Can Large Pension Funds Beat the Market?

Asset Allocation, Market Timing, Security Selection, and the Limits of Liquidity

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Abstract

We analyze the three components of active management (asset allocation, market timing and security selection) in the net performance of U.S. pension funds and relate these to fund size and the liquidity of the investments. On average, the funds in our sample have an annual net alpha of 89 basis points that is evenly distributed across the asset allocation, market timing, and security selection components. Stock momentum fully explains the positive alpha in security selection, whereas "time series momentum" drives market timing. While larger pension funds have lower investment costs, this does not lead to better net performance. Rather, all three components of active management exhibit substantial *dis*economies of scale directly related to illiquidity. Our results suggest that especially the larger pension funds would have done better if they invested more in passive mandates without frequent rebalancing across asset classes.

Keywords: pension fund performance, asset allocation, market timing, security selection, dis-economies of scale, liquidity.

JEL Classifications: G11; G23.

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1. Introduction

Can large, sophisticated investors beat the market? And if so, what investment skills are most prevalent? Can investors outperform by periodically changing strategic asset allocation weights, by deviating from those in short-term market timing, or by selecting particular securities within asset classes? Are there (dis)economies of scale and liquidity limitations in asset allocation, market timing or security selection? In this paper, we try to address these questions by investigating a unique database of the largest U.S. defined benefit (DB) pension funds.

Questions of investment skill and the importance of size and liquidity have been most intensively investigated in the mutual fund literature. However, this literature has focused almost exclusively on the third component of active management, security selection, largely sidestepping the performance in asset allocation and market timing. We are the first, to the best of our knowledge, to examine the returns from changes in asset allocation of institutional investors, as until now a large data sample on strategic asset allocation policy has not been available. On market timing performance, Blake, Lehmann and Timmermann (1999) and Blake, Timmermann, Tonks and Wermers (2012) find that external managers employed by U.K. pension funds did not have superior market timing (also called tactical asset allocation) skills across asset classes. Among mutual funds, Bollen and Busse (2001) and Jiang, Yao and Yu (2007) find that actively managed equity funds have some positive timing ability, whereas Chen, Ferson and Peters (2010) find that bond mutual funds have neutral to weakly positive market timing skills. All of these studies conflate changes in strategic asset allocation with more short-term market timing. Using our unique data on the strategic asset allocation policy weights, we can directly assess asset allocation skills and distinguish them more accurately from market timing decisions (which are captured by the deviations between the policy weights and the actual asset allocation weights).

There is a very large literature on security selection performance, especially among mutual funds. For example, Malkiel (1995), Gruber (1996) and Chan, Chen, and Lakonishok (2002) find that, on average, mutual funds underperform the market by about the amount of expenses charged to investors. However, Kacperczyk, Sialm, and Zheng (2008) and Cremers and Petajisto (2009) document evidence that at least some subset of mutual fund managers may have skill. Kosowski, Timmermann, Wermers and White (2006) find not only that a sizable subgroup of mutual fund managers exhibits stock-picking skills, but also that the superior alphas of these managers persist.

We focus on pension funds and our main contribution to the security selection literature is to document the average security selection skills at the total fund level, rather than at the level of portfolios managers hired by the pension funds, as considered by Lakonishok, Shleifer and Vishny (1992), Goyal and Wahal (2008) and Blake, Timmermann, Tonks and Wermers (2012). The existing pension fund literature focuses primarily on equity investments through external managers. As external managers are often hired by more than one pension fund and funds typically employ more

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than one external manager, such research does not allow for direct analysis of the total performance of pension funds. We study the overall fund performance, which incorporates the performance in equity, fixed income and alternative assets.[1] Pension funds in our sample have both internal and external managers, and combine both active and passive strategies.

Moreover, we are the first paper to explore the role of size and liquidity for all three components of asset management: asset allocation, market timing and security selection. In an important paper, Chen, Hong, Huang and Kubik (2004) find *dis*economies of scale related to mutual fund size, but economies of scale related to mutual fund family size. They relate the former primarily to within-fund organizational and liquidity problems and the latter to the advantage of centralizing research and marketing efforts. More recently, Lopez-de-Silanes, Phalippou and Gottschalg (2010) document diseconomies of scale for private equity and Fung, Hsieh, Naik and Ramadorai (2008) for hedge funds. Pension funds seem particularly interesting vehicles to study questions related to size and liquidity in investment management performance. With their larger average size (about $10 billion in our sample), they are vastly larger than typical mutual funds, and may be more akin to mutual fund families rather than individual mutual funds. Further, incentives differ substantially. Mutual funds with the best performance receive large cash inflows (see e.g. Sirri and Tufano (1998)). As mutual fund manager pay depends on the size of the assets under management and the relative performance compared to the benchmark, this can create substantial incentives for mutual fund managers to engage in active management or chase short-term performance. Defined benefit pension funds' inflows do not depend on performance, but on actuarial and demographic factors. This long-term liability structure further enables pension funds to make substantial investments in illiquid assets.

As a result, the role of size and liquidity for pension fund performance is *ex ante* unclear. On the positive side, less liquid investments have potentially higher expected returns. Large scale may provide significant bargaining power vis-a-vis external money managers or allow funds to attract investment talent internally. On the negative side, larger size may make trading in less liquid securities much more difficult, may limit the investment strategies available and create organizational complexities. Moreover, the size of the assets of DB plans is driven by the number of plan members and pension promises made to the workers, and not by scale efficiency considerations (unlike mutual funds that can be closed to new investments due to diseconomies of scale).

To answer these questions, we use the unique CEM dataset, comprised of 557 U.S. defined benefit pension funds for the period 1990-2010. Our main findings are six-fold, collectively suggesting some

[1] A closely related paper is Blake, Lehmann and Timmermann (1999), who investigate the asset allocation and performance of U.K. pension funds throughout the period 1986-1994. Their data includes only U.K. funds that maintained the same external management group during the entire sample period. Another related paper is Brown, Garlappi and Tiu (2010), who consider endowment funds. Similar to pension funds, endowment funds also invest in multiple asset classes. However, the amount of assets under management of pension funds is substantially larger. According to Brown, Garlappi and Tiu (2010), endowment funds had on average $287 million assets, while the mean holdings of pension funds in our sample is $10 billion.

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evidence for the ability of the pension funds in our sample to modestly outperform at the total fund level, though this outperformance is subject to significant liquidity and size limitations.

First, pension fund investment costs are on average 37 basis points per year. Investment costs are stable during the first half of our sample, but increase to 55 basis points in 2010 due to the higher allocation to alternative assets. We document significant scale advantages in costs: one standard deviation increase in the log of assets reduces the total investment costs by 7 basis points. The scale advantage is much more pronounced for alternative investments, where a one-unit increase in the log of alternative assets results in 111 basis points lower costs. As expected, funds managing a greater percent of their assets through active and external mandates have higher investment costs.

The second contribution is methodological. We decompose pension fund returns in three components (asset allocation, market timing and security selection) and evaluate the performance of each. The first component, asset allocation, consists of the changes over time in each fund's *ex-ante* declared strategic (target) asset allocation policy weights times the self-declared benchmark returns of the different asset classes. For each asset class within each fund, we observe the self-declared benchmark as well as the return on these benchmarks. Asset allocation performance evaluation thus compares the performance of the change in policy weights over last year, relative to not changing last year's policy weights.

The second component is market timing (tactical asset allocation), defined as the difference between strategic policy and actual (realized) allocation weights. Market timing thus captures the performance related to overweighting or underweighting particular asset classes, relative to the target weights in that year.[2] We further decompose this market timing component into a passive and an active part, where the passive part consists of changes in actual weights due to benchmark market movements and the active part is due to reallocations of investments, taking market movements into account.

The third component is security selection, corresponding to net benchmark-adjusted returns or the difference between realized net returns and benchmark returns for a given asset class. This captures the returns due to picking securities and timing industries and styles within an asset class.

Third, we find that pension funds have, on average at the total fund level, positive abnormal returns of 89 basis points per year after risk-adjusting for equity market, size, value, liquidity and fixed income market factors, to which each of three components of active management contributes about equally. Pension funds obtain 25 basis point annual alpha from setting the asset allocation policy weights and 26 basis points annual alpha due to timing of asset allocation decisions. Security selection produces returns that are on average 25 basis points per year above the benchmark returns, but this becomes

[2] For instance, if a fund's strategic weight for equity is 60%, but the realized weight is 65% (and say for fixed income the strategic weight is 40% and the realized weight is 35%), the market timing components for equity (fixed income) equals +5% (-5%), multiplied by the relevant benchmark return. The main difference between asset allocation and market timing is horizon. Strategic asset allocations change less frequently: 32.67% of the fund-years observations show no change in these strategic weights in year *t* as compared to year *t-1*. Market timing is shorter-term, as only 0.51% of the fund-years observations have no difference between the target and the actual weights in any given year.

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insignificant after controlling for risk factors (and can completely be attributed to momentum in equity markets).

Pension funds obtain positive returns from changes in the strategic asset allocation mainly by increasing their exposure over time to alternative assets in years in which these asset classes had high positive returns. The 26 basis points abnormal market timing returns can be fully attributed to passive exposure to 'time series' momentum, and not to any active rebalancing. Times series momentum is the phenomenon that past returns in a particular asset class tend to be predictive for the return in the asset class, as documented by Moskowitz, Ooi and Pedersen (2012). They find that '12-month time series momentum profits are positive, not just on average across these assets, but for *every* asset contract we examine (58 in total).' Combined with the insignificant security selection performance, this suggests that pension funds benefit from simultaneously investing in multiple asset classes, but would do better (after costs and on average) if they would have invested exclusively in passive mandates without frequent rebalancing across asset classes. For comparison, the average investment cost of passive mandates is 5.67 basis points compared to 45.22 basis points for active mandates.

Fourth, we relate the risk-adjusted returns for asset allocation, market timing and security selection components to the total size and liquidity of the funds' holdings. Our proxy for liquidity is the fund's loading on the traded liquidity factor of Pastor and Stambaugh (2003). We find that the direct association between the size of the assets under management and performance is only significantly associated for market timing, which smaller funds do more effectively. In general, the scale advantage in costs is thus not translated into better overall performance for larger funds.

All three components of active management exhibit significant liquidity limitations related to size. The economic effects are meaningful and comparable across the three components of active management. For example, increasing liquidity by lowering the liquidity beta by 10 percentage points is associated with an improvement of the alpha of a fund at the 75^{th} size percentile by 13 basis points per year more than the improvement of the alpha of a fund at the median size percentile.

Fifth, as previously mentioned, our results suggest that especially the largest pension funds would have performed better if they had invested more in passively managed mandates. We group all funds into three groups depending on the percentage of their assets that is actively managed. The most actively managed group has significantly greater size-induced liquidity constraints, and the largest funds in this group underperform similarly sized funds with much less active management by about 62 basis points a year. We thus document three reasons for the attractiveness of passive management, especially for the largest funds. First, pension funds on average had insignificant risk-adjusted security selection performance. Second, passive management is much cheaper than active management. Third, performance in passive mandates is less subject to liquidity-related diseconomies of scale.

Sixth and finally, we document strong performance persistence for both market timing and security selection using annual quintile rankings. Funds are more likely to end up in a better performing

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quintile next year, if they also do so this year, and they are more likely to perform worse in the ranking next year if they performed relatively poorly this year. Such persistence is a useful confirmation that we are able to pick up skill, even though our performance data is limited to the annual frequency.

Blake, Lehmann and Timmermann (1999) find negative returns from market timing, attributed to negative timing returns within foreign equity (see also Timmermann and Blake (2005)). One important difference in the construction of the market timing return component is that we have access to the strategic asset allocation weights and self-determined benchmarks, whereas Blake, Lehmann and Timmermann (1999) use one benchmark index per asset class as a return proxy for all pension funds and estimate the strategic weights based on the trend in realized weights. Another difference is that we also include *internal* mandates across all asset classes in our analysis. Moreover, we do not require that a single external manager is employed during the entire sample period.

Similar to our findings, the security selection returns of U.K. funds are positive, but not always significant (Blake, Lehmann and Timmermann (1999)). Busse, Goyal and Wahal (2010) document that institutional asset management firms hired by U.S. pension funds deliver alphas statistically indistinguishable from zero. In line with our findings, they also find that the security selection alphas of these institutional managers are mainly driven by momentum in equity markets.

Our findings of liquidity-related diseconomies of scale and the inability to take concentrated positions in equity among pension funds are consistent with Chen, Hong, Huang and Kubik (2004), who exclusively focus on security selection by mutual funds. That paper does not directly assess any fund's exposure to liquidity, but indirectly infers this by comparing the performance of small-cap funds to large caps funds (which presumably are more liquid). In contrast, we directly estimate each fund's loading to the systematic traded liquidity factor of Pastor and Stambaugh (2003).

Our results partially contradict the existence of economies of scale in pension fund management as discussed in Dyck and Pomorski (2011), as we find that larger U.S. funds do not perform better than smaller U.S. funds both before and after risk-adjusting performance. The difference in results can largely be explained by a difference in methodology: we analyze not only the non-risk-adjusted returns, but we also risk-adjust fund performance for factor returns, investigate the importance of momentum and control for fund fixed effects. Dyck and Pomorski (2011) do not risk-adjust returns and focus on specifications without fund fixed effects and without controlling for momentum.[3] In our view, especially risk-adjustment is critical for performance evaluation and merely benchmark-adjusting is insufficient, as is borne out by our results.

Persistence in security selection performance has been documented by Tonks (2005) and Blake, Timmermann, Tonks and Wermers (2012) among U.K. pension funds' domestic equity investments, even after risk-adjusting. When analyzing the security selection skills of U.S. domestic equity

[3] In Appendix Table A.4 we replicate part of Dyck and Pomorski (2011) findings of economies of scale among pension funds before risk-adjusting.

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institutional managers, Busse, Goyal and Wahal (2010) find only modest evidence of persistence using three-factor models and little to none using four-factor models. Our contribution is to document persistence in both market timing and security selection returns on a total fund level, which incorporates the performance of all managers in all assets. However, we only have access to annual data and thus cannot test persistence in risk-adjusted alphas.

The paper proceeds as follows. Section 2 describes the CEM dataset and considers possible self-reporting biases. Section 3 explains the methodology to decompose fund returns into asset allocation, market timing and security selection components. Section 4 focuses on the effects of investment style and size on costs. Section 5 presents the returns from asset allocation, market timing and security selection before and after risk-adjusting. Section 6 describes the relation between fund risk-adjusted performance and its characteristics. Section 7 briefly discusses the persistence in pension fund performance. Concluding comments are provided in section 8.

2. Characteristics of the CEM database

CEM Benchmarking Incorporated (CEM) collects U.S. pension fund data through yearly questionnaires.[4] We focus on defined benefit (DB) funds only, where the pension fund's Board makes the asset allocation decisions and is responsible for performance. In defined contribution (DC) funds, plan sponsors select the menu of available investment options, while each plan member individually is responsible for the asset allocation decision. Thus, asset allocation outcomes within DC funds belong more to the literature on individual investors' decision making. The CEM database includes details on each fund's strategic and actual asset allocation decisions, the self-declared benchmarks for each asset class, and the precise cost structure and performance for all separate asset classes and their benchmarks. Table 1 provides the number of funds reporting to CEM. In the period 1990–2010, a total of 557 U.S. pension funds have reported to CEM. The pension funds in our sample on average had around $10 billion assets under management. Fund size is positively skewed, indicating that the CEM universe consists of several very large and many smaller funds. For instance, the 25 percentile, median and 75 percentile of fund size are $1.3, $3.0 and $8.6 billion, respectively.

The main motive for funds to enter the database is to benchmark their investment costs against peers. Funds sometimes decide to stop submitting the questionnaires to CEM for various reasons, such as termination of the service due to costs savings, mergers, acquisitions and bankruptcies of the underlying corporations, etc. As reporting to CEM is voluntary, the dataset is potentially vulnerable to self-reporting bias. Bauer, Cremers and Frehen (2010) address the self-reporting bias by matching the CEM data with the Compustat SFAS data and testing whether the decision to either start or stop

[4] Other papers using the CEM database are French (2008), Andonov, Bauer and Cremers (2012), Bauer, Cremers and Frehen (2010), Andonov, Eichholtz and Kok (2012) and Dyck and Pomorski (2011).

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reporting is related to the overall fund performance. Their results indicate that there is no evidence of a self-reporting bias related to performance in the exiting and entering years.

Here, we address the self-reporting problem by constructing a Cox proportional hazard model. We test whether the decision of a particular pension fund to exit the database is related to its returns, costs or size. The event of interest is the decision of the pension funds not to report to CEM in a given year. In the Cox hazard model, we treat each fund re-entry as a new fund, which explains why the number of units in Table 2 is higher than the total number of funds presented in Table 1. The results in Table 2 indicate that fund size (*LogSize*, i.e. log of the total assets under management) has the strongest effect on the fund's exit rate, with smaller funds much more likely to exit the CEM database. This is consistent with the idea that specialized benchmarking services provided by CEM are more relevant and cost-effective for larger funds.

Further, we relate the fund exit rate to pension fund gross returns, net returns, benchmark returns and benchmark-adjusted returns. Benchmark returns are calculated using the benchmarks reported by pension funds for every asset class in which they invest. CEM asks funds to report, separately for every asset class in which a fund has holdings, the exact definition of the benchmark they employ as well as the return on that benchmark. We specify net benchmark-adjusted returns as gross returns minus costs, and minus benchmark returns. The hazard ratios on net returns, benchmark returns and net benchmark-adjusted returns are always insignificant, so exit events are not related to funds underperforming or outperforming their benchmark.[5] Hence, we find no evidence that the CEM database suffers from self-reporting bias related to performance.[6]

Funds included in the CEM database cover a substantial share of the pension fund assets under management and stock market capitalization. Over 1990-2010, U.S. funds included in the CEM database account for approximately 30-40% of the asset under management by U.S. pension funds. In 2010, the holdings in U.S. equity of U.S. pension funds included in the CEM universe represent 4.2% of the market capitalization of the NYSE, NASDAQ and AMEX and their fixed income holdings are equal to about 2% of the total outstanding U.S. bond market debt in 2010.[7]

We can distinguish the following asset classes, with their average portfolio weights over the full sample: equity (57.52%), fixed income (31.31%), cash (1.98%) and alternatives (9.19%). Figure 1 presents the time trend in the allocation to equity, fixed income, cash and alternative assets. In the period 1990-2000, allocations to equity increase, while declining significantly after 2005. During the second decade of our sample period, alternative assets have been growing in importance at the expense

[5] In Appendix Table A.3 we sort the funds into five quintiles based on their market timing and security selection returns. For both return components, the percentage of funds exiting the database is similar across all quintiles, i.e. top performers have very similar exit rates as the worst performers.

[6] Total costs are somewhat negatively related to the exit rate of U.S. funds. The hazard ratio of -0.009 indicates that an increase in costs by one basis point results in 0.9% decrease in the exit rate. Funds with higher costs may benefit more from the cooperation with CEM, because the company is specialized in advising on costs.

[7] For the comparison, we used market capitalization data from the World Federation of Exchanges (WFE).

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of declining allocations to equity and fixed income. Around 85% of the pension funds invested in alternative assets, which include investments in real estate, private equity, hedge funds, commodities, natural resources, infrastructure and global tactical asset allocation. The most important alternative asset class is real estate, while funds allocate also a significant percentage of their assets to private equity and, especially recently, to hedge funds.

Figure 2 plots the time variation in asset allocation within equity, fixed income and alternative asset classes. Panel A shows that pension funds invest the majority of their equity holdings in the domestic U.S. stock market, with international diversification increasing over time. For instance, funds invested 89.47% of their total equity holdings in U.S. markets in 1990, while this percentage decreased to 58.76% in 2010. The decrease in domestic equity is reallocated to either an EAFE mandates (equity investments in Europe, Australasia and Far East), capturing about 18% of the equity holdings, or a global equity (ACWxUS) mandates, which account for 17.21% of the equity assets in 2010.

Panel B in Figure 2 plots the time variation of allocation to various fixed income asset classes. Here, the focus on domestic investments is even more striking. In 1990, funds held 96.64% of their fixed income investments in the U.S. market, with only very limited international diversification since then. For instance, the allocations to EAFE, Emerging Markets and Global fixed income mandates remain low and stable over the 1990–2010 period (less than 8% combined).

In addition to realized (actual) asset allocation weights, CEM also provides information on the pension fund strategic (target) policy weights, which are determined by the pension funds' Boards. The changes in policy weights from year *t-1* to year *t* show how pension fund strategic allocations evolve over time. Table 3 shows that funds modified their strategic allocation by adding more alternative assets at the expense of equity, fixed income and cash. Table 3 further presents that the differences between the reported strategic weights and actual weights are close to zero on average, but exhibit substantial (averaged across time) cross-sectional standard deviations of 2.36% to 5.50%.

On the total fund level (All Assets), Table 4 shows that pension funds paid on average 37 basis points for investing in all asset classes during 1990-2010. Figure 3 presents the trend in pension fund investment costs. Over the entire period, alternatives are the most expensive asset classes (average fees of 133 basis points),[8] while the least expensive assets are fixed income (20 basis points). The total investment costs are steady during the 1990-2000, but significantly increase after 2000 from 31 basis points in 2000 to 55 basis points in 2010. This trend is primarily due to the increasing costs for alternative investments as well as the greater allocations to these alternative assets.

Table 4 reports also the return summary statistics. The average gross return during the 1990-2010 is 9.89 percent. Figure 4 presents the annual gross returns on a fund level and separately for equity, fixed

[8] This estimation understates the actual costs of investing in some alternative assets, like private equity (see Phalippou (2009)), as it captures only management fees, while performance fees are subtracted directly from the returns. In the calculation of private equity net returns both management and performance fees are deducted.

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income and alternative assets. On average, funds obtain positive net benchmark-adjusted returns on a total fund level, which are primarily due to positive performance in equity and fixed income.[9] From the alternative asset classes, pension funds obtained lower gross returns than the stock market and net benchmark-adjusted returns equal to zero. However, returns on alternative investments have significantly higher cross-sectional variation compared to equity and fixed income investments, which can be seen in the high standard deviation. These high standard deviations imply that pension funds experience high volatility and large differences in performance in alternative asset classes.

3. Methodology

First, we analyze the overall level of investment costs, the differences in costs for equity, fixed income and alternative assets, and the role of investment style and size as determinants of cost differences. To disentangle effects of pension fund size, allocation decisions and investment style, we use pooled panel regressions with year and fund-fixed effects:

$$C_{i,t} = \beta_0 + \beta_1 LogSize_{i,t} + \beta_2 \%Act_{i,t} + \beta_3 \%Ext_{i,t} + \beta_4 \%FI_{i,t} + \beta_5 \%Alter_{i,t} + YD_t + f_i + u_{i,t}, \quad (1)$$

where $C_{i,t}$ refers to the investment costs of fund *i* in year *t*, f_i captures fund-fixed effects and $u_{i,t}$ are idiosyncratic errors. $LogSize_{i,t}$ is the log of the US$ value of the pension fund assets, $\%Act_{i,t}$ and $\%Ext_{i,t}$ refer to the percentage allocation to active mandates and external managers, respectively. $\%FI_{i,t}$ and $\%Alter_{i,t}$ represent the percentage of pension fund *i* holdings invested in fixed income and alternative asset classes in year *t*.

Pension funds make three distinct active asset management decisions. First, they define their strategic asset allocation policy, which changes infrequently. For instance, 32.67% of the fund-years observations show no change in these strategic allocation weights in year *t* as compared to year *t-1*. Second, pension funds engage in market timing by overweighting or underweighting particular asset classes relative to the strategic weights. Third, pension funds engage in security selection and try to beat their self-declared benchmarks within particular asset classes.

Our total return ($R_{i,t}$) measure represents a sum of these three active asset management components:

$$R_{i,t} = \sum_{j=1}^{M} (w_{i,j,t} r_{i,j,t} - w_{i,j,t-1}^{AA} r_{i,j,t}^{BM}) \quad (2)$$

where $w_{i,j,t}$ is the actual (realized) weight of fund *i* for asset class *j* in year *t*, and $r_{i,j,t}$ is the realized net return of fund *i* in asset class *j* in year *t*. In the second term, $w_{i,j,t-1}^{AA}$ represents the strategic asset

[9] These are the most frequently reported benchmarks by the pension funds: U.S. equity – S&P500, Russell 1000, Russell 2000 and Russell 3000; U.S. fixed income – Citi Group US Big Index and Barclays US Aggregate; Real estate – NCREIF and NAREIT; Private equity – Wilshire 5000, Cambridge Private Equity, Venture Economics and custom benchmarks; Hedge funds – CSFB Tremont, HFRI Indices and custom benchmarks.

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allocation policy weight of fund *i* for asset class *j* in year *t-1*, and $r_{i,j,t}^{BM}$ is the benchmark return on asset class *j* for fund *i* from the end of year *t-1* to the end of year *t* (i.e., in year *t*).

Next, we examine separately the contribution of each asset management return component. To estimate and evaluate the asset allocation skills of pension funds, we look at the yearly changes in pension fund strategic asset allocations. We look at the outcome of active decisions made by the pension fund to modify the strategic asset allocation policy in year *t* compared to year *t-1*. The returns due to such changes ($R_{i,t}^{AA}$) are estimated as the difference between pension fund's *i* strategic policy (i.e., target) weights for asset class *j* at the end of year *t* compared to the policy weights at the end of year *t-1*, multiplied with the benchmark return of that asset class from the end of year *t-1* to the end of year *t*:

$$R_{i,t}^{AA} = \sum_{j=1}^{M} \left(w_{i,j,t}^{AA} - w_{i,j,t-1}^{AA}\right) r_{i,j,t}^{BM} \tag{3}$$

where $w_{i,j,t}^{AA}$ is the policy weight of fund *i* for asset class *j* in year *t*, and $r_{i,j,t}^{BM}$ is the benchmark return on asset class *j* for fund *i* from the end of year *t-1* to the end of year *t* (i.e., in year *t*).

We define market timing as the pension fund return due to a deviation from the strategic asset allocation policy weights. Therefore, $R_{i,t}^{MT}$ captures market timing as the difference between actual realized weights and target asset allocation weights in different asset classes, times the benchmark return on each asset class:

$$R_{i,t}^{MT} = \sum_{j=1}^{M} \left(w_{i,j,t} - w_{i,j,t}^{AA}\right) r_{i,j,t}^{BM} \tag{4}$$

The market timing term will account for returns due to changes only in the weights *between* asset classes, not *within* a particular mandate. For instance, it will capture returns due to a higher allocation to equity at the expense of bonds, or returns due to a higher allocation to domestic equity instead of an EAFE mandate. However, the market timing component will not capture returns due to overweighting particular industry sectors within the U.S. equity mandate.

In general, the differences between actual and policy weights can result from either market movements or active rebalancing decisions of investment managers. If the fund does not actively change asset allocations, then naturally asset classes with higher (lower) returns will have increased (decreased) actual weights. We decompose the market timing return component into these two parts, which allow us to distinguish changes in actual weights due to market movements versus active rebalancing.

In order to do so, we construct hypothetical actual asset allocation weights that the pension fund would have achieved if it would not have rebalanced across asset classes within a particular calendar year. The hypothetical weights are constructed in two steps. In the first step for each fund we multiply the actual asset weights at the end of year *t-1* with the benchmark returns in year *t*, resulting in a

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hypothetical portfolio at the end of year *t*. In the second step, we rescale this portfolio such that the year *t* weights sum to 1. Using these hypothetical weights ($w_{i,j,t}^{HYP}$) we estimate the passive market timing return of fund *i* in year *t* (attributed to market movements) as:

$$R_{i,t}^{PasMT} = \sum_{j=1}^{M} \left(w_{i,j,t}^{HYP} - w_{i,j,t}^{AA}\right) r_{i,j,t}^{BM} \tag{5}$$

Next, the active market timing returns due to rebalancing ($R_{i,t}^{ActMT}$) is the difference between the actual asset allocation weights and the hypothetical allocation weights, times the benchmark returns in each asset class:

$$R_{i,t}^{ActMT} = \sum_{j=1}^{M} \left(w_{i,j,t} - w_{i,j,t}^{HYP}\right) r_{i,j,t}^{BM} \tag{6}$$

The third and last component of active management is security selection ($R_{i,t}^{SS}$) estimated as the difference between the realized net returns and the benchmark returns. Hence, the security selection component is equivalent to net benchmark-adjusted returns and accounts for all returns that are not attributable to asset allocation policy decisions or market timing across asset classes (though it would include any market timing done within asset classes). Our security selection return component $\left(R_{i,t}^{SS}\right)$ of fund *i* in year *t* represents net benchmark-adjusted returns, i.e. returns that are due to deviations from self-declared benchmarks within particular asset classes:

$$R_{i,t}^{SS} = \sum_{j=1}^{M} w_{i,j,t} \left(r_{i,j,t} - r_{i,j,t}^{BM}\right) \tag{7}$$

When risk-adjusting the changes in asset allocation, market timing and security selection return components on a fund level, we run the following random coefficient model:

$$R_{i,t}^{k} = \alpha_i + \beta_{1,i} MKT_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} MOM_t + \beta_{5,i} LIQ_t + \beta_{6,i} FIMKT_t + \varepsilon_{i,t} \tag{8}$$

where $k = AA, MT, SS$. The model assumes that α_i and β_i, the coefficients for fund *i*, are drawn independently from a distribution with constant mean and variance. We use the following factors: MKT (excess market return), SMB (small-minus-big), HML (high-minus-low), FIMKT (fixed income excess market return) and LIQ (traded liquidity factor). We also add MOM, (momentum factor) to the risk-adjusting model to control for returns on momentum trading strategies. MKT, SMB, HML, MOM are taken from Kenneth French’s website. The fixed income excess returns (FIMKT) are the returns on U.S. Broad Investment-Grade Bond Index (US BIG) from City Group.

The traded liquidity factor has been defined by Pastor and Stambaugh (2003) as the value-weighted return on the 10-1 portfolio from a sort of stocks into decile groups depending on their historical liquidity betas, or stock sensitivities to innovations in the aggregate liquidity. The aggregate liquidity captures the temporary price fluctuations induced by order flow and measures the liquidity dimension

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associated with the strength of volume-related return reversals, which seem most relevant for large investors (like pension funds) susceptible to market movements.

We examine separately the performance of pension funds in equity, fixed income and alternative assets (which includes real estate, private equity, hedge funds and other assets). For equity return components we run the following risk-adjusting random-coefficient model:

$$R_{i,t}^{k} = \alpha_i + \beta_{1,i}MKT_t + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}MOM_t + \beta_{5,i}LIQ_t + \varepsilon_{i,t} \tag{9}$$

where $k = AA, MT, SS$. The return components capture changes in asset allocation, market timing and security selection within equity assets.

Following Blake, Elton and Gruber (1993), Elton, Gruber and Blake (1995) and Cici and Gibson (2010), we risk-adjust the performance of fixed income assets using the following factors: MKT (equity market), FIMKT (fixed income market), HY (high yield) and OPTION (option-like characteristics of mortgage securities):

$$R_{i,t}^{k} = \alpha_i + \beta_{1,i}MKT_t + \beta_{2,i}FIMKT_t + \beta_{3,i}HY_t + \beta_{4,i}OPTION_t + \varepsilon_{i,t} \tag{10}$$

where $k = AA, MT, SS$. HY is the return difference of the Merrill Lynch High Yield and Government index for U.S. funds. OPTION is estimated as the return difference of the US BIG Mortgage Index and US BIG Government Index.

We use the random coefficient model because it allows for heteroskedasticity and fund-specific betas, while being more robust to outliers than the standard Fama-MacBeth (1973) approach. As Swamy (1970) explains, the random coefficient model is similar to a generalized least squares approach that puts less weight on the return series of funds that are more volatile.

In addition, we are interested in the relation between certain pension fund characteristics and pension fund performance. Particularly, we would like to see whether fund characteristics like asset size and investment style have a systematic association with any of the three return components. These relations are tested using Fama-MacBeth (1973) regressions of changes in asset allocation, security selection and market timing return components on the characteristics:

$$R_{i,t}^{k} = \alpha_t + \beta_t LogSize_{i,t} + \gamma_t InvestmentStyle_{i,t} + u_{i,t} \qquad i = 1,2, \dots N \text{ for each year } t \tag{11}$$

$$\hat{\alpha} = \frac{1}{T}\sum_{t=1}^{T}\hat{\alpha}_t \qquad \hat{\beta} = \frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_t \qquad \hat{\gamma} = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_t \tag{12}$$

where $R_{i,t}^{k}$ refers to the return components of fund *i* in year *t* and is a normally distributed zero-mean error term. We correct the standard errors for autocorrelation and heteroskedasticity using the Newey-West procedure with three lags. *LogSize* is the log of pension fund assets under management (fund size), and *InvestmentStyle* refers to the percentage allocation to active mandates or externally managed mandates.

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We run the Fama-MacBeth regressions on both non-risk-adjusted and risk-adjusted return components. When using the risk-adjusted return components, the estimation proceeds in two steps. In the first step, we perform a time-series regression of each fund's returns on the factor models as described above. We run these regressions for every fund that has at least one more observation than coefficients to be estimated (our findings do not change when we include only funds with at least 2, 3 or 4 more observations than coefficients, see Appendix Table A.1)**.** In the second step, we run Fama-MacBeth regressions of the alphas plus residuals retrieved in the first step, correcting standard errors for autocorrelation and heteroskedasticity using the Newey-West procedure.

4. Pension fund investment costs

Table 5 presents the results of pooled panel costs regressions. The investment costs include the costs of all internal and external money managers hired by the pension fund to invest in all asset classes. Internal investment costs include direct investment costs (compensation and benefits of employees managing internal portfolios and support staff, related travel and research expenses, etc.) and allocated overhead costs. External investment costs include all fees paid to third-party managers including investment management fees, fund-of-fund fees, performance-based fees, commitment fees and 'hidden' fees netted from the returns as well as fees paid to investment consultants.[10] External investment costs also include the costs for internal staff whose sole responsibility is overseeing the external managers.

Regressions for total costs in Table 5 (columns 1–3) indicate that larger pension funds realize scale advantages in their investment costs, but only after controlling for the percentage allocation to the most expensive asset class of alternative assets in columns 2 and 3. Focusing on column 3, a one standard deviation increase in the log of the pension fund holdings reduces the costs by some 4.4 basis points (1.464 * 4.816), when controlling also for investment style, percentage allocations to fixed income and alternative assets, year and fund-fixed effects.

Unsurprisingly, allocations to active and externally managed mandates increase the investment costs. For example, a 10 percentage points increase in the allocation to actively managed assets results in 1.8 (0.1 * 18.130) basis points higher total costs.

In columns 4 – 6 we document economies of scale in investment costs on an asset class level. Pension funds that invest more assets in equity, fixed income and alternatives obtain lower costs in every asset class. The economies of scale are especially strong in alternative assets, where a one-unit increase in the log of assets results in 111 basis points lower investment costs. In line with the results for total

[10] The exception is that for private equity and real estate the performance fees, carried interest and rebates are subtracted directly from the returns and are not incorporated in the costs figures. Hence, the costs estimations for these alternative assets usually include only the management fees and understate the total investment costs. However, the returns even for these alternative assets are net of both management and performance fees.

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costs, a greater allocation to actively managed mandates and external managers results in higher investment costs for equity and fixed income assets. For alternative assets, an allocation to fund-of-funds results in substantially higher costs. For example, in column (6), a 10 percent points increase in the allocation to fund-of-funds results in 48 basis points (0.1 * 478.236) increase in the investment costs in alternative assets.

Bauer, Cremers and Frehen (2010) also document a negative relationship between fund size and costs for investing in U.S. equities. Andonov, Eichholtz and Kok (2012) find cost economies of scale in real estate investments of U.S., Canadian, European and Australian funds. This negative relationship is robust to the investment style, i.e. it is not driven by the higher proportion of passive and internal investments among larger funds. Larger funds are able to negotiate lower fees for external mandates and organize more cost-efficient internal mandates. We find that the negative relationship between fund size and costs exists on a total fund level as well as within all asset classes. Summarizing, we document that larger pension funds realize strong scale advantages in their investment costs. On the other hand, greater active management, external management and allocation to fund-of-funds considerably increase the overall investment costs. In section 6, we will consider whether the scale advantage in costs is translated into higher net performance.

5. The performance of pension funds

In this section, we discuss whether asset allocation, market timing and security selection decisions result in outperformance or underperformance of pension funds. We first analyze the performance on a fund level and then look separately at the performance in equity, fixed income and alternative assets. Our focus is on the changes in asset allocation, market timing and security selection return components as defined previously.

5.1. Risk-adjusted performance at the pension fund level

In Figure 5, we show the average total returns and the three components at the (aggregated across asset classes) pension fund level. Security selection returns (the fourth bar in any given year) exhibit substantially higher volatility as compared to changes in asset allocation and market timing returns.

Table 6 indicates that U.S. pension funds on average obtain positive returns from their active asset management decisions. For the total return and for each component of active management, we first run a random coefficient regression with just a constant (columns (1), (4), (7) and (10)). Next, we estimate random coefficient models that include multiple factors to assess whether the outperformance remains after risk-adjusting the returns. This adjustment is important because benchmarks are chosen (and reported) by the funds themselves, such that funds could potentially choose benchmarks that are relatively easy to beat. The standard model we employ includes five factors, namely the standard three

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Fama-French factors (market, size and value) augmented with the Pastor-Stambaugh (2003) traded liquidity factor and the excess return on a fixed income market index. We compare results using this baseline 5-factor model with using a 6-factor model that also includes the Carhart (1997) momentum factor. Results in Table 6 show the annual alpha and beta coefficients on these factors, plus the root mean squared error (RMSE) of the residuals. The robustness of our risk-adjusted results can be checked by comparing Appendix Table A.1 with Table 6, where we include only pension funds with a higher number of observations per fund in the regressions.

The results in column (1) show that pension funds obtain a positive return of 57 basis points at the total fund level from their active asset management decisions before risk-adjusting. After risk-adjusting, their total return increases to 89 basis points. The total return becomes insignificantly positive after controlling for momentum in column (3). However, if we include only funds with a higher number of observations, for which we can estimate risk loadings more accurately, the total return is significantly positive and equal to 55 basis points (see Appendix Table A.1). The total return incorporates all three asset management decisions: changes in asset allocation, market timing and security selection. Next, we look at each return component separately.

Before risk-adjusting, changes in the asset allocation policy produce an insignificant return of 5.2 basis points. After risk-adjusting (5), the changes in asset allocation policy deliver a significant positive alpha of 25 basis points per year. Inclusion of the momentum factor (6) increases the estimated asset allocation alpha of U.S. funds to 30 basis points per year. This suggests that changes in target weights are not made in order to capture asset class momentum. Positive returns from the changes in asset allocation policy over time are due to changes in policy weights across broader asset classes over time. For example, funds on average increased their policy allocation to private equity, hedge funds and other alternative assets at the expense of fixed income and equity.

In columns (7)–(9) of Table 6, we find that market timing delivers about 25 basis points return per year before risk-adjusting. This is not materially affected by risk-adjusting with the 5- and 6-factor models. The beta coefficients indicate that pension funds, on average, do not systematically overweight a particular style. There is an economically small positive marginally significant coefficient on the SMB factor, but all other coefficients are statistically indistinguishable from zero. These results confirm the findings in Table 3, as the time averages of the mean differences for all asset classes are close to zero. However, Table 3 shows that pension funds' actual weights fluctuate substantially around reported policy weights. The results in Table 6 show that these fluctuations co-vary positively with benchmark returns, evidenced by the positive coefficient of the constant, indicating market timing skill.

The random coefficient model results for security selection (i.e., net benchmark-adjusted returns) show positive abnormal returns of 25 basis points per year from security selection (column 10). However, after risk-adjusting (column 11), security selection does not deliver a significant alpha. Once

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we add the momentum factor, the performance becomes even (though insignificantly so) negative: -9 basis points per year. These results indicate that momentum trading strategies on average deliver around 35 basis points annually.[11]

Overall, our paper provides clear evidence that pension funds obtain positive alphas from intentional changes in strategic asset allocation and market timing (or tactical asset allocation) decisions. The insignificantly negative security selection alpha (after controlling for momentum) offsets part of the positive returns from strategic asset allocation and market timing. These results suggest that pension funds have most expertise in dynamically maneuvering between various asset classes, rather than in security selection or identifying superior active managers for given asset classes.

5.2. Market timing returns

In Table 6, we document that pension funds obtain positive returns from market timing, i.e. from overweighting or underweighting particular asset classes, relative to the target weights in that year. In this section, we examine the sources of positive market timing returns in greater detail. First, we distinguish between market timing returns due to market movements (not rebalancing) versus performing resulting from active rebalancing decisions. Second, we examine the market timing returns within the two main asset classes of equity and fixed income, where funds can rebalance across multiple domestic, international and global sub-asset classes.

In Table 7, we distinguish between passive market timing and active market timing. Passive market timing can be interpreted as the performance when not rebalancing the portfolio, i.e. letting the portfolio drift towards or away from the strategic allocation weights depending on the benchmark returns. Active market timing can be interpreted as intentional deviations from strategic asset allocation weights, i.e. active rebalancing of the portfolio with actual trading. Such active rebalancing can be also be due to guidelines where funds define *ex ante* in which range individual asset class weights are allowed to drift (bandwidths).

Panel A of Table 7 shows that U.S. pension funds could have obtained substantially high alphas from market timing if they would have not rebalanced their portfolios. They would have obtained passive market timing returns of 108 basis points before and 130 basis points after risk-adjusting. The large positive alphas on the passive market timing component indicate that the market timing returns of pension funds in Table 6 are mainly due to market-wide movements, or the phenomenon that past asset class returns tend to positively predict future returns in the same asset class, termed ‘time series’ momentum by Moskowitz, Ooi and Pedersen (2012). However, pension funds cannot fully exploit

[11] Controlling for momentum has even stronger effect on the security selection returns if we focus only on the 1990–2008 period. When examining only this shorter time period the security selection alpha is significantly negative and equal to -105 basis points after controlling for momentum factor. The momentum factor has weaker effect when adding the last two years of our sample period, because in 2009 this factor has an extreme negative return of -83.29 percent.

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time series momentum, as they are typically bound by the bandwidths stated in their investment guidelines. Columns (3) and (4) document that pension funds underperform when trying to actively rebalance money across asset classes, 84 basis points before and 106 basis points after risk-adjusting. The net (or aggregated) effect of passive and active market timing can be found in Table 6 (25 basis points before and 19 after risk adjusting).

In Panel B of Table 7, we present the market timing results within equity and fixed income, which can be measured only when funds invest in at least two categories within equity or fixed income assets.[12] Results in columns 5 and 6 indicate that pension funds can create abnormal returns from timing their allocation decisions within equity investments. Before risk-adjusting, U.S. pension funds can beat their *ex ante* stated equity benchmarks by about 22 basis points per year using market timing. After risk-adjusting and controlling for momentum, the alpha remains 21 basis points. As the market timing results at the total fund level produced about 26 basis points alpha per year, this implies that a large part of the abnormal market timing return is due to timing the performance across various equity classes (such as moving from domestic equity to international equity), rather than timing the performance across broader asset classes (such as moving from equity to fixed income or real estate).

In columns 7 and 8, we examine the fixed income market timing returns. Our results indicate that market timing within fixed income assets does not deliver any abnormal returns. Before and after risk-adjusting, U.S. pension funds are not able to generate abnormal returns from timing their allocations between various fixed income categories.

5.3. Security selection returns per asset class

Table 8 presents the results for security selection returns separately for equity, fixed income and alternative assets. In columns (1)–(3), we focus on the security selection, i.e. net benchmark-adjusted returns within equity before and after risk-adjusting. We risk-adjust the security selection returns for exposure to MKT, SMB, HML and LIQ factors. In column (3) we also add momentum. In line with our findings at the total fund level, pension funds on average demonstrate security selection skills within equity, but only when not adjusting for momentum. Before risk-adjusting, the average fund beats its equity benchmarks by about 23 basis points using security selection. After controlling for risk factors, the alpha from random coefficient regressions on equity net benchmark-adjusted returns equals 37 basis points and is still significant at the 10% level. However, when we also control for momentum, the alpha from security selection becomes insignificant at 7 basis points. Again, these

[12] For example, based on the strategic policy a pension fund should invest in 50% in U.S. equity, 30% in EAFE equity and 20% in Emerging markets equity. If the actual allocation percentages are different from the above-mentioned policy weights, that fund will generate returns from market timing within equity, measured as the difference between actual and policy weights times the benchmark returns. However, it does not capture returns from overweighting certain industries within U.S. equity mandate.

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results show that the momentum factor plays an important role in explaining pension fund security selection returns.

In (4) and (5), we examine security selection skills within fixed income assets. Using a random-coefficient model, we risk-adjust the fixed income net benchmark-adjusted returns for MKT, FIMKT, HY and OPTION. Pension funds are able to outperform their benchmarks within fixed income assets before risk-adjusting (4). However, the results in (5) show that alphas disappear after controlling for the high yield spread and option elements in fixed income returns. In Figure 6, we also observe that security selection returns within fixed income became much more volatile in the last three years of our sample period (2008 – 2010). This trend closely matches the returns on high yield assets. Overall, pension funds are not able to obtain positive abnormal returns in fixed income assets after risk-adjusting.

Finally, we investigate the security selection skill of pension funds in alternative assets. Alternative assets include investments in external global tactical asset allocation (GTAA) mandates, commodities, natural resources, real estate, infrastructure, private equity and hedge funds. Results in column (6) of Table 8 indicate that pension funds' benchmark-adjusted performance in all alternative assets together is negative, but insignificant.[13]

6. Pension fund characteristics and performance

In this section, we relate the risk-adjusted total return, asset allocation, market timing and security selection alphas to certain characteristics of pension funds using Fama-MacBeth regressions. Specifically, we examine whether differences in performance are associated with fund (asset class) size, liquidity, investment costs and investment style (referring to whether assets are managed internally or externally, and passively or actively). Fund size reflects the total size of the pension fund holdings, which is a sum of holdings in all asset classes, while 'asset class size' reflects the size of the holdings in a particular asset class, like equity or fixed income. The analysis again is first conducted on a fund level and later by individual asset class.

Table 9 presents the results for the total return and its three components (asset allocation, market timing and the security selection returns). Estimation consists of two steps. In the first step, we risk-adjust returns using a six factor model that includes MKT, SMB, HML, LIQ, FIMKT and MOM. In the second step, we augment the alphas with the error terms retrieved from the first step and run Fama-MacBeth regressions, while correcting for autocorrelation and heteroskedasticity using Newey-West standard errors with three lags.

[13] This paper focuses on overall pension fund performance, such that we combine all alternative assets together as this group of assets represents only small part of total fund holdings, on average around 10 percent. We leave detailed analysis of pension fund performance in individual alternative asset classes, like private equity and hedge funds, for future research.

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When analyzing the total return, which represents the sum of all three return components, pension fund size (LogSize) is negatively related to performance, especially for funds whose investments have exposure to systematic liquidity risk. Columns (2) and (3) indicate that a one unit increase in the logsize (i.e. doubling the fund size) results in 11-15 basis points lower performance. The interaction between fund size and the fund's liquidity beta (i.e. the exposure to the Pastor-Stambaugh traded liquidity factor) is negative and significant. Based on column (3), increasing liquidity by lowering the liquidity beta by 10 percentage points, would be associated with an improvement of the alpha of funds at the 75th size percentile by 16 basis points per year (= -0.1 * -1.539 * (ln[8582]-ln[3025]) more than the improvement of the alpha of a fund at the median size percentile. This result shows that larger pension funds face diseconomies of scale when redesigning their strategic asset allocation policy, timing the market in multiple asset classes and deviating from the benchmarks by active security selection.

Pension funds using more external managers realize lower total returns from asset management decisions. Column (3) shows that a 10 percentage points increase in the proportion of externally managed assets is associated with 5.4 basis points lower annual total returns. This may be partly due to lower investment costs for internal management (see Table 5). In addition, Lakonisok, Shleifer and Vishny (1992) suggest that external management may create potential agency conflicts or that incentives of internal managers may be better aligned with those of the overall pension fund.

When examining the return component separately, we find that fund size is not related directly to the abnormal returns from changes in asset allocation policy. However, the interaction between fund size and the fund's liquidity beta (i.e. the exposure to the Pastor-Stambaugh traded liquidity factor) is negative and significant. The interaction coefficient equals -1.991 in column (6) of Table 9. Economically, this coefficient means that increasing liquidity by lowering the liquidity beta by 10 percentage points, would be associated with an improvement of the alpha of funds at the 75th size percentile by 21 basis points per year (= -0.1 x -1.991 x (ln[8582]-ln[3025]) more than the improvement of the alpha of a fund at the median size percentile. This finding implies that larger funds face significant liquidity limitations when redesigning their strategic asset allocation: shifts in the strategic asset allocation towards more illiquid assets hurt the performance of larger funds relative to smaller funds.

In columns (7)–(9) of Table 9, we consider the relation between market timing returns and pension fund characteristics. Fund size is negatively related to market timing abilities. Additionally, the interaction between fund size and the fund's liquidity beta is negative and highly significant. In columns (8) and (9), a one-unit increase in LogSize, i.e. doubling the fund size, reduces the market timing returns by 4.3 basis points. The interaction effect of size and liquidity has an even stronger economic effect on the market timing returns (see columns (8) and (9)).

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In the last part of Table 9, we analyze the relation between fund characteristics and the security selection component (net benchmark-adjusted returns). At the fund level, U.S. fund security selection performance is unrelated to fund size (column 12). Again, the security selection performance of larger funds seems particularly constrained by liquidity, as evidenced by the large, negative coefficients on the interaction between fund size and the liquidity beta. The interaction coefficient equals -1.250 in column 12 of Table 9. Economically, this coefficient means that increasing liquidity by lowering the liquidity beta by 10 percentage points, would be associated with an improvement of the alpha of funds at the 75th size percentile by 13 basis points per year (= -0.1 * -1.250 * (ln[8582]-ln[3025]) more than the improvement of the alpha of a fund at the median size percentile.

We also look at the influence of pension fund characteristics on performance on a lower level of aggregation, or how concentration, size, liquidity, costs and investment style relate to the performance in individual asset classes. Appendix Table A.2 shows the results for pension fund security selection performance within equity. Funds with higher allocations to equity (as a percentage from total assets) have better performance in equity. Based on column (3), an increase in the allocation to equity of 10 percent points results in 21 basis point better net benchmark-adjusted returns in equity. The effect of the concentration in equity assets on the performance of equity is even stronger after risk-adjusting. However, our results in columns (5) and (7) indicate that the relation between concentration in equity and performance becomes insignificant, once we control for the liquidity-size interaction. This suggests that larger funds face liquidity constraints when investing in equity and cannot allocate a substantial share of their assets to equity investments. It likewise suggests that funds with high equity allocations tend to deviate from their benchmark by selecting relatively illiquid stocks, which only results in better performance if the funds are relatively small.

We also study the relation between pension fund characteristics and their performance in fixed income assets. In unreported results, we do not find a significant effect of the allocation to fixed income assets, size of the holdings or investment style on the cross-sectional differences in fixed income performance. Compared to equity, the influence of pension fund characteristics has a much lower effect on the fixed income performance.

Next, we examine whether larger pension funds consider the liquidity-related diseconomies of scale when designing their investment approach. We split the pension funds into tertiles based on their percentage of assets allocated to actively managed mandates. In the first tertile, the median percentage of actively managed assets is 59 percent, whereas in the second and third tertile this precentage is 80 and 98 percent of the total assets, respectively. Pension fund size plays an important role when designing the investment approach. In line with our evidence on liquidity-diseconomies of scale, larger pension funds manage greater percentages of their assets passively. The median size of a pension fund belonging to the tertile with lowest active management is $10.37 billion, while the median size of the funds in the second and third tertile is $4.82 and $4.05 billion, respectively.

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Table 10 compares the relation between size and performance for the tertiles with lowest and highest degree of active management. In columns (1) and (5) we show that pension funds in both tertiles obtain positive total returns after risk-adjusting. However, the size-liquidity interaction has a significantly different association with the performance across the two tertiles. In both tertiles, the interaction term has a negative coefficient, but the economic magnitude is significantly larger in the tertile with highest percentage of actively managed assets (coefficient of -2.269***) compared to the passively managed tertile (coefficient of -0.887**). Here, it is important to note that the liquidity betas themselves are not significantly different across the tertiles (average coefficient of -0.041, -0.022 and -0.029 in the three respective tercile groups).

In columns (4) and (8), we include dummy variables capturing the smallest and largest pension funds. These dummy variables are obtained by independently sorting the fund into quartiles based on their size, such that the Small (Large) dummy equals one for funds in the smallest (largest) quartile size group, and zero otherwise. The median size of the small quartile is $1.3 billion assets, while the median size of the funds in the large quartile is $34 billion. In the more passively managed tertile, the Small and Large dummy variables are similar and insignificant. However, in the more actively managed tertile, the dummy variable capturing the largest funds is significantly negative and reduces substantially their risk-adjusted total return. The most actively managed group of funds thus has significantly greater size-induced liquidity constraints, and its funds that are in the largest quartile group underperform similarly sized funds with much less active management by about 62 (= 45.8 + 40.1 – 91.7 + 68.0) basis points a year, which difference is statistically significant at 5%.

To sum up, we find that the economies of scale in pension fund costs do not materialize in better returns. Larger pension funds perform worse in all three components of active management if they invest in less liquid assets (i.e., that have exposure to systematic liquidity risk). Large funds seem to experience liquidity-related diseconomies of scale, including in their largest asset class, equity. Larger pension funds that are predominantly actively managed may have done better if they would have implemented a more passive approach.

7. Persistence in pension fund performance

Previous sections showed that pension funds obtain positive returns from market timing and security selection, some of which remain significant even after risk-adjusting. If this is due to skill, an important robustness check is whether there is any persistence in pension fund performance. To answer this question we split pension funds into five quintiles based on either their market timing or their net security selection performance (after costs). We run an ordered logit model, where the dependent variable is the quintile ranking based on the performance in year *t+1* and the main independent variable is the quintile ranking in year *t*. Marginal effects from the ordered logit model for

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every outcome (quintile ranking) are presented in Table 11. Panel A presents the results for market timing returns, whereas Panel B covers the persistence in security selection returns of U.S. funds.

Results indicate that funds are more likely to end up in a better performing quintile next year, if they belong to a better performing quintile already this year. Pension funds are also more likely to be ranked among the worst performers next year, if they performed relatively poorly this year. The persistence is observed in both market timing and security selection returns. For example, looking at U.S. funds market timing returns (Panel A), an increase in the quintile ranking from 3 to 4 reduces the probability of ranking among the worst performers in year t+1 by 3.3%. Results in columns 2, 3 and 4 show that the marginal effects of last year's ranking remain even after controlling for fund size, costs, and the percentage of assets managed actively and externally.

In Appendix Table A.3 we present the actual transition matrixes. The percentage of funds repeating as best performers is in all cases higher than the percentage of best performers of last year ending in one of the four lower quintiles this year. The same holds for the worst performing funds. We also look at the returns in year *t+1* of funds ranked in the lowest and highest quintile in year *t*. Funds ranked in the top quintile have higher average returns in the following year than the funds ranked in the bottom quintile.

These persistence tests are performed directly on the benchmark-adjusted market timing and security selection returns. As we only have access to annual data, we cannot use the risk-adjusted performance in these estimations. Hence, we do not test whether pension funds can persistently deliver abnormal returns, or estimate the effect of liquidity constraints on persistence. Nevertheless, these results show that certain pension funds are persistently better in outperforming their benchmarks using market timing and security selection.

8. Conclusion

After risk-adjusting and net of all costs, pension funds obtain a positive return of 89 basis points per year from their asset management decisions, i.e. compared to maintaining the strategic asset allocation policy from the previous year and investing in the benchmark. Pension funds are thus on average able to provide positive returns to their participants. To identify the sources of the positive total return, we decompose it into three active asset management components: asset allocation, market timing and security selection. For each of the three return components, pension funds are able to beat their benchmarks before and after risk-adjusting. Changes in asset allocation policy result in positive abnormal returns of 25 basis points per year. These abnormal returns are due to pension funds changing their asset allocation policy across broader asset classes over time, not to changes within equity or fixed income.

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Market timing delivers a positive alpha of 26 basis points per year. This abnormal return is larger among smaller funds. Market timing alpha is completely due to passive market movements, i.e. the ability of pension funds to exploit 'time series' momentum by investing in multiple asset classes. Pension funds do not have active rebalancing skills. In addition, more than half of the alpha comes from market timing within different equity styles (such as domestic versus international stocks, and large versus small cap stocks). Overall, these results suggest that funds that try to stay as close as possible to their strategic asset allocation policy may miss market timing opportunities. If fund managers can obtain positive returns from the passive market movements due to time series momentum (see Moskowitz, Ooi and Pedersen (2012)), as our results indicate, letting the actual weights deviate from the strategic weights and not rebalancing back immediately can in fact improve performance, in line with Sharpe's (2010) idea of an 'adaptive asset allocation policy.'

Security selection delivers an insignificant return of 25 basis points per year after risk-adjusting, which is driven by the momentum factor. Once we control for this factor, security selection delivers an insignificant negative alpha of -10 basis points per year.

Larger pension funds do not manage to transfer their lower investment costs into higher net returns. Rather, we document *dis*economies of scale in pension fund performance. The diseconomies of scale are primarily apparent for funds investing in less liquid assets, as proxied by fund total return loadings on the traded systematic liquidity factor. As a result, the performance of large pension funds seems to be subject to size-induced liquidity limitations. These liquidity limitations related to size are significant in all three asset management components. Larger funds face liquidity constraints even when investing in public equity. Our results suggest that funds with high equity allocations tend to deviate from their benchmark by selecting relatively illiquid stocks, which only results in better performance if the funds are relatively small. Smaller pension funds obtain higher total returns and especially higher market timing returns. The better market timing returns of smaller funds can be explained by two effects. First, smaller funds can be regulated in a more flexible way with wider bandwidths that enable them to deviate further from their strategic asset allocation weights and exploit the across asset class momentum. Second, even if smaller pension funds have to rebalance to restore their strategic weights, such rebalancing has lower market impact.

Lastly, we find persistence in pension funds' ability to deliver higher market timing and security selection returns. Funds belonging to the best performing quintile this year are more likely to remain among the best performers in the following year.

Overall, pension funds seem to have most expertise in designing strategic asset allocation and market timing policies, rather than in actively selecting securities or in finding external managers with superior security selection skills. Pension funds benefit significantly from time series momentum across multiple asset classes. Our results thus suggest that pension funds, and especially the larger funds, would have done better if they invested in passive mandates without frequent rebalancing

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across asset classes. This conclusion is confirmed when we compare the total performance of funds depending on the percentage of their assets that is actively managed. The most actively managed group of pension funds has significantly greater liquidity-related diseconomies of scale, as its funds that are in the largest quartile group underperform similarly sized funds with much less active management by about 62 basis points a year. Our paper thus documents three separate reasons for the attractiveness of passive management, especially for the largest pension funds. First, pension funds on average had insignificant risk-adjusted security selection performance. Second, passive management is much cheaper than active management. Third, performance in passive mandates is less subject to liquidity-related diseconomies of scale.

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Table 1: Number of funds and fund size

This table presents the number of U.S. pension funds in the CEM database in the sample period 1990-2010. We also show the number of funds entering and exiting the database in a given year. The 'Fund Size' column presents the average assets under management in billion USD. The 'Total' row shows the total number of funds reporting at least one year to the CEM and the time series average of cross-sectional mean fund size.

Year	U.S. pension funds			
	# Funds	# Enter	# Exit	Fund Size
1990	35	35	0	9.46
1991	63	39	11	7.28
1992	83	38	18	7.45
1993	134	70	19	5.92
1994	168	68	34	4.85
1995	192	62	38	5.64
1996	185	36	43	6.22
1997	168	29	46	7.73
1998	174	37	31	9.11
1999	182	40	32	10.41
2000	164	22	40	12.02
2001	176	36	24	10.56
2002	156	15	35	10.80
2003	158	27	25	11.02
2004	167	26	17	12.18
2005	156	15	26	13.12
2006	147	18	27	15.79
2007	218	88	17	12.76
2008	212	37	43	12.25
2009	203	34	43	12.22
2010	201	42	44	13.32
Total	557			10.00

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Table 2: Cox proportional hazard model and self-reporting bias

This table presents the results of a survival analysis using the Cox proportional hazard model. The event of interest is the decision of the pension funds not to report to CEM in a given year. We treat each fund re-entry as a new fund which explains why the # Units is higher than the # Funds presented in Table 1. # Exit Events presents the number of observations when pension funds decided not to report to CEM again. Observations presents the total number of observations in the database. Independent variables included in the model are Log(Size) – logarithm of the asset under management, Total Costs in basis points, Gross returns in percentage points, Net returns in percentage points, Net benchmark-adjusted returns in percentage points and Benchmark returns in percentage points. In this table the hazard ratios for each independent variable are reported together with their standard errors in brackets and significance levels with *, ** and ***, which correspond to 0.10, 0.05 and 0.01, respectively. All regressions use robust standard errors clustered by year.

Interpretation of the hazard ratios:
LogSize: when the logsize increases by 1 unit, the dropping rate decreases by 26.1% (-0.261). Total costs: when the total costs increase by 1 basis point, the dropping rate decreases by 0.9% (-0.009).

Dependent variable: Exit event – decision of a pension fund not to report to CEM				
	(1)	(2)	(3)	(4)
LogSize	-0.261***	-0.261***	-0.260***	-0.262***
	[0.043]	[0.043]	[0.044]	[0.042]
Total costs	-0.009***	-0.009***	-0.009***	-0.009***
	[0.003]	[0.003]	[0.003]	[0.003]
Gross return	0.006			
	[0.011]			
Net returns		0.006		
		[0.011]		
Net benchmark-adjusted return			-0.004	-0.008
			[0.016]	[0.013]
Benchmark return				0.008
				[0.012]
Units	798	798	798	798
Exit events	596	596	596	596
Observations	3298	3298	3298	3298

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Table 3: Summary statistics: strategic (policy) and actual asset allocation

This table presents the strategic policy weights of the pension funds and the realized policy weights. Column Policy weight presents the time series averages of cross-sectional mean strategic policy weights (target weights) for different asset classes for the period 1990–2010. We present the reults for equity, fixed income, cash and alternative assets. Alternative assets include investments in tactical asset allocation, commodities, natural resources, real estate, infrastructure, private equity and hedge funds. Column Actual weight presents the time series averages of cross-sectional mean realized weights for different asset classes for the period 1990–2010. Mean column of $Actual_t$ – $Policy_t$ displays the time series averages of cross-sectional mean differences between the actual weights and strategic policy weights, whereas the StDev column presents the time series average of cross-sectional standard deviations of the mean differences between the actual (realized) weights and strategic (target) weights. Mean column of $Policy_t$ – $Policy_{t-1}$ displays the time series averages of cross-sectional mean differences between the strategic policy weights in year *t* and the strategic policy weights in the previous year *t-1*, whereas the StDev column presents the time series average of cross-sectional standard deviations of the differences between the strategic policy weights from year *t* and year *t-1*.

	Policy weight		Actual weight		$Policy_t$ – $Policy_{t-1}$		$Actual_t$ – $Policy_t$	
	Mean	StDev	Mean	StDev	Mean	StDev	Mean	StDev
Equity	57.46%	11.54%	57.52%	12.15%	-0.18%	4.65%	0.06%	5.50%
Fixed income	31.71%	11.07%	31.31%	11.57%	-0.22%	4.45%	-0.40%	4.95%
Cash	1.16%	2.60%	1.98%	3.14%	-0.10%	1.43%	0.82%	2.36%
Alternatives	9.68%	8.53%	9.19%	8.47%	0.51%	3.57%	-0.49%	5.21%

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Table 4: Summary statistics: returns and costs

This table presents the pension fund costs, benchmark returns and realized return in percentages. Descriptive Statistics include the time-series averages of cross-sectional, annualized mean gross returns, costs, net returns, benchmark returns and net benchmark-adjusted returns ("Net-Bench Return," i.e. the security selection return (SS) component) for the 1990-2010 period. Standard deviations are given between the brackets. 'All Assets' uses the overall returns in all asset classes on a fund level. We also report the results separately for equity, domestic equity, fixed income, domestic fixed income and alternative assets.

	Gross return	Costs	Net return	Bench. return	Net-Bench return (SS)
All Assets	9.89	0.37	9.52	9.21	0.31
	[3.85]	[0.19]	[3.83]	[2.58]	[2.91]
Equity	11.05	0.33	10.72	10.44	0.28
	[3.81]	[0.17]	[3.80]	[2.27]	[3.24]
Domestic equity	11.21	0.29	10.92	10.74	0.18
	[3.34]	[0.17]	[3.33]	[1.54]	[3.26]
Fixed income	8.17	0.20	7.96	7.54	0.42
	[3.14]	[0.15]	[3.11]	[2.33]	[2.29]
Domestic fixed income	7.89	0.19	7.70	7.24	0.46
	[2.73]	[0.15]	[2.70]	[1.60]	[2.29]
Alternatives	9.80	1.33	8.47	8.47	0.00
	[12.67]	[0.99]	[12.80]	[7.73]	[11.80]

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Table 5: Costs regressions

This table reports the results of pooled panel regressions of the pension fund investment costs. Regressions (1), (2) and (3) report the results of pooled panel regressions of the total investment costs. In models (4)–(6) we use equity-, fixed income- and alternatives investment costs as dependent variables. Alternative assets include investments in real estate, private equity, hedge funds, tactical asset allocation, infrastructure, commodities and natural resources. As independent variables, we include the log of pension fund assets in millions of dollars (LogSize), and the percentage allocations to externally (%Ext) and actively (%Act) managed mandates. When analyzing the alternatives costs, we also include the percentage of assets allocated to fund-of-funds (%FoF) as independent variable. In models (4)-(6), LogSize refers to the logarithm of holdings in the particular asset class. In models (2) and (3) we control for the percentage allocation to alternative assets (%Alternatives), whereas in model (3) we also add the percentage allocation to fixed income assets (%FixedIncome) as independent variable. In the pooled panel regressions we include with year dummies and fund-fixed effects. All regressions use robust standard errors clustered by fund. We report standard errors in brackets and significance levels with *, ** and ***, which correspond to 0.10, 0.05 and 0.01, respectively.

	Dependent variable: Investment costs in basis points					
	Total costs (1)	Total costs (2)	Total costs (3)	Equity (4)	Fixed income (5)	Alternatives (6)
LogSize	-2.430	-4.411**	-4.816**	-4.053**	-5.119**	-111.023**
	[3.343]	[2.113]	[2.196]	[1.609]	[2.189]	[45.989]
%Act	29.086***	17.348***	18.130***	26.717***	8.223***	
	[5.965]	[3.528]	[3.594]	[2.052]	[2.433]	
%Ext	13.967*	11.291**	9.823**	15.219***	14.669***	120.638**
	[8.410]	[4.845]	[4.402]	[5.206]	[3.380]	[51.442]
%FoF						478.236***
						[148.984]
%Alternatives		123.615***	118.675***			
		[9.579]	[10.341]			
%FixedIncome			-14.845**			
			[5.762]			
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,342	3,342	3,342	3,325	3,329	2,845
R-squared	0.809	0.878	0.880	0.868	0.607	0.812

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Table 6: Risk-adjusted performance per return components on a total fund level

This table reports the net risk-adjusted performance at the fund level for all assets using a random coefficients model. First, we run the random coefficient model with a constant only for every return component. When risk-adjusting the return components, the following factors are included in the regressions: MKT, SMB and HML are the Fama-French factor returns, MOM – momentum factor, LIQ – Pastor and Stambaugh (2003) traded liquidity factor, FIMKT – fixed income excess market return. In Columns (1) – (3) the dependent variable is the total return which represents a sum of all three active asset management decisions: asset allocation, market timing and security selection. In Columns (4) – (6) the dependent variable is the return due to changes in asset allocation policy, which is calculated as the return due to changes in the strategic asset allocation weights in year *t* compared to year *t-1* multiplied with the benchmark return $R_{i,t}^{AA} = \sum_{j=1}^{N}(w_{i,j,t}^{AA} - w_{i,j,t-1}^{AA})r_{i,j,t}^{BM}$. In Columns (7) – (9) the dependent variable is the market timing component of fund returns $R_{i,t}^{MT} = \sum_{j=1}^{N}(w_{i,j,t} - w_{i,j,t}^{AA})r_{i,j,t}^{BM}$, where $w_{i,j,t}^{AA}$ is the policy weight for fund *i* for asset class *j* and year *t*, $w_{i,j,t}$ is the actual realized weight for fund *i* for asset class *j* and year *t* and $r_{i,j,t}^{BM}$ is the benchmark return for fund *i* for the asset class *j* and period *t*. In Columns (10) – (12) we use the security selection component of fund returns as dependent variable $R_{i,t}^{SS} = \sum_{j=1}^{N} w_{i,j,t}(r_{i,j,t} - r_{i,j,t}^{BM})$, where $r_{i,j,t}$ is the realized net return on the asset class *j* for the year *t* by fund *i*. We report the annual alpha (Constant) and betas with standard errors in brackets and significance levels with *, ** and ***, which correspond to 0.10, 0.05 and 0.01, respectively. RMSE is the root mean square error.

	Dependent variable: Return components in percentage points											
	Total return components			Asset allocation component			Market timing component			Security selection component		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	0.572***	0.886***	0.535	0.052	0.246***	0.303*	0.251***	0.264***	0.193**	0.252***	0.251	-0.095
	[0.096]	[0.265]	[0.423]	[0.039]	[0.093]	[0.179]	[0.035]	[0.069]	[0.090]	[0.082]	[0.188]	[0.273]
MKT		-0.010	0.001		-0.012***	-0.013**		-0.005	-0.003		0.014*	0.025**
		[0.010]	[0.014]		[0.004]	[0.006]		[0.003]	[0.003]		[0.008]	[0.010]
SMB		0.034**	0.045***		0.006	0.007		0.005*	0.007**		0.032***	0.041***
		[0.014]	[0.013]		[0.004]	[0.004]		[0.003]	[0.003]		[0.008]	[0.011]
HML		0.007	0.016		-0.010***	-0.011**		-0.002	-0.000		0.016**	0.027***
		[0.009]	[0.013]		[0.003]	[0.006]		[0.003]	[0.003]		[0.007]	[0.010]
LIQ		-0.020	-0.017		-0.008	-0.009		-0.001	0.001		-0.008	-0.015
		[0.020]	[0.020]		[0.005]	[0.008]		[0.005]	[0.005]		[0.012]	[0.018]
FIMKT		-0.066*	-0.074**		-0.000	0.001		0.004	0.004		-0.055**	-0.077***
		[0.034]	[0.037]		[0.014]	[0.015]		[0.008]	[0.009]		[0.022]	[0.023]
MOM			0.026**			-0.001			0.003			0.032***
			[0.012]			[0.004]			[0.003]			[0.010]
Funds	133	133	133	134	134	134	169	169	169	169	169	169
Observations	1766	1766	1766	1780	1780	1780	2304	2304	2304	2277	2277	2277
RMSE	2.955	2.900	2.880	1.243	1.210	1.211	1.216	1.213	1.211	3.027	2.969	3.010

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Table 7: Market timing returns

In Panel A we split the market timing return into two parts. The passive market timing return component captures the returns due to market movement. The active market timing component captures the returns dues to active rebalancing. In Panel B we estimate the market timing alphas within equity and fixed income assets. Within equity and fixed income assets, we can estimate the returns due to market timing, because both of them incorporate multiple asset classes. We risk-adjust the market timing returns within equity for MKT, SMB, HML, LIQ and MOM. We risk-adjust the market timing returns within fixed income for MKT, FIMKT, HY and OPTION. We report the annual alpha with standard errors in brackets and significance levels with *, ** and ***, which correspond to 0.10, 0.05 and 0.01, respectively. RMSE is the root mean square error.

	Panel A: Two market timing components				*Panel B: Market timing return per asset class*			
	Passive market timing		Active market timing		MT within equity		MT within fixed income	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	1.080***	1.300***	-0.842***	-1.055***	0.224***	0.208***	0.026	0.011
	[0.063]	[0.208]	[0.045]	[0.138]	[0.038]	[0.067]	[0.024]	[0.034]
MKT		-0.033***		0.026***		0.004		-0.003
		[0.007]		[0.005]		[0.004]		[0.003]
FIMKT		0.069***		-0.068***				0.008
		[0.019]		[0.013]				[0.009]
SMB		0.011**		-0.000		0.003		
		[0.006]		[0.005]		[0.004]		
HML		-0.022***		0.020***		0.003		
		[0.007]		[0.004]		[0.002]		
LIQ		-0.014		0.013**		0.002		
		[0.010]		[0.005]		[0.005]		
MOM		-0.020***		0.022***		-0.002		
		[0.006]		[0.004]		[0.004]		
HY								0.011**
								[0.005]
OPTION								-0.000
								[0.024]
Funds	134	134	134	134	191	191	210	210
Observations	1780	1780	1780	1780	2447	2447	2571	2571
RMSE	1.899	1.758	1.376	1.187	1.184	1.180	1.210	1.187

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Table 8: Security selection returns per asset class

In this table we analyze the security selection (net benchmark-adjusted) returns on an individual asset class level. For equity and fixed income assets, we run a random coefficient model with a constant only and we also risk-adjust the returns. We risk-adjust the security selection returns within equity using the following factors: MKT, SMB and HML – the Fama-French factor returns, MOM – momentum factor and LIQ – Pastor and Stambaugh (2003) traded liquidity factor. Within fixed income, security selection returns are risk-adjusted using the following factors: FIMKT – fixed income excess return, HY – high yield spread, OPTION – option-like characteristics of mortgage securities returns and MKT – equity excess return. For alternative assets, security selection returns (net benchmark-adjusted returns) we just run a random coefficient model with a constant. Alternative assets include investments in tactical asset allocation, commodities, natural resources, real estate, infrastructure, private equity and hedge funds. We report the annual alpha with standard errors in brackets and significance levels with *, ** and ***, which correspond to 0.10, 0.05 and 0.01, respectively. RMSE is the root mean square error.

	Dependent variable: security selection (net benchmark-adjusted returns) per asset class					
	Equity (1)	Equity (2)	Equity (3)	Fixed income (4)	Fixed income (5)	Alternatives (6)
Constant	0.233**	0.366*	0.071	0.330***	-0.061	-0.672
	[0.095]	[0.212]	[0.296]	[0.080]	[0.103]	[0.724]
MKT		-0.016*	-0.010		0.012	
		[0.009]	[0.010]		[0.008]	
FIMKT					0.041*	
					[0.025]	
SMB		0.063***	0.073***			
		[0.012]	[0.013]			
HML		0.002	0.012			
		[0.009]	[0.010]			
LIQ		-0.022	-0.022			
		[0.016]	[0.019]			
MOM			0.022**			
			[0.010]			
HY					0.066***	
					[0.016]	
OPTION					0.036	
					[0.066]	
Funds	191	191	191	211	207	343
Observations	2412	2412	2412	2530	2513	2576
RMSE	3.598	3.497	3.519	3.220	2.758	15.499

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Table 9: Pension fund characteristics and return components on a total fund level

In this table in the first step we regress the total returns as well as the three return components, asset allocation (AA), market timing (MT) and security selection (SS) returns, on a six factor model that includes the MKT, SMB, HML, LIQ, MOM and FIMKT. In the second step we augment the alphas retrieved from the first step with the error terms of the first step and run Fama-MacBeth regressions and correct for autocorrelation and heteroskedasticity (using Newey-West with three lags). We include the following characteristics in all models: LogSize – log of average pension fund holdings in a given year, %Act – percentage of all holdings invested in active mandates and %Ext – percentage of all holdings invested in external mandates. Size*Liq is an interaction term of the log fund size with the first step fund-specific loading on the liquidity factor. The last row reports the number of observations included in the analysis. We report the coefficients with standard errors in brackets and denote significance levels with *, ** and ***, which correspond to 0.10, 0.05 and 0.01, respectively.

	Dependent variable: Risk-adjusted return components in percentage points											
	Total return components			Asset allocation return component			Market timing return component			Security selection return component		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	1.204*	1.148**	1.833***	0.114	0.468	-0.390	0.629***	0.587***	0.563***	-0.908	-1.400**	0.257
	[0.724]	[0.463]	[0.530]	[0.257]	[0.320]	[0.457]	[0.206]	[0.150]	[0.103]	[0.718]	[0.680]	[0.776]
LogSize	-0.069	-0.111**	-0.151***	0.031	-0.031	-0.002	-0.053**	-0.043**	-0.043***	0.106	0.137*	-0.005
	[0.073]	[0.051]	[0.056]	[0.027]	[0.040]	[0.041]	[0.022]	[0.017]	[0.013]	[0.070]	[0.074]	[0.097]
%Act			0.170			0.671***			0.024			0.286
			[0.327]			[0.193]			[0.085]			[0.692]
%Ext			-0.541**			0.082			-0.003			-0.881
			[0.214]			[0.146]			[0.065]			[0.554]
Size*Liq		-1.517***	-1.539***		-2.005***	-1.991***		-1.804***	-1.734***		-1.069***	-1.250***
		[0.443]	[0.449]		[0.273]	[0.270]		[0.089]	[0.085]		[0.230]	[0.183]
Observations	1766	1766	1766	1780	1780	1780	2277	2277	2277	2277	2277	2277

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Table 10: Pension fund active management tertiles: the relation between size and performance

In this table we sort the pension funds into tertiles base on their percentage allocation to actively managed assets. Afterwards, we regress the total returns on a six factor model that includes the MKT, SMB, HML, LIQ, MOM and FIMKT. In the next step we augment the alphas retrieved from the risk-adjusting regressions with the error terms of the first step and run Fama-MacBeth regressions and correct for autocorrelation and heteroskedasticity (using Newey-West with three lags). We include the following characteristics in all models: LogSize – log of average pension fund holdings in a given year and Size*Liq is an interaction term of the log fund size with the first step fund-specific loading on the liquidity factor. We also include two dummy variables Small and Large. These dummy variables are constructed by independently sorting the pension funds into four quartiles based on their assets under management. Small dummy refers to the pension funds belonging to the smallest size quartile, while Large captures the pension funds from the largest quartile. Columns (1) – (4) present the results for the tertile with the lowest percentage of actively managed assets. Columns (5) – (8) show the results for the tertile with the highest percentage of actively managed assets. The last row reports the number of observations included in the analysis. We report the coefficients with standard errors in brackets and denote significance levels with *, ** and ***, which correspond to 0.10, 0.05 and 0.01, respectively.

	Tertile with the lowest percentage active				Tertile with the highest percentage active			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.669***	0.984	1.172**	0.458*	0.811***	1.619	-0.993	0.917***
	[0.178]	[0.854]	[0.519]	[0.278]	[0.238]	[1.463]	[0.974]	[0.226]
LogSize		-0.034	-0.093			-0.105	0.168	
		[0.091]	[0.063]			[0.144]	[0.125]	
Size*Liq			-0.887**				-2.269***	
			[0.396]				[0.767]	
Small				0.351				0.023
				[0.387]				[0.761]
Large				0.401				-0.680**
				[0.379]				[0.341]
Observations	596	596	596	596	582	582	582	582

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Table 11: Persistence in pension fund performance

This table presents the marginal effects after an ordered logit model. The dependent variable is the quintile ranking based on returns in year *t+1* with 1 being lowest quintile ranking and 5 being the quintile with highest returns. The LY ranking independent variable is the quintile ranking in the previous year *t*. We also include the following variables: LogSize – log of average pension fund holdings in a given year, Costs – total fund costs, %Act – percentage of all holdings invested in active mandates and %Ext – percentage invested in external mandates. The marginal effects are estimated at the median values. In the ordered logit model we also add year dummy variables and cluster the standard errors by funds. Panel A presents the marginal effects for U.S. funds market timing returns and Panel B for U.S. funds security selection returns. The marginal effects are presented with their standard errors in brackets. We denote significance levels with *, ** and ***, which correspond to 0.10, 0.05 and 0.01, respectively.

Ranking	**Model 1**	**Model 2**		**Model 3**		**Model 4**		
	LY ranking	LY ranking	LogSize	LY ranking	Costs	LY ranking	%Act	%Ext
Panel A: Market Timing Returns								
1	-0.033***	-0.033***	0.003	-0.033***	-0.067*	-0.032***	0.017	-0.047*
	[0.009]	[0.009]	[0.006]	[0.009]	[0.036]	[0.009]	[0.034]	[0.029]
2	-0.009	-0.009	0.001	-0.009	-0.018	-0.009	0.005	-0.014
	[0.006]	[0.006]	[0.002]	[0.006]	[0.016]	[0.006]	[0.011]	[0.013]
3	0.007	0.006	-0.001	0.006	0.013	0.006	-0.003	0.008
	[0.006]	[0.006]	[0.001]	[0.006]	[0.013]	[0.006]	[0.006]	[0.009]
4	0.016***	0.016***	-0.002	0.016***	0.032*	0.016***	-0.008	0.023*
	[0.003]	[0.003]	[0.003]	[0.003]	[0.017]	[0.003]	[0.016]	[0.014]
5	0.020***	0.020***	-0.002	0.020***	0.041*	0.020***	-0.011	0.030
	[0.006]	[0.006]	[0.003]	[0.006]	[0.025]	[0.006]	[0.021]	[0.022]
Panel B: Security Selection Returns								
1	-0.017***	-0.016**	-0.014*	-0.017***	0.055	-0.017**	-0.004	0.049
	[0.005]	[0.008]	[0.007]	[0.006]	[0.035]	[0.008]	[0.031]	[0.036]
2	-0.007***	-0.007	-0.006	-0.007***	0.023	-0.006	-0.002	0.019
	[0.003]	[0.005]	[0.004]	[0.003]	[0.014]	[0.005]	[0.012]	[0.017]
3	0.001	0.002	0.001	0.002	-0.005	0.002	0.001	-0.006
	[0.002]	[0.006]	[0.006]	[0.002]	[0.009]	[0.006]	[0.004]	[0.020]
4	0.009***	0.008***	0.007**	0.009***	-0.029	0.009***	0.002	-0.026
	[0.003]	[0.003]	[0.003]	[0.003]	[0.018]	[0.003]	[0.016]	[0.016]
5	0.013***	0.013*	0.011*	0.013***	-0.043*	0.012*	0.003	-0.036
	[0.004]	[0.007]	[0.006]	[0.004]	[0.026]	[0.007]	[0.023]	[0.026]

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Figure 1: Asset allocation of U.S. pension funds

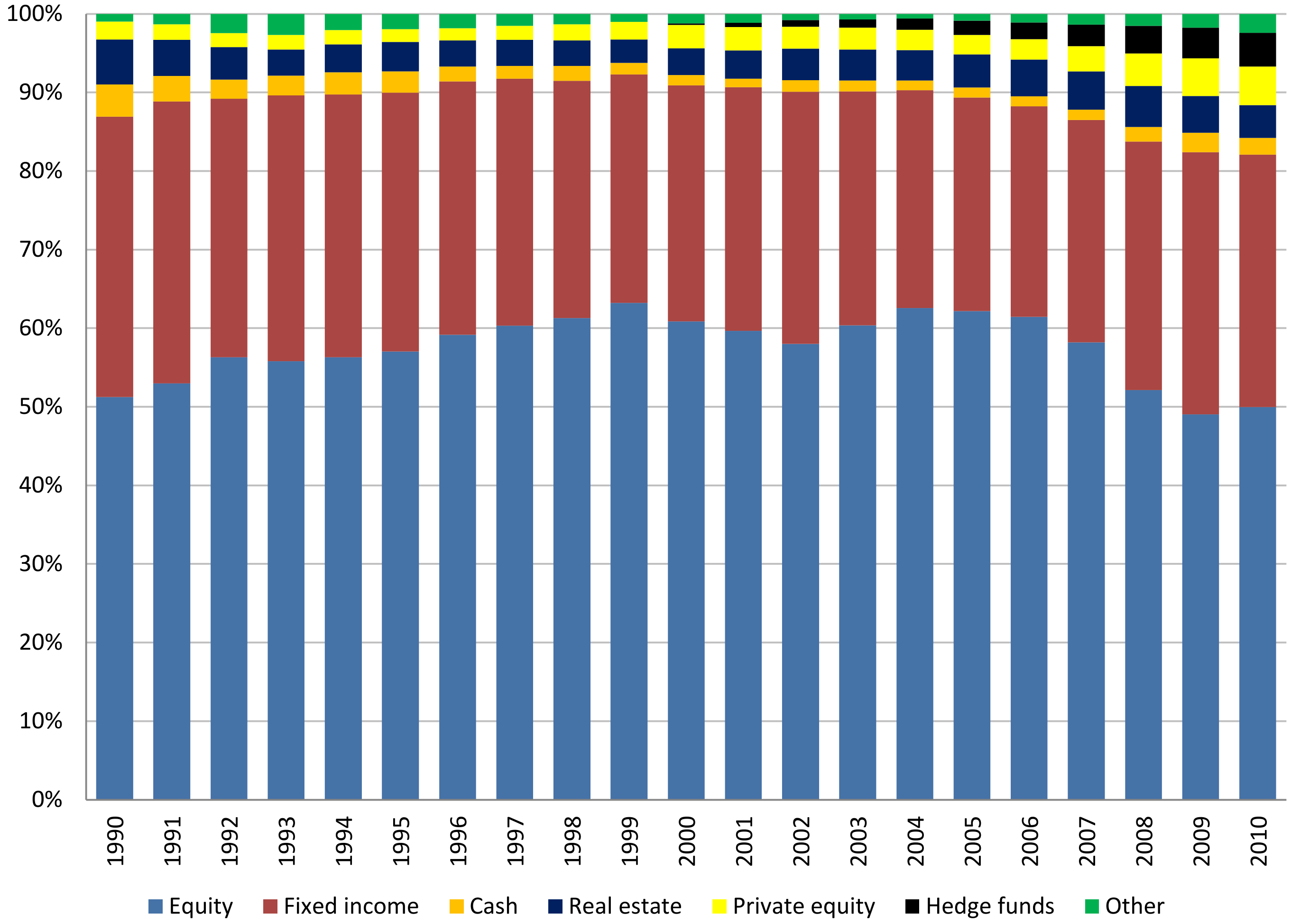

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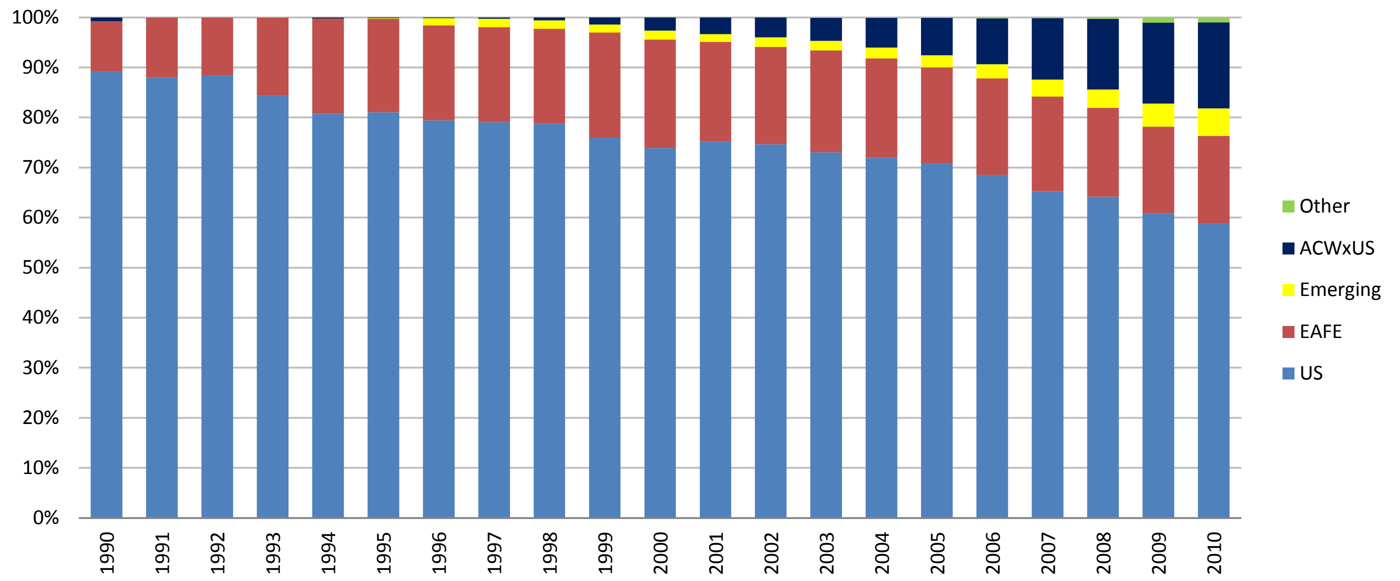
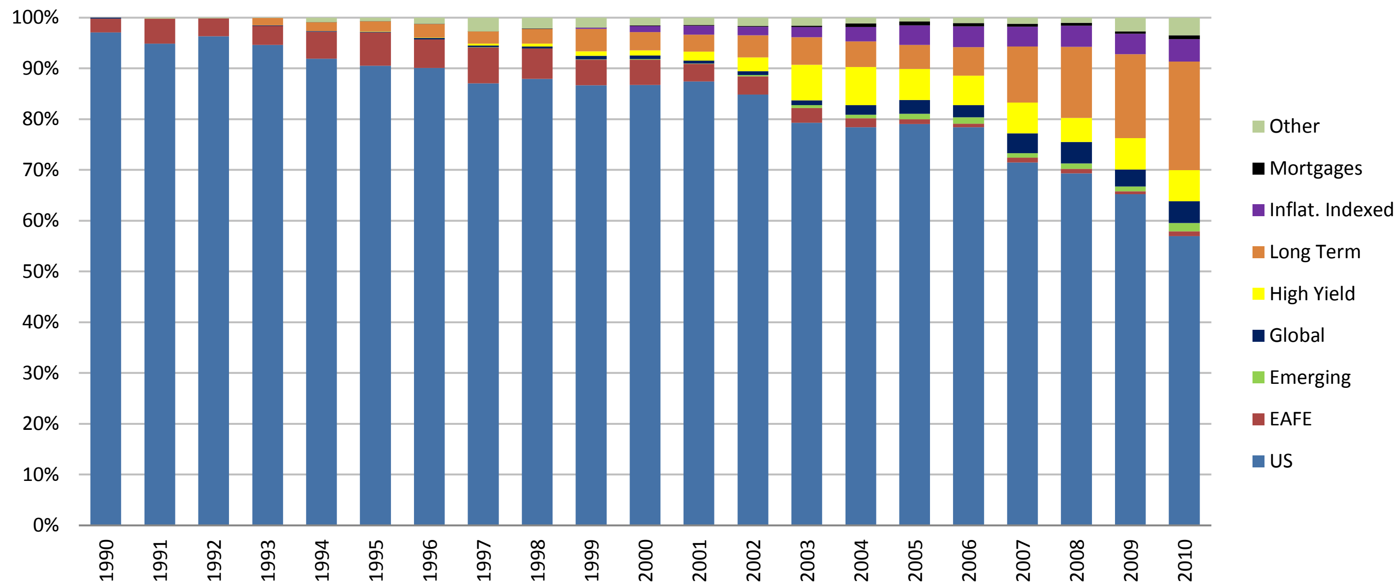
Figure 2: Asset allocation of U.S. funds within equity, fixed income and alternatives

Panel A: Average allocation within equity



Panel B: Average allocation within fixed income



Panel C: Average allocation within alternative assets

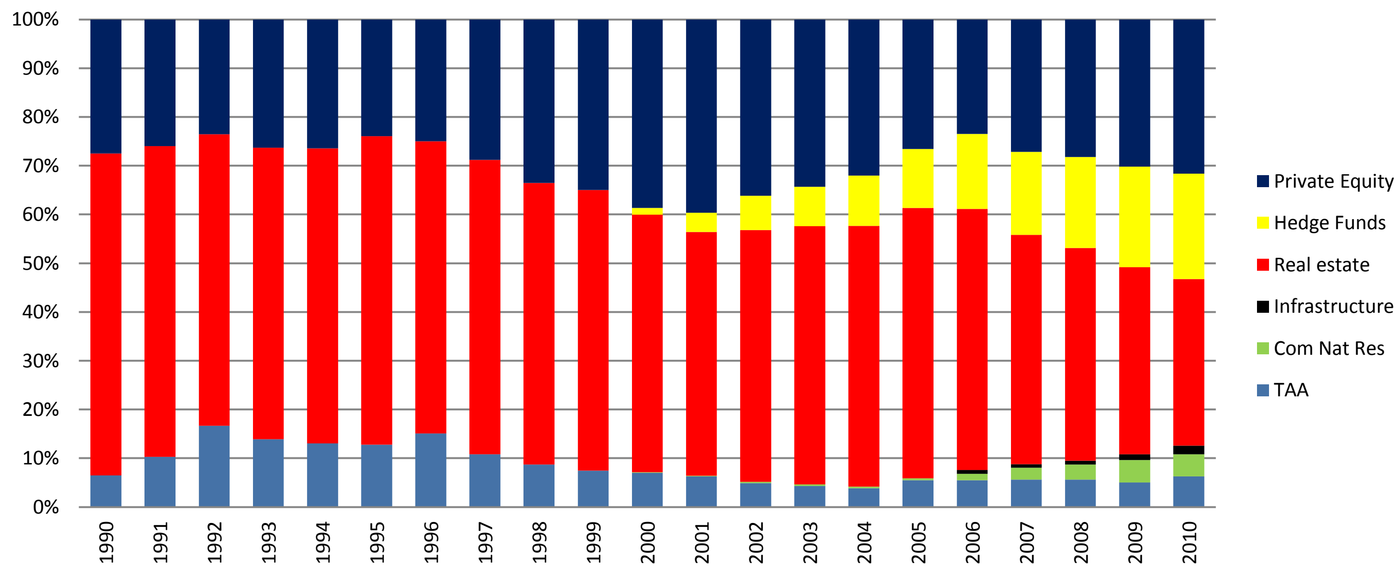


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Figure 3: Annual average investment costs on an overall fund level (all assets) and separately by asset class in basis points

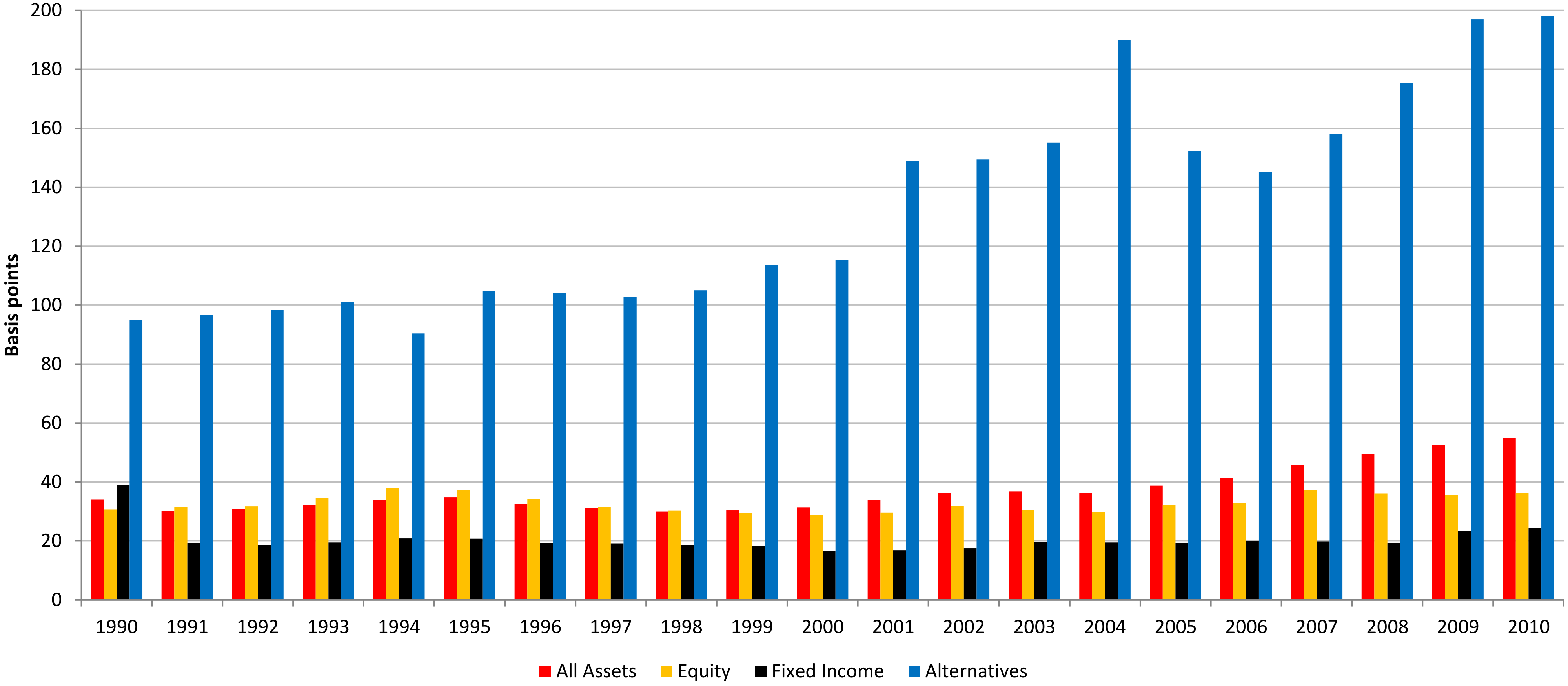

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Figure 4: Annual average gross returns on an overall fund level (all assets) and separately by asset class in percentage points

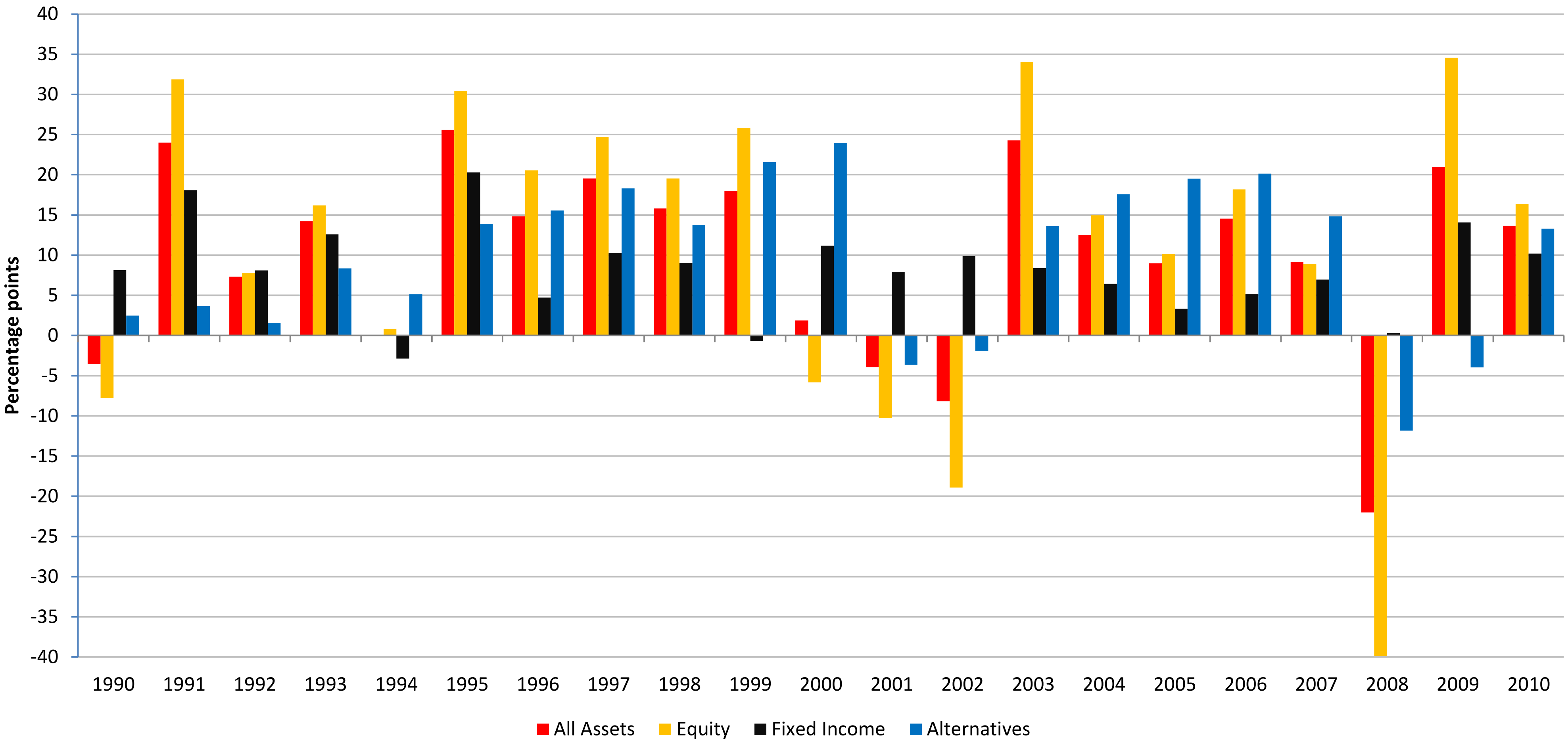

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Figure 5: Annual average return components on a fund level (all assets): total returns (TR), changes in asset allocation (AA), market timing (MT) and security selection (SS)

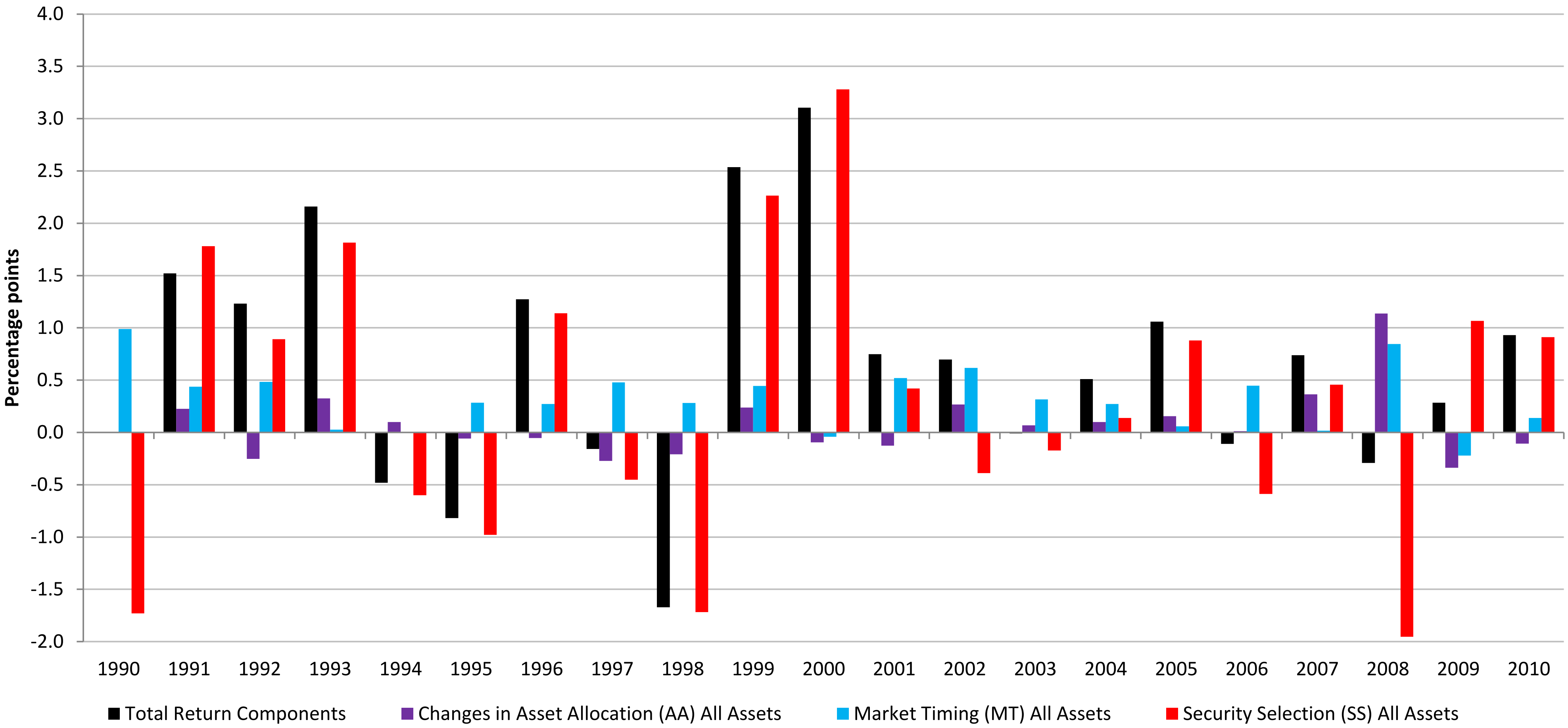

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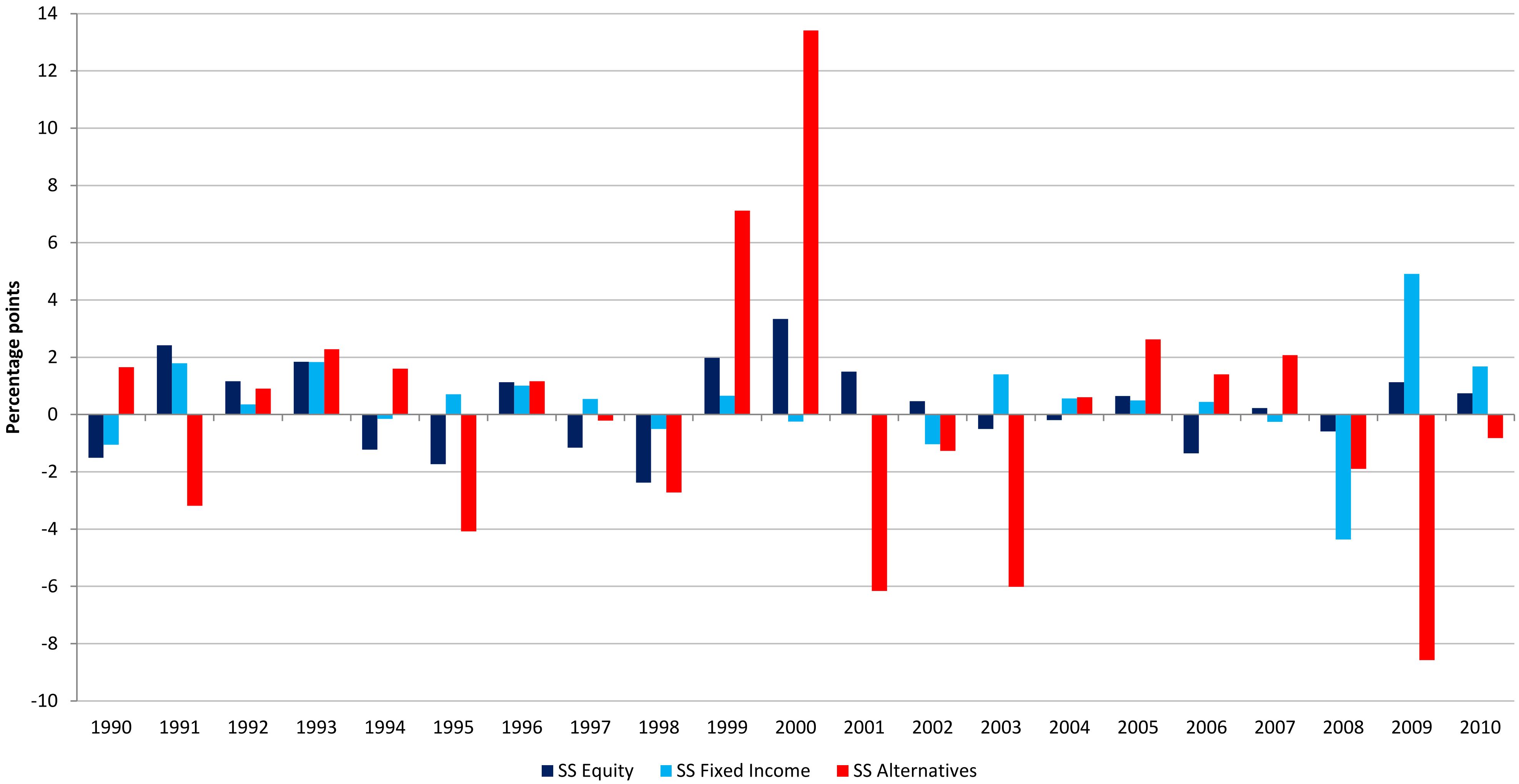
Figure 6: Annual average security selection returns (net benchmark-adjusted returns) by asset class



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Appendix Table A.1: Risk-adjusted performance per return components in all asset classes on a fund level (related to Table 6)

Robustness check – every fund included in the regressions below has at least 13 observations.

This table reports the net risk-adjusted performance at the fund level for all assets using a random coefficients model. First, we run the random coefficient model with a constant only for every return component. When risk-adjusting the return components, the following factors are included in the regressions: MKT, SMB and HML are the Fama-French factor returns, MOM – momentum factor, LIQ – Pastor and Stambaugh (2003) traded liquidity factor, FIMKT – fixed income excess market return. In Columns (1) – (3) the dependent variable is the total return which represents a sum of all three active asset management decisions: asset allocation, market timing and security selection. In Columns (4) – (6) the dependent variable is the return due to changes in asset allocation policy, which is calculated as the return due to changes in the strategic asset allocation weights in year *t* compared to year *t-1* multiplied with the benchmark return . In Columns (7) – (9) the dependent variable is the market timing component of fund returns , where is the policy weight for fund *i* for asset class *j* and year *t*, is the actual realized weight for fund *i* for asset class *j* and year *t* and is the benchmark return for fund *i* for the asset class *j* and period *t*. In Columns (10) – (12) we use the security selection component of fund returns as dependent variable , where is the realized net return on the asset class *j* for the year *t* by fund *i*. We report the annual alpha (Constant.) and betas with standard errors in brackets and significance levels with *, ** and ***, which correspond to 0.10, 0.05 and 0.01, respectively. RMSE is the root mean square error.

	Dependent variable: Return components in percentage points											
	Total return components			Asset allocation component			Market timing component			Security selection component		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	0.512***	0.828***	0.554***	0.060	0.319***	0.324***	0.256***	0.265***	0.198**	0.233**	0.166	-0.062
	[0.107]	[0.226]	[0.201]	[0.049]	[0.084]	[0.110]	[0.040]	[0.072]	[0.086]	[0.092]	[0.184]	[0.190]
MKT		-0.005	0.003		-0.012***	-0.012***		-0.005	-0.002		0.015**	0.021***
		[0.008]	[0.008]		[0.004]	[0.004]		[0.003]	[0.003]		[0.007]	[0.007]
SMB		0.044***	0.052***		0.007*	0.006*		0.004	0.006		0.033***	0.041***
		[0.010]	[0.011]		[0.003]	[0.004]		[0.003]	[0.003]		[0.009]	[0.009]
HML		0.008	0.015		-0.010***	-0.011***		-0.004	-0.002		0.015**	0.021***
		[0.009]	[0.010]		[0.003]	[0.004]		[0.003]	[0.003]		[0.008]	[0.008]
LIQ		-0.026*	-0.022*		-0.014***	-0.014***		-0.001	0.001		-0.006	-0.003
		[0.014]	[0.011]		[0.005]	[0.005]		[0.004]	[0.004]		[0.010]	[0.009]
FIMKT		-0.067***	-0.070***		-0.001	0.000		0.010	0.010		-0.049**	-0.056***
		[0.024]	[0.022]		[0.009]	[0.010]		[0.009]	[0.009]		[0.020]	[0.021]
MOM			0.018**			-0.001			0.003			0.016**
			[0.008]			[0.003]			[0.003]			[0.007]
Funds	75	75	75	76	76	76	98	98	98	98	98	98
Observations	1186	1186	1186	1203	1203	1203	1610	1610	1610	1590	1590	1590
RMSE	3.098	3.042	3.027	1.226	1.182	1.182	1.196	1.193	1.191	3.047	2.996	2.985

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Appendix Table A.2: Pension fund characteristics and security selection returns in equity investments

In Columns 1–3 we do not risk-adjust the security selection (net benchmark-adjusted returns) returns in and directly estimate the relations between them and pension fund characteristics using Fama-MacBeth regressions and correcting for autocorrelation and heteroskedasticity using Newey-West with three lags. Estimations in Columns 1–3 include all funds (observations), whereas in Columns 4–7 we risk-adjust the equity returns and include only funds with at least seven observations. In Columns 4–7 in the first step we regress the equity security selection returns on a five factor model that includes the MKT, SMB, HML, LIQ and MOM. In the second step we augment the alphas retrieved from the first step with the error terms of the first step and run Fama-MacBeth regressions and correct for autocorrelation and heteroskedasticity (using Newey-West with three lags). The following characteristics are included in the Fama-MacBeth regressions: %Equity – percentage allocation to equity from total assets, LogSize – log of the total equity holdings, Costs – investment costs, %Act – percentage in active mandates and %Ext – percentage in external mandates from the equity holdings. We also include Size*Liq, which is an interaction term of the log mandate size with the first step fund-specific loading on the liquidity factor. The Observations row presents the number of observations included in the analysis. We report the coefficients with standard errors in brackets and denote significance levels with *, ** and ***, which correspond to 0.10, 0.05 and 0.01, respectively.

	Security selection returns in equity			*Risk-adjusted security selection returns in equity*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.697*	-0.168	-0.278	-1.236***	0.341	-0.682	1.767
	[0.356]	[0.609]	[0.758]	[0.432]	[1.066]	[0.550]	[2.148]
%Equity	1.692**	1.313*	2.109**	2.529***	-0.576	2.574***	-1.725
	[0.661]	[0.754]	[0.851]	[0.789]	[0.997]	[0.774]	[2.068]
LogSize			-0.105		-0.005		-0.148
			[0.120]		[0.081]		[0.179]
Costs		-0.797				-1.780	
		[1.121]				[1.395]	
%Act			1.447				1.795
			[1.422]				[1.784]
%Ext			-1.018				-1.058
			[0.768]				[0.844]
Size*Liq					-1.432***		-1.493***
					[0.254]		[0.274]
Observations	3268	3268	3268	2412	2412	2412	2412

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Appendix Table A.3: Persistence in pension fund performance

In Panel A funds are placed into quintiles based on their market timing returns. In Panel B funds are placed into quintiles based on their security selection (net benchmark-adjusted) returns. High row or column represents the quintile with the highest market timing return. Percentages represent the probability that a fund which was ranked in one of the 5 quintiles in year *t* ends up in one of the quintiles in year *t+1* or exits the database. Exit column presents the percentage of funds exiting the CEM database in year *t+1*. Return in *t+1* columns present the market timing or security selection returns in year *t+1* of the top and bottom quintiles, which are formed in year *t*. Test Diff column is a t-statistic of the difference in returns between the low and high quintile.

Panel A: U.S. Funds Market Timing Returns

		Year *t+1* ranking						Return in *t+1*		Test
		Low	2	3	4	High	Exit	Low	High	Diff
Year *t* ranking	Low	**22.71%**	17.26%	11.95%	13.13%	12.54%	22.42%	0.086	0.211	1.36
	2	16.44%	**18.09%**	16.89%	12.11%	10.46%	26.01%			
	3	12.44%	16.19%	**19.94%**	15.59%	11.84%	23.99%			
	4	11.66%	15.55%	15.99%	**18.24%**	13.75%	24.81%			
	High	17.75%	10.17%	11.23%	15.63%	**20.64%**	24.58%			

Panel B: U.S. Funds Security Selection Returns

		Year *t+1* ranking						Return in *t+1*		Test
		Low	2	3	4	High	Exit	Low	High	Diff
Year *t* ranking	Low	**20.06%**	12.87%	13.77%	14.82%	13.77%	24.70%	0.130	0.450	1.27
	2	12.71%	**16.79%**	16.94%	16.49%	11.04%	26.02%			
	3	13.24%	16.89%	**16.89%**	15.53%	13.09%	24.35%			
	4	12.25%	16.04%	18.31%	**17.10%**	14.52%	21.79%			
	High	15.82%	11.83%	12.29%	14.29%	**20.58%**	25.19%			

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Appendix Table A.4: Replication of Dyck and Pomorski (2011)

This table can be compared with Table 3 of Dyck and Pomorski (February 2011). The dependent variable is the overall fund net benchmark-adjusted return in year *t* (security selection return component on a fund level). The main independent variable is the log of year t-1 fund size. Regressions are estimated over the pooled sample of U.S. and Canadian funds (All) or on a single-country level and, where indicated, we use also year fixed effects. Corporate is a dummy variable, which is equal to 1 if the pension fund is classified as corporate and 0 otherwise. Panel A presents the results using the entire sample period 1990–2010 period, whereas in Panel B we use a shorter sample period (1990–2008), which is comparable with Dyck and Pomorski (2011).

	U.S.	U.S.	U.S.	Canada	All
Panel A: Sample period 1990 – 2010					
Log of end of year t-1 plan size	0.054	0.051	0.075		
	(1.11)	(1.10)	(1.58)		
Corporate plan dummy			0.386		
			(2.81)		
Observations	2501	2501	2501		
R-squared	0.001	0.136	0.139		
Year fixed-effects	NO	YES	YES		
Plan fixed-ffects	NO	NO	NO		
Panel B: Sample period 1990 – 2008					
Log of end of year t-1 plan size	0.108	0.090	0.107	0.068	0.086
	(2.28)	(1.97)	(2.31)	(1.50)	(2.65)
Corporate plan dummy			0.268	0.179	0.221
			(1.98)	(1.38)	(2.22)
Observations	2175	2175	2175	1393	3568
R-squared	0.002	0.144	0.145	0.236	0.118
Year fixed-effects	NO	YES	YES	YES	YES
Plan fixed-effects	NO	NO	NO	NO	NO

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