Journal of Asset Management
https://doi.org/10.1057/s41260-023-00346-9

ORIGINAL ARTICLE

Endowment asset allocations: insights and strategies

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Revised: 29 November 2023 / Accepted: 2 December 2023

Abstract
Using monthly data from 1997 to 2023, we construct mean-variance optimized portfolios of common university endowment asset classes, including domestic equity, international equity, global bonds, hedge funds, private equity, real estate, and natural resources. We find substantial variation in optimal allocations to these asset classes across subperiods. Some asset classes are substantially more persistent in receiving allocations than others, while some asset classes rarely receive sizable allocations at all. Our results highlight the relevance of asset allocation in portfolio performance and may inform future decisions by institutional investors and endowment portfolio managers.

Keywords Allocation · Hedge funds · Institutional investing · Optimization · Endowments

JEL Classification G1 · G11 · G23

Introduction

Asset allocation is an essential determinant of both institutional investment policy and performance. Institutions and endowments generally first choose their allocations to various asset classes and, then, implement their strategy either by executing themselves or outsourcing to an external advisor or manager bound by the investment mandate (Jenkinson et al. 2016; Gerakos et al. 2021). Additionally, asset allocation is crucial in explaining the variation in performance of an institution's portfolio (Brinson et al. 1986, 1991; Ibbotson and Kaplan 2000; Vardharaj and Fabozzi 2007). Given the relative importance of asset allocation to both the formulation of institutional investor investment policy and the subsequent performance of their portfolios, we construct mean-variance optimized portfolios of the predominant asset classes that endowments—in particular, US university endowments—invest in.

When constructing mean-variance optimized portfolios, we include domestic equity, international equity, global fixed income, hedge funds, private equity, real estate, and natural resources asset classes. We consider numerous hedge fund strategies to determine which offers a performance or diversification benefit. Given the voluminous literature that documents biases in hedge fund return indices and databases (Fung and Hsieh 2002; Aiken et al. 2013; Fung et al. 2008; Getmansky et al. 2015), we additionally penalize hedge fund returns to more appropriately reflect returns representative of what might be achievable in practice. We examine optimized portfolios under various return targets and constraints and across numerous subperiods to examine the need for rebalancing. Finally, we consider our optimal allocation results within the context of, and relative to, average US university endowments.

Our results show substantial variation in optimal allocations to various asset classes across numerous subperiods in our sample. However, some asset classes, such as international equity, real estate, and natural resources, seldom earn allocations in unconstrained optimized portfolios. Notably, and given the decline of hedge fund performance documented by Bollen et al. (2021) following the Global Financial Crisis, the presence of hedge funds in optimized portfolios falls substantially before re-emerging in more recent years. Despite our corrections for hedge fund reporting biases, hedge fund strategies frequently earn allocations, particularly market neutral, event-driven, and global macro strategies. Finally, we observe that survey data show universities hold equities and fixed income in weights similar to our computations. However, they differ in allocations to

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Published online: 20 May 2024

hedge fund and private equity strategies by somewhat underweighting the former while overweighting the latter.

Our findings have implications for academics, portfolio managers, and endowments. We understand that liquidity, spending needs, constraints, and investment mandates prohibit portfolio construction that explicitly follows the Markowitz (1952) portfolio optimization model we employ. We therefore offer this work as guidance and as a historical examination, considering market distortions that have frequented this century (i.e., the Dot-com bubble, the Global Financial Crisis, and the COVID-19 pandemic). Nevertheless, practitioners might consider our finding that certain asset classes consistently offer subdued Sharpe ratios and high correlations to other more attractive classes when evaluating such assets' positions in their portfolios.

Finally, we introduce areas for further research, notably the rise of alternative risk premia that offer systematic and low-cost exposure to long/short strategies across asset classes. While recent survey evidence suggests alternative risk premia strategies are not yet widely adopted by institutional investors, some strategies exhibit sizable Sharpe ratios with low correlations to other common endowment asset classes and may be of significant interest moving forward.

This paper proceeds as follows: Section "Literature and contribution" discusses the relevant literature motivating our study, as well as this paper's contribution to this literature. In Section "Data and Hypotheses", we discuss the data and formulate our hypotheses. Section "Methodology and results" describes our methodology, including the mean-variance optimization procedure, and presents the primary results. In Section "Subperiod analysis", we conduct a subperiod analysis and examine the performance of portfolios for the complete sample period, pre- and post-crises, and with various corrections and constraints. Section "Implications and areas for future research" discusses the applicability and implications of our results and offers future research opportunities, while Section "Conclusion" concludes.

Literature and contribution

Asset allocation

Institutional investor portfolio construction broadly consists of (1) the decision of overall allocations to broad asset classes and (2) the selection of securities and investments within classes. Xiong et al. (2010) find that asset allocation explains about 40% of the cross section of excess returns, while Barber and Wang (2013) find that asset allocation is the most important determinant of superior returns of elite universities and top-performing endowments from 1990 to 2011. Brinson et al. (1986) find that, on average, 93.6% of the variation in pension plan returns is attributable to investment policy rather than security selection or timing. In a follow-up paper, Brinson et al. (1991) confirm their earlier paper's results, showing that as much as 91.5% of the variation in quarterly total returns in large pension plans is due to investment policy.

Thus, there are differences in the literature regarding the relative importance of allocation to performance. Ibbotson and Kaplan (2000) argue that the debate over the importance of allocation is partly due to the variability in performance *within* a fund versus *across* funds. They find that asset allocation policy explains about 90% of within-fund return variability and about 40% of across-fund return variability. While this literature is seemingly mixed on the relative importance of asset allocation versus security selection, it is clear that asset allocation remains a substantial determinant of institutional investor portfolio performance. The significance of asset allocation, in part, motivates our research. We hope to guide practitioners in these vitally important asset allocation decisions by constructing optimal risky portfolios of common institutional asset classes.

Endowments and endowment portfolios

Our study contributes to the literature on institutional investor allocations, particularly university and college endowment allocations. Barberis and Shleifer (2003) note that style investing, or investing across assets that can be categorized based on shared characteristics, is particularly useful among pension plan sponsors, foundations, endowments, and other institutional investors. Given that they often follow self-imposed asset allocation rules, style investing and asset allocation simplify the investing choice and help in performance evaluation. Cejnek et al. (2014) classify university and endowment asset allocation into both strategic (long run) and tactical (temporary or shorter term). Our work contributes to each: we develop optimal portfolios that might represent strategic allocations but offer tactical insights by exploring optimal allocations across various subperiods within our full sample.

Other studies examine endowment performance and offer explanations for average endowment asset allocations. Barber and Wang (2013) find that some funds earned positive alphas for the twenty years ending in 2011, particularly among elite institutions and top performers (about 1.7% to 3.8% per year relative to stock and bond benchmarks). On average, however, they find fund alphas are near zero. Schoar et al. (2007) document that the best-performing funds aggressively allocate capital to alternative investments. Dimmock (2012) finds that universities with more "background risk," or high volatility of income from tuition, government appropriations, grants, gifts, and other non-endowment income, allocate substantially less to alternative assets and more to fixed income. Lo et al. (2021) similarly find that endowment funds with volatile contributions invest more conservatively and hold more cash.

These surveys and academic studies summarize and characterize performance, return distributions, and the effects of asset allocations on return variation. Our paper contributes to this broader literature in that we construct mean-variance optimized portfolios and find that optimal asset allocations often vary from what is common among university endowments. For example, our results indicate that hedge funds generally earn sizeable positions in optimized portfolios. While university and college endowments in the USA have increased their allocation to hedge funds from about 5.1% in 2000 to 14.87% in 2022 (NACUBO-TIAA Study of Endowments, hereafter 2022 NTSE), we find that substantially larger hedge fund allocations would have, in many cases, resulted in higher Sharpe ratios.[1] Additionally, the 2022 NTSE indicates that endowments allocate approximately 18.5% to non-US equities, but we find that international equities seldom earn an allocation in optimized portfolios. We intend for our findings to be informative rather than prescriptive, given the substantial variation in constraints that endowments are subject to. For example, Cejnek et al. (2023) note that considerable variation in endowment size, spending rates, and donations leads to variation in optimal endowment portfolios. Further, endowment payouts increasingly comprise a greater percentage of university revenues, and payout activity often deviates from stated policy following negative shocks (Brown et al. 2014).

The optimal allocations we compute for the various asset classes vary over time. For example, Bollen et al. (2021) document deterioration in hedge fund performance following the Global Financial Crisis and found that selectivity based on hedge fund performance predictors would not have been effective in avoiding hedge fund performance declines.[2] Our paper complements the Bollen et al. (2021) finding in that we observe reduced hedge fund allocations following the financial crisis. However, we offer an extension to their work by documenting a re-emergence of hedge fund strategies following the recession and market turmoil brought about by the COVID-19 pandemic.

[1] Historical NACUBO-TIAA Study of Endowments reports are available at https://www.nacubo.org/Research/.

[2] Bollen, Joenväärä, and Kauppila (2021) consider seven previously used predictors of hedge fund performance, including alpha, strategy distinctiveness, market timing, volatility timing, liquidity timing, macro timing, and option delta. They find "an allocation to top-quintile hedge funds as selected by all predictors would have significantly increased the performance of a multi-asset-class portfolio relative to a stock/bond portfolio in the 1997–2007 subperiod but provided no benefit in the 2008–16 subperiod."

Hedge fund reporting biases

Hedge funds were prohibited from advertising their performance or strategies directly to consumers until the 2012 Jumpstart Our Business Startups (JOBS) Act and the easing of Commodity Futures Trading Commission (CFTC) restrictions in 2014. Despite rule changes to the marketing environment, direct ownership of hedge funds remains available only to accredited investors. As such, hedge funds primarily draw attention to their performance by reporting results to commercial databases rather than through traditional marketing channels (Kosowski et al. 2007). Getmansky et al. (2015) argue that "the primary motivation for participating in a [hedge fund] database is for marketing purposes, funds generally seem to begin contributing their returns to a database after a period of outperformance." Given that a hedge fund often chooses to report its performance to databases for self-promotion, a selection bias may persist whereby only the top-performing funds are included rather than a representative cross-sample of funds in the industry. Therefore, we carefully consider and control for reporting biases in hedge fund returns when constructing our optimized portfolios.

Previous literature documents the prevalence of reporting biases. Returns of hedge funds represented in common databases exceed the returns typical of hedge funds overall (Fung and Hsieh 2002; Fung et al. 2008; Getmansky et al. 2015). Aiken et al. (2013) find substantial differences between funds that report to commercial databases and those that do not: the alpha of database funds is approximately 120 basis points per quarter, while those not reporting is a statistically insignificant 5 basis points per quarter. Hedge fund indices are exposed to this selection bias, potentially leading to an oversampling of hedge funds with good performance that desire to draw attention to their success.

Additionally, hedge fund indices may be subject to survivorship bias, backfill bias, and liquidation bias.[3] Survivorship bias arises when a hedge fund index represents only those hedge funds that remain in-sample through continued operations while removing (or never including) return histories of those funds that liquidate. Such a scenario may lead to an upward bias in reported returns. For example, Credit Suisse requires that a hedge fund have at least $50 million in assets under management and one year of operating history before including that fund in its index. All hedge funds that fail to exist for at least a year or reach $50 million in assets under management would not appear, nor their performance documented, in the index. Backfill or "instant history" bias occurs when database vendors include a hedge fund's historical return information in the index once it becomes eligible

[3] See Anson (2006), Chapter 9, for a detailed discussion of these biases.

for inclusion. Again, this exerts an upward bias on reported index returns by oversampling successful funds. Liquidation bias occurs when hedge funds cease reporting returns to a database months before liquidating, masking several periods of poor returns. Such biases may overestimate annual performance by 3–4.5% (Anson 2006).

Our study takes into account the existence of such biases. Given our hedge fund index as described in the next section attempts to mitigate biases associated with survivorship, backfilling, and liquidation, we choose to reduce reported hedge fund returns by a conservative 0.50–2% annually to account for selection bias. As our results show in Section "Methodology and results", increasing the magnitude of this return penalty to hedge fund data can substantially reduce their allocation or cause a reallocation to other competing hedge fund strategies.

Subperiod analysis

Our sample period from 1997 through 2023 includes three prominent financial crises: the Dot-com bubble, the Global Financial Crisis of 2007, and the 2020 stock market crash and subsequent recession brought about by the onset of the COVID-19 pandemic. Therefore, we construct optimal portfolios over the full sample and within each of these periods to determine the portfolios that would have performed best. However, Dimmock et al. (2023) show that endowment allocations can differ substantially from target allocations during crises, given the illiquidity of their alternative asset holdings, while Chambers et al. (2020) find that endowments invest countercyclically during crises by increasing their allocations to riskier assets. Thus, our results do not imply that the optimal portfolios we construct should have dictated investment policy at the time but rather are illustrative and informative of how optimal weightings change given different shocks and conditions.

Data and Hypotheses

Index return data

We obtain monthly total returns from January 1997 to July 2023 for several indices, including domestic equity, international equity, global bond, hedge fund, private equity, real estate, and natural resources.[4] We choose these asset classes as they, together with cash, comprise nearly 98% of the average academic endowment fund per Dimmock et al. (2023). Our computations rely on various indices to proxy for the returns associated with these asset classes. *Domestic Equity* is the return on the S&P 500 index. *International Equity* is the return on the MSCI EAFE index, which captures large- and mid-cap equity performance across 21 developed markets worldwide, excluding the US and Canada.[5] *Global Bond* is the return on the Bloomberg Global Aggregate Bond Index, which tracks investment grade debt from global governments, municipalities, and corporations in developed and emerging markets worldwide.[6]

Moving to common alternative asset classes, *Hedge Fund* is the return on the Credit Suisse Hedge Fund Index, a leading asset-weighted hedge fund index that tracks the performance of approximately 9,000 hedge funds.[7] The funds must have a minimum of $50 million in assets under management, one year of operating history, and audited financial statements. The index reflects the performance net of all performance fees and expenses. The index attempts to minimize the effects of backfill and survivorship bias: new funds added to the index contribute on a "going-forward" basis only, and funds in the liquidation process are not removed. *Private Equity* is the total return on the Thomson Reuters Refinitiv Private Equity Buyout Index, which seeks to track the aggregate performance of the US private equity index through liquid, publicly listed assets.[8] *Real Estate* is the S&P US REIT Index measuring the total return of publicly traded real estate investment trusts domiciled in the USA.[9] *Natural Resources* is the S&P North American Natural Resources Index, tracking US-traded securities classified under the GICS energy and materials sector, excluding chemicals and steel.[10] We obtain 1-month US Treasury bill returns from Kenneth French's website as our proxy for the risk-free rate.[11]

Table 1 presents the average monthly returns, standard deviations, and Sharpe Ratios for these indices. The indices with the highest average monthly returns are *Private Equity* (1.37%), *Domestic Equity* (0.83%), and *Natural Resources* (0.79%). *Hedge Fund*, while ranking only above *Global Bond* in average monthly return among the non-risk-free

[4] We list the indices used in this paper in the "Appendix".

[5] The 21 developed markets include Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, Australia, Hong Kong, Japan, New Zealand, and Singapore. Additional detail is available at https://www.msci.com/documents/10199/822e3d18-16fb-4d23-9295-11bc9e07b8ba.

[6] Additional details on the Global Aggregate Bond Index are available at https://data.bloomberglp.com/indices/sites/2/2016/08/Factsheet-Global-Aggregate.pdf.

[7] See https://lab.credit-suisse.com/#/en/home.

[8] See https://www.refinitiv.com/en/financial-data/indices/private-equity-index#overview.

[9] See https://www.spglobal.com/spdji/en/indices/equity/sp-united-states-reit/#overview.

[10] See https://www.spglobal.com/spdji/en/indices/equity/sp-north-american-natural-resources-sector-index/#overview.

[11] Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 1 Summary statistics

Asset class	Return (%)	25th (%)	75th (%)	σ (%)	Sharpe
US Treasury, 1-month	0.161	0.010	0.320	0.167	–
Domestic Equity	0.831	−1.667	3.726	4.516	0.148
International Equity	0.558	−2.178	3.483	4.817	0.082
Global Bond	0.287	−0.715	1.286	1.673	0.075
Hedge Fund	0.542	−0.227	1.140	1.811	0.211
Private Equity	1.374	−1.844	4.646	6.882	0.176
Real Estate	0.556	−2.529	3.969	5.842	0.068
Natural Resources	0.785	−3.225	4.952	6.936	0.090

This table presents summary statistics of the major indices used in our study. The returns are the monthly average. The standard deviation σ is the sample standard deviation of the monthly returns. An index's *Sharpe* ratio is the average return less the average of the 1-month US Treasury return, divided by the index's standard deviation. The indices are defined in the "Appendix". The sample period is the 319 months from January 1997 to July 2023.

indices, offers the highest reward per unit of risk with a Sharpe Ratio of 0.211. *Real Estate* has the lowest Sharpe Ratio (0.068), lagging behind that of *International Equity* (0.082) and *Global Bond* (0.075). We graphically depict the asset classes' average monthly returns (y-axis) and standard deviations (x-axis) over the full sample period in Fig. 1. We revisit this figure and the summary statistics of Table 1 in the next subsection to motivate our hypotheses.

Table 2 presents correlations between the monthly returns of the indices presented in Table 1 over the full sample period. *Domestic Equity* and *International Equity* are highly correlated ($\rho = 0.850$) while maintaining relatively low correlations to the *Global Bond* index ($\rho = 0.227$ and $\rho = 0.385$, respectively). *Hedge Fund*'s correlations to *Domestic Equity* and *International Equity* are quite similar ($\rho = 0.612$ and $\rho = 0.650$, respectively), and its correlation to the *Global Bond* index (ρ = 0.174) is lower than *Global Bond's* correlation to either the domestic or international equity index. *Private Equity* is highly correlated with *Domestic Equity* ($\rho = 0.808$) but not highly correlated with other asset classes. Both *Real*

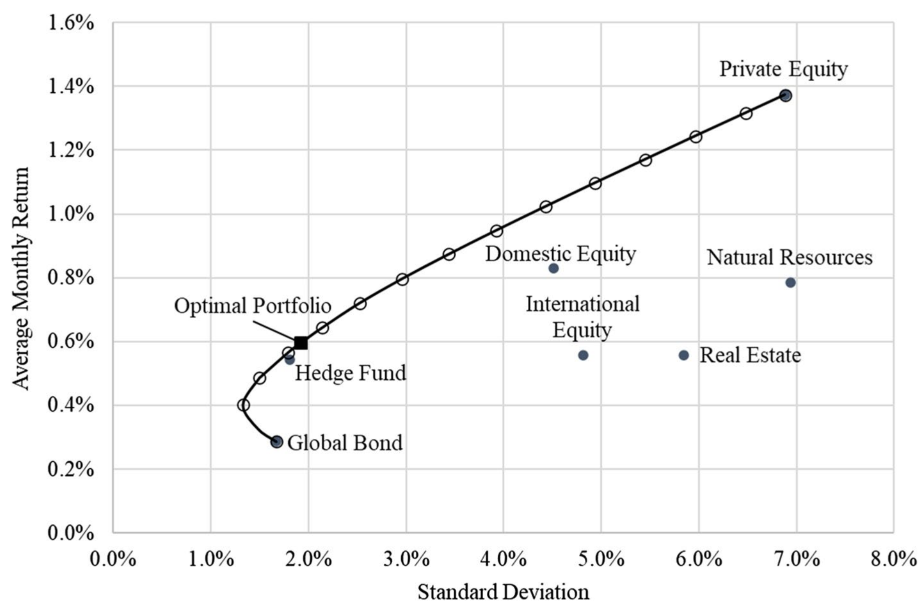

Fig. 1 Asset classes risk and return plot. This figure presents the risk and return profiles of the major indices used in our study, as well as a smooth curve representing the investment opportunity set of various portfolios constructed of these asset classes. The indices are defined in the "Appendix". The Optimal Portfolio offers the greatest Sharpe ratio achievable through combining the asset classes in a long-only portfolio. The sample period is January 1997–July 2023.

Table 2 Correlations

	Dom. Equity	Int. Equity	Global Bond	Hedge Funds	Private Equity	Real Estate	Nat. Res.
Dom. Equity	–						
Int. Equity	0.850	–					
Global Bond	0.227	0.385	–				
Hedge Funds	0.612	0.650	0.174	–			
Private Equity	0.808	0.694	0.233	0.515	–		
Real Estate	0.622	0.592	0.339	0.407	0.437	–	
Nat. Resources	0.672	0.686	0.237	0.544	0.571	0.463	–

This table presents the correlation matrix of monthly returns of the major indices used in our study. The indices are defined in the "Appendix". The sample period is January 1997–July 2023.

Estate and *Natural Resources* tend to have moderate to low correlations with the other asset classes, suggesting they might offer a diversification benefit. However, their Sharpe ratios (Table 1) may not be sizable enough to earn them significant allocations in an optimized portfolio.

Hypotheses

Given our observations of the summary statistics and correlations, we formulate the following hypotheses.

- **Hypothesis 1 (H1)**—attractive Sharpe ratios and correlations of certain asset classes, such as *Hedge Fund* and *Private Equity*, will result in their receiving sizable allocations in optimized portfolios.
- **Hypothesis 2 (H2)**—other asset classes, such as *International Equity*, *Natural Resources*, and *Real Estate*, will not offer substantial diversification benefits given their high correlations to other asset classes and/or unattractive Sharpe ratios.
- **Hypothesis 3 (H3)**—optimal allocations will vary substantially through time.
- **Hypothesis 4 (H4)**—optimal allocations will vary from average observed endowment allocations due to investing frictions and constraints.

Regarding H1, *Hedge Fund* and *Private Equity*'s relatively large Sharpe ratios (0.211 and 0.176, respectively) suggest they will earn sizable allocations in mean-variance optimized portfolios. However, the previously documented hedge fund database reporting biases (Fung and Hsieh 2002; Aiken et al. 2013; Fung et al. 2008; Getmansky et al. 2015) may result in falling *Hedge Fund* allocations if returns are adjusted to correct for such biases. Given that one might expect hedge fund allocations to fall if their returns are adjusted to account for reporting biases, we will examine the magnitude of their allocation reduction and how capital might be efficiently allocated to other hedge fund strategies and asset classes.

Regarding H2, *International Equity* is unlikely to earn allocations in optimized portfolios, given the high correlation between *Domestic Equity* and *International Equity* (Table 2) coupled with *Domestic Equity*'s superior Sharpe ratio (Table 1). Figure 1 depicts *Domestic Equity* to the northwest of *International Equity*, and the two indices have a correlation of $\rho = 0.850$. We also believe that the diversification benefit offered by *Natural Resources* and *Real Estate* will not be enough to overcome their relatively low Sharpe Ratios. As such, we expect the presence of these two indices to be limited in mean-variance optimized portfolios. Figure 1 shows these two indices near the southeast portion of the plot. Indeed, the *Global Bond* portfolio falls below both *Natural Resources* and *Real Estate* on this same plot, but this index has substantially lower correlations with the other asset classes (ranging from $\rho = 0.174$ to $\rho = 0.339$, see Table 2) with a Sharpe ratio exceeding that of *Real Estate* (0.075 vs. 0.068, see Table 1).

Regarding H3, it is well known that correlation profiles among asset classes can vary dramatically over time, particularly around significant market events (Loretan and English 2000). As such, we expect optimal allocations to endowment asset classes will substantially vary during subperiods within our sample. For example, in untabulated results, we show that the correlation between *Domestic Equity* and *Global Bond* is slightly negative before the GFC ($\rho = -0.06$) but positive following the GFC ($\rho = 0.39$). Additionally, while the aggregate summary statistics imply hedge funds likely warrant sizable allocations, we suspect the deterioration of hedge fund performance following the GFC (Bollen et al. 2021) will meaningfully reduce their allocations in certain subperiods. However, some asset classes maintain high positive correlations, such as *Domestic Equity* and *International Equity* ($\rho = 0.79$ and $\rho = 0.89$ before and after the GFC, respectively.) Some asset classes are therefore more likely to earn allocations in optimized portfolios across subperiods, while others are less likely to earn allocations at all.

Finally, and concerning H4, market frictions, spending needs, and investing constraints such as those documented by Cejnek et al. (2023) will result in average endowment allocations that differ from our optimal computations. We will introduce certain constraints, such as target returns and minimum and maximum asset class limits, to observe portfolios that may be more indicative of what is observed in practice.

Methodology and results

Optimization procedure

We construct Markowitz efficient portfolios (Markowitz 1952) for the indices in this study by the standard procedure. We obtain

$$\underset{\mu_p, \sigma_p}{Max}\ S_p = \frac{\mu_p - r_f}{\sigma_p} \tag{1}$$

where S_p is the Sharpe ratio for portfolio p, r_f is the risk-free rate, proxied by the return on 1-month T-bills (Fama and French 1993). μ_p is the return for portfolio p,

$$\mu_p = \sum_{i=1}^{N} \omega_i \mu_i \tag{2}$$

or the sum of the product of all asset i returns (μ) and their respective weights (ω). σ_p is the standard deviation of returns for portfolio p,

$$\sigma_p = \sqrt{\sum_{i=1}^{N} \omega_i^2 \sigma_i^2 + 2 \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \omega_i \omega_j \sigma_{ij}} \tag{3}$$

where σ_{ij} is the covariance between assets i and j. This optimization is subject to the constraints that the sum of all weights equals one:

$$\sum_{i=1}^{N} \omega_i = 1 \tag{4}$$

and no shorting of indices permitted:

$$\omega_i \geq 0 \tag{5}$$

We compute optimal allocations for risky assets, thus arriving at optimal *risky* portfolios. The investor might then allocate a portion of their total wealth or endowment between the optimal risky portfolio and the risk-free asset. Any combination of the risk-free asset and the optimal risky portfolio we compute will thus have the same reward per unit of risk. In additional tests, we consider common institutional investor target returns by setting μ_p in Equation (2) equal to values ranging from 7% to 10% annually, solving for weights ω subject to the constraints in Equations (4) and (5). We further impose asset weight constraints of between 3% and 50%, the approximate weight range across asset classes for university endowments in Dimmock et al. (2023).

Full sample results: optimized portfolios

Table 3 presents various portfolios using the optimization procedure described in the previous subsection. The sample consists of 319 monthly returns from January 1997 to July 2023. Panel A shows the results for unconstrained portfolios of varying target returns, while Panel B shows the results for portfolios where asset class weights are constrained such that the minimum weight of any class is 3% and the maximum weight is 50%. We determine first the optimal portfolio weights without a target annual return, then target annual returns of 7%, 8%, 9%, and 10%. The summary statistics for monthly returns, monthly standard deviations, and Sharpe ratios are included for each portfolio we construct on the right side of each panel.

Beginning with the first row of Panel A of Table 3, we determine that the mean-variance optimized portfolio constructed from monthly data spanning January 1997 to July 2023 consists of 13.7% in *Global Bond*, 75.5% in *Hedge Fund*, and 10.7% in *Private Equity*. *Domestic Equity*, *International Equity*, *Real Estate*, and *Natural Resources* have no allocation. The average monthly return on this portfolio is 0.60%, the standard deviation is 1.92%, and the Sharpe Ratio is 0.227. The average annualized return of this portfolio is approximately 7.44%. The subsequent rows in Panel A show the various weights and portfolio statistics with targeted annual returns ranging from 7% to 10%. Consistent with H1, *Hedge Fund* and *Private Equity* earn allocations given their attractive full-period Sharpe ratios. *Global Bond*'s low correlation to all other asset classes (Table 2) aids in diversification, explaining its presence in the portfolios.

Revisiting Figure 1, we plot the investment opportunity set of the various portfolios we constructed. The smooth curve connects the *Global Bond* portfolio, the minimum variance portfolio (with monthly returns of 0.402% and a standard deviation of 1.331%), the mean-variance optimized portfolio, and several portfolios of various return targets, including all those in Panel A of Table 3. The substantial allocation to *Hedge Fund* in the optimized portfolio becomes apparent from the figure—the *Hedge Fund* index lies near the optimal portfolio we compute and has similar risk-return characteristics.

Several additional notable results are apparent from Table 3. First, and consistent with H2, *International Equity*, *Real Estate*, and *Natural Resources* do not earn allocations. Second, there is no allocation to *Domestic Equity* in Panel A for any portfolio we construct. This is a somewhat surprising result, consistent with H4, as it is unlikely that a US university endowment would have no allocation to domestic equities at all. Nevertheless, per the 2022 NTSE, endowments over $1 billion on average allocate as little as 8.8% to this otherwise popular asset class (domestic equities generally represent a larger portion of smaller endowments, as much as 44.7% of endowments under $25 million). We attribute this finding to *Domestic Equity*'s high correlation to and lower Sharpe ratio than *Private Equity*. Third, *Hedge Fund* earns a substantial allocation, which we will further explore in the next subsection.

Next, given the unlikelihood that endowments would eschew entire asset classes entirely, we introduce constraints requiring each asset class to have a minimum allocation of 3% and a maximum allocation of 50% in Panel B of Table 3. Dimmock et al. (2023) and the 2022 NTSE show that average endowment allocations across asset classes often fall within this range. In imposing such restrictions, we find the constrained mean-variance optimized portfolio exhibits higher monthly returns than the unconstrained portfolio (0.64% monthly, approximately 7.96% annually, versus the 0.60% monthly returns of the unconstrained portfolio in Panel A). However, this portfolio exhibits greater volatility of monthly returns (2.37% monthly standard deviation vs. 1.92% monthly standard deviation) and a lower Sharpe ratio (0.202 vs. 0.227) than the unconstrained portfolio. In each of the constrained portfolios, the allocation to *Hedge Fund*

Table 3 Optimal portfolio weights

Target return	Portfolio Weights							Portfolio Statistics		
	Dom. Equity (%)	Int. Equity (%)	Global Bond (%)	Hedge Fund (%)	Private Equity (%)	Real Estate (%)	Nat. Res. (%)	Monthly Return (%)	Monthly σ (%)	Sharpe
Panel A: Long-Only, Unconstrained										
None	0.0	0.0	13.7	75.5	10.7	0.0	0.0	0.60	1.92	0.227
7%	0.0	0.0	18.7	72.8	8.5	0.0	0.0	0.57	1.79	0.226
8%	0.0	0.0	6.2	79.7	14.1	0.0	0.0	0.64	2.14	0.226
9%	0.0	0.0	0.0	78.5	21.5	0.0	0.0	0.72	2.52	0.222
10%	0.0	0.0	0.0	69.3	30.7	0.0	0.0	0.80	2.96	0.215
Panel B: Long-Only, Constrained, 3% < Asset Class Weight < 50%										
None	3.0	3.0	21.6	50.0	16.4	3.0	3.0	0.64	2.37	0.202
7%	3.0	3.0	28.5	50.0	9.5	3.0	3.0	0.57	2.02	0.201
8%	3.0	3.0	21.3	50.0	16.7	3.0	3.0	0.64	2.38	0.202
9%	3.0	3.0	14.2	50.0	23.8	3.0	3.0	0.72	2.78	0.201
10%	3.0	3.0	7.1	50.0	30.9	3.0	3.0	0.80	3.20	0.199

This table presents optimal asset class weights and portfolio statistics. We present first a portfolio with no target return, then portfolios with target annual returns of 7%, 8%, 9%, and 10%. Portfolios in Panel A are long-only and unconstrained in that they have no minimum or maximum asset class weights. Portfolios in Panel B are constrained such that each asset class must be at least 3% and no more than 50% of the portfolio. The indices are defined in the "Appendix". The sample period is January 1997–July 2023.

reaches the 50% asset class weight ceiling, regardless of the target return, while *Domestic Equity*, *International Equity*, *Real Estate*, and *Natural Resources* remain at the asset class weight floor, earning no more than a 3% weighting regardless of the target return.

Hedge fund strategies

Given the substantial allocations that *Hedge Fund* earns in the various mean-variance optimized portfolios presented in the previous subsection, we explore the components of the hedge fund index to examine which strategies contribute to the sizable allocation overall. Credit Suisse separates the *Hedge Fund* index into subcategories based on investment strategy.[12] *Convertible Arbitrage* includes funds that aim to profit from the purchase of convertible securities and subsequent shorting of the corresponding stock when a perceived error in the conversion factor of the security exists. *Emerging Markets* consists of funds primarily investing in currencies, debt, equities, and other financial instruments in emerging and developing markets. *Equity Market Neutral* funds generally take long and short stock positions to reduce exposure to systematic risk. *Event-Driven* funds take positions in various asset classes, attempting to exploit mispricings related to mergers, bankruptcies, financial stress, operational stress, restrictions, spin-offs, litigation, regulatory changes, and various corporate events. This index consists of the strategies *Distressed*, *Multistrategy*, and *Risk Arbitrage*. The *Distressed* index includes funds taking positions across the capital structure of firms subject to operational distress or bankruptcy. The *Event Multistrategy* index includes funds that invest in a mix of event-driven equities and debt. The *Risk Arbitrage* index consists of funds exploiting spreads in the difference between transaction bids and trading prices of acquired firms. The *Multistrategy* index includes funds that allocate capital across various hedge fund strategies. The *Fixed Income Arbitrage* index measures the performance of funds seeking to profit on arbitrage opportunities among related fixed income securities. *Global Macro* funds seek to time price movements in equity, currency, interest rates, and commodity markets based on political trends and global macroeconomic events. The *Long/Short Equity* index includes funds that typically maintain both long and short equity positions, with the aim of diversification and hedging. *Managed Futures* funds, often referred to as Commodity Trading Advisors (CTAs), typically employ systematic trading strategies relying on historical pricing movements and trends to invest in bond, equity, and commodities futures.[13]

Panel A of Table 4 summarizes these indices' risk and return profiles. *Multistrategy*, *Event Distressed*, and *Global Macro* have the highest Sharpe ratios of the strategies over our sample period. *Distressed*, *Emerging Markets*, and *Market Neutral* have the lowest Sharpe ratios of the strategies over this same period. We plot these strategies along with the overall *Hedge Fund* index in Figure 2. As the figure shows, the *Multistrategy*, event-driven, and *Global Macro* strategies have attractive risk-return profiles, while the *Market Neutral* portfolio offers the lowest reward per unit of risk. Panel B of Table 4 presents the correlations between these strategies and the *Domestic Equity*, *International Equity*, *Global Bond*, *Private Equity*, *Real Estate*, and *Natural Resources* indices. On average, the correlations between these strategies and the other asset classes are moderate to low. Of note are the particularly low correlations between *Global Bond* and the other strategies (the highest correlation between *Global Bond* and any of the strategies is $\rho = 0.290$ with *Event Arbitrage*). In particular, *Market Neutral* and *Fixed Income* strategies predictably maintain low correlations to the other classes, indicating they may garner allocations in optimized portfolios if their diversification benefit is enough to overcome their relatively low Sharpe ratios.

Given these risk-return profiles, we now reconstruct optimal portfolios. Rather than consider the *Hedge Fund* index overall, we run the optimization procedure with separate hedge fund strategies to determine which earn allocations. Panel A of Table 5 presents the unconstrained portfolios, and Panel B presents portfolios with the 3% to 50% allocation constraints. While we include all 11 hedge fund strategies in the optimization procedure, we present only those strategies that earn an allocation in the optimized portfolios (*Event Distressed*, *Multistrategy*, *Event Arbitrage*, and *Global Macro*.)

The first row of Panel A in Table 5 shows that the optimal portfolio over the sample period consists of 1.7% in *Global Bond*, 10.2% in *Event Distressed*, 55.7% in *Multistrategy*, 9.1% in *Event Arbitrage*, 21.1% in *Global Macro*, and 2.2% in *Private Equity*. This portfolio has an average monthly return of 0.60% (annualized return of approximately 7.44%), a standard deviation of 1.35%, and a Sharpe ratio of 0.326. This Sharpe ratio is substantially higher than the unconstrained portfolio from Panel A of Table 3, given the sizable decrease in the standard deviation between these two portfolios (1.35% vs. 1.92%). As the target annual return increases from 7% to 10% in Panel A, *Global Macro* and *Private Equity* allocations increase at the expense of the other hedge fund strategies and *Global Bond*.

[12] See https://lab.credit-suisse.com/#/en/index/SECT/SECT/overview for additional details on these indices.

[13] The "Appendix" provides a summary table of these indices (as well as the other asset class indices) and their corresponding identifiers. We do not include Managed Futures in our optimization procedure. See morganstanley.com/im/publication/insights/investment-insights/ii_aremanagedfuturesthesameashedgefunds_us.pdf.

Table 4 Hedge fund strategies summary statistics

	Return (%)	25th (%)	75th (%)	σ (%)	Sharpe
Panel A: Returns and Risk					
Arbitrage	0.49	−0.229	1.307	1.78	0.184
Emerging Markets	0.56	−0.907	2.322	3.41	0.116
Market Neutral	0.32	−0.212	1.195	2.60	0.061
Event-Driven	0.55	−0.153	1.650	1.95	0.201
Event Distressed	0.58	−0.193	1.622	1.79	0.236
Event Multistrategy	0.54	0.199	1.775	2.17	0.175
Event Arbitrage	0.43	−0.118	1.060	1.32	0.201
Multistrategy	0.58	0.047	1.285	1.40	0.296
Fixed Income	0.37	0.116	0.999	1.46	0.141
Long/Short	0.65	−0.794	1.992	2.58	0.189
Global Macro	0.70	−0.268	1.704	2.30	0.234

	Dom. Equity	Int. Equity	Global Bond	Private Equity	Real Estate	Nat. Res.
Panel B: Correlations						
Arbitrage	0.391	0.459	0.142	0.359	0.333	0.428
Emerging Markets	0.581	0.655	0.162	0.495	0.355	0.514
Market Neutral	0.276	0.285	0.082	0.157	0.348	0.206
Event-Driven	0.666	0.704	0.137	0.580	0.455	0.640
Event Distressed	0.598	0.628	0.062	0.498	0.416	0.564
Event Multistrategy	0.655	0.695	0.144	0.577	0.442	0.639
Event Arbitrage	0.529	0.596	0.290	0.469	0.390	0.516
Multistrategy	0.470	0.545	0.209	0.400	0.417	0.479
Fixed Income	0.341	0.425	0.165	0.258	0.372	0.347
Long/Short	0.696	0.738	0.240	0.608	0.403	0.561
Global Macro	0.250	0.249	0.082	0.235	0.171	0.318

This table presents summary statistics of hedge fund strategy indices used in our study. Panel A presents the return and risk characteristics. The returns are the monthly average. The standard deviation σ is the sample standard deviation of the monthly returns. An index's *Sharpe* ratio is the average return less the average of the 1-month US Treasury return, divided by the index's standard deviation. Panel B shows the return correlations of each hedge fund with the primary asset classes presented in Tables 1 through 3. The indices are defined in the "Appendix". The sample period is the 319 months from January 1997–July 2023.

As in Table 3, the total allocation to hedge funds overall is substantial. Allowing for individual exposures to the hedge fund indices results in a combined allocation of 96.1% to hedge funds overall in the mean-variance optimized portfolio. Inducing minimum and maximum constraints of 3% and 50% in Panel B of Table 5 results in substantially higher allocations to *Global Bond* at the expense of the hedge fund strategies.[14] As seen in Table 4, *Global Bond* has a low return correlation with several hedge fund strategies, offering a favorable diversification benefit. However, Sharpe ratios suffer in the constrained portfolios, ranging from 0.236 to 0.247 relative to the range of 0.283 to 0.326 in the unconstrained portfolios of Panel A.

In sum, the collective results of Tables 3 and 5 show that optimized portfolios constructed using return data over the full sample period from 1997 to 2023 would have allocated substantial weight to hedge funds, in particular event-driven and global macro strategies. Private equity's risk and return characteristics make it an attractive asset class as well, and portfolios that target higher returns consistently tilt more to private equity. These findings are consistent with H1. *International Equity*, *Real Estate*, *Natural Resources*, and even *Domestic Equity* do not appear in optimized portfolios unless we introduce constraints that require them to appear, consistent with H2 and H4. However, constraining the portfolios by imposing minimum and maximum asset class weights, while perhaps a prudent and reasonable investment policy, reduces Sharpe ratios.

[14] Note that hedge funds as an asset class, across *all* strategies, are subject to the weight constraints. We do not require each hedge fund strategy to be individually subject to the 3% minimum, and the strategies combined cannot exceed 50% of the portfolio.

Fig. 2 Hedge fund strategies risk and return plot. This figure presents the risk and return profiles of the major hedge fund strategies used in our study. The indices are defined in the "Appendix". The sample period is January 1997–July 2023.

Hedge fund reporting biases

Given the substantial allocations to hedge fund strategies in mean-variance optimized portfolios we constructed in the previous subsection, we next consider to what degree hedge fund database reporting biases affect allocations. To do so, we reconstruct optimized portfolios with an 8% targeted annual return, but we reduce annual hedge fund index returns by values ranging from 0.5% to 2.0%. Table 6 presents these results. Panel A shows unconstrained portfolios, while Panel B imposes minimum asset class weights of 3% and maximum asset class weights of 50%. Within each panel, we first consider the overall index *Hedge Fund*, and then consider the 11 hedge fund strategies separately, presenting only those hedge fund strategies that ever earn an allocation.

Panel A of Table 6 shows that *Hedge Fund* earns sizable allocations despite sizable return adjustments. With an annual reduction of 2% on *Hedge Fund*, the unconstrained optimized portfolio targeting a return of 8% consists of 33.5% in *Global Bond*, 30.7% in *Hedge Fund*, and 35.8% in *Private Equity*. If we consider separately the various hedge fund strategies, the optimized portfolio targeting 8% annual returns with an annual reduction of 2% on all hedge fund strategies consists of 0.1% in *Global Bond*, 40.7% in *Multistrategy*, 39.7% in *Global Macro*, and 19.5% in *Private Equity*. While one might expect that reducing hedge fund returns reduces allocations to those asset classes, we show that increasing the return penalty from 0% to 2% *increases* allocations to *Global Macro* at the expense of *Multistrategy* within hedge fund strategies (Panel A).

In these tests, we emphasize the magnitude of the reduction in hedge fund allocations given various penalties, how managers might reallocate endowment dollars across asset classes, and whether certain asset classes previously absent from optimized portfolios emerge. A key takeaway is that hedge funds remain a part of an optimized portfolio despite instituting 2% return penalties. However, the magnitude of the allocation reduction can be significant, from a 75.5% allocation with no penalty to a 30.7% allocation with a 2% penalty (Panel A).

Applying penalties to hedge fund returns does not result in additional allocations to *Domestic Equity*, *International Equity*, *Real Estate*, or *Natural Resources* unless we impose allocation weight constraints. Panel B of Table 6 shows that these four asset classes comprise the minimum 3% of the portfolio with such constraints. Notably, *Global Bond* takes on sizable allocations in the presence of hedge fund return penalties when we consider separately the various hedge fund strategies in Panel B. Hedge funds overall still maintain the maximum 50% allocation across *Multistrategy* and *Global Macro* in this setting where exposures to individual strategies are possible.

The Sharpe ratios of both the unconstrained and constrained portfolios presented in Table 6 fall relative to the comparable portfolios in Tables 3 and 5. A modest annual return adjustment of 0.50% on an unconstrained portfolio targeting 8% over our sample period would have achieved a Sharpe ratio of 0.294 (Table 6, Panel A, where we allow allocations to individual hedge fund strategies), while the portfolio targeting 8% without the return adjustment to hedge fund returns would have achieved a Sharpe ratio of 0.324 (Table 5, Panel A).

Table 5 Optimal Portfolio Weights with Hedge Fund Strategies

Target Return	Portfolio Weights										Portfolio Statistics		
	Dom. Equity (%)	Int. Equity (%)	Global Bond (%)	Hedge Fund Strategies				Private Equity (%)	Real Estate (%)	Nat. Res. (%)	Monthly Return (%)	Monthly σ (%)	Sharpe
				Event Distrs. (%)	Event Arbitrage (%)	Multistrat. (%)	Global Macro (%)						
Panel A: Long-Only, Unconstrained													
None	0.0	0.0	1.7	10.2	9.1	55.7	21.1	2.2	0.0	0.0	0.60	1.35	0.326
7%	0.0	0.0	5.9	9.7	14.3	51.1	18.3	0.7	0.0	0.0	0.57	1.25	0.324
8%	0.0	0.0	0.0	11.0	0.0	59.3	25.2	4.6	0.0	0.0	0.64	1.49	0.324
9%	0.0	0.0	0.0	0.0	0.0	50.8	36.6	12.6	0.0	0.0	0.72	1.83	0.307
10%	0.0	0.0	0.0	0.0	0.0	32.0	47.5	20.6	0.0	0.0	0.80	2.25	0.283
Panel B: Long-Only, Constrained, 3% < Asset Class Weight < 50%													
None	3.0	3.0	29.5	0.0	0.0	20.7	29.3	8.6	3.0	3.0	0.61	1.81	0.247
7%	3.0	3.0	32.9	0.0	0.0	24.6	25.4	5.1	3.0	3.0	0.57	1.65	0.246
8%	3.0	3.0	26.5	0.0	0.0	17.4	32.6	11.5	3.0	3.0	0.64	1.96	0.246
9%	3.0	3.0	20.2	0.0	0.0	10.2	39.8	17.8	3.0	3.0	0.72	2.31	0.242
10%	3.0	3.0	13.9	0.0	0.0	3.2	46.8	24.1	3.0	3.0	0.80	2.70	0.236

This table presents optimal asset class weights and portfolio statistics. We present first a portfolio with no target return, then portfolios with target annual returns of 7%, 8%, 9%, and 10%. While we include all hedge fund indices reported in Table 4 in our computations of optimal allocations, we present only those hedge fund indices that earn an allocation. Portfolios in Panel A are long-only and unconstrained in that they have no minimum or maximum asset class weights. Portfolios in Panel B are constrained such that each asset class must be at least 3% and no more than 50% of the portfolio. The indices are defined in the "Appendix". The sample period is January 1997–July 2023.

Table 6 Adjusting for Hedge Fund Reporting Biases

Return Adj.	Portfolio Weights										Portfolio Statistics		
	Dom. Equity (%)	Int. Equity (%)	Global Bond (%)	Hedge Fund (%)	Hedge Fund Strategies			Private Equity (%)	Real Estate (%)	Nat. Res. (%)	Monthly Return (%)	Monthly σ (%)	Sharpe
					Event Distrs. (%)	Multistrat. (%)	Global Macro (%)						
Panel A: Long-Only, Target Return = 8%, Unconstrained													
None	0.0	0.0	13.7	75.5				10.7	0.0	0.0	0.60	1.92	0.226
−0.50%	0.0	0.0	16.6	69.0				14.4	0.0	0.0	0.59	2.04	0.211
−1.00%	0.0	0.0	20.5	60.3				19.2	0.0	0.0	0.60	2.21	0.198
−1.50%	0.0	0.0	25.8	48.3				25.9	0.0	0.0	0.63	2.50	0.188
−2.00%	0.0	0.0	33.5	30.7				35.8	0.0	0.0	0.70	2.97	0.182
None	0.0	0.0	0.0		11.0	59.3	25.2	4.6	0.0	0.0	0.64	1.49	0.324
−0.50%	0.0	0.0	0.0		5.1	56.2	30.0	8.7	0.0	0.0	0.64	1.64	0.294
−1.00%	0.0	0.0	0.0		0.0	53.5	34.0	12.5	0.0	0.0	0.64	1.81	0.267
−1.50%	0.0	0.0	0.0		0.0	46.8	37.1	16.1	0.0	0.0	0.64	1.97	0.244
−2.00%	0.0	0.0	0.1		0.0	40.7	39.7	19.5	0.0	0.0	0.64	2.14	0.225
Panel B: Long-Only, Target Return = 8%, Constrained, 3% < Asset Class Weight < 50%													
None	3.0	3.0	21.6	50.0				16.4	3.0	3.0	0.64	2.37	0.202
−0.50%	3.0	3.0	17.6	50.0				20.4	3.0	3.0	0.66	2.59	0.194
−1.00%	3.0	3.0	12.3	50.0				25.7	3.0	3.0	0.70	2.89	0.186
−1.50%	3.0	3.0	14.0	39.9				34.1	3.0	3.0	0.76	3.31	0.180
−2.00%	3.0	3.0	25.0	15.6				47.4	3.0	3.0	0.86	3.98	0.176
None	3.0	3.0	26.5		0.0	17.4	32.6	11.5	3.0	3.0	0.64	1.96	0.246
−0.50%	3.0	3.0	24.8		0.0	15.5	34.5	13.2	3.0	3.0	0.64	2.05	0.235
−1.00%	3.0	3.0	23.1		0.0	13.5	36.5	14.9	3.0	3.0	0.64	2.15	0.225
−1.50%	3.0	3.0	21.4		0.0	11.6	38.4	16.6	3.0	3.0	0.64	2.25	0.215
−2.00%	3.0	3.0	19.6		0.0	9.6	40.4	18.4	3.0	3.0	0.64	2.35	0.206

This table presents optimal asset allocation weights and portfolio statistics for optimized portfolios with a target annual return of 8% and hedge fund reporting bias corrections of 0.00%, 0.50%, 1.00%, 1.50%, and 2.00%. Portfolios in Panel A are long-only and unconstrained in that they have no minimum or maximum asset class weights. Portfolios in Panel B are constrained such that each asset class must be at least 3% and no more than 50% of the portfolio. The indices are defined in the "Appendix". The sample period is January 1997–July 2023.

Discussion of results

In sum, there are several key findings from the presentation of the results in this section. In an unconstrained optimized portfolio, 75.5% would be allocated to *Hedge Fund*, 13.7% to *Global Bond*, and 10.7% to *Private Equity* over the sample period. If we consider separately individual exposure to various hedge fund strategies, approximately 96.1% would have been allocated to hedge funds (across *Event Distressed*, *Multistrategy*, *Event Arbitrage*, and *Global Macro*), 2.2% to *Private Equity*, and 1.7% to *Global Bond*. Optimal allocations to common institutional and endowment asset classes differ substantially from the average allocations of these institutions. NTSE data show average allocations of about 30% to public equity, 15% to hedge funds, 10% to fixed income, 30% to private equity and venture capital, 10% to real assets, and 3% to other categories. Imposing weight constraints and hedge fund return adjustments on optimized portfolios, however, results in portfolios more representative of average observed endowment portfolios, though hedge fund strategies are still underrepresented in endowment strategies relative to these optimized portfolios.

The characteristics of these portfolios might be deduced from the summary statistics of the various asset classes. *Domestic Equity* as an asset class has a respectable Sharpe ratio, but *Private Equity*'s Sharpe ratio is higher with generally lower correlations to other asset classes. *International Equity*'s relatively poor Sharpe ratio (0.082) and relatively high correlation to various hedge fund strategies partly explains its absence in optimized portfolios. *Real Estate* and *Natural Resources* garner no allocations in unconstrained optimized portfolios, in part due to their relatively poor historical performance and relatively high volatility. These findings are consistent with our hypotheses.

Subperiod analysis

Next, we explore the evolution of optimal allocations across asset classes through time to address H3. In the previous subsection, we show that applying return adjustments to hedge funds results in optimal portfolio allocations more typical of average endowment strategies reported by NTSE studies and Dimmock et al. (2023). However, our sample period includes several significant market distortions, notably the Global Financial Crisis of 2007 (GFC), the Dot-com bubble, and the COVID-19 pandemic. We consider optimal portfolios prior to and around these breakpoints separately.

The global financial crisis

First, we construct mean-variance optimized portfolios for the period before the GFC, from January 1997 through September 2007 (129 months), and then from October 2007 through July 2023 (190 months). Table 7 presents these results, broken into Panel A for the pre-GFC period and Panel B for the post-GFC period. Within each panel, we first show allocations to the asset classes *Domestic Equity*, *International Equity*, *Global Bond*, *Hedge Fund*, *Private Equity*, *Real Estate*, and *Natural Resources*. Then, we show allocations separately for the various hedge fund strategies within each panel.[15] We also compute three sets of portfolios in each period. Rows labeled *A* and *A1* in Table 7 have no targeted annual returns, weight constraints, or adjustments to hedge fund returns. Rows labeled *B* and *B1* have an 8% targeted annual return, asset class weight constraints of between 3% and 50%, and annual hedge fund return adjustment penalties of 1%. Rows labeled *C* and *C1* have an 8% targeted annual return, asset class weight constraints of between 3% and 50%, and hedge fund return penalties of 2%

We first compare the portfolios in rows labeled *A* pre- and post-crisis. There is a sizable shift in optimal allocation to *Domestic Equity* from 0% to 28.9%, the elimination of *Global Bond* from 33.8% to 0%, and an increase in *Hedge Fund* allocation from 58.0% to 64.7%. *International Equity*, *Private Equity*, *Real Estate*, and *Natural Resources* optimal allocations are largely unchanged pre- and post-crisis. The Sharpe ratio dramatically falls, from 0.317 in the pre-period to 0.178 in the post-period. This result is significant, as *Domestic Equity* emerges as an asset class worthy of an allocation. The absence of direct exposure to domestic equities previously presented in the full sample results was largely driven by the pre-crisis period. We reiterate, however, that endowments would likely have ample exposure to equities, both domestic and international, through various hedge fund strategies that do earn allocations in optimized portfolios.

Computing the optimal allocations using the *Hedge Fund* index, rather than the individual strategies, obfuscates the shift in preferable hedge fund strategies from before the crisis to after the crisis. Allowing for separate exposures to individual hedge fund strategies shows a sizable shift from *Market Neutral* strategies prior to the crisis (with an allocation of 63.5% of the portfolio in Panel A, Row A1) to *Event Arbitrage* and *Global Macro* strategies (with allocations of 27.3% and 31.3% following the crisis in Panel B, Row A1).

In imposing constraints and correcting for hedge fund database reporting biases in the *B* and *C* rows of Table 7, we observe a pattern more indicative of endowment allocations presented by NTSE and Dimmock et al. (2023) data. Post GFC, there is a shift to *Domestic Equity*, from a 3% allocation (Panel A, Rows B1 and C1) to 31.7% (Panel B, Row B1) and 44.5% (Panel B, Row C1), allocations to hedge

[15] As in Tables 5 and 6, we include all hedge fund strategies in our computation of optimized portfolios, but we omit those strategies that never earn an allocation from the Tables.

Table 7 Portfolio Allocations around the Global Financial Crisis

	Portfolio Weights														Portfolio Statistics		
	Dom. Equity	Int. Equity	Global Bond	Hedge Fund	Hedge Fund Strategies							Private Equity	Real Estate	Nat. Res.	Monthly Return	Monthly σ	Sharpe
					Arbitrage	Market Neutral	Event Distrs.	Event Arbitrage	Multistrat	Fixed Income	Global Macro						
Panel A: Pre-Global Financial Crisis																	
A	0.0%	0.0%	33.8%	58.0%								7.2%	0.0%	1.0%	0.80%	1.57%	0.317
B	3.0%	3.0%	50.0%	19.4%								3.0%	18.6%	3.0%	0.64%	1.58%	0.216
C	3.0%	3.0%	48.8%	36.0%								3.3%	3.0%	3.0%	0.64%	1.41%	0.241
A1	0.0%	0.0%	1.8%		0.0%	63.5%	4.9%	0.0%	29.0%	0.0%	0.9%	0.0%	0.0%	0.0%	0.83%	0.67%	0.789
B1	3.0%	3.0%	35.0%		6.4%	27.0%	0.0%	0.0%	4.5%	12.0%	0.0%	3.0%	3.0%	3.0%	0.64%	0.99%	0.344
C1	3.0%	3.0%	35.0%		8.4%	30.6%	0.0%	0.0%	8.9%	1.1%	1.0%	3.0%	3.0%	3.0%	0.64%	1.02%	0.335
Panel B: Post-Global Financial Crisis																	
A	28.9%	0.0%	0.0%	64.7%								6.3%	0.0%	0.0%	0.53%	2.60%	0.178
B	50.0%	3.0%	18.9%	12.0%								10.1%	3.0%	3.0%	0.64%	3.69%	0.157
C	50.0%	3.0%	26.9%	3.0%								11.1%	3.0%	3.0%	0.64%	3.71%	0.156
A1	5.1%	0.0%	0.0%		0.0%	0.0%	0.0%	27.3%	36.3%	0.0%	31.3%	0.0%	0.0%	0.0%	0.41%	1.42%	0.246
B1	31.7%	3.0%	3.0%		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	40.2%	16.1%	3.0%	3.0%	0.64%	3.32%	0.175
C1	44.5%	3.0%	3.0%		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	32.2%	11.3%	3.0%	3.0%	0.64%	3.51%	0.165

This table presents the optimal asset class weights and portfolio statistics for optimized portfolios. Panel A presents the results from January 1997 to September 2007. Panel B presents the results from October 2007 to July 2023. Rows labeled "A" and "A1" have no target annual return, no weight constraints, and no hedge fund return adjustments. Rows labeled "B" and "B1" have an 8% target annual return, asset class weight constraints of greater than 3% and less than 50% per asset class, and an annual hedge fund return adjustment of -1%. Rows labeled "C" and "C1" have an 8% target annual return, weight constraints of greater than 3% and less than 50% per asset class, and an annual hedge fund return adjustment of -2%. The indices are defined in the "Appendix".

funds of between 32.2% and 40.2% (via the *Global Macro* strategy, Panel B), and the emergence of *Private Equity*, with an allocation of 16.1% (Panel B, Row B1) and 11.3% (Panel C, Row C1).

Thus, Table 7 highlights a sizable and systematic shift in mean-variance optimized allocations following the GFC, consistent with H3. Optimal portfolios consist of more capital directed to *Domestic Equity* post-GFC and a general increase in *Private Equity* allocations. *Global Macro* strategies earned substantially higher allocations, even with return penalties. However, Sharpe ratios suffered across the board post-crisis through higher standard deviations and lower achievable monthly returns in untargeted and unconstrained settings.

Additional subperiods

In addition to the GFC, our sample includes two other periods of significant economic uncertainty and heightened volatility, the Dot-com bubble of the early 2000s and the COVID-19 pandemic beginning in 2020. We therefore consider these periods as "breakpoints" before and after which we construct optimized portfolios. We construct portfolios for the pre-Dot-com era (44 months: January 1997 through August 2000), the Dot-com to GFC era (85 months: September 2000 through September 2007), the GFC to COVID-19 era (149 months: October 2007 through February 2020), and the post-COVID-19 era (41 months: March 2020 through July 2023).

We present this subperiod analysis in Table 8. As in Table 7, rows in Table 8 labeled *A* and *A1* are unconstrained mean-variance optimized portfolios, while rows labeled *B* and *B1* are portfolios targeting an annual return of 8%, with 3% minimum and 50% maximum asset weight constraints and hedge fund return penalties of 1%, and rows labeled *C* (and *C1*) are portfolios targeting an annual return of 8%, with 3% minimum and 50% maximum asset weight constraints and hedge fund return penalties of 2%.

We consider first portfolios with exposure to the index *Hedge Fund* rather than the individual hedge fund strategies. Several interesting findings become apparent from this table. First, consistent with previous findings, *International Equity*, *Real Estate*, and *Natural Resources* seldom earn sizable allocations in optimized portfolios. *International Equity*, in particular, is only represented in any subperiod when we require a minimum 3% weight (Rows B1 and C1 in each panel). Second, and perhaps expected, we observe that *Domestic Equity* earns a sizable allocation of 34.6% before the Dot-com bubble (Panel A, Row A) but earns no allocation in the subperiods between the Dot-com bubble and COVID (Panels B and C, Row A) given the relatively lower performance of the equity index during these periods.[16] *Private Equity* similarly earns an allocation before the Dot-com bubble (Panel A, Row A) that disappears in the run-up before the GFC (Panel B, Row A). An allocation re-emerges following the GFC but again disappears post-COVID. We attribute this finding to *Private Equity* offering slightly lower average monthly returns and a higher standard deviation than *Domestic Equity* while maintaining a very high correlation with the domestic equity portfolio in the post-COVID period.[17]

The evolution of allocations to *Hedge Fund* is apparent. Before the Dot-com bubble and leading up to the GFC, *Hedge Fund* allocations were substantial in unconstrained optimized portfolios (Row A: 50.3% pre-Dot-com and 81.1% from Dot-com to GFC). We show that in the *Global Financial Crisis to COVID* period, *Hedge Fund* has no presence in the optimized portfolio unless we require a minimum 3% allocation (Panel C, Rows A, B, and C). The results presented by Bollen et al. (2021) provide some context to our findings. The authors document a decline in aggregate hedge fund performance following the GFC. They also show that from 1997 to 2007, hedge fund cumulative returns substantially outpaced the returns of a 50/50 stock/bond benchmark portfolio (225% vs. 125%), while hedge fund returns lagged the 50/50 benchmark from 2008 to 2016 (25% vs. 70%). Further, they find that about 20% of hedge funds delivered statistically significant and positive alpha from 1997 until 2008, after which this percentage fell to about 10%. Over that same period, about 5% of funds had statistically significant and negative alpha, after which this percentage rose rapidly, exceeding 20% several times through 2016. Finally, the authors present some evidence that heightened regulatory oversight following the GFC, the passage of Dodd-Frank reforms, and central bank interventions may have led to this decline in hedge fund performance. This deterioration in performance is consistent with the limited allocation to hedge funds we compute during this period.

In the *Post-COVID* period, however, we see hedge funds re-emerge, earning 67.3% (Row A) in the optimized portfolio and the maximum 50% allocation even with 1% and 2% return corrections (Rows B and C). We consider the individual hedge fund strategies to further explore the evolution of the allocations over these sample periods. Each panel presents these results in rows A1, B1, and C1. *Market Neutral* comprises the bulk of hedge fund allocations before the crisis, with 67.5% and 52.0% of the overall portfolio

[16] The average monthly return to the *Domestic Equity* index in the pre-Dot-com period was 1.88% before falling to 0.22% before the GFC, 0.71% after the GFC but before COVID, and 1.37% in the post-COVID period.

[17] *Private Equity* has average monthly returns of 1.19% versus 1.37% for *Domestic Equity* during this period. The standard deviations are 9.67% and 5.70%, respectively, and the correlation of their monthly returns is $\rho = 0.94$.

Table 8 Subperiod Analysis of Portfolio Allocations

	Portfolio Weights														Portfolio Statistics		
	Dom. Equity	Int. Equity	Global Bond	Hedge Fund	Hedge Fund Strategies							Private Equity	Real Estate	Nat. Res.	Monthly Return	Monthly σ	Sharpe
					Arbitrage	Market Neutral	Event Distrs.	Event Arbitrage	Multistrat	Fixed Income	Global Macro						
Panel A: Pre-Dot-com																	
A	34.6%	0.0%	0.0%	50.3%								15.1%	0.0%	0.0%	1.70%	3.97%	0.325
B	3.0%	3.0%	50.0%	30.2%								3.0%	7.8%	3.0%	0.64%	1.65%	0.140
C	3.0%	3.0%	50.0%	32.3%								3.0%	5.7%	3.0%	0.64%	1.67%	0.139
A1	0.0%	0.0%	0.0%		0.0%	67.5%	0.0%	0.4%	32.1%	0.0%	0.0%	0.0%	0.0%	0.0%	1.13%	0.77%	0.936
B1	3.0%	3.0%	35.0%		2.3%	7.2%	0.0%	0.0%	21.5%	18.9%	0.0%	3.0%	3.0%	3.0%	0.64%	1.05%	0.221
C1	3.0%	3.0%	35.0%		5.8%	8.3%	0.0%	0.0%	23.4%	12.6%	0.0%	3.0%	3.0%	3.0%	0.64%	1.06%	0.219
Panel B: Dot-com to Global Financial Crisis																	
A	0.0%	0.0%	17.2%	81.1%								0.0%	1.7%	0.0%	0.70%	1.00%	0.455
B	4.9%	3.0%	42.1%	40.9%								3.0%	3.0%	3.0%	0.64%	1.23%	0.323
C	3.0%	3.0%	42.1%	37.4%								3.9%	7.7%	3.0%	0.64%	1.29%	0.308
A1	0.0%	0.0%	0.0%		0.0%	52.0%	19.3%	0.0%	0.0%	0.0%	27.9%	0.0%	0.8%	0.0%	0.87%	0.61%	1.020
B1	3.0%	3.0%	35.0%		0.0%	44.3%	2.3%	0.0%	0.0%	0.0%	3.4%	3.0%	3.0%	3.0%	0.64%	0.91%	0.435
C1	3.0%	3.0%	35.0%		0.0%	35.6%	4.7%	0.0%	0.0%	0.0%	9.8%	3.0%	3.0%	3.0%	0.64%	0.93%	0.427
Panel C: Global Financial Crisis to COVID																	
A	0.0%	0.0%	73.1%	0.0%								26.9%	0.0%	0.0%	0.51%	2.07%	0.220
B	3.0%	3.0%	42.6%	3.0%								42.4%	3.0%	3.0%	0.64%	3.16%	0.187
C	3.0%	3.0%	42.3%	3.0%								42.7%	3.0%	3.0%	0.64%	3.18%	0.186
A1	0.0%	0.0%	20.0%		0.0%	0.0%	0.0%	16.4%	25.0%	0.0%	33.1%	5.5%	0.0%	0.0%	0.38%	1.22%	0.265
B1	3.0%	3.0%	41.3%		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	4.7%	42.0%	3.0%	3.0%	0.64%	3.13%	0.189
C1	3.0%	3.0%	42.7%		0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	3.0%	42.3%	3.0%	3.0%	0.64%	3.14%	0.188
Panel D: Post-COVID																	
A	24.6%	0.0%	0.0%	67.3%								0.0%	0.0%	8.2%	0.85%	3.10%	0.242
B	23.9%	3.0%	14.1%	50.0%								3.0%	3.0%	3.0%	0.64%	3.14%	0.172
C	26.5%	3.0%	11.5%	50.0%								3.0%	3.0%	3.0%	0.64%	3.25%	0.166
A1	14.3%	0.0%	0.0%		0.0%	31.3%	0.0%	15.0%	18.6%	0.0%	20.2%	0.0%	0.0%	0.6%	0.64%	1.97%	0.272
B1	24.7%	3.0%	13.3%		0.0%	30.3%	0.0%	0.0%	1.6%	0.0%	18.0%	3.0%	3.0%	3.0%	0.64%	2.93%	0.184
C1	27.3%	3.0%	10.7%		0.0%	31.4%	0.0%	0.0%	0.3%	0.0%	18.3%	3.0%	3.0%	3.0%	0.64%	3.03%	0.178

This table presents optimal asset class weights and portfolio statistics for optimized portfolios. Panel A presents the results from January 1997 to August 2000. Panel B presents the results from September 2000 to September 2007. Panel C presents the results from October 2007 to February 2020. Panel D presents the results from March 2020 to July 2023. Rows labeled "A" and "A1" have no target annual return, no weight constraints, and no hedge fund return adjustments. Rows labeled "B" and "B1" have an 8% target annual return, asset class weight constraints of greater than 3% and less than 50% per asset class, and an annual hedge fund return adjustment of -1%. Rows labeled "C" and "C1" have an 8% target annual return, weight constraints of greater than 3% and less than 50% per asset class, and an annual hedge fund return adjustment of -2%. The indices are defined in the "Appendix" allocation in the two subperiods preceding the crisis (Panel A, Row A1 and Panel B, Row A1). There is a reallocation to the *Global Macro* and event-driven strategies following the GFC, before the re-emergence of the *Market Neutral* strategy in the *Post-COVID* period.

Return adjustments of 1% and 2% to the hedge fund indices (Rows B, C and Rows B1, C1 in each panel) indeed reduces allocations to various hedge fund strategies but rarely reduces allocations substantially to hedge funds as an asset class overall. A notable exception is in Panel C, the period between the GFC and COVID. Again, consistent with Bollen et al. (2021), the decline in hedge fund performance resulted in lower allocations to the asset class. In implementing return adjustments, the total allocation across all hedge fund strategies falls from the maximum of 50% to 3% as we move from column A1 to B1 and C1 in Panel C.

Discussion of results

We present several key results of the subperiod analysis in this section. First, and consistent with H3, optimal allocations pre- and post-GFC shift markedly, and subperiod analysis at various breakpoints similarly shows significant variation in allocations across asset classes. Certain asset classes, such as *Domestic Equity*, *Private Equity*, *Hedge Fund*, and various hedge fund strategies, enter and exit as asset classes with weights in optimized portfolios. However, other classes, such as *International Equity, Real Estate,* and *Natural Resources*, tend not to earn a presence in mean-variance optimized portfolios regardless of the subperiod. Second, we show that *Market Neutral*, *Global Macro*, and event-driven strategies in particular tend to maintain a presence except for post-GFC but before COVID. Third, including return adjustments for hedge fund database reporting biases reduces hedge fund allocations or reallocates weights to other hedge fund strategies but does not necessarily eliminate hedge fund allocations entirely.

Implications and areas for future research

While average endowment allocations differ from mean-variance optimized allocations we compute, there are several ways in which they are similar. Consider our computed post-COVID optimal allocations for a weight-constrained portfolio with a targeted 8% return and a 2% hedge fund return adjustment (Table 8, Panel C, Row C1). We find an allocation of 27.3% to public equities while the 2022 NTSE finds average allocations of 29% to this asset class. We compute an allocation of 10.7% to *Global Bond* while 2022 NTSE finds an average of 10% in fixed income. Yet, we compute a 50% allocation to hedge funds (across *Market Neutral*, *Event Multistrategy*, and *Global Macro*) and 3% to *Private Equity*, while on average endowments allocate about 15% to marketable alternatives (including hedge funds) and 30% to private equity and venture capital per the 2022 NTSE. Indeed, the variation across subperiods indicates that no optimal allocation is persistent, nor is any allocation consistently optimal. However, certain asset classes are consistently absent, while other asset classes are consistently present in optimized portfolios. Such patterns might inform asset allocation decision making. We stress that liquidity, constraints, and investment mandates prohibit portfolio construction that explicitly follows the Markowitz (1952) portfolio optimization model we employ, and we would not expect endowments to be able to strategically shift allocations quickly in response to changes in market conditions. Nevertheless, our findings are informative to the practitioner.

While we consider the most common institutional investor asset classes in our tests, we note that additional opportunities are available. Accredited investors may benefit from the emergence of investable alternative risk premia (ARP) strategies as a supplement to—and perhaps even a replacement of—hedge fund strategies. ARP strategies represent a low-cost and liquid systematic-based investment strategy, taking long and short positions across and within asset classes. Such ARP strategies are investable and increasingly available through funds or total return swaps (Jorion 2021). However, according to the *2019 Institutional Investor Survey* by J.P. Morgan Capital Advisory Group, 24% of the 209 survey respondents allocated capital to ARP strategies, ranging from 8% of family offices to 46% of consultants. Only about 13% of endowments and foundations allocate capital to ARP.[18] ARP strategies are often market-neutral and represent uncorrelated risks, unlike traditional long-only smart beta or factor investing approaches (Reid and Van Der Zwan 2019).

Boal et al. (2021) summarize five common ARP styles, including *Carry* (long high-yield and short low-yield assets), *Curve* (long assets with longer maturities and short assets with shorter maturities), *Liquidity* (long illiquid and short liquid assets), *Momentum* (long past winners and short past losers), and *Value* (long undervalued and short overvalued assets). Various asset classes, including equities, foreign exchange, and rates, have investible ARP strategies associated with these styles. Jorion (2021) documents that many ARP strategies earned significant positive returns from 2010 to 2020 while remaining low-cost relative to hedge funds and that market factors and a selection of ARP strategies largely subsume hedge fund excess returns. However, Boal et al. (2021) warn of the risk of data mining, with more academic and practitioner research needed to support ARP strategies over the long term. In untabulated results, we preliminarily explore ARP strategies by constructing an equal-weight

[18] The *2019 Institutional Investor Survey* by J.P. Morgan Capital Advisory Group is available at https://www.jpmorgan.com/content/dam/jpm/cib/complex/content/prime-services/institutional-investor-survey-2019/pdf-0.pdf.

index of the S&P ARP strategies discussed in Boal et al. (2021) and find no allocation to ARP as an asset class when considered together with the other asset classes used in this paper. Further research into these strategies may be necessary if their adoption increases among endowments and institutions.

Conclusion

Institutional investors are most commonly faced first with the asset allocation decision before proceeding to either select securities or outsource security selection and timing decisions. In this paper, we construct a range of mean-variance optimized portfolios under various constraints and across periods. Seldom are asset classes ever-present across periods in the optimal portfolios we construct. However, some asset classes, notably *International Equity*, *Real Estate*, and *Natural Resources*, rarely—if ever—comprise a substantial portion of an unconstrained optimized portfolio in our sample periods. Even with corrections for hedge fund database reporting biases, exposure to hedge funds is often present in optimized portfolios. In particular, event-driven, market neutral, and global macro strategies frequently earn allocations across the various investible hedge fund strategies. Average endowment allocations differ in some ways from what would have been optimal under a Markowitz (1952) portfolio optimization model, though we expect frictions might explain some of these differences.

Our results are informative to practitioners. We demonstrate the relevance of various asset classes through time, highlight the importance of asset allocation, and document Sharpe ratios and risk-return characteristics of various investible portfolios. Future work should explore the emergence of alternative risk premia strategies and what benefit, if any, they offer in diversification.

Appendix

Index definitions and descriptions

This Appendix table describes the various indices used in this study.

Term	ID/Ticker	Description
Domestic Equity	SPX	S&P 500 Index (Us Equity Index)
International Equity	MXEA	MSCI EAFE Index (Non-Us Equity Index).
Global Bond	LEGATRUU	Bloomberg Barclays Global—Aggregate Total Return Index Value Unhedged (Global Bond Index)
Hedge Fund	HEDGNAV	Credit Suisse Hedge Fund Index
Private Equity	TRPEI	Thomson Reuters Private Equity Buyout Index
Real Estate	STCGUSRE	S&P United States REIT Index
Natural Resources	SPGINRTR	S&P North American Natural Resources Index
Arbitrage	HEDGCONV	Credit Suisse Convertible Arbitrage Hedge Fund Index
Emerging Markets	HEDGEMGM	Credit Suisse Emerging Markets Hedge Fund Index
Market Neutral	HEDGNEUT	Credit Suisse Equity Market Neutral Hedge Fund Index
Event-Driven	HEDGDRIV	Credit Suisse Event-Driven Hedge Fund Index
Event Distressed	HEDGDIST	Credit Suisse Event-Driven Distressed Hedge Fund Index, a substrategy of Event-Driven HEDGDRIV
Event Multistrategy	HEDGEDMS	Credit Suisse Multistrategy Hedge Fund Index, a substrategy of Event-Driven HEDGDRIV
Event Arbitrage	HEDGRISK	Credit Suisse Event-Driven Risk Arbitrage Hedge Fund Index, a substrategy of Event-Driven HEDGDRIV
Multistrategy	HEDGMSTR	Credit Suisse Multi-Strategy Hedge Fund Index
Fixed Income	HEDGFIAR	Credit Suisse Fixed Income Arbitrage Hedge Fund Index
Long/Short	HEDGLSEQ	Credit Suisse Long/Short Equity Hedge Fund Index
Global Macro	HEDGGLMA	Credit Suisse Global Macro Hedge Fund Index

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