The Rise of Alternatives*

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Abstract

Since the 2000s, U.S. public pensions have rotated heavily out of public equities and into alternative assets like private equity and hedge funds. This behavior is typically attributed to reaching-for-yield incentives created by the secular decline in safe interest rates, like those related to pension underfunding or binding portfolio constraints. We argue that such mechanisms are unlikely to explain the rise of alternatives without a concurrent shift in beliefs. Several facts support the idea that the perceived risk-adjusted return of alternatives has increased over time. Pension beliefs appear to be shaped by consultants, peers, and experience in the 1990s.

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1 Introduction

Over the last few decades, public pensions in the United States have fundamentally changed the way they take risk. At the turn of the century, risky investments – defined as any holding outside of fixed income and cash – were mostly in the form of public equities. Alternative assets like private equity, real estate, and hedge funds accounted for just 13% of risky investments in 2001 but grew to 40% by 2021.[1] These national trends also mask considerable heterogeneity across pensions. For example, the alternative-to-risky share for pensions in states like Maine, Indiana, New Mexico, Arizona, and Texas has increased by an average of 58pp since 2001, whereas it has hardly changed for pensions in South Dakota, Nevada, Colorado, Georgia, and Iowa.

What has driven the steep increase in the aggregate alternative-to-risky share and why have some pensions shifted so aggressively into alternatives? A common answer to this question is that pensions have become severely underfunded, providing them with incentives to close funding gaps using riskier and higher yielding assets like alternatives (Pennacchi and Rastad, 2011; Mohan and Zhang, 2014; Lu et al., 2019).[2] A related rationale is that public pensions invest in alternatives to meet nominal return targets, which have become harder to hit as safe interest rates have fallen, yet are sticky because of how pension liabilities are discounted in the United States (Andonov et al., 2017). In this paper, we posit and provide evidence for a complementary explanation: alternatives have grown in popularity because many pensions have become more bullish about their risk-reward properties relative to public equities.

To gain intuition, we first show that agency based channels should not impact the alternative-to-risky share in textbook models of portfolio choice (Markowitz, 1952; Merton, 1969; Campbell and Viceira, 2002). In these models, any force that creates incentives for pensions to take more risk (e.g., underfunding) can be viewed as a decline in risk aversion, which does not alter the composition of risky investments when Tobin (1958)'s two-fund separation theorem holds. Consistent with

[1] The overall risky share went from 69% to 77% over the same period.

[2] In their seminal work, Novy-Marx and Rauh (2011) find that pension funding gaps were as large as $2.5 trillion in 2009 when computed using economically appropriate discount rates. Giesecke and Rauh (2022) update this estimate in 2021 and show that the funding gap has grown to $6.5 trillion.

this intuition, we find virtually no correlation between the alternative-to-risky share and funding status, return targets ("hurdle rates"), or fund maturity in the cross-section of public pensions, both in long-run changes and levels. For example, a simple cross-sectional regression of changes in the alternative-to-risky share between 2001 and 2020 on changes in pension funding yields an R^2 of less than 5%. These broad conclusions are robust to several regression specifications and different measures of risk-taking incentives, including initial funding levels, funding ratios based on market discount rates, and whether plan sponsors have failed to make actuarial required contributions.

In standard models, higher risk-seeking motives can affect the composition of risky investments if investors face a maximum constraint on their risky share (e.g., a leverage constraint). We explore this mechanism using two different approaches, both of which cast doubt on the ability of binding portfolio constraints to explain the rise in alternatives. First, we develop a measure of constraint tightness based on deviations of actual from target risky shares and show that it has little predictive power for the alternative-to-risky share in the cross section of pensions. Second, we simulate a standard portfolio choice model (Merton, 1969; Campbell and Viceira, 2002) with binding portfolio constraints, which allows us to quantify the strength of this potential channel without needing proxies for constraint tightness or pension risk aversion. In particular, we draw beliefs about the expected risk and return of public equities and alternatives from a wide distribution and determine the risk aversion needed to match the aggregate pension portfolio in 2001. Holding beliefs fixed, we then lower risk aversion and assume that pensions are constrained from raising their risky share above its observed level in 2020. In virtually all simulations (99.5%), it is not possible to lower risk aversion enough to match the observed change in the alternative-to-risky share. This is because the low alternative-to-risky share in 2001 implies that pensions would shift toward public equities and not alternatives when their portfolio constraints bind.

The main point of this exercise is not to rule out mechanisms that involve risk-seeking or binding portfolio constraints. Rather, the model highlights that neither of these channels can generate the observed shift in the composition of risky investments without a concurrent shift in beliefs. We take this observation more seriously in the latter half of the paper and explore the idea that the perceived "alpha" of alternatives relative to public equities has risen in aggregate, as has disagreement across pensions.[3] Several pieces of additional evidence support this view. For one, public pensions, corporate pensions, and university endowments have all increased their alternative-to-risky share since the 2000s, yet not all have increased their overall risky share. UK corporate pensions provide a striking example of these diverging trends. From 2004 to 2020, their alternative-to-risky share went from 11% to 50% whereas their risky share more than halved from 69% to 31%. Beliefs are an appealing explanation of these patterns because they can account for why institutions that vary widely in governance, regulation, funding, and economic function (e.g, endowments vs defined-benefit pensions) have all shifted the composition of their risky investments – but not their overall risky share – in the same way.

Next, we study the role of investment consultants, who provide advice on portfolio construction for most U.S. public pensions (Andonov et al., 2023). General consultant identity is far more predictive of which pensions use alternatives compared to a wide range of attributes like funding and size. These "consultant effects" are economically meaningful: clients of the 5th percentile consultant have an average alternative-to-risky share of 7%, whereas clients of the 95th percentile consultant have an average share of 45%. A natural interpretation of this finding is that consultants vary in their beliefs about the alpha of alternatives and their clients' portfolios reflect those beliefs. In line with this view, the alternative-to-risky share is similar for private and public sector investors who share a consultant, but the same is not true of the risky share. Moreover, consultant effects are large but only weakly correlated for private equity, real asset, and hedge fund shares, suggesting that consultants do not always agree on the optimal mix of alternatives. Matching between consultants and their clients based on shared beliefs may also explain these results. Either way, belief heterogeneity appears important for why consultants correlate so strongly with alternative use in the cross-section of U.S. pensions.[4]

An analysis of consultant beliefs directly shows that their perceived alpha of alternatives has

[3]Alpha is formally defined as $\alpha = \mu_a - \beta \mu_e$, where μ_a and μ_e are the expected excess returns of alternatives and public equities, respectively. β is their expected covariance divided by the variance of public equities.

[4]In Section 5.2.2, we provide evidence that selection and catering are not fully responsible for the consultant effects. We also evaluate mechanisms based on agency frictions.

indeed risen since the 2000s. Following Couts et al. (2023), these beliefs are extracted from reports on capital market assumptions (CMAs) that are published by many of the major investment consultancies. Though our panel of CMAs is limited in size, it confirms that consultant-reported beliefs about alpha have risen steadily through time, increasing by about 80 basis points since 2001. Simulations show that this change is large enough to generate the entire observed increase in the aggregate alternative-to-risky share for the myopic long-run investor modeled in Campbell and Viceira (2002).

In the cross-section, there also is a strong and positive relationship between a consultant's reported alpha and the alternative-to-risky share of its U.S. public pension clients, after controlling for pension attributes like funding, size, or even the overall risky share. Moreover, pensions tend to invest more in a specific type of alternative (e.g., hedge funds) when their consultant reports it to have a relatively larger alpha. This test is important because we are able to absorb any factor that drives a general preference for alternatives using pension-by-time fixed effects. Within alternatives, agency frictions unrelated to funding or size could still cause some pensions to prefer the "quiet life" that unmarked assets like private equity can provide relative to hedge funds (Bertrand and Mullainathan, 2003). As one way to emphasize and isolate the role of beliefs, we show that consultant-reported alpha explains why some pensions invest more in private equity over real assets, despite the fact that both offer a similar ability to conceal risk (Stafford, 2022; Couts et al., 2020).

Motivated by household finance research on belief formation and social networks (Bailey et al., 2018, 2022), we also test whether pension beliefs are influenced by their peers, where peers are based on distance. Consistent with this idea, pensions allocate more to alternatives if their peers do, and the estimated magnitude of the effect is large compared to the impact of pension funding, size, or hurdle rates. To account for consultant effects and common unobserved economic shocks (Angrist, 2014), peer effects are identified using variation within the same consultant, year, and census division. There are at least two possible interpretations of these findings. The first is that pensions learn about the risk-reward trade-off of alternatives from pensions who are geographically close, perhaps because their investment staffs share information or attend local investment conferences. Another interpretation is based on the model of Scharfstein and Stein (1990), whereby pensions herd with their nearby peers to avoid public backlash for contrarian behavior. In reality, both channels are likely present in the data, however we rule in the first by showing that pensions with low incentives to herd still allocate similarly to their peers.

Drawing on the literature linking belief formation to experience (Malmendier and Nagel, 2016; Andonov and Rauh, 2021), we provide suggestive evidence that pensions who experienced relatively poor performance during the 1990s were more inclined to move towards alternatives in the 2000s. Experience in the 1990s alone accounts for one-fifth of the variation in changes in the alternative-to-risky share from 2002 to 2020 across pensions. Our interpretation is that pensions that were late to invest in equities during the dot-com bubble of the late 1990s experienced lower returns, leading them to then perceive alternatives as more favorable than public equities. Notably, the experience in the 1990s retains its predictive power even after controlling for funding levels in 2002, cutting against the notion that poor performance worsened funding frictions and instead supporting a belief-based channel. However, it is important to note that missing return data from the 1990s for some pensions limits the strength of this conclusion.

Taken together, these facts suggest to us that beliefs have played a critical role in the adoption of alternatives over the past two decades. A different interpretation is that agency frictions have driven the rise of alternatives. Our analysis helps pin down the nature of any such friction. For one, it would need to cause a wide range of institutions that differ in governance, regulation, and geography to prefer alternatives over public equities, but not risky assets overall. Moreover, the friction must vary in the cross-section of both public and private pensions and be orthogonal to a host of pension attributes including funding and size. Finally, it must lead to matching with consultants in a way that lines up with the alpha they report in CMAs, even within asset classes that provide a similar scope for hiding risk like private equity and real assets. While agency-based mechanisms of this form are possible, beliefs offer a simpler explanation of the facts.

Supply-side factors may also have contributed to the rise in alternatives. For example, investor access to privately held firms via private equity limited partnerships has improved over time. Indeed, as we show in Section 6.1, the supply of alternatives has expanded from 2% of all global risky assets in 2000 to 8% in 2020. Though these types of supply-side factors are certainly relevant for understanding aggregate pension behavior, they cannot explain the large cross-sectional variation in alternative adoption.

This paper contributes to both public economics and finance, starting with research on how interest rates influence investor behavior. Much of this literature has focused on why investors appear to take more risk as interest rates fall (Borio and Zhu, 2012), with common explanations centering around agency frictions (Becker and Ivashina, 2015), institutional constraints (Campbell and Sigalov, 2022), and behavioral biases (Lian et al., 2018). In the context of US public pensions, underfunding and accounting distortions have been used to explain why the risky share has increased from 69% to 77% since the turn of the century (Pennacchi and Rastad, 2011; Mohan and Zhang, 2014; Andonov et al., 2017; Lu et al., 2019). In contrast, we ask why pensions have shifted the composition of their riskier assets away from public equities and toward alternative assets over this period. This compositional shift is arguably more important than the change in the risky share: since 2001, for every dollar that has flowed out of fixed income, \$2.95 has moved into alternatives and \$1.95 has flowed *out* of public equities.[5] Consistent with intuition from the two-fund separation theorem (Tobin, 1958), we argue that shifting beliefs are necessary to understand the adoption of alternatives.

An important precursor to our paper is Ivashina and Lerner (2018), who document that private and public sector pension funds around the globe have all increased their overall portfolio share of alternatives since 2008. We extend their research by studying the evolution of the alternative-to-risky share in conjunction with the risky share. This analysis reveals that rise in alternatives has been driven by a shift in the composition of risky investments, as opposed to a broader global expansion into all types of risky assets. For example, the alternative-to-risky shares for US and UK corporate pensions have both increased since the early 2000s, yet their overall risky shares have

[5]Even under the assumption that hedge funds only invest in the stock market, the net decline in the portfolio share of public equities is 9.4 pp, as opposed to 14.2 pp without netting (see Section 2.2.2).

both decreased. Our paper suggests that beliefs can help to jointly explain these trends.

Finally, our research connects to a growing literature that studies the relationship between beliefs and heterogeneity in household investment behavior (e.g., Pástor, 2000; Leombroni et al., 2020; Beutel and Weber, 2022; Giglio et al., 2023). We highlight this link in the context of U.S. public pensions. In particular, our findings imply that disagreement about the alpha of alternatives may explain why dispersion in the alternative-to-risky share has risen so sharply since the 2000s. It is natural to expect disagreement in our setting given the challenges associated with measuring the risks of alternatives (Stafford, 2022; Couts et al., 2020; Korteweg, 2019). This discussion also raises a related question of how beliefs are formed. Consistent with prior work, we show that consultants, peers, and past experience all likely play a role (Foerster et al., 2017; Bailey et al., 2022; Bordalo et al., 2022).

The subsequent sections of the paper are structured as follows. Section 2 provides an overview of the data utilized in our analysis and presents several facts about U.S. public pension investment behavior that serve as the foundation for our study. Section 3 uses the portfolio choice model of Campbell and Viceira (2002) to illustrate the types of channels that can explain these facts, most notably the change in the alternative-to-risky share. Section 4 investigates the ability of explanations based on funding, liability discounting, and nominal return targeting to explain the data. Section 5 lays out the main pieces of evidence supporting our argument that beliefs have played a central role in the rise of alternatives. Section 6 concludes. Additional details and results are available in an online appendix.

2 Data and Motivating Facts

We draw data primarily from the Public Plans Data (PPD) that is maintained by the Center for Retirement Research (CRR) at Boston College. This section describes these data and its coverage of the broader U.S. defined benefit pension system. We then document that the aggregate alternative-to-risky share has risen sharply since the early 2000s, as has dispersion in the cross-section of U.S.

public pensions.

2.1 Sample description and variable definitions

2.1.1 Individual Pension Plan Data

We obtain annual information on individual pension plans (e.g., size) using the PPD. These data are based on comprehensive annual financial reports (CAFRs) that are filed annually by each DB public pension in the United States. The exact content and format of CAFRs varies across pensions and years, but all contain data on various plan characteristics like portfolio composition, assumed asset returns, actuarial value of liabilities, contribution rates, and information on beneficiaries. We supplement the PPD using hand collected data on the identity of investment consultants (see Section 5.2.1). Information on chief investment officers and their salaries is taken directly from Lu et al. (ming).

Data in the PPD are reported at the plan level, though in many cases the assets of multiple plans are pooled and managed by pension "systems." For example, the board of the Colorado Pension Public Employees' Retirement Association invests and manages the pension assets of Colorado state employees, local school districts, the state's judicial system, and many local municipalities. Because our focus is on asset allocation decisions, our main unit of analysis is therefore at the system level. We map individual plans to larger pension systems based on hand collected information and data from the Center for Retirement Research, and then aggregate plans to the system level accordingly.[6]

Asset class definitions are not standardized across CAFRs. For example, some pensions report allocations to international and domestic public equities separately in their CAFRs, whereas others combine them into a single category. In its "Detailed Investment Dataset," PPD copies asset class names, weights, and performance benchmarks (if available) directly from CAFRs. We then aggregate each raw asset class into one of eight broad categories based on its reported name and

[6]Our mapping takes into account a handful of pension mergers that have occurred during our sample period and is available upon request.

benchmark. The nine categories are: (i) cash; (ii) fixed income; (iii) public equities; (iv) private equity; (v) private credit; (vi) real assets, including real estate, infrastructure, and commodities; (vii) hedge funds; and (viii) other alternatives.

These nine categories are then aggregated as follows. Risky investments are defined as everything outside of cash and fixed income. Alternatives include private equity, private credit, real assets, hedge funds, and other alternatives. The alternative-to-risky share is defined as the portfolio share of alternatives scaled by the portfolio share of risky investments.

We clean the PPD data in several ways. First, we exclude plans that are missing information on either the market value of assets or the value of liabilities under GASB 25 standards. Second, we screen observations for plan p and fiscal year t based on the sum of actual portfolio weights (A_{pt}) and the sum of target portfolio weights (T_{pt}). Specifically, we drop observations if both $|A_{pt} - 1|$ and $|T_{pt} - 1|$ are greater than 0.05. If $|A_{pt} - 1| > 0.05$ but $|T_{pt} - 1| \leq 0.05$, we replace actual weights with target weights, and vice versa. Third, we focus on the period between 2001 and 2021. After aggregating to the pension system level, the resulting panel has 2,966 system-year observations. Annual dates are based on pension plan fiscal years, not calendar years, and the fiscal year for most plans begins in July and ends in June. Unless otherwise noted, target weights are used in our subsequent analysis of the PPD data because these are chosen by pensions, whereas actual weights will also reflect market fluctuations.

Table 1 presents summary statistics for our sample of U.S. public pension funds, broken out over four equally-spaced time periods. We discuss these summary statistics and the PPD sample in greater detail in Internet Appendix A.1, where we also validate it against data from the U.S. Census Bureau. From 2006 onwards, the PPD covers over 90% of total U.S public pension assets. The table further shows that the PPD coverage is also fairly large in comparison to the broader U.S. pension system (roughly one-quarter), defined as the total amount of assets held by all private and public sector pension funds in Table L.117 of the Financial Accounts of the United States.

2.2 Trends in Portfolio Composition

We now present some basic facts about the investment behavior of U.S. public pensions, starting with the overall risky share and then turning to the composition of risky investments.

2.2.1 The Risky Share in the Aggregate and Cross-Section

Though our main focus is the composition of risky investments, it is useful to characterize the evolution of the risky share as well. Recall that risky investments are defined as all holdings outside of investment grade-debt and cash. In principle, high-yield debt securities should be included in risky investments but granular data on the credit rating of fixed income investments is limited.[7] Consistent with prior work on public pensions (e.g., Andonov et al., 2017), the plot shows that the risky share has risen steadily since the turn of the century. From 2001 to 2021, it went from 69% to 77%.

Figure 1b provides a longer-run perspective using the U.S. Census Bureau's Quarterly Survey of Public Pensions (QSPP), which covers the largest 100 pensions in the country starting in 1968. The first thing to notice is that risky shares from the QSPP and PDD largely overlap when both are available, providing some comfort about the quality of the PPD data.[8] The second and more striking thing is that the 8 pp increase in the risky share since the 2000s is relatively small in comparison to the 35 pp increase that occurred between 1970 and 2000. The risky share increased by nearly 17 pp in the 1990s alone, most of which was drive by a rotation out of U.S. Treasuries (see Internet Appendix B.1.1). Figure 1b also suggests that the risky share for U.S. public pensions may have reached a new steady state of just under 80% in the last five years.

Figure 1c visualizes the cross-sectional distribution of the risky share using PPD data from 2002 onward, showing only even years for readability. Consistent with the aggregate trends in Figure 1a, the risky share has increased for the median pension over time. However, the plot also

[7]The PPD does have a "PensionCreditRating" dataset that contains fixed income holdings by credit rating for a subset of pensions from 2004 to 2018. We discuss this data and its limitations in more detail in Internet Appendix A.1.2.

[8]Another, more minor difference, is that PPD is defined based on target portfolio weights whereas QSPP reflects actual ones.

highlights a fair amount of heterogeneity in the risk-taking. For instance, in 2021 the risky share for the 10th percentile pension system was 68% and for the 90th percentile it was 85%. This degree of heterogeneity has declined slightly over time, as the spread between the 10th and 90th percentile pension in 2002 was 20 pp. In Internet Appendix B.1.2, we show that this plot masks some turnover in which pensions take the most or least risk. We also discuss outliers in the risky share and provide a geographical sense of the risky share at the state level.

2.2.2 The Composition of the Aggregate Risky Portfolio

Underneath the increase in the aggregate risky share since the 2000s, there has been a considerable change in the *way* that pensions take risk. To see this more clearly, Figure 2a starts by plotting the raw portfolio weights for fixed income (cash, investment-grade, high-yield debt), public equities, and alternatives based on PPD data. The first thing that stands out from the plot is the rise in alternatives. From 2001 to 2021, the share of alternatives in the national portfolio increased from 9% to 30%, mirroring a broader trend by pensions around the world (e.g., Ivashina and Lerner, 2018). At the same time, the share of public equities fell from 61% to 46%. These flows imply that for every dollar that has shifted out of fixed income since 2001, $2.95 has moved into alternatives and $1.95 has flowed *out* of public equities.

The preceding decomposition may overstate how much pension capital has flowed out of public equities if hedge funds ultimately invest in the stock market. Figure 2b sheds some light on this issue by breaking out alternatives into subcategories for both 2001 and 2020. Hedge fund exposure has indeed increased by 4.8 pp during this period, though this change is not large enough to offset the contemporaneous decline of 14.2 pp decline in the public equity share. Thus, even if hedge funds are fully invested in public equities, public pensions have still decreased their exposure to the stock market by 9.4 pp.

Figure 2b further shows that all forms of alternatives have risen since the turn of the century. In 2001, the respective shares of real assets, private equity, hedge funds, and private credit in were 4%, 4%, 0% and 1%. Real assets are defined as investment in real estate, infrastructure, and commodities. In 2021, their respective shares were 12%, 9%, 5%, and 4%.

As a simple way to summarize how the nature of risk-taking has changed, Figure 2c plots the evolution of the alternative-to-risky share (as opposed to raw shares). This object is a useful summary statistic for our purposes because it on depends on beliefs and not risk aversion in portfolio choice models where the two-fund separation theorem of Tobin (1958) holds (see Section 3). From 2001 to 2021, the alternative-to-risky share rose from 13% to 40%. Thus, U.S. public pensions are increasingly turning to alternatives over public equities when they make riskier investments.

2.2.3 Heterogeneity in the Composition of Risky Investments

We now analyze how the composition of risky investments varies across public pensions, which we summarize using the alternative-to-risky share $\tilde{a}_{pt}$ for pension p in year t. Figure 3a shows the distribution of $\tilde{a}_{pt}$ for each even year since 2001. There is a striking degree of cross-sectional variation in $\tilde{a}_{pt}$: in 2021, the alternative-to-risky shares for the 10th and 90th percentile pensions were 18% and 59%, respectively. This dispersion has also widened considerably over time. In 2001, the spread between the 10th and 90th percentile pensions was 26 pp.

Figure 3b shows the distribution of changes in $\tilde{a}_{pt}$ across pensions systems from 2002 to 2021. Echoing the widening dispersion in Figure 3a, the shift into alternatives has varied strongly across pensions: the 25th pension increased its alternative-to-risky share by 15 pp whereas the 75th percentile increased by 36 pp. Table A1b of the Internet Appendix shows that these changes have resulted in some amount of turnover in terms of the pensions with the highest alternative-to-risky share. For example, 19% of the pensions who were in the top quartile of $\tilde{a}_{pt}$ in 2021 were in the bottom quartile in 2002. At the same time, 17% of pensions who were in the bottom quartile of $\tilde{a}_{pt}$ in 2021 were also in the top quartile in 2002.

In Internet Appendix B.2, we discuss specific outlier pensions in terms of alternative usage, provide state-level summaries of the alternative-to-risky share, and repeat our cross-sectional analysis on the portfolio share of alternatives (as opposed to the alternative-to-risky share). Overall, the results in this section reveal large heterogeneity in the use and adoption of alternatives across

U.S. pensions.

3 Intuition from a Standard Portfolio Choice Model

In this section, we present a standard portfolio choice model in the tradition of Markowitz (1952) and Merton (1969).[9] The goal of the model is to highlight potential reasons why the level and dispersion of the alternative-to-risky share have both risen. We also use it to guide our empirical analysis in subsequent sections.

3.1 Baseline Model

We begin by describing a model of portfolio choice for a power-utility investor who lives two periods and has initial wealth W_0. As discussed in detail in Campbell and Viceira (2002), the optimal portfolio choice for this investor is identical to that of a long-run investor who ignores intertemporal hedging motives (Merton, 1973). We discuss the applicability of this model to U.S. public pensions in Section 3.4.

The investor consumes their final period wealth $W = R_p W_0$, where R_p is the portfolio return. Investor utility is $U = \frac{W^{1-\gamma}-1}{1-\gamma}$, with $\gamma > 1$ and $U = \log(W)$ if $\gamma = 0$. There are three assets: a riskless asset with log return r_f, public equity with log return r_E, and alternatives with log return r_A. Let ω_f be the portfolio weight on the riskless asset, ω_E be the portfolio weight on risky public equity, and ω_A be the portfolio weight on alternative assets. The asset returns on public equity and alternatives are jointly log-normally distributed. Log *excess* returns $[r_A - r_f, r_E - r_f]'$ have mean μ and variance-covariance matrix Σ:

$$\mu = \begin{bmatrix} \mu_A \\ \mu_E \end{bmatrix}, \sigma^2 = \begin{bmatrix} \sigma_A^2 \\ \sigma_E^2 \end{bmatrix}, \Sigma = \begin{bmatrix} \sigma_A^2 & \sigma_{AE} \\ \sigma_{AE} & \sigma_E^2 \end{bmatrix}.$$

[9] There is an extensive literature on solving the optimal portfolio choice problem of pensions (e.g., Campbell and Viceira, 2006; Lucas and Zeldes, 2009; Pennacchi and Rastad, 2011; van Binsbergen and Brandt, 2016).

It will be useful for us to express μ_A, σ_A^2, and σ_{AE} as functions of public equity fundamentals (μ_E and σ_E^2) and α, β, the constant and coefficient of a CAPM-style regression of alternatives' excess return on the public equity market portfolio:

$$r_A - r_f = \alpha + \beta(r_E - r_f) + \varepsilon. \tag{1}$$

The investor's objective function is $\max \mathrm{E}[u] = \mathrm{E}\left[\frac{W^{1-\gamma}}{1-\gamma}\right] \Longrightarrow \max \frac{W_0^{1-\gamma}}{1-\gamma}\mathrm{E}[R_p^{1-\gamma}]$. Taking logs of $\mathrm{E}[R_p^{1-\gamma}]$ and re-arranging, and the investors' maximization problem becomes

$$\begin{aligned}
&\max_{\omega_r} \mathrm{E}[r_p] + \frac{1}{2}(1-\gamma)\mathrm{Var}[r_p], && (2)\\
s.t. \quad &\mathrm{E}[r_p] = r_f + \omega_r{}'\mu + \frac{1}{2}\omega_r'\sigma^2 - \frac{1}{2}\omega_r{}'\Sigma\omega_r, \\
&\mathrm{Var}[r_p] = \omega_r{}'\Sigma\omega_r, \\
&w_f = 1 - w_A - w_E \geq 0.
\end{aligned}$$

The optimal portfolio allocation satisfies

$$\begin{aligned}
\omega_A &= \frac{1}{\gamma}\left(\frac{\alpha}{\sigma_\varepsilon^2} + \frac{1}{2}(\beta-1)\beta\frac{\sigma_E^2}{\sigma_\varepsilon^2} + \frac{1}{2}\right), && (3)\\
\omega_E &= \frac{1}{\gamma}\left(\frac{\mu_E}{\sigma_E^2} - \frac{\alpha\beta}{\sigma_\varepsilon^2} + \frac{1}{2}(1-\beta)(\beta^2\frac{\sigma_E^2}{\sigma_\varepsilon^2}+1)\right), && (4)\\
\omega_f &= 1 - \omega_A - \omega_E,
\end{aligned}$$

where we expressed fundamental beliefs about alternatives in terms of CAPM regression coefficients.[10]

[10]The CAPM regression coefficients α and β are related to the asset characteristics of alternatives as follows: $\mu_A = \alpha + \beta\mu_E$, $\sigma_A^2 = \beta^2\sigma_E^2 + \sigma_\varepsilon^2$, and $\sigma_{AE} = \beta\sigma_E^2$.

3.2 The Role of Beliefs

The first thing to note from Equations (3) and (4) is that a change in risk aversion cannot explain the rise in the alternative-to-risky share in the model, meaning $\frac{\partial \omega_A^*}{\partial \gamma} = 0$. This follows from the fact that γ^{-1} cancels out of the expression for ω_A^*. In other words, risk aversion does not impact the composition of the optimal risky portfolio in the baseline model because the two-fund separation of (Tobin, 1958) holds.

In contrast, a change in the beliefs about the alpha of alternatives relative to public equities (α) can affect the composition of the risky portfolio. Formally, Equations (3) and (4) imply that the alternative-to-risky share is increasing in α:

$$\frac{\partial \omega_A^*}{\partial \alpha} = \frac{\frac{1}{\sigma_\varepsilon^2}\left(\beta \omega_A + \omega_E\right)}{\left(\omega_A + \omega_E\right)^2} > 0$$

when $\beta \omega_A + \omega_E > 0$, which is trivially fulfilled for $\beta > 0$ and positive weights. In the cross-section, this simple result also suggests that dispersion in the alternative-to-risky share could arise if some public pensions have become more bullish about alternatives (relative to public equities) than others.

Though our focus is not on the evolution of the risky share, it is interesting to note that it too depends on α:

$$\frac{\partial \omega_E + \omega_A}{\partial \alpha} = \frac{1}{\gamma} \frac{1}{\sigma_\varepsilon^2} \left(1 - \beta\right)$$

This is because the optimal holding of the risky portfolio depends on its Sharpe ratio, which is impacted by α. If $\beta < 1$, an increase in α will also lead to an increase in the overall risky share. Figure A19 shows this condition holds for the reported beliefs of pensions' investment consultants. In Internet Appendix D.2, we further show that the implied alpha of these consultants has risen by enough to also explain the rise in the risky share in our model.

3.3 Portfolio Constraints

We extend the model above by assuming that pensions solve the portfolio problem in Eq. 2, but face a constraint on the minimum amount of riskless investment, $\omega_f \geq \omega_f^{min}$. This constraint can loosely be thought of as capturing minimum investment requirements in safe fixed income. Whenever $\omega_f^{min} = 0$, the constraint represents a leverage constraint.

The portfolio is identical to the portfolio described by Eqs. (3) and (4) as long as the minimum fixed income share constraint is not binding. When the constraint is binding, we show in Appendix Section A that the optimal portfolio shares are:

$$\begin{aligned} w_f &= w_f^{min}, \\ w_A &= \frac{1}{\gamma}K + (1 - w_f^{min})C, \\ w_E &= -\frac{1}{\gamma}K + (1 - w_f^{min})(1 - C), \end{aligned} \tag{5}$$

where

$$\begin{aligned} K &= \frac{(\alpha + (\beta - 1)\mu_{\mathrm{E}})/\sigma_{\mathrm{E}}^2}{(\beta - 1)^2 + \sigma_\varepsilon^2/\sigma_{\mathrm{E}}^2} + \left(\frac{\beta - 1}{(\beta - 1)^2 + \sigma_\varepsilon^2/\sigma_{\mathrm{E}}^2} + \frac{1}{2} \right), \\ C &= \frac{1 - \beta}{(\beta - 1)^2 + \sigma_\varepsilon^2/\sigma_E^2}. \end{aligned}$$

Risk-aversion γ and asset allocation With a binding fixed income share constraint, a change in risk aversion γ will not only affect the risky portfolio share $\omega_E + \omega_A$, but also the composition of the risk-portfolio ω_A^*. We can show that

$$\frac{\partial \omega_A^*}{\partial \gamma} = -\frac{1}{\gamma^2} \frac{1}{1 - w_f^{min}} K < 0,$$

as long as $K > 0$. Thus, for certain beliefs (embedded in K), a decline in risk-aversion γ can also generate an increase in the alternative-to-risky share ω_A^* when there is a binding portfolio constraint.

3.4 Discussion

The model highlights two potential explanations for increase in the alternative-to-risky share documented in Section 2.2. The first is that risk aversion has declined and portfolio constraints on the minimum amount of safe assets have simultaneously become binding. Under this explanation, risk aversion γ does not need to embed a true preference parameter and could instead reflect agency frictions that impact pensions' desire to take risk (e.g., underfunding). The second is that beliefs about the risk-reward properties of alternatives have changed, namely that α has increased. In reality, both mechanisms may drive pension behavior, though in what follows we explore them separately to gauge their relative empirical strength.

Though intentionally simple, our illustrating model illustrates two mechanisms that reflect the broad intuition of the Tobin (1958)'s mutual fund separation theorem, which holds in a broader class of preferences outside of power utility (Cass and Stiglitz, 1970). There are also several reasons to think the model laid out in this section reasonably approximates the behavior of U.S. pensions, even if this behavior is not necessarily optimal for a long-run investor. For one, consultant and pension annual reports rarely make mention of large-scale market-timing strategies, but often mention standard elements of mean-variance optimization. This suggests that U.S. public pensions may ignore or respond weakly the intertemporal hedging motives of Merton (1973).[11] Instead, pensions may be better thought of as solving a sequence of myopic portfolio optimizations, where the primitives of the optimization – namely risk aversion and beliefs – are revisited during asset allocation studies that typically occur every three to five years.

4 Evaluating Popular Explanations for the Rise in Alternatives

Many of the popular explanations for the rise in alternatives revolve around a change in the effective risk aversion of public pensions. As we showed in the previous section, such a decline could

[11] Equation 3.20 of Campbell and Viceira (2002) shows that the optimal portfolio for a long-run investor who also hedges changes in interest rates can be written as the sum of a myopic portfolio and a intertemporal hedging portfolio. Thus, if U.S. pensions ignore the second term, they will behave as the myopic investor in our simplified model.

generate the alternative-to-risky share in standard models if also paired with a binding portfolio constraint. In this section, we empirically evaluate the explanatory power of this mechanism in three steps. First, we lay out and test a few related ways that effective pension risk aversion might decline or vary in the cross-section, including those created by pension underfunding. Second, we propose a method to measure binding portfolio constraints and test whether it explains cross-pension variation in the composition of the risky portfolio. Third, we use the model from Section 3 to simulate a decline in risk aversion plus a binding portfolio constraint and gauge whether it can credibly generate the portfolio shifts we observe empirically.

4.1 Funding, Hurdle Rates, and Accounting-Based Explanations

The first hypothesis we test stems from the observation that the secular decline in interest rates has caused U.S. pensions to become increasingly underfunded. We confirm this fact in Figure A7 of the internet appendix, which plots the evolution of the national funding ratio when measured according to Statement 25 of the Governmental Accounting Standards Board (GASB), an independent organization that establishes accounting and reporting standards for U.S. state and local governments. At the beginning of the 2000s, U.S. pensions were overfunded according to GASB 25 standards, but their assets were only 70% of liabilities by 2020.[12]

The deterioration in funding creates natural incentives for U.S. pensions to "reach-for-yield" (Lu et al., 2019), similar to those facing corporate equity holders when approaching default (Jensen and Meckling, 1976).[13] This agency friction is often cited as the reason why the aggregate risky share for U.S. pensions has risen in recent decades, though the post-2000s increase was much smaller compared to the one that took place between 1970 and 2000 (Section B.1.1 in the Internet Appendix). A related and popular idea is that underfunding has caused pensions to turn more

[12]Under so-called GASB 25 standards, funding ratios are computed from: (i) smoothed asset values that minimize the impact of short-term market fluctuations and (ii) liabilities that equal future benefits discounted using each plan's assumed long-run investment return.

[13]By reach-for-yield, we mean the propensity to take more risk as interest rates fall, though this is one of many ways that the term has been used in the literature. For example, Lian et al. (2018) show that investors may exhibit reach-for-yield behavior for behavioral reasons, as opposed to institutional or agency frictions.

to alternatives, which are generally thought to embed more risk but also promise higher returns (Gillers, 2021).

As a simple way to explore the link between underfunding and alternative usage, we run the following cross-sectional regression:

$$\Delta w_{atr,p} = a + \beta \Delta X_p + \varepsilon_p,$$

where $\Delta w_{atr,p}$ is the change in the alternative-to-risky share for pension p between 2002 and 2020. Throughout this section and in subsequent analyses, we utilize target weights instead of actual weights to mitigate the influence of market value fluctuations on portfolio weights. The explanatory variable ΔX_p is the contemporaneous change in each pension's GASB 25 funding ratio, though we also explore other covariates below. Standard errors are clustered by state for regressions run at the system level and are otherwise robust.

Consistent with popular intuition, Column (1) of Table 2 shows that deterioration in funding is correlated with an increase in the use of alternatives. However, the link between the two is weak in both statistical and economical terms. The estimated point estimate is marginally significant ($p = 0.07$) and implies that moving from the 90th to 10th percentile of the change in funding is associated with a 7% increase in the alternative-to-risky share. Over this period, the actual spread between the 90th and 10th percentile of the change in the alternative-to-risky share equals 39%. Moreover, the R^2 of 4% in the regression indicates that most of the cross-pension variation in the shift to alternatives cannot be explained by deterioration in funding. We show further in Internet Appendix C.1.1 that the poor model fit is not driven by a non-linear relationship between funding and alternative adoption.

One issue with the analysis in column (1) is that funding is measured according to GASB 25 standards. As Brown and Wilcox (2009), Novy-Marx and Rauh (2011), and others have pointed out, GASB 25 funding ratios overstate the true economic funding gap because liabilities are discounted using the expected rate of return on pension assets ("hurdle rates"), rather than more appropriate discount rates based on federal or local government debt. As one way to handle this measurement issue, column (2) replaces GASB 25 funding ratios with those provided by the U.S. Bureau of Economic Analysis (BEA), who uses the yield-curve for AAA-rated corporate bonds to discount liabilities. The regression is run at the state level because this is the unit of observation for which BEA-funding ratios are available. The point estimate in this case is effectively zero and the R^2 is once again low, confirming that the measurement of funding deterioration is not responsible for its weak relationship with the adoption of alternatives.

A related hypothesis about the rise in alternatives revolves around nominal return targets or hurdle rates. To the extent that U.S. pensions have nominal hurdle rates that are fixed or sticky, then a decline in interest rates makes it harder for them to clear their hurdle rate. Pensions, in search of higher expected returns, may consequently turn to alternative investments. We test this proposition directly in column (3) of Table 2 by regressing changes in the alternative-to-risky share on contemporaneous changes in each pension's hurdle rate. If anything, the regression coefficient suggests a negative, not positive, correlation between alternative adoption and changes in liability discount rates. However, much like funding, the relationship is small in both statistical and economic terms and does not explain most of the variation in changes in the alternative-to-risky share.

Andonov et al. (2017) point out that hurdle rates may be sticky precisely because lowering them causes U.S. pensions to appear more underfunded by GASB 25 accounting. They further argue that this incentive increases with the fraction of retired members because more mature pensions have larger accrued liabilities and thus higher actuarial required contributions. Column (4) extends the logic of Andonov et al. (2017) by testing whether pensions who have had more members retire are also those who have shifted more to alternatives. While there is a positive relationship between the two, the regression coefficient is not statistically different from zero and the model fit is poor.

All in all, we find no compelling empirical evidence to support funding status, hurdle rates, or GASB 25 accounting standards as explanations for the cross-sectional variation in the alternative-to-risky share.

Robustness The results in Table 2 cut against the idea that pensions have shifted their risky investments toward alternatives in response to underfunding or for accounting reasons.[14] In Internet Appendix C.1, we reinforce this conclusion in a few complimentary ways. First, we document that the initial levels of the covariates in Table 2 also do not predict subsequent changes in the alternative-to-risky share. For example, it is not the case that pensions who were more underfunded in 2002 shifted more aggressively to alternatives from 2002 to 2020. There is also no relationship between the change in the alternative-to-risky share and pension size or the failure to make actuarial required contributions. Second, we show that the findings in Table 2 are not driven by our choice of a linear regression specification. Third, the relationship between the alternative-to-risky share and funding remains weak when employing panel regressions in levels or focusing solely on levels in more recent data. Fourth, by categorizing pensions into bins according to their funding and hurdle rates, we demonstrate that there are no distinct trends in the alternative-to-risky share across these bins.

The fact that there is a weak relationship between the alternative-to-risky share and funding or accounting-based factors in Table 2 is not surprising from the perspective of canonical portfolio choice models (Section 3). The reason why is that these factors can all be thought of as proxies for the effective risk aversion of public pensions. Isolated changes in risk aversion do not impact the alternative-to-risky share when the two-fund separation theorem holds, as is the case in conventional models. However, this reasoning loses validity in situations where investors encounter binding portfolio constraints. For instance, in the classic mean-variance framework of Markowitz (1952), investors could tilt risky investments towards alternatives if they hit a constraint on the minimum amount of safe assets (or maximum amount of risky assets). We explore this mechanism more carefully in the next subsection.

[14] Campbell and Sigalov (2022) show reach-for-yield behavior can arise if investors are constrained to maintain current wealth in expectation ("sustainable spending"). We view the model of Campbell and Sigalov (2022) as a better description of university endowments rather than U.S. public pensions, mainly because pensions are increasingly facing calls to run down wealth for payments to existing beneficiaries and simultaneously phase out defined benefit plans for active employees (Giesecke and Rauh, 2022).

The Risky Share Although not our primary focus, we explore the role of funding and accounting-based mechanisms in explaining the increase of the overall risky share in Internet Appendix C.2. Surprisingly, we find only a weak cross-sectional correlation between underfunding and the rise in the risky share. For instance, a cross-sectional regression of changes in the risky share on changes in BEA-adjusted funding ratios yields an R^2 of less than 5%. In line with the findings of Andonov et al. (2017), we do observe a positive relationship between the risky share and changes in the fraction of retirees and liability discount rates, albeit with relatively low R^2's (less than 10%). These results suggest that funding and accounting-based explanations are unlikely to fully explain why U.S. pensions have taken on more risk in recent years.

4.2 Binding Portfolio Constraints

We now investigate whether binding portfolio constraints can explain why some pensions have a relatively high alternative-to-risky share. The main challenge we face is that the binding constraints are difficult to distinguish from pure risk preferences, as a pension with a low risky share may not be constrained from taking additional risk and could simply have high risk aversion. We overcome this measurement issue by studying deviations $l_{pt} = \text{actual}_{pt}^{risky} - \text{target}_{pt}^{risky}$ of actual from target risky shares.[15] The basic idea is as follows. Market fluctuations will naturally move each pension's actual risky share from its target, after which pensions must rebalance to bring the two in line. For example, in 2022, Calpers – the largest pension in the US – targeted a public equity allocation of 42% and allowed for a range of 7 pp around the target. If a pension wants to take risk but is constrained from doing so (e.g., by statute), it will want to rebalance quickly when its actual risky share falls below target. Conversely, it should be slower to rebalance when its actual risky share is above target because it prefers to take on the extra risk. Under this logic, positive values of l_{pt} should be indicative of binding risk constraints, after accounting for fluctuations in market values.

[15] We plot and discuss the time-series properties of l_{pt} in Internet Appendix C.1.4.

We operationalize this idea using variants of the following panel regression:

$$a_{pt} = \alpha_t + \theta l_{pt} + \beta R_{pt} + \varepsilon_{pt}$$

where a_{pt} is the target alternative-to-risky share of pension p in year t and R_{pt} is the associated one-year return. The coefficient of interest in the regression is θ. The time fixed effect α_t in the regression means that θ is not identified using common time-series variation. In some cases, we also include a pension fixed effect to identify θ purely from within-pension time-series variation. All standard errors are double clustered by state and time.

Assuming l_{pt} proxies well for binding portfolio constraints, then θ should be positive if these constraints induce pensions to shift risky investments towards alternatives. Column (1) of Table 3 indicates that the opposite is true: if anything, pensions who are more risk-constrained appear to invest less in alternatives. The magnitude of the point estimate is only marginally significant and is economically small. For example, the estimated coefficient in column (1) implies that a one-standard deviation increase l_{pt} is only associated with a 1.1 decline in the alternative-to-risky share. The second column of Table 3 shows that the point estimate is similarly small and statistically insignificant once we add a pension fixed effect to the regression.

In columns (3) and (4), we compute the cross-sectional median of l_{pt} in each year t and then define an indicator for whether each pension is above or below median in year t. We replace l_{pt} in the regression with this indicator variable to account for any potential non-linearities. The point estimates in this case are estimated with relative precision but are negative and small in economic magnitude, regardless of whether we include a pension fixed effect or not.

It is natural to think that the actual risky share for risk-constrained pensions should consistently be above target, yet the proxies used in columns (1)-(4) do not reflect any such persistence. In columns (5)-(6), we therefore replace l_{pt} with its three-year moving average of l_{pt}. The estimated coefficients continue to indicate a small and negative relationship between our proxy for risk-constraints and the alternative-to-risky share. Overall, the results in Table 3 weigh against the idea that portfolio constraints are why US public pensions have shifted risky investments toward alternatives.

4.3 Simulation Evidence

One potential issue with our analysis thus far is measurement. For example, funding may not perfectly capture a pension's effective risk aversion because the link between legally mandated contributions and the funding gap may vary at the state or even local level. Such complexities would introduce measurement error into our proxies for risk aversion or binding portfolio constraints, consequently attenuating the relationship with pension investment behavior.

We address this concern via a simulation exercise. Using the model of Section 3.3, we simulate how a decline in risk aversion coupled with a binding portfolio constraint would impact pensions' portfolio composition for a wide range of beliefs that are held fixed throughout each simulation. The goal of the exercise is to see whether for a range of reasonable assumptions about the risky asset characteristics, the model is able to explain the shift towards risky-assets and the shift towards alternatives for the aggregate pension portfolio between 2001 and 2020. Let us now describe this simulation in more detail.

In 2001, we assume that the aggregate pension portfolio was unconstrained but then hits a binding constraint on fixed income in 2020. This means that the observed fixed income share in 2020 is the minimum required share ω_f^{min}. We then draw a random set of beliefs from the following uniform distributions: (i) expected excess returns on public equities, $\mu_E \sim U(0.02, 0.08)$; (ii) the variance of excess equity returns, $\sigma_E^2 \sim U(0.02, 0.09)$; (iii) risk-adjusted expected returns to alternatives relative to equities, $\alpha \sim U(0, 0.05)$; (iv) the CAPM- beta of alternatives relative to equities, $\beta \sim U(0, 1.5)$. Realized excess returns on alternatives are therefore given by:

$$r_A - r_f = \alpha + \beta(r_e - r_f) + \varepsilon_A,$$

where σ_ε^2 is the idiosyncratic variance of alternatives. Together, these parameters fully define the expected excess return and variance-covariance matrix that determine optimal asset allocation. For each parameter draw, we therefore set σ_ε^2 to match the aggregate share of alternative assets in risky portfolios $\omega_A^* = \frac{\omega_A}{\omega_A+\omega_E}$ in 2001 according to Equations (3)-(4). Finally, we select γ_1 as the risk aversion that would also match the initial overall risky share in 2001, again assuming that pensions are not constrained. These last two steps ensure that each belief set is consistent with the 2001 aggregate pension portfolio. We restrict the set of beliefs S^* to imply positive idiosyncratic variance $\sigma_\varepsilon^2 > 0$, at least $\gamma_1 \geq 1$, and $\sigma_A^2 \leq 0.25$, and draw as many random belief sets until $S^* = 100,000$.[16] Given a set of admissible initial beliefs, we then assume the portfolio becomes constrained in 2020 ($\omega_f = \omega_f^{min}$) and solve for the new risk aversion γ_2 needed to generate the $\Delta\omega_A$ in the data. Panels A and B in Table 4 summarize the simulation approach.

Panel C of Table 4 contains a breakdown of our simulation results. Most importantly, in roughly 99.5% of simulations (99,500 out of 100,000), there is *no* change in risk aversion that is able to match the observed change in the alternative share. The main reason why is simple: in 2001, public equities were a large portion of the risky portfolio. Consequently, for most beliefs that match this initial composition, the investor would want to shift towards public equities and not alternatives when she becomes constrained. There is a much smaller subset of simulations where there is no change in risk aversion that can match the observed $\Delta\omega_A$ because risk aversion would have to go implausibly below 1 in order to do so.

Panel C of Table 4 shows that only 0.5% of simulations (500 out of 100,000) can generate the observed $\Delta\omega_A$ with a decline in risk aversion. Figure 4a shows that the implied average reduction in γ is about 4.93. We then calculate the implied shadow cost of the binding leverage constraint. Recall that $M = \mathbb{E}[r_p] + \frac{1}{2}(1-\gamma)\mathbb{V}[r_p]$, i.e., the function that investors maximize. We define the shadow cost of the portfolio constraint as:

$$ShadowCost = M_{counterfactual} - M_{portfolio}, \tag{6}$$

where $M_{portfolio}$ is the value investors get in the constrained region in 2020 and $M_{counterfactual}$ is

[16] See Figure A18 in the Internet Appendix for the histograms of admissible beliefs.

the value investors get in absence the portfolio constraint. The counterfactual assumes that there is no portfolio constraint and hence the optimal risky portfolio is always the tangency portfolio. Thus, we can interpret the shadow cost as the fee that pensions would be willing to pay to relax the constraint and invest in the tangency portfolio. The unit of the shadow cost is the same as the log return. Figure 4b presents the distribution of the shadow cost across the 500 simulations in which risk aversion could feasibly generate the observed $\Delta\omega_A$. The average shadow cost across these simulations is 862 basis points, which we view as implausibly large given that asset hurdles for most public pensions are around 700 basis points. This is especially true given the simulations assume a fairly high minimum fixed income constraint of roughly 25%, the aggregate level in 2020. Taken together, our simulation evidence weighs against the ability of mechanisms relating to declines in effective risk aversion (e.g, reach-for-yield) and binding portfolio constraints to explain the increase in the alternative-to-risky share since the 2000s.

5 The Role of Beliefs

This section presents novel facts on the potential drivers of the rise in alternatives. Our preferred interpretation of this evidence is that since the early 2000s beliefs about the alpha of alternatives relative to public equities have changed. We discuss other interpretations in Section 6.2, specifically those related to agency frictions that are orthogonal to the ones considered above.

5.1 The Rise in Alternatives Among Institutional Investors

We start by documenting trends in the portfolio composition of DB pensions sponsored by US corporations and unions, UK corporations, as well as US endowments. Data for US corporate pensions is based on the corporate pension funding study by Milliman, which contains asset allocation data for the top 100 US corporate DB pensions by assets. These pensions held \$1.8 trillion of assets as of 2021. Asset allocation data for UK corporate DBs comes from the UK Pension Protection Authority and US endowment information comes from the National Association of College and University Business Officers (NACUBO). Internet Appendix A contains more background on these sources and their aggregate coverage.

Figure 5a plots the alternative-to-risky share for each institution through time, revealing a clear and common upward trend for all institutions.[17] In contrast, Figure 5b shows that there is no such common trend in the overall risky share. Despite starting at relatively similar levels in the mid-2000s, the risky share for corporate pensions in the UK and US has sharply declined, whereas it has slightly increased for US endowments and public pensions. UK pensions provide the most striking example of these diverging trends. From 2004 to 2021, their alternative-to-risky share more than tripled from 11% to 50% while their risky share more than halved from 69% to 31%.

These findings are closely related to the work of Ivashina and Lerner (2018), who document that public and private sector DB pensions have both increased their overall share of alternatives since 2008. We extend their results by showing that this trend cannot be explained by a common desire of all institutions to take on more risk and has instead largely occurred through a change in the *composition* of risky investments. Beliefs about the asset characteristics are a natural explanation for this fact, especially from the perspective of canonical portfolio choice models. For instance, it seems natural to expect that investors have updated their beliefs about the risk-reward properties of alternatives as the asset class has matured. It is also conceivable that the structural forces behind the decline in interest rates have simultaneously impacted the perceived benefits of alternatives. These types of belief-based explanations are appealing because they can account for why institutions that vary widely in governance structure, regulation, funding, and economic function (e.g, endowments vs DB pensions) have all shifted the composition of their risky investments – but not their overall risky share – in the same way.

A second explanation is that there is a common agency friction that has led all types of institutions to prefer alternatives over public equities as interest rates have fallen. The analysis in this section helps to pin down the nature of any such friction. For instance, it cannot depend on local funding nor regulation, and it cannot lead institutions to all want to increase their risky share

[17] Gabaix, Koijen, Mainardi, Oh, and Yogo (2022) document a similar rise in alternatives among ultra-rich households.

(Figure 5b). While we do not seek to rule out this type of agency-based story, beliefs offer a somewhat simpler explanation.[18] Next, we develop this argument further by studying how investment consultants shape portfolio composition.

5.2 Consultants

5.2.1 Consultant Effects

Most public pension investment boards rely on an outside consultant to provide advice on portfolio construction. The nature of advice provided by consultants can range from broad asset allocation decisions to specific portfolio manager selection. Given that our current focus is on broader asset allocation decisions, we hand-collect data on the identity of the general consultant used by each pension for each year in the PPD data. In some cases, this information can be found easily on publicly available comprehensive annual reports. When it is not available from publicly available sources, we file Freedom of Information Act requests (FOIAs) with the pensions directly, asking for the "identity of the consultant that primarily advises on broad asset allocation decisions (e.g., percent in public equities, fixed income, private equity, etc.)." These collection efforts produce a fairly high coverage rate in our sample, as we have general consultant information for about 90% of the system-year observations in the PPD data.[19]

Armed with a panel of matched consultants and pensions, we use a series of fixed-effects regressions to test whether pension portfolio structure varies systematically with consultants. Specifically, we estimate the following regression:

$$y_{pct} = \alpha_t + \sum_k \beta_t^k \times X_{pt}^k + \lambda_c + \varepsilon_{pct} \tag{7}$$

[18] A third possibility is that access to privately held firms (via limited partnerships) has improved. While these types of supply-side factors certainly play a role, they cannot explain the large cross-sectional variation in alternative usage. See Section 6.1 for a more in-depth discussion.

[19] After accounting for mergers and name changes, there 69 distinct consultants that have multiple public pension clients in a given year. Consistent with Andonov and Rauh (2020), we find that the industry is dominated by a few large players. The top ten consultants in terms of AUM account for over 90% of the pension assets and 80% of the pension systems by count.

where y_{pct} is the alternative-to-risky share for pension p matched with consultant c in fiscal year t. α_t is a time fixed effect and X^k_{pt} is the set of pension attributes whose coefficients are allowed to vary through time. The set of attributes that are included are (log) size, GASB 25 funding, asset hurdle rates, the ratio of required actuarial contributions to payroll, and the ratio of administrative expenses to payroll.

The first row of Table 5 presents the adjusted R^2 obtained from estimating the model with only time fixed effects and the second provides an additional benchmark by adding pension attributes. Consistent with our previous findings, the inclusion of pension attributes in the model leads to a mere 2 percentage point increase in explanatory power, even when their coefficients are allowed to vary through time. In contrast, the third row shows that consultant fixed effects add a considerable amount of explanatory power, as the adjusted R^2 rises by 16 pp after their inclusion. The F-statistic and associated p-value reflect this large incremental R^2 and indicate that a test of equal consultant effects is easily rejected by conventional statistical standards.

While the F-statistic offers statistical insights into the existence of consultant effects, it is less informative about magnitudes. As one way to assess economic size, Figure 6 plots the distribution of the consultant fixed effects after applying a Bayesian shrinkage to account for sampling error (Casella, 1992, Eqs. 7.11 and 7.13). The average alternative-to-risky share is added back to fixed effects to facilitate their interpretation. The plot illustrates that consultant effects are an economically important source of cross-pension variation in portfolio choice. Clients of the 5th percentile consultant have an average alternative-to-risky share of 7%, whereas clients of the 95th percentile consultant have an average share of 45%. It is important to emphasize that these estimates are orthogonal to pension attributes, most notably size and funding.

5.2.2 Interpretation

How should one interpret the existence of large consultant fixed effects? To clarify the central issues around interpretation, let $c(p)$ be the consultant for pension p and suppose that pension p's alt-to-risky share, a_p, is given by:

$$a_p = \beta r_{c(p)} + \varepsilon_p, \tag{8}$$

where $r_{c(p)}$ is consultant c's recommend share. We think of $r_{c(p)}$ as reflecting c's beliefs about the risk-return properties of alternatives relative to public equities, though it can also be thought of as arising due to agency frictions that exist at the consultancy (e.g., career concerns). ε_p represents pension p's preference for alternatives. Like with consultants, this preference could be due to beliefs or agency frictions at the pension. The coefficient β in Equation (8) represents the causal impact of consultants on client portfolios.

Define $\mathbb{E}_c[x]$ as the expectation of a random variable x conditional on consultant c. If $\mathbb{E}_c[\varepsilon_p] = \mathbb{E}[\varepsilon_p]$, then we say there is no selection because knowing the identity of a pension's consultant provides no information about its own preferences. Next, consider what the consultant fixed effects λ_c would measure in this setup. Equations (8) implies:

$$\lambda_c = \mathbb{E}_c[a_p] = \beta r_{c(p)} + \mathbb{E}_c[\varepsilon_p].$$

The variance $\mathbb{V}$ of the consultant fixed effects is given by:

$$\mathbb{V}(\lambda_c) = \beta^2 \mathbb{V}\left(r_{c(p)}\right) + \mathbb{V}\left(\mathbb{E}_c[\varepsilon_p]\right). \tag{9}$$

The F-tests of equal consultant fixed effects in Table 5 depend on whether $\mathbb{V}(\lambda_c) = 0$. If there is no selection, then $\mathbb{E}_c[\varepsilon_p] = \mathbb{E}[\varepsilon_p]$ and the second term in Equation (9) will be zero. Consequently, consultant fixed effects will arise only if consultants have a causal impact on their clients ($\beta \neq 0$). However, $\mathbb{V}(\mathbb{E}_c[\varepsilon_p]) \neq 0$ if there is selection, in which case consultant fixed effects will still appear even if consultants have no causal impact on clients ($\beta = 0$). This is the precise sense in which selection confounds the interpretation of consultant fixed effects.

This reasoning highlights two classes of explanations for the large observed consultant effects in Table 5. The first is based on agency frictions and the second is based on beliefs. To better distinguish between these two, we also study the portfolio choices of consultants' private-sector clients. Specifically, for each consultant c in year t, we compute the average alternative-to-risky and risky share of U.S. public pension clients, denoted by $\bar{a}_{c,t}^{public}$ and $\bar{r}_{c,t}^{public}$, respectively. In addition, we compute the average alternative-to-risky and risky share of U.S. private-sector defined-benefit and endowment clients, denoted by $\bar{a}_{c,t}^{private}$ and $\bar{r}_{c,t}^{private}$, respectively. Cross-sectional data on U.S. private-sector pensions comes from S&P's Money Market Directory, which we discuss in detail in Internet Appendix A.3.

Figure 7a shows a binned scatter plot of $\bar{a}_{c,t}^{public}$ versus $\bar{a}_{c,t}^{private}$, after controlling for time fixed effects. The plot shows a strong cross-sectional relationship between a consultant's public and private sector risky portfolio composition. In the cross-section, a 10 pp increase in the alternative-to-risky share of a consultant's private sector clients is associated with a 6 pp ($t = 6.60$) increase in the alternative-to-risky share of its public sector clients. Figure 7b shows the same is not true for the overall risky share, as the pass-through of private-sector to public-sector clients within each consultant is an order of magnitude smaller and statistically indistinguishable from zero.

As with our analysis of aggregate trends in Section 5.1, Figure 7 is useful because it highlights the nature of agency frictions needed to explain consultant fixed effects in Table 5. Any such friction would need to cause a subset of both public and private sector pensions to prefer alternatives over public equities, but not risky assets overall. This immediately rules out frictions that are specific to either group, such as those caused by the regulatory or accounting environment (e.g., liability discounting). Importantly, the friction must be orthogonal to pension attributes like funding or size, since we control for them when estimating consultant fixed effects in Table 5. For instance, suppose that the non-pecuniary benefits to investing in alternatives have risen over time for a subset of private and public-sector pensions, perhaps because some have come to prefer the ability of alternatives to mask risk (Couts et al., 2020; Stafford, 2022). In this case, consultant effects will be observed if consultants also vary in their belief or willingness to recommend alternatives and then match with clients accordingly.

While we cannot rule this story out entirely, a simpler explanation is that consultants vary in their belief about the risk-reward properties of alternatives and provide consistent advice across all of their clients, regardless of whether they are in the public or private sector. Rows (5)-(16) of Table 5 provide additional evidence in favor of a belief-based explanation by testing whether there are consultant effects for different types of alternatives, not just the overall alternative-to-risky share. Rows (7), (11), and (15) respectively indicate that there are also large consultant fixed effects for private equity, hedge fund, and real asset investments. It is harder for us to imagine how agency frictions could explain these results, since they would need to generate a preference for a specific type of alternative (e.g., hedge funds) that is orthogonal to pension attributes and also leads to specific consultant matching.[20] In contrast, the belief-based explanation is that simply that consultants have different beliefs about the risk-reward properties of asset classes within alternatives and advise their clients accordingly.

The preceding discussion of beliefs has implicitly assumed that consultants have a causal impact on clients ($\beta > 0$). However, it is possible that pensions also vary in their beliefs about alternatives and select consultants who share their beliefs. One way to rule in causality is to include pension fixed effects when estimating consultant fixed effects in Table 5. Rows (4), (8), (12), and (16) all show that consultant fixed effects survive the inclusion of pension fixed effects, which is clean evidence of causality if pension beliefs are time-invariant. In Internet Appendix D.1, we develop a more elaborate identification strategy based on the idea that come pension-consultant relationships are chosen based on geographical distance, as opposed to shared beliefs. This analysis suggests that consultant effects are not entirely driven by selection, though the degree of selection does appear to vary with pension size.

Taking a step back, we want to emphasize that our goal is not to settle whether consultant effects arise due to selection or causality, as both are likely to occur in reality. Regardless of whether consultants have a causal effect on clients, the evidence in Table 5 and Figure 7 makes a broader point, namely that beliefs are likely an important driver of why cross-pension variation in

[20]The private equity effects have a correlation of 14% and 19%, respectively, with the real asset and hedge fund effects. The real asset and hedge fund effects are 26% correlated. These relatively low correlations suggest some consultants are bullish about specific types of alternatives, as opposed to being uniformly bullish about all types.

the composition of risky investments loads so heavily on consultant identity. This interpretation echos the findings of Foerster et al. (2017), who find similarly large advisor effects within a sample of Canadian households. They further emphasize the role of beliefs by showing that advisors invest their own portfolios in a similar manner to their clients.

5.2.3 Evidence from Consultant-Reported Beliefs

To reinforce the importance of beliefs for understanding the rise in alternatives, we now directly study how consultants' own reported beliefs have evolved over time and in the cross-section. The data for this analysis is based on Capital Market Assumptions (CMAs) that almost every major consultancy produces each year. A typical CMA contains beliefs about expected returns, volatilities, and correlations of different asset classes.[21] Depending on the consultant, these can range from five to thirty-year forecasts. Additional details on these data can be found in Internet Appendix A.6. In terms of coverage, the consultants for whom we have CMA data manage a meaningful share of U.S. pension assets (~45%) but are limited in total count ($C = 8$).

Figure 8a plots the cross-sectional median reported alpha of alternatives relative to U.S. public equities for each year since 2001.[22] Alternatives include only real estate, private equity, and hedge funds, and alpha is computed based on asset classes that are available for each consultant-year. The perceived alpha for the median consultant has risen steadily since the early-2000s, going from 119 basis points in 2001 to 200 bps in 2020. This increase in alpha is large enough to generate the observed rise in alternatives within the baseline model from Section 3. To see this more clearly, we alter the simulation exercise from Section 4.3 by dropping the assumption that pensions face portfolio constraints and instead allowing beliefs about alternatives to change. Specifically, we use the same set $S^* = 100,000$ of random initial beliefs and risk aversion parameters from Section 4.3 that can match the aggregate pension portfolio in 2001. Within each simulation, we then solve for the increase in perceived CAPM-alpha α of alternatives relative to public equities that is needed to

[21] In recent work, Couts et al. (2023) use CMA data to study the factor structure of subjective expected returns.

[22] Alpha is computed using the expected excess return of each asset class over core fixed income and the variance-covariance matrix in the CMAs. These may not be the true beliefs of consultants and could instead reflect agency frictions (e.g., career concerns). Distinguishing between these two interpretations is beyond the scope of our paper.

match the alternative-to-risky share ω_A^* in 2020. Unsurprisingly, an increase in α can rationalize $\Delta\omega_A^*$ for all $100,000$ initial beliefs. Figure 8b shows how the implied increase in α varies across simulations. We winsorize the distribution at the 98th percentile to make the plot more readable. The average required increase in α across simulations is 90 bps and is strikingly close to the actual consultant-reported increase in alpha of roughly 80 bps shown in Figure 8a.[23]

Next, we study the cross-sectional relationship between consultant beliefs and the composition of client portfolios. Figure 8c depicts this relationship through a binscatter plot of each pension's alternative-to-risky share in year t against its consultant's reported belief about the alpha of alternatives in the same year, after controlling for year fixed effects, funding, (log) size, and hurdle rate. The binscatter also displays the associated regression line and coefficient, with standard errors clustered by consultant to account for alphas are repeated within each consultant-year cell and by pension to account for persistence in portfolio weights.

Figure 8c clearly shows a strong and positive relationship between a consultant's reported beliefs about the alpha and the alternative-to-risky share of its U.S. public pension clients. Importantly, the correlation survives even after we control for each pension's overall risky share, indicating that the composition of risky investments (and not its overall level) lines up with consultant beliefs about the alpha of alternatives relative to public markets.[24] As an even more stringent test, we leverage the fact that beliefs about specific subcategories of alternatives are observed for each consultant. Namely, we run the following panel regression:

$$\widetilde{w}_{p,a,t} = f_{p,t} + \beta V_{c(p),a,t} + \varepsilon_{p,a,t} \tag{10}$$

where $\widetilde{w}_{p,a,t}$ is the weight (relative to risky assets) of pension p in alternative type a at time t and $V_{c(p),a,t,}$ is the contemporaneous alpha of a reported by their consultant $c(p)$. $f_{p,t}$ in the regression is a pension-by-time fixed effect. Standard errors in the regression are again double-clustered by

[23]Internet Appendix D.2 shows that a shift of this size could also generate the increase in the aggregate risky share.

[24]The estimated slope falls slightly to 5.63 and has a t-statistic of 7.92. In addition, the regression estimates embedded in Figure 8c remain statistically significant after residualizing all variables to time fixed effects and pension attributes, then running the regression using data collapsed to the consultant-year level.

consultant and pension.

Figure 8d visualizes regression (10) using a binned scatter plot of $\widetilde{w}_{p,a,t}$ against $V_{c(p),a,t}$, after absorbing a pension-by-time fixed effect. Subcategories of alternatives in the plot are either hedge funds or private-markets (private equity, real assets, and private credit). The estimated coefficient equals 2.41 (t =4.50) and indicates that pensions tend to allocate more toward a specific type of alternative when their consultant reports it as having a high alpha. The within-R^2 further shows that 35% of within-pension variation in the composition of alternative investments is explained by consultant-reported alphas.

It is difficult to imagine an explanation for Figure 8d that does not involve pension beliefs, whether through the casual influence of consultants or through matching based on shared beliefs. The reason why is the pension-by-time fixed effect $f_{p,t}$ absorbs any characteristic that leads pensions to prefer alternatives at a given point in time, including those related to agency frictions. It could still be the case that some pensions have stronger agency incentives to invest in private markets, perhaps due to their ability to hide risk (Stafford, 2022). These pensions would also need to select consultants who report that private markets have higher relative alpha. One way to control for this potential channel is to run regression (10) only for private equity and real assets, both of which offer a similar ability to hide risk. The estimated coefficient in this case is still large, positive, and statistically significant (β =1.16, t =3.78). These patterns therefore strongly suggest that beliefs play a critical role in generating cross-pension variation in the use of alternatives.

5.3 Peer Effects

Next, we investigate whether pension portfolio decisions can be explained by the behavior of peers. This line of inquiry is motivated by recent research in household finance showing that beliefs about asset prices and product selection are shaped by social networks (Bailey et al., 2018, 2022). We define peer networks in our context based on geographical distance. More formally, for each pension p in year t, we define the target alternative-to-risky share of peers as follows:

$$n_{pt} = \sum_{k \neq p} w_{pk} a_{kt}$$

with $w_{pk} = \frac{d_{pkt}^{-1}}{\sum_{j \neq p} d_{pjt}^{-1}}$. a_{kt} is the target share of alternatives for pension k and d_{pkt} is the distance (in kilometers) between the headquarters of pension p and pension k in year t. We measure distance using the 5-digit zipcodes of each pension in our sample.[25] The weights w_{pk} are therefore based on the inverse distance between pension systems.

We then measure the degree of peer effects using variants of the following panel regression:

$$a_{pt} = \alpha_{cdt} + \beta_z n_{pt} + \theta' \mathbf{X}_{pt} + \varepsilon_{pt}, \tag{11}$$

where α_{cdt} is a consultant-by-time-by-census-division fixed effect and $\mathbf{X}_{pt}$ is a vector of pension observables that includes each pension's GASB 25 funding ratio, asset hurdle rate, log size, required actuarial contribution relative to payroll, and administrative expenses relative to payroll. The fixed effect α_{cdt} is included for two reasons. First, if peers are more likely to choose the same consultant, then β_z will overstate impact of peers because it will also reflect consultant effects (Section 5.2.1). Second, a common issue in the peer effects literature is separating the impact of peers from common shocks that may affect portfolio choice (Angrist, 2014). For example, pensions who are close in distance may allocate similarly because they face similar local economic conditions. The inclusion of the fixed effect controls for both potential confounding factors and means that β_z is identified from variation with the same consultant, census division, and year. Standard errors in the regression are clustered by state and time.

Column (1) of Table 6 reports our baseline estimate of the regression specification in (11). The point estimate is estimated with statistical precision and indicates a fairly large pass-through of peer portfolio choices. On average, a 10 pp increase in the alternative-to-risky of a pension's peers is associated with a 6.8 pp increase in its own alternative-to-risky share. This elasticity further

[25] For pension systems located in the same zipcode, we assume they are 1.6 kilometers (1 mile) apart.

suggests that the composition of risky investments is far better explained by peer behavior than by a pension's own funding level, hurdle rate, or the other reach-for-yield proxies considered in Tables 2 and 3.

There are at least two possible interpretations of this finding. The first is that pensions learn about the risk-reward tradeoff of alternatives from pensions who are geographically close. There are several ways this type of learning could occur,. For example, it seems plausible that the investment staff and chief investment officers (CIOs) of nearby pensions are more likely to interact with each other, perhaps by attending the same investment conferences or workshops. Another interpretation is based on the herding model of Scharfstein and Stein (1990), whereby pensions herd with their nearby peers to avoid public backlash for contrarian behavior. In reality, both channels are likely present in the data. However, given our focus on beliefs, in columns (2)-(4) we provide suggestive evidence for the first channel by testing whether peer effects are still present in subsets of the data where herding incentives are likely weaker.

In column (2), we develop a test based on the idea that CIOs with more job security have less of an incentive to herd. We measure job security by first computing CIO tenure for each pension-year observation in our sample. CIO identities are taken from Lu et al. (ming) and are only available for a subset of pensions from 2001 onward. This means that we cannot perfectly measure tenure for CIOs who began prior to 2001. As one way to get around this issue, we create an indicator variable based on whether CIO tenure is at least five years and only estimate regression (11) using data after 2005. The cutoff of five is roughly the median tenure in the post-2005 data. This indicator variable should capture CIOs who are relatively "established", even if we cannot perfectly measure their tenure. When estimating regression (11), we then interact the indicator variable with the alternative-to-risky share of each pension's peer and include it (along with the indicator itself) in the regression. The positive interaction term in column (2) suggests that, if anything, peer effects are stronger for established CIOs, however the estimate is not statistically different from zero.

In column (3), we instead create an indicator variable for whether a pension is well-funded, defined as being in the top quartile of GASB 25 funding over our full sample. In practice, this means we only include pensions whose GASB 25 funding is above 89%. The assumption in this test is that well-funded pensions are under less public scrutiny and therefore have less incentive to herd. The negative interaction term in column (3) is consistent with this assumption, but nonetheless implies that well-funded pensions are responsive to their peers.

Finally, in column (4), we create an indicator variable based on whether a pension is in top quintile of overall performance. Similar to column (3), the idea is that high performing pensions have less negative public scrutiny and should therefore be less inclined to herd as in Scharfstein and Stein (1990). The negative interaction term in column (3) suggests that this may be the case, but much like our previous results, we continue to find an economically and statistically meaningful peer pass-through coefficients for this subgroup of pensions.

For robustness, in column (5) we replace the contemporaneous alternative-to-risky share of peers with its lagged value. Though imperfect, this is one way to allay fears that the regression coefficients are driven by reverse causality. The point estimate in column (5) is similar in magnitude to that in column (1) and remains statistically significant. We therefore interpret the findings in Table 6 as evidence that peers likely have some influence on pension beliefs about the risk and return of alternatives. These results also support our broader argument that beliefs have played a large role in the rise in alternatives, especially in light of the fixed effects and controls used in Table 6.

5.4 Experience

Thus far, our analysis in this section has highlighted the importance of beliefs for understanding cross-pension differences in alternative investment intensity, with a specific focus on the role of consultants and peers in shaping beliefs. Beliefs are also often shaped by experience. For example, Malmendier and Nagel (2016) show how individual inflation expectations are strongly influenced by the amount of realized inflation experienced during one's lifetime. Andonov and Rauh (2021) show public pension return expectations are influenced by past returns. Motivated by this work, we now provide suggestive evidence that investment experience during the 1990s shaped the subsequent evolution of beliefs about the risk-reward benefits of alternatives.

Figure 9a plots the change the alternative-to-risky share for each pension between 2002 and 2021 (Δa_p) against its geometric average return from 1992-2002 (e_p). The sample size for the plot is lower than our main analysis sample because many pensions do not report 10-year returns on their annual reports and we generally do not have annual reports prior to the 2000s. With that said, the 37 pension systems in the plot are fairly large and cover 49% of PPD assets in 2002. The figure clearly shows that the pensions who had low performance during the 1990s were also more likely to shift to alternatives after the 2000s. Experience alone can explain 20.6% of the cross-sectional variation in the change in alternatives. As a point of comparison, we observed R^2s of less than 5% in Table 2 when explaining Δa_p with contemporaneous changes in funding and other reach-for-yield proxies.

Our preferred interpretation of Figure 1 is as follows: many U.S. pensions rapidly increased their overall risky share during the 1990s (see Panel b of the figure), primarily through an increase in public equities.[26] Public markets during the 1990s famously went through a large boom and bust cycle that culminated with the bursting of the dot-com bubble in 2000. Pensions who were late to shift into equities were therefore more exposed to the bursting of the bubble relative to pensions who invested earlier, resulting in lower relative returns for the period between 1992 and 2002. The poor experience then caused these pensions to view alternatives as more favorable relative to public equities on a risk-return basis, thereby explaining why they shifted more aggressively towards alternatives after the 2000s.

A different interpretation of Figure 9a is that poor performance in the 1990s led to a decline in funding and thus a desire to reach-for-yield via alternatives. However, there are a few reasons why we do not think this is the case. Most importantly, the level of GASB 25 funding in 2002 does not predict the change in the alternative-to-risky share from 2002 to 2021 (see Internet Appendix C.1.2). Moreover, we obtain a similarly strong relationship between Δa_p and e_p even after

[26]Based on aggregate data from the ASPP, virtually every dollar that left fixed income during the 1990s went into public equities.

controlling for the level of GASB 25 funding in 2002. For instance, the point estimate of a linear regression of Δa_p on e_p moves from -6.3 (t = -3.0) to -7.0 (t = -3.1) after controlling for the level of 2002 funding, whereas the coefficient on funding is not statistically different from zero.

Interesting, Figure 9b shows performance between 1992 to 2002 also predicts the change in the overall risky share between 2002 and 2021 (Δr_p). However, the predictive relationship is weaker compared to the alternative-to-risky share. The estimated coefficient of β = -3.9 (t = -2.3) is smaller and so is the R^2 (13.1 vs 20.6%). These facts are consistent with a story in which relatively poor performance in the 1990s led some pensions to want more portfolio risk, but not because they were underfunded. For instance, poorly performing pension managers may get disutility from lagging behind their peers. These pensions then favored alternatives over public equities due to the bursting of the dot-com bubble.

Overall, Figures 9a and 9b point to experience during the 1990s playing a meaningful role in the subsequent rise in alternatives through its impact on beliefs. With that said, we view the evidence in Figure 9 as more suggestive in nature given the lack of complete data.

6 Discussion and Conclusion

6.1 Supply-Side Explanations

Thus far, we have exclusively considered demand-based explanations for the rise in alternatives, though supply-side factors are also potentially important. For example, the development of the private equity industry over the last thirty years has arguably made it easier for institutional investors to take equity stakes in firms that are not publicly listed. This implies that the portfolio trends observed in U.S. public pensions might be a passive reflection of this technological change. Figure 10 provides one way to assess this mechanism by showing how the global supply of alternative assets has evolved relative to all risky assets since 2000. The supply of alternatives is defined as the net asset value of all private-market funds based on data from Preqin and the global AUM of hedge funds from the Hedge Fund Research database. Risky assets equal the supply of alternatives plus the worldwide market capitalization of all publicly traded firms according to the World Bank. The plot shows that the global alternative-to-risky share rose from 2% in 2000 to just over 8% in 2020. Though this increase is consistent with supply playing a role in the rise of alternatives, it is important to note that supply-based explanations cannot account for the wide cross-sectional heterogeneity in the adoption of alternatives across U.S. public pensions (Section 2.2.3).[27]

6.2 Conclusion

Since the early 2000s, there has been a notable shift in the investment strategies of public pensions in the United States, with a significant emphasis on alternative investments such as private equity, real estate, and hedge funds. The conventional explanations for this trend, including underfunding, portfolio constraints, and the need to meet nominal return targets, only offer limited support according to our findings. Instead, we propose an alternative perspective based on beliefs, which suggests that pensions increasingly perceive alternative investments to provide a more favorable risk-return profile when compared to public equities. This belief-based perspective helps explain the long-term increase in the alternative-to-risky share among US public pensions and the variation observed across different pensions. While our research provides some insight into the formation of these beliefs, future research is needed to analyze whether these beliefs about alternative assets are rational. This question is critical for assessing the welfare implications of alternatives for pension beneficiaries, especially given the costs and complexity of investing in this asset class (Metrick and Yasuda, 2010; Phalippou et al., 2018; Begenau and Siriwardane, 2022).

[27] In addition, Figure 10 indicates that the rotation by U.S. pension towards alternatives has far outpaced global supply, resulting in a portfolio that heavily overweights alternatives relative to public markets.

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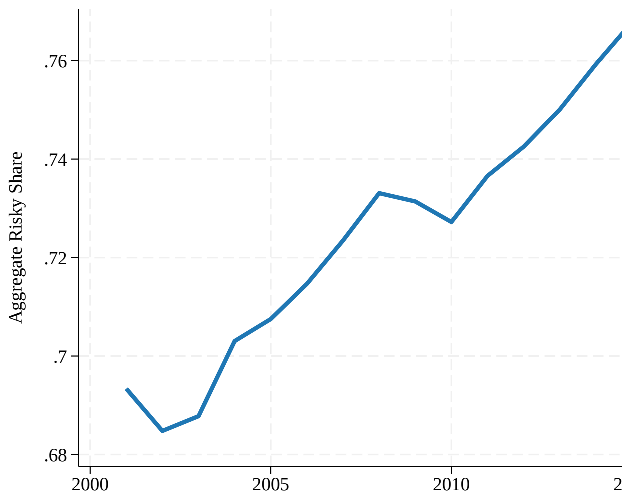
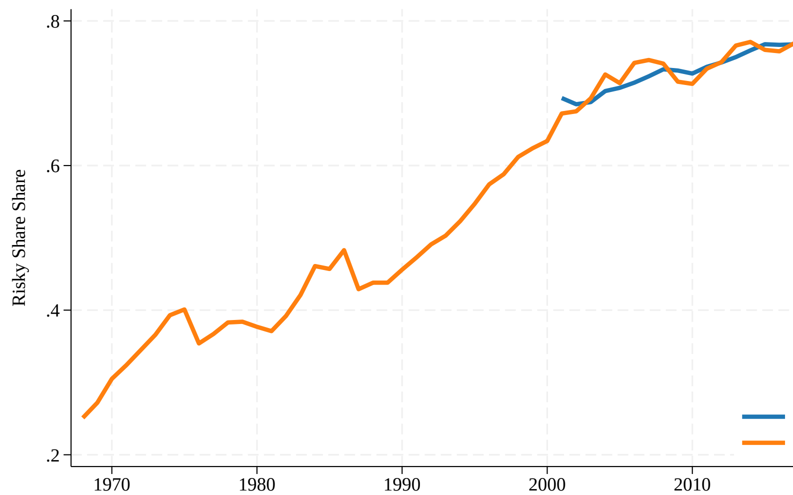
Figure 1: The Risky Share

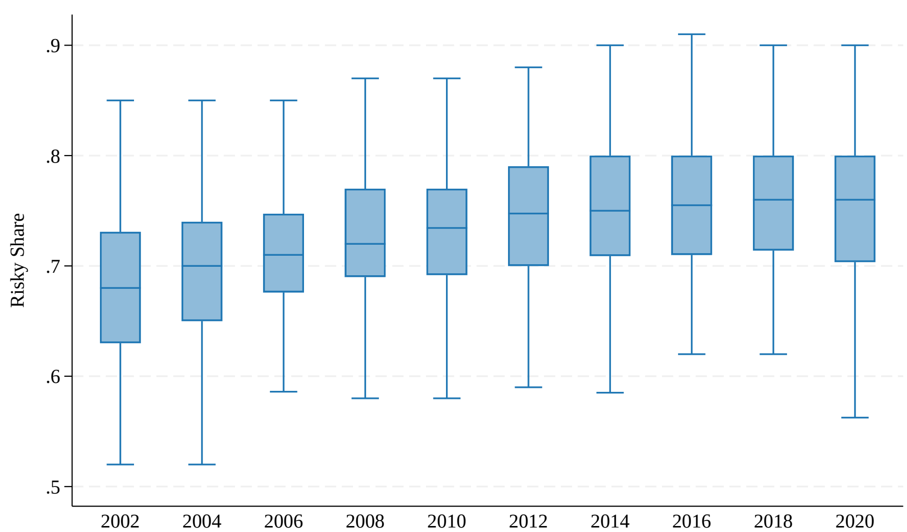
(a) Aggregate, Post-2000



(b) Aggregate, Post-1968

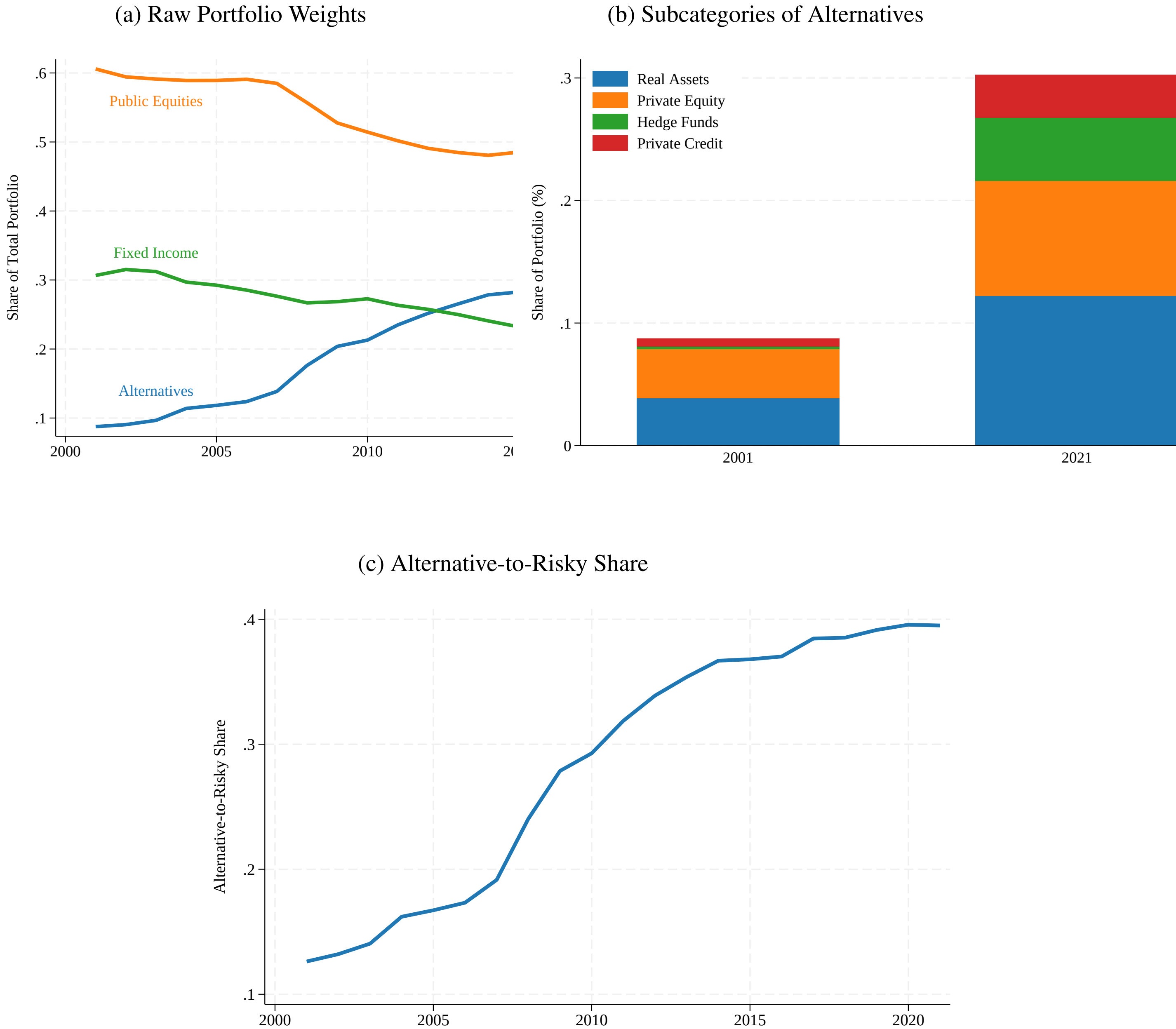


(c) Cross-Sectional Distribution



Notes: Panel (a) plots the risky share based on data from the PPD, where the risky share is defined as any holding outside of fixed income and cash. Panel (b) adds a longer-history of the risky share using data from the U.S. Census Bureau's Quarterly Survey of Public Pensions (QSPP). The risky share in the QSPP similarly excludes fixed income and cash. Panel (c) visualizes the cross-section of the risky share using the PPD data. See Section 2 for complete details.

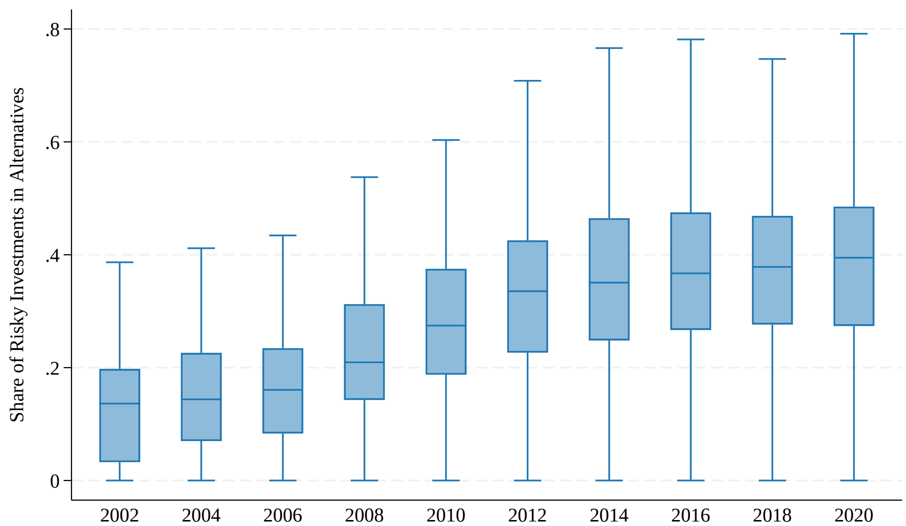
Figure 2: The Composition of the Aggregate Risky Portfolio



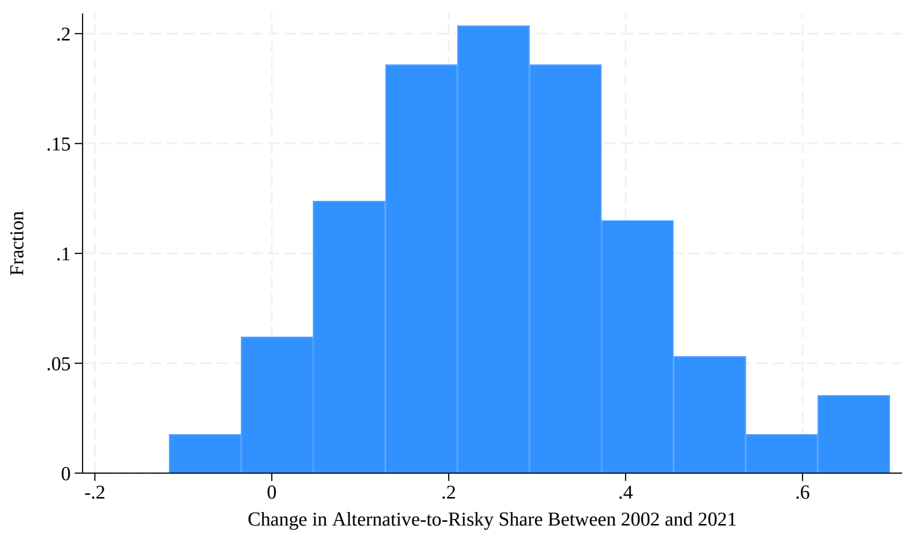
Notes: Panel A of the figure plots the target share of public equities, alternatives, and fixed income (including cash) for the aggregate U.S. public pension portfolio. Panel B shows the aggregate portfolio shares of different categories of alternatives for 2001 and 2021. Panel C plots the share of alternatives in the risky portfolio. All data is based on the PPD. Risky investments are defined as any holding outside of fixed income and cash.

Figure 3: Alternative-to-Risky Share in the Cross Section of Pensions

(a) Distribution of the level through time



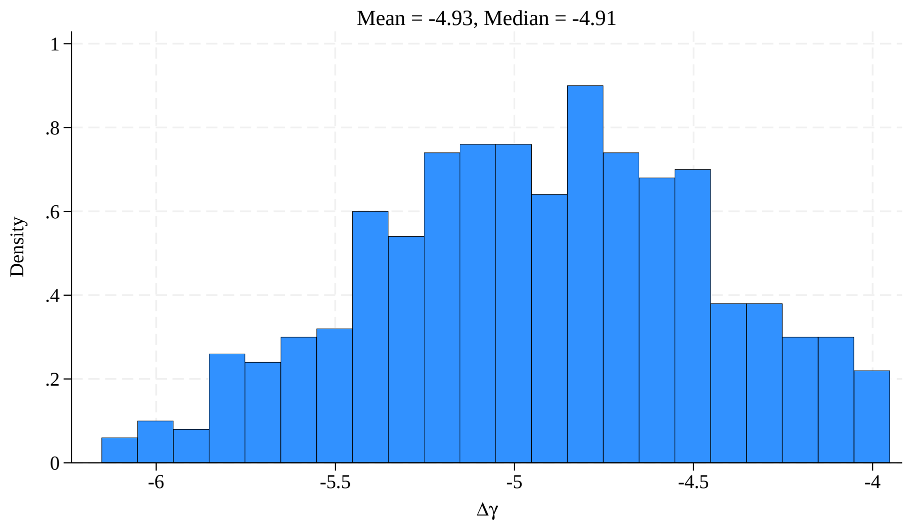
(b) Change from 2002 and 2021



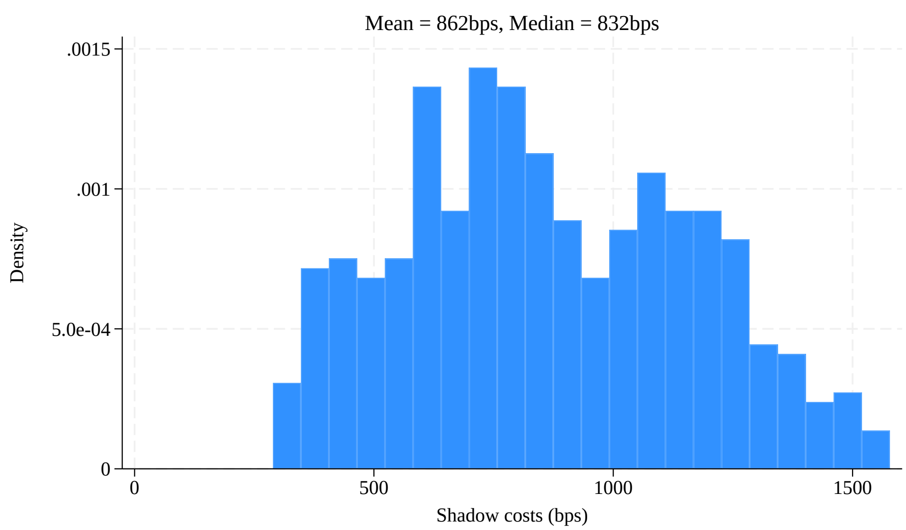
Notes: Panel A of the figure depicts the distribution of the alternative-to-risky share across pension systems through time. Each box plot summarizes the distribution for the corresponding year on the *x*-axis. Only even years are plotted to make the graph more readable. Panel B plots the distribution of the change in alternative-to-risky share across U.S. pension systems between 2002 and 2021. All data is from the PPD.

Figure 4: Simulating a Decline in Risk Aversion Plus Binding Portfolio Constraints

(a) Implied Change in Risk Aversion



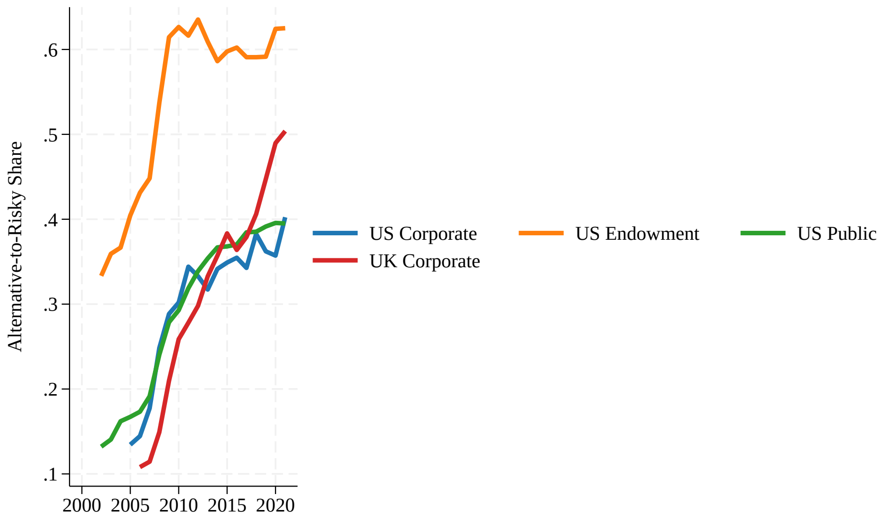
(b) Implied Shadow Cost



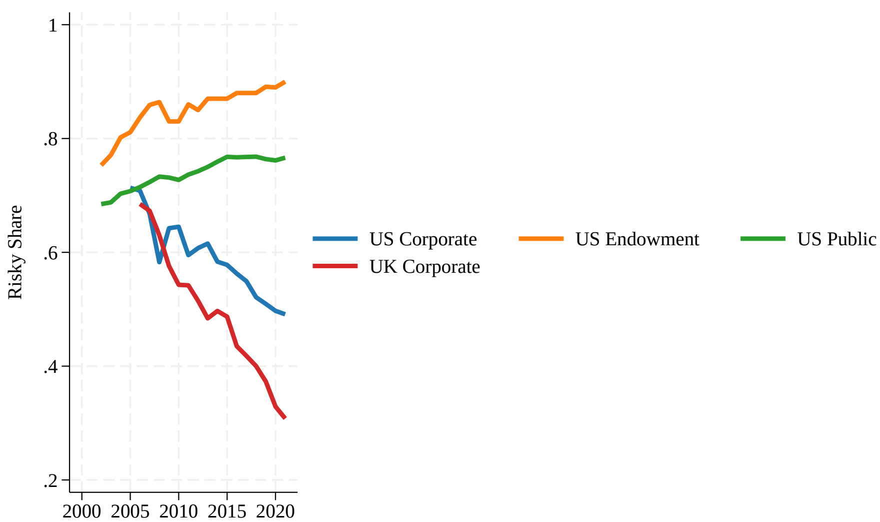
Notes: This figure shows simulation results based on the model in Section 3.3, in which pensions face a minimum constraint on fixed income investment. Panel A of the figure shows how the change in risk aversion required to match portfolio weights in 2001 and 2020 varies across simulations of initial beliefs in 2001. Panel B shows the distribution of the implied shadow cost of the portfolio constraint, expressed in units of returns. The simulations in this figure target aggregate portfolio weights, assume that the aggregate pension portfolio faced a minimum constraint on fixed income that became binding in 2020, and hold initial beliefs in 2001 constant. Out of 100,000 initial simulations that match the initial portfolio weights with reasonable initial beliefs in 2001, the plots in this figure show the 500 simulations in which a decline in risk aversion would explain the aggregate portfolio shifts. In 99.5% of the simulations, no change in risk aversion rationalizes the portfolio weights in 2020. See Section 4.3 for details.

Figure 5: Portfolio Behavior Across Institutions

(a) Alternative-to-Risky Share

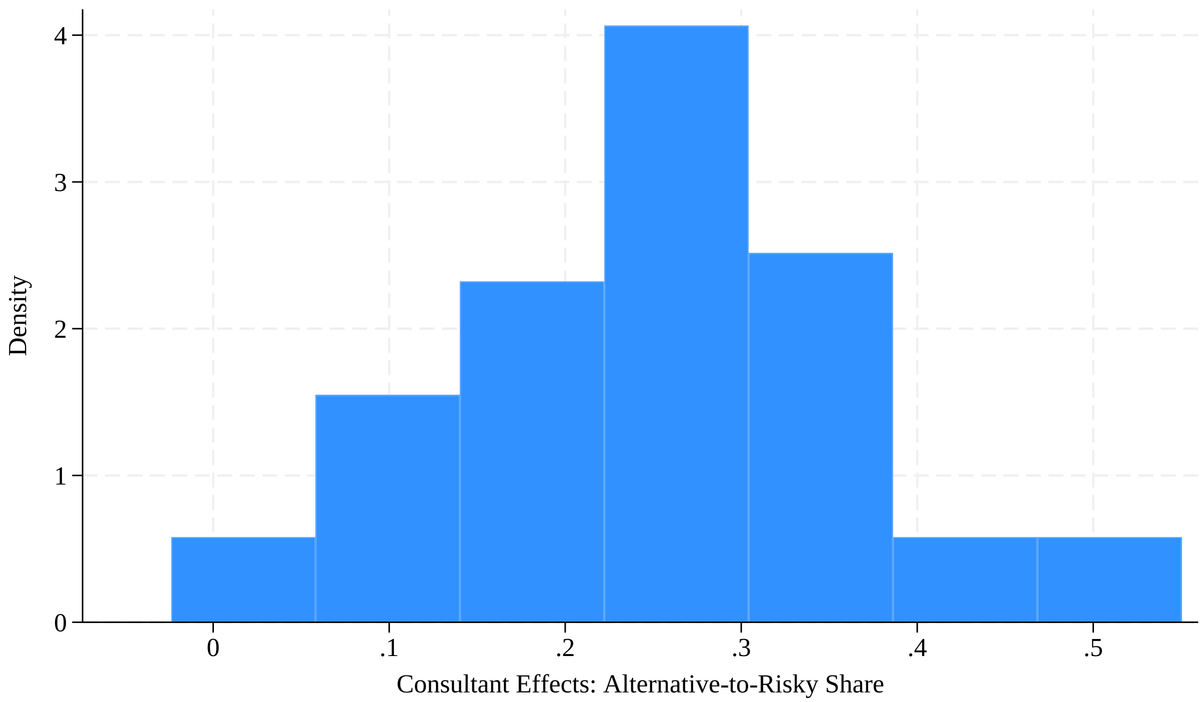


(b) Risky Share



Notes: Panels (a) and (b) of the panel plot the alternative-to-risky and risky shares, respectively, of different institutions through time. Endowment data is from NACUBO historical endowment studies, UK corporate defined-benefit pension data is from the UK Pension Protection Authority, and US corporate pension data is from the Milliman Corporate 100 report. See Section 5.1 and Section A of the Internet Appendix for more details on the data.

Figure 6: Consultant Fixed Effects



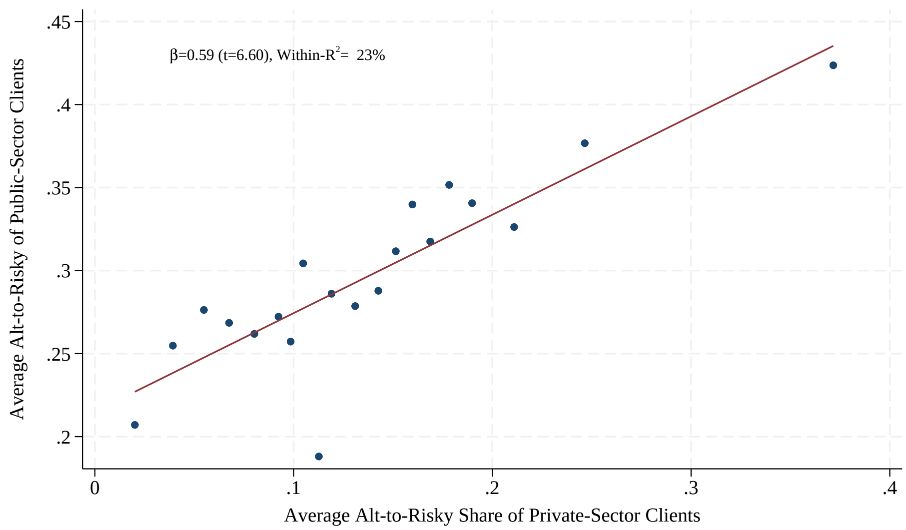
Notes: This figure shows the distribution of estimated consultant effect λ_c's from the following regression:

$$a_{pct} = \alpha_t + \sum_k \beta_t^k \times X_{pt}^k + \lambda_c + \varepsilon_{pct}$$

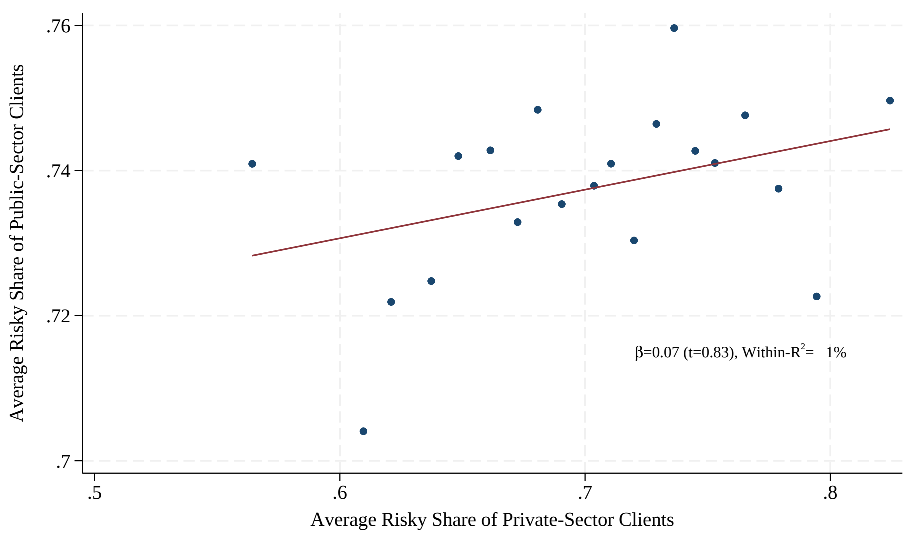
where a_{pct} is the alternative-to-risky share for pension p matched with consultant c in fiscal year t. α_t is a time fixed effect and X_{pt}^k is the set of covariates including (log) size, GASB 25 funding, asset hurdle rates, the ratio of required actuarial contributions to payroll, and the ratio of administrative expenses to payroll. The estimated consultant fixed effects are then shrunk towards their mean using an empirical Bayes estimate (Casella, 1992) to account for sampling error.

Figure 7: U.S. Public vs Private-Sector Clients by Consultant

(a) Alternative-to-Risky Share

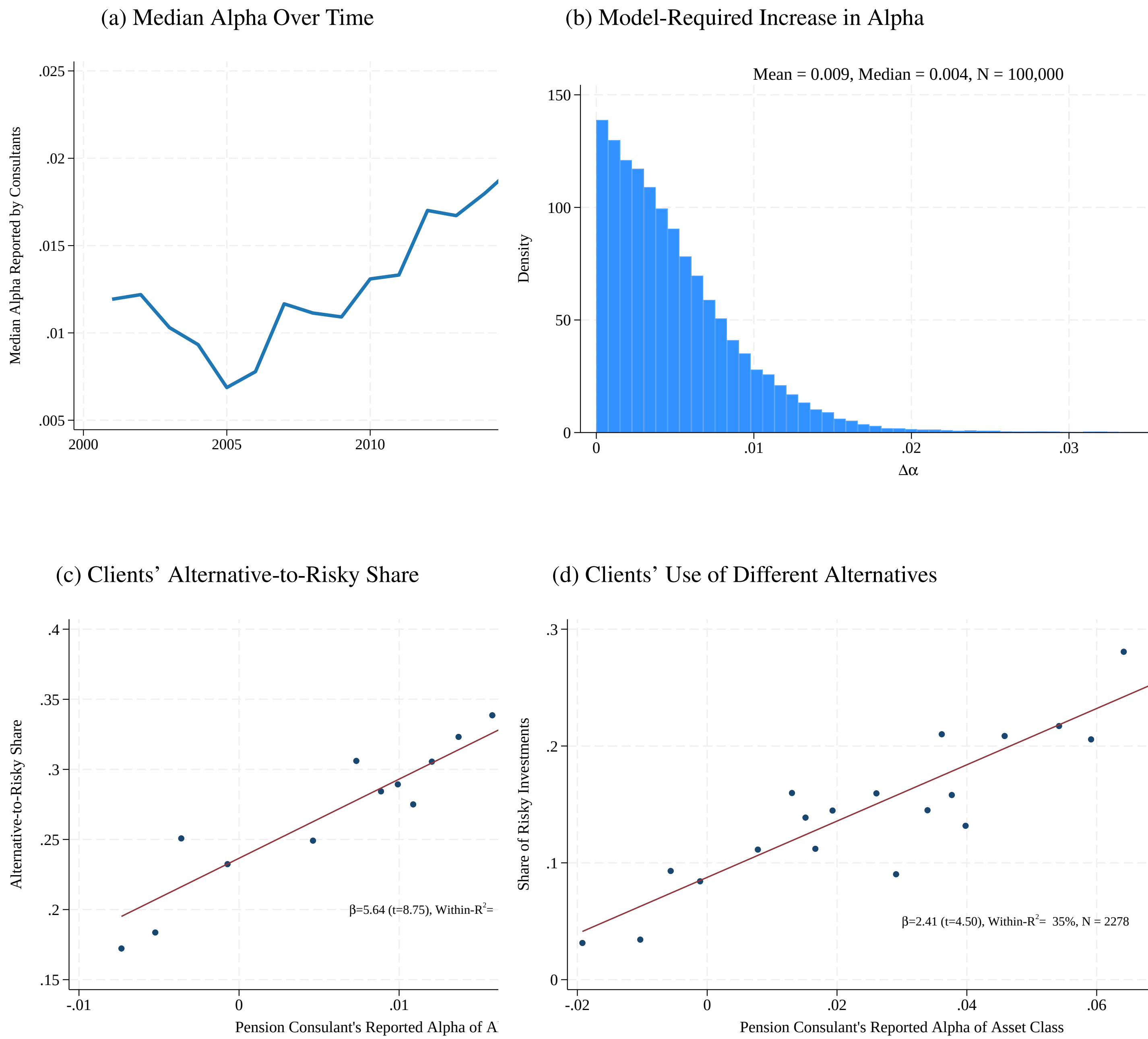


(b) Risky Share



Notes: For each consultant c in year t, we compute the average alternative-to-risky and risky share of U.S. public pension clients, denoted by $\bar{a}_{c,t}^{public}$ and $\bar{r}_{c,t}^{public}$, respectively. In addition, we compute the average alternative-to-risky and risky share of U.S. private-sector defined-benefit and endowment clients, denoted by $\bar{a}_{c,t}^{private}$ and $\bar{r}_{c,t}^{private}$, respectively. Panel (a) is a binscatter of $\bar{a}_{c,t}^{public}$ against $\bar{a}_{c,t}^{private}$ and panel (b) is a binscatter of $\bar{r}_{c,t}^{public}$ against $\bar{r}_{c,t}^{private}$. Both binscatters absorb a year fixed effect. The standard errors reported in each plot are for the regression line and are clustered by consultant. Consultants must have at least five private-sector clients to be included in the plot. Public sector allocations are based on the PPD and private-sector allocations are based on S&P's Money Market Directory. See Internet Appendix A for more details on the data.

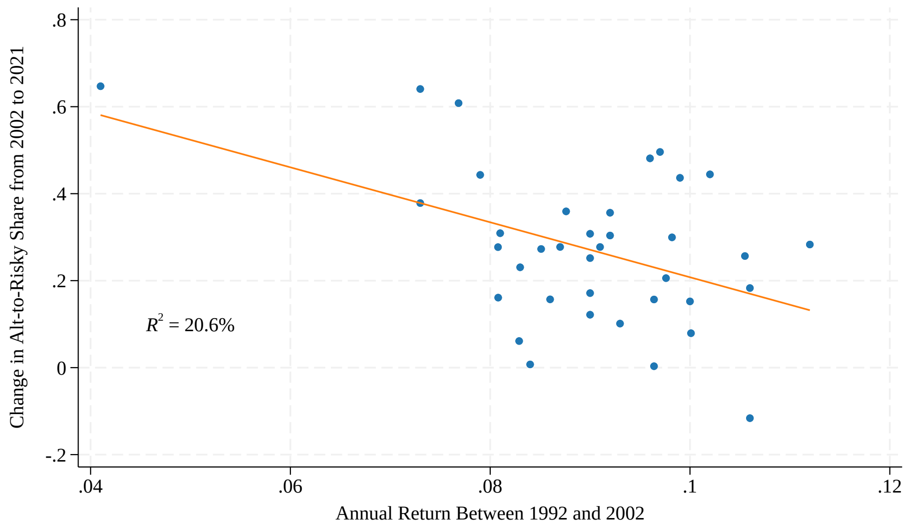
Figure 8: Consultant's Reported Beliefs about the Alpha of Alternatives



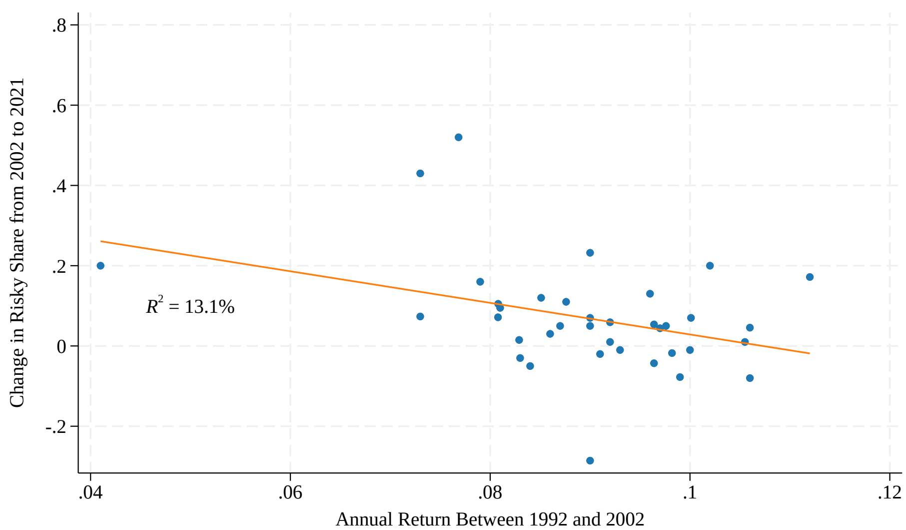
Notes: Each year in Panel (a) shows the median perceived alpha of alternatives relative to large-cap US equities across consultants. The data for the plot is based on hand-collected capital market assumption (CMA) reports that were obtained under confidentiality agreements. Panel (b) shows the required change in alpha needed to generate the observed rise in the alternative-to-risky share across simulations of the model in Section 3. We assume the same initial sets of beliefs as used in Section 4.3 that match the initial portfolio weights in 2001, and then calculate the change in CAPM $-\alpha$ required to match the change in the aggregate alternative-to-risky share in 2020. Panel (c) is a binscatter of each pension's alternative-to-risky share against its consultant's reported alpha, after controlling for year fixed effects, funding status, log(size), and hurdle rates. Panel (d) is a binscatter of each pension's allocation of risky investments to subcategories of alternatives (hedge funds vs private assets) against its consultant's reported alpha in each subcategory, after controlling for a pension-by-time fixed effect. The reported t-statistic in panels (c) and (d) are based on standard errors that are clustered by consultant and pension. See Sections 4.3 and 5.2.3 for details.

Figure 9: Experience in the 1990s and the Rise in Alternatives

(a) Alternative-to-Risky Share

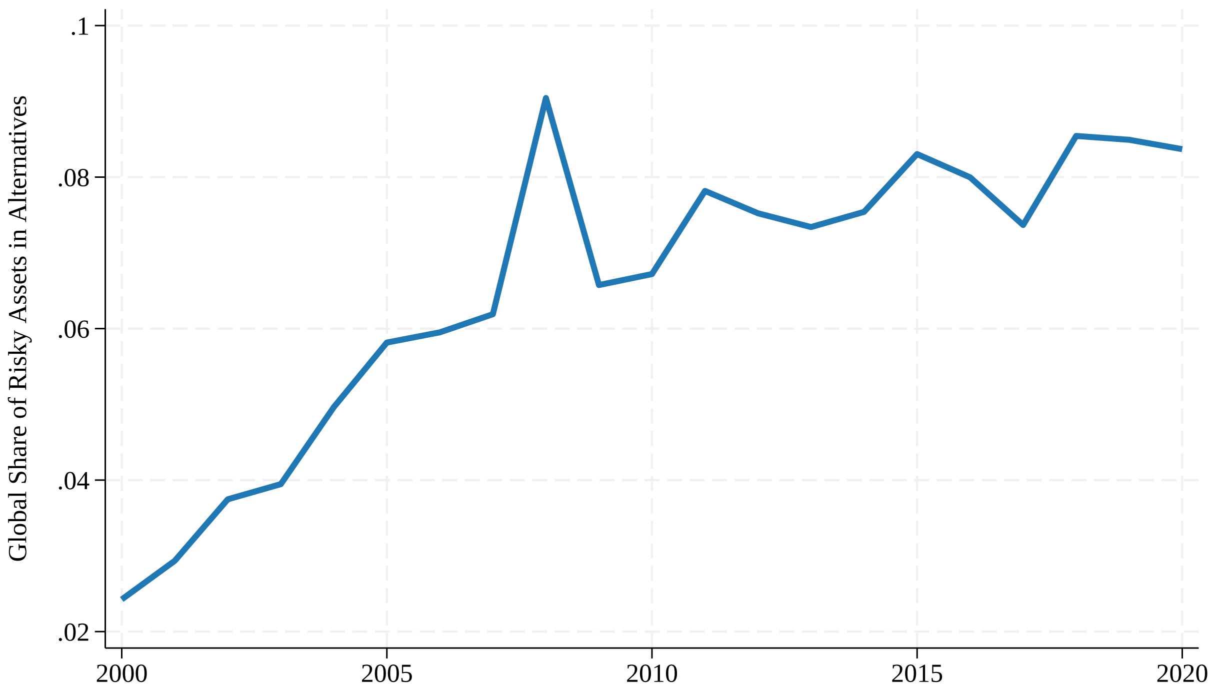


(b) Risky Share



Notes: Panel A of this figure plots each pension's change in the alternative-to-risky share between 2002 and 2021 against its geometric average return between 1992 and 2002. Panel B instead plots the change in the risky share between 2002 and 2021 against the geometric average return between 1992 and 2002. The sample size is lower for this plot because not all pensions report 10-year returns on their annual reports and we do not have a complete panel of annual reports prior from 1992 to 2002.

Figure 10: The Supply of Alternatives



Notes: This figure shows the global supply of alternatives relative to all risky assets. The global stock of alternatives equals the total net asset value of all private-capital funds from Preqin plus the AUM of global hedge funds from Hedge Fund Research. The total stock of risky assets equals the stock of alternatives plus the market capitalization of all global public stock markets from the World Bank.

Table 1: National Summary Statistics

	Subsample			
	2001-2005	2006-2010	2011-2015	2016-2021
Number of Systems	157	180	190	194
Members (mm)	21	24	25	27
Percent Retired	28	31	35	37
AUM ($ bn)	2,101	2,623	3,140	4,020
GASB 25 Funding (%)	91	81	73	72
Assumed Asset Return (%)	8.0	7.9	7.6	7.2
Annual Investment Return (%)	5.2	6.2	9.1	10.0
National Coverage (%)				
Public DB Pensions	86	90	91	91
All Private and Public Pensions	24	25	23	22
Portfolio Composition (%)				
Fixed Income	30	27	25	23
Public Equities	59	55	49	47
Alternatives	11	18	27	30

Notes: This table provides national-level summary statistics for defined benefit public pensions in the United States from 2001 to 2021. Individual pension plans are aggregated to pension systems when the assets of multiple plans are legally pooled and managed together. GASB 25 funding is defined as the ratio of actuarial assets to liabilities, where liabilities are computed by discounting future promised benefits using each plan's assumed long-run rate of return on assets. The row listed below *National Coverage* reports the average annual ratio of assets in PPD to defined benefit pension assets listed in the U.S. Census Bureau's Annual Survey of Public Pensions and total public and private-sector pension assets listed in the Flow of Funds. The rows listed below *Portfolio Composition* show the percent of the aggregate public pension portfolio that is invested in fixed income (including cash), public equities, and alternatives. Alternatives encompasses investments in hedge funds, private equity, private debt, and real assets (e.g., real estate private equity). Data is based primarily on the Public Plans Database (PPD) that is maintained by the Center for Retirement Research at Boston College.

Table 2: Funding-Based Explanations for the Rise in Alternatives

	ΔAlternative-to-Risky Share			
	(1)	(2)	(3)	(4)
Δ GASB 25 Funding Ratio	-0.19*			
	(-1.87)			
Δ BEA-Adjusted Funding Ratio		0.02		
		(0.06)		
Δ Liability Discount Rate			-1.97	
			(-0.49)	
Δ Fraction of Retired Members				0.18
				(1.09)
Aggregation	System	State	System	System
Total R^2	0.04	0.00	0.00	0.01
N	116	47	115	116

Notes: This table shows regressions of changes in the alternative-to-risky share on contemporaneous changes in several covariates. Risky investments are any holdings outside of fixed income and cash. Alternatives encompass investments in hedge funds, private equity, private debt, and real assets (e.g., real estate private equity). GASB 25 funding ratios are based on liabilities that equal future promised benefits discounted at the assumed long-term rate of return for each plan. BEA-adjusted funding ratios instead discount future benefits using AAA-rated corporate borrowing rates. The liability discount rate is the one used for computing GASB 25 funding ratios and is also the system's return hurdle rate. The row labeled aggregation specifies whether the regression is run at the system or state level. All changes are computed between 2002 and 2021. Standard errors are clustered by state for regressions run at the system level and are robust for regressions run at the state level. t-statistics are listed below point estimates. ** indicates a p-value of 0.05 and * indicates a p-value of 0.10. See Section 2.1 for how we filter the data.

Table 3: Leverage Constraints and the Rise in Alternatives

	Alternative-to-Risky Share					
	(1)	(2)	(3)	(4)	(5)	(6)
Actual-Minus-Target Risky Share	-0.22	-0.26*				
	(-1.54)	(-1.99)				
Above-Median Actual-Minus-Target Risky Share			-0.02**	-0.01**		
			(-3.25)	(-2.71)		
Actual-Minus-Target, MA3					-0.31*	-0.39**
					(-1.83)	(-2.15)
One-Year Return	-0.06	-0.05**	-0.05	-0.05**	-0.08	-0.07**
	(-1.43)	(-3.14)	(-1.23)	(-4.15)	(-1.70)	(-4.53)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Pension Fixed Effect		Yes		Yes		Yes
Within-R^2	0.01	0.02	0.01	0.01	0.01	0.02
Total R^2	0.32	0.77	0.33	0.76	0.33	0.77
N	2,961	2,961	2,961	2,961	2,961	2,961

Notes: This table shows a panel regression of the alternative-to-risky share on different proxies for the tightness of leverage constraints. In columns (1)-(2), the proxy is defined as the difference l_{pt} between the actual and target risky share for pension p in year t. In columns (3)-(4), we first compute the median $\bar{l}_t$ across all pensions in year t. The proxy is then an indicator for whether $l_{pt} > \bar{l}_t$. In columns (5)-(6), the proxy is defined as the moving three-year average of l_{pt}, inclusive of year t. Risky investments are defined as any holdings outside of fixed income and cash. Alternatives encompass investments in hedge funds, private equity, private debt, and real assets (e.g., real estate private equity). All regressions control for the contemporaneous 1-year portfolio return and include a time fixed effect. Some regressions also include a pension fixed effect. Standard errors are clustered by state and time. t-statistics are listed below point estimates. ** indicates a p-value of 0.05 and * indicates a p-value of 0.10.

Table 4: Simulation Exercise: Parametrization

Panel A: Randomly drawn parameters

Parameter	Definition	Sampling Distribution
μ_E	Expected excess returns of public equities	$U[0.02, 0.08]$
σ_E^2	Variance of public equities	$U[0.02, 0.09]$
α	Alpha of alternatives	$U[0, 0.05]$
β	Beta of alternatives	$U[0, 1.5]$

Panel B: Inferred Parameters

Parameter	Definition	Method
μ_A	Expected excess return of alternatives	$\mu_A = \alpha + \beta\mu_E$
σ_A^2	Variance of alternatives	$\sigma_A^2 = \beta^2\sigma_E^2 + \sigma_\varepsilon^2$
σ_{AE}	Covariance of public equities and alternatives	$\sigma_{AE} = \beta\sigma_E^2$
σ_ε^2	Idiosyncratic variance of alternatives	Chosen to match initial risky portfolio composition (Eq. 3-4)
w_{rf}^{min}	Minimum constraint on riskless asset	Based on observed fixed income share

Panel C: Sample Size	Sample size
Admissible beliefs S^*:	$100,000$
Risk aversion able to explain $\Delta\omega_A$:	500
Risk aversion unable to explain $\Delta\omega_A$:	$99,500$
Pensions shift to public equities when constrained	$98,869$
$\gamma_2 < 1$	631

Panel A of this table summarizes the distributions from which beliefs are drawn in Section 4.3, where we simulate a decline in risk aversion paired with a binding portfolio constraint. Panel B summarizes how the remaining parameters are backed out from the model in Section 3. Panel C provides a breakdown of when simulations are able to generate the observed aggregate portfolio shifts from 2001 to 2020 with reasonable declines in risk aversion. See Section 4.3 for more details.

Table 5: Consultants and the Composition of Risky Investments

(a) Consultant Fixed Effects

			Fixed Effects							
	Dep. Variable:	Controls	Time	Consultant	Pension	F	p	Adj. R^2	C	N
(1)	Alternatives		x					0.32		2,961
(2)	Alternatives	x	x					0.33		2,914
(3)	Alternatives	x	x	x		13.74	0.00	0.49	69	2,914
(4)	Alternatives	x	x	x	x	8.29	0.00	0.79	65	2,419
(5)	Private Equity		x					0.09		2,961
(6)	Private Equity	x	x					0.17		2,914
(7)	Private Equity	x	x	x		11.78	0.00	0.35	69	2,914
(8)	Private Equity	x	x	x	x	4.53	0.00	0.74	65	2,419
(9)	Hedge Funds		x					0.13		2,961
(10)	Hedge Funds	x	x					0.13		2,914
(11)	Hedge Funds	x	x	x		7.81	0.00	0.26	69	2,914
(12)	Hedge Funds	x	x	x	x	5.30	0.00	0.62	65	2,419
(13)	Real Assets		x					0.15		2,961
(14)	Real Assets	x	x					0.16		2,914
(15)	Real Assets	x	x	x		11.54	0.00	0.34	69	2,914
(16)	Real Assets	x	x	x	x	5.08	0.00	0.71	65	2,419

Notes: This table shows fixed effects regressions of the following form:

$$y_{pct} = \alpha_t + \sum_k \beta_t^k \times F_{pt}^k + \lambda_c + \varepsilon_{pct}$$

where y_{pct} is one of several target asset allocations for pension system p matched with consultant c in fiscal year t. α_t is a year fixed effect, F_{pt}^k is characteristic k of pension p in year t, and λ_c is a consultant fixed effect. Control variables include (log) size, GASB 25 funding, asset hurdle rates, the ratio of required actuarial contributions to payroll, and the ratio of administrative expenses to payroll. Some regressions also include a pension fixed effect. The listed F-statistic is the result of testing the null hypothesis that the consultant effects λ_c are equal to each other. C is the number of consultant effects that are included in the test. Sample sizes differ across models because we drop singleton groups for any included fixed effects. All allocations are relative to the overall share of risky investments.

Table 6: Peer Effects

	Alternative-to-Risky Share				
	(1)	(2)	(3)	(4)	(5)
Peers' Alt-to-Risky Share	0.68**	0.55**	0.70**	0.69**	
	(3.22)	(3.26)	(3.22)	(3.27)	
× Established-CIO		0.25			
		(1.43)			
× Well-Funded			-0.20		
			(-1.45)		
× High-Performing				-0.15	
				(-1.35)	
Lagged Peers' Alt-to-Risky Share					0.71**
					(3.27)
Consultant× Year × Division FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Within-R^2	0.13	0.17	0.14	0.14	0.13
Total R^2	0.68	0.62	0.68	0.68	0.68
N	1,910	867	1,910	1,910	1,788

Notes: The dependent variable in all regressions is the target alternative-to-risky share for pension system p in year t. For each pension and year, peers' target share of alternatives is defined as a weighted average of all other pensions target share of alternatives, where weights are defined as the inverse of distance between each pension. All regressions include consultant-by-time-by-census division fixed effects and control for funding ratio, asset hurdle rate, log(size), required actuarial contributions relative to payroll, and administrative expenses relative to payroll. Column (1)-(4) show the baseline relationship between the alternative-to-risky for pension p in year t and its peers' share, as well as the interaction with several characteristics. In all cases, the regression includes both the characteristic and its interaction with peer target share of alternatives. The indicator variable "Established CIO" in column (2) equals one if the pension has had the same CIO for at least five years. The regression in column (2) is estimated only using data after 2005. The indicator for Well-Funded in column (3) equals one if the pension is in the top quartile of funding for the entire sample. The indicator for High-Performing in column (4) equals one if the pension is in the top quintile of annual performance in a given year. Column (5) shows the regression of the alternative-to-risky share on the lagged peer target alternative share. Standard errors are clustered at the year and state levels, and t-statistics are listed below point estimates in parentheses.