Available online at www.sciencedirect.com

ScienceDirect

Journal of Financial Markets 13 (2010) 268–294

Journal of FINANCIAL MARKETS

www.elsevier.com/locate/finmar

Asset allocation and portfolio performance: Evidence from university endowment funds

Keith C. Brown[a], Lorenzo Garlappi[b], Cristian Tiu[c,*]

[a]*McCombs School of Business, B6600, The University of Texas at Austin, Austin, TX 78712, USA*
[b]*Sauder School of Business, The University of British Columbia, 2053 Main Mall, Vancouver, BC, Canada V6T 1Z2*
[c]*School of Management, University at Buffalo, Buffalo, NY 14260, USA*

Available online 7 January 2010

Abstract

We use university endowment funds to study the relationship between asset allocation decisions and performance in multiple asset class portfolios. Although endowments differ substantially in asset class composition, policy portfolio returns and volatilities are remarkably similar across the sample. The risk-adjusted performance of the average endowment is negligible, but actively managed funds generate significantly larger alphas than passive ones. This is consistent with endowment managers exploiting their security selection abilities by over-weighting asset classes in which they have superior skills. Contrary to both theory and prevailing beliefs, asset allocation is *not* related to portfolio returns in the cross-section but does indirectly influence performance.

JEL classification: G11; G23

Keywords: Endowment funds; Asset allocation; Investment performance

1. Introduction

Asset allocation—the process of distributing investment capital across the various asset classes in an allowable universe—is widely regarded as one of the most important decisions an investor faces. The ultimate goal of this process is to construct portfolios that are optimal with respect to some pre-specified objectives. According to the paradigm of

*Corresponding author. Tel.: +1 716 645 3299.
E-mail addresses: kcbrown@mail.utexas.edu (K.C. Brown), lorenzo.garlappi@sauder.ubc.edu (L. Garlappi), ctiu@buffalo.edu (C. Tiu).

1386-4181/$ - see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.finmar.2009.12.001

modern portfolio theory that originated with Markowitz (1952), the exercise of constructing optimal portfolios is ultimately one of the balancing expected returns against their contribution to portfolio risk.

In the investment management industry, it is commonly accepted that an investor's initial strategic asset allocation decision is the most important determinant of the portfolio's investment performance (see, e.g., Brinson et al., 1986, 1991; Bogle, 1994). However, empirical evidence on mutual fund and pension fund investment practices seem to cast some shadows on this belief. Both Ibbotson and Kaplan (2000), using data on US mutual and pension funds, and Blake et al. (1999), using data on U.K. pension funds, conclude that while asset allocation decisions are the major determinant of return variation over time, they are considerably less important in explaining return variation in the cross-section.

In this paper, we revisit the question of the importance of asset allocation to the performance of multiple asset class portfolios by using a unique database of university endowments. Due to their specialized characteristics—such as an unlimited investment horizon, relatively modest spending needs, and a generally flexible set of policy constraints—university endowment funds represent an ideal setting to examine this issue in greater detail. The access to detailed information of endowment asset allocation practices allows us to provide also an explanation for the puzzling dual role of strategic asset allocation in the time series and cross-section.[1]

Our analysis is based on portfolio information and performance statistics for more than 700 public and private university endowment funds collected in two separate and distinctive data sets: (i) a series of annual surveys from 1984 to 2005, administered by the National Association of College and University Business Officers (NACUBO), an advocacy organization devoted to improving management practices in the higher education industry; and (ii) proprietary self-collected quarterly data from 1994 to 2005. To isolate the part of returns originating from the asset allocation decision we follow the methodology proposed by Brinson et al. (1986) and *decompose* the total return of each endowment into three components related to: (i) the *strategic asset allocation* (policy) decision; (ii) the *tactical asset allocation* (market timing) decision; and (iii) the *security selection* decision. The strategic asset allocation decision is often referred to as the *passive* element of a fund manager's decision-making process while market timing and security selection are the *active* components of this process.

Using the asset allocation return obtained from such a decomposition, we generalize the tests of Ibbotson and Kaplan (2000) and study the contribution of strategic asset allocation to endowment return variation. Consistent with their findings for US mutual and pension funds and with those of Blake et al. (1999) for U.K. pension funds, we also find that asset allocation still emerges as the main determinant of return level and variation in the time series. Its contribution to time series return variation is about 75%, somewhat lower than the values documented for other institutional investors. More strikingly, however, the average contribution of an endowment manager's asset allocation decision to cross-sectional variation in performance is only about 10%, which is once again significantly lower than previously established in other institutional settings. This evidence seems to

[1]It is common to draw a distinction between *strategic* (long-term) and *tactical* (short-term) asset allocation. In this paper, we use "asset allocation" to refer to the strategic, long-term decision of an institution and label as "market timing" the short-term allocation decision.

indicate that the average endowment manager follows a much less passive investment strategy than what appears to be the norm for either mutual fund or pension fund managers.

Having access to a detailed panel of actual portfolio weights of endowments allows us to better understand the nature of this discrepancy in explanatory power of the asset allocation decision in the time series versus the cross-section. We demonstrate that the limited amount of cross-sectional explanatory power associated with the policy return component originates from a remarkable lack of variation in the ex post returns attributable to the strategic asset allocation decision. Conversely, we also show that asset allocation weights vary dramatically across the endowments in our sample. While the first finding is consistent with what Blake et al. (1999) document for U.K. pension funds, the second is in clear contrast with the homogeneity in asset allocation weights in their sample.

Our findings have interesting implications for the role of active management in the performance of university endowments. The largely invariant sample-wide level of passive risk we document implies that endowments target a common level of volatility for their policy portfolio, thus ending up with very similar passive returns. Given that total returns are the sum of the passive and active return components, a common level of passive return across endowments means that any cross-sectional variation in overall performance *must* come from the active decisions within the portfolio. We therefore investigate how endowments that rely more on security selection (active endowments) fare in comparison to endowments who rely more on asset allocation (passive endowments). Our main finding is that active endowments significantly out-perform passive ones, despite the fact that, as a group, university endowments do not seem to produce significant risk-adjusted returns. The top quartile of active endowments have risk-adjusted returns that are 2.92–8.39% larger than those of the bottom active quartile. This suggests that the documented heterogeneity in portfolio weights across funds represents an attempt by endowment managers to select their exposures to broad asset classes based on both their familiarity and selection abilities within that class.

To the best of our knowledge ours is the first study that attempts to quantify the relationship between the asset allocation decision and investment performance for a comprehensive sample of college and university endowment funds. Much of the previous literature in this area has been mainly concerned with understanding the nature of the endowment investment process, with relatively little being known about how these portfolios have actually performed over time.[2] Two more recent studies have also used data from NACUBO as we do. Dimmock (2008) uses one year of data from the NACUBO Endowment Survey to assess the role of background risk (proxied by non-investment income volatility) on endowment portfolio choice while Lerner et al. (2008) rely on similar data to document that Ivy League school endowments have performed much better than non-Ivy league schools in managing their commitments to alternative investments. Finally, Lerner et al. (2007) document that endowments have exceptional abilities in selecting the right venture capital partnerships. These last two papers emphasize how some endowments excel in their security selection process. Our paper completes and extends these findings by

[2]For example, Cain (1960), Tobin (1974), Litvack et al. (1974) and Dybvig (1999) have analyzed investment practices of university endowment funds. Carpenter (1956) and Davidson (1971) examined endowment return behavior, although neither study explicitly addressed the issue of risk-adjusted performance.

showing that it is not the returns to a few selected market segments (e.g., alternative assets) that drives the performance of these institutions, but security selection *as a whole* across the entire asset class universe that is the key determinant of an endowment's overall success.

The remainder of the paper is organized as follows. In the next section, we describe and summarize the endowment data used in the study. Section 3 rigorously defines the concept of *passive asset allocation* as part of an endowment's portfolio while Section 4 relates the variation in passive returns to the variation of total fund returns. Section 5 formally tests the relationship between asset allocation and performance for endowment funds and Section 6 concludes the study. Appendix A contains useful results from the Treynor and Black (1973) model that serves as a basis for some of our tests.

2. Data description

Our primary database is the set of NACUBO's Endowment Studies, which are annual publications based on surveys that gather information about asset allocation patterns, investment performance, spending rules and rates, and manager and custodial relationships of college and university endowments throughout the United States, Canada, and Puerto Rico. The data cover the period from 1984 to 2005.[3]

Although the NACUBO surveys began in 1984, the participating institutions were not identified during the 1984–1988 period meaning that, for these five years, the asset allocation survey data cannot be merged with the information on assets under management, endowment fund payout or investment performance. As a consequence, the majority of our analysis will be limited to the post-1988 period. However, for the 1989–2005 period, identification of member endowments is possible and we obtained this information from NACUBO directly. Although the NACUBO studies are publicly available, identification of the members is not.

We only consider an endowment to have reported a complete set of information if it provides institution-identifiable data in each of the three categories: asset class portfolio weights, investment-return performance *net of fees and expenses*, and total assets under management. The number of endowments meeting these conditions increased steadily throughout the sample period, starting with a total of 200 in 1984 and ending with 709 in 2005.[4]

Over the course of the surveying process, NACUBO has changed the definition of the asset classes in which the endowment funds invest. In our study, we adopt the most recent definition of these asset classes.[5] The "granularity" of these asset allocation definitions changed twice during the 1989–2005 sample period, in 1998 and again in 2001. To preserve

[3]TIAA-CREF has administered the survey since 2000; from 1988 to 1999, the survey was conducted in partnership with Cambridge Associates and before 1988 by the NACUBO Investment Committee.

[4]We also group together pools of money that belong to the same university or college. Before grouping, there are 206 respondents to the survey in 1984 and 753 in 2005.

[5]Specifically, in 2005, NACUBO characterizes asset allocation across 12 different asset classes: US equity, non-US equity, US fixed-income, non-US fixed-income, public real estate, private real estate, hedge funds, venture capital, private equity (buyout), natural resources, cash, and other assets. We will refer to the combination of venture capital and private equity buyout as the private equity asset class. "Other assets" comprises assets that are difficult to classify into any of the other broad asset classes, such as college infrastructure or oil wells. Oil wells do not follow the returns of crude oil (and hence are not classified as a natural resource) because of depreciation.

the most recent set of definitions, we combined some asset classes that were reported separately in previous surveys.[6]

Another important adjustment in the NACUBO surveying process during our sample period involves the collection of information on both the *actual* as well as the *intended* (i.e., policy) asset allocation schemes. In their surveys during the 2002–2005 period, NACUBO asked participating endowments to report not only their actual asset allocation but also their target levels for the next year. In the work to follow, we interpret this target allocation as deriving from the fund's policy, inasmuch as it represents the institution's desired exposure to the various asset classes as a general mandate for the investment process.

Unfortunately, the low frequency (i.e., annual observations) of the NACUBO data makes it challenging to verify the robustness of our findings at the time series level. To address this issue, we also collected similar data on a *quarterly* basis for 111 university and college endowments with more than $200 million of assets under management. Of these 111 endowments, 109 are also represented in the NACUBO sample. For these institutions we were able to collect actual asset allocation weights and raw returns reported at a quarterly frequency between 1994 and 2005, as well as assets under management reported at an annual frequency.[7]

Because our main data come from surveys it is important to dispel some natural concerns regarding accuracy and potential biases due to sample selection and survivorship. To ensure accuracy, NACUBO employs a set of filters designed to prevent erroneous filing. Whenever an apparent reporting discrepancy arises, NACUBO contacts the respective institution to seek a reconciliation before the results of the study are published. We have also learned from private interviews with various endowment staff personnel that the data from NACUBO are often used for compensation purposes, and as such the studies are viewed as being highly reliable by industry participants. Furthermore, the custodians of the assets at the institutions in our samples are sensitive to issues such as stale pricing, thus making the data on endowment performance as accurate as possible. With regard to sample selection bias, although the NACUBO data are the largest sample of its kind, it is possible that it still misrepresents the universe of colleges and universities. To alleviate this concern, we replicated our results for subsamples of endowments with small and large assets under management, low and high payout ratios, public and private institutions, as well as for our separately collected quarterly database. The conclusions throughout the study withstand restrictions on size, payout, and whether the institution is public or private. Lastly, NACUBO does not restate the content of its previous surveys when institutions subsequently drop out of the sample, which means that our primary data set is entirely free from survivorship bias.

Since NACUBO offers a larger sample size in the cross-section and more endowment fund characteristics than our quarterly sample, we report our results in the following

---

[6]Precisely, for the 1999–2001 sample period, we combined the "absolute return-event driven," "absolute return-general," and "distressed securities" hedge fund classes together and classified the result as hedge funds. "High yield bonds" were similarly combined with the rest of the US fixed-income. Also, the "non-US emerging bonds" and "non-US developing bonds" were included with the rest of the non-US fixed-income and the "faculty mortgages" were included in the private real estate category while "timber" was merged within the natural resources asset class. Similar adjustments were made for the 1989–1998 period, with the additional placement of "leveraged buyouts" into the private equity category.

[7]We are grateful for the cooperation of a large financial institution (which preferred to remain unnamed) in helping us to identify and secure these data in a manner that preserved the anonymity of the endowments included.

Table 1
Cross-sectional summary of endowments characteristics.

The table reports annual cross-sectional means of the target and actual asset allocations (in percent) and of assets under management (AUM), as well as means and standard deviations of returns and payout ratios from the endowments contained in the NACUBO database. *Eq.*: public equity, *FI*: fixed income, *RE-pub*: public real estate (i.e., REITs), *RE-priv.*: private real estate, *VC*: venture capital, *PE*: private equity, *Nat. res.*: natural resources.

	US eq.	Non-US eq.	US FI	Non-US FI	RE-pub.	RE-priv.	Cash	Other	Hedge funds	VC	PE	Nat. res.	AUM ($ mill.)	Return		Payout		No. of obs.
														Mean	Std.	Mean	Std.	
2005														9.16	3.29	4.78	1.40	709
Actual	45.7	12.7	20.5	0.9	1.2	2.0	3.4	1.4	8.9	0.8	1.6	1.0	352.6					
Target	44.7	12.8	21.5	1.0	1.3	2.2	1.6	0.8	9.0	1.5	2.5	1.2						
2004														15.02	4.42	4.88	1.62	705
Actual	48.7	11.1	21.1	0.8	1.0	1.8	3.6	1.6	7.5	0.8	1.4	0.6	324.5					
Target	47.2	11.3	22.7	0.8	1.3	2.1	1.4	0.9	8.1	1.5	2.1	0.8						
2003														2.69	3.67	5.21	1.51	665
Actual	47.4	9.7	24.9	0.7	1.0	1.8	3.9	1.6	6.3	0.8	1.4	0.4	294.9					
Target	48.5	10.4	24.8	0.7	1.1	1.8	1.7	1.0	6.1	1.5	1.9	0.4						
2002														−5.95	4.23	5.22	1.54	535
Actual	46.4	10.1	25.9	1.1	1.2	1.4	4.0	1.6	5.6	1.0	1.2	0.4	336.9					
Target	49.6	10.6	25.1	0.7	1.0	1.2	1.6	1.2	4.9	1.9	1.9	0.3						
Actual only																		
2001	49.6	10.0	23.9	1.0	0.8	1.3	4.0	5.8	0.6	1.5	0.9	0.4	393.1	−3.24	6.31	5.17	1.43	568
2000	50.7	11.6	22.1	1.3	0.7	1.2	4.0	4.0	0.7	2.4	1.0	0.3	462.5	12.67	10.12	4.97	1.40	507
1999	53.9	10.5	22.2	1.6	0.6	1.3	3.9	0.6	3.1	1.3	0.7	0.2	410.3	10.79	4.71	4.82	1.24	467
1998	53.1	10.9	23.9	1.6	2.1	1.3	2.2	0.6	1.6	0.9	0.5	1.2	371.2	18.06	3.97	4.69	1.21	445
1997	52.5	11.2	23.9	1.8	1.7	0.3	4.6	0.5	2.2	0.8	0.3	0.2	328.3	20.10	4.44	4.80	1.77	456
1996	51.8	9.4	25.9	1.8	1.6	0.4	5.4	0.7	1.9	0.8	0.3	0.2	282.2	17.25	4.02	4.84	1.30	405
1995	46.9	7.9	28.1	1.9	1.7	0.4	6.5	3.9	1.6	0.7	0.2	0.3	236.1	15.06	4.15	4.95	1.48	422
1994	46.2	7.4	30.0	1.8	1.6	0.3	7.4	2.8	1.4	0.7	0.2	0.3	189.1	3.25	4.35	5.24	1.75	375
1993	48.1	4.2	33.6	1.3	0.0	1.6	7.3	2.0	0.7	0.2	0.6	0.3	196.0	13.15	4.28	n.a.	n.a.	394
1992	48.1	3.0	35.0	0.9	1.8	0.6	9.4	0.0	0.4	0.5	0.2	0.2	196.3	13.00	4.94	n.a.	n.a.	318
1991	47.5	2.3	35.3	0.7	2.1	0.7	10.2	0.0	0.3	0.6	0.2	0.2	171.9	7.25	4.89	n.a.	n.a.	328
1990	47.5	2.3	35.0	0.6	2.2	0.7	10.3	0.0	0.3	0.6	0.2	0.2	174.3	10.02	6.01	n.a.	n.a.	298
1989	47.0	1.7	30.9	0.8	2.4	0.5	12.9	2.9	0.0	0.6	0.2	0.1	165.4	13.58	4.65	n.a.	n.a.	281

analysis using the NACUBO data unless otherwise specified. When necessity dictates, such as for our time series tests, we also provide results obtained using the higher frequency data. It should be noted, however, that we have replicated a complete set of findings using just the higher frequency sample and none of our conclusions change in a substantive way.

Table 1 provides a broad overview of our sample of university endowments. Overall, the data show tremendous cross-sectional heterogeneity in both assets under management and returns net of fees.[8] In the table we also report the cross-sectional average allocation (in percentage of AUM) to each of the 12 NACUBO asset classes for the entire endowment universe. Additionally, for the years from 2002 to 2005, we also report the average fund's intended strategic policy (i.e., *target*) allocation for the subsequent year. Many of the trends represented in these data (e.g., increased allocations over time to non-US equity and alternative assets, decreased allocations to fixed-income) have been well-chronicled elsewhere and need not be discussed in further detail.[9] It should be noted, though, that these movements are consistent with the broad characterization of the endowment fund industry as generally unrestricted, in a manner similar to individual investors (see Merton, 2003), making funds free to pursue allocation strategies believed to produce superior risk-adjusted return outcomes (see Hill, 2006).

We also compared, but do no report, actual asset allocations for large (i.e., the top assets under management quartile) versus small (i.e., the bottom assets under management quartile) funds. We observed considerable cross-sectional heterogeneity in the listed asset class weights, indicating that the level of a fund's size is significantly related to its allocation decision. Small funds allocate substantially more than large funds to public equities and traditional fixed-income securities. Conversely, large endowments have been mainly responsible for the trend toward investing in the alternative asset classes.

3. Anatomy of endowment fund returns

To quantify the contribution of asset allocation to a portfolio's total return, we follow a methodology similar to that used by Brinson et al. (1986, 1991) and Daniel et al. (1997) and decompose the returns of endowments into their three fundamental components: (i) asset allocation policy (i.e., benchmark), (ii) tactical allocation (i.e., market timing), and (iii) security selection. This decomposition reflects closely the investment decision within a typical endowment: the first of these components represents a passive decision typically made by the endowment's board while the latter two are active decisions made by the endowment's investment staff.[10]

[8]We have in fact analyzed separately private and public endowment funds. For any given year, there are roughly 3–4 times more participating private school endowments than public ones and the typical private fund manages a slightly larger portfolio. While it does not appear that private and public schools differ meaningfully in terms of their spending policies, private school funds generated a higher average return than public schools in 12 out of the 17 sample years.

[9]See, for example, the annual benchmark studies produced by NACUBO (Morley and Heller, 2006) and Commonfund Institute (Griswold, 2008).

[10]There is substantial survey evidence that decomposing returns in this manner is a reasonable way to characterize the endowment management process. For instance, Griswold (2008) shows that endowments invest between 65% and 85% of the funds dedicated to a particular asset class in actively managed portfolios, with the remaining being passively indexed.

Formally, let $R_{i,t}$ be the realized return on fund i at the end of period t, $w_{i,j,t}$ the actual portfolio weight of fund i in asset class $j = 1, \ldots, N$ at the end of period t, $w^B_{i,j,t-1}$ the *policy* or strategic asset allocation weight at the end of period $t-1$, $r_{i,j,t}$ the period-t return on asset class j, and $r^B_{j,t}$ the return on a *benchmark* index for asset class j. The realized return can hence be decomposed as follows:

$$\begin{aligned} R_{i,t} &= \sum_{j=1}^{N} w_{i,j,t-1} r_{i,j,t} \\ &= \sum_{j=1}^{N} w^B_{i,j,t-1} r^B_{j,t} + \sum_{j=1}^{N} (w_{i,j,t-1} - w^B_{i,j,t-1}) r^B_{j,t} + \sum_{j=1}^{N} w_{i,j,t-1} (r_{i,j,t} - r^B_{j,t}) r^B_{j,t} \\ &\equiv R^B_{i,t} + R^T_{i,t} + R^S_{i,t}. \end{aligned} \tag{1}$$

The quantity $R^B_{i,t}$ indicates the return from asset allocation policy (*benchmark return*), $R^T_{i,t}$ is the return from *market timing*, and $R^S_{i,t}$ is the return from *security selection*. In our data we can observe, at annual (quarterly) intervals, the total endowment return $R_{i,t}$ and the actual weights $w_{i,j,t-1}$ but not the individual asset returns $r_{i,j,t}$. We complete the construction of security selection returns $R^S_{i,t}$ as a residual, after computing benchmark and market timing returns. Due to its residual nature, the term $R^S_{i,t}$ will contain not only returns generated by security selection but all returns that are not attributable to policy decisions or timing decisions. For example, while there is evidence that mutual fund managers owe part of their outperformance to industry timing strategies (Avramov and Wermers, 2006), such an outcome will be part of $R^S_{i,t}$ in our study. Thus, for brevity, we will still refer to this residual return element as the ‘‘security selection’’ component.

A key aspect in performing the decomposition described in (1) is the determination of benchmark asset class returns $r^B_{j,t}$ and policy weights $w^B_{i,j,t-1}$ necessary for the construction of a portfolio benchmark return $R^B_{i,t}$.

As described in Section 2, for each year from 2002 to 2005 the NACUBO survey reports every endowment's target allocations for each asset class. When available, we use these weights as our proxy for the benchmark weights. For years prior to 2002, we follow Blake et al. (1999) and use a measure of policy weights constructed by linearly interpolating the initial and terminal portfolio weights. Specifically, given a time series of T portfolio weights $w_{i,j,t}$, we defined the benchmark weight for endowment i in asset class j at time t as

$$w^B_{i,j,t} = w_{i,j,1} + \frac{t}{T}(w_{i,j,T} - w_{i,j,1}). \tag{2}$$

Although these quantities suffer from a look-ahead bias, they have the appealing property of accounting for non-stationarity in portfolio weights. To check the robustness of our results, we also replicated our analysis using several other proxies: simple average portfolio allocation over the sample period (also used by Blake et al., 1999); an average of the allocations calculated not over the entire sample but over 2, 3, or 4 years prior; lagged actual weights; and the cross-sectional average weight in each asset class. The results are qualitatively similar across all these proxies.

The choice of a benchmark index $r^B_{j,t}$ in (1) also requires careful consideration. Conceptually, the perfect choice of a benchmark index for a particular asset class j would be a portfolio containing *all* the holdings of *all* the endowments in the respective asset class.

Table 2
Asset class benchmarks.

The table reports summary statistics for the asset class representative indices. SR is the Sharpe ratio, α's (and their t-statistics) are computed relative to the model in Eq. (7):

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,\mathrm{mkt}} MKT + \beta_{i,\mathrm{smb}} SMB_t + \beta_{i,\mathrm{hml}} HML_t + \beta_{i,\mathrm{umd}} UMD_t + \beta_{i,\mathrm{term}} TERM_t + \beta_{i,\mathrm{def}} DEF_t + \varepsilon_{i,t},$$

where $R_{i,t}$ is the return on asset class i and the regressors are discussed in Section 5.3.

	Asset class	Benchmark index	Summary statistics					
			Mean	Std.	Median	SR	α	t-stat.
1.	US equity	CRSP WV market portfolio	11.47	13.09	13.13	0.56	−0.00	−0.98
2.	Non-US equity	MSCI World (Excl. US)	4.46	13.31	5.82	0.02	1.02	0.22
3.	US fixed income	Lehman bond aggregate	8.04	4.41	8.64	0.88	0.54	0.52
4.	Non-US fixed income	Salomon Brothers non-US bond index	7.89	9.08	7.60	0.41	4.99	1.02
5.	Public real estate	NAREIT	13.27	12.79	9.06	0.71	−1.77	−0.34
6.	Private real estate	NCREIF	7.81	6.55	8.07	0.56	4.59	1.07
7.	Hedge funds	HFRI-all fund composite	14.31	7.61	13.09	1.34	7.13	2.01
8.	Venture capital	Cambridge associate VC index	26.59	56.20	17.42	0.40	26.07	1.47
9.	Private equity	Cambridge associate PE index	14.76	13.74	15.38	0.77	5.87	1.27
10.	Natural resources	AMEX oil (before 1992), GSCI (after 1992)	7.02	16.87	1.33	0.17	6.07	0.59
11.	Other investments	–	–	–	–	–	–	–
12.	Cash	30-day US T-Bill	4.14	1.92	4.73	0.00	0.00	–

		Correlations											
		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
1.	US equity	1.00											
2.	Non-US equity	0.64	1.00										
3.	US fixed income	−0.04	−0.57	1.00									
4.	Non-US fixed income	−0.06	−0.11	0.26	1.00								
5.	Public real estate	−0.01	0.20	0.08	−0.17	1.00							
6.	Private real estate	0.16	0.17	−0.31	−0.57	0.02	1.00						
7.	Hedge funds	0.58	0.56	−0.05	0.07	0.03	−0.46	1.00					
8.	Venture capital	0.37	0.45	−0.31	−0.20	−0.30	0.21	0.53	1.00				
9.	Private equity	0.81	0.80	−0.32	−0.22	0.14	0.36	0.56	0.56	1.00			
10.	Natural resources	0.81	0.47	−0.42	−0.09	−0.12	0.28	0.18	0.49	0.28	1.00		
11.	Other investments	–	–	–	–	–	–	–	–	–	–	–	
12.	Cash	0.24	−0.21	0.32	−0.35	−0.40	−0.04	0.23	0.21	0.01	−0.09	–	1.00

Unfortunately, with two exceptions, this information was not readily available.[11] For the other asset classes, we chose a specific index that we regard as representative of a well-diversified portfolio for that category and then treat that portfolio as the *common* benchmark for all the endowments in our sample. While the choice of these benchmarks is motivated by their frequent use in practice, these are not the only available proxies. To establish the robustness of our choices, we repeated the subsequent analysis with several different index definitions—especially for the alternative asset classes—and found no meaningful effect on our main results. These benchmark definitions are shown in Table 2, which also lists several summary statistics for the investment performance within and across the asset class categories.[12]

Table 3 lists cross-sectional summary statistics for the total (R), policy benchmark (R^B), market timing (R^T), and security selection (R^S) return components for the full universe of NACUBO college endowment funds. For each year, we report the sample-wide mean of the particular return component, as well as the *benchmark-adjusted* return $R - R^B$, which is often used in practice as a proxy for the active part of the portfolio's performance.[13] From the reported cross-sectional means, the allocation component R^B constitutes the largest part of the typical endowment's total return, whereas the remaining two components are almost negligible. Further, judging by the benchmark-adjusted return proxy for active investment prowess, the average endowment fund manager appears to have invested reasonably well. The mean annual average of $R - R^B$ is 0.64% over the entire sample period and the active returns are positive in 10 out of the 16 years reported.

4. Asset allocation and endowment return variation

The return decomposition of the previous section allows us to investigate how asset allocation decisions contribute to the overall return variation of a university endowment both in the time series and in the cross-section.[14]

[11]For the private equity and venture capital asset classes, we have used the Cambridge Associates value-weighted indexes, which track the performance of the actual investments in their universe of endowment funds. These indices are available at https://www.cambridgeassociates.com/indexes/.

[12]Note that although the most popular US equity benchmark used by endowments is the Russell 3000 index, we have used the CRSP value-weighted market index portfolio instead. The reason is that for the period of our study, the Russell 3000 slightly underperforms relative to the Fama–French model (see also Cremers et al., 2008). Since US equity is the predominant asset class held by endowments, such a benchmark choice may potentially understate the performance of endowments' passive portfolios, and hence we preferred to utilize the "more aggressive" index. The results of this study do not change with the choice of the benchmark and are available upon request.

[13]Despite the fact that the difference $R - R^B$ is commonly employed as a performance measure, we stress that benchmark-adjusted returns do not explicitly control for the risk in the actual endowment portfolio, as do the factor model-adjusted returns reported in Section 5.3.

[14]There is plenty of anecdotal evidence suggesting that *strategic asset allocation* plays a primary role in the investment process of the typical endowment fund. For example, the 2007 Yale Endowment Report states on page 2 that "Yale's superb long-term record resulted from disciplined and *diversified asset allocation policies*, superior active management and strong capital market returns." (Emphasis added.) Similarly, on p. 11 of the 2007 Harvard Endowment Report, it is stated that the Harvard Management Company "seeks to add value in every element of the investment stream starting at the *asset allocation* level." (Emphasis added.) In their 2007 annual report, on a section dedicated to investment strategy, asset allocation, and performance, the University of Texas Investment Management Company (UTIMCO) also states that it follows an "allocation policy [...] developed through a careful asset allocation review with the UTIMCO Board in which potential returns for each asset category were balanced against the contribution to total portfolio risk by each category." (http://www.utimco.org/funds/allfunds/2007annual/faq_investment.asp.)

Table 3
Components of endowment fund returns.

The table reports summary statistics for the endowment fund returns components. The benchmark returns are defined as $R^B_{i,t} = \sum_{j=1}^{N} w^B_{i,j,t-1} r^B_{j,t}$. When target weights are not available, we assume that $w^B_{i,j,t-1} = w_{i,j,1} + ((t-1)/T)(w_{i,j,T} - w_{i,j,1})$, where $w_{i,j,1}$ is the allocation of fund i to asset class j at the first time period when this weight is available and $w_{i,j,T}$ is the allocation of fund i to asset class j at the last time (T), where such allocation is available. The returns due to timing are $R^T_i = \sum_{j=1}^{N}(w_{i,j,t-1} - w^B_{i,j,t-1}) r^B_{i,j,t}$. The returns due to security selection are $R^S_{i,t} = R_{i,t} - R^B_{i,t} - R^T_{i,t}$. For comparison of relative magnitudes, we also report the mean total return R.

Year	R	R^B	R^T	R^S	$R-R^B$
2005					
Mean	9.80	9.98	−0.52	0.34	−0.18
Std	3.15	1.62	0.83	2.53	2.48
2004					
Mean	15.75	15.82	−0.48	0.41	−0.07
Std	4.08	2.20	1.55	3.05	3.30
2003					
Mean	2.37	3.12	0.30	−1.05	−0.76
Std	3.41	1.37	1.13	3.21	3.43
2002					
Mean	−6.09	−6.60	−0.89	1.40	0.51
Std	4.17	2.23	2.44	3.99	4.13
2001					
Mean	−3.45	−7.19	−1.73	5.48	3.74
Std	6.22	2.54	2.94	6.16	6.36
2000					
Mean	12.87	12.79	−0.30	0.38	0.08
Std	10.53	4.88	4.48	7.26	8.38
1999					
Mean	10.77	11.48	0.50	−1.21	−0.71
Std	4.81	1.82	2.03	4.61	4.75
1998					
Mean	18.23	17.11	0.94	0.18	1.12
Std	3.93	2.22	2.52	3.81	4.06
1997					
Mean	20.13	17.72	0.84	1.57	2.41
Std	4.39	2.10	2.48	4.17	4.53
1996					
Mean	17.32	16.00	−0.73	2.05	1.32
Std	4.07	2.30	3.20	4.22	3.87
1995					
Mean	15.20	15.72	0.15	−0.67	−0.52
Std	4.11	1.95	2.47	4.13	4.21
1994					
Mean	3.36	2.34	−1.06	2.08	1.02
Std	4.43	1.28	1.11	4.14	4.34
1993					
Mean	13.40	13.51	−0.17	0.05	−0.12
Std	4.06	1.53	1.51	4.08	4.10
1992					
Mean	12.96	11.65	0.54	0.76	1.31
Std	4.01	1.14	1.20	4.02	4.08

Table 3 (*continued*)

Year	R	R^B	R^T	R^S	$R-R^B$
1991					
Mean	7.22	6.74	0.62	−0.13	0.48
Std	4.99	1.06	1.50	5.02	4.80
1990					
Mean	10.21	8.95	−0.06	1.33	1.26
Std	6.69	1.06	0.23	6.77	6.76
Grand mean	9.99	9.35	−0.13	0.77	0.64

Following the methodology of Ibbotson and Kaplan (2000), we quantify the degree to which asset allocation contributes to return variability *over time*, by regressing the time series of total annual returns of each fund i on each of the three return components, i.e.,

$$R_{i,t} = a_i + b_i R^k_{i,t} + \varepsilon_{i,t}, \quad i = 1, \ldots I, \tag{3}$$

where I denotes the number of funds in our sample and $R^k_{i,t}$ is, in turn, the policy allocation return component ($R^B_{i,t}$) of fund i, the market timing component ($R^T_{i,t}$), and the security selection component ($R^S_{i,t}$) from (1).[15] For each fund-specific time series regression, we are interested in the R-squared coefficient, i.e., the contribution of the variation in the respective return component R^k to the variation of the overall endowment return R.

Similarly, to estimate the contribution of asset allocation to *cross-sectional* variation in returns, for each sample year t we estimate separate cross-sectional regressions for the total return of each endowment on its three component parts:

$$R_{i,t} = a_t + b_t R^k_{i,t} + \varepsilon_{i,t}, \quad t = 1, \ldots, \tau, \tag{4}$$

where as before $R^k_{i,t}$ represents, respectively, the asset allocation ($R^B_{i,t}$), market timing ($R^T_{i,t}$), and security selection ($R^S_{i,t}$) return components of endowment i at time t.[16]

Table 4 lists the results of these two tests. Panel A reports summary statistics for the distribution of the adjusted R-squared coefficients in the endowment sample for the time series regressions in (3) while Panel B presents the summary statistics of the R-squared values from the yearly cross-sectional regressions in (4).

The results in Table 4 are consistent with—but more extreme than—those established elsewhere for mutual funds and pension funds. From Panel A, we observe that, on average, asset allocation explains 74.42% of the variation of each endowment's returns, whereas the timing and security selection components explain just 14.59% and 8.39%, respectively. Thus, for the typical endowment, the asset allocation decision is arguably the most important investment decision made by the fund, being responsible for most of the variation in the portfolio's returns over time. However, this interpretation changes dramatically when the results from the cross-sectional regressions are considered. From the

[15] Because we eliminate funds with fewer than five yearly observations to run these regressions, $I = 704$ in the analysis summarized below.

[16] Although similar in spirit, our methodology here differs from that in Ibbotson and Kaplan (2000) since instead of pooling the results of τ cross-sectional regressions, as we do, they compute an annualized return for each institution in their sample and then run a single regression. We adopt our procedure in order to avoid dealing with panels of endowment returns that are unbalanced.

Table 4
Time-series and cross-sectional return variation.

Panel A reports summary statistics from the cross-sectional distribution of adjusted R-squared coefficients obtained from performing the following time-series regression for each endowment:

$$R_{i,t} = a_i + b_i R^k_{i,t} + \varepsilon_{i,t}, \quad i = 1, \ldots, 704,$$

where $R_{i,t}$ is the return on endowment i at time t and $R^k_{i,t}$ is, in turn, the asset allocation return component $R^B_{i,t}$, the market timing component $R^T_{i,t}$ and the security selection component $R^S_{i,t}$ from (1). Panel B reports the summary statistics from the time-series distribution of adjusted R-squared from the 16 cross-sectional regressions:

$$R_{i,t} = a_i + b_i R^k_{i,t} + \varepsilon_{i,t}, \quad t = 1, \ldots, 15,$$

where $k = B, T, S$. We require at least five datapoints to run each regression.

	Mean (%)	Median (%)	p-25 (%)	p-75 (%)	Std. dev. (%)
Panel A: Time-series R-squared values					
R^B	74.42	81.94	67.82	91.25	26.13
R^T	14.59	10.54	−7.04	34.87	29.84
R^S	8.39	−0.41	−7.69	17.69	28.29
Panel B: Cross-sectional R-squared values					
R^B	11.10	4.69	2.79	11.06	14.37
R^T	3.30	2.43	0.80	4.34	4.11
R^S	74.69	77.17	61.23	87.13	15.80

findings in Panel B, we observe that the variability in the returns generated by asset allocation explains on average only 11.10% of the cross-sectional variation of total endowment returns. Security selection is mostly responsible for the cross-sectional variation in returns, explaining an average of 74.69%. Our findings are more pronounced in the cross-section than what Ibbotson and Kaplan (2000) find for mutual funds, where the asset allocation explains an average of 40% of the cross-sectional return variance.

In summary, these tests show that while asset allocation is *the* most important decision in each endowment and explains the vast majority of the variation in each endowment's returns, it is security selection that makes the endowment returns heterogenous across the entire sample.

5. Asset allocation and endowment fund performance

The results of the previous section are puzzling, especially in light of the frequently accepted tenet that strategic asset allocation is the most important decision in the investing process. Its failure to explain return variation across endowments calls for a better understanding of the contribution of asset allocation to return variation in both the time series and the cross-section. Addressing this apparent discrepancy allows us to discuss the relative merits of relying on the passive asset allocation decision to produce superior investment returns.

5.1. Understanding asset allocation in the cross-section and time series

To better understand the results in Section 4, we need to analyze more closely the cross-sectional return properties of our endowment fund sample. Because the asset allocation component R^B is the product of policy weights w^B and benchmark return r^B, the lack of explanatory power of the return component within a peer group at a particular point in time can have three possible causes: (i) the portfolio weights across endowments are identical, in which case, by construction, all funds in the sample will be assigned the same asset allocation return R^B, (ii) the benchmark indices used are identical to each other, meaning that it does not matter if different endowments hold different policy portfolios in these indices, or (iii) the product of policy weights and benchmark returns is similar across the sample despite the cross-sectional variation of weights and benchmark returns when viewed separately.[17]

Earlier, we documented the existence of meaningful cross-sectional differences between the policy weights of large and small endowments. To further refine this analysis, Table 5 reports the cross-sectional dispersion of: (i) the portfolio weights for each year in our sample, (ii) the returns r^B to each of the benchmark indices, measured as the dispersion of the periodic returns to the 12 asset class benchmarks at time t, and (iii) the policy allocation returns, R^B. From the display, it appears that the cross-sectional standard deviation of the policy returns (R^B column) is typically much smaller than the cross-sectional standard deviation of either the weights (first 12 columns) or the benchmark returns (r^B column). However, because the weights have cross-sectional dispersion, and because the policy returns are the product of the benchmark returns (which are fixed in the cross-section) and the asset allocation weights, we would expect the cross-sectional standard deviation of the overall policy returns to be small as a consequence of a pure diversification effect.[18]

Consequently, we are interested in knowing whether the cross-sectional dispersion of the passive return is lower than what one would expect under the assumption that the distribution of weights in the cross-section was *independent* across funds. If this is the case, then we can claim that endowment funds act as if they consciously ‘‘constrain’’ their investment weights in order to achieve similar levels of passive risk and return. To verify this supposition in our sample, for each year we have calculated the variance of the policy returns assuming the weights of all asset classes except ‘‘other assets’’ were drawn independently.[19] Using a single-tailed chi-square test, we then checked whether the sample variance of the policy returns is equal to the theoretical value under the null hypothesis

[17]A fourth possibility is that all endowments keep roughly the same actual asset allocation, regardless of what they state as their policy allocations. We eliminate this possibility since the actual weights in our sample do exhibit substantial cross-sectional variation. These results are available upon request.

[18]The fact that the returns on asset class benchmarks r^B have cross-sectional dispersion at each point in time (as apparent from the standard deviation reported in Table 5, column r^B) is necessary in order to generate variance in the policy returns. If all asset classes had identical returns (i.e., zero cross-sectional dispersion), the various policy portfolios would have been identical in the cross-section, no matter what the weights are.

[19]Weights are obviously not independent because their sum is one. Technically, our test refers to the independence of $N-1$ of the N weights, or, equivalently, whether they are subject to additional constraints other than the summing up constraint. While we acknowledge that some of the $N-1$ weights may well be dependent on one another, we do not have sufficient information to account for such correlations in the specification of our test. Moreover, imposing any dependencies across investment weights would bias the examination in favor of finding lower cross-sectional dispersion among passive returns. Thus, to avoid this bias, in the construction of our null hypothesis we adopt the conservative assumption of independence across the $N-1$ weights.

Table 5
Cross-sectional dispersion of policy weights, and benchmark returns.

The table reports the cross-sectional standard deviation (in %) of the policy weights in each of the 12 asset classes, the standard deviation of the returns r^B across the benchmark indices (excluded the "Other" category for which no benchmark has been defined), and the standard deviation of the asset allocation returns $R^B_{i,t} = \sum_{j=1}^{N} w^B_{i,j,t-1} r^B_{j,t}$ across endowments. *Eq.*: public equity, *FI*: fixed income, *RE-Pub*: public real estate (i.e., REITs), *RE-priv.*: private real estate, *VC*: venture capital, *PE*: private equity, *Nat. res.*: natural resources.

	US eq.	Non-US eq.	US FI	Non-US FI	RE-pub.	RE-priv.	Cash	Other	Hedge funds	VC	PE	Nat. res.	r^B	R^B
2005	15.13	7.74	9.82	3.61	2.64	4.13	5.38	3.43	9.85	2.75	4.01	2.58	11.38	1.62
2004	14.46	7.53	10.05	3.53	2.51	4.84	3.78	4.44	9.89	2.76	3.57	1.95	10.98	2.20
2003	14.18	7.42	9.89	2.80	2.30	3.86	5.75	6.01	9.36	2.93	3.56	1.37	10.14	1.37
2002	13.08	6.76	9.84	2.75	2.21	2.37	4.31	6.97	7.84	3.40	3.60	1.12	14.82	2.23
2001	16.17	10.39	11.37	3.87	1.68	2.77	6.28	10.04	2.95	4.87	2.56	1.74	15.75	2.54
2000	12.93	7.43	10.33	3.66	1.66	2.49	4.45	2.42	6.80	2.94	2.14	0.86	59.40	4.88
1999	13.32	7.36	10.84	4.00	3.90	2.48	4.75	1.88	4.65	1.92	1.56	4.78	21.68	1.82
1998	12.94	8.10	11.03	3.90	3.01	1.29	4.96	1.55	5.45	1.86	1.15	0.84	15.37	2.22
1997	13.03	7.78	11.27	3.73	2.85	1.57	7.53	1.76	4.78	1.82	1.04	0.94	13.71	2.10
1996	14.87	6.78	12.87	3.45	3.11	1.79	8.12	11.78	4.12	1.74	0.95	1.47	17.04	2.30
1995	14.68	7.97	14.13	3.17	2.93	1.38	8.51	7.10	4.16	1.58	0.76	1.63	10.57	1.95
1994	15.04	5.88	15.21	2.84	0.22	3.47	8.48	5.57	3.27	0.67	1.64	1.22	7.25	1.28
1993	15.37	4.95	15.38	2.16	3.81	2.15	12.47	0.00	1.30	1.39	0.77	0.56	11.82	1.53
1992	15.41	4.59	15.51	1.87	4.74	2.43	10.69	0.00	1.11	1.46	0.84	0.59	11.06	1.14
1991	14.69	4.66	15.07	1.58	6.69	2.26	10.56	0.00	1.17	1.57	0.89	0.60	7.02	1.06
1990	15.14	3.54	14.01	2.22	5.66	1.39	12.23	7.93	0.00	1.55	1.20	0.39	6.08	1.06

that the weights are chosen independently. In 14 out of the 16, years we reject the null hypothesis that the weights are independent; in 12 of these years, the rejection is very strong (i.e., at a significance level smaller than 1%). Since the cross-sectional variance of the returns generated from asset allocation is small, it appears as if cross-sectional policy returns are constant in each period of our sample. Thus, since policy returns are a linear combination of endowment asset allocation weights and the returns of the asset classes specific to that time period, it appears that endowments do act as if subjected to an implicit linear constraint on their policy weights, which in turn causes the variance of the policy returns to be relatively small in the cross-section. We conclude that the policy returns are similar in the cross-section not because all endowments have comparable actual allocations but, rather, because these funds effectively subject themselves to a *similar constraint* in their strategic policy decision; that is, $\sum_{j=1}^{N} w^B_{i,j,t-1} r^B_{j,t}$ is similar across all funds i.

Further, Table 1 documents little cross-sectional variation in payout ratios, suggesting that risk attitudes should not vary considerably in the endowment sample. This may justify the similarity in the risk and return levels produced by their policy portfolios. In summary, the analysis thus far indicates that an endowment manager's ability to shift capital between asset classes is not completely unrestricted but rather subject to certain volatility constraints, or, more precisely, to a self-imposed *risk budget*.[20]

[20]As defined in Litterman (2003), by *risk budget* we simply refer to the particular allocation of risk within a portfolio that the endowment managers are allowed to take. Various aspects of this allocation between passive and active return components are considered elsewhere in the literature (Clarke et al., 2002; Berkelaar et al., 2006; Leibowitz, 2005).

Given this finding, a natural question to ask is why do endowments choose to hold different asset allocation weights? The answer might lie in the extent to which endowments can find skilled active managers within each asset class (i.e., the "alpha-generating" capability of the asset class). If the various asset classes were completely identical in terms of alpha potential then, given that endowments seem to target a certain overall level of risk, every endowment would have similar amounts of both passive (R^B) and active ($R - R^B$) returns. This would imply low cross-sectional variation in total returns as well. From Table 3, however, we observe that in most cases the cross-sectional standard deviation in the total return R is more than double the variation of passive returns R^B despite having similar means. Hence, different asset classes do seem to offer the endowment managers different opportunities to produce superior active returns. The observed variation in the target weights might then be due to the fact that different funds are trying to expose themselves to different asset classes believed to be more fertile territory for finding skilled active managers (e.g., hedge funds). To formally test this conjecture, we would need access to the actual returns generated by each asset class within an endowment portfolio. Unfortunately, like hedge funds and pension funds, endowments do not disclose that information.

5.2. Active returns and endowment performance

In light of the remarkable heterogeneity in the level and volatility of policy return documented above, any observed cross-sectional variation must originate from active management (i.e., security selection). The interesting question at this point is to see whether funds who decide to rely more on active management do so because of their security selection skills. If this is the case, we should expect more active funds to outperform passive funds who rely more on the asset allocation decision to produce returns. In this section, we show that this is generally the case in our sample: endowments whose returns are generated mostly from passive asset allocation tend to *under-perform* their more active peers.

To construct our tests, we adopt the Treynor and Black (1973) model of portfolio choice with skilled managers. We show in the Appendix that if an investor maximizes the reward-to-risk ratio, the time-series R-squared coefficient obtained from regressing the total return of the investment on the benchmark return, is inversely related to the total returns themselves. This follows because when a larger part of the total return is attributable to the investor's skill (i.e., alpha), by construction the explanatory power of the benchmark will be lower.

The above framework provides us with a natural definition of active and passive endowments. Active (passive) endowments exhibit low (high) R-squared values when regressing their total annual returns on the benchmark returns. In our first test, we directly verify whether active endowments have relatively higher returns than passive ones. For each fund i, we compute (i) the total annualized return over its life, and (ii) the time-series R-squared coefficient. The relationship between total returns and R-squared is negative and statistically significant (the coefficient estimate is -0.03 with a t-statistic of 2.46).

Although these findings might suggest that active endowments (i.e., low R-squared) have higher total returns, we need to be cautious in drawing that conclusion. The above analysis is, in fact, admittedly crude in that each fund is assigned a unique R-squared value computed using its available time series of returns and thus it is possible that our results could be driven by funds that became more active in the most recent years of our sample. To mitigate this concern, we develop more precise tests of the relation between asset allocation and investment performance. The idea is to create a measure that has some affinity with R-squared but, at the same time, possesses time-variation that can be used in a panel analysis.

In the Appendix we show that, in the context of the Treynor and Black (1973) framework, the fraction R^B/R of total return accounted for by the asset allocation return corresponds to the R-squared coefficient of a regression of total returns on benchmark returns, if we assume that the realizations of the random asset returns are equal to their unconditional mean. Using this intuition and the return decomposition of Section 3, we then construct the following return ratios:

$$\theta_{i,t}^k = \frac{R_{i,t}^k}{|R_{i,t}|}, \quad k = B, T, S, \tag{5}$$

where $R_{i,t}^k$ can be the benchmark return ($k = B$), the market timing return ($k = T$), or the security selection return ($k = S$) and $R_{i,t}$ is the total return. The presence of the absolute value in the denominator of (5) is necessary in order to be able to interpret the quantities θ^k as rank variables for the relevance of the strategic allocation, market timing, or security selection components, even when total returns are negative.[21] Finally, to prevent θ^k from becoming infinite for low levels of returns, we eliminate from the analysis observations where the absolute annual returns are less than 0.01%.

From Table 3 it is apparent that the policy returns R^B are very close to the total returns R. This suggests that θ^B should be close to 1.0. Indeed, the average of θ^B is close to 1.0 in almost every year from 1990 to 2005. Cross-sectional standard deviations of θ^k average about 1.5% for the years in which the average value of θ^B is close to 1.0 and are much larger (e.g., in the vicinity of 10%) when the averages of θ^B are farther away from 1.0.

To determine the *marginal* contribution of each of the three return ratios (θ^B, θ^T, and θ^S) to the generation of overall endowment returns, we perform a Fama and MacBeth (1973) regression analysis. Specifically, for each year of the sample period, we regress total returns of the endowments on their return ratios from (5). For each year t, we then estimate the following model:

$$R_{i,t} = a_t + b_t\theta_{i,t}^k + c_t Y_{i,t} + \varepsilon_{i,t}, \quad t = 1, \ldots, \tau, \tag{6}$$

where $R_{i,t}$ is the fund's return in year t, $\theta_{i,t}^k$ represents, in turn, $\theta_{i,t}^B$, $\theta_{i,t}^T$, and $\theta_{i,t}^S$. Also, $Y_{i,t}$ indicates the set of control variables, including the logarithm of asset under management (logAUM) and two dummy variables that track whether at each point in time a particular institution is in the top quintile among its peers for the size of its investment in either private equity and venture capital (PE/VC) or hedge funds (HF). The intuition for including these factors as controls is that endowments that are both larger and leaders in moving their asset allocations toward alternative asset classes may also be capable of selecting the best managers within those categories. Hence, what might appear to be

[21] To illustrate this point, consider the case of two endowments with identical total negative return $R_1 = R_2 = -1\%$. In the first endowment, the passive component is $R_1^B = 4\%$ while in the second it is $R_2^B = -4\%$. For simplicity, suppose both endowments have a zero market timing component, i.e., $R_1^T = R_2^T = 0$. The asset allocation decision of the first endowment is clearly more successful than the second. However, if we were to rank the two funds based on the simple ratio R^B/R, we would attribute a "score" of -4 to the first and a score of $+4$ to the second and conclude that the second fund has a better asset allocation than the first.

superior performance generated within these alternative asset classes could very well be the consequence of a "first mover" advantage.

Because there is a significantly negative relationship between θ^B and θ^S (a Pearson correlation coefficient of -0.9354), we cannot include both of these ratios in our regressions at the same time.[22] The correlation between the HF dummy and the PE/VC dummy is smaller at 0.1947, suggesting that endowments that are aggressively invested in hedge funds do not necessarily overlap substantially with those heavily invested in private equity and venture capital.

The regression results, which consist of the time-series averages of the coefficients estimated in (6), are contained in Table 6. In both the univariate (Model 1) and multivariate regressions (Models 4 and 7), the mean parameter on the relative asset allocation component (θ^B) turns out to be negative and statistically reliable at the 1% level. In contrast, the coefficient on the security selection variable (Models 3, 6, and 9) is consistently and significantly positive. Further, market timing seems to contribute much less to the production of total returns. Moreover, in unreported results we found that unlike asset allocation and security selection, the statistical significance of the timing component is not robust to different specifications for the benchmark weights.

Collectively, these findings strongly suggest that endowments for which the passive asset allocation decision contributes a higher percentage of the total return tend to be associated with *smaller* overall returns, corroborating our earlier R-squared tests. The results in Table 6 are indicative of the fact that an endowment that tilts its return composition toward the policy allocation decision is, on average, *hurt* in comparison to its more active peers. Conversely, employing managers with security selection abilities seems to enhance a fund's return. Notice also that endowment returns are strongly positively related to the lagged value of assets under management. This is another indication that, all else being equal, managers at larger endowments exhibit superior portfolio management skills compared to their small fund counterparts. Somewhat surprisingly, there is only modest evidence that endowments that are heavily invested in private equity or venture capital benefit greatly from that decision. However, it appears that a bigger commitment to hedge funds affects cross-sectional performance. To the extent that hedge fund investments provide more opportunity for superior performance, migration to this asset class seems to have helped those endowments that pursued them.

5.3. *Risk-adjusted return tests*

The preceding analysis can be further refined by explicitly adjusting the endowment returns for risk. As in Fama and French (1993) and Carhart (1997), we calculate abnormal returns by using variations of the following model:

$$R_t - R_{f,t} = \alpha_i + \beta_{\text{mkt}} MKT_t + \beta_{\text{smb}} SMB_t + \beta_{\text{hml}} HML_t + \beta_{\text{umd}} UMD_t + \beta_{\text{term}} TERM_t + \beta_{\text{def}} DEF_t + \varepsilon_t, \tag{7}$$

where R_t is the equally weighted portfolio return of all the endowments at time t, MKT is the value-weighted return on the index of all NYSE, AMEX, and NASDAQ stocks at time t in excess of the risk-free rate ($R_{f,t}$), SMB is the difference in the average returns to

[22] This level of correlation is to be expected from the definition of these ratios. Suppose, for example, that returns are always positive, $R > 0$ and that $R^T = 0$. In this case $corr(\theta^B, \theta^S) = -1$ by construction.

Table 6
Contribution of asset allocation to cross-sectional fund performance.

We regress $R_{i,t}$ against the variables listed in the first column. θ^B is the asset allocation ratio, θ^T the market timing ratio, and θ^S the security selection ratio defined in (5); logAUM is the logarithm of asset under management, PE/VC a dummy variable set equal to one every time the portfolio weights in private equity, and venture capital of an endowment is in the top quintile. The dummy variable HF does the same for the case of portfolio weights in hedge funds. The t-statistics from the Fama–MacBeth procedure are corrected for heteroskedasticity and auto-correlation (see Newey and West, 1987).

Models	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Const.	0.145	0.102	0.102	0.095	0.034	0.051	0.032	0.005	0.023
t-stat.	3.89	4.42	4.36	2.32	1.17	1.91	1.08	0.22	1.13
θ^B	−0.048			−0.047			−0.022		
t-stat.	−3.76			−3.71			−10.06		
θ^T		0.035			0.035			0.014	
t-stat.		2.21			2.31			2.65	
θ^S			0.042			0.042			0.020
t-stat.			4.10			4.05			4.59
logAUM				0.004	0.006	0.004	0.003	0.004	0.003
t-stat.				3.92	4.87	4.64	2.86	4.56	2.80
PE/VC							0.001	0.001	0.002
t-stat.							0.21	0.14	0.39
HF							0.004	0.006	0.005
t-stat.							2.56	2.86	2.02
Average adj. R^2	0.355	0.028	0.336	0.383	0.071	0.364	0.313	0.097	0.311

small-cap and large-cap portfolios, HML is the difference in the average returns to high book-to-market and low book-to-market portfolios, UMD is the difference in the average returns to high prior-return and low prior-return portfolios, TERM is return difference between the long-term government bond and the one-month Treasury bill, and DEF is the return difference between a portfolio of long-term corporate bonds and the long-term government bond. All of these risk factor data were annualized from monthly observations to coincide with the reporting period for the endowment fund returns.[23]

Because our supplementary sample of higher frequency data contains larger endowments with a more pronounced emphasis on hedge fund investing, when analyzing these observations we augment Eq. (7) with the three Primitive Trend-Following Strategy (*PTFS*) factors proposed by Fung and Hsieh (2004). These *PTFS* factors are portfolios of lookback straddle positions from the bond markets (*PTFSBD*), currencies (*PTFSFX*), and commodities (*PTFSCOM*).[24]

To determine the risk-adjusted returns of the average endowment, we regress the equally weighted returns R_t against various combinations of the designated risk factors described above. Values of the respective coefficients to each of these model variations are reported

[23]The annualized returns are computed to take into account that the fiscal years of the majority of endowments end on June 30.

[24]We thank Ken French for providing the monthly data necessary to construct the appropriate annual measures for *MKT*, *SMB*, *HML*, and *UMD*, and David Hsieh for providing the monthly data for the *PTFS* factors. Yearly measures for *TERM* and *DEF* were constructed using monthly observations provided by Ibbotson Associates for the period 1989–2005.

Table 7
Risk-adjusted returns.

The table reports estimated coefficients for different specifications of the risk-factor model in Eq. (7). Panel A presents the estimation of the model using the annual data from the NACUBO database and Panel B reports estimations obtained using data from the quarterly return subsample. Panel C presents estimates of the model (7) where the left-hand side returns are the security selection returns of the portfolio. Panel D estimates model (7), with the returns in the left-hand side being the active returns using data from the quarterly subsample.

Panel A. Cross-sectional average results: NACUBO

	α	MKT	SMB	HML	UMD	DEF	TERM	R-sq.
Model 1	0.020	0.541						0.952
t-stat.	(3.59)	(15.38)						
Model 2	0.012	0.582	−0.021	0.058				0.953
t-stat.	(1.62)	(12.90)	(−0.42)	(1.56)				
Model 3	0.007	0.586	0.014	0.055	0.047			0.963
t-stat.	(0.95)	(14.56)	(0.28)	(1.65)	(1.83)			
Model 4	0.012	0.572	0.024	0.080		−0.417	−0.049	0.952
t-stat.	(1.54)	(12.34)	(0.38)	(1.94)		(−1.32)	(−0.73)	
Model 5	0.007	0.586	0.016	0.057	0.045	−0.032	−0.009	0.951
t-stat.	(0.75)	(11.88)	(0.25)	(1.15)	(0.90)	(−0.06)	(−0.11)	

Panel B. Cross-sectional average results: quarterly subsample

	α	MKT	SMB	HML	UMD	DEF	TERM	PTFSBD	PTFSFX	PTFSCOM	R-sq.
Model 1	0.009	0.520									0.892
t-stat.	(3.51)	(18.69)									
Model 2	0.007	0.547	0.007	0.063							0.894
t-stat.	(2.59)	(16.75)	(0.19)	(1.52)							
Model 3	0.005	0.567	0.034	0.084	0.052						0.898
t-stat.	(1.65)	(16.48)	(0.83)	(1.96)	(1.60)						
Model 4	0.007	0.568	0.089	0.062		−0.648	−0.066				0.913
t-stat.	(2.79)	(18.74)	(2.09)	(1.63)		(−3.00)	(−0.91)				
Model 5	0.003	0.562	0.094	0.047	0.013	−0.613	−0.052	−0.728	0.759	−0.499	0.911
t-stat.	(0.52)	(16.48)	(2.06)	(1.05)	(0.39)	(−2.74)	(−0.69)	(−1.02)	(1.08)	(−0.55)	

Table 7 (*continued*)

Panel C. Cross-sectional average results, security selection: NACUBO

	α	MKT	SMB	HML	UMD	DEF	TERM	R-sq.
Model 1	−0.023	−0.084						0.316
t-stat.	(−4.27)	(−2.56)						
Model 2	−0.029	−0.031	0.104	0.036				0.705
t-stat.	(−6.09)	(−1.09)	(3.23)	(1.53)				
Model 3	−0.028	−0.032	0.098	0.036	−0.008			0.676
t-stat.	(−5.17)	(−1.06)	(2.67)	(1.48)	(−0.43)			
Model 4	−0.027	−0.027	0.100	0.036		0.047	−0.036	0.688
t-stat.	(−5.18)	(−0.92)	(2.51)	(1.35)		(0.24)	(−0.83)	
Model 5	−0.026	−0.029	0.101	0.039	−0.007	−0.013	−0.042	0.639
t-stat.	(−3.87)	(−0.87)	(2.34)	(1.18)	(−0.21)	(−0.04)	(−0.76)	

Panel D. Cross-sectional average results, security selection: quarterly subsample

	α	MKT	SMB	HML	UMD	DEF	TERM	PTFSBD	PTFSFX	PTFSCOM	R-sq.
Model 1	−0.006	−0.075									0.155
t-stat.	(−2.77)	(−2.95)									
Model 2	−0.008	−0.048	−0.010	0.053							0.172
t-stat.	(−3.21)	(−1.63)	(−0.29)	(1.42)							
Model 3	−0.007	−0.056	−0.020	0.046	−0.019						0.159
t-stat.	(−2.57)	(−1.73)	(−0.52)	(1.15)	(−0.63)						
Model 4	−0.009	−0.033	0.038	0.047		−0.305	0.034				0.244
t-stat.	(−3.49)	(−1.13)	(0.94)	(1.30)		(−1.47)	(0.49)				
Model 5	−0.008	−0.061	0.015	0.003	−0.054	−0.371	0.042	−0.884	0.928	−0.220	0.256
t-stat.	(−1.53)	(−1.89)	(0.35)	(0.06)	(−1.74)	(−1.76)	(0.59)	(−1.31)	(1.40)	(−0.26)	

in Table 7. Panel A reports the results for (7) using the annual NACUBO data while Panel B presents results obtained by including the PTFS factors in (7) and using the quarterly data from the hand-collected subsample. Panel C reports the results of the same regressions where the excess returns in the left-hand side of (7) are the weighted security selection returns from the NACUBO database while Panel D reports the results with the returns in the left-hand side of (7) being the equally weighted security selection returns from our quarterly subsample.

Overall, as an entire institutional class, endowments do not seem to exhibit significant risk-adjusted performance when the stock momentum factor, UMD, is added to either the stock-only model (Model 3) or the most general specification (Model 5).[25] Furthermore, as Panels C and D of Table 7 show, the security selection components of the average endowment generates *negative* risk-adjusted returns.

However, if we stratify the sample according to the ratio of the return fraction generated by the policy allocation decision, we find that the *difference* in risk-adjusted returns between the low θ^B portfolio and the high θ^B portfolio is both large (at least 6.48% per year) and statistically significant for all models (Table 8, Panel A). Moreover, passive endowments consistently have significantly negative risk-adjusted returns, whereas these returns are always significantly positive for the more active funds.

Panel B of Table 8 confirms this finding using the higher frequency observations in the quarterly subsample and after accounting for the PTFS variables as risk factors. Because the *t*-statistic of the risk-adjusted return for this subset is very low at 0.52 (see Panel B of Table 7), in order to separate active and passive funds, we have compared the portfolio of the smallest decile of θ^B endowments with the portfolio of the highest θ^B decile. Although none of the active or passive portfolios have significant risk-adjusted performance (positive or negative) separately, the difference in risk-adjusted returns between the two portfolios remains significant at conventional levels.[26] Additionally, Panels C and D of Table 8 show the same outcome obtains when we assess the relationship between the risk-adjusted returns of the security selection components of the more active versus less active endowments.

Recall that this analysis was motivated by the observation in Section 4 that university endowments seem to constrain their risk levels while making strategic asset allocation decisions. The intriguing question that remains to be answered is *why* this might be the case. A possible explanation is that the payouts that endowments are mandated to make to their beneficiaries are similar in the cross-section, as documented in Table 1.[27] If

[25]It is possible that the alpha values based on equally weighted endowment portfolios that are listed in Panel A actually *understate* abnormal performance in the endowment sample by *over-representing* the importance of the smaller funds. To address this issue, we replicated the results in Table 7 by forming size-weighted portfolio returns based on fund AUM levels. While the full set of these additional findings are not reported here, the alpha values (*t*-statistics) for the five models are as follows: 3.73% (3.37), 3.23% (2.38), 1.83% (1.44), 4.02% (2.65), 1.77% (0.95). Two things are notable about these data. First, the estimated alpha values are two-to-four times larger for the AUM-weighted fund portfolio than in the equally weighted one, confirming again the investment dominance of large funds over small funds. Second, the alpha values for the models that include momentum as a factor (Models 3 and 5) remain statistically insignificant, leaving the previous conclusion intact.

[26]The finding that more active endowment funds tend to perform better than passive funds is similar to recent evidence from the mutual fund literature. For example, Kacperczyk et al. (2005) show that mutual funds that deviate more from the overall market by focusing on particular industries tend to perform better, while Cremers and Petajisto (2006) document that funds diverging more from their benchmarks also tend to perform better.

[27]The source for this puzzling uniformity in payout rates can lie, for example, in institutional inertia or the fact that the charters of newer endowments imitate those of existing ones.

Table 8
Asset allocation and risk-adjusted returns.

Panel A reports alpha differentials for the full NACUBO endowment sample between funds with a higher weight on passive asset allocation (high θ^B quartile) and more active funds (funds in the low θ^B quartile), for different specifications of the risk-factor model in Eq. (7). Panel B reports similar differentials for high and low θ^B deciles using the quarterly return subsample. Panel C reports alpha differential between the security selection components of the more passive funds (high θ^B) and the less passive (low θ^B) from the NACUBO database, while Panel D presents the same differentials using the quarterly subsample. The models considered are summarized in this table.

	MKT	SMB	HML	UMD	DEF	TERM	PTFS-BD	PTFS-FX	PTFS-COM
Model 1:	×								
Model 2:	×	×	×						
Model 3:	×	×	×	×					
Model 4:	×	×	×		×	×			
Model 5 (NACUBO):	×	×	×	×	×	×			
Model 5 (Quarterly):	×	×	×	×	×	×	×	×	×

Panel A. Alpha differentials for the NACUBO database: large θ^B−small θ^B

	Model 1	Model 2	Model 3	Model 4	Model 5
Large θ^B	−1.90	−2.52	−2.52	−2.72	−2.83
t-stat.	(−3.18)	(−3.74)	(−3.24)	(−3.50)	(−2.80)
Small θ^B	6.00	5.38	3.96	5.67	4.18
t-stat.	(5.24)	(3.72)	(3.68)	(4.17)	(2.99)
Difference	−7.89	−7.90	−6.48	−8.39	−7.02
t-stat.	(−6.11)	(−4.95)	(−4.88)	(−5.36)	(−4.06)

Panel B. Alpha differentials for the quarterly subsample: large θ^B−small θ^B

	Model 1	Model 2	Model 3	Model 4	Model 5
Large θ^B	−0.53	−0.69	−0.48	−0.53	−1.05
t-stat.	(−1.29)	(−1.52)	(−0.93)	(−1.12)	(−1.16)
Small θ^B	3.35	3.25	2.62	3.32	1.87
t-stat.	(5.38)	(4.72)	(3.52)	(5.01)	(1.42)
Difference	−3.88	−3.94	−3.09	−3.85	−2.92
t-stat.	(−5.19)	(−4.77)	(−3.43)	(−4.72)	(−1.83)

Panel C. Alpha differentials for the NACUBO database, security selection: large θ^B−small θ^B

	Model 1	Model 2	Model 3	Model 4	Model 5
Large θ^B	−5.86	−6.18	−5.76	−6.07	−5.77
t-stat.	(−7.05)	(−8.73)	(−7.96)	(−7.97)	(−5.97)
Small θ^B	1.40	0.78	0.32	1.13	0.67
t-stat.	(2.92)	(1.19)	(0.50)	(1.88)	(0.94)
Difference	−7.26	−6.97	−6.08	−7.20	−6.44
t-stat.	(−7.56)	(−7.20)	(−6.31)	(−7.42)	(−5.37)

Panel D. Alpha differentials for the quarterly subsample, security selection: large θ^B−small θ^B

	Model 1	Model 2	Model 3	Model 4	Model 5
Large θ^B	−2.93	−3.02	−2.58	−2.95	−2.87
t-stat.	(−6.93)	(−6.40)	(−5.07)	(−5.80)	(−3.08)
Small θ^B	2.28	2.25	1.90	2.14	1.48
t-stat.	(4.41)	(3.94)	(3.00)	(3.82)	(1.31)
Difference	−5.21	−5.27	−4.48	−5.09	−4.36
t-stat.	(−7.80)	(−7.12)	(−5.51)	(−6.73)	(−2.96)

endowments are risk averse, we would expect them to assume only enough risk to generate the returns necessary to cover those required distributions. Hence, risk aversion, coupled with the historical similarity in payouts, may explain why over a particular investment period endowments take similar risks and end up generating comparable benchmark returns. Given this, we should then observe benchmark returns of roughly the same magnitude as payout rates. Specifically, if endowments are concerned with preserving their purchasing power (or their principal), we should see benchmark returns that are roughly equal to the payout rates plus inflation. Thus, assuming an average inflation rate of 3.00%, the mean annual payout of slightly more than 5.00% (Table 1) would suggest an average benchmark return in excess of 8.00%, which is broadly consistent with the observed 9.35% grand mean of the benchmark returns (Table 3). This, then, implies that similarity in payout ratios may be the source of the phenomenon we document. Alternatively, as Leibowitz and Bova (2005) note, it is also possible that ‘‘dragon’’ (i.e., unquantifiable) risks generate similar investment constraints, which chain the asset allocation policies of all university endowments in the cross-section to similar volatilities.

6. Conclusion

Conventional wisdom in the investment management industry holds that an investor's initial strategic asset allocation decision is likely to be the most important determinant of the portfolio's investment performance. However, the empirical evidence available from investigations of mutual fund and pension fund investment practices both confirm (in the time series) and refute (in the cross-section) this proposition. Due to their unique characteristics—such as an unlimited investment horizon, relatively modest spending needs, and a generally flexible set of policy constraints—university endowment funds represent an ideal setting to examine this issue in greater detail.

We use a distinctive and comprehensive data set of the portfolio characteristics and returns to university endowments in the US, Canada, and Puerto Rico, spanning the period from 1984 to 2005, to investigate whether the strategic allocation decisions do indeed influence the return and overall performance of a fund. We show initially that asset allocation seems to be unrelated to the returns produced by the typical endowment fund. Indeed, we find that policy-related returns are remarkably similar across endowments, despite a wide dispersion in the asset allocation weights those portfolios deploy. Second, we document that, although the average endowment does not produce any significant risk-adjusted performance, more actively managed funds have alphas that are between 3% and 6% percent greater than those for more passive endowments. Combined with the observed heterogeneity in asset allocation weights, we conjecture that this finding is consistent with endowments attempting to exploit their security selection ability by over-weighting asset classes in which they appear to have superior active management skills.

Acknowledgments

We are grateful to Jessica Shedd of the National Association of College and University Business Officers and Gary Hill of the University of Texas Investment Management Company for their assistance in furnishing much of the data used in this project and thank Yang Cao, Courtney Griffin, Hsin-han Shen, and Rui Zhu for research assistance. We are particularly indebted to Bruce Lehmann (the editor) and an anonymous referee for their insightful comments. We have also benefited from comments from Kee Chung, Steve Dimmock, Elroy Dimson, William Goetzmann, John Griffin, Bing Han, Jennifer Huang, Ravi Jagannathan, Bing Liang, Jeff Kubik, Clemens Sialm, Laura Starks, Antoinette Schoar, Sheridan Titman, Raman Uppal, Bas Werker, Roberto Wessels, seminar participants at University of Texas and the 2007 Western Finance Association Meetings, as well as discussions with several people involved in the endowment management process, most notably Bob Boldt and Andrea Reed (Perella Weinberg), Cathy Iberg and Uzi Yoeli (University of Texas Investment Management Company), Jim Hille (TCU Endowment Fund), Van Harlow (Fidelity Investments), John Griswold (Commonfund), Larry Siegel (Ford Foundation), Chad Burhance (International Fund Services) and Joanne Hill (Goldman Sachs). We also gratefully acknowledge the financial support of The Institute for Quantitative Research in Finance (Q-Group). We are responsible for all errors in the paper.

Appendix A. Active and passive returns in Treynor and Black (1973) model

Consider the case of a single, investable, passive portfolio (the "benchmark") and a single investable active portfolio (the "active manager").[28] We denote by $\tilde{B}$ the return (in excess of the risk-free rate) on the benchmark asset that is assumed to be normal with mean μ_B and standard deviation σ_B, $\tilde{B} \sim \mathcal{N}(\mu_B, \sigma_B)$. The active manager excess return is given by

$$\tilde{A} = \alpha + \beta\tilde{B} + \tilde{\varepsilon}, \quad \tilde{\varepsilon} \sim \mathcal{N}(0, \sigma_\varepsilon), \quad \text{cov}(\tilde{B}, \tilde{\varepsilon}) = 0. \tag{A.1}$$

The investor's portfolio problem is hence a two-asset problem, consisting of choosing the optimal mix $w = (w_A, w_B)$ to allocate to the manager (active portfolio) and to the benchmark asset (passive portfolio). Because returns are normal, the portfolio problem can be written as

$$\max_w w^\top \mu - \frac{\gamma}{2} w^\top \Sigma w, \tag{A.2}$$

where μ is the vector of expected returns, Σ the covariance matrix, and $\gamma > 0$ a parameter capturing the investor's risk aversion. The weight in the risk-free asset is $1 - w_A - w_B$. The optimal portfolio is $w^* = 1/\gamma\Sigma^{-1}\mu$ and the optimal *relative* weights ω^* in the active and passive part of the portfolio are

$$\omega^* = \frac{w^*}{w_A + w_B} = \begin{pmatrix} \omega_A^* \\ \omega_B^* \end{pmatrix} = \frac{1}{\mu_B\sigma_\varepsilon^2 - \alpha(\beta - 1)} \begin{pmatrix} \alpha\sigma_B^2 \\ \mu_B\sigma_\varepsilon^2 - \alpha\beta\sigma_B^2 \end{pmatrix}. \tag{A.3}$$

Notice that in the absence of skill ($\alpha = 0$), no weight is assigned to the active manager.

Given the optimal weights (A.3) and the distributional properties of the risky asset, we can compute the total risky return $R(\omega^*)$ from implementing the optimal portfolio. Empirically, this quantity would be the observed return on each of the endowments in our sample. The return from the optimal portfolio strategy is

$$R(\omega^*) = \omega_B^*\tilde{B} + \omega_A^*\tilde{A} = \frac{1}{\mu_B\sigma_\varepsilon^2 - \alpha(\beta - 1)}(\alpha^2\sigma_B^2 + \mu_B\sigma_\varepsilon^2\tilde{B} + \alpha\sigma_B^2\tilde{\varepsilon}). \tag{A.4}$$

[28] The case of multiple benchmark and managers can easily be derived but it does not add further insight to the single benchmark, single manager case.

A quantity of interest in understanding the role of active and passive allocation is the ratio θ of total return accounted for by the "passive component." In the stylized model of this section, such ratio is equal to:

$$\theta = \frac{\omega_B^* \tilde{B} + \omega_A^* \beta \tilde{B}}{R(\omega^*)} = \frac{\mu_B \sigma_\varepsilon^2 \tilde{B}}{\alpha^2 \sigma_B^2 + \alpha \sigma_B^2 \tilde{\varepsilon} + \mu_B \sigma_\varepsilon^2 \tilde{B}}. \tag{A.5}$$

The above quantity describes the ratios of two normal random variables and follows a Cauchy distribution.[29] An interesting property of this ratio is obtained if we look at its "steady state" behavior, which is derived by assuming that the random variables $\tilde{B}$ and $\tilde{\varepsilon}$ are drawn equal to their unconditional mean, μ_B and 0, respectively. It is easy to show that the steady state value $\overline{\theta}$ of the ratio (A.5) simplifies to

$$\overline{\theta} = \frac{1}{1 + \dfrac{(\alpha/\sigma_\varepsilon)^2}{(\mu_B/\sigma_B)^2}} = \frac{\mathrm{var}(\mu_B \sigma_\varepsilon^2 \tilde{B})}{\mathrm{var}(R(\omega^*))} = R^2. \tag{A.6}$$

The last equality states that the steady state value of the ratio of passive to total returns is equivalent to the percentage of variation in the total risky return explained by variation in the benchmark, i.e., the R-squared coefficient of an hypothetical regression of total return on the benchmark.

References

Avramov, D., Wermers, R., 2006. Investing in mutual funds when returns are predictable. Journal of Financial Economics 81, 339–377.

Berkelaar, A.B., Kobor, A., Tsumagari, M., 2006. The sense and nonsense of risk budgeting. Financial Analysts Journal 62, 63–75.

Blake, D., Lehmann, B.N., Timmermann, A., 1999. Asset allocation dynamics and pension fund performance. Journal of Business 72, 429–461.

Bogle, J.C., 1994, Bogle on Mutual Funds: New Perspectives for the Intelligent Investor. Irwin.

Brinson, G.P., Hood, L.R., Beebower, G.L., 1986. Determinants of portfolio performance. Financial Analysts Journal 42, 39–48.

Brinson, G.P., Singer, B.D., Beebower, G.L., 1991. Determinants of portfolio performance II: an update. Financial Analysts Journal 47, 40–48.

Cain, J.H., 1960. Recent trends in endowment. Review of Economics and Statistics 42, 242–244.

Carhart, M.M., 1997. On persistence in mutual fund returns. Journal of Finance 52, 57–82.

Carpenter, A.E., 1956. College and university endowment funds: how much common? Financial Analysts Journal 12, 63–65.

Clarke, R.G., de Silva, H., Wander, B., 2002. Risk allocation versus asset allocation. Journal of Portfolio Management 29, 9–30.

Cremers, M., Petajisto, A., Zitzewitz, E., 2008. Should benchmark indices have alpha? Revisiting performance evaluation. Working paper, Yale School of Management.

Cremers, M., Petajisto, A., 2006. How active is your fund manager? A new measure that predicts performance. Working paper, Yale School of Management.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035–1058.

Davidson, H.A., 1971. Investing college endowment funds: a comparison of internal and external management. Financial Analysts Journal 27, 69–74.

Dimmock, S.G., 2008, Portfolio choice, background risk, and university endowment funds. Working paper, Michigan State University.

[29] See Hinkley (1969). For such random variable, the mean is not defined and the second moment is infinite.

Dybvig, P.H., 1999. Using asset allocation to protect spending. Financial Analysts Journal 55, 49–62.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.
Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 81, 606–636.
Fung, W., Hsieh, D.A., 2004. Hedge fund benchmarks: a risk based approach. Financial Analysts Journal 60, 65–80.
Griswold, J.S.E., 2008. Commonfund Benchmarks Study: Educational Endowment Report, Commonfund Institute, Wilton CT.
Hill, J.M., 2006. Alpha as a net zero-sum game. Journal of Portfolio Management 32, 24–32.
Hinkley, D.V., 1969. On the ratio of two correlated normal random variables. Biometrika 56, 635–639.
Ibbotson, R.G., Kaplan, P.D., 2000. Does asset allocation policy explain 40, 90, or 100 percent of performance?. Financial Analysts Journal 56, 26–33.
Kacperczyk, M., Sialm, C., Zheng, L., 2005. On the industry concentration of actively managed equity mutual funds. Journal of Finance 60, 1983–2012.
Leibowitz, M., Bova, A., 2005. Allocation betas. Financial Analysts Journal 61, 70–82.
Leibowitz, M.L., 2005. Alpha hunters and beta grazers. Financial Analysts Journal 61, 32–39.
Lerner, J., Schoar, A., Wang, J., 2008, Secrets of the academy: the drivers of university endowment success. Working paper. MIT, Cambridge.
Lerner, J., Schoar, A., Wongsunwai, W., 2007. Smart institutions, foolish choices: the limited partner performance puzzle. Journal of Finance 42, 731–764.
Litterman, B., 2003. Modern Investment Management: An Equilibrium Approach. Wiley, Hoboken, NJ.
Litvack, J.M., Malkiel, B.G., Quandt, R.E., 1974. A plan for the definition of endowment income. American Economic Review 64, 433–437.
Markowitz, H.M., 1952. Portfolio selection. Journal of Finance 7, 77–91.
Merton, R.C., 2003. Thoughts on the future: theory and practice in investment management. Financial Analysts Journal 59, 17–23.
Morley, J.E., Heller, N., 2006, NACUBO Endowment Study NACUBO and TIAA-CREF, Washington DC.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Tobin, J., 1974. What is permanent endowment income?. American Economic Review 64, 427–432.
Treynor, J.L., Black, F., 1973. How to use security analysis to improve portfolio selection. Journal of Business 46, 66–86.