Internet Appendix B shows that our main results are similar if we use only asset managers or only investment consultants.

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.

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 financial research. As a consequence, it is plausible that CMAs reflect 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.

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 modal horizon being 10 years (which comprises 45.2% of the institution-year observations for which we observe horizon).[8] 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.[9]

Table 1 shows the list of managers and consultants that have at least one CMA in our sample.[10] As it is clear from the table, our sample covers many of the major asset managers

[8]In our baseline analysis, we combine data from all institution-year observations regardless of forecasting horizon. This empirical decision does not create any conceptual issue with our analysis since our expected return decomposition framework introduced in Subsection 1.1 holds for any given belief horizon. This is similar to how a version of the CAPM holds for any given investors' horizon (see Levhari and Levy (1977)) and also when investors have heterogeneous horizons (see Lee, Wu, and Wei (1990) and Brennan and Zhang (2020)). 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, in Internet Appendix B, we show that our main results are similar if we control for horizon heterogeneity in the belief aggregation process (for the time series analysis) and in the variance decomposition process (for the disagreement analysis).

[9]In Internet Appendix B, 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 (e.g., the worry that institutions send us historical projections that rely on their current models/methods).

[10]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

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).[11] 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.[12] 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 a "risk-free" asset class proxy (US Cash) as well as 9 risky asset classes, which are chosen to match the asset classes for which we have data on the portfolio weights of US public pension funds (discussed in the next paragraph), which is our proxy for the wealth portfolio. 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 we have at least one institution covering Cash, Fixed Income (US), Equity (US), and Real Estate, which are the asset classes

more on investment advising for wealthy individuals (e.g., CWO). Second, many institutions (e.g., BNY Mellon, Cliffwater, and Envestnet) have both an asset management business as well as a consulting or wealth advising business. The classification in Table 1 is based on our (somewhat subjective) assessment of whether the asset management side of a given institution is large enough to justify classifying it as an asset manager (e.g., by analysing their AUM and website self-descriptions). However, our classification has no impact on our main analysis since all results presented in the main text are based on a sample that combines asset managers and investment consultants. Our classification only plays a role when we provide results (consistent with our main results) separately for asset managers and investment consultants (in Internet Appendix B).

[11] Years are defined based on the approximate timing of the institution's information set. For instance, if a CMA contains $\mathbb{E}_{2000}[R_{2001\to2010}]$, then our year variable is 2000.

[12] 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.

that dominate the wealth portfolio weights.

For each CMA (i.e., institution-year observation), we have expected returns and expected volatilities for each asset class as well as the expected correlation matrix across asset classes.[13] We use these quantities to obtain institution j subjective expected excess returns ($\mu_{j,t}$) and subjective covariance matrix of excess returns ($\Sigma_{j,t}$).[14] 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 weights from all types of institutional investors, 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.2 for details).[15] Figure 2 displays the wealth portfolio weights used in our baseline analysis (note that 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

[13] 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 B 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

[14] Specifically, letting $\mathbb{E}_{j,t}[R]$ and $\Sigma^R_{j,t}$ represent the subjective expect return vector and covariance matrix for institution j at time t (with US Cash as the first asset class), we obtain expected excess returns as $\mu_{j,n,t} \equiv \mathbb{E}_{j,t}[r_n] = \mathbb{E}_{j,t}[R_n] - \mathbb{E}_{j,t}[R_f]$ and covariance matrices of excess returns as $\Sigma_{j,t} = \Omega\Sigma^R_{j,t}\Omega'$, where $\Omega = [-1, \mathrm{I}]$, with 1 representing a column vector of ones and I an identity matrix.

[15] If an institution-year observation does not have belief data for a given asset class, 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.

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 B also considers an alternative version of our analysis in which Equity (US) proxies for the wealth portfolio. The results are qualitatively similar to the ones we report in the main text.

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 two 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, 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 ratio of portfolios r_p and $\phi \cdot r_p$ are the same for any $\phi > 1$ so that we have an infinite number of maximum Sharpe ratio portfolios. So, the separation between risk quantity and risk price boils down to a normalization on the sum of the weights for the maximum Sharpe ratio portfolio (recall that any positive sum of weights would be valid since the remaining weights would reflect a position on the risk-free asset). 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 a preference structure to tell us what represents risk to investors. Our simple CAPM (derived from mean-variance preferences) does that, which explains why we can separately identify risk quantity and risk price. 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

Our beliefs data described in the prior subsection results in an unbalanced panel of institution-year observations. We use belief elements aggregated across institutions (at each t) in all analyses that study time variation in expected returns and its components.[16] 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):

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

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

$$\theta_{n,t} = \left(\frac{1}{T}\cdot\sum_{t=1}^{T}\overline{\theta}_{n,t}\right) + \left(\theta^{fe}_{n,t} - \frac{1}{T}\cdot\sum_{t=1}^{T}\theta^{fe}_{n,t}\right) \tag{5}$$

where $\overline{\theta}_{n,t} = \frac{1}{J_t}\sum_{j=1}^{J_t}\theta_{j,n,t}$, and 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 takes the time demeaned $\theta^{fe}_{n,t}$ and adds to it the time-series average of the cross-section averages of $\theta_{j,n,t}$, which is an estimate for $\mathbb{E}[\theta_n]$.

Note that the time-series average of $\theta_{n,t}$ matches the time-series average of the alternative aggregated series $\overline{\theta}_{n,t}$ (which reflects the cross-sectional average for asset class n at time t).

[16] 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 B, 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).

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

1.4 Time Variation and Disagreement in Expected Returns

Our analysis focuses on decomposing time variation and disagreement in expected returns into their components. 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 $\sigma_{\mu,n,t} = \sqrt{\mathbb{V}ar_t[\mu_{j,n,t} - \overline{\mu}_{n,t}]}$.[17] Clearly, for all asset classes, we have substantial time series variation as well as disagreement in expected returns considering that μ reflects long-term expected returns (recall that the modal forecasting horizon in our data is 10 years).[18]

While we do not study the connection between expected excess returns and subsequent realized excess returns in this paper, Couts, Gonçalves, and Loudis (2024) show that $\mu_{n,t}$ values analogous to ours (adjusted to reflect a 1-year horizon) forecast next year realized excess returns across asset classes and over time with a slope coefficient close to one (and statistically indistinguishable from one). Moreover, Dahlquist and Ibert (2024a) show that long-term equity expected excess returns from institutions similar to ours vary one-to-one with a measure of objective long-term equity expected excess returns, with Couts, Gonçalves, and Loudis (2024) extending this finding over time and Dahlquist and Ibert (2024b) 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 largely captures variation in objective expected returns as opposed

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

[18] 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 (2024b) provide a plot of the objective risk premium in the bond market that features a similar decline.

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 summarizes 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 the resulting expected return components.

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%).[19] That is, we estimate $\gamma_{j,t}$ by comparing the subjective

[19]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 the theory in Subsection 1.1 (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 observation would recover $\gamma_{j,n}$, which is also not consistent with theory.

expected returns of asset classes with different subjective risk quantities as perceived by institution j at time t.[20,21] 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. While our projection across asset classes is subject to more estimation error (since we have at most nine asset classes for each institution-year observation), it avoids 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 4 provides a visual analysis of the link between $\widehat{\gamma}$ and γ^{CAPM}. From Figure 4(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 4(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

[20] 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.

[21] In Internet Appendix B, 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.

at the aggregate, we are far from the $\widehat{\gamma} = \gamma^{CAPM}$ prediction. In particular, Figure 4(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 3 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 is not perfectly consistent with the CAPM. 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.

For the rest of this paper, we use our estimated risk aversion values and refer to them simply as $\gamma_{j,t}$ and γ_t (without the hat). Nevertheless, Internet Appendix B 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.

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 4 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.[22]

Table 4 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 later reflecting disagreement. For instance, the wealth portfolio μ has a time-series standard deviation of 0.4% and a cross-institution standard deviation of 0.8%, with both of these numbers being non-trivial in comparison to the time-series average for the wealth portfolio μ, which is 4.7%. Moreover, the wealth portfolio λ has a similar variability as its μ, with a time-series standard deviation of 0.5% and a cross-institution standard deviation of 1.0%.

Table 4 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.,

[22]Note that even though risk aversion does not vary across asset classes, the risk aversion average values in Table 4 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.

$\mathbb{C}or[\mu_{n,t}, \lambda_{n,t}]$). In the columns under "Cross-Institution Correlations", each value reflects the time-series average of the cross-institution correlation between the respective expected return component (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 Expected Return Variation with $\gamma_{j,t} = \overline{\gamma}$

The prior section shows that λ tends to be as volatile as μ and that λ and ν tend to be highly correlated with μ (more so than α and γ). These empirical facts suggest that variation in λ (through ν) is likely an important determinant of variation in μ. In this section, we rely on a constant and homogeneous risk aversion ($\overline{\gamma}$) to quantify the fraction of μ variation that is explained by λ variation through ν in the absence of γ variation (we return to exploring the time-varying and heterogeneous risk aversion in Section 4). Removing the variation in γ provides a simple way to show one of our key results: variation in risk quantity is an important determinant of variation in expected returns. Subsection 3.1 decomposes μ time variation and Subsection 3.2 decomposes μ disagreement.

3.1 Decomposing Expected Return Time Variation with $\gamma_{j,t} = \overline{\gamma}$

To start, rewrite Equation 6 as

$$\mu_{n,t} \;=\; \alpha_{n,t}^{\overline{\gamma}} \;+\; \lambda_{n,t}^{\overline{\gamma}} \;=\; \alpha_{n,t}^{\overline{\gamma}} \;+\; \overline{\gamma} \cdot \nu_{n,t} \tag{8}$$

where $\alpha_{n,t}^{\overline{\gamma}} = \alpha_{n,t} + (\gamma_t - \overline{\gamma}) \cdot \nu_{n,t}$. If $\gamma_t = \overline{\gamma}$ (so that $\alpha_{n,t}^{\overline{\gamma}} = \alpha_{n,t}$), then $\lambda_{n,t}^{\overline{\gamma}} = \overline{\gamma} \cdot \nu_{n,t}$ captures the true effect of risk premia on expected returns. Otherwise, $\lambda^{\overline{\gamma}}$ misses the component of risk premia related to γ time variation, which is incorporated into alphas through the $(\gamma_t - \overline{\gamma}) \cdot \nu_{n,t}$ term.

Figures 5(a) and 5(b) plot $\mu_{n,t} - \overline{\mu}_n$ against $\alpha_{n,t}^{\overline{\gamma}} - \overline{\alpha}_n^{\overline{\gamma}}$ and $\lambda_{n,t}^{\overline{\gamma}} - \overline{\lambda}_n^{\overline{\gamma}}$, with each variable

capturing time variation in the respective expected return component.[23] There is a strong connection between μ time variation and $\lambda^{\overline{\gamma}}$ time variation (e.g., a correlation of 0.46), whereas the connection between μ time variation and $\alpha^{\overline{\gamma}}$ time variation is much weaker (e.g., a correlation of 0.28).

To formalize the visual results from Figures 5(a) and 5(b), we consider the following decomposition for μ time variation:

$$\begin{aligned} \mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n] &= \mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \, , \, \alpha^{\overline{\gamma}}_{n,t} - \overline{\alpha}^{\overline{\gamma}}_n] + \mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \, , \, \lambda^{\overline{\gamma}}_{n,t} - \overline{\lambda}^{\overline{\gamma}}_n] \\ &\Downarrow \\ 1 &= \underbrace{\frac{\mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \, , \, \alpha^{\overline{\gamma}}_{n,t} - \overline{\alpha}^{\overline{\gamma}}_n]}{\mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n]}}_{\mathbb{V}(\alpha^{\overline{\gamma}})} + \underbrace{\overline{\gamma} \cdot \frac{\mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \, , \, \nu_{n,t} - \overline{\nu}_n]}{\mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n]}}_{\mathbb{V}(\lambda^{\overline{\gamma}})} \end{aligned} \tag{9}$$

which follows directly from Equation 8.

Table 5 Panel A provides the estimates and t-statistics for $\mathbb{V}(\alpha^{\overline{\gamma}})$ and $\mathbb{V}(\lambda^{\overline{\gamma}})$ for the wealth portfolio, all asset classes combined, and each individual asset class.[24] Most of the time variation in the expected returns on the wealth portfolio is explained by risk quantity time variation since $\mathbb{V}(\lambda^{\overline{\gamma}}) = 86.1\%$ ($t_{stat} = 2.54$). In fact, we have a statistically insignificant $\mathbb{V}(\alpha^{\overline{\gamma}}) = 13.9\%$ ($t_{stat} = 0.41$) for the wealth portfolio. When combining all asset classes, we have $\mathbb{V}(\lambda^{\overline{\gamma}}) = 63.0\%$ ($t_{stat} = 3.56$), which indicates that risk quantity also drives the overall time variation in μ. However, in this case alphas also play a quantitatively important role with $\mathbb{V}(\alpha^{\overline{\gamma}}) = 37.0\%$ ($t_{stat} = 2.09$). Results vary by asset class, and Figure 6(a) provides a

[23] We construct $\lambda^{\overline{\gamma}}_{n,t} = \overline{\gamma} \cdot \nu_{n,t}$ using $\overline{\gamma} = 2.86$, which is the time series average risk aversion from Section 2. We construct $\lambda^{\overline{\gamma}}_{j,n,t} = \overline{\gamma} \cdot \nu_{j,n,t}$ in the next subsection using the same $\overline{\gamma}$ value. Note that estimating $\overline{\gamma}$ as the slope coefficient from a linear projection of $\mu_{n,t}$ onto $\nu_{n,t}$ would produce a biased $\overline{\gamma}$ estimate if the true risk aversion is time varying and/or heterogeneous (which is the case). So, we instead use the time series average risk aversion, which is a consistent estimator for $\overline{\gamma}$ whether or not the true risk aversion is time varying and/or heterogeneous.

[24] We estimate $\mathbb{V}(\lambda^{\overline{\gamma}})$ for asset class n as the slope coefficient from an OLS regression of $\lambda^{\overline{\gamma}}_{n,t}$ onto $\mu_{n,t}$ (and use Newey and West (1987, 1994) for standard errors). We estimate $\mathbb{V}(\lambda^{\overline{\gamma}})$ for all asset classes combined as the slope coefficient from an OLS regression of $\lambda^{\overline{\gamma}}_{n,t}$ 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). $\mathbb{V}(\alpha^{\overline{\gamma}})$ is estimated analogously with $\alpha^{\overline{\gamma}}_{n,t}$ replacing $\lambda^{\overline{\gamma}}_{n,t}$, but note that $\mathbb{V}(\alpha^{\overline{\gamma}}) = 1 - \mathbb{V}(\lambda^{\overline{\gamma}})$ by construction.

visual representation of the decomposition.[25]

3.2 Decomposing Expected Return Disagreement with $\gamma_{j,t} = \overline{\gamma}$

Analogous to the prior subsection, we rewrite Equation 7 as

$$\mu_{j,n,t} \;=\; \alpha^{\overline{\gamma}}_{j,n,t} \;+\; \lambda^{\overline{\gamma}}_{j,n,t} \;=\; \alpha^{\overline{\gamma}}_{j,n,t} \;+\; \overline{\gamma} \cdot \nu_{j,n,t} \tag{10}$$

where $\alpha^{\overline{\gamma}}_{j,n,t} = \alpha_{j,n,t} + (\gamma_{j,t} - \overline{\gamma}) \cdot \nu_{j,n,t}$. If $\gamma_{j,t} = \overline{\gamma}$ (so that $\alpha^{\overline{\gamma}}_{j,n,t} = \alpha_{j,n,t}$), then $\lambda^{\overline{\gamma}}_{j,n,t} = \overline{\gamma} \cdot \nu_{j,n,t}$ captures the true effect of risk premia on expected returns. Otherwise, $\lambda^{\overline{\gamma}}$ misses the component of risk premia due to γ time variation and heterogeneity, which is incorporated into alphas through the $(\gamma_{j,t} - \overline{\gamma}) \cdot \nu_{j,n,t}$ term.

Figures 5(c) and 5(d) plot $\mu_{j,n,t} - \overline{\mu}_{n,t}$ against $\alpha^{\overline{\gamma}}_{j,n,t} - \overline{\alpha}^{\overline{\gamma}}_{n,t}$ and $\lambda^{\overline{\gamma}}_{j,n,t} - \overline{\lambda}^{\overline{\gamma}}_{n,t}$, with each variable capturing disagreement in the respective expected return component.[26] There is a strong connection between μ disagreement and both $\alpha^{\overline{\gamma}}$ and $\lambda^{\overline{\gamma}}$ disagreement. However, in this case the connection is stronger for $\alpha^{\overline{\gamma}}_{j,n,t} - \overline{\alpha}^{\overline{\gamma}}_{n,t}$.

Analogous to the prior subsection, we formalize the visual results from Figures 5(c) and 5(d) using the following decomposition for μ disagreement:

$$\begin{aligned} \mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}] \;&=\; \mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}\,,\; \alpha^{\overline{\gamma}}_{j,n,t} - \overline{\alpha}^{\overline{\gamma}}_{n,t}] \;+\; \mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}\,,\; \lambda^{\overline{\gamma}}_{j,n,t} - \overline{\lambda}^{\overline{\gamma}}_{n,t}] \\ &\Downarrow \\ 1 \;&=\; \underbrace{\frac{\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}\,,\; \alpha^{\overline{\gamma}}_{j,n,t} - \overline{\alpha}^{\overline{\gamma}}_{n,t}]}{\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]}}_{\mathbb{D}(\alpha^{\overline{\gamma}})} \;+\; \overline{\gamma} \cdot \underbrace{\frac{\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}\,,\; \nu_{j,n,t} - \overline{\nu}_{n,t}]}{\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]}}_{\mathbb{D}(\lambda^{\overline{\gamma}})}. \end{aligned} \tag{11}$$

which follows directly from Equation 10.

Table 5 Panel B provides the estimates and t-statistics for $\mathbb{D}(\alpha^{\overline{\gamma}})$ and $\mathbb{D}(\lambda^{\overline{\gamma}})$ for the wealth portfolio, all asset classes combined, and each individual asset class.[27] A substantial fraction

[25] In Figure 6 and all subsequent barplots depicting variance decompositions, we limit the y axis to the [0%,100%] range for visual clarity. The detailed numbers (and respective t-statistics) are provided in tables.

[26] For the purpose of Figures 5(c) and 5(d), we restrict the sample to $t \geq 1999$ to ensure there are at least 5 institutions in each year so that we can properly measure deviations from consensus in all years considered.

[27] We estimate $\mathbb{D}(\lambda^{\overline{\gamma}})$ for asset class n as the slope coefficient from an OLS regression of $\lambda^{\overline{\gamma}}_{j,n,t}$ onto $\mu_{j,n,t}$

(but not the majority) of the expected return disagreement in the data is due to disagreement about risk quantity (ν), which is reflected in $\lambda^{\overline{\gamma}}$ disagreement. For instance, we have $\mathbb{D}(\lambda^{\overline{\gamma}}) = 41.9\%$ ($t_{stat} = 6.29$) for the wealth portfolio and $\mathbb{D}(\lambda^{\overline{\gamma}}) = 34.3\%$ ($t_{stat} = 3.57$) when we combine all asset classes. So, in this case it is clear $\alpha^{\overline{\gamma}}$ has a stronger effect on expected return variation than $\lambda^{\overline{\gamma}}$. Figure 6(b) provides a visual representation of the decomposition for each asset class separately, confirming the overall importance of $\alpha^{\overline{\gamma}}$.

While alphas seem to play the major role in explaining disagreement in this analysis, it is important to recall that this section shuts off heterogeneity in risk aversion from risk premia, incorporating it in alphas. In the next section, we show that risk premia variation play the major role in both time variation and disagreement when we allow risk aversion to vary over time and across investors (albeit alphas continue to be quantitatively important in explaining disagreement). Crucially for our message, risk quantity continues to be very important in the next section as it explains the majority of the risk premia effect on expected returns.

4 Decomposing Expected Return Variation with $\gamma_{j,t} \neq \overline{\gamma}$

The prior section highlights the importance of risk quantity as a determinant of variation in expected returns under the assumption that risk aversion is constant and homogeneous (i.e., $\gamma_{j,t} = \overline{\gamma}$). However, as we show in Subsection 2.1, in reality risk aversion is time-varying and heterogeneous (i.e., $\gamma_{j,t} \neq \overline{\gamma}$). Consequently, this section decomposes expected return time variation and disagreement using our $\gamma_{j,t}$ estimates from Subsection 2.1 (at the cost of a slightly more complex decomposition framework). Subsection 4.1 decomposes expected return time variation whereas Subsection 4.2 decomposes expected return disagreement.

with time fixed effects (and use Driscoll and Kraay (1998) with Newey and West (1994) lag selection for standard errors). We estimate $\mathbb{D}(\lambda^{\overline{\gamma}})$ for all asset classes combined as the slope coefficient from an OLS regression of $\lambda^{\overline{\gamma}}_{j,n,t}$ onto $\mu_{j,n,t}$ with asset class by year fixed effects (and use standard errors clustered by year, asset class, and institution). $\mathbb{D}(\alpha^{\overline{\gamma}})$ is estimated analogously with $\alpha^{\overline{\gamma}}_{j,n,t}$ replacing $\lambda^{\overline{\gamma}}_{j,n,t}$, but note that $\mathbb{D}(\alpha^{\overline{\gamma}}) = 1 - \mathbb{D}(\lambda^{\overline{\gamma}})$ by construction.

4.1 Decomposing Expected Return Time Variation with $\gamma_{j,t} \neq \overline{\gamma}$

This subsection focuses on expected return time variation and its components based on Equation 6 (reproduced here for convenience):

$$\mu_{n,t} \;=\; \alpha_{n,t} \;+\; \lambda_{n,t} \;=\; \alpha_{n,t} \;+\; \gamma_t \cdot \nu_{n,t} \tag{12}$$

4.1.1 Components of Expected Return Time Variation

To start, Figures 7(a) and 7(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 7(c) and 7(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. This result is the main motivation for the prior section, where we evaluate the risk quantity (ν) effect while assuming $\gamma_{j,t} = \overline{\gamma}$.

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

Figure 8 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 9 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).

Next, we formally decompose expected return time variation into its components. We show that, in line with Figures 7 to 9, overall expected return time variation is dominated by risk quantity (ν) movements. However, we also demonstrate that γ plays a large role in more short-term movements in μ (which we refer to as the expected return transitory time variation).

4.1.2 Decomposing Expected Return Overall Time Variation

Note that Equation 12 implies the following decomposition for μ time variation:

$$\begin{aligned} \mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n] \;&=\; \mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \,,\, \alpha_{n,t} - \overline{\alpha}_n] \;+\; \mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \,,\, \lambda_{n,t} - \overline{\lambda}_n] \\ &\Downarrow \\ 1 \;&=\; \underbrace{\frac{\mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \,,\, \alpha_{n,t} - \overline{\alpha}_n]}{\mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n]}}_{\mathbb{V}(\alpha)} + \underbrace{\frac{\mathbb{C}ov[\mu_{n,t} - \overline{\mu}_n \,,\, \lambda_{n,t} - \overline{\lambda}_n]}{\mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n]}}_{\mathbb{V}(\lambda)} \end{aligned} \tag{13}$$

Table 6 Panel A reports 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. Our method for estimation and inference is analogous to what we use for $\mathbb{V}(\alpha^{\overline{\gamma}})$ and $\mathbb{V}(\lambda^{\overline{\gamma}})$ (see Footnote 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 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 10(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). A key challenge to accomplish this objective is that $\lambda_{n,t} = \gamma_t \cdot \nu_{n,t}$ is a non-linear equation. We address this issue by

rewriting the λ equation in a way such that the γ and ν effects become additive (in the spirit of the decomposition in Chen, Da, and Zhao (2013)). Specifically, we define the function $\lambda(\gamma, \nu) = \gamma \cdot \nu$, which satisfies $\lambda(\gamma_t, \nu_{n,t}) = \lambda_{n,t}$. Then, we rewrite the λ equation as:[28]

$$\lambda_{n,t} \ = \lambda(\overline{\gamma}, \overline{\nu}_n) \ + \ \lambda^{\gamma}_{n,t} \ + \ \lambda^{\nu}_{n,t} \tag{14}$$

where

$$\lambda^{\gamma}_{n,t} \ \equiv 0.5 \cdot \{ [\, \lambda(\gamma_t, \nu_{n,t}) - \lambda(\overline{\gamma}, \nu_{n,t}) \,] \ + \ [\, \lambda(\gamma_t, \overline{\nu}_n) - \lambda(\overline{\gamma}, \overline{\nu}_n) \,] \} \tag{15}$$

$$\lambda^{\nu}_{n,t} \ \equiv 0.5 \cdot \{ [\, \lambda(\gamma_t, \nu_{n,t}) - \lambda(\gamma_t, \overline{\nu}_n) \,] \ + \ [\, \lambda(\overline{\gamma}, \nu_{n,t}) - \lambda(\overline{\gamma}, \overline{\nu}_n) \,] \} \tag{16}$$

which implies we can decompose the risk premia effect on expected return time variation as

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

Table 6 Panel B reports 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.[29] 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

[28] 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.

[29] 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 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 approach is not related to "endogeneity concerns").

asset classes combines we have $\mathbb{V}_\lambda(\nu) = 89.8\%$ ($t_{stat} = 8.78$) and $\mathbb{V}_\lambda(\gamma) = 10.2\%$ ($t_{stat} = 1.00$).[30] Results vary by asset class, and Figure 10(b) provides a visual representation of the decomposition. For each asset class except for Private Equity and Infrastructure, almost the entire effect of risk premia on expected return time variation is driven by risk quantity.

4.1.3 Decomposing Expected Return Transitory Time Variation

The decompositions in Equations 13 and 17 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 12, resulting in the alternative variance decompositions

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

and

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

which we estimate following a procedure analogous to the decompositions in Equations 13 and 17.

Table 7 Panel A reports 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

[30] Internet Appendix Table IA.2 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 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.

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 11(a) provides a visual representation of the decomposition.

Table 7 Panel B reports 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 11(b) provides a visual representation of the decomposition. Contrasting Figure 11(b) with Figure 10(b) 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.

4.2 Decomposing Expected Return Disagreement with $\gamma_{j,t} \neq \overline{\gamma}$

This subsection focuses on expected return disagreement and its components based on Equation 7 (reproduced here for convenience):

$$\mu_{j,n,t} \;=\; \alpha_{j,n,t} \;+\; \lambda_{j,n,t} \;=\; \alpha_{j,n,t} \;+\; \gamma_{j,t} \cdot \nu_{j,n,t} \tag{20}$$

To start, Figures 12(a) and 12(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 stronger with the later. 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 12(c) and 12(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.

We formalize the visual results from Figure 12 using the following decompositions for μ

disagreement:

$$1 \;=\; \underbrace{\frac{\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}\,,\; \alpha_{j,n,t} - \overline{\alpha}_{n,t}]}{\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]}}_{\mathbb{D}(\alpha)} \;+\; \underbrace{\frac{\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}\,,\; \lambda_{j,n,t} - \overline{\lambda}_{n,t}]}{\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]}}_{\mathbb{D}(\lambda)}. \tag{21}$$

and

$$1 \;=\; \underbrace{\frac{\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}\,,\; \lambda^{\gamma}_{j,n,t} - \overline{\lambda}^{\gamma}_{n,t}]}{\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}\,,\; \lambda_{j,n,t} - \overline{\lambda}_{n,t}]}}_{\mathbb{D}_{\lambda}(\gamma)} \;+\; \underbrace{\frac{\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}\,,\; \lambda^{\nu}_{j,n,t} - \overline{\lambda}^{\nu}_{n,t}]}{\mathbb{C}ov[\mu_{j,n,t} - \overline{\mu}_{n,t}\,,\; \lambda_{j,n,t} - \overline{\lambda}_{n,t}]}}_{\mathbb{D}_{\lambda}(\nu)} \tag{22}$$

which follows directly from Equation 20 with

$$\lambda_{j,n,t} \;= \lambda(\overline{\gamma}_t, \overline{\nu}_{n,t}) \;+\; \lambda^{\gamma}_{j,n,t} \;+\; \lambda^{\nu}_{j,n,t} \tag{23}$$

where

$$\lambda^{\gamma}_{j,n,t} \;\equiv 0.5 \cdot \{[\,\lambda(\gamma_{j,t}, \nu_{j,n,t}) - \lambda(\overline{\gamma}_t, \nu_{j,n,t})\,] \;+\; [\,\lambda(\gamma_{j,t}, \overline{\nu}_{n,t}) - \lambda(\overline{\gamma}_t, \overline{\nu}_{n,t})\,]\} \tag{24}$$

$$\lambda^{\nu}_{j,n,t} \;\equiv 0.5 \cdot \{[\,\lambda(\gamma_{j,t}, \nu_{j,n,t}) - \lambda(\gamma_{j,t}, \overline{\nu}_{n,t})\,] \;+\; [\,\lambda(\overline{\gamma}, \nu_{j,n,t}) - \lambda(\overline{\gamma}, \overline{\nu}_{n,t})\,]\} \tag{25}$$

Table 8 Panel A reports 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. Our method for estimation and inference is analogous to what we use for $\mathbb{D}(\alpha^{\overline{\gamma}})$ and $\mathbb{D}(\lambda^{\overline{\gamma}})$ (see Footnote 27). 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 13(a) provides a visual representation of the decomposition. For instance, for Fixed Income (US and ex US) the alpha effect dominates.

Table 8 Panel B reports 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.[31] In contrast to the λ effect

[31] 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

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 $\mathbb{D}_\lambda(\gamma) = 51.6\%$ ($t_{stat} = 8.43$) and $\mathbb{D}_\lambda(\nu) = 48.4\%$ ($t_{stat} = 8.06$). 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 13(b) provides a visual representation of the decomposition.

5 Conclusion

This paper studies the risk-based determinants of time variation and disagreement in subjective return expectations. The findings indicate that market risk premia account for most of the time variation in expected returns, with the remainder attributed to alphas, which capture factors beyond market risk premia. 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-term 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,

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.

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-term expected return movements, the overall time variation in expected returns is largely due to variation in risk perceptions.

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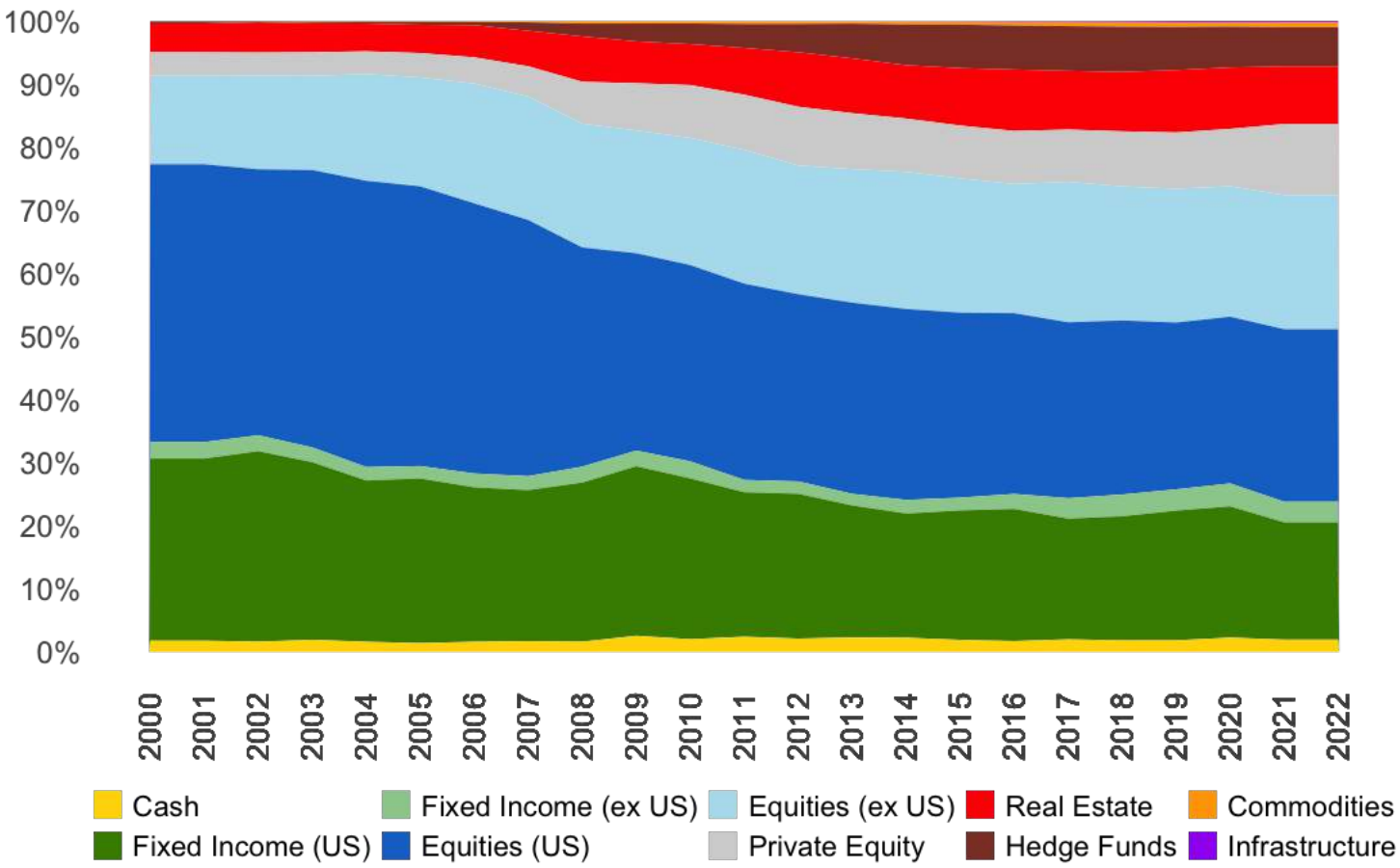


Figure 2
Wealth Portfolio Weights from US Public Pension Funds

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.2 for details). Since we do not observe weights before 2001, all weights for $t \leq 2001$ are set to match the 2001 weights.

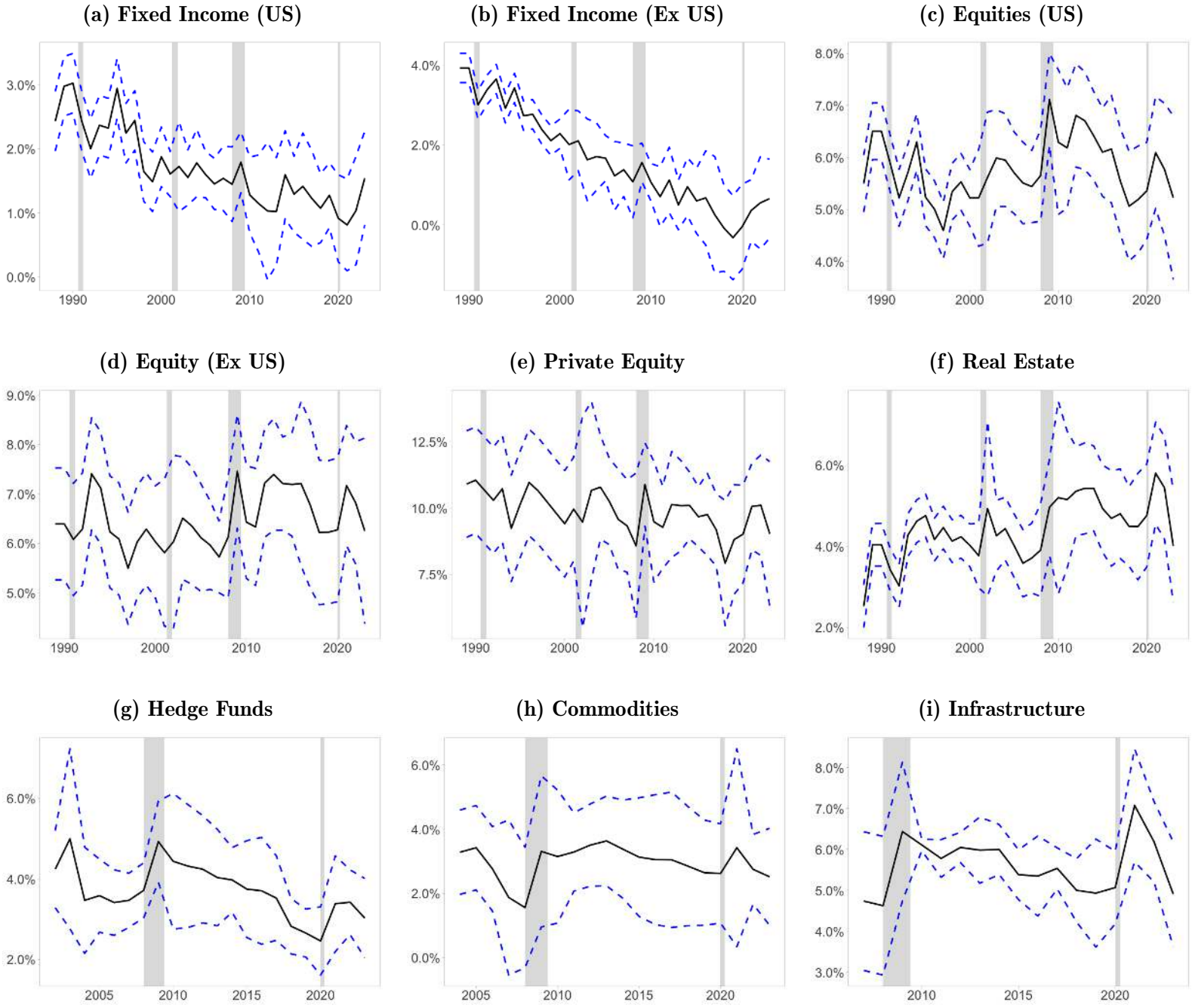


Figure 3
Expected Return Time Variation and Disagreement: $\mu \pm \sigma_\mu$

This figure depicts (in the black solid line) the time series of subjective expected excess returns aggregated across institutions ($\mu_{n,t}$) for each asset class in our analysis. We also show (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.

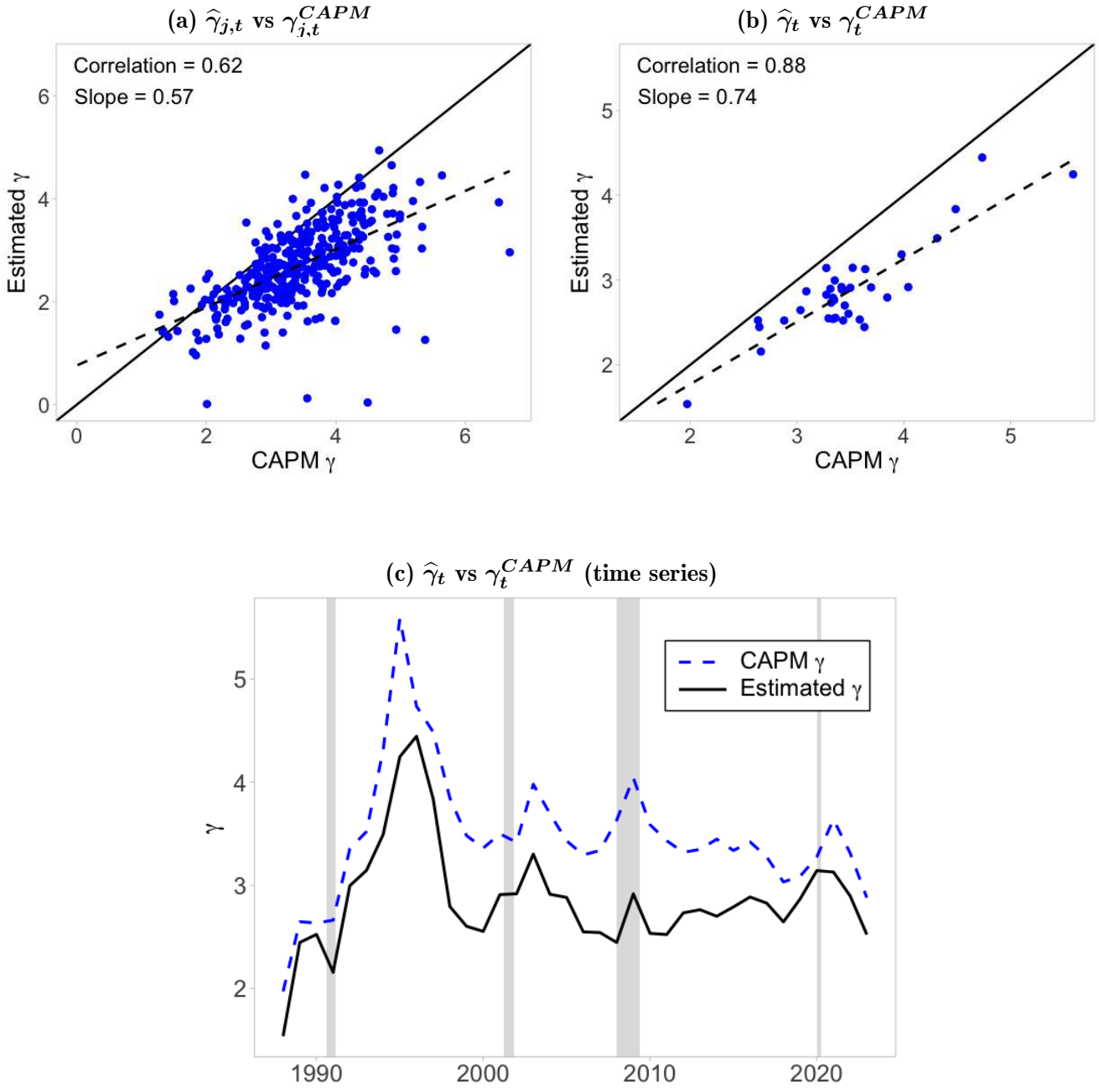


Figure 4
Estimated Risk Aversion vs CAPM Risk Aversion

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 2.1 explains our risk aversion estimation procedure and discusses the results in this figure.

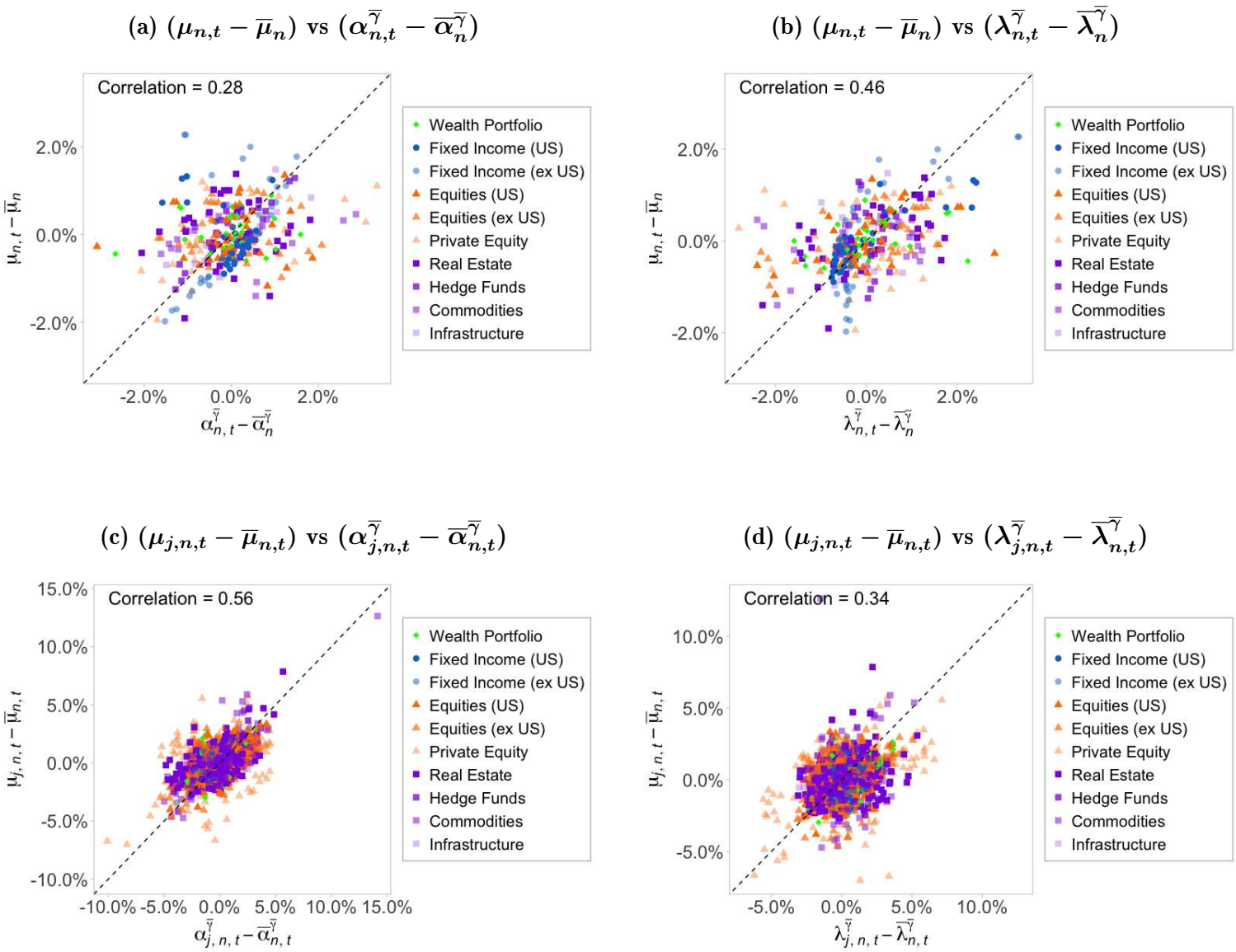
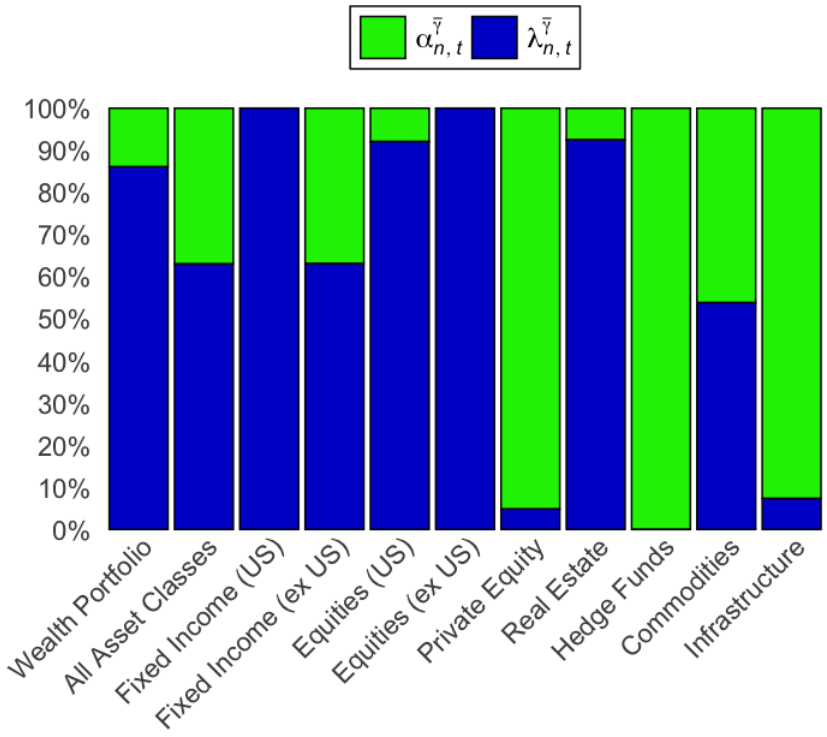


Figure 5
Components of Expected Return Variation with $\gamma_{j,t} = \overline{\gamma}$

This figure depicts scatterplots of demeaned expected returns against their components for the wealth portfolio and each asset class in our analysis (under constant and homogeneous risk aversion, $\gamma_{j,t} = \overline{\gamma}$). Panels (a) and (b) focus on time variation in aggregate expected returns $(\mu_{n,t} - \overline{\mu}_n)$ with the respective components related to alphas $(\alpha^{\overline{\gamma}}_{n,t} - \overline{\alpha}^{\overline{\gamma}}_{n,t})$ and risk premia $(\lambda^{\overline{\gamma}}_{n,t} - \overline{\lambda}^{\overline{\gamma}}_{n,t})$. Panels (c) and (d) focus on cross-institution variation (i.e., disagreement) in expected returns $(\mu_{j,n,t} - \overline{\mu}_{n,t})$ with the respective components related to alphas $(\alpha^{\overline{\gamma}}_{j,n,t} - \overline{\alpha}^{\overline{\gamma}}_{j,n,t})$ and risk premia $(\lambda^{\overline{\gamma}}_{j,n,t} - \overline{\lambda}^{\overline{\gamma}}_{j,n,t})$. Subsection 1.2 describes our beliefs data while Section 3 discusses the results from this figure.

(a) Decomposing $\mathbb{V}ar[\mu]$ over Time



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

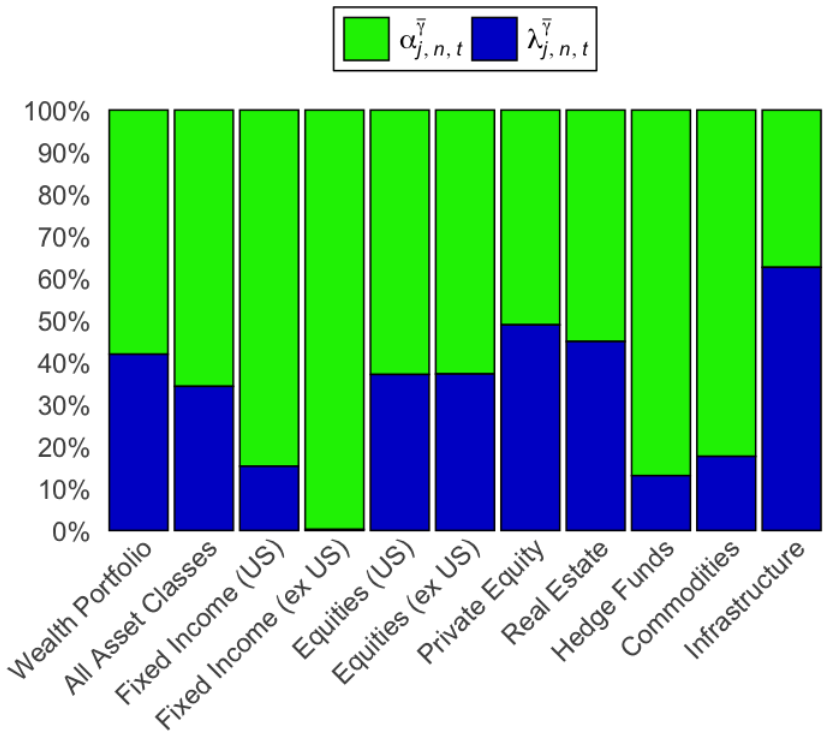


Figure 6
Decomposing Expected Return Variation with $\gamma_{j,t} = \overline{\gamma}$

Panel (a) depicts decompositions of aggregate expected return time variation, $\mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n]$, based on Equation 9. Panel (b) depicts decompositions of institution-level expected return cross-institution variation (i.e., disagreement), $\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]$, based on Equation 11. Both panels rely on decompositions under constant and homogeneous risk aversion, $\gamma_{j,t} = \overline{\gamma}$. Subsection 1.2 describes our beliefs data while Section 3 discusses the results from this figure.

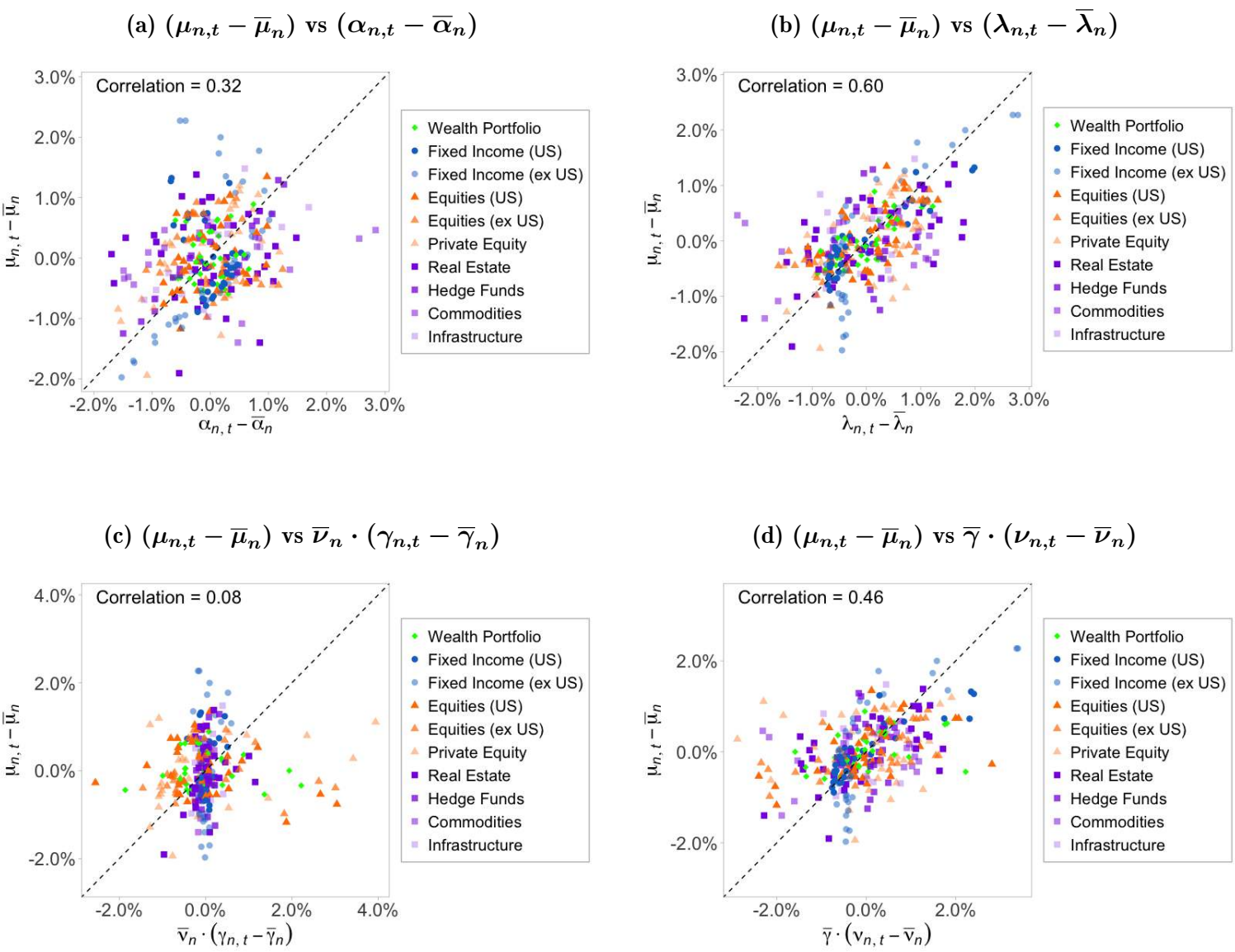


Figure 7
Components of Expected Return Time Variation with $\gamma_{j,t} \neq \overline{\gamma}$

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 4.1.1 discusses the results from this figure.

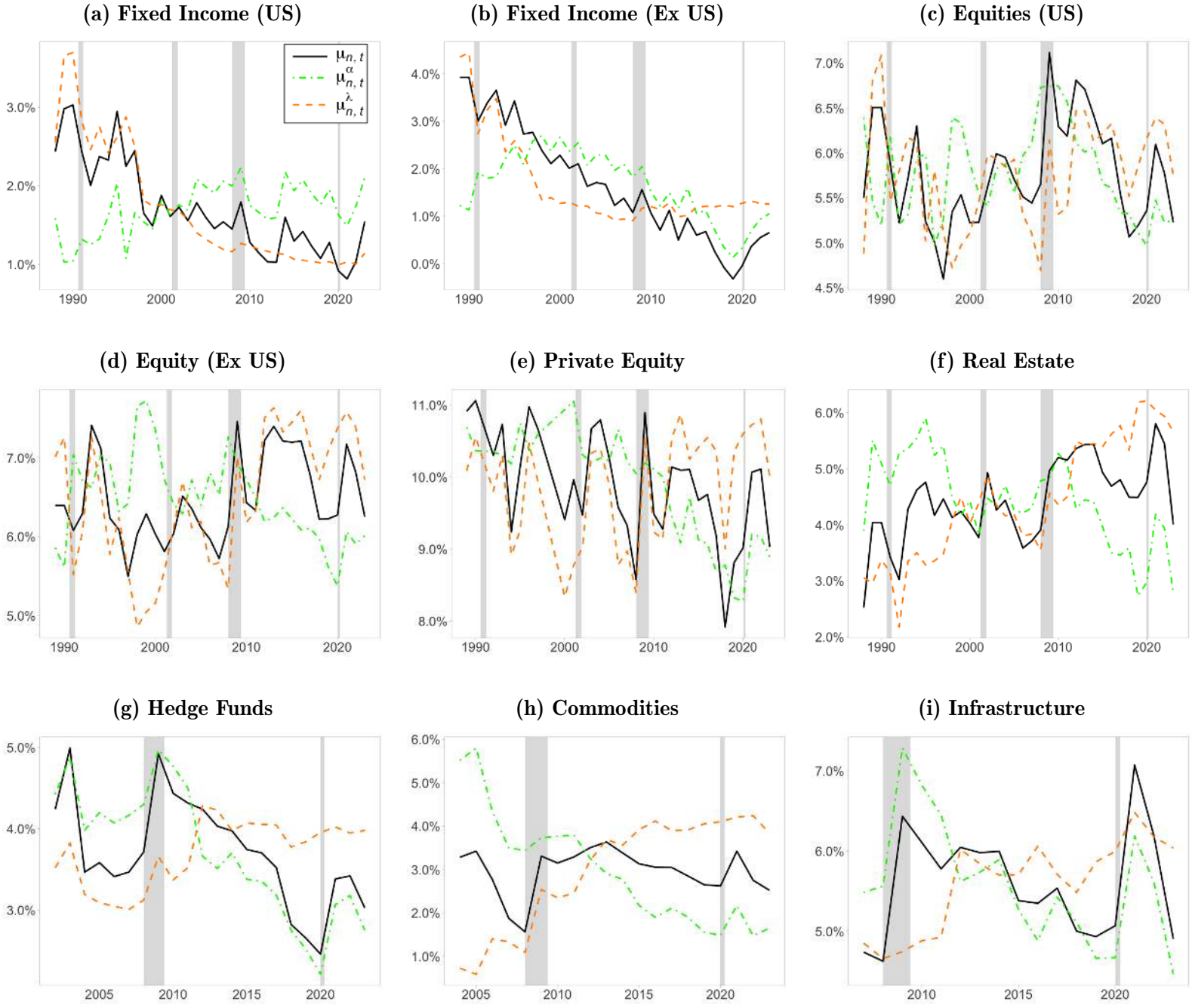


Figure 8
Time Series of Expected Return Components with $\gamma_{j,t} \neq \overline{\gamma}$

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 4.1.1 discusses the results from this figure.

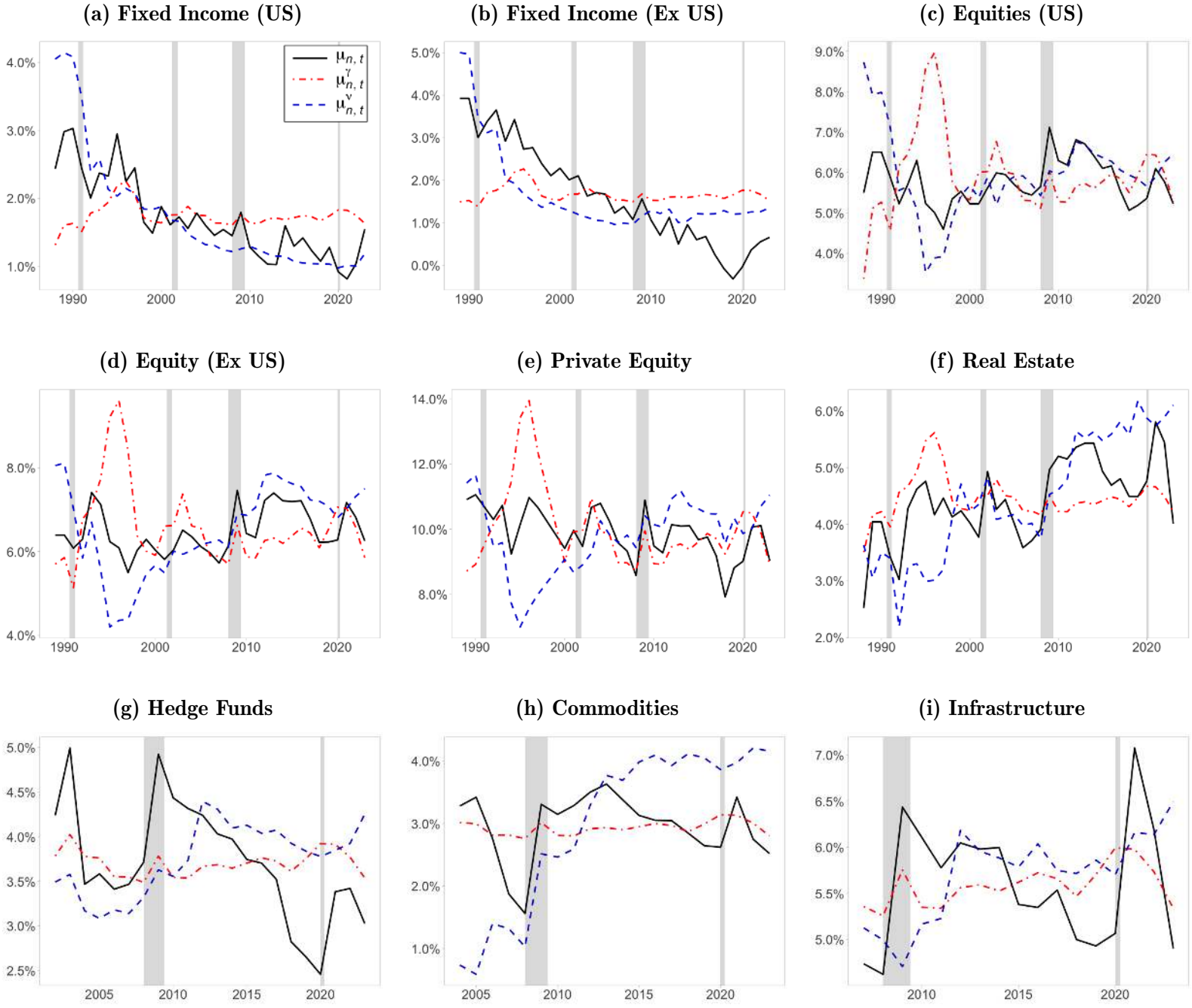
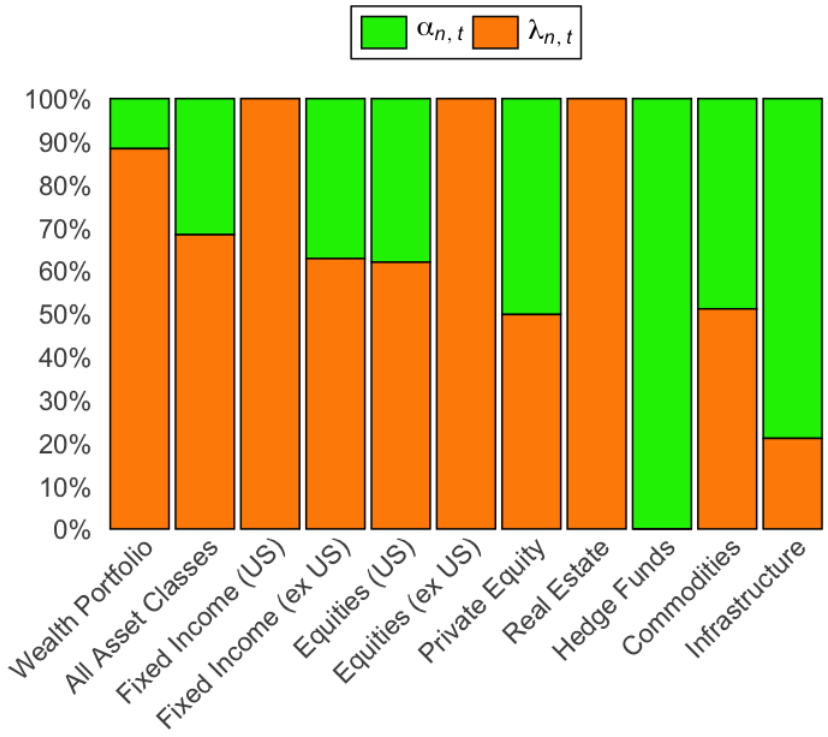


Figure 9
Time Series of Risk Premia Components with $\gamma_{j,t} \neq \overline{\gamma}$

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 4.1.1 discusses the results from this figure.

(a) Decomposing $\mathbb{V}ar[\mu]$



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

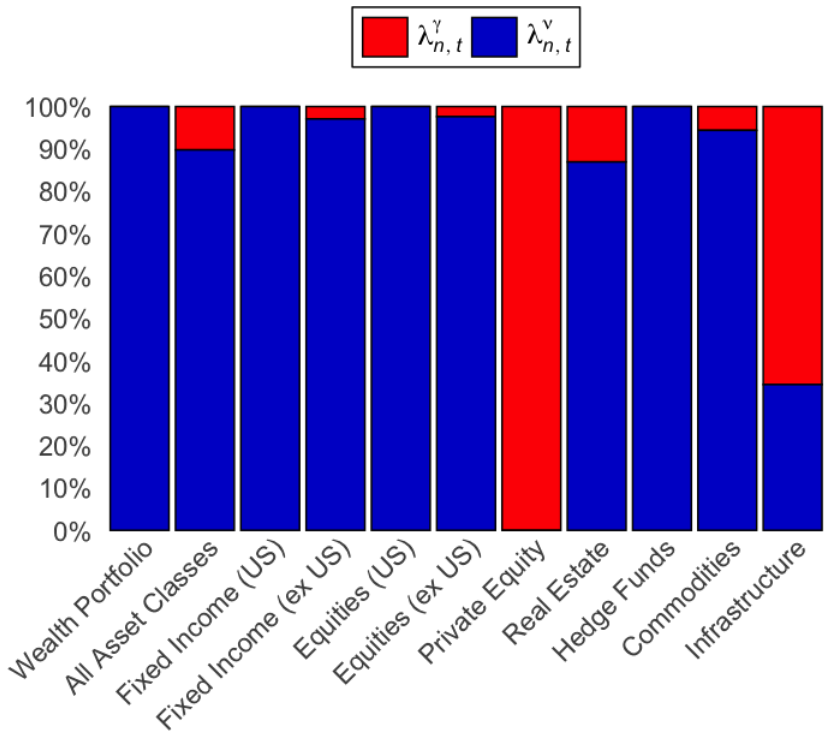
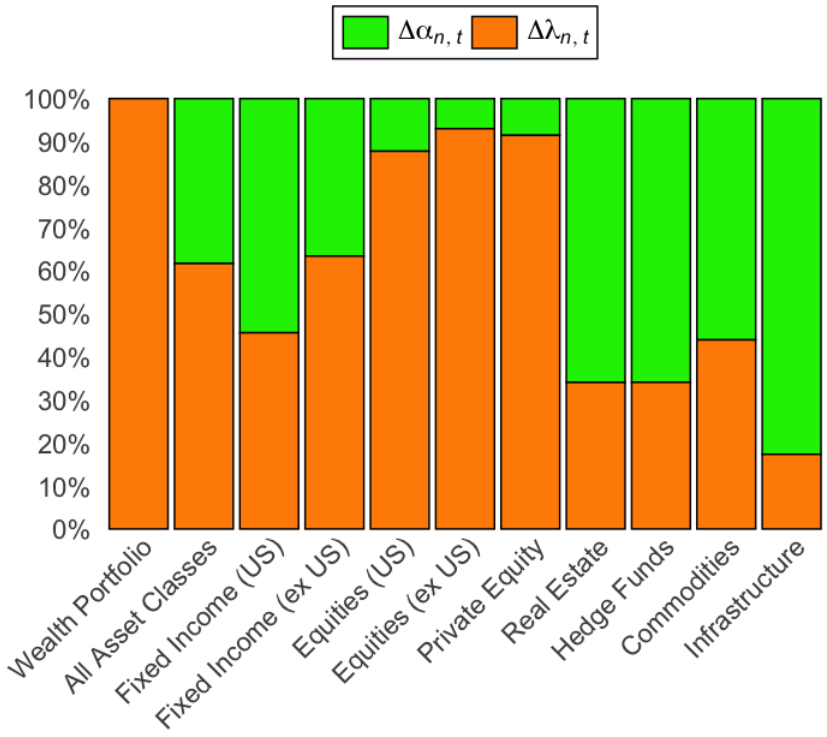


Figure 10
Decomposing Expected Return Overall Time Variation with $\gamma_{j,t} \neq \overline{\gamma}$

Panel (a) depicts decompositions of aggregate expected return overall time variation, $\mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n]$, based on Equation 13. Panel (b) 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 17. Subsection 1.2 describes our beliefs data while Subsection 4.1.2 discusses the results from this figure.

(a) Decomposing $\mathbb{V}ar[\Delta\mu]$



(b) Decomposing $\mathbb{C}ov[\Delta\mu, \Delta\lambda]$

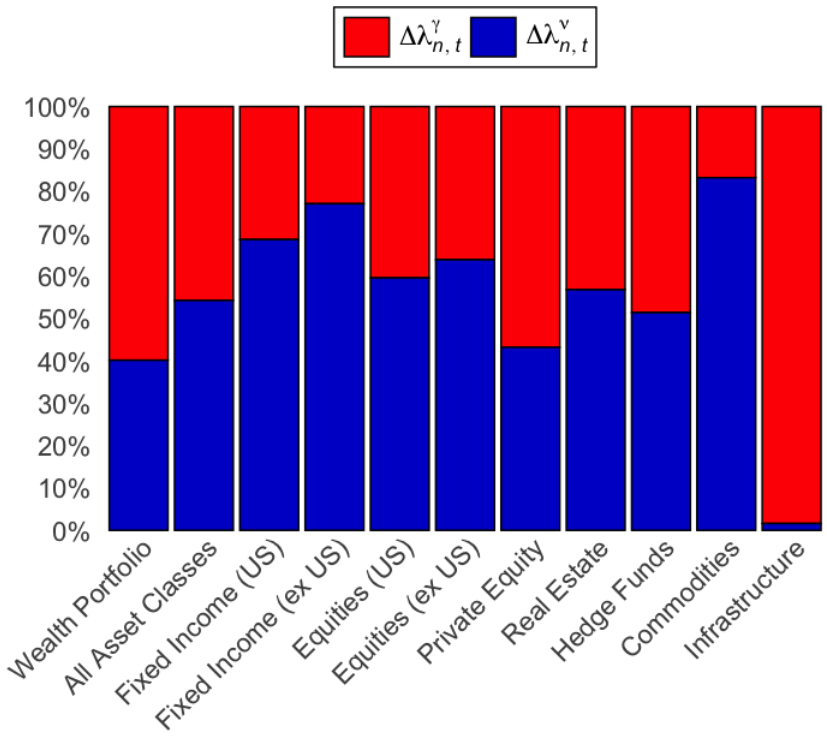


Figure 11
Decomposing Expected Return Transitory Time Variation with $\gamma_{j,t} \neq \overline{\gamma}$

Panel (a) depicts decompositions of aggregate expected return transitory time variation, $\mathbb{V}ar[\Delta\mu_{n,t} - \overline{\Delta\mu}_n]$, based on Equation 18. Panel (b) depicts decompositions of the risk premium effect on aggregate expected return transitory time variation, $\mathbb{C}ov[\Delta\mu_{n,t} - \overline{\Delta\mu}_n, \Delta\lambda_{n,t} - \overline{\Delta\lambda}_n]$, based on Equation 19. Subsection 1.2 describes our beliefs data while Subsection 4.1.3 discusses the results from this figure.

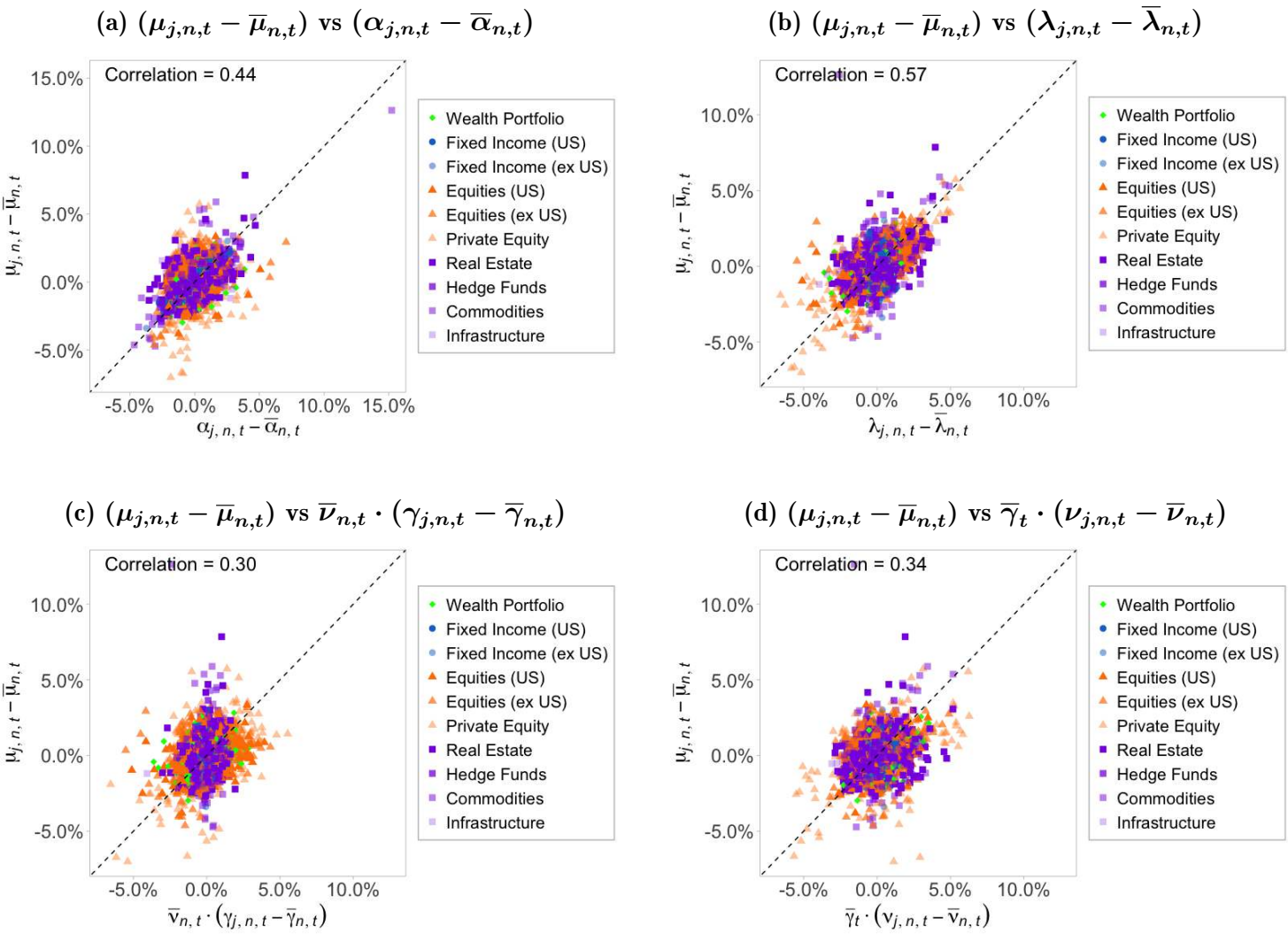
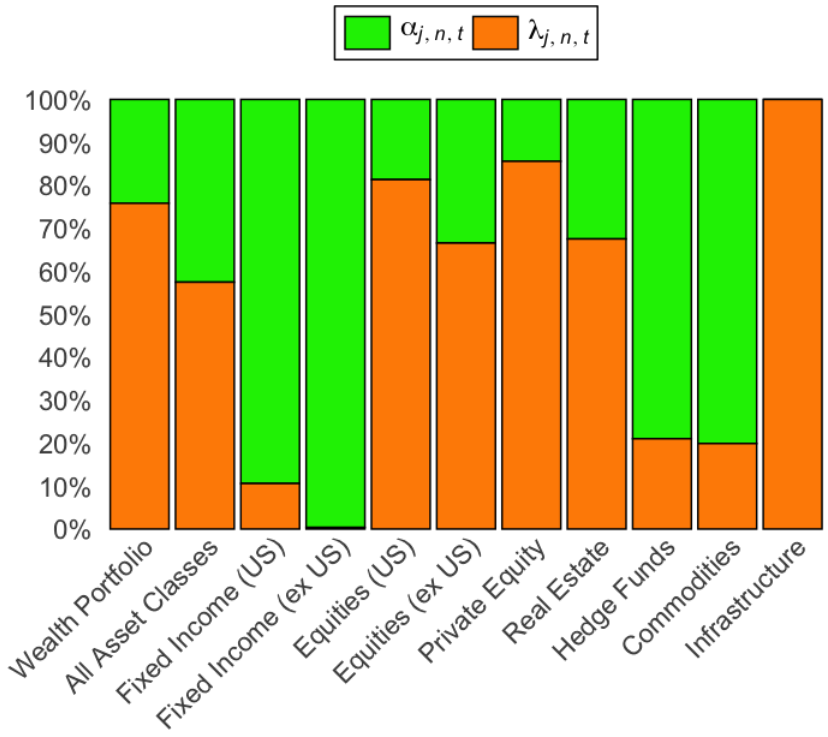


Figure 12
Components of Expected Return Disagreement with $\gamma_{j,t} \neq \overline{\gamma}$

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 4.2 discusses the results from this figure.

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



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

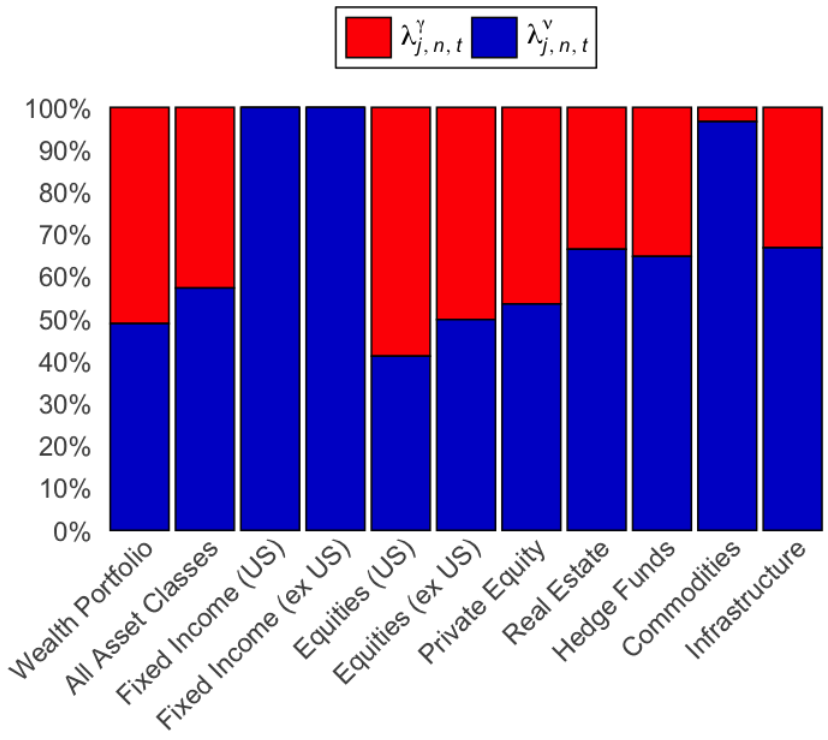


Figure 13
Decomposing Expected Return Disagreement with $\gamma_{j,t} \neq \overline{\gamma}$

Panel (a) depicts decompositions of expected return disagreement across institutions, $\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]$, based on Equation 21. 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 22. Subsection 1.2 describes our beliefs data while Subsection 4.2 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	≥ 55.1%	≥ 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
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 2.1 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 4
Summary of Expected Return Components

Panel A provides average values for each expected return component. 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 over time and across institutions. 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 5
Decomposing Expected Return Variation with $\gamma_{j,t} = \overline{\gamma}$

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 9. Panel B reports values associated with decompositions of institution-level expected return cross-institution variation (i.e., disagreement), $\mathbb{V}ar[\mu_{j,n,t} - \overline{\mu}_{n,t}]$, based on Equation 11. Footnote 24 (Footnote 27) provides details about estimation and standard errors for Panel A (Panel B). Both panels rely on decompositions under constant and homogeneous risk aversion, $\gamma_{j,t} = \overline{\gamma}$. Subsection 1.2 describes our beliefs data while Section 3 discusses the results from this table.

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

	% of $\mathbb{V}ar[\mu]$ due to $\alpha^{\overline{\gamma}}$		% of $\mathbb{V}ar[\mu]$ due to $\lambda^{\overline{\gamma}}$	
	Estimate	**(t-stat)**	**Estimate**	**(t-stat)**
Wealth Portfolio	13.9%	(0.41)	86.1%	(2.54)
All Asset Classes	37.0%	(2.09)	63.0%	(3.56)
Fixed Income (US)	-28.9%	(-1.01)	128.9%	(4.52)
Fixed Income (Ex US)	36.9%	(1.63)	63.1%	(2.79)
Equity (US)	7.9%	(0.22)	92.1%	(2.49)
Equity (Ex US)	-10.3%	(-0.32)	110.3%	(3.43)
Private Equity	95.2%	(2.77)	4.8%	(0.14)
Real Estate	7.5%	(0.55)	92.5%	(6.72)
Hedge Funds	102.9%	(6.52)	-2.9%	(-0.18)
Commodities	46.2%	(0.58)	53.8%	(0.68)
Infrastructure	92.7%	(5.15)	7.3%	(0.41)

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

	% of $\mathbb{V}ar[\mu]$ due to $\alpha^{\overline{\gamma}}$		% of $\mathbb{V}ar[\mu]$ due to $\lambda^{\overline{\gamma}}$	
	Estimate	**(t-stat)**	**Estimate**	**(t-stat)**
Wealth Portfolio	58.1%	(8.71)	41.9%	(6.29)
All Asset Classes	65.7%	(6.85)	34.3%	(3.57)
Fixed Income (US)	84.7%	(15.1)	15.3%	(2.72)
Fixed Income (Ex US)	99.7%	(20.0)	0.3%	(0.05)
Equity (US)	62.9%	(12.1)	37.1%	(7.13)
Equity (Ex US)	62.8%	(14.1)	37.2%	(8.34)
Private Equity	51.1%	(7.24)	48.9%	(6.93)
Real Estate	55.0%	(7.40)	45.0%	(6.04)
Hedge Funds	87.0%	(7.52)	13.0%	(1.13)
Commodities	82.4%	(9.17)	17.6%	(1.96)
Infrastructure	37.4%	(2.56)	62.6%	(4.28)

Table 6

Decomposing Expected Return Overall Time Variation with $\gamma_{j,t} \neq \overline{\gamma}$

Panel A reports values associated with decompositions of aggregate expected return overall time variation, $\mathbb{V}ar[\mu_{n,t} - \overline{\mu}_n]$, based on Equation 13. 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 17. Footnotes 24 and 29 provide details about estimation and standard errors for Panels A and B, respectively. Subsection 1.2 describes our beliefs data while Subsection 4.1.2 discusses the results from this table.

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

	% of $\mathbb{V}ar[\mu]$ due to α		% of $\mathbb{V}ar[\mu]$ due to λ	
	Estimate	**(t-stat)**	**Estimate**	**(t-stat)**
Wealth Portfolio	11.6%	(0.65)	88.4%	(4.96)
All Asset Classes	31.6%	(2.49)	68.4%	(5.38)
Fixed Income (US)	-21.9%	(-1.77)	121.9%	(9.85)
Fixed Income (Ex US)	37.2%	(1.66)	62.8%	(2.81)
Equity (US)	38.0%	(1.97)	62.0%	(3.21)
Equity (Ex US)	-19.5%	(-1.46)	119.5%	(8.97)
Private Equity	50.2%	(2.75)	49.8%	(2.73)
Real Estate	-2.8%	(-0.17)	102.8%	(6.22)
Hedge Funds	101.9%	(4.42)	-1.9%	(-0.08)
Commodities	48.9%	(0.68)	51.1%	(0.71)
Infrastructure	78.9%	(5.31)	21.1%	(1.42)

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

	% of $\mathbb{C}ov[\mu, \lambda]$ due to γ		% of $\mathbb{C}ov[\mu, \lambda]$ due to ν	
	Estimate	**(t-stat)**	**Estimate**	**(t-stat)**
Wealth Portfolio	-2.4%	(-0.10)	102.4%	(4.28)
All Asset Classes	10.2%	(1.00)	89.8%	(8.78)
Fixed Income (US)	-0.8%	(-0.07)	100.8%	(8.18)
Fixed Income (Ex US)	2.9%	(0.26)	97.1%	(8.54)
Equity (US)	-62.5%	(-0.99)	162.5%	(2.59)
Equity (Ex US)	2.4%	(0.10)	97.6%	(3.90)
Private Equity	104.1%	(1.29)	-4.1%	(-0.05)
Real Estate	13.1%	(2.18)	86.9%	(14.5)
Hedge Funds	-59.9%	(-0.08)	159.9%	(0.21)
Commodities	5.6%	(0.73)	94.4%	(12.3)
Infrastructure	65.6%	(1.39)	34.4%	(0.73)

Table 7

Decomposing Expected Return Transitory Time Variation with $\gamma_{j,t} \neq \overline{\gamma}$

Panel A reports values associated with decompositions of aggregate expected return transitory time variation, $\mathbb{V}ar[\Delta\mu_{n,t} - \overline{\Delta\mu}_n]$, based on Equation 18. Panel B reports values associated with decompositions of the risk premium effect on aggregate expected return transitory time variation, $\mathbb{C}ov[\Delta\mu_{n,t} - \overline{\Delta\mu}_n, \Delta\lambda_{n,t} - \overline{\Delta\lambda}_n]$, based on Equation 19. Footnotes 24 and 29 provide details about estimation and standard errors for Panels A and B, respectively. Subsection 1.2 describes our beliefs data while Subsection 4.1.3 discusses the results from this table.

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

	% of $\mathbb{V}ar[\Delta\mu]$ due to $\Delta\alpha$		% of $\mathbb{V}ar[\Delta\mu]$ due to $\Delta\lambda$	
	Estimate	**(t-stat)**	**Estimate**	**(t-stat)**
Wealth Portfolio	-1.3%	(-0.12)	101.3%	(9.14)
All Asset Classes	38.3%	(4.04)	61.7%	(6.51)
Fixed Income (US)	54.4%	(3.59)	45.6%	(3.01)
Fixed Income (Ex US)	36.6%	(1.42)	63.4%	(2.46)
Equity (US)	12.2%	(1.03)	87.8%	(7.38)
Equity (Ex US)	7.0%	(0.57)	93.0%	(7.58)
Private Equity	8.5%	(1.73)	91.5%	(18.6)
Real Estate	65.9%	(5.24)	34.1%	(2.70)
Hedge Funds	65.9%	(10.0)	34.1%	(5.20)
Commodities	56.1%	(2.49)	43.9%	(1.95)
Infrastructure	82.6%	(13.2)	17.4%	(2.77)

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

	% of $\mathbb{C}ov[\Delta\mu, \Delta\lambda]$ due to $\Delta\gamma$		% of $\mathbb{C}ov[\Delta\mu, \Delta\lambda]$ due to $\Delta\nu$	
	Estimate	**(t-stat)**	**Estimate**	**(t-stat)**
Wealth Portfolio	59.9%	(5.10)	40.1%	(3.42)
All Asset Classes	45.8%	(3.89)	54.2%	(4.61)
Fixed Income (US)	31.4%	(1.69)	68.6%	(3.68)
Fixed Income (Ex US)	22.9%	(6.80)	77.1%	(22.9)
Equity (US)	40.4%	(1.54)	59.6%	(2.26)
Equity (Ex US)	36.1%	(1.67)	63.9%	(2.95)
Private Equity	56.8%	(6.47)	43.2%	(4.92)
Real Estate	43.2%	(1.51)	56.8%	(1.98)
Hedge Funds	48.6%	(7.09)	51.4%	(7.49)
Commodities	16.8%	(1.81)	83.2%	(8.99)
Infrastructure	98.4%	(1.42)	1.6%	(0.02)

Table 8
Decomposing Expected Return Disagreement with $\gamma_{j,t} \neq \overline{\gamma}$

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 21. 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 22. Footnote 27 (Footnote 31) provides details about estimation and standard errors for Panel A (Panel B). Subsection 1.2 describes our beliefs data while Subsection 4.2 discusses the results from this table.

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

	% of $\mathbb{V}ar[\mu]$ due to α		% of $\mathbb{V}ar[\mu]$ due to λ	
	Estimate	**(t-stat)**	**Estimate**	**(t-stat)**
Wealth Portfolio	24.2%	(3.02)	75.8%	(9.49)
All Asset Classes	42.5%	(3.33)	57.5%	(4.49)
Fixed Income (US)	89.4%	(15.4)	10.6%	(1.82)
Fixed Income (Ex US)	99.6%	(22.9)	0.4%	(0.09)
Equity (US)	18.7%	(2.61)	81.3%	(11.4)
Equity (Ex US)	33.4%	(5.89)	66.6%	(11.7)
Private Equity	14.4%	(3.54)	85.6%	(21.0)
Real Estate	32.5%	(6.06)	67.5%	(12.6)
Hedge Funds	79.0%	(7.89)	21.0%	(2.10)
Commodities	80.1%	(6.84)	19.9%	(1.70)
Infrastructure	-5.7%	(-0.38)	105.7%	(7.14)

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

	% of $\mathbb{C}ov[\mu, \lambda]$ due to γ		% of $\mathbb{C}ov[\mu, \lambda]$ due to ν	
	Estimate	**(t-stat)**	**Estimate**	**(t-stat)**
Wealth Portfolio	51.1%	(8.43)	48.9%	(8.06)
All Asset Classes	42.7%	(4.66)	57.3%	(6.25)
Fixed Income (US)	-21.6%	(-1.43)	121.6%	(8.06)
Fixed Income (Ex US)	-165.9%	(-0.09)	265.9%	(0.14)
Equity (US)	58.8%	(11.0)	41.2%	(7.72)
Equity (Ex US)	50.2%	(10.2)	49.8%	(10.1)
Private Equity	46.5%	(5.89)	53.5%	(6.78)
Real Estate	33.5%	(5.28)	66.5%	(10.5)
Hedge Funds	35.2%	(1.49)	64.8%	(2.73)
Commodities	3.4%	(0.20)	96.6%	(5.68)
Infrastructure	33.2%	(4.11)	66.8%	(8.28)

Internet Appendix

"Institutional Investors' Subjective Risk Premia: Time Variation and Disagreement"

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

This Internet Appendix is organized as follows. Section A provides a full description of the data sources and measurement for the analysis and Section B describes additional results that supplement the main findings in the paper.

A Data and Measurement Details

A.1 Subjective Beliefs Data and Measurement

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 on 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 B, 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 the data. 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 risk-free asset class proxy (US Cash) 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.2). 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 US 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 distributed. In mathematical terms, they report (for each asset class n)

[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 US Cash here).

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

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 loosing 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 B 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

[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.

returns when available and expected arithmetic returns when expected geometric returns are not available

A.2 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* dividend 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 dividend by the allocation on FIUS+FIExUS

3. ω_{EQUS} is the allocation on EQUS dividend 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.

B Supplementary Empirical Results

This section describes additional results that supplement the main findings in the paper. The different subsections discuss different changes to our empirical procedure. We replicate our main results (Figures 10, 11, and 13) under these different empirical procedures and provide all results in Figures IA.1 to IA.3. 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.

B.1 Alternative $\gamma_{j,t}$ 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 $\gamma_{j,t}$.

B.1.1 $\gamma_{j,t}$ Implied by the CAPM

As discussed in Subsection 2.1, 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.1 to IA.3) 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.

B.1.2 $\gamma_{j,t}$ 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.1 to IA.3) are very similar to our baseline results.

B.1.3 $\gamma_{j,t}$ 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.1 to IA.3) are very similar to our baseline results.

B.2 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.

B.2.1 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.1 to IA.3) 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 eah (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.

B.2.2 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.1 to IA.3) 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.

B.3 Alternative Constructions of Subjective Beliefs

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

B.3.1 $\mathbb{E}[R]$ 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 loosing 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.1 to IA.3) 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.

B.3.2 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.1 to IA.3) are very similar to our baseline results.

B.4 Alternative Variance Decomposition Estimation Methods

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

B.4.1 Decomposing μ Variation Adjusting for Horizon Heterogeneity

The forecasting horizons in our CMAs vary from 4 years to 30 years, with the modal horizon being 10 years. Conceptually, this is not an issue since a version of the CAPM holds with investors that have heterogeneous horizons, as we discuss in the main text. 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.1 to IA.3) are very similar to our baseline results.

B.4.2 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.1 to IA.3) are very similar to our baseline results.

References for Internet Appendix

Couts, S. J., A. S. Gonçalves, and J. A. Loudis (2024). "The Subjective Risk and Return Expectations of Institutional Investors". Working Paper.

Dahlquist, M. and M. Ibert (2024). "Equity Return Expectations and Portfolios: Evidence from Large Asset Managers". In: *Review of Financial Studies* 37.6, pp. 1887–1928.

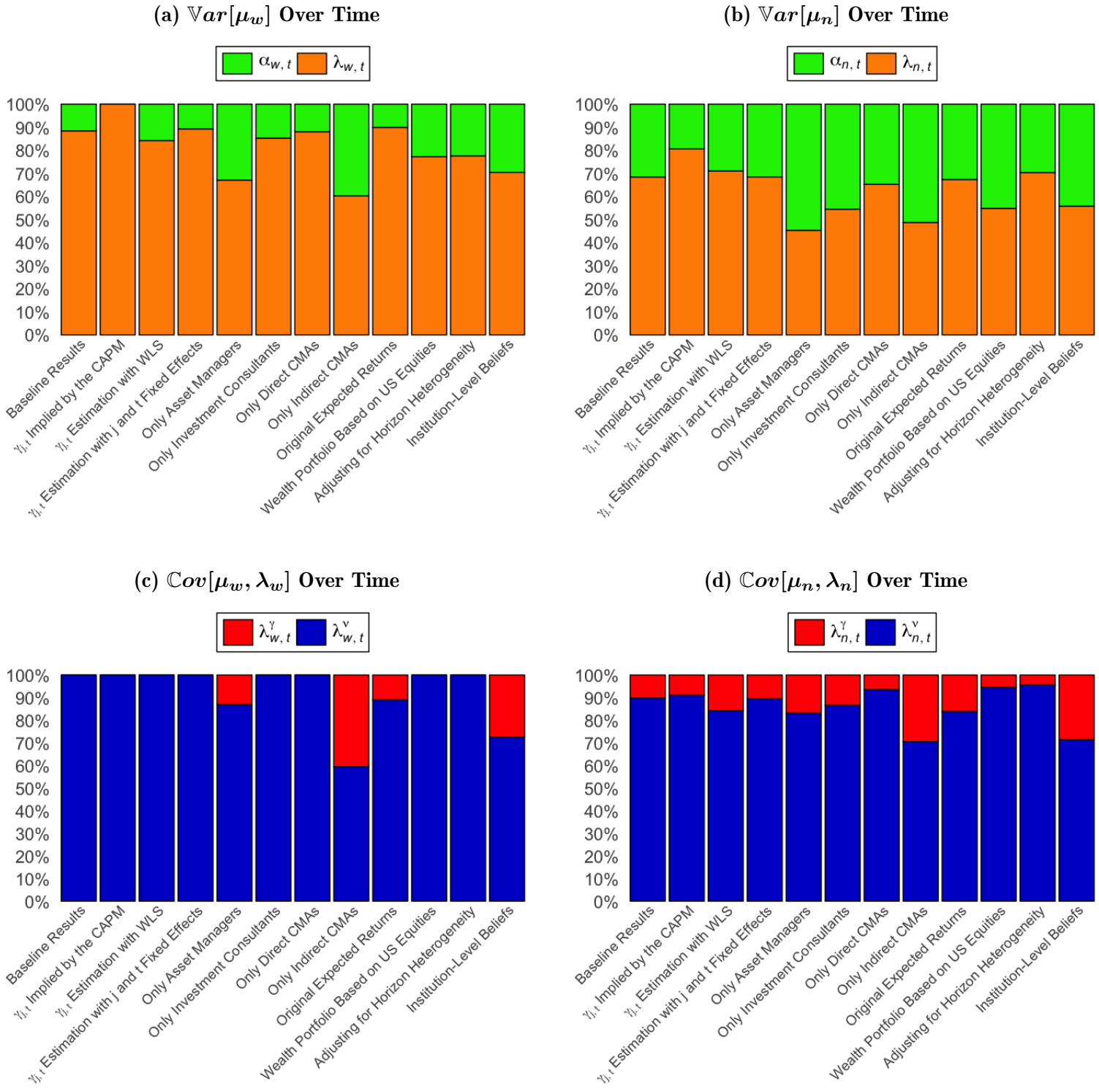


Figure IA.1
Decomposing Expected Return Overall Time Variation: Alternative Specifications

This figure reproduces the key results from Figure 10 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 B provides details on the alternative empirical specifications and discusses the results from this figure.

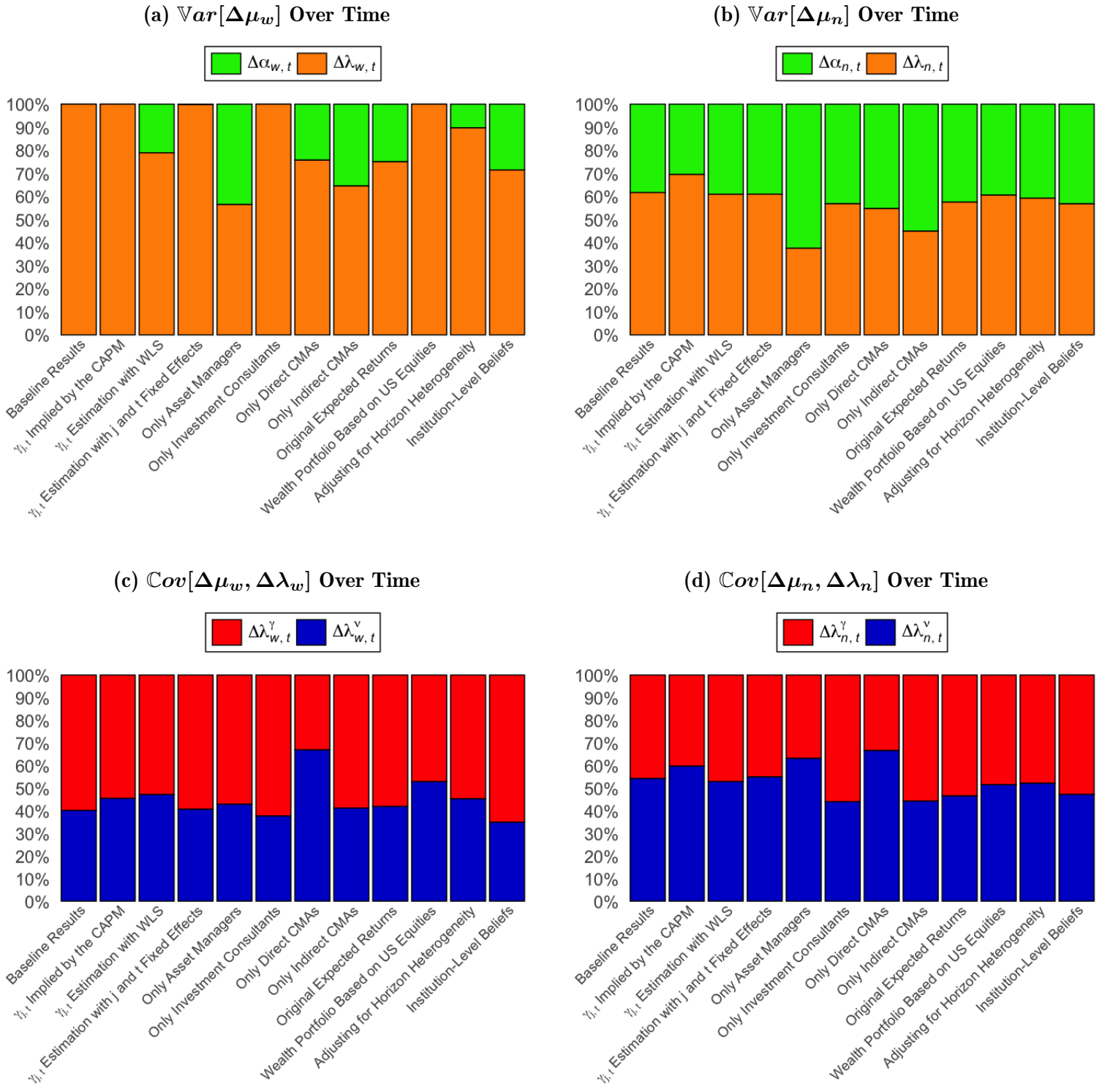


Figure IA.2
Decomposing Expected Return Transitory Time Variation: Alternative Specifications

This figure reproduces the key results from Figure 11 in the main text using alternative empirical specifications. Panel (a) reproduces the decomposition of $\mathbb{V}ar[\Delta\mu_w]$, Panel (b) reproduces the decomposition of $\mathbb{V}ar[\Delta\mu_n]$ with all asset classes, Panel (c) reproduces the decomposition of $\mathbb{C}ov[\Delta\mu_w, \Delta\lambda_w]$, and Panel (d) reproduces the decomposition of $\mathbb{C}ov[\Delta\mu_n, \Delta\lambda_n]$ with all asset classes. Section B provides details on the alternative empirical specifications and discusses the results from this figure.

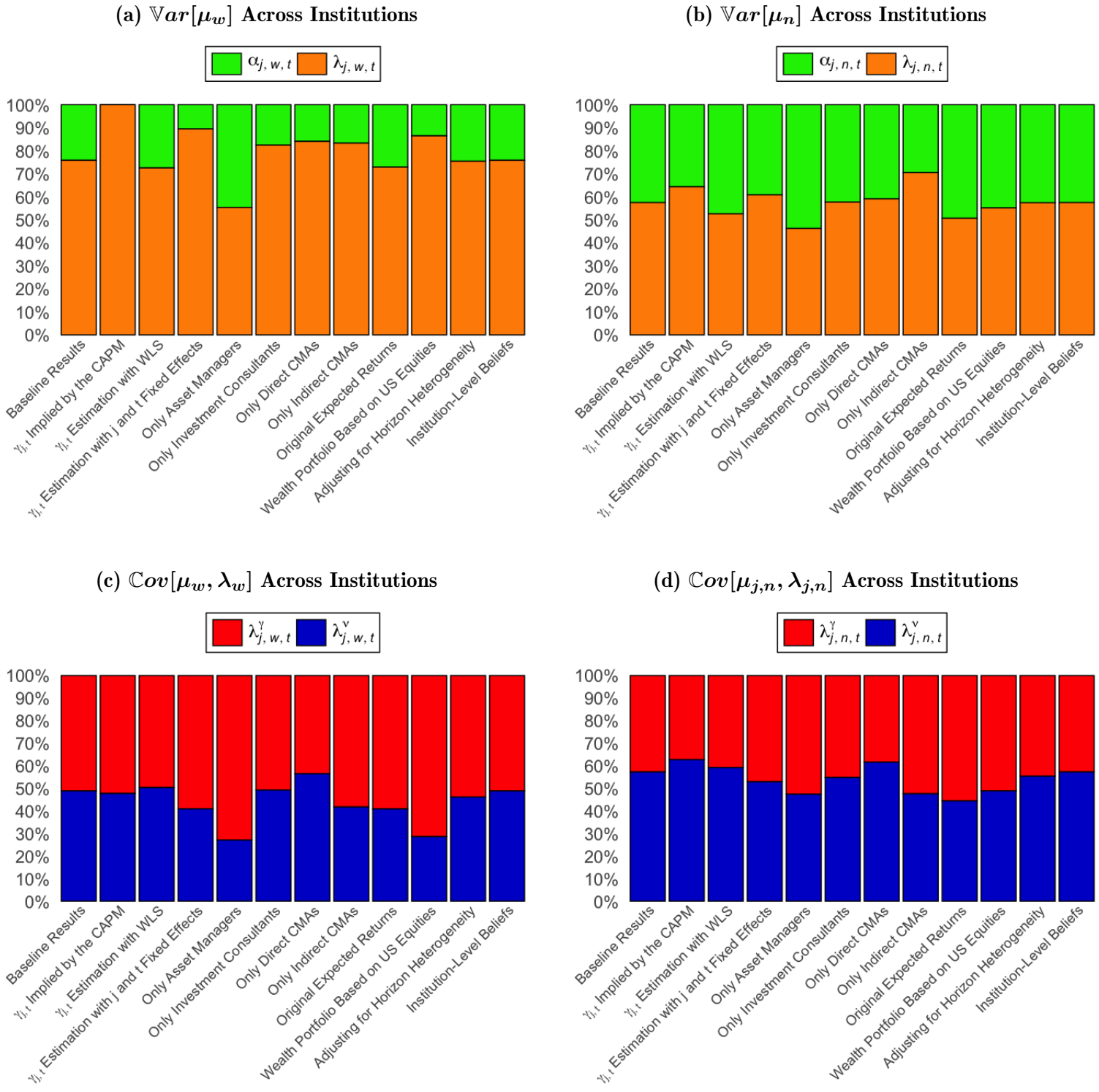


Figure IA.3
Decomposing Expected Return Disagreement: Alternative Specifications

This figure reproduces the key results from Figure 13 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 B 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 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 class 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
Decomposing Expected Return Variation: Split Sample in 2 Halves

This table provides out main results after splitting our sample period into two halves (1987 to 2004 and 2005 to 2022). Panel A provides results associated with Figures 10(a), 11(a), 13(a), which focus on decomposing $\mathbb{V}ar[\mu]$ into the effects of alphas (α) and risk premia (λ). Panel B provides results associated with Figures 10(a), 11(a), 13(a), 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 30 of the main text.

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

	% of $\mathbb{V}ar[\mu]$ due to α				% of $\mathbb{V}ar[\mu]$ due to 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)
Transitory Time Variation:								
Wealth Portfolio	33.4%	(1.42)	43.9%	(3.97)	66.6%	(2.82)	56.1%	(5.08)
All Asset Classes	45.1%	(5.87)	48.4%	(4.05)	54.9%	(7.15)	51.6%	(4.31)
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 $\mathbb{C}ov[\mu, \lambda]$

	% of $\mathbb{C}ov[\mu, \lambda]$ due to γ				% of $\mathbb{C}ov[\mu, \lambda]$ due to 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)
Transitory Time Variation:								
Wealth Portfolio	69.2%	(4.47)	74.0%	(7.63)	30.8%	(1.99)	26.0%	(2.68)
All Asset Classes	47.2%	(3.86)	61.8%	(5.65)	52.8%	(4.31)	38.2%	(3.50)
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)